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Présentée par Betty Alosa MULIANGA

Assessing spatial heterogeneity and temporal dynamics of sugarcane landscape in Western Kenya by remote sensing: Implications for environmental services

Soutenue le 12 décembre devant le jury composé de

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DEDICATION

To my husband, daughters and the very under privileged yet zealous woman; may this piece of work inspire and empower you to achieve your dreams in life. May it form the basis for your strength, courage and endurance today and always!

ABSTRACT

The objective of this thesis was to explore the contribution of remote sensing towards sustainable management of cultivated sugar cane areas in Western Kenya. Although widespread, burnt harvest sugarcane practice bans the use of crop residues for soil cover at the local scale, it contributes to decrease in physicochemical properties of soils and increase erosion risks. With this in mind, we worked on three specific investigations conducted at different scales: (i) the relationship between remote sensing data and sugarcane yield (biomass) at regional scale, (ii) the role of remote sensing data in mapping cropping practices and (iii) the impact of such practices on soil erosion at local scale. These questions were answered through a landscape approach and so we made use of remote sensing techniques integrated with GIS and expert knowledge, to describe and analyze the link between environmental services and landscape as seen from space.

At regional scale, we explored the suitability of Normalized Difference Vegetation Index (NDVI) from Moderate Resolution Imaging Spectrometer (MODIS) to forecast sugarcane yield on an annual base. We developed a statistical model between a new NDVI-based descriptor (wNDVI), that takes into account the growth period of the sugarcane crop, and historical yield data over 11 years and six growing zones. Correlation between yield and wNDVI is mainly drawn by the spatial dimension of the data set ($R^2 = 0.53$, when all years are aggregated together), rather than by the temporal dimension of the data set ($R^2 = 0.1$, when all zones are aggregated). A test on 2012 and 2013 showed that yield forecast with this model realized a RMSE less than 5 t ha^{-1} (4.2 t ha^{-1} and 1.6 t ha^{-1} respectively), leading to a mean RMSE of less than 5%. We showed that despite the use of broad resolution satellite images (250 m) in a smallholder agriculture conditions, it was possible to establish a yield forecast model at regional scale.

At local scale, a time series of Landsat 8 images were obtained for Kibos sugar management zone over 20 dates (April 2013 to March 2014) to characterize cropping activities. Sugarcane fields were mapped with 83.8% accuracy, and the harvest mode - green or burnt – was mapped for each field with 90% accuracy. A t-test on three spectral indicators - SWIR (Short Wavelength InfraRed reflectance), NDVI and NDWI (Normalized Difference Water Index) - between each two dates for sampled fields showed that at harvest time the change in SWIR were strong. Furthermore, NDWI differences (before and after harvest) were significantly different at $P = 0.000$ for green and burnt harvest modes, with a threshold value of 0.27 (> 0.27 for burnt harvest fields, and < 0.27 for green harvested fields), while NDVI differences were not significant. These results showed the role of the SWIR band in description of sugarcane harvest practice. On the same area, the impact of cropping activities on soil erosion risks was investigated using a fuzzy based soil erosion model FuDSEM. Maps produced exhibited a mosaic of low to high erosion risk depending on slope, crop type and practices. Seasonal variation in erosion risk was also demonstrated with the minimum risk in September (1.08) and the maximum risk in February (2.04). In conclusion, we showed that free satellite images could be used to characterize crop and quantify crop production and environmental services of agriculture – erosion control – in complex landscape such in the Kenyan sugarcane production area. However, future satellite missions like Sentinel-2 should permit monitoring sugarcane production at a finer resolution and so should improve the quantification of performances in agriculture.

Keywords: remote sensing, sugarcane, yield, soil erosion, cropping practices, environmental services.

RESUME

L'objectif de cette thèse est d'étudier la contribution de la télédétection à la gestion durable des zones de canne à sucre dans l'ouest du Kenya. Nous avons travaillé sur trois questions spécifiques menées à différentes échelles: (i) la relation entre les données de télédétection et le rendement de la canne à sucre (biomasse) à l'échelle régionale, et (ii) le rôle de la télédétection pour la cartographie des pratiques agricoles et (iii) l'impact de ces pratiques sur l'érosion des sols à l'échelle locale. Pour répondre à ces questions, nous avons adopté une approche paysagère et mis en œuvre des outils de télédétection, d'analyse spatiale et des connaissances expertes, pour décrire et analyser le lien entre les services de l'environnement et le paysage agricole vu de l'espace. A l'échelle régionale, nous avons exploré la pertinence de l'indice de végétation NDVI (Normalized Difference Vegetation Index) calculé à partir de données acquises avec le capteur MODIS (Moderate Resolution Imaging Spectrometer) pour prévoir le rendement de la canne à sucre sur une base annuelle. Nous avons développé un modèle statistique entre un descripteur original basé sur le NDVI (wNDVI), qui prend en compte la période de croissance de la canne, et des données historiques de rendement sur 11 ans et sur 6 régions de production. La corrélation entre le rendement et wNDVI est essentiellement d'ordre spatial ($R^2 = 0.53$, lorsque toutes les années sont agrégées ensemble), plus que temporel ($R^2 = 0.1$, lorsque toutes les régions sont agrégées). Un test sur 2012 et 2013 a montré que les prévisions de rendement ainsi modélisées avaient une erreur quadratique moyenne inférieure à 5 t ha^{-1} (4.2 t ha^{-1} et 1.6 t ha^{-1} respectivement), ce qui conduit à une erreur moyenne relative inférieure à 5%. Nous avons montré que malgré la faible résolution spatiale des images utilisées (250 m), il a été possible d'établir un modèle de prévision de rendement à l'échelle régionale pour une agriculture essentiellement familiale. A l'échelle locale, une série temporelle d'une vingtaine d'images Landsat 8 (avril 2013 à mars 2014) a été utilisée pour caractériser la zone agricole de Kibos. Les parcelles de canne ont été cartographiées avec 84% de précision, et le mode de récolte - en vert ou brûlé - a été cartographié avec 90% de précision. Un test statistique sur la différence entre deux dates de trois indicateurs spectraux - MIR (moyen infrarouge), NDVI et NDWI (Normalized Difference Water Index) - estimés sur des parcelles d'entrainement a montré un fort changement des valeurs dans le MIR au moment de la récolte. En outre, les différences de NDWI avant et après récolte sont significativement différentes (p = 0.000) pour les deux modes de récolte étudiés (> 0.27 pour les champs de récolte brûlés, et < 0.27 pour les champs récoltés en vert), tandis que les différences de NDVI ne sont pas significatives. Ces résultats ont souligné le rôle de la bande MIR dans la caractérisation des pratiques de récolte de la canne à sucre. Sur la même zone, on a étudié l'impact des pratiques agricoles sur les risques d'érosion des sols à l'aide du modèle FuDSEM. Les cartes produites présentent une mosaïque de risques d'érosion faible à élevés en fonction de la pente, de la culture et des pratiques de récolte. Les variations saisonnières ont également été montrées avec un risque d'érosion minimum en Septembre (1.08) et un risque maximum en Février (2.04). En conclusion, nous avons montré que les images satellites pourraient être utilisées pour quantifier la production agricole cannière à l'échelle régionale et pour cartographier les services environnementaux de l'agriculture – le contrôle de l'érosion - dans les paysages agricoles complexes de l'Ouest kenyan. Dans un avenir proche, les missions satellitaires de type Sentinel-2 devraient permettre un suivi plus fin de la production cannière et ainsi améliorer la quantification des performances du secteur agricole.

Mot-clés: télédétection, canne à sucre, rendement, érosion des sols, pratiques culturales, services environnementaux.

QUOTE

"We delight in the beauty of the butterfly, but rarely admit the changes it has gone through to achieve that beauty."

Maya Angelou

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1. INTRODUCTION

Sugarcane is produced in 127 countries around the world, with an annual contribution of 175.9 million tons of sugar (Andersson, 2010). In the year 2012, the world's largest sugar producer was Brazil, followed by India, China, Thailand, Pakistan, Mexico, Columbia, Australia, USA and the Philippines. Of this production, Africa's share was 5.8% with South Africa taking the lead, followed by Egypt, Sudan, and Swaziland (Andersson, 2010). Production of sugar in East Africa in 2012 was 1 million tons with Kenya contributing 50%. Sugarcane growing in Kenya started in the early 1900 around Lake Victoria, having been introduced by Indians who were engaged in the construction of the East African Railway. Sugarcane is now grown in Western and is currently being introduced in the coastal region. Compared to the low altitude coastal zone, the western Kenya landscape is unique with a hilly landscape and two agro-ecological zones (AEZ) comprising six sugar zones: (i) Chemelil, Kibos-Miwani and Muhoroni within a sub humid AEZ; and (ii) Mumias, Nzoia and Sony within a humid AEZ of Kenya. The western Kenya sugarcane landscape occupies a surface area of 202,304 ha with an annual average sugarcane yield of 68 t ha^{-1} (KSB 2013). This production is majorly rain fed in all the five sugar zones except in Kibos-Miwani zone where some irrigation is undertaken (KSB, 2012). Additionally, burnt harvest practice is widely conducted in Kibos with farmers giving reasons for this preference as reduced harvesting labour and minimized risks to attacks from snakes (Jamoza et al., 2013). Although burnt harvest sugarcane practice bans the use of crop residues for livestock and soil cover, at the local scale, it contributes to decrease in physicochemical properties of soils and increase erosion risks which impact sugarcane yield. Sugarcane yield is affected by factors that include; climatic, edaphic, agronomic, and varietal (KESREF, 2012) and therefore variation in yield differs from one zone to the other. Based on such factors, the sugarcane industry in Kenya is in difficulty today because of decreasing sugarcane yield, and increasing soil erosion.

A decreasing sugarcane production

The Kenyan annual sugarcane average yield, 69 t ha^{-1} that is based on fresh millable stalk, has been decreasing from the potential 100 t ha^{-1} for rain fed sugarcane (Jamoza et al., 2013) over the years and is now far lower than most of the East African sugarcane growing countries such as Ethiopia with 120 t ha^{-1}, Egypt 115 t ha^{-1}, or Tanzania 100 t ha^{-1} (FAOstats, 2013). In the leading sugar factory of Kenya (Mumias), this yield decreased by 42% between 1997 (110 t ha^{-1}) and 2009 (64 t ha^{-1}), while in Kibos-Miwani zone, it decreased by 17% between 2008 (73 t ha^{-1}) and 2012 (60 t ha^{-1}). This worrying trend is reported similarly in the other individual factories (KESREF, 2012) reporting spatial variability in zonal sugarcane yields and yet; the Kenyan sugar industry generates about Kshs 12 billion annually and supports directly and indirectly over 7 millions of its population. In this population, 291,000 are farmers, 7,462 are permanent employees in the factories and plantations; while the rest are their direct and indirect dependants. Sugarcane is the third largest contributor to Agricultural Gross Domestic Product (GDP) after tea and horticulture. Kenya's domestic demand for sugar is 780,000 metric tons against an average production of 500,000 metric tons which leaves a deficit of up to 280,000 tons that is met by imports from regional sugar producers. This low yield influences high social and economic impacts to the farmer and sugar industry at large, **and these calls for the urgent**

need to investigate the drivers for the spatio-temporal variability of yield and how to improve sugarcane productivity in this region.

Increasing soil erosion

Mendoza et al. (2001) found that sugarcane cropping has an advantage of protecting soil quality due to its spatio-temporal characteristic that provides vegetation cover in the landscape through the year based on management practices adopted by the farmer. Further, they realized that green sugarcane harvesting provides sufficient trash that minimizes inter-row cultivation by 50%, increasing water retention of the soils and thus reducing soil erosion. Opposed to green sugarcane harvesting in the humid AEZ of western Kenya, majority of farmers in the sub-humid AEZ, harvest burnt sugarcane exposing bare soils to agents of soil erosion. Furthermore, this sugarcane landscape extents from the plains into the escarpment foot with Kibos-Miwani zone, where galleys expose a threat of soil erosion risk in the heterogeneous sugarcane farms. The impact of this heterogeneity on regulatory ecological processes such as soil transport from the sloppy terrain into valleys and carbon sequestration using water as a facet for matter cycling in sugarcane fields is necessary to determine their influence on crop production and ecosystem functioning, for improved crop management and regulation of environmental services in space and time.

Whereas disadvantages of soil erosion have been documented, there is little etiquette in evaluating soil degradation characteristics in western Kenya. Knowledge on impact of sugarcane cultivation and harvest mode on soil degradation is critical in undertaking effective soil conservation for sustainable management of Western Kenya ecosystems (Gunnula et al., 2011; Oldeman et al., 2001). This is because this study assumes that harvest mode is a key determinant of erosion. **Therefore, there is an urgent need to investigate the spatial and temporal dynamics of soil erosion risk of sugarcane landscape to assess potential soil erosion based on environmental and human determinants.**

A complex land use system

Western Kenya is characterized by a great variability of ecosystems in relation to altitude, ranging from 1000 to 2000m, topography and soil types on short distances. The region produces the bulk of sugarcane besides the subsistence food crops such as maize, legumes and sorghum, due to its ideal climatic conditions that favor diversification and intensification of cropping systems. Sugarcane growing in the western region is mainly under rain fed conditions. It is grown in large-scale commercial schemes and also in detached small schemes among different land uses, in different agro-ecological zones. It is usually planted between April and September during the rainfall peaks. Harvesting is conducted all through the year depending on variety maturation using either green or burnt harvesting methods. These variable agro-environmental conditions coupled with crop management practices influence different maturity periods even for sugarcane that is planted at the same date, introducing high spatial and-temporal variability in the sugarcane cropland. Monitoring sugarcane cultivation in this landscape is therefore important in studying interactions in such heterogeneous landscapes due to its ratoon ability that makes it a perennial crop compared to other crops.

Furthermore, the combination of commercial sugarcane farming, subsistence food cropping and natural vegetation within the same geographical space provides configurational heterogeneity with landscape properties such as fragmentation, diversification, intensification and connectivity. This heterogeneity stems from a combination of inherent environmental variables that affect sugarcane cultivation such as topography, soil types, vegetation type, land use systems and crop management practices which are distributed as elements of the landscape. Spatial heterogeneity in agricultural landscapes has been attributed to adoption of ad hoc behavioral assumptions (KESREF, 2010). Different crop management practices such as tillage, fertilizer use, crop rotation and weeds and pests management contribute to different responses of the crop to climatic conditions. It is this human influence that affects landscape conservation, water quality, soil fertility and consequently, influence crop production.

As a consequence, spatial patterns that are observed in such diverse landscapes result from complex interactions between biological, physical and social factors. **Such complex spatial patterning may have an impact on agro-ecosystems functioning (Martinez and Molliconel., 2012) and on provision of environmental services in the landscape.**

Remote sensing: a tool to study landscape dynamics

Remote sensing technology provides the tools and methods to study the spatial and temporal dynamics of the agro environmental conditions and cropping practices and their impact on variations in sugarcane yield through a landscape approach. Moreover, temporal remote sensing data has been commended for monitoring spatio-temporal variability in vegetation development in response to changes in the environment and human management practices to which sugarcane phenology and productivity is dependent (Zarco-Tejada et al., 2005; Bégué et al., 2010). This is because of the high spatio-temporal characteristics of the landscape and two growing seasons in western Kenya.

Working hypothesis

The timelines of sugarcane cropping practices (planting and harvesting) in relation with the environmental variables (rainfall season, topography and soil characteristics) affect the rate of soil run off which further exacerbates spatio-temporal variability of this sugarcane production. It is important to ensure that planning for land preparation, planting and harvesting of crops in the hilly terrain is done in cognizance of climate and protection of soils from degradation for sustainable production by embracing mitigation and adoptive measures of soil conservation. Investigation of the link between crop production, climate and cropping practices and their impact on soil erosion is thus important because it is the demand for enhanced production that influences land degradation if mitigation and adoptive measures are not observed (Jolande and Paul, 2009; Oldeman et al., 2001).

We assume that there is a significant link between the landscape and environmental services, and therefore hypothesize that the landscape can be described in its spatial and temporal dimensions using remote sensing images. Figure 1 illustrates this hypothesis.

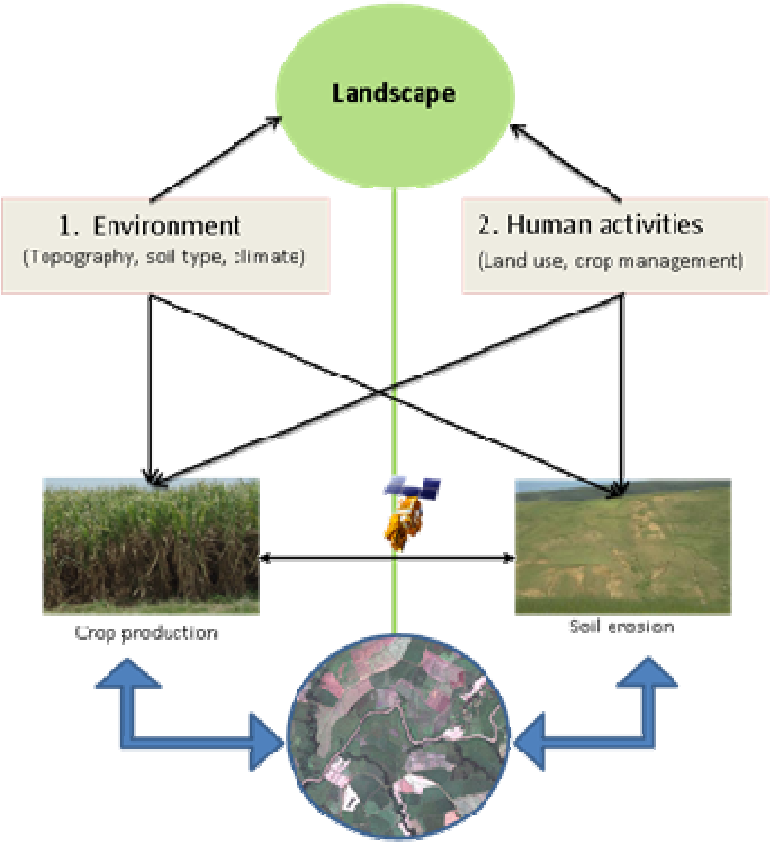

Figure 1: The observed agro-ecosystem using remote sensing; links between the Landscape and Environmental services at different scales.

Objectives

Based on these hypotheses, and taking into account the Western Kenya context, **the general objective of the study is to examine the relationship between environmental services and the sugarcane landscapes in Western Kenya, using remote sensing and a soil erosion model.**

Because of the scope of this question, we chose to work on two specific services that are very sensitive for the sugarcane industry in Kenya: i) sugarcane production and ii) soil protection. These two study cases address **three specific objectives conducted at different scales:**

- **To investigate the relationship between remote sensing data and sugarcane yield at regional scale**
- **To investigate the role of remote sensing data in mapping crop management practices at landscape (local) scale.**
- **To investigate the impact of sugarcane cultivation on soil erosion at landscape (local) scale.**

Providing information on yield and cropping practices (e.g. harvest mode) may help growers to change their actual practices. We therefore chose to answer these objectives through a landscape approach, and so we made use of remote sensing techniques integrated with GIS and expert knowledge, to describe and analyze the link between environmental services and landscape as observed from space. This approach is described in this document, through the following:

- Chapter 2: Background.

  It is a bibliographic review that provides the sugarcane context of western Kenya and the associated environmental services
- Chapter 3: Materials and methods.

  Presentation of the study area, the agronomic and satellite data used, the image processing methods and the soil erosion model.
- Chapter 4: Results
  - Part I: Regional scale: Forecasting regional sugarcane yield based on time integral and spatial aggregation of MODIS NDVI. This work was published in *Remote Sensing* journal (see Annex): Mulianga B., Bégué A., Simoes M., Todoroff P., 2013. *Remote Sensing*, 5, 2184-2199; doi:10.3390/rs5052184.

- Part II: Landscape scale: Cropping practices mapping (crop type, harvest date and mode) using Landsat8 30 m time series.
- Part III: Local scale: Analysis of the impact of the cropping practices and the environment on the soil erosion risk using a fuzzy based soil erosion model (FuDSEM).

- Chapters 5 and 6: General discussion and conclusion.

  The results are discussed in light of the usefulness for the sugarcane industry (How can the results be used by sugarcane industry?) and in link with KESREF research (What are the remote sensing research perspectives for KESREF?)

The results have been published (part I) and in preparation for publication (part II) in international journals. The in-form paper is given in the annex.

This research should permit to address operational questions

1. Which remote sensing indicator and environmental effects help in crop and landscape monitoring and provide information for sustainable management of sugarcane production in western Kenya?
2. How can spatial and temporal information contained in the satellite images be interpreted in terms of indicators for crop and landscape management
3. What is the impact of cropping practices and landscape organization on soil erosion risk of Kibos-Miwani landscape?

2. BACKGROUND

2.1. Sugarcane production context in Western Kenya

The sugarcane, a semi perennial crop

Sugarcane, Saccharum officinarum is of the tribe of Andropogonae and Gamineae family, and is defined as a semi perennial grass which grows within the tropics. It is known as a renewable agricultural resource, providing sugar, besides fiber, fertilizer and biofuel under ecological sustainability and as a product, it is an indispensable raw material in manufacture of various food, soft drinks and pharmaceutical products. After planting this crop and its maturing, it is harvested at variable periods which may be long depending on its variety, soil, topography, climatic conditions and farmer's management practices. The lengthy harvesting period influences varied regeneration of the crop (referred to as a ratooning), which introduces heterogeneity both in physiological development of sugarcane and crop yield (Bégué et al., 2010) even within similar agro-climatic conditions.

Agriculture in western Kenya

Presently, sugarcane is grown in six sugar zones of western Kenya under mainly rain fed conditions. These six sugar zones lie within two distinct agro ecological zones (AEZ) (Figure 2): the humid and sub humid zones. Mumias, Nzoia and Sony zones lie within the humid AEZ receiving an annual rainfall of 1700 mm – 1900 mm, while Chemelil, Muhoroni and Kibos-

Miwani zones lie within the sub humid AEZ with an average rainfall of 1400 mm – 1550 mm (Ribot et al., 2005). Sugarcane is grown mainly on the gentle slopes and plain areas within an altitude of 1000 m to 1600 m above mean sea level. It is planted between April and September, a season when there is sufficient soil water moisture from the bimodal rainfall (Shisanya et al., 2011). The sugarcane maturation period in this area lengthens to between 16-24 months and 14-18 months for plant and ratoon crop respectively (KESREF, 2010) depending on variety. Examples of diverse varieties planted in western Kenya is: C0421 which matures in 24 months for plant crop and 21 months for ratoon crop; while a neighbor may plant D8484 which matures in 16 months for plant crop and 14 months for ratoon crop (KESREF, 2010). In practice, the crop may not be harvested in time causing over maturation which may result in sugar loss (KSB, 2013). The variation in variety, planting dates, availability of labor and factory preparedness (capacity transport and mill) introduces different harvesting dates which combined with varied land utilization, introduces spatial heterogeneity in the landscape.

There are diverse farming scales at: i) industrial scale where the farmer grows sugarcane in pure stand, mainly under one variety for each field; while small scale farmers grow sugarcane besides subsistence crops such as: maize, beans and groundnuts, aiming at crop diversification and intensification either through intercropping or besides sugarcane fields. The multiple planting and harvesting dates, together with these subsistence crops lead to a landscape with vegetation throughout the year which is assumed to reduce the rate of run off, consequently reducing soil erosion (Mendoza et al., 2001). As opposed to the coastal region of Kenya where sugarcane is being introduced at low altitude (less than 100 m above mean sea level) fully under irrigation, In western Kenya, an altitude below 1800 m above mean sea level, an average of 1500 mm rainfall over the growing period and maximum daily temperature range, between 20°C– 30°C is ideal for this agricultural system; while rainfall below 1500 mm attracts supplementary irrigation (KESREF, 2010). It is assumed that sugarcane yield and that of other crops is affected by this variation in altitude, temperature and rainfall distribution and quantity (Amolo et al., 2009) which is a threat to food productivity in cases of climate change and also a threat to local effects of deforestation on expansion of agricultural land.

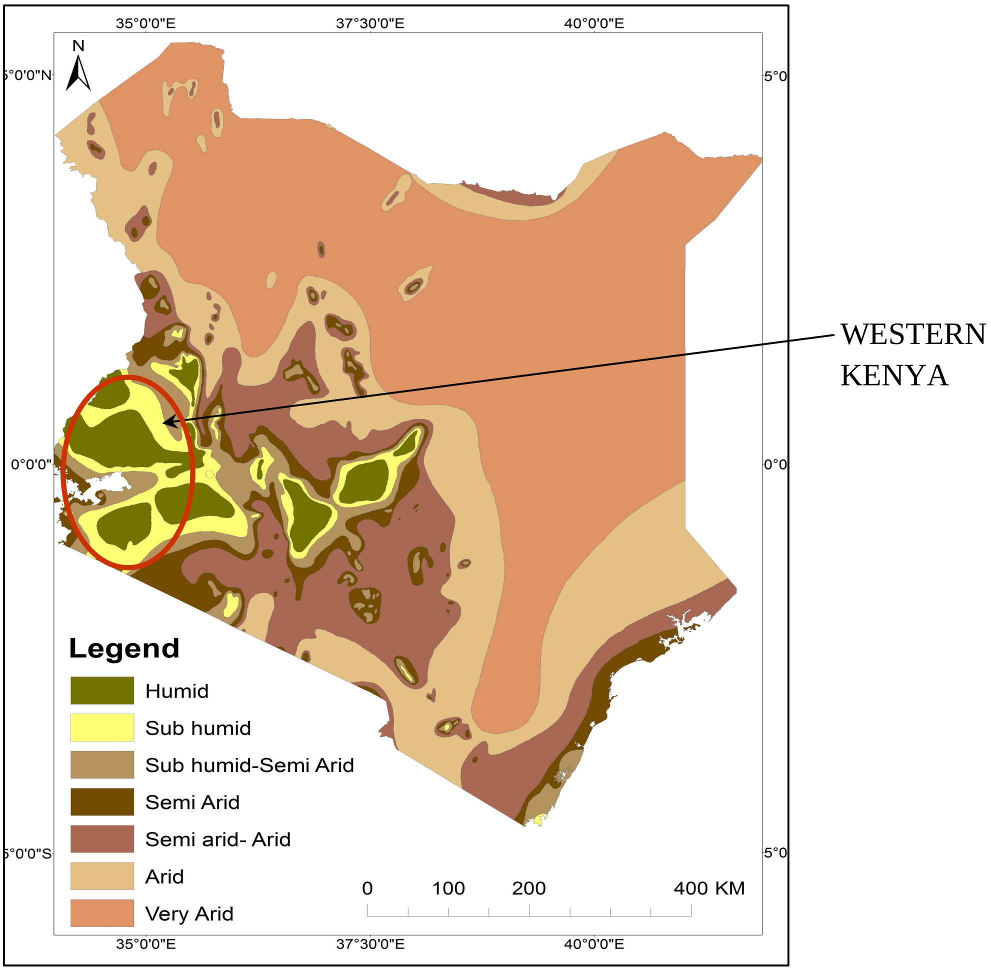

Figure 2: A map of Kenya showing Agroecological zones. The western Kenya region lies within the humid and sub humid agrocecological zones. Source: Ribot et al., 1985.

The sugarcane yield and acreage

Sugarcane yield in the humid AEZ is at 69 tons of cane per hectare (t ha^{-1}), while that of sub humid AEZ is at 57.1 t ha^{-1} (KSB, 2012). This production trend contributes to about 70% of the domestic sugar requirement in Kenya, while 30% deficit is met through imports (Wawire, 2005). There is a rather stable sugarcane yield of about 71 t ha^{-1} between 2001 and 2008; while, during the 2009 and 2013 period, there is an average yield of 63 t ha^{-1} and this shows a decrease of 6% in yield. Similarly, the evolution of surface area under sugarcane in western Kenya region has significantly increased (35% between 2001 and 2008, and by 53% between 2009 and 2013), with inter-annual variations (Figure 3) such as the decrease in the sugarcane surface area by 7% between the year 2008 and 2009 (KSB 2013), consequently decreasing the mean calculated yield, by 8 t ha^{-1}. This decline in production and yield (Figure 3) implies that various factors such as environmental (rainfall, temperature), land fragmentation, soil degradation, and socio-economic factors; had an effect on this production.

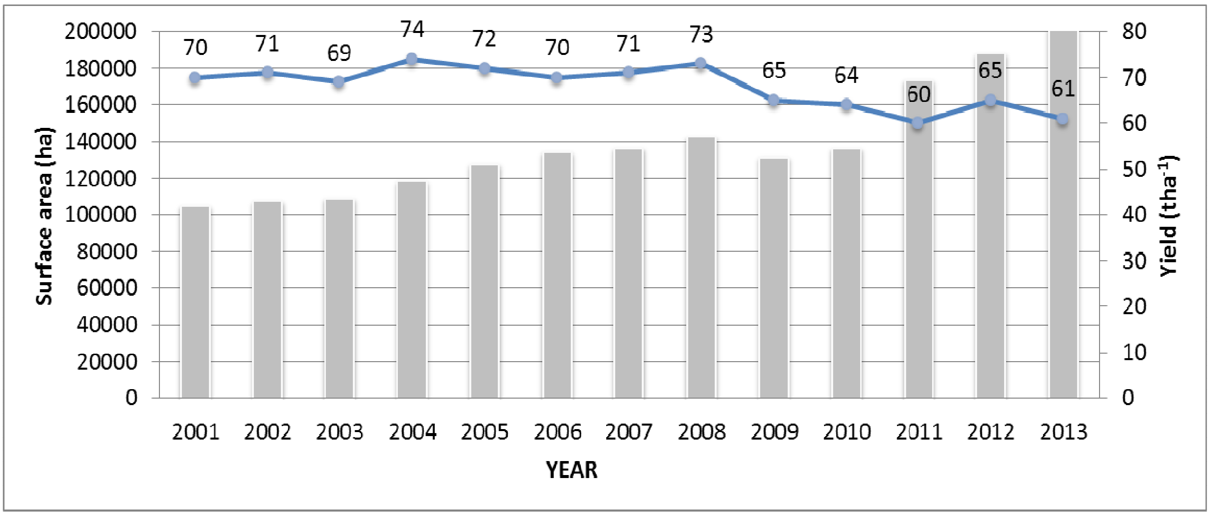

Figure 3: Evolution of the annual surface area under sugarcane (grey bars) and sugarcane yield (blue line) in Western Kenya (2001-2012). Source: Kenya Sugar Board, yearly book of statistics (2012).

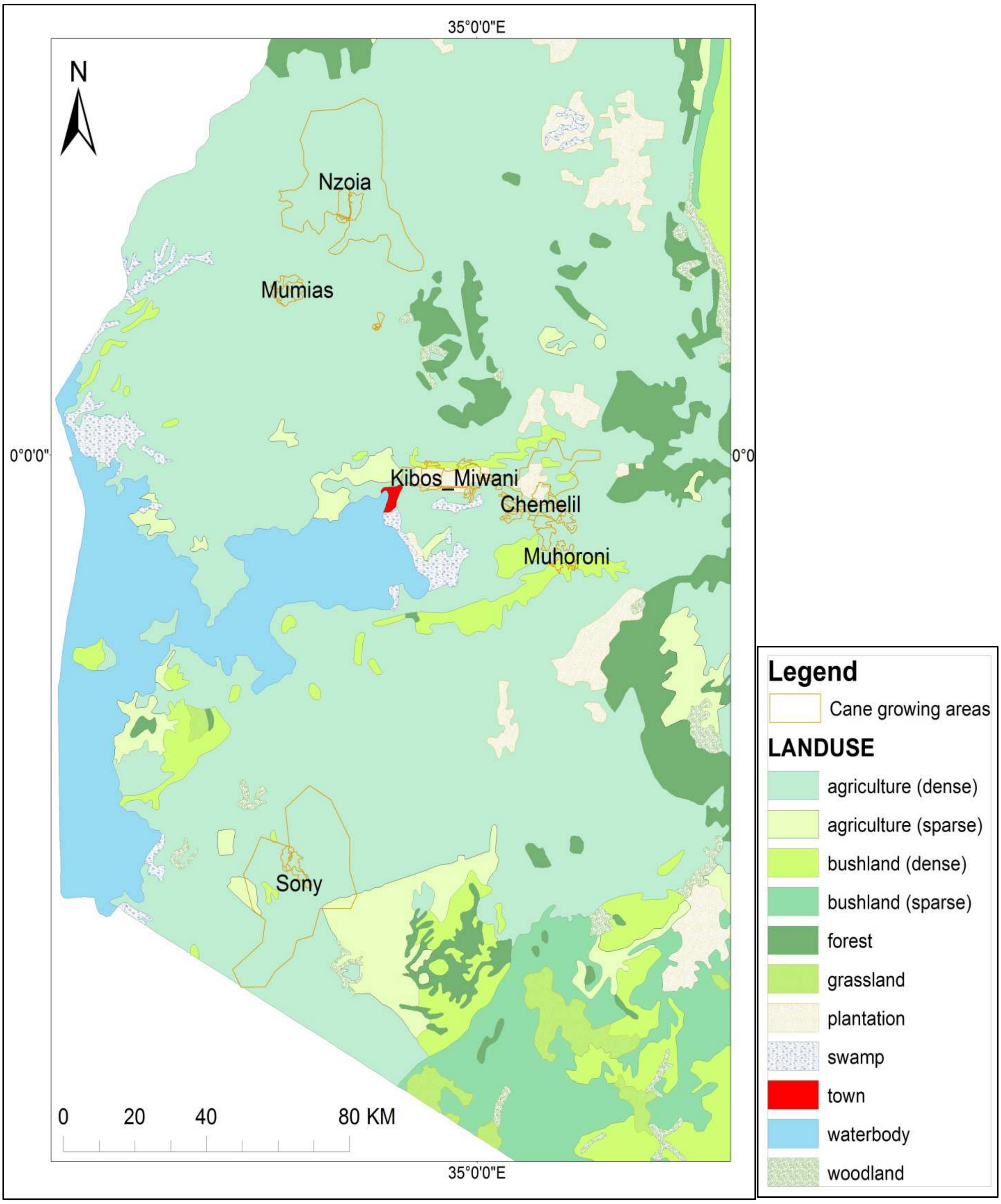

Figure 4: The land use of the western Kenya region with sugarcane (orange polygons) confined to selected areas around Lake Victoria. Source: (FAO, 2012, Atlas 2003).

The western Kenyan environment and farmers' adaptation

Western Kenya is characterized by a great diversity of ecosystem due to its topography that presents of hills, valleys and gentle plains and complex crop mosaics in relation to soil, insolation and altitude. Moreover, deep fertile soils in the lowland that retain moisture for a long period to support agriculture as evidenced in the land use map (Figure 4) (Atlas 2003, FAO 2012).

Deep soils that are well drained with a pH of 5-7 and free from toxic metals are ideal for sugarcane cultivation in Kenya (KESREF, 2010). Soils of western Kenya are dominantly black cotton cambisols in the low lands and sandy loamy acrisols in the highlands (Jaetzold et al., 1985). These soils have been subjected to pressure through intensification, to satisfy the ever increasing population contributing to yield decline over the years (Jaetzold et al., 2005). In their research, Jaetzold et al. (2005) proposed the combination of artificial fertilizers with nutrient recycling such as from farm manure, crop residues and animal excretions, for a sustainable increase in crop yields. In practice, farmers in Western and South Nyanza sugar belts prefer to harvest green sugarcane and trash line sugarcane residues between sugarcane rows. It is assumed that nutrient provision from decomposing litter minimizes use of artificial fertilizers to enhance sugarcane productivity (Mendoza et al., 2001). Furthermore, Mendoza et al. (2001) emphasize that sugarcane trash lining minimizes inter-row cultivation by 50% by suppressing development of weeds, increasing water retention of the soils and reducing soil erosion.

The sugarcane industry organization

Until 2010, transportation of harvested sugarcane in western Kenya was charged on farmers depending on distance from the mill. Farmers were encouraged to supply their sugarcane to a mill within 40 km radius from their farms (KESREF 2010) to minimize on this cost by industry and ensure timely delivery of the harvested sugarcane to minimize sugar loss (KSB, 2010). This regulation has since been waived with introduction of privately owned mills and farmers are now charged a flat transportation rate (same transport cost per ton regardless of the distance). This flat transport cost is meant to address the farmers' need for a free market and to encourage competition within the sugar Industry, aimed at increasing sugarcane production. Although not yet legalized, the introduction of the free market in the sugar industry has encouraged farmers to sell their sugarcane to the factory that pays the highest rate for higher financial flow. It is assumed that this competition for high financial flows motivated farmers to expand the surface area under cane by 51,000 ha between the year 2010 and 2012 up from the constant average of 10,000 ha since the year 2001 (Figure 3).

2.2. Link between landscape and environmental services

The landscape is a spatial human –ecological system that delivers a range of functions that are valued by mankind due to economic, cultural and ecological benefits. These benefits, also referred to as environmental services, include: food production, climate regulation, erosion control, carbon storage, clean air, clean water and biodiversity (Chan et al., 2006; Jolande and Paul, 2009). Consequently human activities such as depletion of natural resources, decreased production and soil erosion may reduce the provision of ecosystem services as feedback. Research has shown that human induced activities on soil in Africa (Bezuayehu and Sterk, 2010) have subjected agro ecosystems to vulnerability of soil erosion. Tropical regions are most vulnerable due to rainy climate, fragile soils (Claessens et al., 2008) and improper land uses (Pimetel, 2006; Metternicht and Gonzalez, 2005). Balanced actions of managing natural resources are critical in achievement of enhanced productivity of the landscape (Andersson, 2010). The actual functioning of the landscape therefore depends on the interaction between physical structures that influence natural processes and human activities. The challenge that faces populations is to maintain the provision of these environmental services under changing climatic conditions to support the functioning of natural ecosystems (Eswaran et al., 2001). Increase in populations initiate varied demands on the agricultural landscape for provision of environmental services to the society. These services are provided by the landscape if humans embrace an integrated management approach considering both mitigation and adaptation measures in their use of the landscape (Jolande and Paul, 2009). Further, Jolande and Paul (2009) state that if management practices of the landscape are changed, both mitigation and adaptation measures will be included in the utilization of landscapes for resilience against climate change. Figure 5 shows a typical landscape of western Kenya providing environmental services such as: erosion control (hedges, terraces) and food production.

