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Rapid Erosion Modeling in a Western Kenya Watershed using Visible Near Infrared Reflectance, Classification Tree Analysis and ^{137}Cs

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Abstract

Human induced soil erosion has severe economic and environmental impacts throughout the world. It is more severe in the tropics than elsewhere and results in diminished food production and security. Kenya has limited arable land and 30 percent of the country experiences severe to very severe human induced soil degradation. The purpose of this research was to test visible near infrared diffuse reflectance spectroscopy (VNIR) as a tool for rapid assessment and benchmarking of soil condition and erosion severity class. The study was conducted in the Saiwa River watershed in the northern Rift Valley Province of western Kenya, a tropical highland area. Soil ^{137}Cs concentration was measured to validate spectrally derived erosion classes and establish the background levels for difference land use types. Results indicate VNIR could be used to accurately evaluate a large and diverse soil data set and predict soil erosion characteristics. Soil condition was spectrally assessed and modeled. Analysis of mean raw spectra indicated significant reflectance differences between soil erosion classes. The largest differences occurred between 1,350 and 1,950 nm with the largest separation occurring at 1,920 nm. Classification and Regression Tree (CART) analysis indicated that the spectral model had practical predictive success (72%) with Receiver Operating Characteristic (ROC) of 0.74. The change in ^{137}Cs concentrations supported the premise that VNIR is an effective tool for rapid screening of soil erosion condition.

Keywords

erosion; soil degradation; CART; ^{137}Cs ; Kenya

1.0 Introduction

Soil erosion by water is considered the dominant land forming process (Dunne and Leopold, 1978; Toy et al., 2002); however its accelerated and widespread occurrence has severe economic and environmental impact throughout the world (Jones et al., 1997; Pimentel et al., 1995; Lal, 1998). Productivity of the soil is affected through the loss of the nutrient rich

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top soil and rooting zone. Soil erosion is associated with about 85 percent of the world's land degradation, which causes a 17 percent reduction in crop productivity worldwide (Oldeman et. al., 1990). Human and animal activities, coupled with damaging soil erosion and other related degradation processes, can rapidly change highly productive agricultural regions into barren waste lands. Essentially irreversible damage can occur when erosion rates exceed soil formation rates (Wiebe, 2003). More widely, less severe erosion processes systematically decrease soil quality through selective removal of silt, clay and organic matter fractions, which support a soil's nutrient retention capacity and structural integrity.

In the tropics, such as in Sub-Saharan Africa, soil erosion is widely recognized as a bigger problem than non-tropical areas (Sanchez et al., 1982; Lal, 1984; Lal, 1994). Several reasons why the tropics experience such severe land degradation include intense climate, easily eroded soil, steep slopes, poor land management (including poor soil conservation, low levels of agricultural inputs and high population density) and an excessive dependence on subsistence farming (Sanchez et. al., 2003). Large scale erosion and its deleterious effects remain a major concern for soil scientists (Oldeman, 1992; Hartemink, 2002) and results in diminished food production and security.

In Kenya, less than 10 percent of the land surface is arable (CIA, 2006). Nearly 200,000 km² (30 %) of the country's total land surface experiences severe to very severe human-induced soil degradation (FAO, 2005). Consistently, Kenya's farm lands are subject to potentially large reductions in food production (Ovuka and Ekbom, 2001). The World Agroforestry Centre (ICRAF, 2004) estimated that in the Nyando River Basin of western Kenya, about 61 percent of the land is eroded at an average net erosion rate of 43 tons/ha/year and that since 1963, 3.2 million tons of soil from the highly productive western Kenya region has washed into Lake Victoria. Others have reported surface soil loss in areas of Kenya at rates ranging from 15 to 61 tons/ha/yr (Angima et al., 2003; Sjors, 2001), and in badly eroded zones, soil loss was estimated to be more than 90 tons/ha/yr. Mwakubo et. al., (2004) reported an average annual topsoil loss of about 3 mm (52 tons/ha/yr). This extensive soil loss and depletion of soil nutrients has been linked to land abandonment and off-site losses of ecosystem services, leading to secondary economic impacts such as silting in floodplains, reservoirs and infrastructure damage. It is therefore important to be able to quickly and accurately assess and quantify the spatial extent and rates of soil erosion/redistribution in the region.