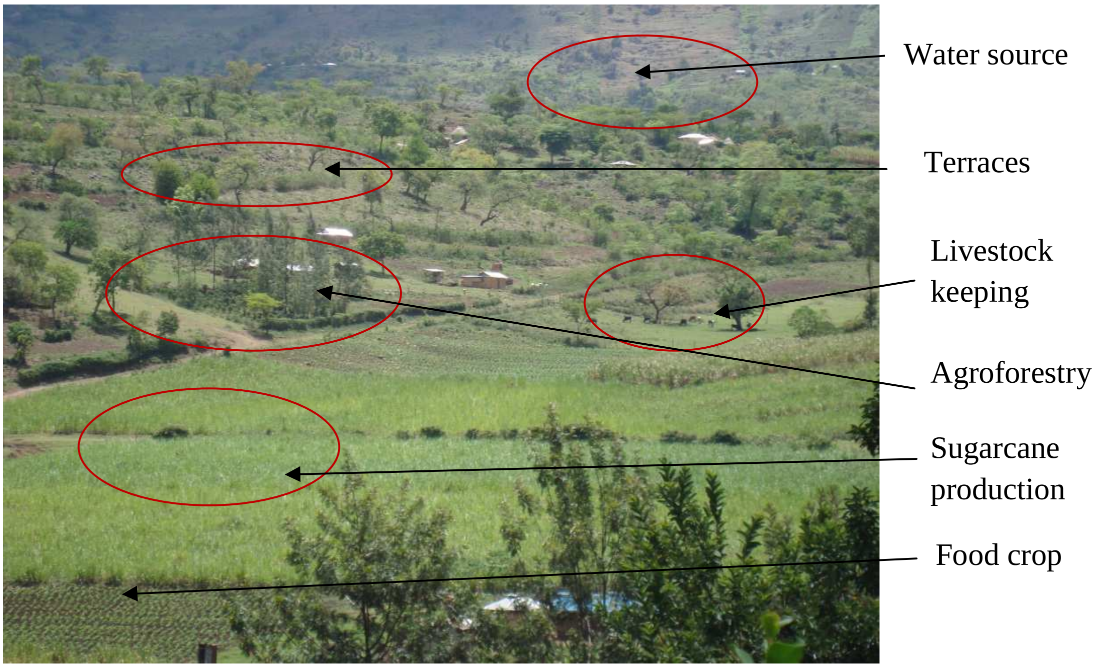

Figure 5: A picture showing an interface between landscape elements in the escarpment and plain. The picture shows a spatially heterogeneous landscape with potential properties upward (trees, wood, hedges, crop mosaic) and open fields with a mosaic of sugarcane and food crops. (Taken by KESREF during a field survey in October 2013)

Different crop management methods applied at given elevations will determine how much water is retained in the soils, soil organic matter content and status, and its impact on food production, plant biomass to diversify livelihoods, soil carbon storage, fodder for increased cattle rearing and natural areas for conservation (Andersson, 2010).

2.2.1 Landscape and sugarcane production

The western Kenya sugarcane landscape presents three contrasted farming systems namely: (i) Nucleus systems, (ii) large scale systems and (ii) small scale systems. Nucleus systems are those that are owned by the factories with each of the fields measuring over 10 hectares. Large scale systems are those that measure over 10 ha and are owned by large scale private farmers. Small scale systems are those that measure below 10 ha and comprise small scale private farmers. The Kenya sugar industry refers to private farmers as out growers with over 85% of the total sugarcane in Kenya being supplied by out growers, whilst the remaining 15% is supplied by nucleus estates (KSB, 2012). The three systems provide three sugarcane stakeholder models in the landscape as: (i) large scale models, (ii) small scale models and (iii) the miller as illustrated by Figure 6. The nucleus and large scale are both composed of pure sugarcane stand; while small scale models are composed of mixed cropping system, usually within diversity of land cover such as trees, hedges, wood. The three models are characterized with high level of intensification (crop types, exchange of services) and variability in yield within the same landscape.

Both large scale and small scale models supply sugarcane to the miller for processing and receive finances paid by the miller. Small scale models offer labor to both the large scale holders and millers. The miller provides fertilizer, processing, financial services and advisory services (technology transfer) on crop management to the large scale and small scale models. The miller further provides land preparation services for contracted small scale models, while those who are not contracted together with large scale holders prepare their own land. These variable land preparation methods include manual and mechanical techniques, which when influenced by rainfall and soil management practices, impact on sugarcane production.

The landscape among small scale models is heavily fragmented with both sugarcane and food crops in respective agronomic fields. A baseline survey by KESREF (2013) revealed that the minimum agronomic field size for a small scale holder was 0.2 ha with more than three food crops in the farm with high levels of crop rotation. These small fields face high costs of input at farm level because farm inputs are charged by the factory at one hectare unit including land preparation; and this becomes uneconomical for such farmers. These high input costs impact negatively on sugarcane yield when farmers lack essential inputs due to poor economic returns. From the baseline survey, about 30% of these farmers apply alternative recommendations such as manure instead of mineral fertilizers, while about 20% prefer intercropping with legumes to fertilizer use to minimize costs. Some factories have intensified services for small scale models by combining their fields into blocks for effective provision of land preparation, delivery of seed cane, educative services, harvesting and transportation at reduced costs. Land preparation for small scale farmers is equally affected with farmers resorting to manual labor who do not plough the necessary depth for root penetration and these impacts negatively on yield. Other land preparation methods such as no tillage and agro-ecology principles have not yet been rolled to the industry because it is still under experimentation by Kenya Sugar Research Foundation (KESREF). The blocking approach however does not reduce the cost of individual farm inputs on fertilizer and seed cane and this affects sugarcane production. Large scale holders on the contrary, enjoy minimum costs of input at farm level and are characterized with high profits for fields that receive all farm inputs. Although small holders provide labor to large scale farmers and the miller for income, they do not spend similar time for their own fields, and this influences spatial variability in yield between these three models in the given landscape. Although the large scale model benefits economies of scale, it is disadvantaged on the benefits that accrue from crop rotation and therefore, their yield is equally affected due to lack of soil nutrients. These conventional intensive practices increase risks of soil erosion and fertility depletion in the long run.

These diversified crop management systems; farming systems, land preparation approaches, planting and fertilizer use introduce heterogeneity in space which this research aims to characterize using remote sensing.

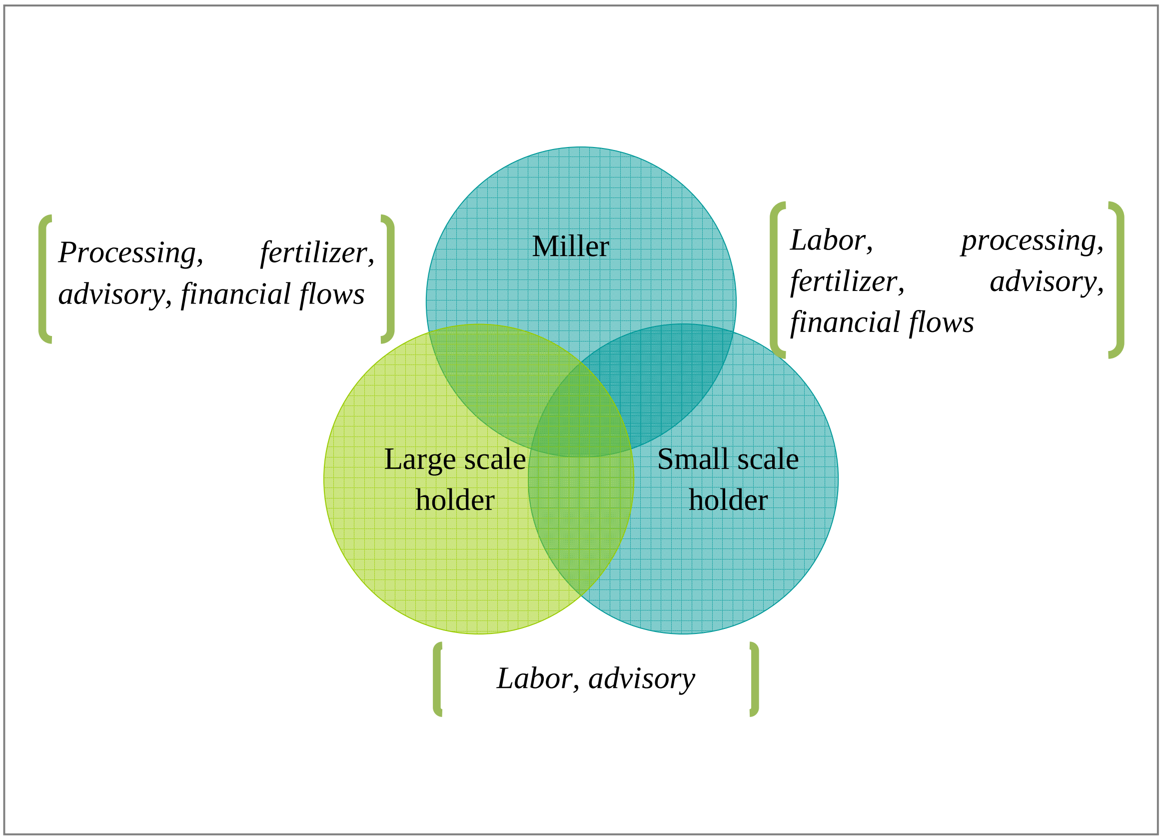

Figure 6: Stake holders in the Kenyan sugarcane agro-ecosystems and interactions among them as influenced by economic and environmental relationships (labor, technology transfer, fertilizer, harvesting, sugar processing, marketing and financial services) among others.

2.2.2 Landscape and soil erosion

Soils fundamentally contribute to primary production, through the supply and recycling of nutrients and water to plants and microorganisms in natural ecosystems as well as in agricultural production ecosystems (Jaetzold et al., 2005). Pressure on these soils through agricultural activities introduce degradation at varied scales in time and space, depending on the topography, soil characteristics and crop management practices in the landscape. The loss of soils from the landscape was seen as a critical phenomenon to natural resources (Saavedra, 2005) in the 21st century (Reich et al., 2000). Soils are lost from areas designated as hot spots (Anejionu et al., 2013) in the agricultural landscape where poor tillage methods and poor soil conservation measures (Valentin et al., 2005) are observed. Soil erosion leads to land degradation which affects crop production and environmental aesthetics. Landscape degradation therefore remains important among global issues of the 21st century due to its negative effects on agricultural productivity (Eswaran et al., 2001). Continuous use of this landscape without observing mitigative and adoptive measures declines the quality of land, impacting heavily on agricultural productivity of both the degraded (eroded) areas and areas of sediment deposits (Eswaran et al., 2001; Jaetzold et al., 2005). Research has shown that productivity of eroded landscapes has declined by 50% in the 21st century, contributing to a continental mean yield loss of 8.2% (Andersson, 2010), by 30 to 90% in West Africa (Mbagwu et al., 1984; Lal, 1998) and by 36% in Kenya (KESREF, 2012; Mutonyi and Muturi, 2013).

Land degradation has been reported to be common in Africa due to human induced activities on landscape (Bezuayehu and Sterk, 2010) in the tropical region that has a rainy climate, fragile soils (Claessens et al., 2008) coupled with improper land uses (Pimetel, 2006; Metternicht and Gonzalez, 2005). Soils washed away from such landscapes carry along nutrients and are deposited in water ways. This erosion is influenced by exogenetic processes such as wind or water flow, exacerbated by human activities. Indicators of soil erosion in agricultural landscapes include rills, gullies, granites and siltation (Okoba and Sterk, 2006), which influence crop production and soil fertility.

It is therefore important to investigate the susceptibility of the landscape to erosion to prevent soil and nutrient loss (Cohen et al., 2008) for a sustainable productivity of any ecosystem. As suggested by Sara et al. (2012), it is important for farmers in the uplands to embrace erosion control measures such as use of terraces and enhanced natural vegetation for continuous soil cover to minimize downstream flooding (Andersson, 2010). Such a conservation measure will minimize erosion and enhance crop productivity in the uplands. In the low lands, siltation of water streams will be reduced and thus clean water service provided for the ecosystem. In the hilly landscape of western Kenya, the multiple cropping system, planting and harvesting dates introduce spatial heterogeneity in the landscape which contribute at different scales to soil erosion risk. As argued by Jolande and Paul (2009), variable land preparation practices may introduce different levels of soil degradation in the landscape unless conservation measures are observed. Although effort has been made on soil conservation, the sensitivity of the landscape to erosion risk has not been documented in western Kenya. This documentation should include potential soil erosion risk for a sustainable land management system at landscape level.

2.2.3 Role of sugarcane in the western Kenya landscape

Sugarcane farming in the western Kenya landscape (Figure 2) provides trash that is useful for improving levels of soil organic matter and in conservation of soil moisture (Eldridge, 2004). Improvement of soil organic matter improves soil fertility and yet enhances sugarcane yield. The more dry mass produced the more organic matter available to the soil. This is influenced by conservation practices such as: no tillage, cover crops and crop residue preservation on fields. Yield in clay soil within the valleys and plains is improved through raking of burnt cane trash from rows (Eldridge, 2004). This partly explains why farmers in the clay rich soils of Kibos-Miwani sugar zone burn their cane before harvesting, while those found within sandy loam, well drained soils in western and south Nyanza sugar belt prefer green cane harvesting. It is assumed that sandy soils are more sensitive and reactive to soil organic matter decrease.

Recent studies have found that burnt cane harvesting reduces yields by 20% while 8% sucrose content is increased in the 3rd ratoon for green harvesting (Wiedenfeld, 2009). In the south Nyanza and western sugarcane belts of Kenya, over 90 % of farmers harvest green sugarcane while 85 % of those in Kibos-Miwani sugar zone burn their cane before harvesting. These two harvesting methods impact the environmental services provided by sugarcane farming such as production, clean air and soil protection. These harvesting modes influence risks of erosion first mechanically with residues or no residues on soil, and secondly, by improving the soil structure.

An exploration on the average yield over 10 years in zones that harvest green cane and burnt cane harvesting in Kenya realized an average yield of between 65 t ha^{-1} and 57 t ha^{-1} respectively, statistically computed at regional scale (KESREF, 2013). The reason for this variability in yield in the different agro ecological zones is therefore attributed to soil degradation, and the different cropping practices (planting date, harvesting mode) coupled with variable rainfall (over 1500 mm in humid agro-ecological zones and below 1500 mm in sub humid agro-ecological zones) (Amolo et al., 2009). Soil carbon emission has also been found to increase in burnt fields impacting on soil moisture and temperature and therefore sugarcane yield variability (Panosso et al., 2009).

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2.3. Remote sensing

2.3.1 Earth observing systems and their derived metrics

Current Earth observing systems have optical sensors ranging from submetric spatial resolution for local studies to hectometric resolution for regional studies (Table 1). These systems provide descriptors of the land cover based on pattern, colour, texture and dynamics of the image radiometry (Table 2). This study will utilize low and high resolution (250 m to 30 m) optical images from MODIS and Landsat respectively, to characterize the landscape of Western Kenya.

Table 1: Examples of optical Earth observing systems.

Satellite/sensor	Description	Resolution
Quick Bird Pléiades	Very high spatial resolution images	Metric and sub-metric resolution
SPOT Landsat	High spatial resolution images	Decametric resolution
MODIS VEGETATION	Low spatial resolution	Hectometric / Kilometric resolution

Table 2: Contribution of satellite image data properties in the description of the landscape elements.

Satellite image	Landscape elements
Spatial resolution	Pattern, networks, texture / structure of the landscape
Spectral bands	Land cover and land use types abundance and dispersion.
Repetitivity	Annual and seasonal variations
Altitude	Topography / 3D landscape

2.3.2 Remote Sensing and sugarcane yield evaluation

The advantage of remote sensing over ground systems, such as that used by the millers, is that they cover wide areas explicitly, providing timely spatial and temporal data. Such temporal data has been commended for monitoring vegetation development in response to changes in the environment and in response to human management practices (Pettorelli et al., 2005; Zarco-Tejada et al., 2005; El Hajj et al., 2009; Bégué et al., 2010). These conditions vary over large areas due to diverse topography, soil type, rainfall distribution and management practices, to which sugarcane phenology and productivity is dependent (Gunnula et al., 2011). Most vegetation indices have proven successful in estimating biomass and crop yield (Lofton et al., 2012). The Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), from remote sensing imagery for example, has been expansively used to determine crop phenology, biomass and productivity. Methods developed depend on the scale of study and on the crop management practices, which influence the temporal and spatial resolutions of the relevant data. The cost of satellite imagery, however, is high when fine resolution is required. Crop monitoring studies have therefore resolved this impasse by successfully using free low resolution images from the

Moderate Resolution Imaging Spectroradiometer (MODIS), SPOT-VEGETATION, or NOAA-AVHRR sensor data for crop studies (Atzberger, 2013).

Recent studies have used low resolution imagery to estimate sugarcane yield production in different countries. In Brazil for example (Fernandes et al., 2011), 1 km SPOT-VEGETATION data was used, taking advantage of its daily temporal resolution and coupling it with meteorological data to monitor sugarcane development. Cropping seasons were identified by the study using the NDVI data and further classification of the yield data was performed in three classes for analysis. In the three yield classes assessed (24-73 t ha^{-1}; 42-110 t ha^{-1}, and 74-85 t ha^{-1}), the yield predicted was consistent with the historical yield with accuracies of 8.3%, 66.7% and 86.5%, respectively. The low accuracy of the first class would be attributed to coarseness of the 1 km image that limits discrimination of individual phenology for plots that are smaller than the pixel size, a case similar to the small scale sugarcane farming community of Kenya. Accuracies for the second and third class were in the municipality areas, characterized with large farms such as the nucleus fields of Kenyan sugar mills that are under pure sugarcane stand.

A similar study, Gunnula et al. (2011) noted that neither average rainfall nor MODIS NDVI integrated over the entire cropping season was related to the average sugarcane yield of the farmers' fields situated within the 5 km radius of the nine weather stations in Brazil. On a larger scale, MODIS NDVI had a positive correlation (R = 0.57) with yield when averaged across all nine management zones with data collected during the long season planting for planted cane. In a different study (Bastiaanssen and Ali, 2003), NOAA-AVHRR 1 km data was utilized to develop and validate a model for forecasting crop yield in Pakistan. District data was then used to validate the model, resulting in a root mean square error of 13.5 $t \cdot ha^{-1}$ for sugarcane yield. In their recommendations, actual daily sunshine hours, air temperature, and a crop map were argued to be indispensable for refinement of the model.

A recent study on forecasting sugarcane crop season in Brazil using simple correlations between time series NDVI from AVHRR and an agro-climatic index on sugarcane yield, realized significant correlations (R = 0.69 to 0.79) after applying a cross correlation method on the datasets used (Gonçalves et al., 2012). In a different study on maize (Funk and Budde, 2009), MODIS NDVI was used in Zimbabwe to realize strong relationships with the national maize production estimates after the data was adjusted to match onset of the rainy season. The strength of correlations in these two studies is attributed to normalization of the time lag in the climate and NDVI data through the methods used. It is inferred that normalization of satellite data through an appropriate method improves the strength of correlations and is appropriate in future studies. It is also important to note that a combination of satellite and climatic datasets such as those used in these studies utilizes newer methods in forecasting sugarcane productivity (Gonçalves et al., 2012) as opposed to traditional NDVI measurements. A similar study in Louisiana used thermal variables (Growing Degree Days accumulated from planting to sensing) to adjust in-field NDVI measurements, and to develop a sugarcane yield forecasting method (Lofton et al., 2012). They obtained a positive exponential correlation, with R^2 improving from 0.20, when using unadjusted NDVI, to $R^2 = 0.46$, when using adjusted NDVI. These authors argued that a weak correlation from application of the model was attributed to the spatial variability of sugarcane fields due to different crop ages and diverse environmental conditions in different locations.

In the agricultural landscape of Kenya, sugarcane crop exhibits extreme age differences alongside diversified subsistence cropping in different environmental conditions and is thus highly heterogeneous (Mulianga et al., 2012). MODIS 250 m data has been used successfully to determine temporal dynamics of crops at local scales due to its good geometric and radiometric properties that make the data interoperable with other GIS datasets (Nguyen, 2005). However, at MODIS 250 m resolution and in a small agriculture region such as in Kenya, the measured radiation is a mixture of different crops and natural vegetation. It is therefore important to apply a method that will decrease the effect of mixed crop and natural vegetation pixels in the satellite data on aggregated NDVI data used for yield forecasting. The effect of mixed pixels while developing a maize yield model using the land cover weighted NDVI rather than the traditional NDVI reduced the unknown variance by 26% in the study of Rojas (2007). It was argued that yield estimation using NDVI may vary during respective months of the crop growth because NDVI is reduced at the end of the rainy season, emphasizing the need for careful consideration on time integration (Bégué et al., 2010).

> *Therefore, this study will test a new method of yield estimation using time integration that takes into account the age of the crop in the contribution of the different sugarcane fields to the final annual harvest tonnage. This time integration was considered in order to minimize errors that accrue from variations in environmental variables during the growth period of sugarcane crop.*

2.3.3 Remote sensing and sugarcane cropping practices

Remote sensing approaches play a crucial role in studying cropping practices of a given area. This is due to their capacity in capturing real time information at any scales of study to enable scientists to develop useful decision support tools for agricultural sector. This is because vegetation changes are a sensitive indicator for environmental changes (Van Wijgaarden, 1991). Remote sensing provides useful information concerning changes in environments and this facilitates management of available natural resources. Temporal samples of remote sensing data play an important role in monitoring trends in cropping practices of a given area. This is because dynamics in vegetation growth cannot be deduced from one date imagery. Lei and Bian (2010) noted that interpretation of temporal variations in such vegetation growth provides valuable information on its spatial dynamics, and estimates of phenological indicators which help to describe cropping practices in the landscape. Time series vegetation indices derived from satellite images is useful for analyzing the spatial patterns in vegetation and in assessment of such vegetation dynamics. Through time series analysis of these indices, the observation of seasonal and annual trends in vegetation cover provides useful conclusions in cropping practices in the given landscape (Wardlow and Egbert, 2008).

In the recent past, the normalized difference vegetation index (NDVI) derived from MODIS 250m time series has helped in understanding the temporal dynamics of vegetation in the landscape by exposing vegetative seasons in the study area, while Landsat 30m NDVI has facilitated exploration of the spatial variability of such landscape due to its finer resolution (Mulianga et al., 2012). A different remote sensing index, the normalized difference water index (NDWI) has been used to monitor moisture conditions of vegetation over large areas (Gu et al., 2008). High NDVI values reflect the vigor and photosynthetic activity of the vegetation, while

NDWI which is derived from the near infrared (NIR) and shortwave infrared (SWIR) channels, illustrate the changes in water content in the mesophyll of vegetation. Through time series on variations in vegetation moisture and vegetation availability conditions, a combination of these two indices facilitates detection of harvested fields and their mode of harvest (Gu et al., 2008).

Thenkabail and Wu (2012) emphasized the need for land use maps to address food security. This is because updated information on land use enables the authorities to find solutions for increased efficiency on food production (Adami et al., 2012). They further suggested the need for automated methods to map land uses for precise yield forecasts. In the Kenyan scenario where 85% of sugarcane is grown among other land uses, mapping of cropping practices is important in ensuring proper planning and management of the natural resources. Until the 1990's, land use mapping was dominated with pixel based classification methods (Blaschke, 2010) that facilitated identification of the land use, eventually providing land use maps. The pixel scale however may sometimes not match the spatial extend of the land cover, sometimes being smaller or larger than the actual object (Fisher and Pathirana, 1994). In either case, remote sensing imagery will provide a guide to identification of the land use through image classification. Sugarcane farming in Kenya is not homogeneous due to multiple planting and harvesting calendar. The mapping situation is exacerbated with small scale fields usually smaller than the Landsat pixel size.

Advanced remote sensing tools offer a solution for monitoring development stages of a crop (Zarco-Tejada et al., 2005) and delineating homogeneous pixels from the neighborhood to form homogeneous development units (HDU) that facilitate classification of sugarcane fields of similar age as an agronomic field or object (Vieira et al., 2012). Recent studies have used remote sensing images to map sugarcane fields through visual interpretation of multi temporal Landsat data (Rudorff et al., 2010) that categorizes sugarcane fields into similar age units. This approach diminishes inaccuracies in mapping disparate fields from a single image that would classify harvested fields as bare land, thus capturing sugarcane fields of different ages from temporal series. In Brazil and other countries, where sugarcane is distributed over large areas such as in Kenya, advanced remote sensing tools based on MODIS (250 m) data were preferred to provide timely information on location of sugarcane fields and their respective area (Vieira et al., 2012) through an object based image analysis (OBIA) approach.

In Kenya where sugarcane fields are small, a finer resolution such as 30m Landsat image that can aid in locating sugarcane fields of similar age is necessary. Similarly, information on sugarcane area and harvesting method in western Kenya landscape is vital in computation of sugarcane yield and advice to the farmers on soil conservation measures. Additionally, in Brazil, remote sensing images have been used to facilitate detection of sugarcane harvest and harvest mode (Aguiar et al., 2011). Either burnt or green harvest methods were detected from time series Landsat TM images through a change detection process on overlaid images.

> *Therefore, this study will use Landsat 8, 30 m NDVI to study the spatial and temporal variability in cropping practices focusing on crop type and harvest mode in Kibos-Miwani landscape, using the temporal dynamics in MODIS NDVI and Landsat NDVI and NDWI series.*

2.3.4 Remote sensing and soil erosion

Remote sensing data, integrated with the digital elevation model and soil datasets have been used in the recent past to account for vegetation properties, (Cohen et al., 2008; De Jong et al., 1999). Among other studies, De Jong et al. (1999) used Landsat TM data to represent vegetation conditions and developed soil erosion model for Mediterranean regions (SEMMED) model, which is applicable at regional scale. Cohen et al. (2008) used temporal series of Landsat TM normalized difference vegetation index (NDVI) to represent the annual variations in vegetation growth and integrated it with spatial data sets from the heterogeneous landscape to develop a fuzzy based dynamic soil erosion model (FuDSEM) at local scale. Remote sensing techniques have therefore proved successful in characterization of heterogeneous landscapes when integrated with spatial dynamic models and expert knowledge to investigate the extent of soil losses in agricultural landscapes (Cohen et al., 2008). This is because remote sensing is able to detect both spatial and temporal characteristics of heterogeneous landscape patterns and processes and identify areas vulnerable to soil erosion (Anejionu et al., 2013). Soil management influences changes in physical, biological and chemical properties of soils in landscapes that produce sugarcane (Panosso et al., 2009). A study on the spatial and temporal variability of these landscapes is therefore crucial in estimation of potential soil erosion from which environmental services that are provided by main land uses to the ecosystem are ascertained (Saavedra, 2005). Remote sensing is therefore a technology that facilitates the exploration of spatial and temporal variability in landscapes. (Pettorelli et al., 2005; Zarco-Tejada et al., 2005; El Hajj et al., 2009; Bégué et al., 2010). Remote sensing provides temporal series datasets that are used in studying the evolution of such landscapes by depicting spatial and temporal changes over the desired study period (Zarco-Tejada et al., 2005).

In the recent past, information from remote sensing imagery was integrated with spatial data to increase accuracy in monitoring changes in land use (Adami, 2012) to provide information on the impact of soil quality on this land use. Additionally, satellite images provide temporal information on changes in environmental variables in space and time, and permit to study the impact of vegetation cover type on soil protection for a sustainable ecosystem. In the Kenyan context where 85% of sugarcane is grown among other land uses with multiple planting and harvesting crop dates, time series normalized difference vegetation index (NDVI) from satellite imagery of such landscape facilitated understanding of the seasonal variations in vegetation and the impact of management practices that determine variations in spatial productivity and susceptibility of such landscape to soil degradation.

Recent studies have used NDVI to identify changes in vegetation cover that are presumed to have resulted from crop management practices. The image acquired on a specific date was presumed to reflect results of crop management practices as impacted by environmental variables such as soil characteristics for that particular space in time (Cohen et al., 2008; Blaschke, 2010; Rudorff et al., 2010). On the other hand, temporal NDVI captures the different stages of land cover from temporal series when integrated with ground data and expert knowledge. This integration provides spatial and temporal information that is critical in fuzzification of the landscape elements used in modelling the vulnerability of an area to different degrees of erosion in order to quantify potential soil erosion over a heterogeneous landscape (Cohen et al., 2008), and investigate their impact on soil erosion control in space and time.

In western Kenya, Kibos-Miwani sugar zone contributes one third of Kenya's sugar demand, while Mumias contributes the highest percentage. In this area, a mosaic of subsistence, sugarcane farming and natural vegetation is found in the escarpment foot. Unlike Mumias which mainly uses green method of harvesting amidst multiple planting and harvesting dates, Kibos-Miwani zone is characterized with multiple planting and harvesting dates for sugarcane crop and mainly burnt harvesting method. Data on land use shows close to 80% of the landscape under sugarcane and this draws our interest in investigating the sensitivity of Kibos-Miwani sugarcane landscape to soil erosion. Sugarcane management systems (planting, harvesting) affect soil conditions which have a direct impact on soil erosion. Further, Panosso et al. (2009) add that sugarcane crop and its residues reduce the rate of soil erosion. Whereas disadvantages of soil erosion have been documented, there is little etiquette in evaluating impacts of cropping practices on soil degradation. Knowledge on impact of sugarcane cultivation on soil degradation is critical in undertaking effective soil conservation for sustainable management of Kibos-Miwani ecosystem (Omuto, 2008).

In this objective, this study will investigate the risk of soil erosion in Kibos-Miwani sugar zone using remote sensing data and an erosion model. The study will focus on sensitivity of erosion risk in relation to slope and vegetation conditions.

2.4. Soil erosion models

Cohen et al. (2008) described soil erosion models as important tools for planning and management of built up, natural and agricultural landscapes. There is need therefore, for spatial modelling and prediction techniques to identify erosion risk areas so that appropriate conservation measures can be put in place. A review on erosion models (Jetten et al., 2003) presents the difficulties related to calibration and validation of spatially distributed soil erosion models. It is explained that soil erosion modelling is associated with the variability in spatial and temporal distribution of soil characteristics and erosion occurrences and the uncertainty associated with input parameter values in prediction of these values. Jetten et al. (2003) conclude that the use of spatial information of various nature types would resolve this paradox. Likewise, Cohen et al. (2008) stated that the use of models was cumbersome for finer scales at catchment or landscape scales due to the tedious demand for labour and detailed data input. They also concluded that inclusion of temporal information was critical in modelling soil erosion through time for a given landscape. Such fine scales are important since they provide information for implementation of efficient soil conservation planning (Dejong et al., 1999; Jetten et al., 2003).

Different large scale soil erosion models have been reported, applied and investigated for their performance on calculating erosion values. They include the WEPP (Nearing et al., 1989), EUROSEM (Morgan et al., 1992), LISEM (De Roo et al., 1998), EROSION 3D (Schmidt et al., 1999) and MEDRUSH (Kirby and McMahon, 1999). Results of these models have been useful in soil conservation measures but their prediction of erosion yield over heterogeneous landscapes is unreliable (Trimble and Crosson, 2000). Reasons attributed to this limitation include (i) little input data of high spatial and temporal resolution (Dejong, 1994); (ii) poor calibration of the models (Folly et al., 1999) and (iii) uncertainties associated with model parameters (De Roo, 1998). Most soil erosion models simulate steady erosion processes to obtain solutions in the absence of temporally dynamic information such as from vegetation growth and ground water dynamic variables (Jetten and Roo, 1999). Results from such models depended on the number of times that the iterations were run, high accuracy being associated with many iterations and this made results subjective. Moreover, when estimating soil erosion over heterogeneous areas, most models are limited (Trimble and Crosson, 2000) due to insufficient spatio-temporal information necessary for the computation of the landscape's erosion risk change. A more recent erosion model that addresses the three limitations (listed above) of large scale models is SEDEM (Van Rompaey et al., 2001) which uses RUSLE to resolve the problem of little distributed data in large catchments. This model however requires intensive calibration due to its empirical nature that is labour intensive.

In the recent past, spatially dynamic models have been used in computation of potential soil erosion in order to recommend appropriate conservation measures for enhanced agricultural productivity (Cohen et al., 2008). Modelling potential soil erosion in heterogeneous landscape patterns such as in Kibos-Miwani requires a model that is applicable at local scale (De Jong et al., 1999) to facilitate recommendations on soil conservation measures that minimize impacts of erosion in a specific environment. There are landscape erosion models that are able to compute temporally dynamic erosion values such as SIBERIA (Willgoose et al., 1991), GOLEM (Tucker and Slingerland, 1994), LAPSUS (Schoorl et al., 2000), CHILD (Tucker et al., 2001) and CAESAR (Coulthard et al., 2002). These models perform successful simulations of spatial and temporal distribution of erosion sediments but do require intensive data input and powerful processors.

More recent studies have addressed problems associated with such conventional models by use of artificial intelligence technologies (Metternicht and Gonzalez, 2005) such as fuzzy logic to simulate complex environmental processes and to improve spatial characteristics of a given model (Ahamed et al., 2000). This is because the Geographic Information System (GIS) based fuzzy models have the advantage of being used in managing uncertainties commonly associated with spatial databases and ecological modelling (Robinson, 2003; Robinson, 2007). Moreover, fuzzy logic is important in simulating complex environments since it is capable of processing and representing uncertain data from complex spatial processes in continuous classes (Cohen et al., 2008; Svoray et al., 2007; Metternicht, 2001), in spatial classification of soil characteristics (Burrough and McDonnell, 1998), and in provision of erosion solutions in heterogeneous environments (Tayfur et al., 2003). These advantages allow modellers to minimize overdependence on empirical features when designing models.

The fuzzy based dynamic soil erosion model (FuDSEM; Cohen et al., 2008) was developed based on physical principles to simulate landscape processes at catchment scale for enhanced decision making. This is because FuDSEM has the advantages of simulating erosion processes, while using known principles; (i) using a fuzzy logic structure that reduces calibration requirements and (iii) using accessible input data that minimizes pre-processing (Cohen et al., 2008). In this case, satellite image is used to provide information on vegetation. The advantage of using satellite images is that they record timely information without altering the state of vegetation, as opposed to the crop factor that has to be computed from global datasets for other models like RUSLE. Another advantage of input data into FuDSEM is its fuzzy nature that permits integration of sampled data through fuzzy models to provide information for areas that were not sampled. Longley et al. (2005) note that collection of physical datasets is quite tedious, costly, time consuming, and is usually associated with errors due to fatigue. Moreover, FuDSEM has been validated at both small and medium scale heterogeneous catchments (Cohen et al., 2008; KESREF, 2013), landscapes that are similar to Kibos-Miwani.

Owing the high spatio-temporal heterogeneity of the Western Kenya landscapes, this study will utilize FuDSEM at a local scale to model potential soil erosion risk using remote sensing data and soil physical characteristics data. This is due to the temporally dynamic fuzzy structure of FuDSEM and its ability to simulate erosion using little information (available data).

3. MATERIALS AND METHODS

3.1. Study area

Part 1 of the study covers the entire western Kenya sugarcane growing region (all the six sugar zones) at the regional scale, while part 2 covers one of the zones, the Kibos-Miwani sugarcane zone at a local landscape scale.

3.1.1 The western Kenya region

Western Kenya region (Figure 7) is located within the western part of Kenya, comprising six sugar management zones that include: (i) Chemelil, Kibos-Miwani and Muhoroni within the sub humid agro-ecological zone; and (ii) Mumias, Nzoia and Sony within the humid agro ecological zone of Kenya. These zones are further grouped under the (i) western sugar belt (Mumias and Nzoia); (ii) south Nyanza sugar belt (Sony) and (iii) the Nyando sugar belt (Kibos-Miwani, Chemelil and Muhoroni). These sugar zones are located between longitudes 34.18°E and 35.87°E, and latitudes 1.25°N and 1.50°S, covering an area of 120,000 ha. Mumias is the highest producer of sugar placed at 39% in 2012 (KSB, 2012). The western Kenya region is characterized with a high diversity of agro-ecosystem because of contrasted topography. The altitude ranges from 1,000 m (Kibos-Miwani) to 1,600 m (Mumias and Nzoia), and to 1,800 m (in Chemelil). The slope rises between 2%, in the plains of Kibos-Miwani zone, and 38% in the hills of Chemelil zone. This topography influences the agro-ecological zones into receiving an average of 1,400 mm and 1,800 mm of rainfall in the sub humid and humid zones respectively

(Ribot et al., 1985). Rainfall in this area is bimodal (Shisanya et al., 2011) with a long rain season between March and July, with planting in March for food crops and April for sugarcane; and a short rain season in September to December with planting in September for all crops (Amolo et al., 2009). This variation in rainfall distribution influences an intensified cropping system with crop diversification and rotation of food crops and sugarcane development stage. Soils of the study area are dominantly black cotton cambisols in the low lands and sandy loamy acrisols in the highlands (Jaetzold et al., 1985). The hilly undulating landscape is unique with most hilly areas dominantly covered by the loamy sandy acrisols.

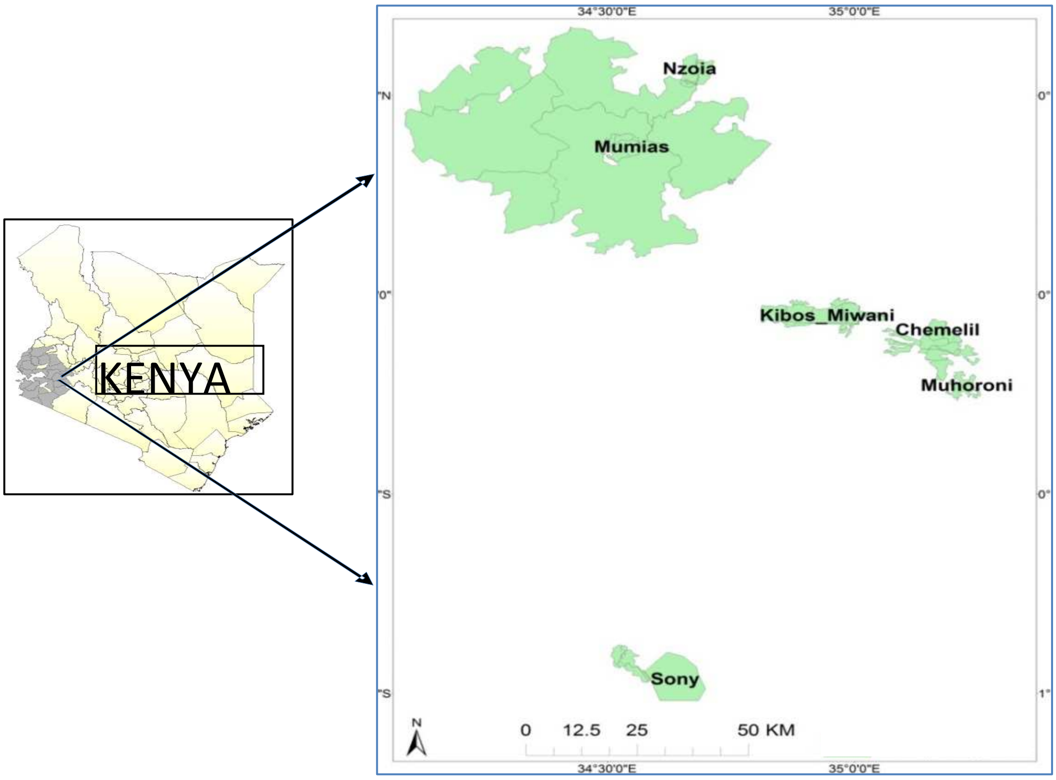


Figure 7: Cane growing area in Western Kenya (green area).