Visible near infrared reflectance (VNIR) is a rapid, non-invasive technique that measures diffuse reflectance of light from an illuminated sample in the visible near-infrared portion of the spectrum (350 – 2,500 nm) to produce a reflectance spectrum. The spectrum provides useful information about the composition of the sample tested. Soil physical and organic materials can be well defined within the VNIR spectrum (Clark, 1999; Ben-Dor, et al., 1995; Shepherd and Walsh, 2002, Shepherd and Walsh, 2007; Shepherd et al., 2003; Vagen et al., 2005). Shepherd and Walsh (2002) developed an VNIR based soil spectral library to measure the chemical and physical properties of soil components in African soils, which was later extended to a global library (Brown et al., 2006).

Cesium-137 (^{137}Cs) is an artificial radionuclide produced by nuclear fission and released through explosions of nuclear weapons in the 1950s and 1960s. ^{137}Cs provides a tool to estimate rates of soil erosion and/or deposition (soil redistribution) throughout landscapes around the world (He and Walling, 1996; He and Walling, 1997; Walling and He, 1997; Ritchie and McHenry, 1990; Wallbrink, 1996; Zhang et al., 2003; Huh and Su, 2004). ^{137}Cs flux is determined by comparing concentrations measured at a local, relatively undisturbed reference site(s) to other specific locations. The reference site(s) represents the local fallout input where there has been no significant soil erosion/deposition. A simple comparison of ^{137}Cs levels to the background level can provide a valuable measure of soil redistribution. Since it is usually more useful to quantify potential soil redistribution rates, several models have been developed for this purpose (Ritchie et al., 1974; Walling and He, 2001). Research (Zhang et al., 2003; Walling et al., 2001; Porto et al., 2001) indicates that isotope concentrations will be lower for disturbed (cultivated) compared to undisturbed (pasture, forest) areas. This is because in undisturbed areas, higher concentrations of ^{137}Cs would be expected to be in the surface soil and decrease exponentially with depth. In order to evaluate soil redistribution, this study compares disturbed (cultivated) soil to undisturbed (uncultivated or background) soil ^{137}Cs levels.

The objectives of this research were to (i) test the use of VNIR as a tool to determine soil erosion conditions and establish soil condition benchmarks, and (ii) use this tool to rapidly index soil erosion in the diverse tropical highland soils of the Saiwa River watershed in the northern Rift Valley Province of western Kenya. In addition, ^{137}Cs measurements were used to validate the spectrally derived erosion classes and establish the background levels for the different land-use types (i.e. cultivated, timbered, pasture) in the study area.

2.0 Methods

2.1 Geographic and Ecological Setting

The project area, as shown in Figure 1, is located within the Saiwa River watershed located north of the town of Kitale, western Kenya, East Africa (Latitude: 1 degree North and Longitude: 35 degrees East). A more detailed description of the basin is included in deGraffenried and Shepherd, (2009).

A reconnaissance survey of the project area was conducted that included interviews with landowners and other residents to gain understanding of land use history, and soil conservation concerns, causes and interventions. The interviews were completed concurrently with field sampling. Sampling data included location (latitude and longitude), specific site characterization information, physiography, erosion characterization, soil depth, and vegetation.