3.1.2 Kibos –Miwani sugar zone

Kibos-Miwani sugar zone (Figure 8) is located between 34.8° E to 35.08° E and 0.01° S to 0.11° S. It stretches from the Kano plains with an altitude of 1000 m to 1800 m in the escarpment. The slope rises from 2% in the plains to >20% in the hilly areas. It is located within the sub humid agro-ecological zone receiving rainfall of between 1400 mm and 1550 mm. The main crop in the zone is sugarcane, besides maize and horticultural crops. Sugarcane is planted in the months of April and September in accordance with the bimodal rainfall in February to June and September to December. Soils of the plain land are dominantly black cotton cambisols that easily clog with increased rainfall and crack during prolonged drought with temperatures rising to 33°C. The highlands are dominantly well drained sandy loamy acrisols. It is the spatially heterogeneous terrain, diversified cropping systems, varied soil types and rainfall in this zone that provide an enabling environment for evaluation of a soil service offered by sugarcane crop to the ecosystem within a space of 104 km^2.

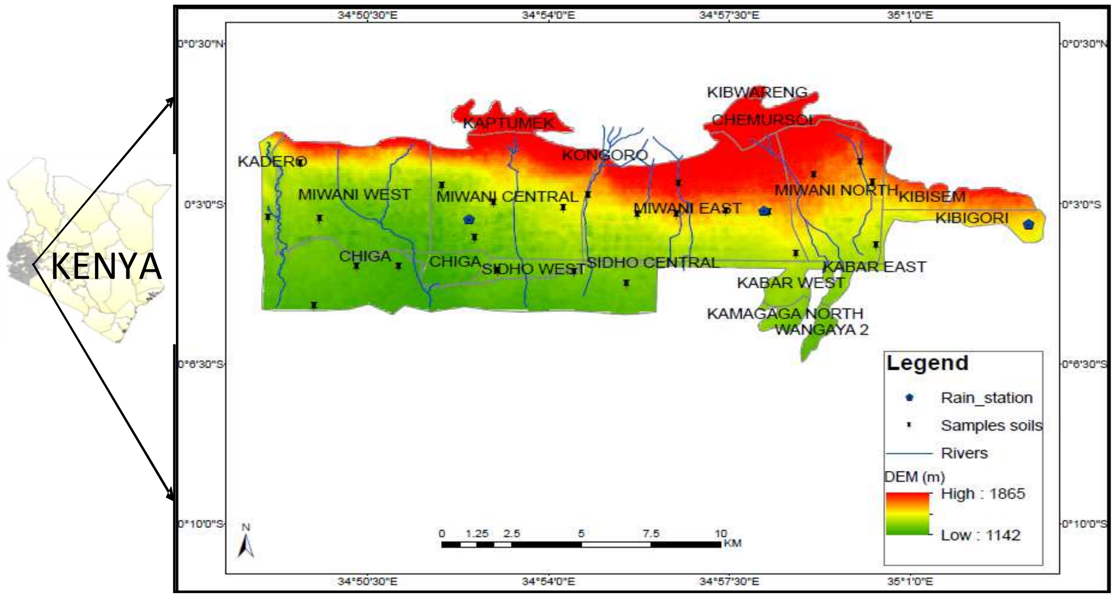


Figure 8: Elevation map of Kibos-Miwani sugar zone. The map was established using 30m ASTER Digital Elevation Model (Mulianga et al., 2013).

3.2. Data

3.2.1 Agronomic and environmental data

Agronomic data

Table 3 presents the main agronomic and climatic data traits used in this study. Average annual rainfall varies from 1,421 mm and 1,869 mm depending on site.

Table 3: Summary of the agronomic and climate data used in the study: mean and standard deviation (in parenthesis) calculated over the 9-year period (2002–2010).

	KIBOS	MUMIAS	CHEMELIL	MUHORONI	SONY	NZOIA
Rainfall ($mm \cdot yr^{-1}$)	1,421 (102)	1,835 (186)	1,426 (263)	1,486 (214)	1,869 (221)	1,763 (252)
PMR**	0.07	-0.03	-0.04	0.06	-0.07	0.01
AEZ	Sub-humid	Humid	Sub-humid	Sub-humid	Humid	Humid
Water	Rainfed/ Irrigated	Rainfed	Rainfed	Rainfed	Rainfed	Rainfed
Yield ($t \cdot ha^{-1}$)	71.1 (9.6)	75.6 (11.1)	62.6 (9.6)	63.9 (7.9)	80.1 (11.3)	75.0 (5.2)
Sugarcane area (ha)	6,480	54,173	12,757	12,264	18,417	21,014
Sugarcane fraction (%)*	32.2 (4.5)	48.7 (2.5)	38.8 (6.3)	50.5 (7.3)	33.3 (5.3)	22.2 (2.7)

* *The sugarcane fraction is calculated as the sugarcane surface area divided by total surface area under farming in the zone*

***PMR is the Precipitation Marginal Response computed from the yield-NDVI slope.*

Sugarcane grown in regions with less than 1,500 mm rainfall is recommended for supplemental irrigation (KESREF, 2010). This irrigation covers about 10% of the nucleus estate of Kibos-Miwani. The reason for higher yield in Kibos (71 t ha^{-1}), compared to the government owned Chemelil and Muhoroni sugar mills in the same AEZ whose yield is around 63 t ha^{-1} is associated with this irrigation. Globally, yield in the humid AEZ (Mumias, Sony, and Nzoia) is higher (between 75 t ha^{-1} and 80 t ha^{-1}) than in the sub-humid AEZ. The yield in Sony (80 t ha^{-1}) is boosted by large scale farmers within the fertile highlands of Sony sugar zone. The agronomic (yield and cropped area) and environmental (rainfall) data were obtained from the respective sugar mills.

Two yield datasets were provided from the factories (estimated *vs* measured yield). Estimated yield is obtained by use of the visual physical approach (VPA) method, where color, vigor, stalk population, and weeds, pests and diseases are surveyed and scored in the fields by a team of observers and averaged to provide the estimated yield for the assessed plot. Measured yield is obtained based on the area harvested and the total tonnage recorded at the factory. Figure 9 illustrates these two yield datasets showing a large scattering of the points, thus demonstrating the limits of actual estimation process.

The measured yield only includes contracted farmers within the zone. Non contracted farmers yield is excluded since they choose where to mill their sugarcane. Estimated yield on the other hand considers all sugarcane within the respective sugar zone. It is the reason why, estimated annual yield data was therefore used in this study as the reference data set.

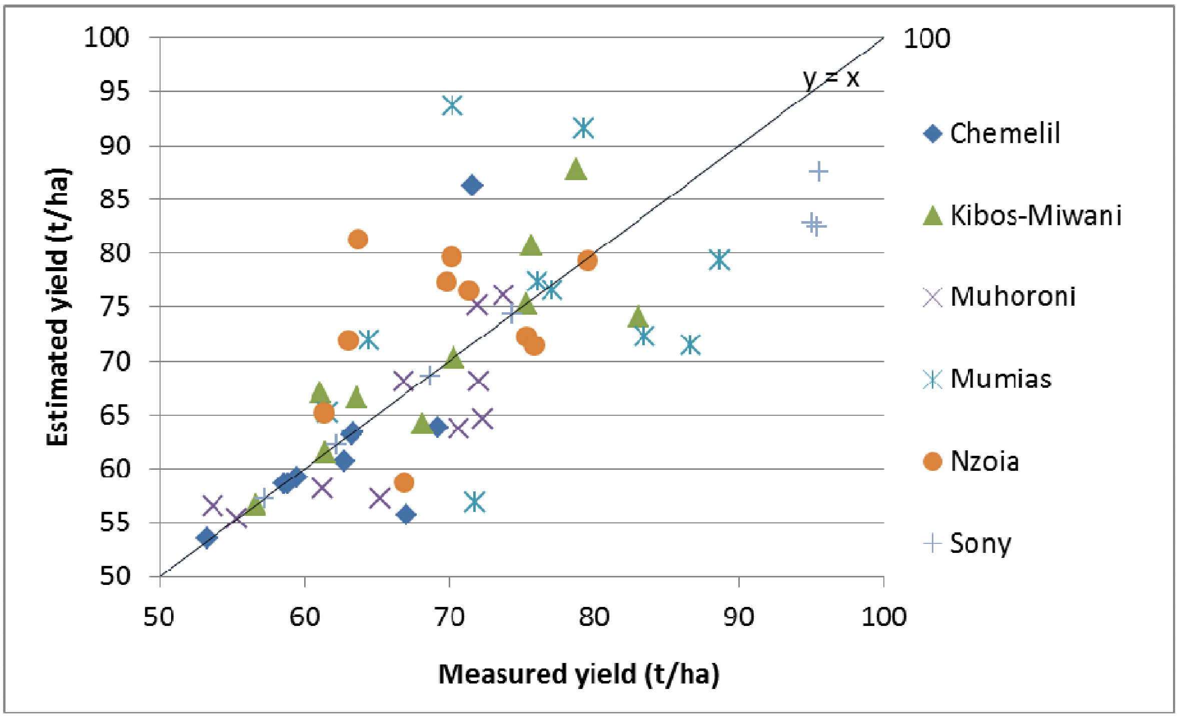


Figure 9: Relationship between measured and estimate yield for the six sugarcane zones in western Kenya during the 2001-2011 period.

In each of the six sugar zones, we got the evolution in estimated sugarcane yield and evolution in the yearly cropped area (Figure 10) for the period 2001-2013. This is because production is the product of yield and cropped area and therefore investigation into evolution of this production through time is useful in enhancement of sugarcane production in Kenya. Crop area data are estimated by physical measurement of area that has been harvested or during land preparation. The yield data for the year 2012 and 2013 were used for quantitative validation of the sugarcane yield model established on the 2001-2011 period.

Annual variations are observed in both yield and surface area from one zone to the other because of crop management practices that vary between the nucleus and out grower fields such as: tillage methods, variety choice, weed management; fertilizer application, edaphic and climatic factors (Jamoza et al., 2013) due to financial disparity between mills and private farmers. Besides, variations in annual surface area depend on crop cycle and availability of land.

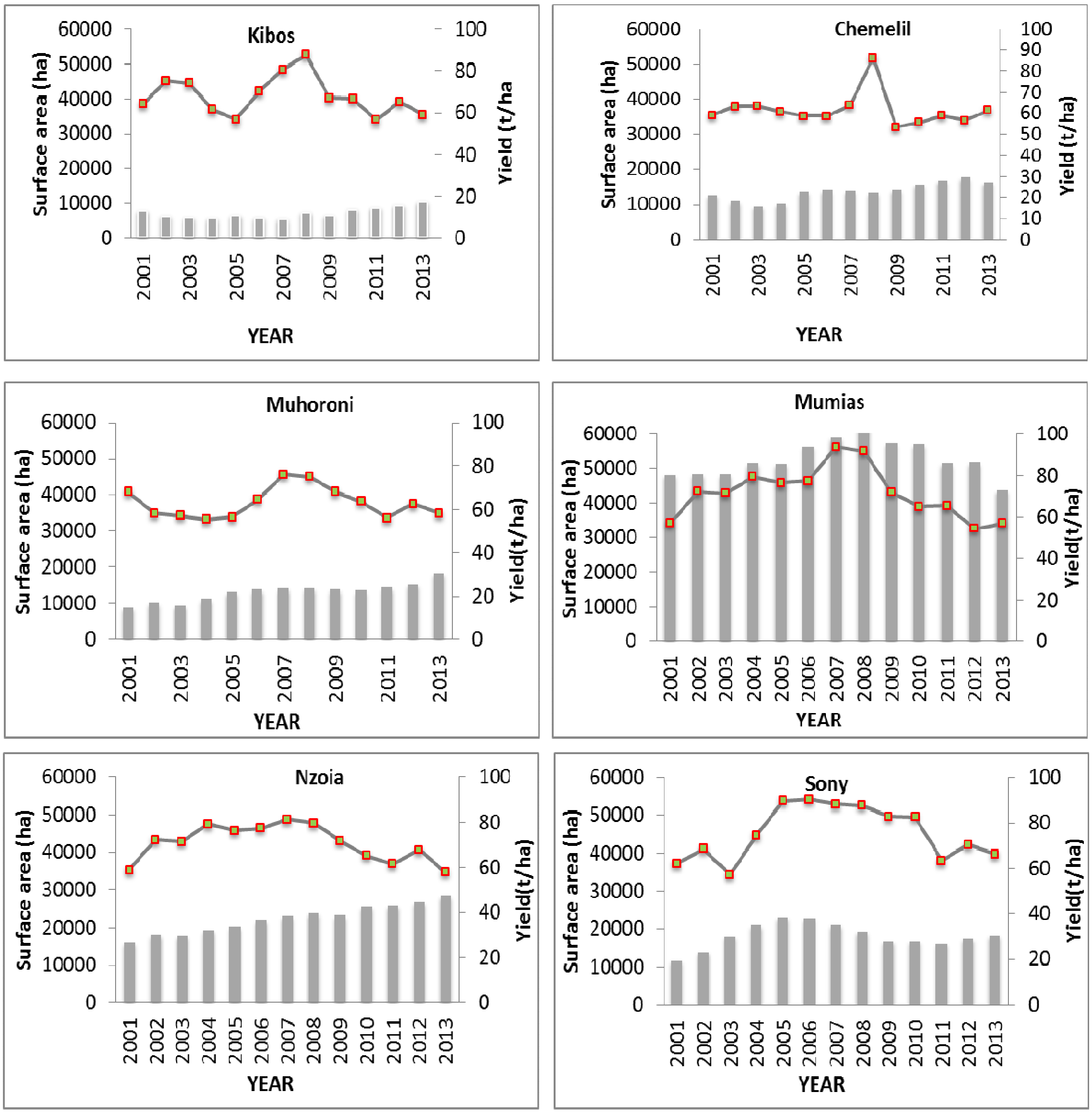


Figure 10: Annual variations of the surface area under sugarcane and sugarcane yield for the six sugar zones (2001- 2013)

Ground survey data

This section details data collection procedure for cropping practices and soil characteristics. Information on the cropping calendar was obtained from all the six factories and summarized in Figure 12.

i.) Cropping Calendar

Information on the cropping calendar was obtained from all the six sugarcane management zones. Planting is undertaken between March and September, while harvesting is conducted throughout the year depending on variety and crop cycle (plant crop or ratoon) as presented in Figure 11. The choice of variety to plant depends on availability of seed cane within the agro-ecological zone. Well managed ratoon crops exceed three cycles depending on sugarcane yield. During the planting season, other food crops are also planted which mature within a maximum of six months. The continuous harvesting is aimed at providing a regular supply of sugarcane to the factories throughout the year and minimizing cane surplus that the milling capacity of factories may not handle.

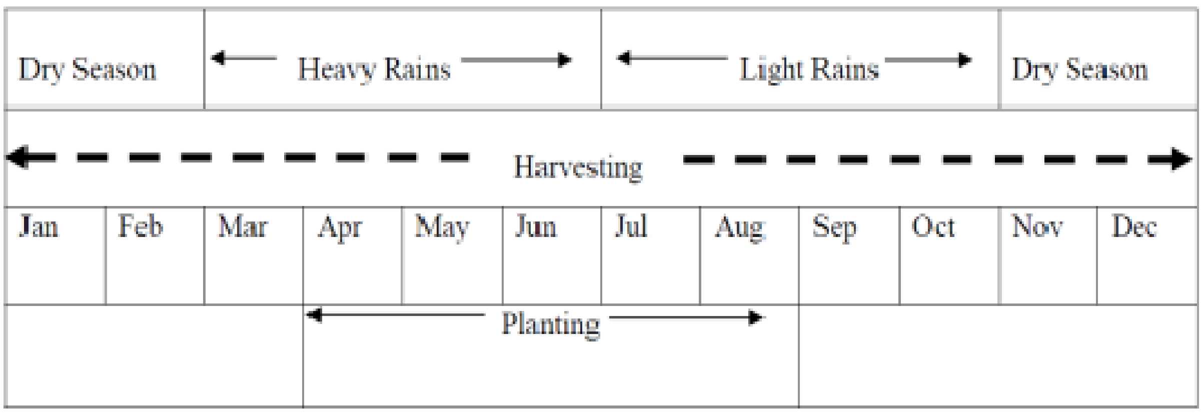


Figure 11: Sugarcane cropping Calendar in Western Kenya.

ii.) Cropping practices

Random sampling was used to collect data on cropping practices in Kibos-Miwani zone using a questionnaire for oral interview and the mobile mapper CX global positioning system (GPS) for field encoding.

During the survey, 384 farmers were interviewed based on a random sample of the population size of 4,000 farmers. This number of sampled farmers was calculated according to Cochran (1963) formula that was developed for selecting a representative sample in an investigation from large populations:

$$n_0 = Z^2 p\, q/e^2$$

Where;

n_0 = sample size;

Z^2 = abscissa of the normal curve that cuts off an area α at the tails ((1 – α) equals the desired confidence level);

e = desired level of precision;

p = maximum variability of farmers that will be studied;

q = 1-p

In this study, Z = 1.96 (for 95%); e= 0.05, p= 0.5, q =0.5; leading to a theoretical number n_0 of 384 farmers to be interviewed.

In total, 1280 fields (800 sugarcane fields and 480 other land cover) belonging to this farmers set were used to create the following datasets i) land cover type (sugarcane or other), ii) planting and harvesting dates and iii) methods of harvesting. Figure 12 illustrates the location of the surveyed points in Kibos-Miwani zone. The ‘other’ land cover referred to in this study consist of other crops, natural vegetation (shrubs and pasture), roads and buildings. These data were collected during (i) a ground survey conducted in October 2013, and (ii) from Kibos Sugar Factory data base.

(i) The ground survey data was composed of 831 observations, where 530 points were sugarcane and 301 points were other land cover. These points were encoded during a ground survey conducted between 14th and 18th October 2013 using the Magellan professional mobile mapper CX global positioning system (GPS) in the Kibos-Miwani sugar zone. Figure 13 illustrates the location of the surveyed points in Kibos-Miwani zone, showing location of those used for training and those used for validation.

(ii) The Kibos Sugar Factory database was composed of 449 points, where 270 points were sugarcane fields and 179 points were other land cover. These data were adopted from the existing land use data set compiled on15th August 2013 by Kibos Sugar factory. Attributes for these fields (planting and harvesting date) were entered in our database in accordance with the factory office record. The factory data was relevant since it was collected within the study time frame of this research.

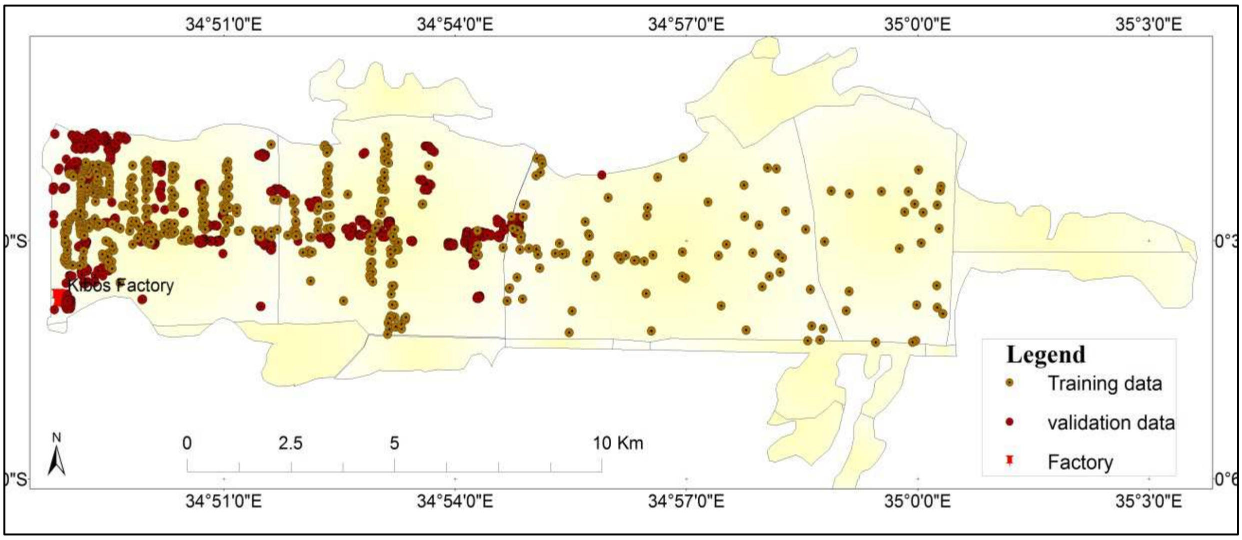


Figure 12: Ground survey points collected in Kibos-Miwani. The field survey was conducted from 14th to 18th October 2013. 75% of the points were used for land use classification training, the other 25 % were used for classification validation.

iii.) **Soil characteristics**

In total, 23 soil samples were collected from Kibos-Miwani sugar zone on 22nd and 23rd October 2013 (Figure 13) by GIS specialist and soil technicians. During sampling, we took cognizance of spatial variability in soil types (based on the digital soil map for Western and Nyanza region at the scale of 1:100,000) of the area, land cover type and relief. Each soil type formed the basis for the layer within which a random number of 3 samples were collected between 0-20 cm, 20-40 cm, and 40-60 cm of depth. These samples were collected using stainless steel cans considering disturbed samples (for texture and particle density) and undisturbed samples for analysis of soil physical properties: bulk density, hydraulic conductivity and porosity. These samples were collected before tillage and not in places compacted by tractors. The soils were mechanically analyzed at KESREF using ISO 17025 laboratory procedures to provide soil input variables for the erosion risk model used in this study.

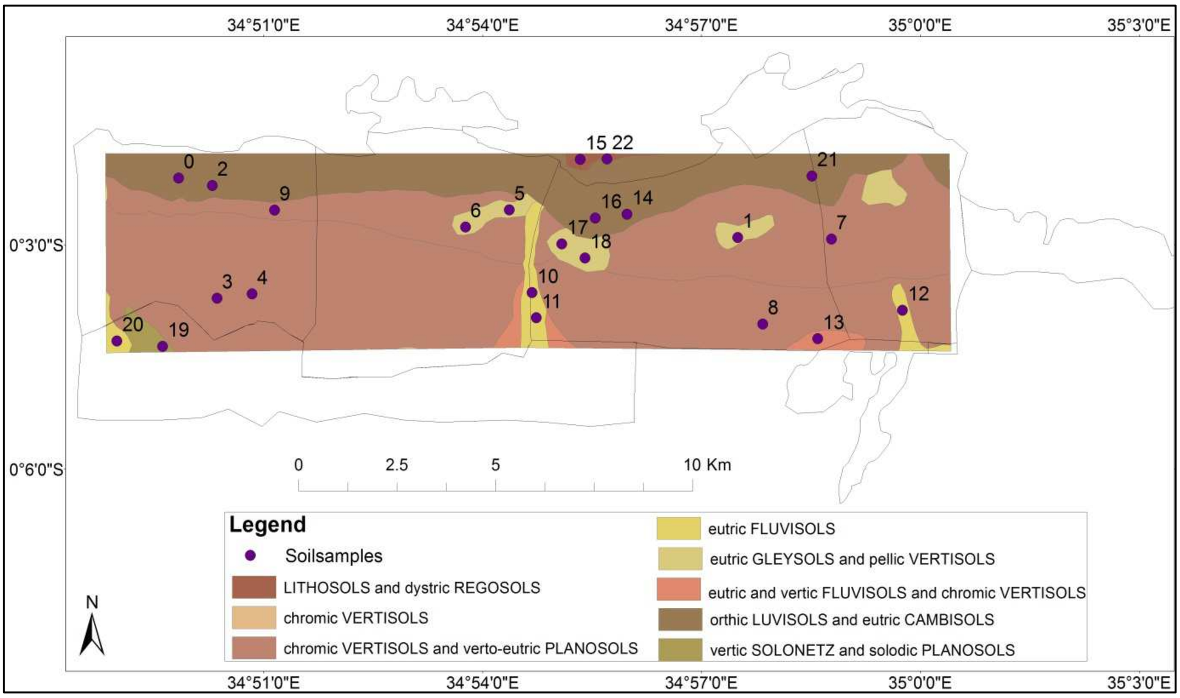


Figure 13: Soils of Kibos-Miwani sugar zone and the positions of 23 sampled soils. Source of the soil map KARI (2012).

These samples were analyzed and computed for their texture, bulk density, porosity, erodibility factor, field capacity, soil moisture content, and hydraulic conductivity. The approach used was the constant head method using a permeameter (Amoozegar, 1989) together with the sieve analysis method (Gee and Bauder, 1986) to determine the particle size distribution of coarse and fine aggregates in soils. Results of soil characteristics analyzed in this study are presented in Table 4. The analyzed values of erodibility index were then compared with the USDA Department of Agriculture (USDFA) soil textural classification triangle (Mitchell and Bubenzer, 1980) for consistency and together with results presented in Table 4, were used as input variables in FuDSEM model.

Table 4: Soil characteristics used in the FuDSEM model. Texture = texture in US system; BD=bulk density; P=Porosity; Erod (k)c=Erodibility factor; FC = Field capacity; Moisture=soil moisture; HC= Hydraulic conductivity. See correspondence of location on figure 14.

Soil No	texture	BD	P	Erod (K)	FC	Moisture	HC
0	silty loam	1.3	0.43	0.38	34	0.27	0.39
1	silty loam	1.46	0.45	0.38	34.1	0.27	0.39
2	silty loam	1.44	0.46	0.38	34.2	0.27	0.39
3	silty clay loam	1.31	0.5	0.32	43	0.32	0.73
4	silty clay loam	1.04	0.61	0.32	43.1	0.32	0.73
5	silty clay loam	1.31	0.51	0.32	43.15	0.32	1.94
6	silty clay loam	1.49	0.44	0.32	43.16	0.32	1.94
7	silty clay loam	1.2	0.55	0.32	43.17	0.32	1.94
8	silty clay loam	1.11	0.58	0.32	43.18	0.32	0.25
9	silty loam	1.25	0.53	0.38	34.3	0.27	0.25
10	silty loam	1.27	0.54	0.38	34.5	0.29	0.3
11	silty clay	1.16	0.56	0.26	43.19	0.34	0.58
12	silty clay	1.3	0.51	0.26	43.2	0.34	0.14
13	silty clay	1.17	0.56	0.26	43.21	0.34	0.58
14	silty clay loam	1.21	0.54	0.32	43.22	0.32	1.26
15	silty clay loam	1.29	0.51	0.32	43.23	0.32	1.26
16	silty clay loam	1.44	0.46	0.32	43.24	0.32	1.26
17	silty clay loam	1.42	0.47	0.32	43.25	0.32	0.75
18	silty clay loam	1.25	0.53	0.32	43.26	0.32	0.75
19	silty loam	1.3	0.51	0.38	43.27	0.27	0.75
20	silty loam	0.89	0.66	0.38	43.28	0.27	0.74
21	silty loam	0.93	0.65	0.38	43.29	0.27	0.74
22	silty loam	0.94	0.64	0.38	43.3	0.27	0.74

Sediment suspension data

In situ data was measured from fields in Kibos-Miwani landscape, comprising sugarcane and other crops respectively. This data was used to test for implementation of FuDSEM model in the study area.

Climatic data

Rainfall data were recorded using 113 rain gauges distributed unequally among all the sugar zones (Figure 14). The rainfall data is submitted to respective millers by weather station attendants who record daily data and monthly rainfall data for the period 2002 to 2012.

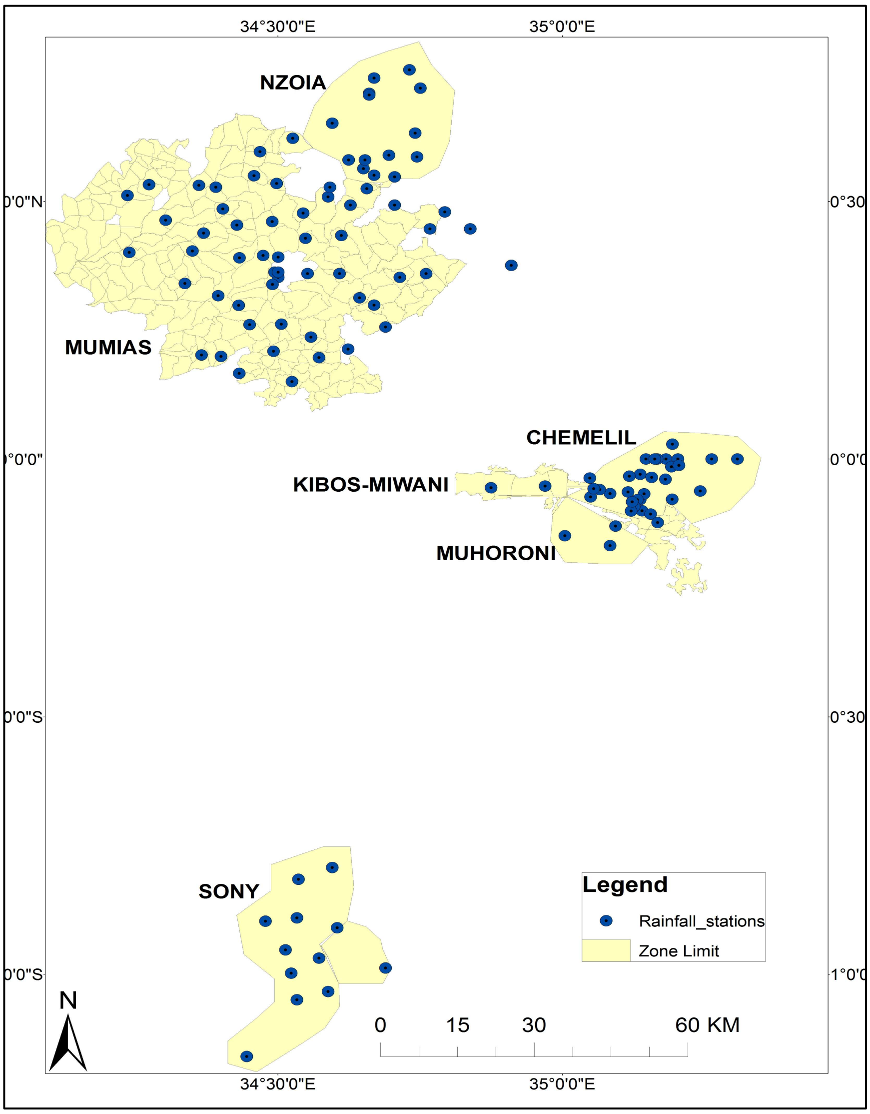


Figure 14: Location of rainfall stations in western Kenya sugarcane growing area.

The annual variations in rainfall in each of the six management zones are shown in Figure 15, while intra-zonal variations in rainfall in the six management zones are illustrated through the mean and standard deviations presented in Table 3.

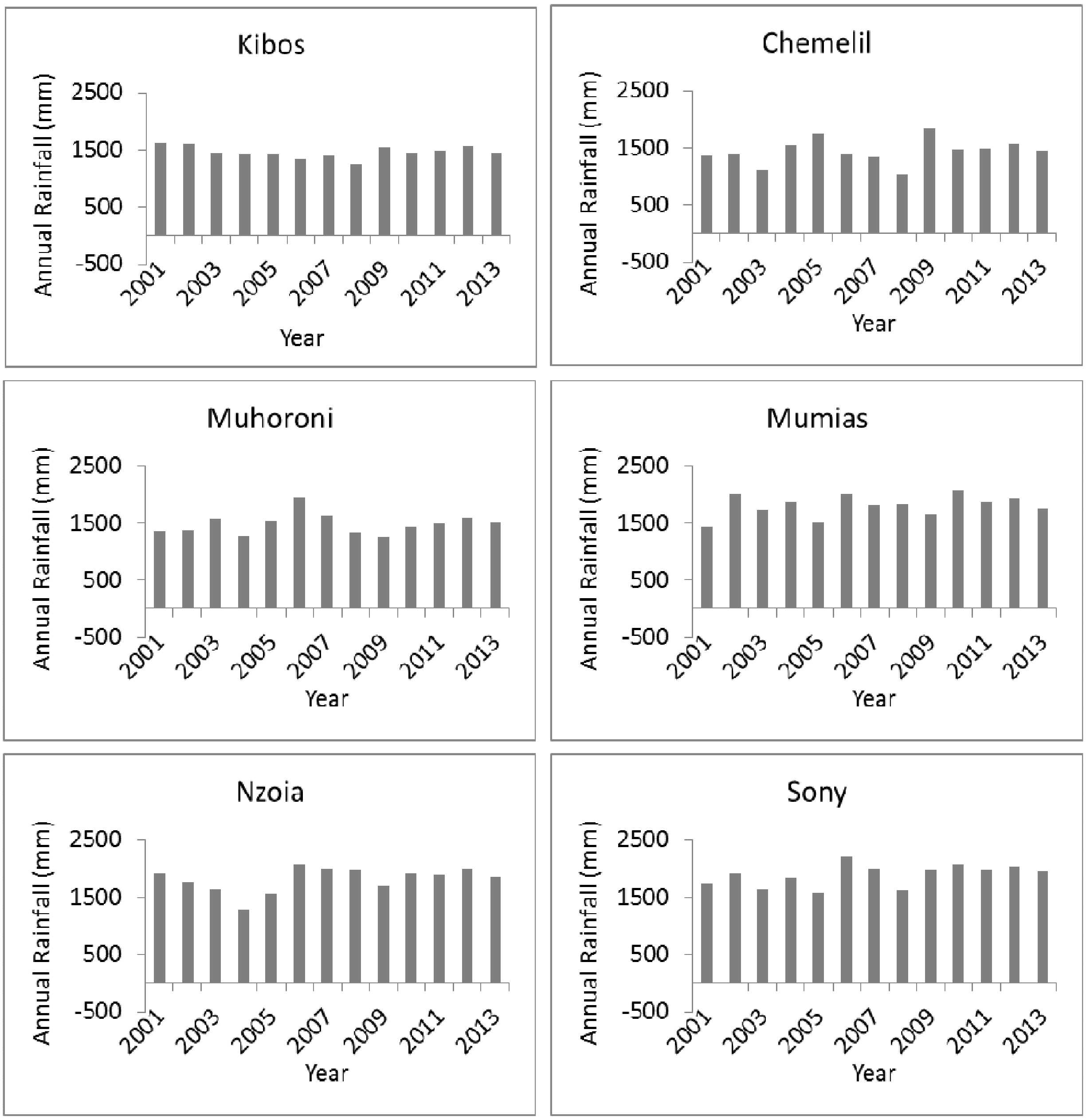


Figure 15: The annual variability of rainfall for each sugarcane zone (2001-2013).

Digital Elevation Model

The 30 m ASTER Digital Elevation Model (DEM) was downloaded from the United States Geological Survey (USGS) website. The DEM was processed using the 3D – raster surface analyst tool in a geographical information system (GIS) to compute the slope curvature and aspect which were required for modelling potential soil erosion of Kibos-Miwani sugar zone (see Figure 8). The slope of Kibos-Miwani rises from 0% in the green area within the plain to 10% in the red area within the escarpment foot (Figure 16).