2.2 Soil Sampling Plan and Analysis

Using the latitude and longitudinal survey grid (1 km²) contained on Kenya Survey topographic maps, a spatially-clustered soil sampling plan was used to establish sample locations in the study area. Thirteen grid intersection points (one per 10 km²) were selected as the center of a 1-km diameter sample-cluster. Each sample-cluster contained thirteen

systematically-located 30 meter diameter sample-plots and designed to ensure locally representative, but spatially diverse data. From the center of each sample-cluster, the plots were located at 2,4,8 and 16 plot diameter distances along three transects separated by 120 degree angles. A total of 169 plots were sampled. Figure 1 illustrates sample cluster and plot locations. The figure inset depicts the ground sampling plan at the cluster and plot levels (Walsh, 2004). Following established ICRAF (personal communication, M. Walsh) and American Standard Testing and Materials (ASTM - 1452-80) soil sampling protocols, a 19 cm inside-diameter open-bucket hand auger was used to collect bulk soil topsoil samples at 0-20 cm and subsoil 20-50 cm. Soil samples were collected, at the plot center and at three set locations around the plot perimeter. A total of eight samples were collected from each plot; one topsoil and one subsoil at the plot center and at three set locations around the plot perimeter. Sample collection was dependent on depth of auger refusal. A total of 1,305 samples were collected and transported to the ICRAF laboratory in Kisumu, Kenya for processing.

Soil samples were air-dried, weighed, hand crushed and passed through a 2-mm sieve to determine the total dry weight, and the coarse rock and gravel content. The soil samples were analyzed at ICRAF's Soil and Plant Analytical Laboratory in Nairobi, Kenya. Following methods described by Harris (2001), The University of California at Davis Stable Isotope Lab measured total soil organic carbon (SOC) and nitrogen (N), on samples previously acidified to remove carbonates, by continuous flow isotope ratio mass spectrometry (20-20 mass spectrometer, PDZ Europa, Northwich, UK) after sample combustion to CO₂ and N₂ at 1000° C in an on-line elemental analyzer (PDZ Europa ANCA-GSL). Soil particle size distribution was determined using the hydrometer method (Gee and Bauder, 1986) and reported as percentages of sand, silt and clay materials.

2.3 Soil Reflectance Measurement

Soil reflectance was measured in the laboratory using a FieldSpec FR spectroradiometer (Analytical Spectral Devices Inc., Boulder, Colorado) at 350 to 2,500 nm using 1 nm spectral sampling intervals. Air-dried soil samples were hand ground using a mortar and pestle and placed in 12 mm deep, 55 mm diameter plastic Petri dishes. Samples were air-dried to minimize spectral variation due to soil moisture. The samples were scanned through the bottom of the Petri dishes using a high-intensity source probe (Analytical Spectral Devices, Boulder, CO). The probe illuminates the sample (4.5 W halogen lamp giving a correlated color temperature of 3000 K; WelchAllyn, Skaneateles Falls, NY) and collects the reflected light from a 3.5-cm-diam. sapphire window through a fiber-optic cable (see Shepherd et al., 2003). To sample within-dish variation, reflectance spectra were recorded at two positions, successively rotating the sample dish through 90° between readings. The average of 25 spectra (the manufacturer's default value) was recorded at each position to minimize instrument noise. Before reading each sample, 10 white reference spectra were recorded using calibrated Spectralon (Labsphere, Sutton, NH) placed in a glass Petri dish. Reflectance readings for each wavelength band were expressed relative to the average of the white reference readings. Shepherd and Walsh (2002) indicate that coefficients of variation for the reflectance values were approximately one percent within samples and two percent for replicate dishes. Spectral data were saved in electronic form for later processing. Prior to

statistical analysis, the spectral reflectance data were compressed by sampling every tenth-nanometer value to reduce amounts of data and to more closely match the 3 to 10 nm spectral resolution of the instrument (Shepherd and Walsh, 2002). Data noise was reduced using first derivative processing and data smoothing by the Savitzky-Golay filter (one nm each side) via The Unscrambler computer software version 9.6 (Camo Inc.). Derivative transformation of the spectra is a common method used to linearize the spectral response and correct baseline offset. It can also increase spectral differences between compounds by standardizing spectrum and reduce same-class variation while increasing the spectral differences between-classes. Waveband regions with low signal-to-noise ratios and/or excessive noise were removed leaving 197 spectral bands to be analyzed. Removed bands included 350-410 nm, 970-010nm, 1780-1820 nm, and 2490-2500 nm.