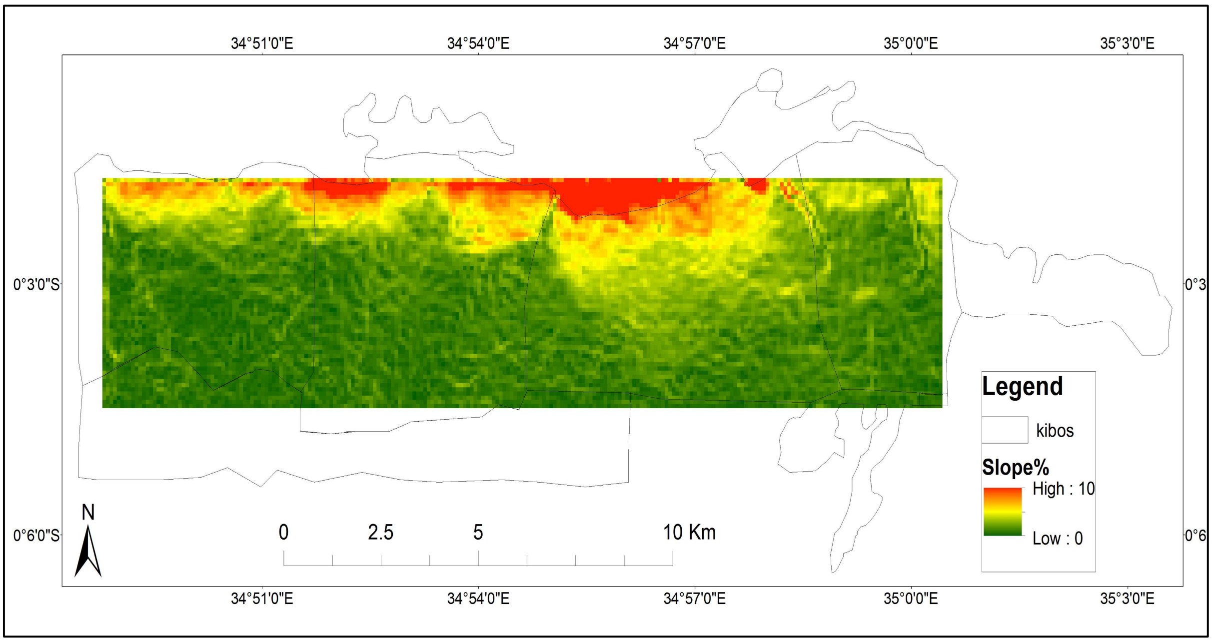


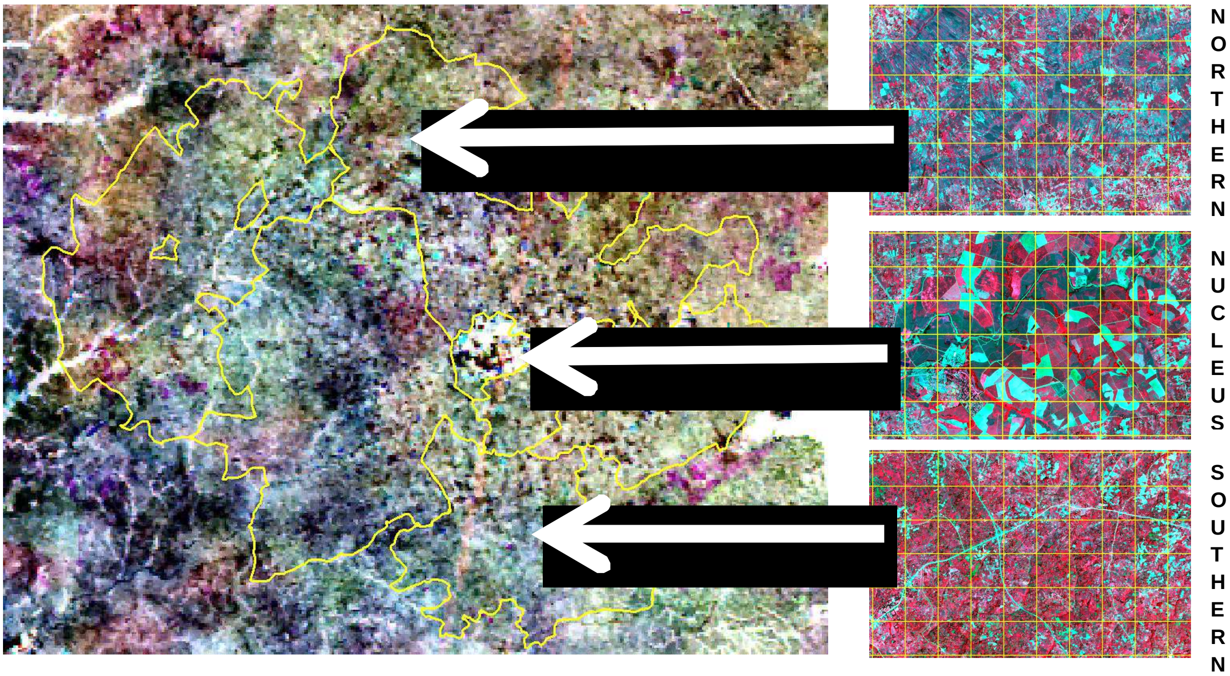
Figure 16: Topography of the studied portion of landscape in Kibos-Miwani, established using a 30 m slope that was computed from ASTER Digital Elevation Model.

3.2.2 Satellite data and preprocessing

MODIS time-series

A complete 11-year time series (2002-2012) of the Surface Reflectance 8-Day L3 Global 250 m product (MOD09Q1) and a 13-year (2000-2012) time series NDVI for Kibos-Miwani; were downloaded through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC: https://lpdaac.usgs.gov/get_data. MOD09Q1 product provides bands 1 (red reflectance; 620–670 nm) and 2 (near infrared reflectance; 841–876 nm) at 250-meter resolution. Each MOD09Q1 pixel contains the `best possible observation during an 8-day period as selected on the basis of high observation coverage, low view angle, the absence of clouds or cloud shadow, and aerosol loading. The accuracy of the version-5 MODIS/Terra Surface Reflectance products has been assessed over a widely distributed set of locations and time periods via several ground-truth and validation efforts, and so they are ready for use in scientific publications (Cunha, et al., 2010). The red (R) and (NIR) reflectance data were used to compute the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974) for all the 460 images.

In addition to the MODIS time series, a multispectral (Green, Red, and Near Infrared) 2.5 m SPOT image was acquired over Mumias in December 2011. This data was used to appraise land cover and use in different sectors of one of the zones (Mumias sugar zone) in a 250 m grid (Figure 17). The data shows the large heterogeneity of the landscape at MODIS scale, and the impossibility to use a sugarcane crop mask on a satellite image at MODIS scale in the area that has heavily fragmented fields (average of 2 ha).



a) MODIS color composition

b) SPOT color composition

(©CNES 2011, Distribution Spot Image)

Figure 17: (a) MODIS 250 m color composition of Mumias zone (sectors within the zone are delineated by a yellow line), and (b) subsets of a December 2011 SPOT 2.5 m image on three sectors; the overlaying yellow grids correspond to the 250 m spatial resolution of MODIS pixels.

Landsat 8 time series

A complete two week time series (April, 2013 - March, 2014) of 20 Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images were downloaded through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC: https://lpdaac.usgs.gov/get_data). The list of the images is given in Table 5.

Landsat 8 products consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. New band 1 (ultra-blue) is useful for coastal and aerosol studies. New band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. Thermal bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. Approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi). Table 6 summarizes Landsat 8 bands that were used in this study.

The image were acquired orthorectified and geo-referenced in WGS84 UTM zone 36S.

Table 5: List of the Kibos-Miwani Landsat 8 images used in this study.

	Date	Sun elevation	Sun azimuth	*Cloud conditions*
1	19-avr-13	61.61		*0%*
2	05-mai-13	59.93		*haze in the east part*
3	21-mai-13	57.82		*0%*
	06-juin-13			*100% (not downloaded)*
4	22-juin-13	54.90		*0%*
5	08-juil-13	54.94		*30%*
6	24-juil-13	56.15		*0%*
7	09-août-13	58.37		*0%*
8	25-août-13	61.19		*0%*
9	10-sept-13	63.92		*10%*
10	26-sept-13	65.71	93.28	*10%*
11	12-oct-13	65.81	108.58	*80% + haze*
12	28-oct-13	64.17	121.62	*60%*
13	13-nov-13	61.42	130.32	*10%*
14	29-nov-13	58.50	134.58	*0%*
	15-déc-13	56.14	135.17	*80% (not downloaded)*
15	31-déc-13	54.82	132.87	*30%*
16	16-janv-14	54.76	128.24	*0%*
17	01-févr-14	55.84	121.56	*0%*
18	17-févr-14	57.73	112.86	*50% haze*
19	05-mars-14	59.81	102.08	*0%*
20	21-mars-14	61.38	89.49	*0%*

Table 6: Landsat 8 bands used in this study (source: http://landsat.usgs.gov/band_designations_landsat_satellites.php)

Landsat 8 Operational Land Imager (OLI) Launched February 11, 2013	**Bands**	**Wavelength (micrometers)**	**Resolution (meters)**
	Band 4 – Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - SWIR 1	1.57 - 1.65	30
	Band 8 - Panchromatic	0.50 - 0.68	15

3.3. Methods

3.3.1 Time-Integration of MODIS NDVI Values

A thematic layer of the limit of the sugarcane growing mill zones was used to extract 8-day NDVI values for each zone. These NDVI values were then spatially aggregated to allow comparison with the mean annual yield, at the same scale. Generally, time integration of NDVI is done throughout the calendar year (KSB, 2012; Goward et al., 1987; Funk and Budde, 2009). At the field scale, Bégué et al. (2010) and Nguyen (2005) considered a seasonal integration approach which utilized either the sowing or the harvesting date, while at the regional scale, Lofton et al. (2012) used growing degree days to compute in season NDVI for estimating yield and obtained good results. At regional scale in Portugal, Cunha et al. (2010) correlated yield of the current year with a 10-day NDVI data to develop a yield estimation model which explained 77% - 88% of wine yield. At state scale in Brazil, Duveiller et al. (2013) used growing degree days instead of the calendar year and estimated sugarcane yield with a RMSE of 1.5 t ha^{-1}

(around 2% of accuracy); however, they used a crop mask and selected sugarcane pixel purity above 95% for the establishment of the regressions.

We tested here a new way of time integration in order to account for the duration of the cropping cycle and harvest calendar. In effect, since the yield is estimated on annual basis, a ratoon crop growing from November 2009 to its harvest in January 2011 - at the age of 15 months - accounts for the 2011 annual yield data. Therefore, this complicates the yield prediction scenario where, in this case, the 2011 annual yield includes the yield of a crop that was almost nonexistent on the 2011 satellite time series (except on the January image). It is argued that predicting yield in such rain fed sugarcane fields is complicated since NDVI from all land uses declines at the end of the rainfall period (Gunnula et al., 2011) and requires a keen consideration of the integration period. In a similar case, a weighted land cover NDVI was used to account for the influence of other land uses on maize yield (Rojas, 2007). We therefore applied a weighting matrix over a period of time corresponding to the growing calendar, and not to the calendar year in order to take into account the active vegetative stages of the crop and minimize any shift in NDVI during sugarcane development (Kastens et al., 2005). To do this we chose two different periods of integration, (1) an 11-month period which corresponds to the approximate length of the growing cycle before maturation, and (2) a 15-month period which corresponds to the approximate length of the whole growing cycle. For both configurations, we calculated a weight for each month corresponding to the probability of a sugarcane field to be harvested during the calendar year of yield estimations, and thus to be accounted for in the annual yield (Figure 18).

Annual NDVI (NDVI) and weighted NDVI (wNDVI_15 and wNDVI_11) for each year was calculated according to Equation (1), with i equals to 15 and 11, respectively. The value 15 corresponds to the length of the usual cropping cycle of the sugarcane (in months), while the value 11 corresponds to the length of the vegetative part (in months) which is mainly related to cane yield (Bégué et al., 2010).

$$wNDVI\_i = \sum_{m=1}^{m=i} NDVI_m \, w_m \qquad \textbf{Equation 1}$$

where, NDVIm is the value of the NDVI for month m, w_m is a coefficient equal to the NDVI normalized weight (Figure 3), and i is the length of the time integration (in months). The sum of the w_m coefficients is equal to 1.

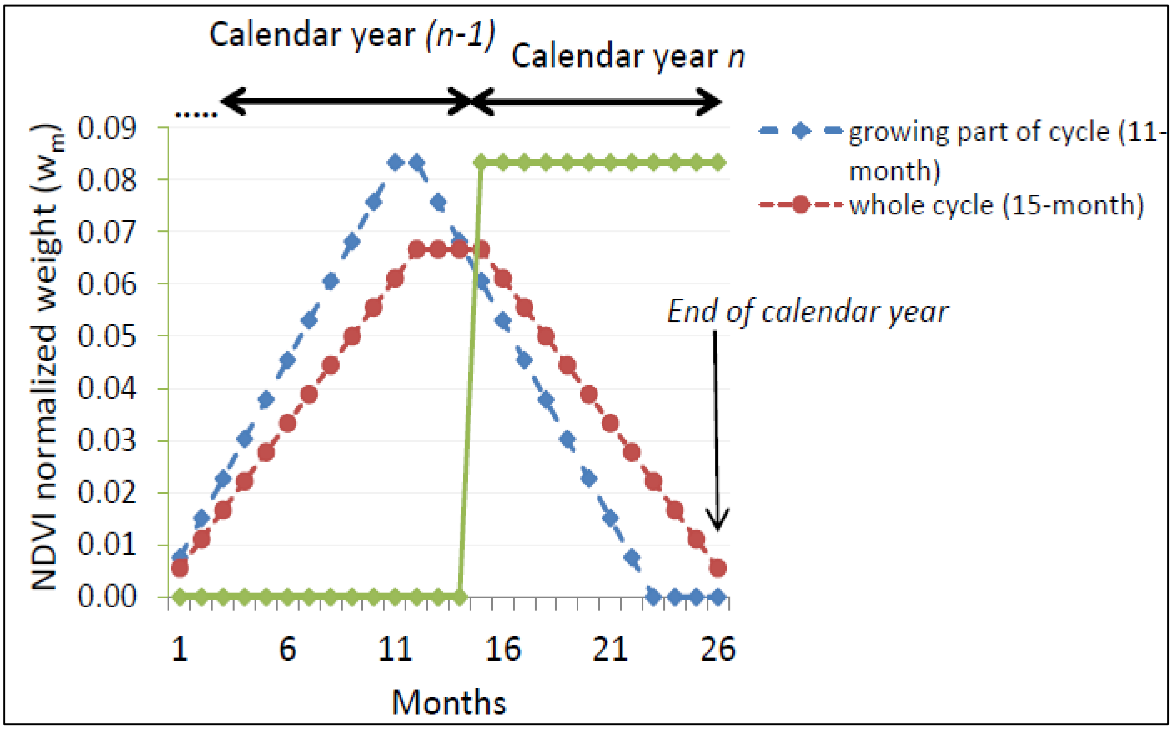


Figure 18: Three sets of weights used to calculate time integration of monthly NDVI values for annual yield estimation (year *n*). The green line (between months 14 to 26) corresponds to weights generally used to calculate the annual NDVI (the calendar year corresponding to the yield measurement). The blue and red lines correspond to weights that take into account the sugarcane cropping calendar (15 months for the whole cycle, and 11 months for the growing period) in the NDVI time integration.

3.3.2 Modelling drivers of spatial variability in yield

Statistical models were used to investigate the drivers of sugarcane yield in western Kenya. A linear regression established through time and space using a one-tailed probability test was adopted (Nguyen, 2005; Rasmussen, 1992; Lofton et al., 2012) while assessing the role of the environmental variables in the relation between yield and wNDVI, by correlating the slope of the "yield-wNDVI" relationships with the rainfall, and with the sugarcane fraction in each respective zone.

The investigated drivers (environmental effects) therefore, were; the zone, yearly sugarcane fraction, rainfall, precipitation marginal response (PMR) and MODIS NDVI effects on sugarcane yield (estimated yield data). PMR was computed by correlating the slope of Yield-wNDVI with the sugarcane fraction in each zone. PMR was tested to investigate the response of sugarcane to each millimeter change in soil moisture. The zone effect was used because these zones are spatially located in different agro ecological zones presenting variations in climatic and edaphic factors. The yearly sugarcane fraction was also considered for this analysis because over different years, the surface area under sugarcane is variable (Figure 10). It was presumed that through these models, the accuracy of forecasting sugarcane yield is improved.

3.3.3 Landsat 8 image analysis

Image processing was performed using ERDAS Imagine® (Intergraph Corp.).

Pre-processing

Subset of the Landsat image, and band selection (visible, NIR and SWIR) was performed based on the extent of the study area. The multispectral bands were merged with the panchromatic band using the *Brovery transform algorithm* resulting in multispectral images at 15 m spatial resolution. Cloud and cloud shadow masks were then prepared based on the *grow properties* drawing tool that was able to trace out areas covered with clouds and shadows.

Calculation of NDVI and NDWI

Two vegetation indices were derived using the following formula:

NDVI = (NIR – RED)/ (NIR + RED) (Rouse et al., 1974)

NDWI = (SWIR – NIR)/ (SWIR + NIR) (Gao, 1996)

NDVI (Normalized Difference Vegetation Index), which is the normalized difference between the near infrared (NIR) and visible RED reflectance, is responsive to changes in vegetation cover and greenness. Higher NDVI values reflect greater vigor and photosynthetic capacity (or greenness) of dense vegetation canopy, whereas low NDVI values are reflective of vegetative stress or senescence, or low vegetation cover.

NDWI (Normalized Difference Water Index), derived from the NIR and SWIR channels, responds to changes in both the water content (absorption of SWIR radiation) and structure (reflectance of NIR radiation) in vegetation canopies, respectively (Gao, 1996). SWIR is used in computation of the NDWI due to its ability to detect moisture absorption by plants. SWIR index is useful in detection of a harvest because it separates harvested residues from any other crop status (Lebourgeois et al., 2010).

Field limits digitalization

A map layer showing the limits of agronomic fields was digitized from the 15 m multispectral Landsat 8 image of 19th April 2013, in ArcGIS 10.1 software. This digital map was used to extract spectral variables from the cloud-free Landsat 8 image time series.

Spectral variables extraction per field

NDVI, NDWI and SWIR images were sequentially stacked to generate 3 images of 20 layers each (20 dates between April 2013 to March 2014; Table 4). The mean and standard deviation of these three image time series were then extracted for each digitized field using the *zonal attribute* function. Cloud pixels were set to 0, and were not taken into account in the statistics.

3.3.4 Mapping cropping practices

Cropping practices (in this document) imply the crop type, sugarcane harvest date and sugarcane harvest mode. These practices were identified through time series analysis of temporal profiles of NDWI, NDVI and SWIR profiles, and classification of the Landsat 8 image time series (table 5). We hypothesized that changes in these indices at harvest time were significantly different. To understand the spatial and spectral variability of the land cover types and crop conditions (harvested crop or standing crop, harvest mode), we studied for a given set of known fields : (1) the temporal variations of NDVI, NDWI and SWIR. The choice of these indices was conducted by Lebourgeois et al. (2010) who documented the use of spectral indices for characterization of sugarcane conditions. (2) True color composites of different sets of Landsat 8 images were examined for color, pattern, shape, and texture to visualize and interpret the land cover type, the harvest date and mode, and explore 3-date combinations identified through temporal analysis of MODIS NDVI. These spatial and temporal analysis were conducted to identify the best index to detect crop type, a harvest (harvest date), and harvest mode in Kibos-Miwani.

Classification of sugarcane fields

A map for sugarcane was produced using the temporal stack of NDVI images (Wardlow and Egbert, 2008) extracted from the 20 Landsat NDVI images in Table 5 with assumption that NDVI was a good descriptor of land cover type. The choice of time series images was in order to investigate the seasonal variability of vegetation in the area based on the main vegetative seasons identified from the temporal analysis of MODIS NDVI.

The sugarcane classification map was produced in two steps:

First, the Landsat time series was classified using ground survey points and a supervised classification into six classes (five classes of 'sugarcane' at different ages, and one class of 'other'; Table 7). 75% of the 1280 dataset (960 points, where 600 were sugarcane and 360 were other land cover,) were used as training data to characterize the multispectral variability of each thematic class, while 25% of the data (320, where 200 were sugarcane and 120 were other land cover points from the ground survey) were used for validation of the classified map. A recent study reported that the decision tree (DT) classifier is superior to the maximum likelihood classifier in areas with large fields over 100 ha in Brazil (Vieira et al., 2012). The Kenyan case is of small fields over 0.20 ha and therefore the maximum likelihood classifier algorithm was adopted in this study for its ability to utilize posterior probability of a pixel to belong to a given class to classify each pixel (Campbell, 2006) in a given space. This algorithm classified the time series into heterogeneous and homogeneous units based on crop age and land cover type. The six characterized units were assigned class names based on field surveyed attributes.

Secondly, recoding and management of the assigned classes (five sugarcane classes and 'other') followed so as to form one sugarcane class, and other land cover class using the Erdas Imagine recoding and management modules which group relatively homogeneous NDVI pixels that form agronomic fields into a land cover class. The resultant map became the sugarcane map for Kibos-Miwani.

Table 7: Distribution of survey points used in classification of five of 'sugarcane' classes at different ages, and one class of 'other'.

Class name	Age (months)	Number of points	% coverage
Sugarcane #1	0-2	131	14%
Sugarcane #2	3-5	129	13%
Sugarcane #3	6-8	150	16%
Sugarcane #4	9-11	100	10%
Sugarcane #5	Over 12	90	9%
Other	-	360	38%

Characterization of cropping practices (harvest date and mode)

We investigated the best index for characterizing cropping practices (harvest date and harvest mode). For each field, we computed differences in NDWI, NDVI and SWIR between each two dates for the 20 image dates (April 2013-March 2014).

First, we assumed that the larger change in SWIR index happened at the harvest time. So it was easy to detect for each field the harvest period (defined in days between two image acquisitions) that corresponds to the maximum difference between two dates.

Secondly, for each field we computed the NDVI and NDWI differences before and after the harvest, for both burnt and green harvest separately. On a set of 58 sample fields, where 29 fields were of green harvest and 29 were of burnt harvest. We checked the significance of these differences for the burnt and green harvest fields using a t-test. In case of 99% confidence level, the frequency of occurrence of the most significant spectral variable was plotted and fitted with polynomial models to check for the threshold that distinguishes between burnt and green harvest.

Accuracy Assessment

Accuracy assessment is important because it estimates the accuracy of the classified image by comparing the classified map with the reference map. Moreover, accuracy assessment provides information on the product quality and identifies probable sources of errors. A confusion matrix is a standardized method to represent the accuracy of classification results derived from remote sensed data by calculating accuracy measurements which include: overall accuracy, producer's accuracy, and user's accuracy (Congalton and Green, 2009).

For the SC map, we evaluated accuracy of the classification by creating a confusion matrix based on the 25% of the unused ground data (320 points).

For the harvest mode map, we evaluated accuracy of the classification by creating a confusion matrix based on the 25% of the unused ground data (200 points).

3.3.5 Soil erosion modelling

This study has used FuDSEM model to estimate the potential soil erosion risk in the sugarcane landscape of Kibos-Miwani zone for informed decision making to improve sugarcane yield based on cropping practices. The FuDSEM model (Cohen et al., 2008) is computed using ArCGIS software®.

The principles of FuDSEM model according to Cohen et al. (2008) are:

- It simulates soil erosion processes by utilizing known deterministic processes.
- It uses fuzzy logic structure to reduce calibration requirements and simplify the results for easy interpretation by providing potential risk and not quantitative maps
- It uses accessible data as input, such as soil characteristics and Landsat data.

This model was computed at the catchment scale by Cohen et al. (2008). In our case, we compute potential erosion risk at a local scale based on a 104 km^2 Kibos-Miwani landscape within which sugarcane growing is undertaken.

The main features of the model presented in Figure 19 are:

- Soil moisture potential is computed spatially based on the field capacity, aspect, time taken after last rainfall and soil moisture measured from the field data.
- Runoff potential is calculated spatially, based on soil moisture potential, vegetation data and digital elevation data
- Transport capacity potential is calculated in consideration of runoff potential and the slope
- Erosion potential is calculated based on transport capacity potential.

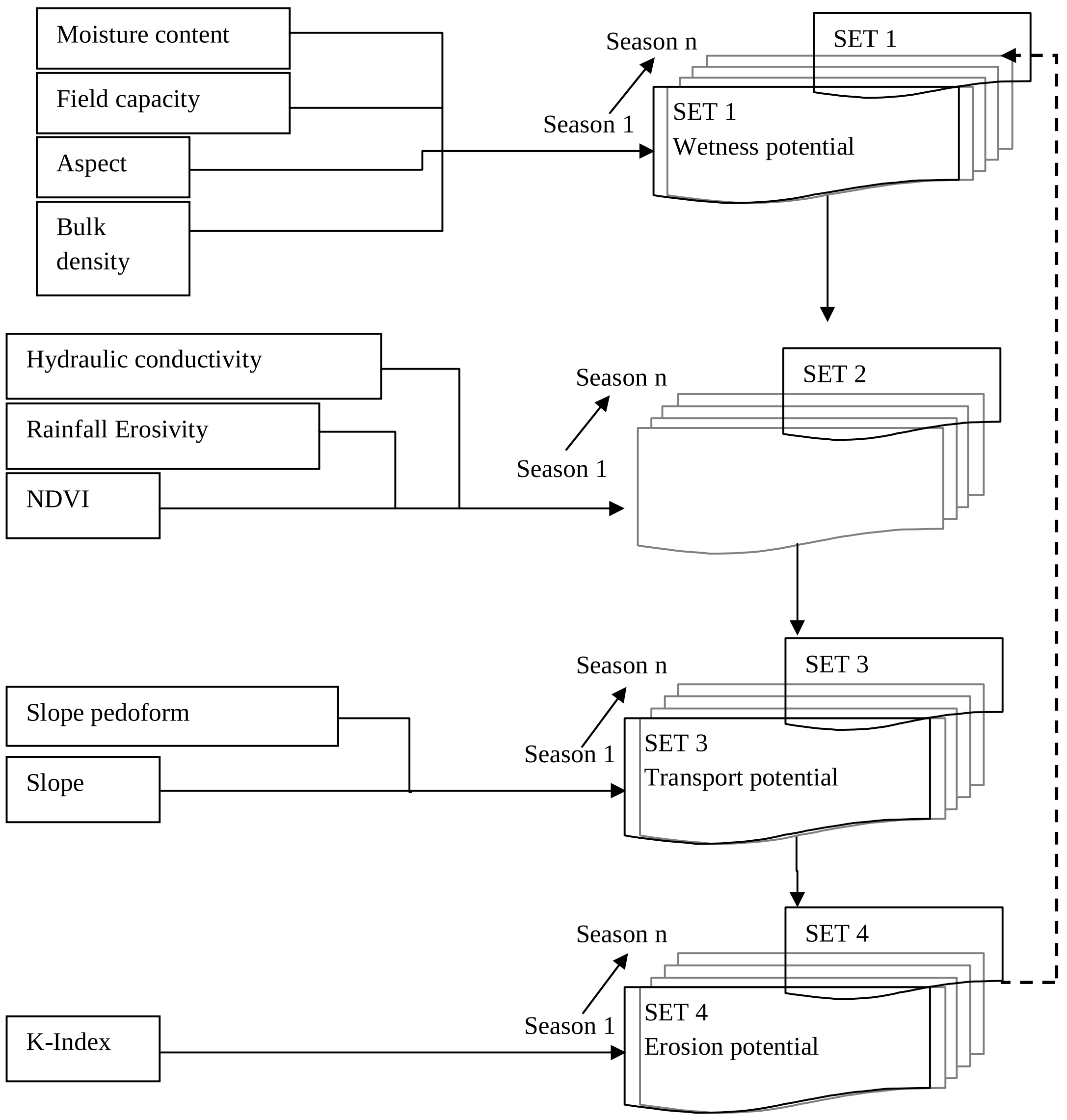


Figure 19: FUDSEM flow chart, adopted from Cohen et al. (2008).

To calculate potential erosion risk, we followed the steps outlined in Figure 19. First, we analysed soil characteristics from the 23 soil samples using methods discussed under SETS 1,2 and 4 (see the characteristics in Table 4). Next, we computed the aspect, slope and slope pedoform, from the 30 m digital elevation model (DEM) using the ArcGIS spatial analyst tool.

We then computed the rainfall erosivity as described under SET 2. Finally, we selected four Landsat 8 NDVI images corresponding to February (the first minimum vegetative season); May, (the first maximum vegetative season); September (the second minimum vegetative season); and November (the second maximum vegetative season), the seasons exposed by MODIS NDVI (Figure 24). These images were aimed at capturing the temporal variations in vegetation. In our simulations, we used soil characteristics data from 19 'sugarcane' fields (13 of burnt harvest and 6 of green harvest) and 4 'other' fields from the sugarcane map to assess the effect of cropping practices on erosion risk. We interpolated these data to the other fields within Kibos-Miwani through spatial analysis in GIS, using ordinary Kriging, based on a linear semivariogram model. The choice of a linear semi-variogram was in line with the semi-variogram scatter plot used in this study. These data (listed in Table 8) were input in FuDSEM model using fuzzy equations detailed under equations 2 to 12.

Soil moisture potential (SET 1)

Soil moisture potential is the energy of water in soil which is measured in energy/mass soil (J/kg). It controls the movement of water in soils. These moisture conditions vary over time (Jetten et al., 1999) depending on soil characteristics, rainfall events, crop development, harvesting method.

SET 1 is computed based on the: i) moisture content (MC), ii) field capacity (FC), iii) the aspect (AS), iv) time elapsed from previous rainfall (Te); and iv) the bulk density (BD)

The moisture content is calculated for each sampled soil as:

$$\mathrm{MC} = (\text{mass of wet soil} - \text{mass dry soil}) / \text{mass of wet soil}$$

A sigmoidal membership score is assigned to MC in Equation 2 due to the exponential ratio in soil moisture decrease with time (Hillel, 1998).

$$A = 1/\{1 + e^{\beta(MC - \alpha)}\}$$ **Equation 1**

Where;

A = the mid membership value of moisture content

MC = moisture content for each sampled soil in %

β = the function slope of MC values.

α = user input variable estimated based on the soil type in accordance with Cohen et al. (2008).

The field capacity, FC, represents the water holding capacity of the soil which may locally vary depending on soil moisture, texture, organic matter and permeability of the soil (Hillel, 1998). A linear membership score is assigned to FC in Equation 3:

$$FC = -(x - P_{min}) / (P_{max} - P_{min})$$ **Equation 2**

Where;

x = FC values in %

P_{min} and P_{max} are function parameters; and are therefore the minimum and maximum values of the dataset in accordance with the approach of Cohen et al. (2008). The linear function in Equation 3 is chosen from ArCGIS fuzzy membership functions library based on the exponential ratio in soil moisture decrease with time (Hillel, 1998).

The aspect AS takes into account the influence of solar radiation on soil moisture. The membership score assigned to AS therefore increases with radial distance from 180°. AS is therefore calculated based on a cosine membership function in Equation 4 (Cohen et al., 2008):

$$AS = \cos^2 \{(\pi (x - P_{min})) / (2 (P_{max} - P_{min}))\} \quad \textbf{Equation 3}$$

Where;

x = input value of the aspect in %

P_{min} and P_{max} are function parameters; and are therefore the minimum and maximum values of the dataset in accordance with the approach of Cohen et al. (2008).

The time that has elapsed since the previous rainfall (T_e) is assigned a sigmoidal membership function:

$$T_e = 1 / [1 + e^{\beta (x-\alpha)}] \quad \textbf{Equation 4}$$

Where;

β = the function slope of T_e values.

α = the mid membership value of x in accordance with Cohen et al. (2008)

The bulk density, BD was measured using the oven drying method based on dry and wet soil weights in Kenya Sugar Research Foundation (KESREF) ISO certified laboratory.

A combination of the four membership functions compute the soil moisture potential (SET 1) in this study using Equation 6

$$\text{SET 1} = \begin{cases} 0.4\,BD + 0.2\,AS + 0.2\,FC + 0.2\,MC & Te > 0, \\ 0.0 & Te = 0 \end{cases} \quad \textbf{Equation 5}$$

Runoff potential (SET 2)

We calculated the runoff potential using four variables: 1) wetness potential (SET 1); 2) hydraulic conductivity (HC); 3) rainfall erosivity (RE); 4) vegetation cover (NDVI).

Hydraulic conductivity, HC, represents how easy the water moves through the soil profile. This parameter was computed using a constant head method using a permeameter.

Rainfall erosivity, RE, was computed based on average rainfall amount and intensity (average monthly rainfall (MR) and average daily rainfall (DR)), above a 40 mm threshold (RI) and below a 40mm rainfall (RS)) and was used because it describes the potential for soil to be washed off by rainfall. RE is calculated using equation (7).

$$RE = (MR \ \ DR) + (RS \ \ RI) \qquad \textbf{Equation 6}$$

Where;

DR = Daily rainfall depth

MR = Monthly rainfall depth

RI = Daily rainfall above threshold of 40 mm/day

RS =Monthly rainfall above threshold of 40 mm/month

NDVI was used to represent vegetation cover data of Kibos-Miwani. It was computed from the Landsat 8 images (Table 5) using the zonal attribute parameter in Erdas Imagine based on the digitized shape file of Kibos-Miwani sugar zone. NDVI image for 5th May, 10th September, 13th November and 17th February for this area was used to simulate the effect of vegetation growing seasons on soil erosion risk. February NDVI represented the first minimum vegetative season, May NDVI for the first maximum vegetative season, September for the second minimum vegetative season and November for the second maximum vegetative season (see Figure 25). The choice of these images was because they are the seasons this study used. These were the best images because besides corresponding to the minimum and maximum vegetative seasons, they were also cloud free.

In our simulations, we used seasonal NDVI images at pixel level as the variable input to enable us capture the influence of management practices and climatic conditions on crop cover in the landscape during different weather seasons. In their simulation, Cohen et al. (2008) chose their images based on each simulation year. Whereas Cohen et al. (2008) captured seasonal variations as in our approach they referred to each year as a seasons, opposed to our seasons which were within one calendar year. The approach in this study aimed at assessing the sensitivity of crop type, slope and soil physical properties of this landscape to soil erosion risk. The functions used (Table 8) are those proposed by Cohen et al. (2008) and also additional information from ground surveys on sugarcane harvesting practices (multiple planting and harvesting dates; and green and burnt harvest modes).

Cohen et al. (2008) stated that weights assigned to NDVI are higher than those assigned to other variables due to its importance in semi-arid environments. In this study, Kibos-Miwani sugar zone does not fall within semi-arid environments and therefore the weights assigned are derived from the cropping calendar and harvesting practices at the particular field scale.

The potential runoff is thus calculated by combining these variables in equation 8:

$$\text{SET 2} = \begin{cases} 0.0 & \text{HC} \leq 0, \\ 0.2\ \text{HC} + 0.2\ \text{RE} + 0.2\ \text{NDVI} + 0.2\ \text{SET 1} & \text{HC} > 0 \end{cases} \qquad \textbf{Equation 7}$$

Transport capacity potential (SET 3)

The influence of vegetation cover and topography of the landscape on runoff is investigated here in accordance with Cohen et al. (2008). Sediments are transported by water from hill slopes in rills which develop into galleys and eventually siltation of the downstream. This capacity is calculated by combining two variables: the slope pedoform (SP) and the slope (S).

The slope pedoform SP is the convexity of the slope, computed from the 30 m Digital elevation model using the 3D analysis curvature function in ArcGIS software. Cells found within convex slopes have a high runoff potential and are considered to be the sources of erosion for downslope cells; while concave slopes have low run off cell values and are considered as sinks.

The slope (S) illustrates effects of gravity on runoff, where steep slopes accelerate runoff which results in higher transport capacity. S in this study is computed from the 30 m Digital elevation model using the 3D analysis slope function in ArcGIS software. A sigmoidal membership function in Equation 9 was used to describe this slope:

$$S = 1/ [1+ e\text{-}^{\beta(x-\alpha)}] \qquad \textbf{Equation 8}$$

where;

x = Slope

β = the function slope of the dataset.

α = user input variable estimated in accordance with Cohen et al. (2008)

The two variables α and β were assigned equal weights since they were assumed to contribute equally to the transport process. Equation 10 combines the parameters to calculate transport capacity as follows:

$$SET\ 3 = 0.33S + 0.33SP + 0.33\ SET\ 2 \qquad \textbf{Equation 9}$$

Soil erosion potential (SET 4)

Top soil erodibility is assumed to influence sediment transportation, accelerating erosion in soils that are susceptible to runoff detachment and transport. Potential erosion is therefore calculated based on the transport capacity and the soil erodibility index (K).

K represents the average soil loss per ton per hectare for a particular soil type and is computed according to Goldman et al. (1986) in equation (11). High K values denote higher erosion potential. Cohen et al. (2008) adopted K-values from Wischmeier and Smith (1978). This study calculated the soil erodibility factor (K) from the sampled soils using the method proposed by Lu et al. (2004).

$$K = (1.292)\,[2.1\ 10^{-6}\ f_p^{1.14}\ (12 - P_{om}) + 0.0325\ (S_{struct} - 2) + 0.025\ (f_{perm} - 3)]$$

Equation 10

In which, $f_p = P_{silt}\ (100 - P_{clay})$

Where;

f_p = the particle size parameter (unitless)

P_{om} = the percent organic matter (unitless)

S_{struc} =the soil structure index (unitless)

f_{perm} = the profile-permeability class factor (unitless)

P_{clay} = the percent clay (unitless)

P_{silt} = the percent silt (unitless)

The potential soil erosion is thus calculated by combining transport capacity and soil erodibility in equation 12:

$$SET\ 4 = 0.1K + 0.9\ SET\ 3$$ **Equation 11**

Comparison of FuDSEM model with RUSLE model

For the year 2013, we compared FuDSEM model results in estimating potential erosion risk through correlation analysis, with results of physical Revised Universal Soil Loss Equation (RUSLE) model for Kibos-Miwani. The Intergovernmental Authority on Development (IGAD) conducted the survey through the African Monitoring of the Environment for Sustainable Development (AMESD) project that used RUSLE model in June 2013 through Regional center for mapping and regional development (RCMRD) offices, Nairobi Kenya (AMESD, 2014). This map was produced at national scale for drought and climate change predictions. We used RUSLE model because its input variables were mostly similar to those used in FuDSEM model in this study which include: (i) 30 m Landsat NDVI after each six months to represent the first and second vegetative seasons of the year; (ii) rainfall erosivity from daily rainfall; (ii) erodibility factor from soil analysis; and, (iii) the slope from 30 m Aster DEM; and (iv) crop management factors (land use). The different variable in RUSLE model was the slope length, while in FuDSEM we used the aspect and slope pedoform.

For this comparison, we extracted potential erosion values for the 23 soil sampled fields from both FuDSEM and RUSLE models. We computed the average of the four seasons (February, May, September and November) of FuDSEM model values; then evaluated these against RUSLE values through regression analysis. The reason for using IGAD data is because in situ measurements were lacking for this validation. Previous researches have also shown the difficulty in evaluating large scale models due to lack of sufficient insitu data (Merrit et al., 2003).

Influence of cropping practices on potential soil erosion risk

For this investigation, we used the classified sugarcane map. First, we observed erosion trends and examined the influence of vegetative seasons through time on potential soil erosion risk by identifying and describing unique areas in the hilly and plain areas of the landscape on all the four erosion risk maps. Secondly, we used an analysis of variance (ANOVA) in R software to evaluate the significance of crop type and harvest modes on soil erosion risk. Erosion risk values from 23 fields from the sugarcane map were used, where, 13 were of burnt harvest, 6 were of green harvest while 4 were of other land cover.

Comparison of erosion risk simulations to field data

A survey by KESREF conducted between 2012-2013 (KESREF, 2013; Unpublished data) conducted measurements on sediment suspension from fields measuring approximately 30 m x 30 m. Ten run off plots (five comprising sugarcane and five comprising other crops such as maize and natural vegetation) were established along the same contour line with a distance interval of 30 m for replications within a slope > 2% and within the silty clay loam soils. The choice of this slope was to minimize on the rate of run off, while the choice of silt clay soils (soils 2, 3, 6 and 7; Figure 34) was because these are the dominant soil type of Kibos. The experiment was set up for one year from May 2012 to April 2013 in the same landscape studied here (see Figure 13) using FuDSEM model. In this experiment, plots were isolated from upstream fluxes using terraces while metal borders were inserted to a depth of 10 cm at each outlet (Rumpel et al., 2006). The total run off was measured after each rainfall event and sediments dried in the oven at 40°C. In total, 70 samples were collected and their means computed. Results of these measurements were compared with the mean potential erosion values from FuDSEM (Table 16). The simulated value was aggregated at the pixel level which measured the size of experimental plots in ArcGIS spatial analyst tool. The purpose of the analysis is to ensure the relevance of simulated data in terms of magnitude and trends.

Table 8: Input variables used in FUDSEM model functions.

	VARIABLE	NAME	UNIT	METHOD (membership function)	REF	DATA SOURCE	SPATIAL property (resolution)	Temporal property
1	Moisture Content	MC		Oven drying (Eq.2)	Barling et al. (1994)	Ground Survey	Point	Daily
2	Field capacity	FC		Sieve analysis (Eq.3)	USDA	Texture	Point	Constant
3	Erodibility factor	K		Sieve analysis	Goldman et al. (1996)	Ground Survey	Point	Constant
4	Aspect	AS	degree	Spatial analyst (Eq. 4)		DEM	30m	Constant
5	Bulk density	BD		Oven drying		Ground Survey	Point	Constant
6	Hydraulic conductivity	HC		Constant head using a permeameter		Ground survey	Point	Constant
7	Rainfall erosivity	RE		Equation 7	Cohen et al. (2008)	Daily & monthly rainfall, rainfall intensity	30m	Constant
8	Vegetation cover			NDVI		Satellite image	30m	Season
9	Slope		degree	Spatial analyst (Eq. 9)	De Jong et al. (1999)	DEM	30m	Constant

4. RESULTS AND DISCUSSION

4.1. Yield estimation models at regional scale

In this chapter we present results from the two approaches we used to identify the remote sensing indicator (NDVI, wNDVI) and environmental effects (zones, rainfall) on sugarcane yield are presented in this section.

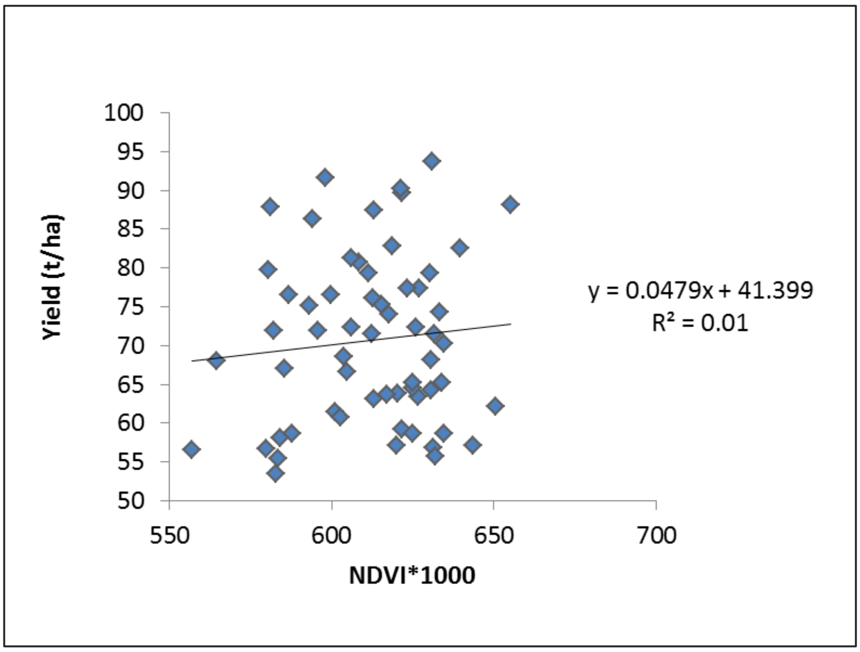
4.1.1 Spatial aggregation and temporal analysis

4.1.2 Relationship between Yield and NDVI

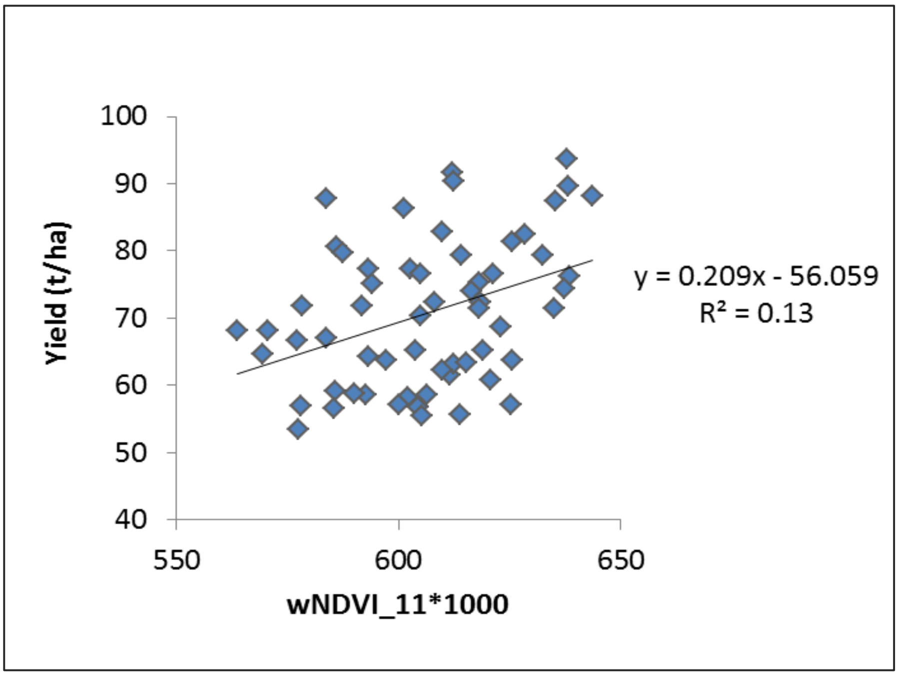
When the whole data set (6 zones and 9 years) is used, the analysis shows that the annual NDVI is not strongly related to the sugarcane yield ($p = 0.1$; Figure 20a). This finding is close to those of Gunnula et al. (2011) whose results showed low significance when correlating historical yield and NDVI at annual level ($P = 0.1$) (Bastidas-Obando and Carbonell-Gonzalez, 2007). However, when adjusted NDVI (wNDVI) is used, the relationship is highly significant for wNDVI_11 ($P = 0.001$) (Figure 20b) and significant for wNDVI_15 ($P = 0.01$) (Figure 20c) with the R^2 increasing from 0.01 for yield-NDVI relationship to $R^2 = 0.12$ for yield-wNDVI_15 and $R^2 = 0.13$ for yield-wNDVI_11 respectively, through linear relationship. This result is in agreement with a study demonstrating that yield estimations based on metrics obtained a little after the peak of APAR can be done without seriously compromising performance (Duveiller et al., 2013). However, the strength of these correlations is weak, justifying further analysis by this study on other factors that affect yield.

When the whole dataset is aggregated over the whole period (2002-2010), at the zone level (spatial analysis), the correlation between yield and wNDVI is significant (Figure 21a) with $R^2 = 0.53$, $P < 0.001$; while when the whole dataset is aggregated over the six zones, at the year level (temporal analysis), there is no significant correlation between yield and wNDVI (Figure 21b). The good result obtained through the spatial analysis is due to different environmental variables exuded through rainfall distribution. The absence of significant results through the temporal analysis could be explained by (1) the difficulty to make coherent yield measurements over a calendar year and wNDVI (considering the length of time sugarcane takes to mature), and (2) the sugarcane cover fraction changes during the 2002-2010 period. This interpretation is exemplified by the variable standard deviation figures over the years (see standard deviation values of the fraction of sugarcane cropped area in each zone, Table 1).

a)



b)



c)

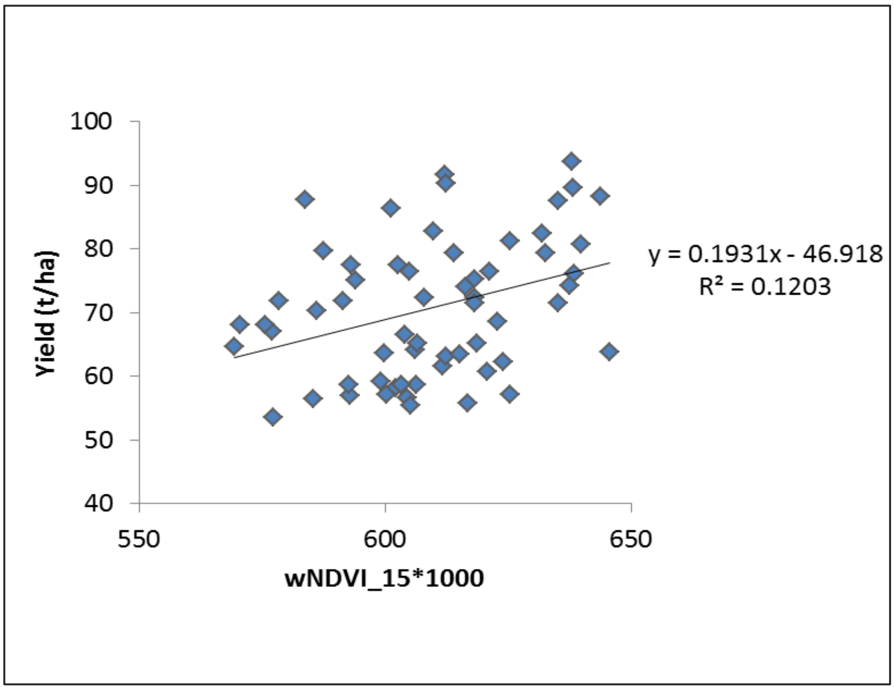
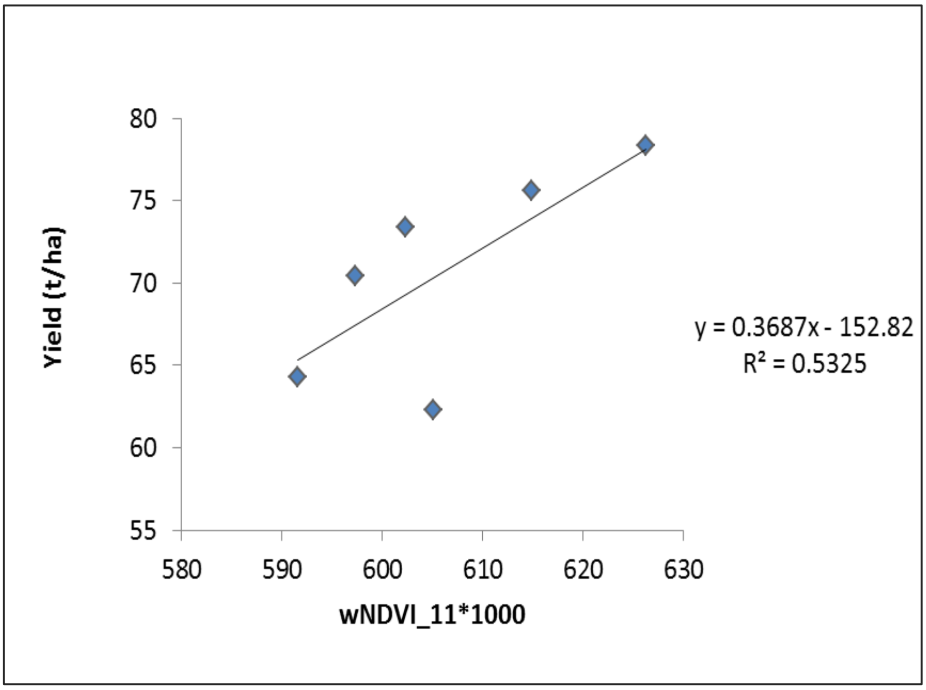


Figure 20: Relationship between (a) yield and annual NDVI, (b) yield and wNDVI_11, and (c) yield and wNDVI_15.

a)



b)

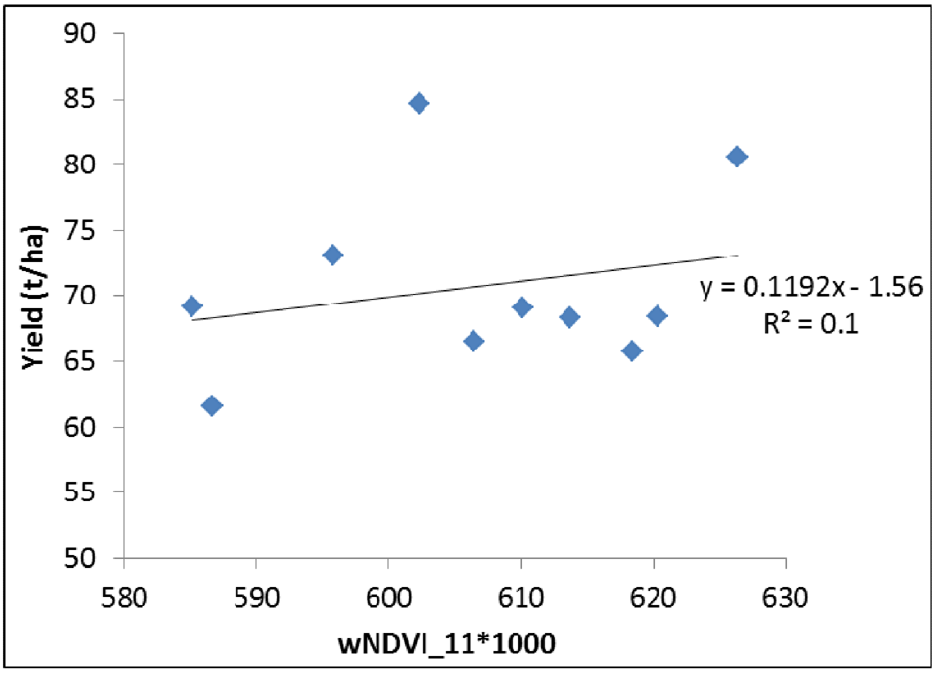


Figure 21: Variability with wNDVI_11 averaged (a) **at zone level on the 2002–2010 periods, and** (b) **at annual level on the six zones.**

4.1.3 Relationship between Yield and Rainfall

In order to better understand the spatial and temporal variability of yield, we studied the relationship between yield and annual rainfall. When using all the data (6 zones * 9 years; Figure 22a), the relation between annual yield and rainfall was significant, but weak ($R^2 = 0.08$; $p = 0.03$). Such a weak relationship has been attributed to the time lag between yield and rainfall because vegetation takes a considerable period to respond to soil moisture (Shisanya et al., 2011). This effect is amplified in Western Kenya, where the annual yield is dependent on the rainfall of the previous year due to the length of the sugarcane cycle. On removal of the time lag through spatial and temporal averaging over the nine year data (6 zones * 9 years; Figure 22b,c), this study showed a strong relationship as noted by other studies (Lofton et al., 2012; Shisanya et al., 2011) with $R^2 = 0.8$ and $p < 0.001$ at the spatial level (Figure 22b). It is assumed that this relationship is stronger because yield is not only affected by rainfall but by other agro-environmental factors that may be specific to different zones. The relationship between yield and rainfall (Figure 22b) is stronger than the relationship between yield and wNDVI (Figure 21a) at the zone scale. This is because unlike rainfall which is an environmental variable, wNDVI value integrates not only sugarcane cultivated area, but also other types of land covers that are in different proportions according to the zone.

The temporal analysis of yield and annual rainfall shows no correlation between both variables (Figure 22c), because (1) rainfall is not the only yield driving factor, and (2) because annual rainfall should be integrated on a longer period and with different weights (as wNDVI) in order to take into account the particular cropping calendar of the sugarcane crop. These results are in agreement with a study that pointed out that rainfall amounts and pattern may not be a reliable predictor of yield (Gunnula et al., 2011). However, rainfall aggregated at zonal level (Figure

22b) shows a significant correlation (R^2 = 0.80, P = 0.001) with yield because each zone has unique agro environmental conditions that impact of yield.

a)

b)

c)

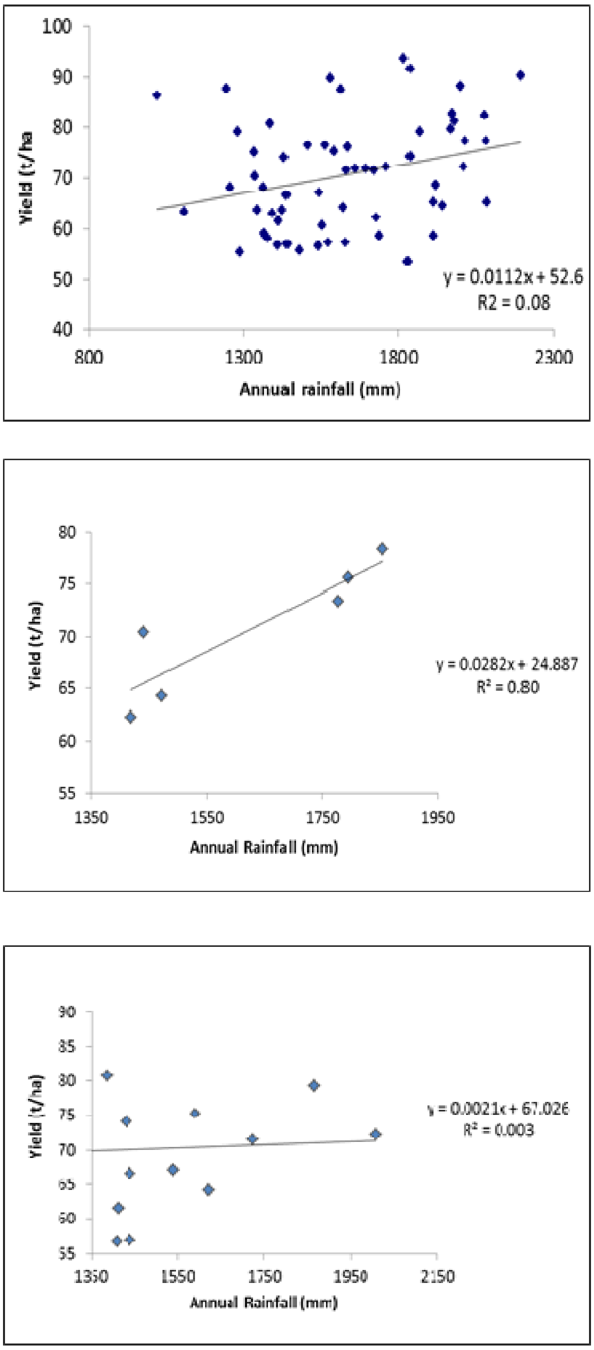


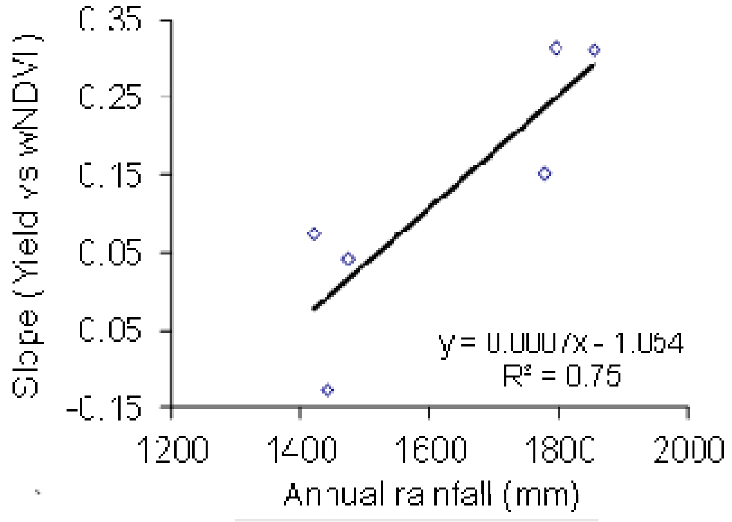
Figure 22: Relationship between yield and rainfall using: (a) all the data, (b) the data aggregated at the zone scale (spatial analysis), and (c) the data aggregated at annual scale (temporal analysis).

4.1.4 Relationship between Yield-wNDVI Slope and with Rainfall and Yield-wNDVI Slope and sugarcane fraction

In order to better understand the main driving factors of the yield-wNDVI relationship, we correlated the slope (residuals or values) of the relation between yield and wNDVI aggregated at the zone scale with the rainfall (Figure 23a), and with the fraction of sugarcane in each zone (Figure 23b). Results show a strong correlation with high significance at $p < 0.001$ in both cases. The sensitivity of the yield-wNDVI variations to each millimeter rainfall received in each management zone also called the Precipitation Marginal Response, or PMR (Veron et al., 2005) separates two groups of these sugar zones, three geographically located in sub humid AEZ from three located in the humid AEZ (Figure 25a). The ability to separate the two climatic regimes in this study therefore strengthens the ability to use wNDVI in forecasting crop yield. Results of the PMR relationship were highly significant with $R^2 = 0.75$; $P = 0.001$. The positive slope of this relationship (Figure 23a) indicates that the sensitivity of the yield to rainfall is higher than the sensitivity of the wNDVI to rainfall.

The negative slope (the higher the fraction, the lower the slope) resulting from the relationship between yield-wNDVI slope and sugarcane fraction $R^2 = 0.42$; $P = 0.01$ (Figure 23b) indicates that wNDVI is not only affected by the amount of rainfall received in the zone, but is also influenced by other surrounding vegetation cover.

a)



b)

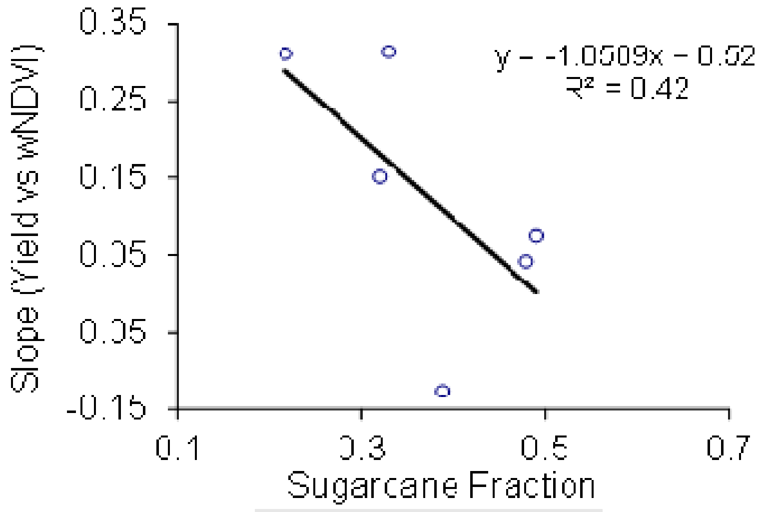


Figure 23: Relationship between the "yield-wNDVI" slope and (a) rainfall, and (b) sugarcane fraction, aggregated at the zone scale.

4.1.5 A Quantitative Evaluation of the sugarcane yield Model

WNDVI_11 data for the period 2001-2011 was used to estimate the 2012 sugarcane yield (Table 9), while wNDVI_11 data for the period 2001-2012 was used to estimate yield for the year 2013 (Table 10) using the models established at the zone scale (Figure 21a). This was done in order to utilize data that is independent from the one used in development of this model.

Table 9: Zonal model validation using 2012 yield data.

Zone	wNDVI_11	Model Yield($t \cdot ha^{-1}$)	Measured Yield ($t \cdot ha^{-1}$)	Error ($t \cdot ha^{-1}$)
Mumias	566.5	54.2	48	6.2
Nzoia	602.8	68.4	64.7	3.7
Chemelil	586.9	62.2	59	3.2
Muhoroni	604.4	69.1	63.6	5.5
Kibos	596.1	65.8	62.7	3.1
Sony	610.5	71.5	69	2.5
RMSE				4.25

In 2012 (Table 9), we obtained a Root Mean Squared Error (RMSE) of 4.25 t ha^{-1}, with all the zones modelled to have higher yields than the measured yields in each zone. The highest yield over-estimation was realized in Mumias zone (6.2 t ha^{-1}), where the land holdings are particularly small (up to 0.1 ha), and where the landscape is very heterogeneous (Figure 18). This result is similar to the low accuracy obtained for fields smaller than the pixel size (Fernandes et al., 2011). When excluding Mumias zone, the RMSE decreases to 3.41 t ha^{-1}, which is below the user specification of RMSE 5 t ha^{-1}.

Table 10: Zonal model validation using 2013 yield data.

Zone	wNDVI_11	Model Yield($t{\cdot}ha^{-1}$)	Measured Yield ($t{\cdot}ha^{-1}$)	Error ($t{\cdot}ha^{-1}$)
Mumias	568.3	56.7	54.29	2.41
Nzoia	601.4	68.7	67.66	1.04
Chemelil	588.5	62.6	61.4	1.2
Muhoroni	589.2	60.1	58.2	1.9
Kibos	591.1	62.3	60.7	1.6
Sony	615.7	67.1	66.2	0.9
RMSE				1.6

In 2013 (Table 10), we obtained a Root Mean Squared Error (RMSE) of 1.6 t ha^{-1}. Like in 2012, all the zones are considered with higher modelled yields than the estimated yields in each zone with the highest over-modelled yield in Mumias (2.41 t ha^{-1}).

4.2. Mapping of cropping practices using remote sensing data

In this chapter, we tested if the spatial and temporal information contained in the satellite images could be interpreted in terms of cropping practices (crop types and sugarcane harvest mode).

4.2.1 Temporal variability

Results of time series analysis on MODIS normalized difference vegetation index (NDVI) captured seasonal variations in vegetation that result from the rainfall pattern in Kibos-Miwani. These seasonal variations facilitated the choice of Landsat images used in characterization of cropping practices in this area and in soil erosion risk modeling. Results demonstrate four main vegetative seasons for the sugarcane crop. These results exhibit two peaks (May and November) and two minimum vegetative seasons (February and September), corresponding to the interaction between sugar-cane physiology and the bimodal rainfall (Shisanya et al., 2011) with a one month time lag (Figure 24). Two minimum vegetative seasons in February and September are also exhibited, corresponding to the dry season. February indicates the first minimum vegetative season while September is the second minimum vegetation season. The first maximum vegetation season is experienced in May, while November is the second maximum vegetative season. We infer that rainfall distribution is the main driver of temporal NDVI variations and that farmers plan their crop management activities based on these two rainfall seasons.

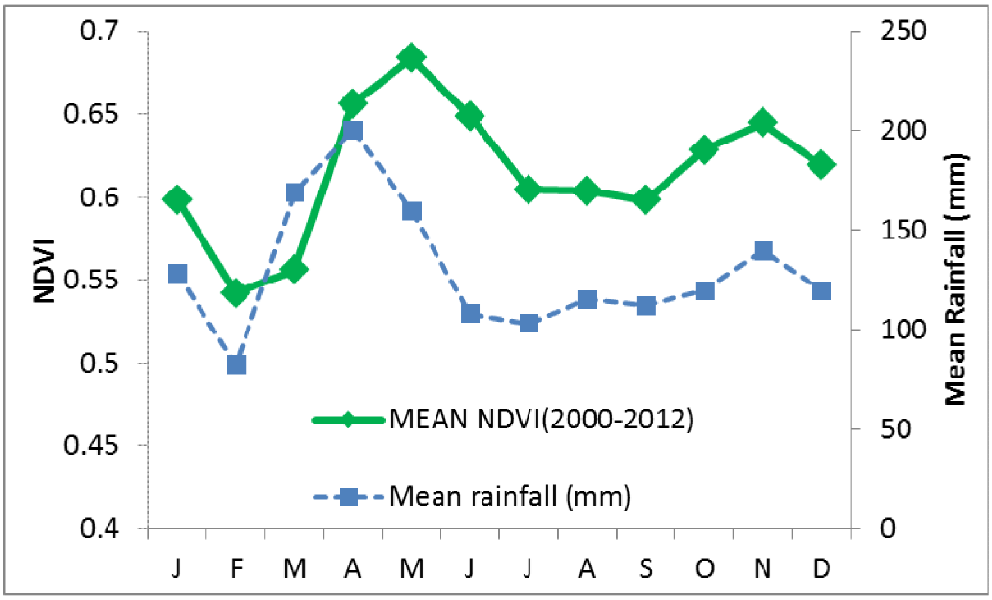


Figure 24: Mean seasonal vegetation conditions as measured by MODIS and monthly rainfall variability for the period 2000-2012 in Kibos.

4.2.2 Spatial variability

A color-composition of 15 m NDVI Landsat images for three vegetative seasons (May, September and November) is displayed in Figure 25. Results show varied cropping practices such as fields with young crop whose germination commenced in May, those harvested in November, mature crop that is due for harvest and other cover crops within Kibos-Miwani. These results have revealed multiple planting and harvesting dates at pixel level, between fields in the area with different types of crops, vegetated and harvested fields exemplified on the image composite. In this study, the variable NDVI pattern in different fields is an indicator of different types and ages of crops in the area where environmental conditions such as the dry season may affect mature crops thereby reducing their NDVI. This finding compliments the cropping calendar of Kibos-Miwani, where food crops are planted during the same period as sugarcane. This result is similar to a different study which showed that low NDVI may indicate start of growth season, for young crop or; for crop of higher age, low NDVI may depict crop stress or start of maturation (senescence) (Vintrou et al., 2012). Landsat8 images have demonstrated spatial variability in vegetation conditions at the pixel scale with vegetated, harvested, planted fields and natural vegetation being identified on the image composite for the selected months. We assert that these cropping practices are the main driver of these local variations.

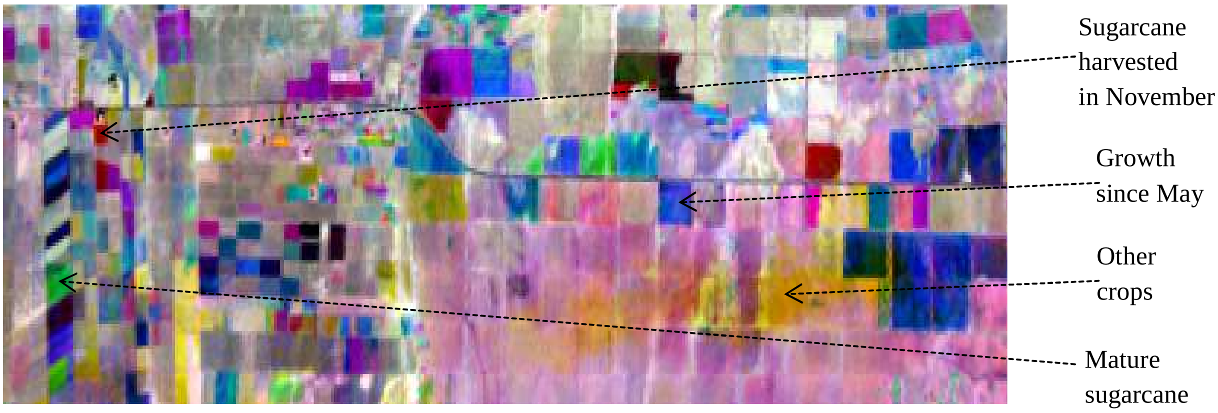


Figure 25: Landsat 8 NDVI colored composite image (R: May 2013; G: September 2013; B: November 2013) Located at 34° 30'E to 35°E and between 0°S to 0° 45'S.

4.2.3 Time profile analysis in terms of cropping practices

The harvest date was detected thanks to an abrupt increase in the SWIR band (see example in Figure 26).

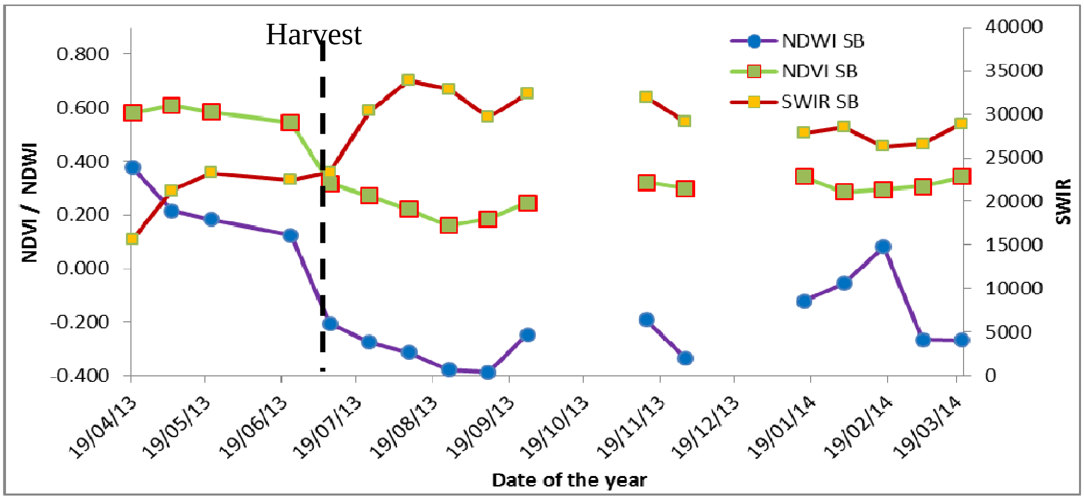


Figure 26: NDVI, NDWI and SWIR for a field that is harvested by burnt method. Where SB= burnt harvest. This field was harvested on 8th July 2013. The dotted line indicates the harvest day.

The harvest mode map was obtained through a characterization of spectral indices selected through a t-test. Table 11 shows results of the t-test on the values of two spectral indices, NDWI and NDVI, before and after the harvest, for sampled fields. Results show that, at harvest time, changes in NDWI are high (mean=0.41) for burnt harvest and low (mean = 0.10) for green harvest. The differences for green and burnt harvest modes are significantly different for NDWI_Diff at P = 0.000, while they are not significant for NDVI_Diff (P = 0.345). These results show that both SWIR and NDWI are useful in description of sugarcane harvest time and harvest mode respectively.

Table 11: Statistics of NDWI and NDVI values for green and burnt harvest fields, and p-value for testing the difference between the two harvest modes (Bef = value before harvest; Aft = value after harvest; Diff= value difference between before and after harvest). Bold values indicate a significant difference at 0.01%.

	NDWI_Bef	NDWI_Aft	NDWI_Diff	NDVI_Bef	NDVI_Aft	NDVI_Diff
Mean Green harvest	0.21	0.11	0.10	0.65	0.39	0.26
Std Green harvest	0.07	0.08	0.06	0.06	0.07	0.08
Mean Burnt harvest	0.26	-0.15	0.41	0.59	0.35	0.24
Std Burnt harvest	0.09	0.07	0.12	0.06	0.05	0.07
P-values (difference Green/Burnt harvest)	**0.002**	**0.000**	**0.000**	**0.000**	0.026	0.345

Figure 27 illustrates the mean and standard deviation of these results which show that at harvest time, NDWI values between green and burnt harvest are significantly different.

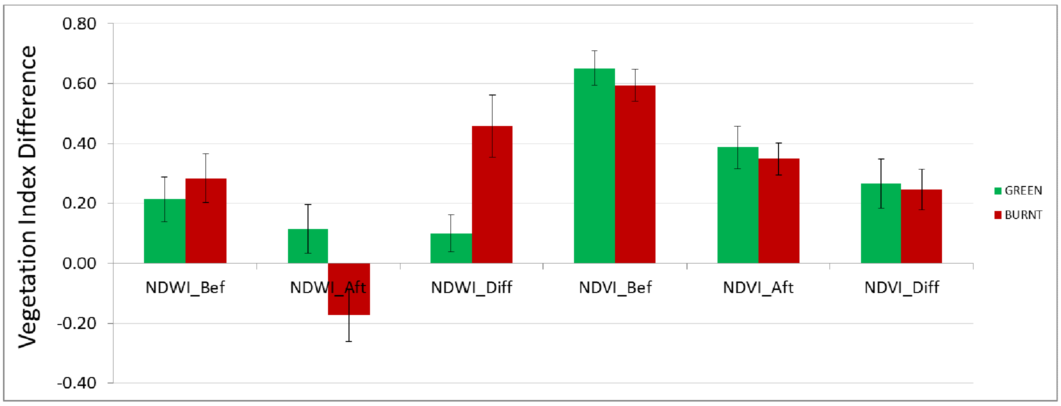


Figure 27: Mean and standard deviation (+/- 1 std) of NDVI and NDWI vegetation indices differences (Bef = value before harvest; Aft = value after harvest; Diff= value difference between before and after harvest), for two harvest modes (Green bars: green harvest – Red bars: burnt harvest).

Figure 28 shows the frequency in value occurrence for differences in NDWI before and after harvest (NDWI_Diff), for green and burnt. The NDWI_Diff frequency of occurrence shows that at harvest, over 90% of the green harvested fields have NDWI_Diff below 0.27 while over 90% of the burnt harvested fields have NDWI above 0.27. We infer that NDWI_Diff value of 0.27 is a threshold for separating the burnt and green harvest classes.

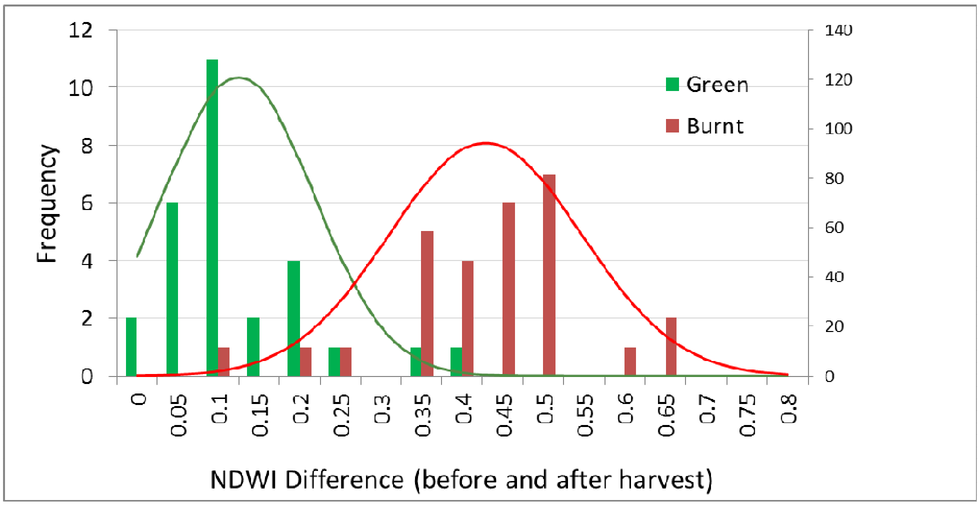


Figure 28: The bars correspond to the frequency distribution of NDWI differences, for green and burnt harvests. The lines correspond to Gauss-fitted frequencies.