2.4 Soil Reflectance Analysis and Prediction of Soil Properties

Soil spectral variation was explored using principal component analysis (PCA) of the first derivative spectra using The Unscrambler software (Camo, Inc.). PCA score information was presented as a two-dimensional scatter-plot of one principal component or latent variable versus another. The first two principal components (PC's) as determined by the PCA explained approximately 81 percent of the data variance.

Multivariate relationships between spectra and soil parameters were determined using partial least squares (PLS) analysis with 10-fold cross validation. For each soil variable, a calibration model was developed using a randomly selected ten percent calibration subset ($n = 130$). The calibration subset was selected by ranking each data point principal component scores by Euclidian distance, placing them into quartiles from which 128 samples, 32 from each quartile, were randomly selected. To assure adequate calibration sample variance, the two most extreme spectral values (one high and one low) were automatically selected. Laboratory analysis was conducted on all 130 selected samples. Seventy percent of these samples were used to calibrate the model and the remaining thirty percent were used to test or validate the predicted soil variables.

The resulting PLS models were developed on transformed soil variables but the predictive model results were back-transformed for evaluation. The regression equations were evaluated in terms of the root mean square error of calibration (RMSEC) and validation (RMSEV), the coefficient of determination, and bias.

A soil fertility index (SFI) using the K-means clustering algorithm (MacQueen, 1967), in conjunction with PCA, was previously developed (deGraffenried and Shepherd, 2009) for soil in the western Kenya basin. Clustering was used to determine the intrinsic grouping within a data set based on the PCA scores. The spectrally-based index incorporated 10 common agronomic parameters and was used to rank soil as low (0), medium (1), or high (2) fertility. Prior to PCA, the parameter values were log transformed to approximate a normal distribution and standardized by dividing by their standard deviations. Fifty iterations of the algorithm were run to optimize cluster configuration. The mean SFI difference for topsoil by erosion class was evaluated using a Chi-square test of proportions.

2.5 Soil Erosion Index Development

Each plot was thoroughly visually inspected for erosion indicators and categorized into four erosion classes: no visible erosion and sheet, rill and gully-erosion. Visual evidence of erosion includes relocated sediment, rock pedestals, exposed vegetation roots, surface-soil textural changes, surface water flow indicators or vegetation mounding. The disadvantages of assessing erosion under field conditions include that (i) symptoms can be subtle, uniformly affecting exposed areas and thus can easily be missed, (ii) short term climate conditions may not represent typical patterns, (iii) vehicles or heavy equipment, pedestrians, animals, wind, or recent land use change may mask signs of erosion, and (iv) assessment is subjective and may vary among observers and over time. Thus visual assessment has the potential for substantial error. Even though it is generally accepted that visual assessment has limited accuracy, its straightforwardness, simplicity and rapidity make it an obviously attractive and common assessment method.

2.6 Soil Erosion Index Spectral Relationship

To test the soil erosion index (SEI) concept and to provide standard spectral definitions of erosion classes, a spectral screening model was developed based on the soil reflectance spectra from soil samples from each sample plot. The spectra for each sample were obtained using the procedure described earlier. The difference between reflectance of eroded (R_E) and non-eroded (R_{NE}) soil was determined by simple subtraction of the two spectra ($R_E - R_{NE} = R$).

To determine the accuracy of the SEI and to identify key spectral wavebands in a soil erosion predictive model, recursive partitioning was applied using the Salford System, Inc. Classification and Regression Tree (CART) software program version 9.6 (Steinberg and Cola, 1997). A classification tree was built to predict SEI using the 197-reflectance wavebands as predictor variables. This tree was constructed using Gini-splitting decision rules, equal costs and equal classes (priors) to recursively divide the spectral data into increasingly homogeneous subsets, providing the best separation (or minimum misclassification error) between erosion classes. The model's stability and predictive performance were evaluated using 10 fold cross-validation (Breiman et al., 1984). A decision tree, which splits on certain wavelengths yielding particular classification rules, was first constructed with the maximum number of nodes, and then reduced to find optimal tree size. For this analysis, a smaller or "best" tree, one that was within one standard error of the optimal tree, had fewer terminal nodes and a higher Receiver Operating Characteristic (ROC) value.