The significance in NDWI value differences at harvest has facilitated the use of NDWI in field by field classification of the harvest mode map.

4.2.4 Sugarcane classification

The NDVI image was used in characterization of the land cover map. Figure 29 illustrates these results which show a classified NDVI image of Kibos-Miwani into six classes. Five classes are 'sugarcane' that results from variation in sugarcane age and one for 'other' class (Table 7).

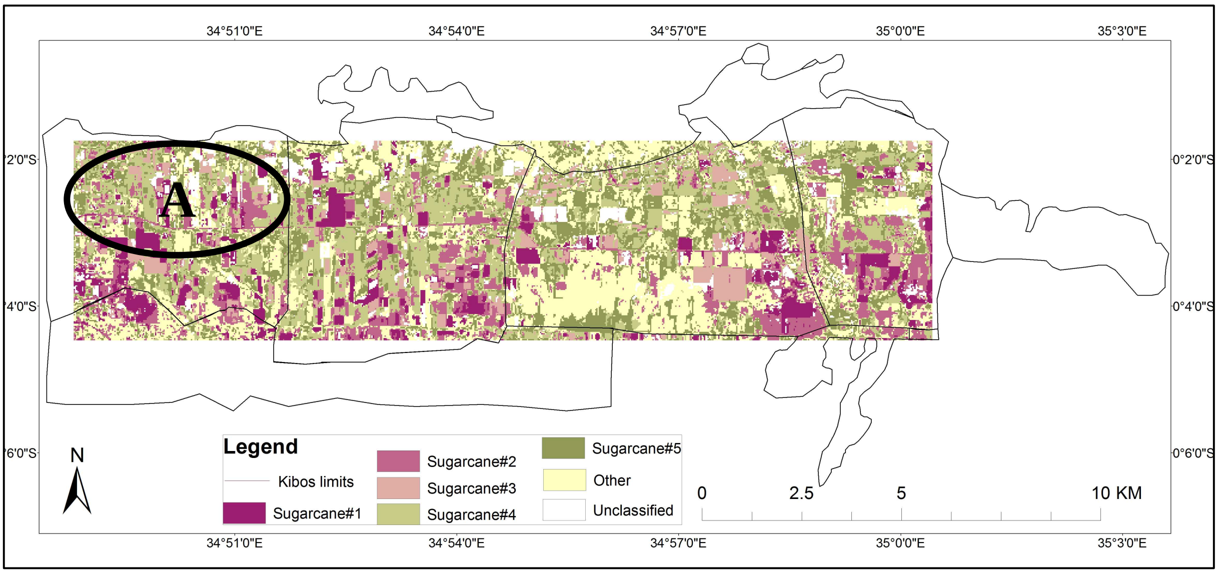


Figure 29: The classified Landsat image of Kibos-Miwani showing six land cover classes: five classes of 'Sugarcane' based on different stages of the crop, and one class of 'Other'.

A zoom on area "A" shows spatial heterogeneity within and between sugarcane fields (Figure 30). This zoom exposes heterogeneity in the landscape resulting from the cropping calendar and alternatives in the crop management systems in Kibos-Miwani. The spatial heterogeneity between sugarcane fields in figure 33 implies that crop management such as weed control, harvesting mode, fertilizer application and soil characteristics (Jamoza et al., 2013) are the drivers of these local variations. This result is similar to a study which showed that sugarcane landscapes are spatially heterogeneous due to variable cropping practices (Mulianga et al., 2012; Zarco-Tejada et al., 2005).

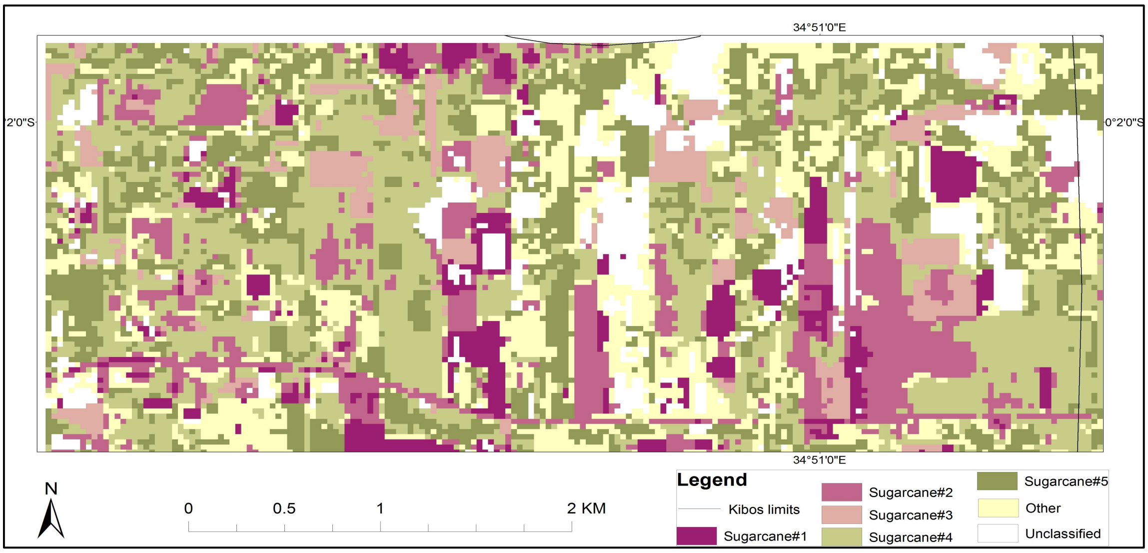


Figure 30: A zoom on the classified Landsat image of Kibos-Miwani sugar zone in area "A".

Figure 31 shows the classified Landsat image of Kibos-Miwani after post classification. The figure illustrates two classes: Sugarcane and other. The figure shows over 85% of the landscape is under sugarcane and heterogeneity in the land cover is driven by cropping activities that are influenced by intensification in the heavily fragmented landscape (Mulianga et al., 2012).

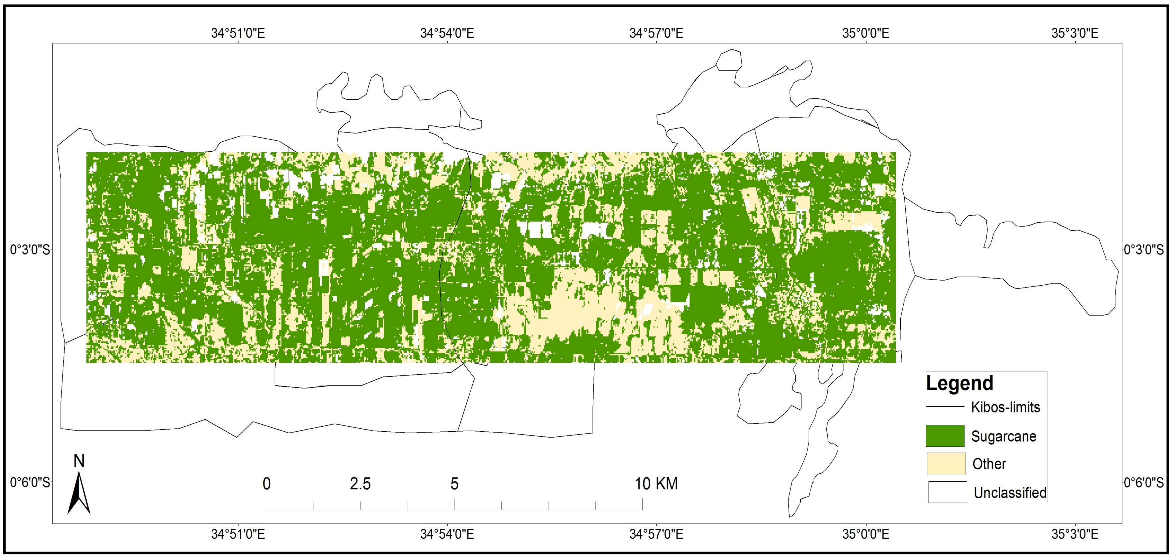


Figure 31: A classified Landsat image of Kibos-Miwani sugar zone after re-coding of all sugarcane and other pixels in two classes: sugarcane and other cover.

Figure 32 presents the result of the crop type map produced through a field by field classification method.

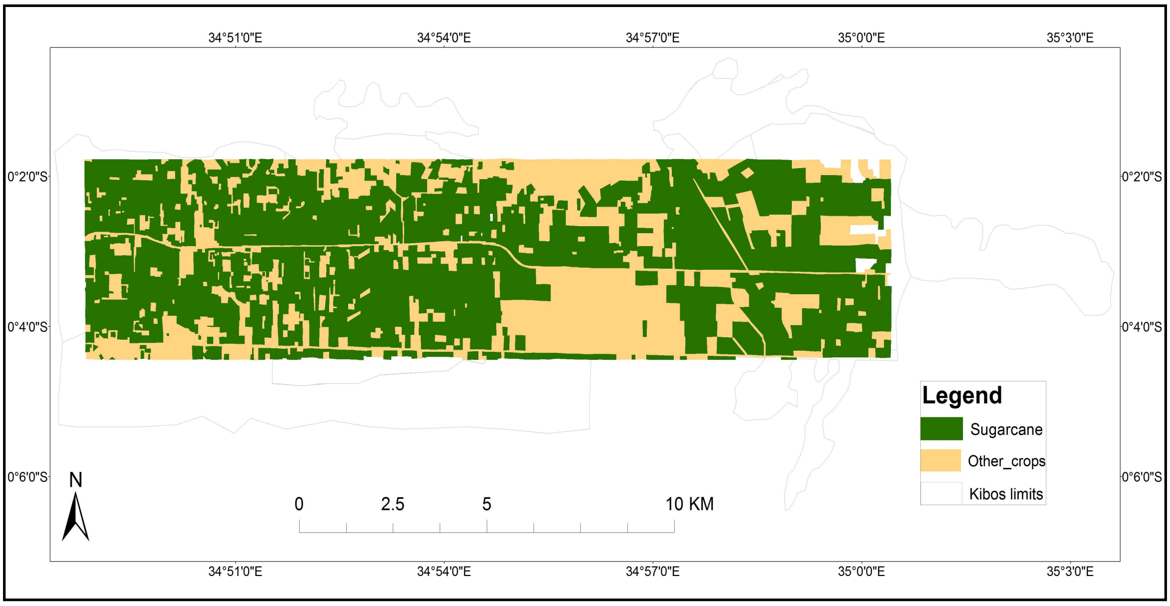


Figure 32: The sugarcane field map classification, obtained using a majority filter applied on the classified Landsat time series (Figure 31)

The sugarcane classification accuracy was based on data that were not used for classification. Results derived from the confusion matrix (Table 12) give an overall classification accuracy of 83.8%. The class "sugarcane" has a user accuracy of 95.8%, while the class "other" has a user accuracy of 83.1%.

Table 12: Confusion matrix of the classified Landsat image for Kibos-Miwani after post-classification. The bold values are the pixels that were classified correctly.

		Classification					
		Sugarcane	Other	Unclassified	Line total	Producer Accuracy	Omission error
Ground truth	Sugarcane	**160**	22	18	200	80.00%	20%
	Other	7	**108**	5	120	90.00%	10%
	Row total	167	130	23	320		
	User Accuracy	95.8%	83.1%			83.8%	
	Commission error	4.2%	16.9%				

where;

User accuracy = Number of pixels of the ground class/total pixel in classification class

Producer accuracy = Number of pixels of the classification class/ total pixels in the ground class

Omission error = 1 - Producer's Accuracy

Commission error = 1- User's Accuracy

Results of this classification show that sugarcane class has 20% omission error and 4.2% commission error, while; the 'other' class has 10% omission error and 16.9% commission error. Only 20 pixels (6% of the sugarcane data set), were not classified.

4.2.5 Sugarcane harvest mode classification

The sugarcane harvest mode was classified using NDWI differences. NDWI Differences > 0.27 were classified as burnt harvest, while NDWI Differences ≤ 0.27 were classified as green harvest. The classified harvest mode (green harvest and burnt harvest) map is displayed in Figure 33. Our results have shown that changes in both SWIR and NDWI are highest at harvest.

We therefore accepted our hypothesis and also concluded that the highest NDWI difference occurs at harvest. NDWI was used in this section due to its ability to distinguish between the two harvest modes. This map shows three classes: green harvest, burnt harvest and fields with other cover.

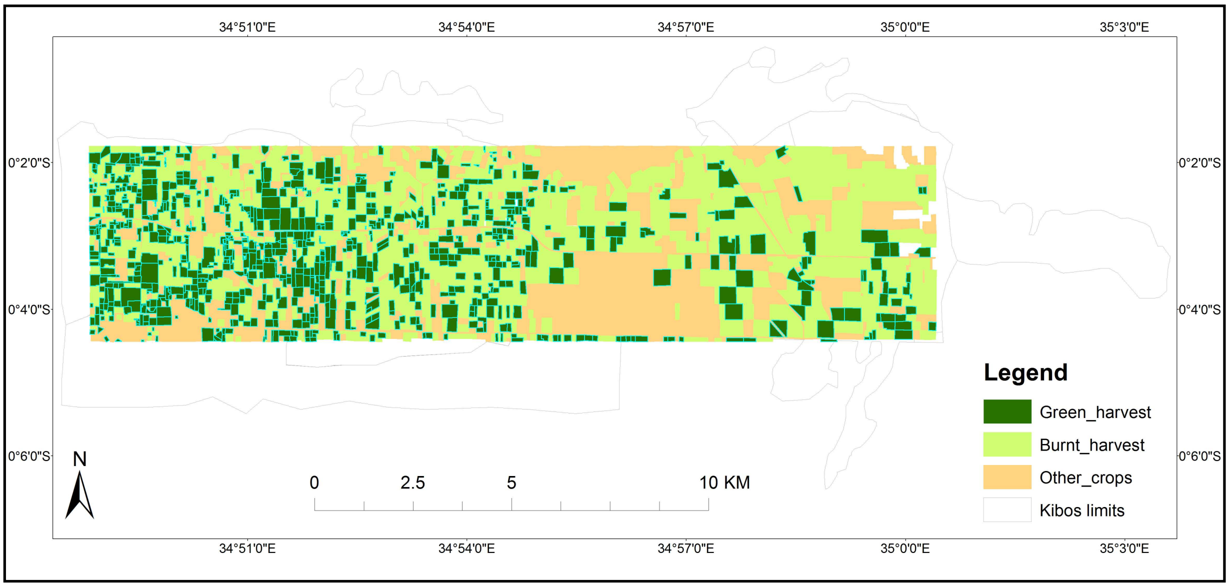


Figure 33 : Map of the sugarcane harvest mode and other cover in Kibos-Miwani.

Table 13 shows the fraction area covered by each class. Area under green harvest mode accounts for 25% of the total area, while area under burnt harvest accounts for 75% of the total area. These results confirm ground information, where, burnt harvest is a dominant practice in Kibos-Miwani with 74.5% coverage compared to 25.5% for green harvest mode.

Table 13: The harvest mode and the percentage coverage in Kibos

Harvest mode	*Total (ha)*	*% coverage*
Green	2,284	25.5
Burnt	6,672	74.5
	8,957	**100**

Results derived from the confusion matrix (Table 14) give an overall classification accuracy of 90%. The class “green harvest” has a user accuracy of 88%, while the class “burnt harvest” has a user accuracy of 92%.

Table 14: Confusion matrix of Kibos-Miwani after post classification of sugarcane fields into burnt and green harvest modes. The bold values are the pixels that were classified correctly.

		Classification				
Ground truth		Green Harvest	Burnt Harvest	Line total	Producer Accuracy	Omission error
	Green Harvest	**90**	8	98	0.92	0.08
	Burnt Harvest	12	**90**	102	0.88	0.12
	Row total	102	98	200		
	User Accuracy	0.88	0.92		90%	
	Commission error	0.12	0.08			

Results of this classification show that green harvest class has 8% omission error and 12% commission error, while the burnt harvest class has 88% omission error and 12% commission error. This result shows the effective use of NDWI in distinguishing harvest modes from a satellite image.

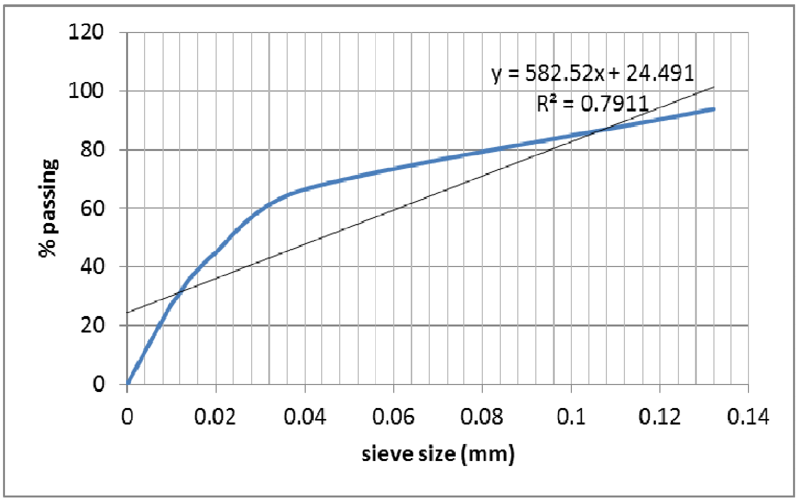
4.3. Soil erosion risk at local scale

In this chapter, we present results on the impact of cropping practices on soil erosion risk of Kibos-Miwani landscape using FuDSEM model at local (field) scale.

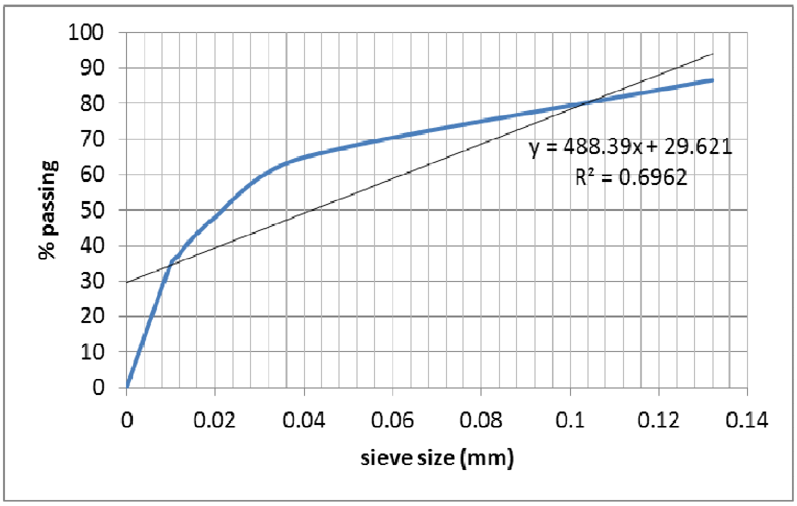
4.3.1 Erodibility factor

The erodibility index K for Kibos-Miwani ranges between 0.26 in the lowlands (with silt clay soil), and 0.38 in the uplands (with silt loam soil) giving a range of 0.20. These values correspond to the particle size distribution of each soil type and 4% and 2% organic matter respectively on a USDA Department of Agriculture (USDFA) soil textural classification triangle which has a range of 0.20 between the highlands and lowlands of the sugarcane landscape (Mitchell and Bubenzer, 1980). Figure 34 illustrates results of the distribution of these erodibility values and the particle distribution curve for each soil in Kibos-Miwani. Further, this range is within the standard range of 0.02 to 0.69 documented by Mitchell and Bubenzer (1980).

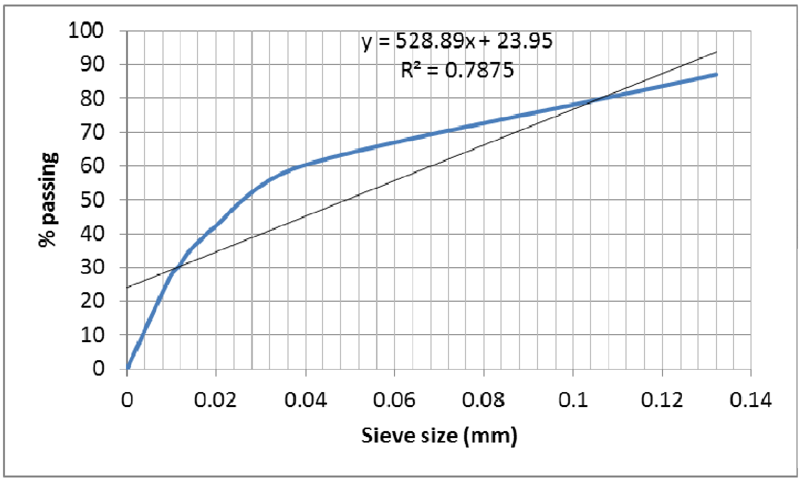
This local variation in the erodibility index in this area is due to variations in soil type with the silt loam soil in the hilly areas resulting in high porosity values (66%) in the silt loam soils of the hilly areas that allows fast percolation of water compared to porosity of 44% in the silt clay lowland soils that retain water.



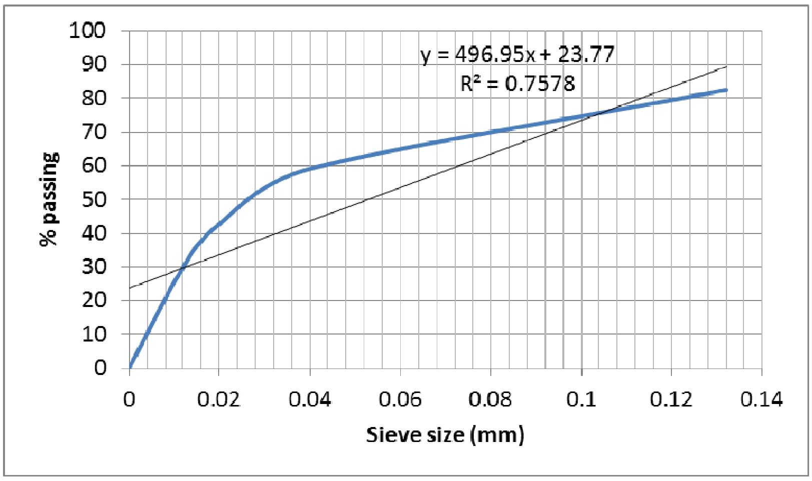
Soil 1
Silt loam
K = 0.38



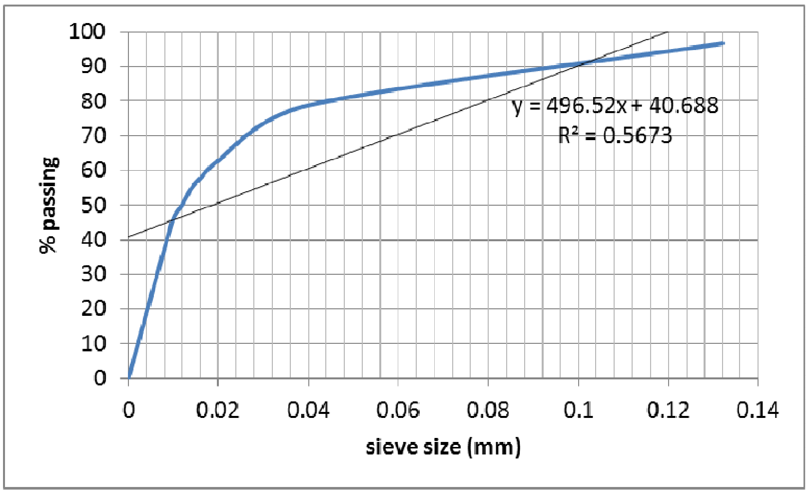
Soil 2
Silty clay loam
K = 0.32



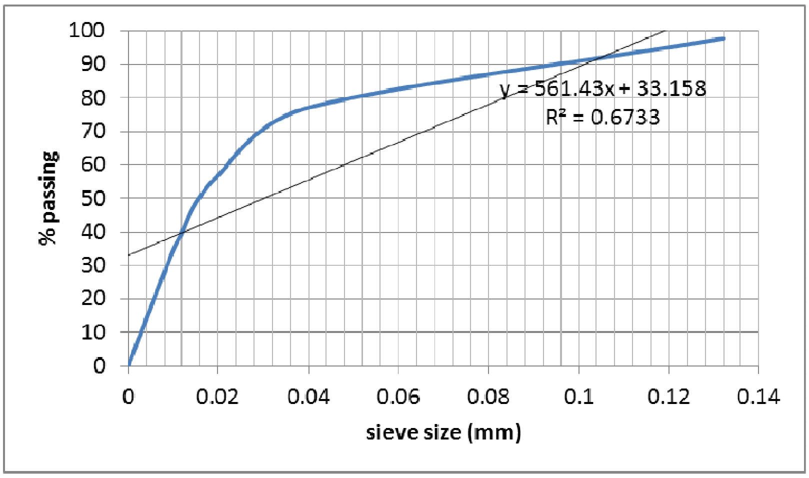
Soil 3
Silty clay loam
K = 0.32



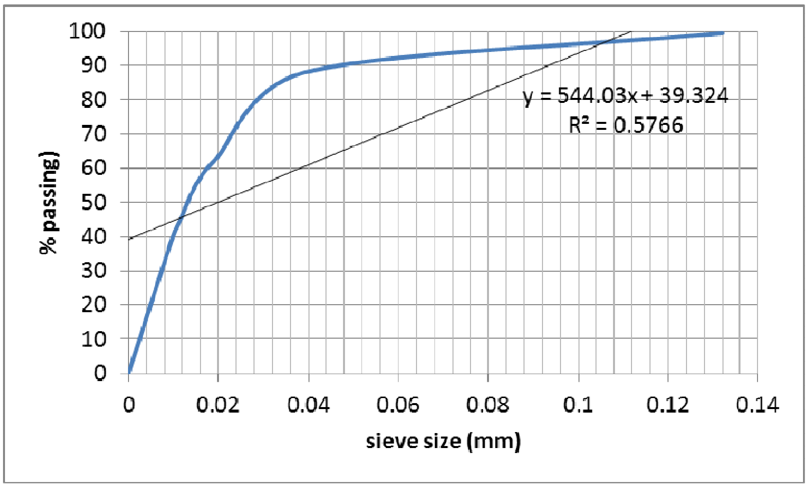
<u>Soil 4</u>
Silt loam
K = 0.38



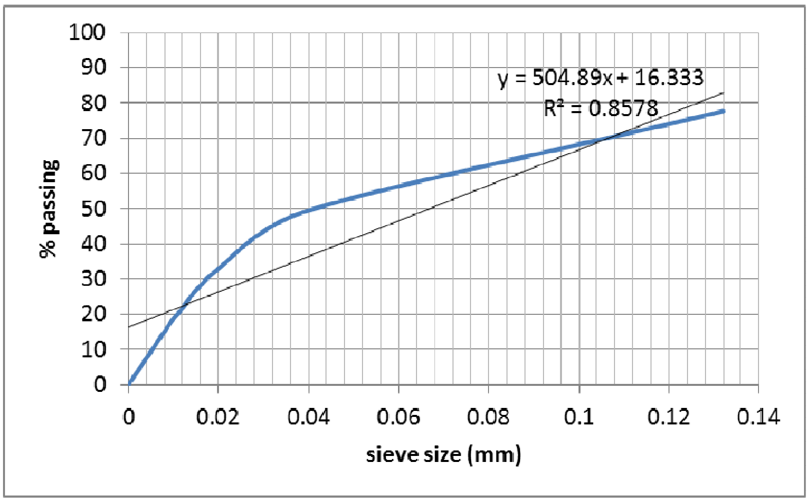
<u>Soil 5</u>
Silty clay
K = 0.26



<u>Soil 6</u>
Silty clay loam
K = 0.32



<u>Soil 7</u>
Silty clay loam
K = 0.32



<u>Soil 8</u>
Silt loam soil
K = 0.38

Figure 34: Particle size distribution and erodibility factor (K) for each of the eight soil types observed in Kibos-Miwani. Where soil 1=Luvisols and Cambisols; soil 2= Chromic Vertisols and Eutrific Planosols; soil 3=Lithosols; soil 4=Gleysols; soil 5=Eutric Fluvisols; soil 6=Chromic Vertisols; soil 7=vertic Fluvisols; soil 8=Solodic Planosols (US classification).

4.3.2 Potential Soil Erosion risk

i.) Temporal vegetative seasons and potential soil erosion risk

The functions and weights used in FuDSEM are the outcome of generalized interpretation of common knowledge of erosion processes. Unlike standard, physically-based models, the weights are not intended to represent an accurate quantitative relationship between the parameters, but to provide a general interpretation of the process, as envisaged by the modeller (Baja et al. 2002; Robinson 2003). This is acceptable, since the model predicts the potential of the parameters, thus representing its relative spatial and temporal distribution, rather than providing a quantitative prediction of erosion yield. Inherently, FuDSEM produces potential, qualitative erosion maps, and not quantitative erosion values.

Resultant erosion risk values range from 0 to 8.1 with a mosaic of low to high erosion risks in both the cropped area and natural vegetation (Figure 36). Globally at the portion of the selected landscape, the mean value for erosion (1.71) changes through time between 2.04 in February, 1.92 in May, 1.08 in September and 1.8 in November. Generally, September presents the lowest erosion risk and this is attributed to presence of highly vegetated sugarcane crop having been planted in March or ratoon which has regenerated after harvest, while February presents the highest erosion risk value due to land preparation activities that expose soils to rainfall (Amolo, 2009).

Marked areas in Figure 36 are distinguished based on risk criteria: always high through time (area 1), low and intermediary (areas 2, 3, 4); intermediary only in September otherwise high (area 5). The spatial pattern realized by this analysis is also linked to the slope, soil map and crop type. Area 1 is within a slope of over 7% in the escarpment foot, covered by perennial vegetation (woodlot) and food crops (other crops) on silt loamy soils. Areas 2, 3 and 4 are within a slope of over 3% with 80% sugarcane and 20% of other crops (maize, natural vegetation) growing on silt loamy soils. Area 5 is found within a plain with slope < 3% and on silt clay loam soils, where 100% of other crops are found (natural vegetation).

Results show a consistent high risk pattern of erosion in area 1 throughout the four seasons studied. Being an area under the escarpment foot and other crops (forest), we infer that the erosion pattern is influenced by slope and the type of crop. The consistent high erosion patches shown in area 1 is likely to be presumptive spots of gulley erosion in the hilly terrain as also found by Valentin et al. (2005) in areas of high risk of gulley formation. Further, Valentin et al. (2005) recommended use of continuous vegetation cover, minimum tillage and use of terraces as conservation measures for sustainability.

Areas 2, 3 and 4 show a spatially variable intermediary erosion pattern through the four seasons. Being an area dominated with sugarcane crop, a mixture of low, moderate and high erosion risk is seen in February. This result is related to the land preparation activities mostly conducted in February-March (Amolo, 2009). In May, moderate erosion risk is seen and this can be attributed to growth of young crop either planted at the onset of rains in March-April or regenerated after harvest; and this has reduced the rate of transport capacity. We infer that enhanced vegetation during the main rain season (May) minimizes erosion risk. Low erosion seen in area 3 is attributed to the impact of pure sugarcane stand of Kibos (Milimani) nucleus which is able to reduce run off and transport capacity except when harvested. We infer that sugarcane crop protects the landscape from erosion risk. In September, potential erosion map exhibit a general decrease in risk value, while in November, an intensified mixture of low and high erosion pattern is seen in areas 2, 3 and 4. The lower erosion risk in September is attributed to the combined effect of dry weather conditions at the end of the main rainy season, minimal land preparation activities, and the presence of vegetation cover over the landscape. The exposed soils in young cropped fields planted during the short rainy season increases erosion risk in November. We infer that this cropping practice is the driver of this erosion pattern. Area 5 exhibits a consistent high erosion risk in February and November, while in May and September this erosion intensity has reduced to moderate and isolated high risk pixels in this area. Being an area covered with other type of vegetation and in land that has not been cultivated for over five years (fallow land), we infer that vegetation cover is sparse in February and November due to open grazing activities exposing soils in area 5 to run off, and therefore crop type is the driver of this erosion risk. This finding is similar to that of Valentin et al. (2005) who found that overgrazing was a driver of soil erosion due to exposure of soils to run off and suggested soil conservation measures to be put in place to minimize potential erosion risk.

Further, our survey results show that crop residues from green harvest are trash lined between rows and this is assumed to protect soils from rain drops, consequently reducing transport capacity and erosion risk. On the contrary burnt harvest exposes soils to rainfall, consequently increasing erosion risk. This presumption is similar to findings of a study which found that green harvesting increases the number of crop cycles and improves soil physical properties (Mendoza et al., 2001), thereby improving sugarcane productivity. This result is verification that FuDSEM model correctly represents the trends cited in literature implying that burnt harvest destroys soil nutrients and depletes soil moisture which is protected by crop residues on harvest thus increasing soil erosion risk. In addition, because positive NDWI values have been observed on green harvested fields, our results have shown that green harvesting method provides available crop residues for soil conservation. Observed data has presented positive soil moisture after a green harvest using the normalized difference water index (NDWI). This implies that on green harvest, crop residues retain soil moisture that supports the next crop cycle. This result corroborates findings of Mendoza et al. (2001) who realized that trash increases soil moisture retention, improves soil nutrients and increases soil resilience to erosion risk. Moreover, other studies recommend green harvesting to provide residues for soil cover to reduce soil erosion risk (Valentin et al., 2005). Besides crop residues, Valentin et al. (2005) and Okoba et al. (2007) recommend increase in vegetation cover; reduced destruction of soil structure through minimum tillage of hilly areas; use of terraces to reduce the slope e for soil conservation purposes.

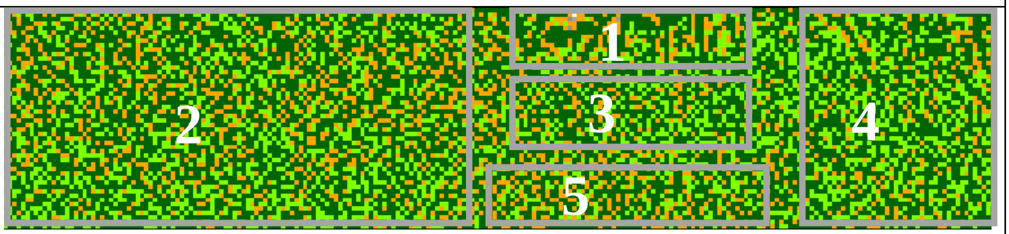
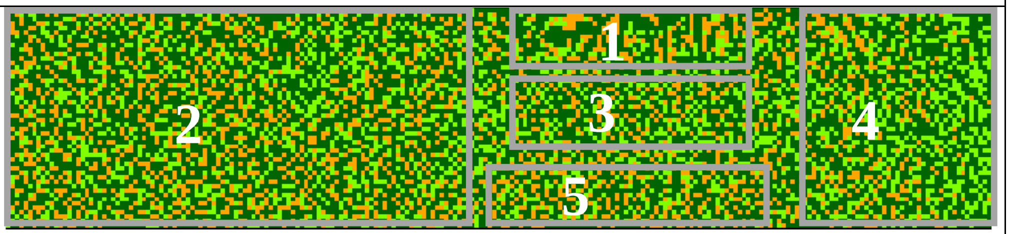
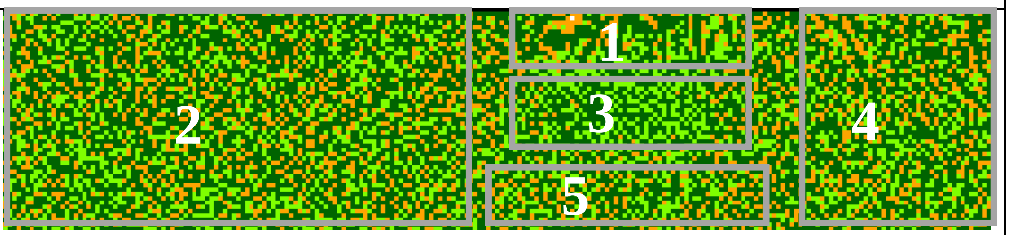
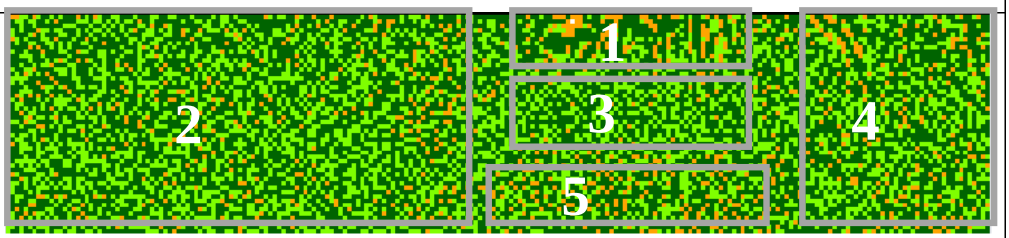
	Mean	
Nov	1.8	
Feb	2.04	
May	1.92	
Sept	1.08	
Legend		Dark green : risk index = 0 (low) Light green : 0 < risk index < 3.6 (medium) Orange : risk index ≥ 3.6 (high)

Figure 35: Potential soil erosion risk in Kibos-Miwani sugarcane zone, calculated using FuDSEM for (a) February, (b) May, (c) September, and (d) November.

Relevance of FuDSEM simulated results in Kibos-Miwani

Potential soil erosion risk values calculated using FuDSEM (calculated by averaging all the four vegetative seasons) were regressed against the corresponding potential erosion values using RUSLE (Renard et al., 1997), a model dedicated to potential risk simulation that do not use fuzzy based approach. Results are shown in Figure 36. A strong linear correlation is observed in 23 sampled fields with an $R^2 = 0.73$; $P=0.001$. This result shows the advantages of FuDSEM that allows drawing maps of potential erosion risk based on limited input data requirement.