2.7 ¹³⁷Cesium Sample Selection and Analysis

Thirty soil samples were selected for ¹³⁷Cs analysis based on spectral properties. These samples were selected using an erosion/sediment index (dSED), developed by ICRAF (personal communication, M. Walsh) that is based on the sediments from Lake Victoria. A dSED value was obtained from for all ($n = 1,305$) of the samples by projecting the soil sample spectra into a principal component model of Lake Victoria sediment and estimating the Mahalanobis distance of the project soil samples to the model centroid. Values close to zero were sediment-like, typically with high organic content and small textural size, whereas

high values are dissimilar from the sediments and have a low fertility and more coarse physical condition. Samples with high dSED values were expected to be historically undisturbed areas or areas with sediment accumulation the dSED values were ranked and divided into quartiles. Twenty eight samples (seven samples from each quartile) were randomly selected in addition to the two extreme values (one high and one low) automatically selected to achieve maximum sample variability in the calibration model. This selection scheme was used in an effort to randomly select samples from both eroded and intact conditions. With the addition of fourteen supplemental samples, selected to assure adequate representation of potential reference locations, such as protected indigenous lands, a total of 44 samples were analyzed. Four sample locations were selected to represent undeveloped background conditions with minimal erosion. These background sites were undeveloped locations with multi-strata vegetative cover (trees, shrubs and herbs).

One of the major challenges involved in the use of the ^{137}Cs technique is identifying appropriate reference sites. In the project area, the largest, historically undisturbed areas are the escarpment slopes of the Kapolete Forest. Because it is prime farm land, most of the relatively flat or gently sloping land has been cultivated for decades. As these prime areas became less available, more forests were cut and converted to agriculture land. The remaining contiguous forests/parks are those physically protected by the Kenyan Government. Of the six potential reference locations, four were selected. Two potential sites were not used as reference locations since they may have been previously cultivated. The undisturbed reference sites consisted of a sloped grassed pasture, a thickly vegetated (trees/shrubs) smallholding, and two sites within the Kapolete National Forest.

The analysis of ^{137}Cs of the soil samples was performed at Wayne State University (WSU), Detroit, Michigan following standard methods (Baskaran et al., 1991). The soil samples were air dried, and mechanically ground into a sediment powder. For each sample, 20 grams of the soil powder was placed in a capped aluminum canister and labeled. The spectroscopic peaks of ^{137}Cs were determined using a GE – Well Detector (GCW 3522 S) and Canberra Genie PC Gamma Spectroscopy system. The gamma counting equipment was calibrated (at 661 KeV and 85.1% Intensity) following standard laboratory procedures and using ^{137}Cs International Atomic Energy Agency (IAEA) standard reference material (IAEA-300). Sample counts were performed between 21.7 to 26.1 hours, depending on the activities of ^{137}Cs and ^{210}Pb . The minimum detection limit of 30 Bq/kg was based on a 24-hour count and a 95% confidence level. Many of the samples had low concentrations and/or were below minimum detection concentration (MDC) limits.

2.8 Statistical Comparison of Soil Erosion Index and Field Parameters

Statistical comparison, using SPSS General Linear Model (GLM) Ordinal Regression (ONR) approach was used to determine the association between SEI and related field conditions. A mixed effects model was employed with intercept included. Standard inference techniques, such as confidence intervals (95%) and Likelihood tests, were used to interpret the model fit and significance.