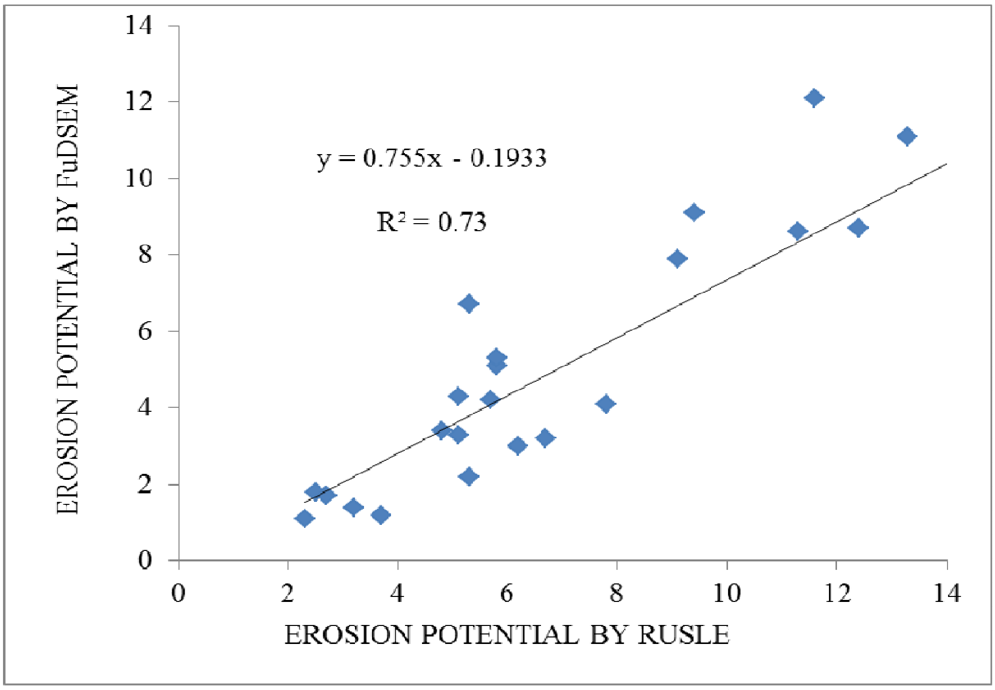


Figure 36: Preliminary validation of FuDSEM versus RUSLE (Renard et al., 1997).

Magnitude of erosion risks in Kibos-Miwani

Table 15a shows observed potential risk results in Kibos-Miwani (KESREF, 2013) as measured in sugarcane experimental plots and plots with other crops. The observed erosion yield values ranged from 1.4 to 3.4 kg m^{-2} y^{-1}. These values fall within the range of erosion risk values observed by Lufafa et al. (2003) as 0 - 9 (kg m^{-2} y^{-1}), for an agricultural landscape in western Kenya, under environmental conditions similar to those of Kibos-Miwani. These values were compared with the simulated erosion risk values under agro-environmental conditions similar to that of experimental plots (Table 15b).

Table 15: (a) Measured erosion yield (KESREF, 2013) and (b) simulated potential erosion risk, in Kibos-Miwani.

(a)	***Measured erosion yield (kg m^{-2} y^{-1})***	
Station	Erosion yield	Crop
1	1.4	SC G
2	1.7	SC B
3	2	Other
4	2.1	SC G
5	2.5	Other
6	1.5	SC G
7	2.3	SC B
8	2.9	Other
9	3	Other
10	3.4	Other

(b) *Potential erosion risk per year using FuDSEM*						
Station	X_Ordinate	Y_Ordinate	Crop	Slope %	Erosion risk value	Soil
1	34°49'32.973"E	0°1'57.964"S	SC G	2.9	1.7	Silty
2	34°51'28.755"E	0°2'3.233"S	SC B	2.6	2.9	loam
3	34°51'51.912"E	0°2'3.986"S	Other	2.7	2.4	clay
4	34°52'32.998"E	0°2'5.492"S	SC G	2.5	2.1	soil
5	34°49'6.829"E	0°1'59.467"S	Other	2.9	2.7	
6	34°52'10.587"E	0°2'7.747"S	SC G	2.4	2.2	
7	34°52'54.662"E	0°1'56.468"S	SC B	2.8	2.5	
8	34°49'53.888"E	0°1'57.213"S	Other	2.7	3.3	
9	34°50'23.02"E	0°1'58.718"S	Other	2.5	3.8	
10	34°50'49.165"E	0°1'55.711"S	Other	3	4.7	

Where SC G = Sugarcane harvested by green mode; SC B = Sugarcane harvested by burnt mode

On Figure 37, simulated potential erosion risk data were plotted with measured erosion yield data. A significant linear relationship was found with $R^2 = 0.86$, $P = 0.001$ (Figure 37). Results from KESREF (2013) have shown that higher risk of soil loss occurred in fields with other crops (1.5 - 3.4 kg m^{-2} y^{-1}) than fields with sugarcane crop (1.4 to 2.5 kg m^{-2} y^{-1}). Owing the significant linear relation obtained, FudSEM represents correctly the differences in erosion risk due to cover characteristics and environmental conditions (slope, location in the landscape). Simulations suggest that burnt harvest mode increases the risk of erosion (2.9) vs. green harvest mode (1.7). Under similar environmental conditions, Lufafa et al. (2003) found higher erosion yield out of covers with food seasonal crops than those with perennial cover. In this study, sugarcane crop is a perennial crop but with a sensitive phase to erosion after harvest. Except on burnt harvest fields with bare soil, sugarcane covers soils over several years including mulching on green harvest, minimizing soil erosion risk. We therefore infer that crop type and sugarcane harvest modes are the main drivers of soil erosion risk in a heterogeneous landscape.

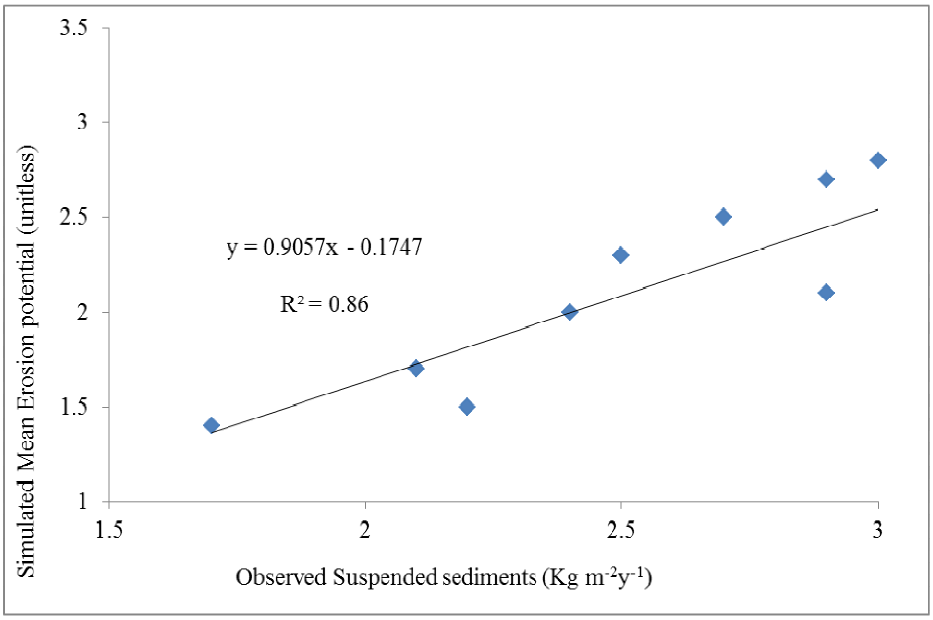


Figure 37: The correlation between measured erosion yield and simulated potential erosion risk within Kibos-Miwani landscape.

5. GENERAL DISCUSSION

5.1. Estimating regional sugarcane yield with remote sensing data

This research has investigated the influence of cropping practices and environmental conditions on sugarcane yield at regional scale through two approaches. Firstly, historical yield was related to annual NDVI with the assumption that yearly sugarcane yield is significantly correlated to annual NDVI. This hypothesis was rejected since the significance of this correlation was only achieved after adjusting the NDVI time integration through the sugarcane growing period. The strength of this relationship was then enhanced when the data were aggregated over the whole period (2002-2010) at the zone level. Secondly, historical yield was related to rainfall and the strength of this relationship was low, although the correlation was of high significance. The relationship was equally strengthened through spatial aggregation and through rain use efficiency. The relation between yield and rainfall exists owing to the fact that sugarcane yield is significantly related to rainfall on removal of time lag at zone scale since crops take a considerable period to respond to rainfall.

This study has shown that remote sensing technology together with environmental information has potential to be used to estimate crop yield and evaluate the impact of environmental conditions to crop production as opposed to physical methods. In effect, it has been reported that accuracy of physical methods such as visual physical approach (VPA) on yield estimation is minimized due to gross errors associated with fatigue, variability in assessment of natural phenomena using the naked human eye, and lack of consideration of diverse environmental variables (such as rainfall) during the growth period of the cane crop. The use of remote sensing data can highlight variations in environmental variables within respective zones, and this is uniquely evidenced by the separation of the two agro-ecological zones through spatial aggregation. Additionally, variations within and between the zones are influenced by environmental variables such as soil characteristics and rainfall distribution over different years. Our findings are in agreement with a study noting that rainfall was not the single determinant of crop yield in different environments, but rather, other factors such as soil characteristics, and other agricultural land use need to be included (Zarco-Tejada et al., 2005).

In summary, our results are in agreement with most of the previous studies on this subject. Through this study, we have contributed knowledge to remote sensing fraternity (1) by developing an original method for NDVI time integration that takes into account the local cropping practices (length of the growing season), and (2) by analyzing the spatial and temporal dimensions of the yield-NDVI relationship and response of its slope to rainfall. Sugarcane yield forecasting has been exemplified through spatial aggregation of weighted NDVI. The information presented in this study is useful for proper, foresighted and informed planning in the Kenya’s Sugar Industry at the zone management scale. This is because the information explains the influence of environmental conditions on sugarcane production, thus providing knowledge for monitoring sugarcane productivity at the zone scale.

5.2. Mapping crop management practices using remote sensing

This research has investigated the spatial and temporal information contained in the satellite images through three approaches.

Firstly, we investigated the temporal variability of spectral response from the effect of rainfall pattern, the effect of the land cover type and the effect of the cropping calendar of sugarcane. To realize this, we compared the time series profiles of NDVI with rainfall (2000-2012) to understand crop conditions in the year, with the assumption that rainfall is the main driver of seasonal variations in vegetation. This hypothesis was accepted when four vegetative seasons (minimum seasons in February and September and maximum seasons in May and November) were identified from this relationship, corresponding to the interaction between sugar-cane physiology and the bimodal rainfall with a one month time lag. Our finding is similar to Shisanya et al. (2011) who realized a bimodal rainfall pattern in Kenya and argued that its pattern influenced vegetation growth. In effect, planting activities in Kenya are scheduled in accordance with climatic conditions (Amolo et al., 2009) and this has been realized by the four vegetative seasons which correspond to the cropping calendar. This study has shown that remote sensing data together with rainfall data can be used to exemplify the effect of agro-environmental variations on physiological conditions of the crop.

Secondly, we undertook crop mapping at field scale to understand the spatial and spectral variability of the land cover types using two approaches: (i) identify the best index to undertake crop mapping, detect a harvest date, and characterize harvest mode; and (ii) undertake crop mapping and harvest mode characterization using the best index. In (i) we assumed that changes in NDVI, NDWI and SWIR (April 2013 - March 2014) at harvest time were significantly different. We investigated this significance by correlating value differences in NDVI, NDWI and SWIR at harvest. Results have shown that NDVI is a good descriptor of land cover having shown significance in value before harvest. We therefore conducted mapping of crop types using time series NDVI. Through a supervised classification our results provided an overall accuracy of 83.3%. This result is similar to a study which used NDVI to separate green vegetation from other surfaces (Sader et al., 2003) and recommended accuracies over 80% (Wardlow and Egbert, 2008) as acceptable. We accepted our hypothesis that NDVI is a good descriptor of land cover type.

Our results have also shown that SWIR is a useful descriptor of sugarcane harvest time. Our finding is similar to a different study that also found SWIR a good descriptor of a harvest time because it presents an immediate increase in value after a harvest (Lebourgeois et al., 2010). Moreover, our results are similar to Daughtry et al. (2004) who realized high reflectance for dry residues and low reflectance for wet residues in the SWIR band due to its ability to separate crop residues from other crop status, presenting high values for harvested fields and low values for vegetated fields.

The harvest mode map was obtained through characterization of NDWI whose results presented significant values for both green and burnt harvest modes. In this classification, NDWI differences > 0.27 were characterized as burnt harvest while those ≤ 0.27 were classified as green harvest, yielding an overall accuracy of 90%. This accuracy is higher than the recommended acceptable accuracies of over 59% (Todd et al., 1980; Longley et al., 2005) and over 80% (Wardlow and Egbert, 2008), implying that NDWI is an effective descriptor of the harvest mode. Moreover, NDWI results have shown negative values on burnt harvest opposed to positive values on green harvest. These results are similar to recent studies that used NDWI to monitor spatial variations in moisture conditions of vegetation over large areas and found negative NDWI values on burnt harvest (Gao, 1996) and on vegetation stress (Sader et al., 2003; Gu et al., 2008; Chen et al., 2005). We infer that on burnt harvest, moisture in the soil evaporates and this is compared to drought stress (Gu et al., 2008) in crops. NDWI has been proposed and evaluated for extraction of surface water features and change detection Rokni et al. (2014) and for vegetation drought monitoring (Gu et al., 2008). Findings of this study associate harvest with crop stress due to drought that drains water from vegetation. Detection of harvest mode using NDWI is a new idea which this study has developed using an original method through a t-test.

5.3. Impact of sugarcane cultivation on soil erosion at landscape scale

This study has used the fuzzy based dynamic soil erosion model (FuDSEM) model to investigate the influence of sugarcane cropping practices on soil erosion risk in Kibos-Miwani zone at local scale through three approaches: (i) Run off potential, (ii) Transport capacity and (iii) Erodibility factor. Input variables in the FuDSEM model included the slope, soil physical properties, rainfall, aspect and vegetation. NDVI was used to represent vegetation because this study has found NDVI value before and after harvest significantly linked to both crop type (sugarcane and other crops) and harvest mode. NDVI was therefore used to represent the spatial and spectral responses to the effect of environmental variables (rainfall and soil characteristics). We hypothesised that cropping practices are the main drivers of soil erosion risk. This hypothesis was accepted because results suggest that both crop type and harvest mode impact on soil erosion risk. Our results give us confidence in use of FuDSEM model with potential simulated risks highly correlated to measured data such as found by Cohen et al. (2008). Based on observations, erosion risks out of sugar cane –a perennial crop- and food crops are consistent with erosion yield found by Lufafa et al. (2003) under similar environmental conditions in Western Kenya.

Moreover, our findings on harvest mode are similar to those of Lovett et al. (2005) who found that post fire erosion on loose soils is usually high. We infer that in Kibos-Miwani where 75% is burnt harvest, post fire erosion in harvested fields influences the spatial and temporal susceptibility of the landscape to erosion risk. In effect, the multiple planting and continuous harvesting together with the crop type (natural vegetation) in areas marked 1 and 5 contribute to the erosion risk pattern which varies from one pixel to the other due to the spatio-temporal heterogeneity exemplified between the sugarcane fields in the area (Mulianga et al., 2012). These results show that cultivation of sugarcane crop minimizes erosion intensity of the landscape on which it is grown, due to its physiological characteristics.

In his study, we found that minimum erosion risk occurred in September. High risk of erosion occurred in May and November, respectively corresponding to mid long and short rainy seasons. Surprisingly, high risk of erosion also appeared in February (2.04) at the beginning of the long rainy season, similar to that in May (1.92) when rainfall is at its first peak. This study attributes the increase in erosion in February to the effect of land preparation activities that expose soils to rainfall in readiness for planting in March (Amolo, 2009; Jamoza et al., 2013). On harvest, management of crop residues, land grading, levelling and terracing among other factors follow, to enhance growth of the ratoon crop and this influences the rate of surface run off (FAO, 2012) depending on the harvest method. In Kibos-Miwani where 75% of sugarcane residues are burnt before harvest, increase in erosion risk is unavoidable. This result shows that cropping practices (crop type and harvest method) and rainfall are the main drivers of erosion risk in the four seasons. This result is similar to a study which demonstrated that soil loss varied according to crop type (Kirkby, 1980).

Transport capacity increases in November (second rainfall peak / short rainy season) rather than May (first rainfall peak / long rainy season) is attributed to influence of cropping practices such as land preparation, harvest mode and crop type. Our results are similar to those of Cohen et al. (2008) who concluded that continuous vegetation cover influences rain drop intensity and rate of infiltration at different levels depending on type of vegetation. Cultivation of sugarcane alongside other crops increases erosion risk on localized spots (such as area 3 in Figure AA) over different vegetative seasons. This is because the perennial rooting system in sugarcane favors quick regrowth which provides quick cover for the soils. This finding is similar to different studies which realized that root network of perennial crops protects landscapes from soil erosion risk (Wood, 1991; Gravois et al., 2011). This result implies that appropriate management of the landscape such as planting of perennial crops, terracing and trash lining of crop residues may reduce the overall risk at the local scale for sustainable crop production.

The K values computed in this study are similar to those of the USDA values for different types of soil (Mitchell and Bubenzer, 1980). Spatio-temporal variability has been shown within fields during classification of land cover and through seasonal variations of erosion risk. We infer that erodibility index is a driver of these spatial variations in erosion. Our findings are similar to a different study which showed that different types of soil influence heterogeneity in landscape vulnerability to erosion risk (Reich et al., 2000). This result is similar to a different study which noted that the impact of heterogeneous landscapes on regulatory ecological processes such as soil transport from the sloppy terrain into valleys and carbon sequestration using water as a facet for matter cycling in sugarcane fields is important. In a different study, Martinez and Mollicone (2012) also found that this matter cycling influences crop production and ecosystem functioning for improved crop management and regulation of environmental services in space and time.

Moreover, our findings are similar to a study that realized sugarcane trash facilitates a reduction in soil loss from sloppy areas and that changes in vegetation conditions such as introduction of trash on harvesting and development of root network on crop maturity introduces other environmental factors such as organic matter which influence erosion amounts in space and pattern of a given landscape (Wood, 1991). Further, Wood (1991) complements our findings by asserting that sugarcane crop offers almost permanent mulch to the landscape in which it is grow. Other studies also found that during vegetative seasons, there is almost no tillage on the gentle sugarcane slopes and this is simultaneous with the rainy season (April to June and October to December) (Shisanya et al., 2011). Our results have shown a higher erosion risk in fields with burnt harvest than those with green harvest. The luck of residues for mulching the sloppy landscape if harvested during the rainy season is the likely reason for the higher erosion risk. The mulch provided by green harvested sugarcane in Kibos-Miwani thus lessens occurrences of erosion even when heavy rains (April-June) are received. Additionally, this mulch has effects on soil physical properties (FC and BD) because of soil organic matter content and soil cover after green harvest (Wood, 1991; Mendoza, et al., 2001).

This study attributes the effect of crop type to crop’s root network and harvest modes as documented by Wood (1991). This result implies that potential erosion is consistent with transport capacity. This is because burnt harvest exposes bare soils to erosion by rainfall while green harvest provides trash that prevents soil erosion. The study has shown that cropping practices (crop type and harvest mode) are the main drivers of local variations in erosion risk in Kibos-Miwani. A comparison of FuDSEM with RUSLE models has been undertaken in this study. Validation of this model with in situ data has been conducted and significant correlations realized. Implementation of this model for similar agro-environmental conditions requires validation of this model with data from varied slopes of the sugarcane landscape.

5.4. A synthesis on landscape: the intermediate object between remote sensing and environmental services

This study has shown that remote sensing is a descriptor of spatial and temporal environmental conditions that result from environmental services offered by the main land uses of a given landscape. In this study, spectral indices from remote sensing have been used to (i) develop yield estimation models, (ii) describe cropping practices and (iii) simulate erosion risk. This is because signatures drawn from spectral indices are associated with a particular vegetation cover type in response to agro environmental conditions. Results of this study have shown that spectral signature variations of respective land cover in Kibos-Miwani are complementary to variations in climatic (rainfall) seasons of western Kenya. Additionally, the study has shown that remote sensing offers opportunities for data that represents wide spatial extents with detailed feature characterization that is collected across spatial scales

Firstly, this study has developed sugarcane yield models at regional scale using remote sensing indicators. Our results have shown that remote sensing is complementary to crop models because it takes into account the impact of the agro-environmental conditions on the crop development while a crop model is limited by the availability of the spatial input data that is costly and time consuming to collect. Our results are similar to a different study which used climate variables to study the effects of climate change on sugarcane yield through a crop model. In this study, vegetation indices have been used because they are indicators of rainfall and soil characteristics of a given space, while in their study, Wuld et al. (2004) realized that sugarcane productivity was positively related to air temperature and rainfall. The response to temperature and rainfall is reflected in the vegetative index through NDVI and rainfall as used in this study. Further, these models may also be used as input data in crop models and production estimations at the zonal level.

Secondly, this study has described cropping practices using remote sensing at landscape scale. The landscape scale has exemplified heterogeneity in crop type and harvesting modes. NDVI has been used to characterize the crop type, exemplifying different ages in sugarcane and other crops. The normalized difference water index (NDWI) has been used to describe harvest modes because at harvest time NDWI difference between green and burnt methods is significantly different. Further, NDWI presents negative values on burnt harvest and positive values on green harvest. NDWI is therefore an environmental indicator of stress conditions in soils and dry crops (Gao, 1996). These varied cropping practices introduce local variations in the landscape that has diversified soil types and characteristics which impact on crop productivity.

In this study, remote sensing has exemplified the impact of rainfall on vegetation conditions of the landscape. Through time series NDVI, a bimodal vegetative season comprising two maximum vegetative seasons (May and November) and two minimum vegetative seasons (February and September) has been exemplified. These seasons are similar to the bimodal rainfall pattern of western Kenya. This result is unique because rather than no vegetation during dry seasons in the area, the bimodal seasons indicate the presence of vegetation through the year with maximum and minimum variations being response to agro environmental conditions. These changes impact environmental services such as crop productivity and soil protection that have been examined in this study. These results as also noted by a different study facilitate policy applications that are focused on understanding the role of the agricultural sector on environmental changes (Wardlow and Egbert, 2008).

Thirdly, FuDSEM model was used to model soil erosion risk using remote sensing and landscape data over four vegetative seasons. The study found that the amount of rainfall influences the rate of run off, while based on slope, the crop type and harvest mode influences transport capacity of sediments. Globally, the erosion risk ranged between low to medium in sugarcane cultivated areas and low to high erosion in areas with natural vegetation, presenting a variable pattern between 30 m pixels in the landscape. These results have shown that crop management activities such as land preparation, crop type (sugarcane or other crops) and harvest mode are the main driver of erosion risk and pattern. This is because based on crop type the intensity of raindrops determines the amount of sediments that are transported by rainfall in Kibos-Miwani. Moreover, results of this study have shown that variations in environmental variables through time are studied through temporal remote sensing data to reveal changes in environmental services such as production and soil protection services.

5.5. Impact of the results for the Kenyan sugarcane industry

This chapter presents four main results obtained in this study and the expected impact of these results for the Kenyan sugar industry:

Firstly, significant statistical sugarcane yield models have been obtained in this study at P>0.00. These statistical models will be improved each year by the introduction of a year and fraction area under sugarcane in the linear model. These models will address sugar Industry census needs such as: (i) Increased accuracy using real time remote sensing data. (ii) Reduced time in conducting sugarcane census by 50%. (iii) Reduced expenditure on sugarcane census by 1.5 million Kenya shillings which if relieved from farmers' levy, will improve their lives through subsidized farm inputs and consequently sugarcane productivity. This is a paradox shift from the previous method which estimated yield using manual methods whose results were prejudiced with errors. Information from sugarcane census is useful for effective planning of sugar industry operations. Production being a product of surface area and sugarcane yied, the sugarcane map is key in realizing effective planning.

The sugarcane map was obtained using NDVI at the accuracy of 83%. Results have proved that time series of NDVI as measured by Landsat (decametric resolution) is important in classification of land cover in Western Kenya. By using NDVI, the Kenyan sugar industry will address their need for a sugarcane crop map and sugarcane production estimates. This is because NDVI is able to visualize locations of sugarcane fields for increased accuracy compared to the conventional methods currently being used. This mapping approach minimizes errors accrued during physical methods of survey to increase accuracy is estimating sugarcane production. The sugarcane map, coupled with NDVI is also a decision support tool. This is because by knowing sugarcane fields, managers will use NDVI, for monitoring crop conditions by identifying critical stages of crop development that need the attention of experts for improved productivity. Cropping practices such as harvesting modes impact on soil fertility and hence productivity, necessitating the need for a harvest mode map.

The sugarcane harvest mode map was produced using time series NDWI differences at an accuracy of 90%. NDWI was used because values for green and burnt harvest are significantly different. The sugar Industry needs this map to evaluate the impact of harvest modes on sugarcane productivity through time and develop sustainable measures for improved sugarcane productivity. The Kenya sugar industry may use these indices to characterize sugarcane landscapes, identify harvested fields, and determine harvest modes for effective planning and management of operations such as transportation and fertilizer supply at the zonal level.

Seasonality of vegetation in the landscape is dependent on cropping practices and rainfall. This study has evaluated soil erosion risk using seasoned NDVI in FuDSEM model to evaluate erosion sensitivity during different vegetative seasons. This information could contribute to the limited documentation on vegetative seasons and their implication on environmental services. A comparison of this model with RUSLE model has shown that that FuDSEM could be used to produce potential erosion risk maps with lower constraints on data input thanks to fuzzy approach. Moreover, our results are consistent with those of Valentin et al. (2005) who also found crop type a driver of soil erosion. Green harvest method investigated in this study avails vegetation cover on the landscape tremendously reducing erosion risk. Other studies have also recommended methods such as use of perennial crops, zero tillage and terracing for sustainable management (Valentin et al., 2005; Okoba et al., 2007).

The Kenya sugar Industry may use the harvest mode map and erosion risk information to develop tools dedicated to sustainable management by integrating data at the field, water shed, and mill management scales for enhanced productivity, profitability, and environmental considerations. If validated, FuDSEM model could be used by the industry to recommend soil conservation measures for sugarcane landscapes in Kenya based on severity of soil erosion risk in specific areas.

6. CONCLUSION AND PERSPECTIVES

6.1 Main research results

The overall objective of this study was to examine the relationship between environmental services and the sugarcane landscapes in Western Kenya using remote sensing and a soil erosion model. The study investigated this objective through establishing (i) the relationship between remote sensing data and sugarcane yield at a regional scale, (ii) the role of remote sensing data in mapping crop management practices at landscape (local) scale; and (iii) the impact of sugarcane cultivation on soil erosion at landscape (local) scale. The relationship between remote sensing data and sugarcane yield at a regional scale has been achieved by using MODIS data to (1) develop an original method for normalized difference vegetation index (NDVI) time integration that takes into account the local cropping practices (length of the growing season); and (2) by analyzing the spatial and temporal dimensions of the yield-NDVI relationship and response of its slope to rainfall and sugarcane fraction. Sugarcane yield forecasting has been exemplified through spatial aggregation of weighted NDVI at eleven months, considering the unique agro-environmental conditions in each sugar management zone. The discrimination of the main agro-ecological zones (humid and sub humid) through spatial aggregation of yearly information has proved the potential of MODIS NDVI in exonerating the impact of environmental conditions on sugarcane production at regional scale. Additionally, the positive slope exemplified through precipitation marginal response (PMR) is an indicator of crop response to environmental variable, rainfall, and thus an implication for production as an environmental service to Kibos ecosystem. The negative slope presented on yield-NDVI slope with sugarcane fraction is an indicator of interdependence of available biomass and cropping practices (area under crop). Remote sensing data has been used to study these environmental effects on sugarcane production and also develop the yield estimation model at the regional scale.

The role of remote sensing data in mapping crop management practices at landscape scale was achieved by using (i) MODIS and rainfall data to describe vegetative seasons and (ii) Landsat data to describe crop type and harvesting mode. MODIS data has exemplified a bimodal minimum and maximum vegetative seasons complementing the bimodal rainfall pattern in western Kenya with a one month time lag, an indicator of a multiple cropping system that is driven by rainfall in the area. This result is important in characterization of land cover and also in choice of images for simulating soil erosion risk. Landsat NDVI has shown great potential for detecting crop type, crop conditions (harvested or growing) and mapping sugarcane cropped areas for medium sized farms over 1 ha in Kibos-Miwani. Farms that are less than 1 ha are however difficult to map at this image scale (15 m - 30 m). Landsat normalized difference water index (NDWI) has been used to develop an original method to characterize sugarcane harvest modes because its values for green and burnt harvest were significantly different. The sugarcane map prepared in this study will be used to provide precise acreages for increased accuracy in yield forecasting, while NDWI will be used in mapping sugarcane harvest modes.

The impact of sugarcane cultivation on soil erosion has been investigated at local scale using fuzzy based dynamic soil erosion model (FuDSEM). Agronomic variables; crop type, rainfall, slope and soil characteristics were input variables. Moderate slope sensitivity to erosion risk has been realized through the four vegetative seasons. Results have shown that sugarcane crop minimizes erosion risk during rainfall peaks and that the erosion pattern shown between neighboring pixels is due to management practices such as crop type (age, cycle) and harvest mode. This study attributes low erosion potential in Kibos-Miwani to continuous sugarcane cover in the landscape throughout the year. This study recommends validation of these results using insitu measurements. Satellite imagery has been able to characterize the spatial and temporal dynamics of Kibos-Miwani landscape by identifying relevant images to feed in the erosion model.

6.2. Research perspectives

The use of MODIS 250 m NDVI in the medium to small scale farms of Kenya has been limited at the zonal scale. There is need for consideration of available data to increase remote sensing strength in monitoring sugarcane crop. Further research is recommended by this study, to refine the zone scale to farm level. The issue of scale is suggested to minimize the influence of other crops and natural vegetation on NDVI extracted from sugarcane fields; and also to address site specific effects of varied crop management practices in the sugarcane landscape of western Kenya. Future Earth Observing satellite systems, such as Sentinel-2 (ESA), with decametric spatial resolution, and a high visiting frequency (10 days in 2015, and 5 days in 2016), will give access to farm level information. This satellite mission will also benefit for sugarcane mapping that is presently done using Landsat time series, with a resolution that is able to capture boundaries of nucleus fields, but not for small growers.

Additionally, the effect of crop residues on soil organic matter has been implied in this study. This study recommends experimental research to assess the effect of harvest mode on soil organic matter in Kibos-Miwani landscape to ascertain its environmental impact on spatially heterogeneous landscapes. The soil erosion sensitivity model in this study is a desk top solution. The study proposes a further study to validate this model for improved soil conservation measures that will improve soil quality and enhance sugarcane productivity. Moreover, a study to validate the presumed galleys in the simulation results will be important to recommend site specific conservation measures for that portion of the landscape. The effect of sugarcane root network on soil erosion risk has also been implied in this study. This study recommends research to assess the effect of sugarcane root network, tillage methods, terraces and agroforestry on soil erosion risk in the sugarcane growing landscape of Kenya for sustainable management.

6.3. Operational perspectives (other environmental services)

This research documents the use of remote sensing and dynamic soil erosion model to exemplify environmental services provided by sugarcane cropping practices in Western Kenya. The Kenya Sugar Research Foundation (KESREF) will implement results of this study in assessment of forecasting of crop yield, harvest modes and erosion risk at the field level in her hilly environs. Similarly, the sugar Industry will implement findings of this study for industrial and sustainable purposes. This is because the use of climatic information to predict sugarcane yield facilitates information on the influence of climatic conditions on crop production. Influence of rainfall amounts on crop production is important in evaluating soil water balance that would inform irrigation rate in stressed crops. Additionally, investigation of soil organic matter in fields that are harvested by burnt and green harvest is important in order to find out its impact on sugarcane production and soil protection.

Additionally, this study found that the multiple crop variety, planting and harvesting practice is the reason for a heterogeneous landscape that offers almost permanent mulch to the landscape. Sugarcane being a conservative crop in the world with a dense crop cover and root network offers a soil protection environmental service in the hilly sugarcane landscape of western Kenya. In the future, other environmental services offered by sugarcane such as: climate regulation, carbon sequestration and emission, clean air and biodiversity should also be studied.

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8. ANNEX

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Article

Forecasting Regional Sugarcane Yield Based on Time Integral and Spatial Aggregation of MODIS NDVI

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Abstract: This study explored the suitability of the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectrometer (MODIS) obtained for six sugar management zones, over nine years (2002–2010), to forecast sugarcane yield on an annual and zonal base. To take into account the characteristics of the sugarcane crop management (15-month cycle for a ratoon, accompanied with continuous harvest in Western Kenya), the temporal series of NDVI was normalized through an original weighting method that considered the growth period of the sugarcane crop (wNDVI), and correlated it with historical yield datasets. Results when using wNDVI were consistent with historical yield and significant at P-value = 0.001, while results when using traditional annual NDVI integrated over the calendar year were not significant. This correlation between yield and wNDVI is mainly drawn by the spatial dimension of the data set (R^2 = 0.53, when all years are aggregated together), rather than by the temporal dimension of the data set (R^2 = 0.1, when all zones are aggregated). A test on 2012 yield estimation with this model realized a RMSE less than 5 $t \cdot ha^{-1}$. Despite progress in the methodology through the weighted NDVI, and an extensive spatio-temporal analysis, this paper shows the difficulty in forecasting sugarcane yield on an annual base using current satellite low-resolution data. This is particularly true in the context of small scale farmers with fields measuring less than the size of MODIS 250 m pixel, and in the context of a 15-month crop cycle with no seasonal cropping calendar. Future satellite missions should permit monitoring of sugarcane yields using image resolutions that facilitate extraction of crop phenology from a group of individual plots

Keywords: MODIS; NDVI; Environment; Sugarcane; Yield forecasting

1. Introduction

Sugarcane (*Saccharum* Spp. Hybrids*)* is a graminae of the tribe of Andropogonae and Poaceae family. It is defined as a tropical semi perennial crop which is harvested through the manual system in Kenya at variable periods depending on the date of planting, variety, tiny climatic variations along the year and mill preparedness. Consequently, re-growth of sugarcane, known as ratooning, matures at different periods, introducing spatio-temporal variability in the sugarcane landscape. In Kenya where sugarcane is rain fed, this variability is exacerbated with an unspecified cropping calendar and diversification of the cropping system both at spatial (sugar management zone) and temporal (inter-annual) levels, presenting a heterogeneous sugarcane landscape. Sugarcane being the second largest contributor to Kenya's agricultural growth saves the country in excess of USD 229,885,057 annually in foreign exchange, while contributing to poverty reduction and national development [1]. Knowledge of crop productivity is therefore necessary for proper, foresighted and informed planning for competitiveness in the sugar industry [2] and national development.

In Kenya, sugarcane yield is estimated using conventional approaches through biennial field surveys by millers and the Sugar Board, basing their methodology on visual physical assessment (VPA) [3]. In VPA, a stratified random sampling approach is used, considering 15% field coverage in each administrative sector of the zones. A monthly productivity index ranging between 0 and 5 is then applied to sample cane crop from the age of one month, while considering the parameters: (i) crop vigour, (ii) crop colour, (iii) crop density, (iv) weed status, pests and diseases at the time of yield assessment. The average scores are then computed against preset reference yields for each crop cycle with the assumption that the crop has been managed under recommended standard guidelines [1]. The estimated yield is used by the Sugar Industry to project sugarcane production for the current and subsequent year. Although this method has been used since sugarcane was first grown in Kenya, accuracy of manual methods has been proven to introduce gross errors in the results due to variability in time scale and fatigue [4]. This manual method assumes that the crop properties remain constant at the age of yield estimation till crop maturity at 14 to 16 months for ratoons, and 18 to 20 months for plant crop, respectively. Further, it is assumed that 15% of the sample is sufficient to represent crop conditions in the entire mill zone. This could only be true if the crop calendar is defined and not in a spatially heterogeneous landscape such as is the case in Kenya. Similarly, the method assumes that environmental variables such as rainfall distribution and amount will not change in the subsequent year. More so, the human eye is limited in its ability to discriminate colors of an object quantitatively, compared to multispectral systems [5]. Additionally, physical ground data collection has been proven to be time consuming and unreliable in its temporal scale [6, 7]. It is the subjectivity of the current traditional method for monitoring sugarcane production that creates most of the gap for a near real time method that will integrate timely environmental variables in estimating sugarcane yield through a remote sensing approach [4].

Remote sensing is the near real time method. The advantage of remote sensing over ground systems, such as that used by the millers, is that they cover wide areas explicitly, providing timely spatial and temporal data. Such temporal data has been commended for monitoring vegetation development in response to changes in the environment and in response to human management practices [7, 8, 9, 10]. These conditions vary over large areas due to diverse topography, soil type, rainfall distribution and management practices, to which sugarcane phenology and productivity is dependent [11]. Most vegetation indices have proven successful in estimating crop yield and biomass [4]. The Normalized Difference Vegetation Index (NDVI) from remote sensing imagery for example, has been expansively used to determine crop phenology, biomass and productivity in spatial distribution [12, 13]. The quality of methods developed depends on the scale of study and on the crop management practices, which influence the temporal and spatial resolutions of the relevant data. The cost of satellite imagery, however, is high when fine resolution is required. Crop monitoring studies have therefore resolved this impasse by successfully using free low resolution images from the Moderate Resolution Imaging Spectroradiometer (MODIS), SPOT-VEGETATION, or NOAA-AVHRR sensor data for crop studies [14].

Recent studies have used low resolution imagery to estimate sugarcane yield production in different countries. In Brazil for example [15], 1 km SPOT-VEGETATION data was used, taking advantage of its daily temporal resolution and coupling it with meteorological data to monitor sugarcane development. Cropping seasons were successfully identified using the NDVI data and further facilitated classification of the data for analysis. In the three yield classes assessed (24–73 $t \cdot ha^{-1}$; 42–110 $t \cdot ha^{-1}$, and 74–85 $t \cdot ha^{-1}$), the yield predicted was consistent with the historical yield with accuracies of 8.3%, 66.7% and 86.5%, respectively. The low accuracy of the first class would be attributed to coarseness of the 1 km image that limits discrimination of individual phenology for plots that are smaller than the pixel size, a case similar to the small scale sugarcane farming community of Kenya. Accuracies for the second and third class were in the municipality areas, characterized with large farms such as the nucleus fields of Kenyan sugar mills that are under pure sugarcane stand. A similar study, [11] noted that neither average rainfall nor average MODIS NDVI was related to the average sugarcane yield of the farmers' fields situated within the 5 km radius of the nine weather stations. On a larger scale, MODIS

NDVI had a positive correlation ($R = 0.57$) with yield when averaged across all nine management zones, but only for the rainy-season planting. In a different study [16], NOAA-AVHRR data was utilized to develop and validate a model for forecasting crop yield in Pakistan. District data was then used to validate the model, resulting in a root mean square error of $13.5\ \mathrm{t \cdot ha^{-1}}$ for sugarcane yield. In their recommendations, actual daily sunshine hours, air temperature, and a crop map were argued to be indispensable for refinement of the model.

A recent study on forecasting sugarcane crop season in Brazil using simple correlations between time series NDVI from AVHRR and an agro-climatic index on sugarcane yield, realized significant correlations ($R = 0.69$ to 0.79) after applying a cross correlation method on the datasets used [17]. In a different study on maize, [18] MODIS NDVI was used in Zimbabwe to realize strong relationships with the national maize production estimates after the data was adjusted to match onset of the rainy season. The strength of correlations in these two studies is attributed to normalization of the time lag in the climate and NDVI data through the methods used. It is inferred that normalization of satellite data through an appropriate method improves the strength of correlations and is appropriate in future studies. It is also important to note that a combination of satellite and climatic datasets such as those used in these studies utilizes newer methods in forecasting sugarcane productivity [17]. A similar study in Louisiana used thermal variables (Growing Degree Days accumulated from planting to sensing) to adjust in-field NDVI measurements, and to develop a sugarcane yield forecasting method [4]. They obtained a positive exponential correlation, with R^2 improving from 0.20, when using unadjusted NDVI, to $R^2 = 0.46$, when using adjusted NDVI. These authors argued that a weak correlation from application of the model was attributed to the spatial variability of sugarcane fields due to different crop ages and diverse environmental conditions in different locations.

In the agricultural landscape of Kenya, sugarcane crop exhibits extreme age differences alongside diversified subsistence cropping in different environmental conditions and is thus highly heterogeneous [19]. MODIS 250 m data has been used successfully to determine temporal dynamics of crops at local scales due to its good geometric and radiometric properties that make the data interoperable with other GIS datasets [20]. However, at MODIS 250 m resolution and in a small agriculture region such as in Kenya, the measured radiation is a mixture of different crops and natural vegetation [19]. It is therefore important to apply a method that will normalize data by removing time lag since this will decrease the effect of mixed crop-natural vegetation pixels in the satellite data used for yield forecasting. The effect of mixed pixels while developing a maize yield model using the land cover weighted NDVI rather than the traditional NDVI reduced the unknown variance by 26% [21]. It was argued that yield estimation using NDVI may vary during respective months of the crop growth because NDVI is reduced at the end of the rainy season, emphasising the need for careful consideration on time integration [11].

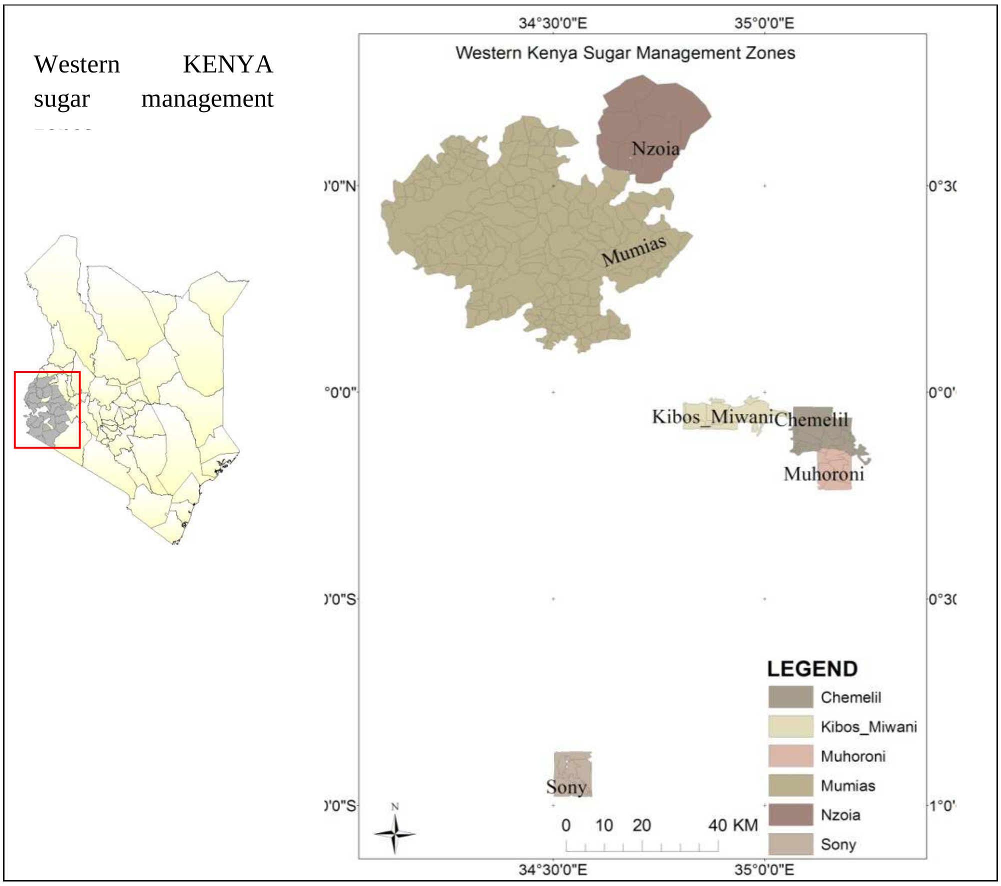
The objective of this study was to test how time integrated Normalized Difference Vegetation Index data from MODIS 250 m imagery can be used for annual sugarcane yield assessment at the sugarcane mill management scales (zones) in Western Kenya. This objective is challenging, since sugarcane in this region is grown in fragmented fields scattered in highly variable environments with various land uses and land covers, soil types, and altitudes. For crop yield forecasting, the ideal approach would be to use crop-specific masks. However, with medium/coarse resolution (about 5–100 ha per pixel) imagery, identifying mono-cropped pixels is not always feasible. This is particularly true in low-producing regions and in regions with sparse crop distribution [14], such as Kenya. Therefore the method proposed here is based on the concept that all vegetation in a region integrates the season's cumulative growing conditions [22]. We first analysed the spatio-temporal variability of the yield-NDVI relationship, using the data set acquired in Western Kenya on six sugarcane zones covering nine years (2002–2010). We used linear models to test the effect of the time integration period of NDVI in relation to the annual yield estimation, and tested the effect of annual rainfall on sugarcane yield. We hypothesize that zones' yield is influenced by cropping practices and environmental conditions at the zonal scale.

2. Data and Methods

2.1. Study Area

The study area (Figure 1) is located within the western part of Kenya, comprising six sugar management zones that include: (i) Chemelil, Kibos and Muhoroni within the sub humid agro-ecological zone; and (ii) Mumias, Nzoia and Sony within the humid agro ecological zone of Kenya. These zones are located between longitudes 34.18°E, and 35.87°E, and latitudes 1.25°N and 1.50°S, covering an area of 120,000 ha [23]. Mumias is the highest producer of sugar placed at 39% in 2011 [23]. The landscape of this area is characterized by a mosaic of hills and valleys, with altitudes ranging from 1,000 m (Kibos) to 1,600 m (Mumias and Nzoia), and 1,800 m (Chemelil), and slope rising between 8%, in the plains of Kibos zone, and 38%, in the hills of Chemelil zone.

Figure 38. Western Kenya sugar management zones (Source: Sugar mills).



The topography influences the agro-ecological zones receiving an average of 1,400 mm and 1,800 mm of rainfall in the sub humid and humid zones, respectively [24]. Rainfall in this area is bimodal [25] with a long rain season between March and July, with planting in March for food crops and April for sugarcane; and a short rain season in September to December with planting in September for all crops [26]. This variation in rainfall distribution influences an intensified cropping system with crop diversification and rotation of food crops and sugarcane age. Soils of the study area are dominantly black cotton cambisols in the low lands and sandy loamy acrisols in the highlands [27].

The location of the study area in different agro-climatic zones, diversified topography, soils types and cropping practices provides an ideal scenario to explore the relationship between sugarcane productivity, environmental variables, and management practices in Western Kenya.

2.2. Data

2.2.1. Satellite Data and Pre-Processing

A complete 11-year time series (2002–2012) of the Surface Reflectance 8-Day L3 Global 250m product (MOD09Q1) was downloaded through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC) [28]. MOD09Q1 product provides bands 1 (red reflectance; 620–670 nm) and 2 (near infrared reflectance; 841–876 nm) at 250-m resolution. Each MOD09Q1 pixel contains the 'best possible observation' during an 8-day period as selected on the basis of high observation coverage, low view angle, the absence of clouds or cloud shadow, and aerosol loading. The accuracy of the version-5 MODIS/Terra Surface Reflectance products has been assessed over a widely distributed set of locations and time periods via several ground-truth and validation efforts, and thus ready for use in scientific publications. The red (R) and (NIR) reflectance data were used to compute the NDVI [29] for all the 460 images.

In addition to the MODIS time series, a multispectral (Green, Red, and Near Infrared) 2.5 m SPOT image was acquired over Mumias in December 2011, This data was used to appraise land cover and use in different sectors of Mumias sugar zone in a 250 m grid (Figure 2), showing the large heterogeneity of the landscape at MODIS scale, and the impossibility to use a sugarcane crop mask on a satellite image at MODIS scale in the area.

2.2.2. Agronomic and Climatic Data

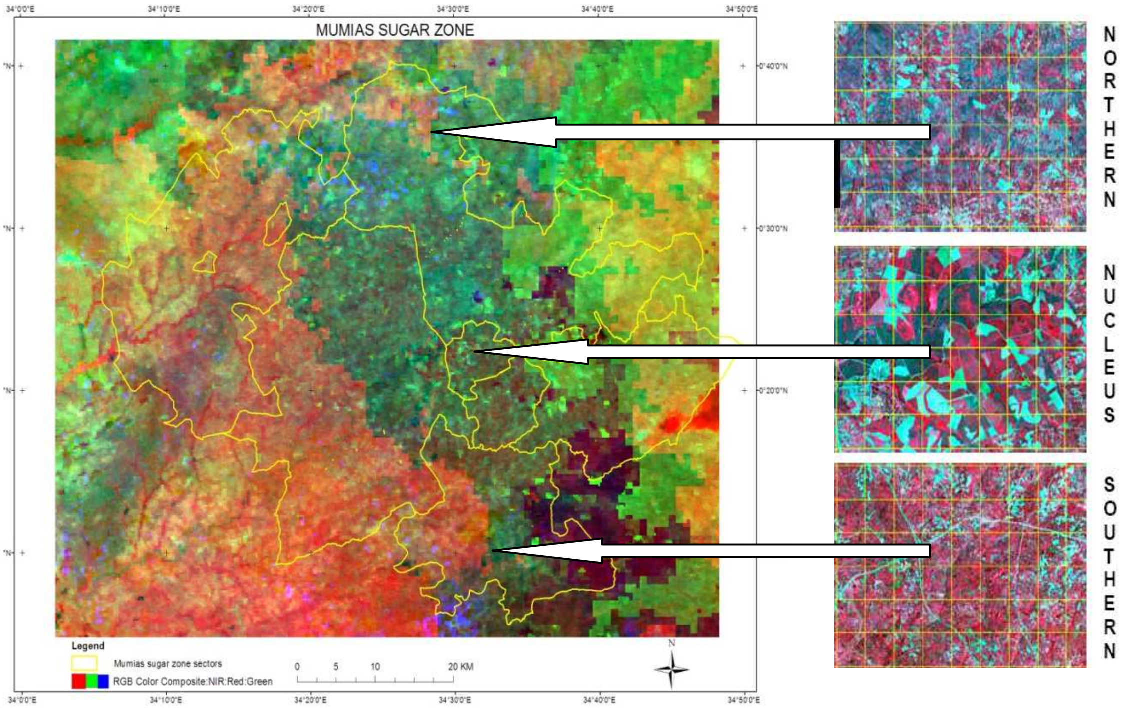
The agronomic (yield and cropped area) and climatic data were obtained from the respective sugar mills. At the zonal scale, yearly cropped area (ha), estimated yield ($tc \cdot ha^{-1}$), and monthly rainfall data were obtained for the period 2002 to 2010. We also obtained yield data for the year 2012 which was used for quantitative validation of the model. Crop area data are estimated by physical measurement of area that has been harvested or during land preparation. On the other hand, yearly yield is obtained using the Visual Physical Assessment method (as presented in the Introduction section).

Rainfall data were recorded using 113 rain gauges distributed unequally among all the sugar zones. The rainfall data was cross tabulated to compute the annual mean for each zone for comparison with the annual yield.

Figure 2. (**a**) MODIS 250 m color composition of Mumias zone (sectors within the zone are delineated by a yellow line), and (**b**) subsets of a December 2011 SPOT 2.5 m image on three sectors; the overlaying yellow grids correspond to the 250 m spatial resolution of MODIS pixels.

(a) MODIS 250 m color composition
@ LP DAAC online data pool

(b) SPOT 2.5 m color composition
(@CNES 2011, Distribution Spot Image)



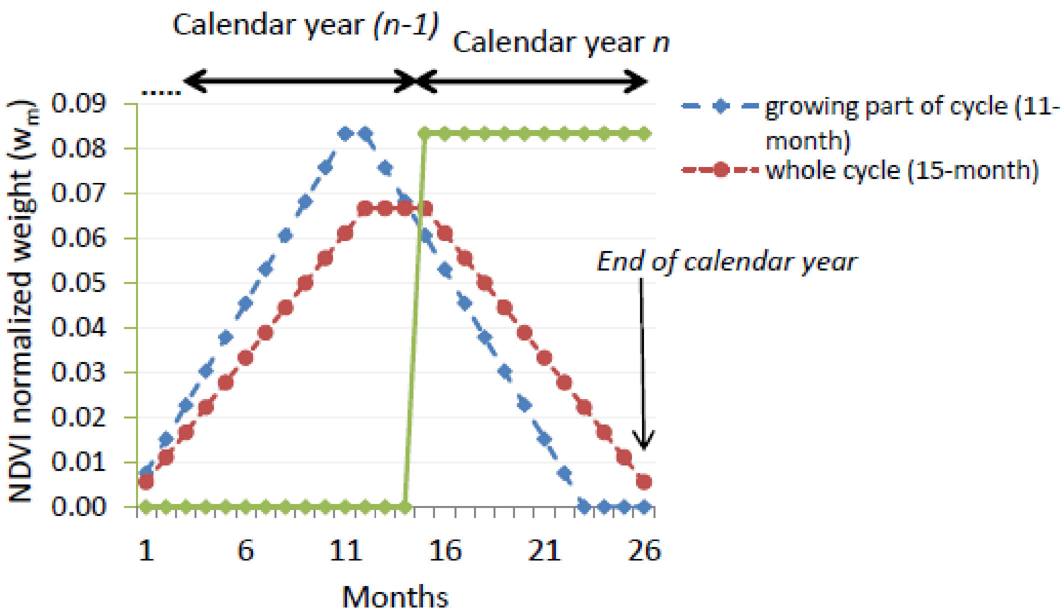
2.3. Data Analysis

2.3.1. Time-Integration of NDVI Values

A thematic layer of the limit of the sugarcane growing mill zones was used to extract 8-day NDVI values for each zone. These NDVI values were then spatially aggregated to allow comparison with the mean annual yield, at the same scale. Generally, time integration of NDVI is done throughout the calendar year [2, 11, 18]. At the field scale, [10, 20] is considered a seasonal integration approach which utilized either the sowing or the harvesting date, while at the regional scale, [4] used growing degree days to compute in season NDVI for estimating yield and obtained good results. At regional scale in Portugal, [30] correlated yield of the current year with a 10-day NDVI data to develop a yield estimation model which explained 77%–88% of wine yield. At state scale in Brazil, [31] used thermal time other than the calendar year and estimated sugarcane yield with a RMSE of 1.5 t/ha (around 2% of accuracy); however, they used a crop mask and selected sugarcane pixel purity above 95% for the establishment of the regressions.

In this study therefore, we tested a new way of time integration in order to account for the local sugarcane cropping practices at zonal scale. In effect, since the yield is estimated on a calendar year base (harvest lasts from January to December), a ratoon crop growing from November 2009 to its harvest in January 2011—at the age of 15 months—accounts for the 2011 annual yield data. Therefore, this complicates the yield prediction scenario where, in this case, the 2011 annual yield includes the yield of a crop that was almost nonexistent on the 2011 satellite time series (except on the January image). It is argued that predicting yield in such small rain fed sugarcane fields is complicated since NDVI from all land uses declines at the end of the rainfall period [11] and requires a keen consideration of the integration period. In a similar case, a weighted land cover NDVI was used to account for the influence of other land uses on maize yield [21]. We therefore applied a weighting matrix over a period of time corresponding to the growing calendar, and not to the calendar year in order to take into account the active vegetative stages of the crop and minimize any shift in NDVI during sugarcane development [22]. To do this we chose two different periods of integration, (1) an 11-month period which corresponds to the approximate length of the growing cycle before maturation, and (2) a 15-month period which corresponds to the approximate length of the whole growing cycle. For both configurations, we calculated a weight for each month corresponding to the probability of a sugarcane field to be harvested during the calendar year of yield estimations, and thus to be accounted for in the annual yield (Figure 3).

Figure 3. Three sets of weights used to calculate time integration of monthly NDVI values for annual yield estimation (year *n*). The green line (between months 14 to 26) corresponds to weights generally used to calculate the annual NDVI (the calendar year corresponding to the yield measurement). The blue and red lines correspond to weights that take into account the sugarcane cropping calendar (15 months for the whole cycle, and 11 months for the growing period) in the NDVI time integration.



Annual NDVI (NDVI) and weighted NDVI (wNDVI_15 and wNDVI_11) for each year was calculated according to Equation (1), with *i* equals to 15 and 11, respectively. The value 15 corresponds to the length of the usual cropping cycle of the sugarcane (in months), while the value 11 corresponds to the length of the vegetative part (in months) which is mainly related to cane yield [10].

$$wNDVI\_i = \sum_{m=1}^{m=i} NDVI_m \, w_m \tag{1}$$

where, $NDVI_m$ is the value of the NDVI for month m, w_m is a coefficient equal to the NDVI normalized weight (Figure 3), and i is the length of the time integration (in months). The sum of the w_m coefficients is equal to 1.

2.3.2. Spatio-Temporal Analysis

The relationship between NDVI, wNDVI and the annual estimated yield was studied with a linear regression [20, 32] and exponential regressions [4] established through time and space using a one-tailed probability test. We then assessed the role of the environmental variables in the relation between yield and NDVI, by correlating the slope of the "yield-NDVI (wNDVI)" relationships with the rainfall, and with the sugarcane fraction in each respective zone.

3. Results and Discussion

3.1. Yield and Climatic Data Variability

Table 1 demonstrates variable annual rainfall distribution within the six zones ranging between 1,421 mm and 1,869 mm. This rainfall groups the sugar zones into two climatic regions: the sub humid with less than 1,500 mm (Kibos, Chemelil and Muhoroni) and humid with about 1,800 mm or more (Sony, Mumias and Nzoia) agro-ecological zones (AEZ) respectively, both lying within the tropical climate of the country.

Table 1. Summary of the agronomic and climate data used in the study: mean and standard deviation (in parenthesis) calculated over the 9-year period (2002–2010).

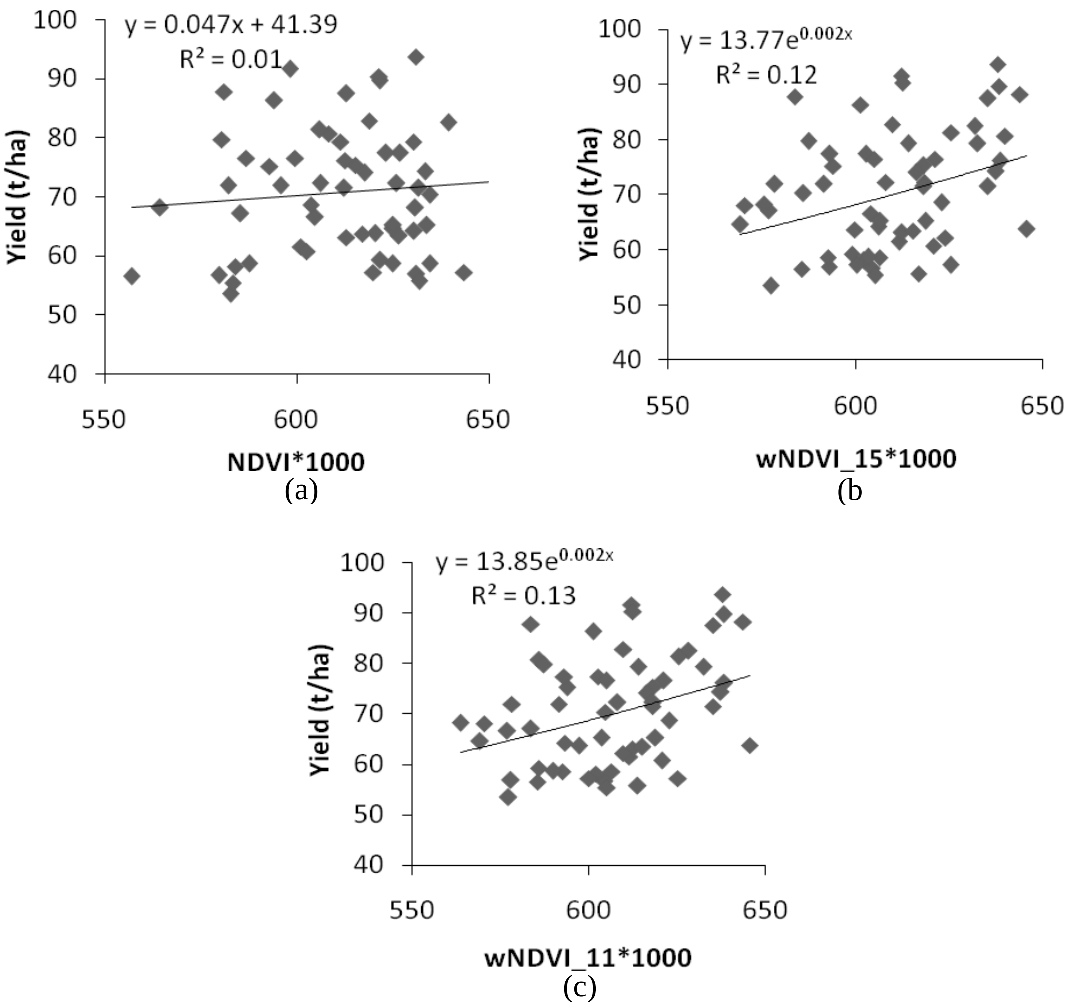
	KIBOS	MUMIAS	CHEMELIL	MUHORONI	SONY	NZOIA
Rainfall ($mm \cdot yr^{-1}$)	1,421 (102)	1,835 (186)	1,426 (263)	1,486 (214)	1,869 (221)	1,763 (252)
Yield ($t \cdot ha^{-1}$)	71.1 (9.6)	75.6 (11.1)	62.6 (9.6)	63.9 (7.9)	80.1 (11.3)	75.0 (5.2)
Sugarcane fraction (%)	32.2 (4.5)	48.7 (2.5)	38.8 (6.3)	50.5 (7.3)	33.3 (5.3)	22.2 (2.7)

Sugarcane grown in regions with less than 1,500 mm rainfall is recommended for supplemental irrigation [1]. The reason for higher yield in Kibos (71 $t \cdot ha^{-1}$), compared to the government owned Chemelil and Muhoroni sugar mills in the same AEZ whose yield is around 63 $t \cdot ha^{-1}$ can be explained by better crop husbandry. Globally, yield in the humid AEZ (Mumias, Sony, and Nzoia) is higher (between 75 and 80 $t \cdot ha^{-1}$) than in the sub-humid AEZ. The yield in Sony (80 $t \cdot ha^{-1}$) is boosted by large scale farmers within the fertile highlands of Sony sugar zone.

3.2. Relationship between Yield and NDVI

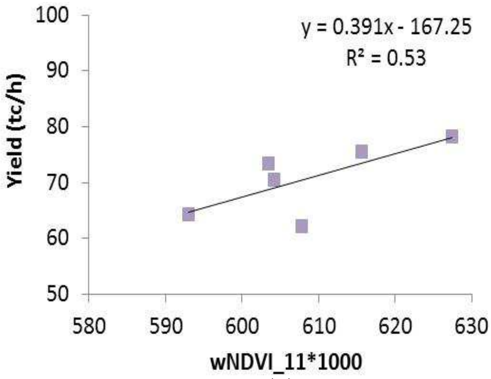
When the whole data set (6 zones and 9 years) is used, the analysis shows that the annual NDVI is not strongly related to the sugarcane yield ($p = 0.1$; (Figure 4a). This finding is close to those who found no relationship between average NDVI and farmers' yield [11] and; whose results showed low significance when correlating historical yield and NDVI at annual level ($P = 0.1$) [2]. However, when adjusted NDVI (wNDVI) is used, the relationship is highly significant for wNDVI_11 ($P = 0.001$) (Figure 4c) and significant for wNDVI_15 ($P = 0.01$) (Figure 4b) with the R^2 increasing from 0.01 to 0.12 and 0.13 respectively through both linear and exponential relationships. This result is in agreement with a study demonstrating that yield estimations based on metrics obtained a little after the peak of APAR can be done without seriously compromising performance [31]. However, the strength of these correlations is weak, justifying further analysis by this study on other factors that affect yield.

Figure 4. Relationship between (**a**) yield and annual NDVI, (**b**) yield and wNDVI_15, and (**c**) yield and wNDVI_11.

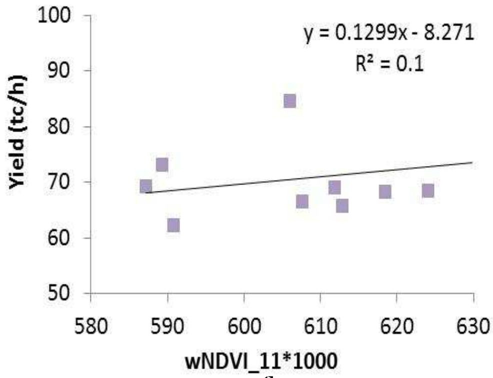


When the whole dataset is aggregated over the whole period (2002–2010), at the zone level (spatial analysis), the correlation between yield and wNDVI is significant (Figure 5a) with R^2 = 0.53, $P < 0.001$; while when the whole dataset is aggregated over the six zones, at the year level (temporal analysis); there is no significant correlation between yield and wNDVI (Figure 5b). The good result obtained through the spatial analysis is due to different environmental variables exuded through rainfall distribution. The absence of significant results through the temporal analysis could be explained by (1) the difficulty to make coherent yield measurements over a calendar year and wNDVI (considering the length of time sugarcane takes to mature), and (2) the sugarcane cover fraction changes during the 2002–2010 period (see standard deviation values of the fraction of sugarcane cropped area in each zone, Table 1).

Figure 5. Variability with wNDVI_11 averaged (**a**) at zone level on the 2002–2010 periods, and (**b**) at annual level on the six zones.



(a)



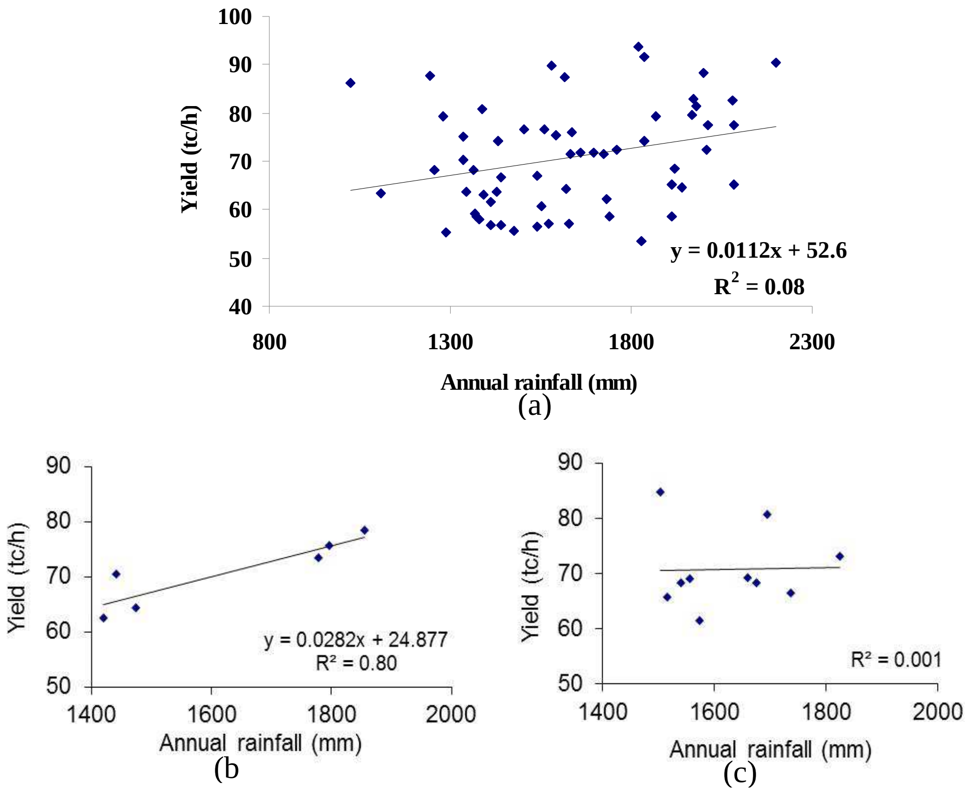
(b

3.3. Relationship between Yield and Rainfall

In order to better understand the spatial and temporal variability of yield, we studied the relationship between yield and rainfall. When using all the data (6 zones * 9 years; Figure 6a), the relation between annual yield and rainfall was significant, but weak ($R^2 = 0.08$; $p = 0.03$). Such a weak relationship has been attributed to the time lag between yield and rainfall because vegetation takes a considerable period to respond to soil moisture [25]. This effect is amplified in Western Kenya, where the annual yield is dependent on the rainfall of the previous year due to the length of the sugarcane cycle. On removal of the time lag through spatial and temporal averaging over the nine year data (6 zones*9 years; Figure 6b,c), this study showed a strong relationship as noted by other studies [4, 25] with $R^2 = 0.8$ and $p < 0.001$ at the spatial level (Figure 6b). The relationship between yield and rainfall (Figure 6b) is stronger than the relationship between yield and wNDVI (Figure 5a) at the zone scale. This is because unlike rainfall which is an environmental variable, wNDVI value integrates not only sugarcane area, but also other types of land covers that are in different proportions according to the zone.

The temporal analysis of yield and rainfall shows no correlation between both variables (Figure 6c), because (1) rainfall is not the only yield driving factor, and (2) because annual rainfall should be integrated on a longer period and with different weights (as wNDVI) in order to take into account the particular cropping calendar of the sugarcane crop. These results are in agreement with a study that pointed out that rainfall amounts and pattern may not be a reliable predictor of yield [11].

Figure 6. Relationship between yield and rainfall using: (**a**) all the data, (**b**) the data aggregated at the zone scale (spatial analysis), and (**c**) the data aggregated at annual scale (temporal analysis).



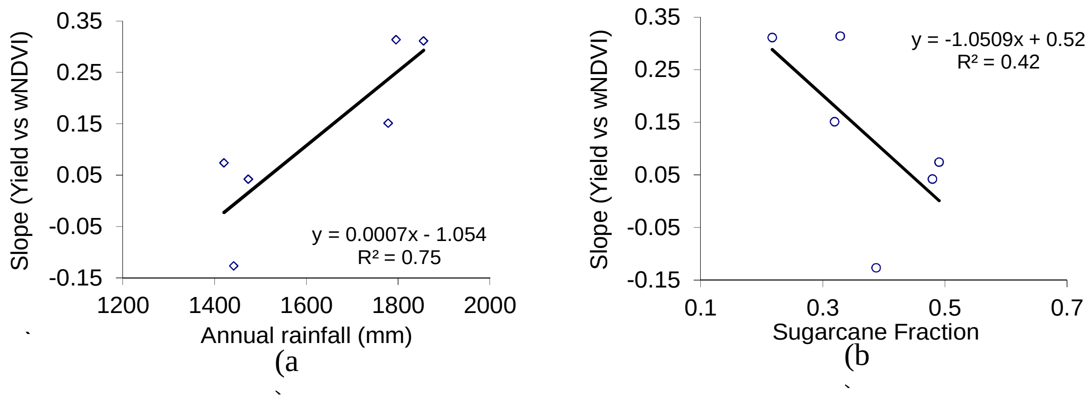
3.4. Relationship between Yield-wNDVI Slope and Rainfall

In order to better understand the main driving factors of the yield-wNDVI relationship, we correlated the slope of the relation between yield and wNDVI aggregated at the zone scale with the rainfall (Figure 7a), and with the fraction of sugarcane in each zone (Figure 7b). Results show a strong correlation with high significance at $p < 0.001$ in both cases.

The sensitivity of the yield-wNDVI variations to each millimeter rainfall received in each management zone also called the Precipitation Marginal Response, or PMR [33], separates two groups of three zones geographically located in sub humid AEZ from those in the humid AEZ (Figure 7a). The ability to separate the two climatic regimes in this study therefore strengthens the ability to use wNDVI in forecasting crop yield. Results of this relationship were highly significant with $R^2 = 0.75$; $P = 0.001$. The positive slope of this relationship (Figure 7a) indicates that the sensitivity of the yield to rainfall is higher than the sensitivity of the wNDVI to rainfall.

The negative slope resulting from the relationship between yield-wNDVI slope and sugarcane fraction (Figure 7b) indicates that wNDVI is not only affected by the amount of rainfall received in the zone, but is also influenced from other surrounding vegetation cover [2] considering that sugarcane has larger biomass than the surrounding environment.

Figure 7. Relationship between the "yield-wNDVI" slope and (**a**) rainfall, and (**b**) sugarcane fraction, aggregated at the zone scale.



3.5 A Quantitative Evaluation of the Model

WNDVI_11 data for the year 2011 and 2012 was used to estimate the 2012 sugarcane yield (Table 2) using the model established at the zone scale (Figure 5a), in order to utilize data that is independent from the one used in development of this model.

Table 2. Model validation using 2012 yield.

Zone	wNDVI_11	Model Yield($t \cdot ha^{-1}$)	Measured Yield ($t \cdot ha^{-1}$)	Squared Error ($t \cdot ha^{-1}$)
Mumias	566.5	54.2	48	38.44
Nzoia	602.8	68.4	64.7	13.69
Chemelil	586.9	62.2	59	10.24
Muhoroni	604.4	69.1	63.6	30.25
Kibos	596.1	65.8	62.7	9.61
Sony	610.5	71.5	69	6.25
RMSE				4.25

We obtained a Root Mean Squared Error (RMSE) of 4.25 $t \cdot ha^{-1}$ when all the zones are considered. The worst yield estimation was realized in Mumias zone (+6.2 $t \cdot ha^{-1}$), where the land holdings are particularly small (up to 0.1 ha), and where the landscape is very heterogeneous (Figure 2). This result is similar to the low accuracy obtained for fields smaller than the pixel size and high accuracies for large fields [15]. When excluding Mumias zone, the RMSE decreases to 3.41 $t \cdot ha^{-1}$, which is in agreement in both cases, with the user specification of RMSE 5 $t \cdot ha^{-1}$.

4. General Discussion and Conclusions

This research has investigated the influence of cropping practices and environmental conditions on yield at zone scale through two approaches. Firstly, historical yield was related to annual NDVI with the assumption that yearly sugarcane yield is significantly correlated to annual NDVI. This hypothesis was rejected since the significance of this correlation was only achieved after adjusting the NDVI through time integration of the sugarcane growing period to remove the time lag in crop growth. The strength of this relationship was then enhanced when the data were aggregated over the whole period (2002–2010) at the zone level. Secondly, historical yield was related to rainfall and the strength of this relationship was low, although the correlation was of high significance. The relationship was equally strengthened through spatial aggregation and through rain use efficiency. The relation between yield and rainfall exists owing to the fact that sugarcane yield is significantly related to rainfall on removal of time lag at zone scale since crops take a considerable period to respond to rainfall.

This study has shown that remote sensing technology together with environmental information has potential to be used to estimate crop yield and evaluate the impact of environmental conditions to crop production as opposed to physical methods. In effect, it has been reported that accuracy of physical methods such as visual physical approach (VPA) on yield estimation is minimized due to gross errors associated with fatigue, variability in assessment of natural phenomena using the naked human eye, and lack of consideration of diverse environmental variables (such as rainfall) during the growth period of the cane crop [6]. The use of remote sensing data can highlight variations in environmental variables within respective zones, and this is uniquely evidenced by the separation of the two agro-ecological zones through spatial aggregation. Additionally, variations within and between the zones are influenced by environmental variables such as soil characteristics and rainfall distribution over different years. Our findings are in agreement with a study noting that rainfall was not the single determinant of crop yield in different environments, but rather, other factors such as soil characteristics, and other agricultural land use need to be included [8].

In summary, our results are in agreement with most of the previous studies on this subject. Through this study, we have contributed knowledge to remote sensing fraternity (1) by developing an original method for NDVI time integration that takes into account the local cropping practices (length of the growing season), and (2) by analyzing the spatial and temporal dimensions of the yield-NDVI relationship and response of its slope to rainfall. Sugarcane yield forecasting has been exemplified through spatial aggregation of weighted NDVI. The information presented in this study is useful for proper, foresighted and informed planning in the Kenya's Sugar Industry at the zone management scale. This is because the information explains the influence of environmental conditions on sugarcane production, thus providing knowledge for monitoring sugarcane productivity at the zone scale.

Further research is recommended by this study, to refine the zone scale to farm level. The issue of scale is suggested to minimize the influence of other land cover on NDVI extracted from sugarcane fields. Future Earth Observing satellite systems, such as Sentinel-2 (ESA), with decametric spatial resolution, and a high visiting frequency, will give access to farm level information.

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Conflict of Interest

The authors declare no conflict of interest.

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