3.0 Results

3.1 Spectral Analysis of Erosion Class

Analyses of mean raw spectra for all soil samples ($n = 1,305$) indicates a significant ($\alpha = 0.05$, $p = 0.017$) albedo difference between erosion class (non-eroded and eroded) across the entire spectrum (350 - 2,500 nm). Because erosion primarily impacts topsoil, a corresponding spectral difference is expected between the erosion classes. The mean spectra of the non-eroded soil had a lower reflectance than eroded soil. The section of the spectrum showing the largest spectral difference occurred between 1,350 and 1,950 nm with the biggest spectral separation occurring at 1,910 nm. Analyses of mean raw spectra for topsoil samples indicates a significant ($\alpha = 0.05$, $p = 0.004$) difference between erosion class (non-eroded and eroded) at 1,910 nm. Figure 2 illustrates the spectral reflectance of topsoil by erosion class from 1,300 to 2,250 nm. An albedo difference by erosion class is noted in both topsoil ($n = 671$) and subsoil samples ($n = 634$). In general, the topsoil and subsoil graphs have similar overall patterns with topsoil samples having the largest spectral difference between erosion classes. This separation is significant ($p = 0.013$) and rapidly increases through the visible spectrum (420-700 nm) and NIR spectrum (700 -1,300 nm) reaching a maximum (0.01128) at 1,910 nm secondary peak at 1,490 nm (0.01056) and then declining to a relative low between 2210-2340 nm. These increases in spectral differences correspond with prominent spectral absorption features in the untransformed spectrum (Figure 2) related to lattice water associated with clay minerals and organics at 1,450 nm and free water at 1,935 nm (Hunt, 1982; Ben-Dor et al., 1999; Clark, 1999; Shepherd and Walsh, 2002). In general, Latz et al., (1984) indicated that as the degree of soil erosion increased, the amount of organic matter decreased, the iron oxide content increased and spectral reflectance in the VNIR increased.

Figure 3 indicates that there is a spectral difference in subsoil samples by erosion class. Even though the separation pattern for the subsoil was generally similar to the topsoil pattern, the difference was much less in the subsoil and not significant. Results of analysis and statistical comparisons ($\alpha = 0.05$) of non-eroded vs. eroded topsoil, indicated that, although there were slight changes in the soil physical components, these were not significant. Silt content tended to decrease slightly with erosion (from 18.7% to 18.1%) but absolute differences were small and within measurement error. Differences due to erosion may be overwhelmed by the large spatial variation in texture.

Analysis of topsoil SOC indicates non-eroded soil has a slightly higher ($\alpha = 0.05$, $p = 0.28$) percentage of organic carbon (3.9%) than eroded soil (3.7%). Soil organic matter is spectroscopically active and exhibits strong absorption features in the entire VNIR range (Ben-Dor et al., 1995; Chang and Laird, 2002). The loss of organic matter in the topsoil due to erosion would reduce the demonstrated absorption.

A soil fertility index (SFI) was previously developed (deGraffenried and Shepherd, 2009) for soil in the western Kenya basin. The spectrally-based index incorporated 10 common agronomic parameters and was used to rank soil as low (0), medium (1), or high (2) fertility. A comparison of mean SFI for topsoil by erosion class, using a Chi-square test of proportions, indicates soil fertility in the basin is significantly ($p = .0001$) reduced by soil

erosion. Non-eroded topsoil has a mean SFI value of 1.31 while eroded topsoil is only lower with a mean SFI of 1.25, compared with a soil with moderate fertility which would have an index value of one. Descriptive statistics of the variables indicated that approximately 50 percent of the non-eroded soils and 40 percent of eroded soils had high fertility and approximately 16 percent of eroded soils and 20 percent of non-eroded soils had low fertility.

3.2 ^{137}Cs Analysis

^{137}Cs concentrated in the upper few centimeters of the soil profile and decreased in concentration with depth. Little ^{137}Cs was detected at depths lower than 20 cm. Twenty-one of the 26 (82 %) top-soil samples had detectable levels of ^{137}Cs , where as only 6 of the 18 sub-soil samples (33 %) contained detectable levels. At five locations both topsoil and subsoil samples were collected. Of these samples, topsoil ^{137}Cs concentrations ranged from 8.96 to 0.00 Bq/kg with a mean value of 2.74 Bq/kg. Topsoil samples had a mean ^{137}Cs value of 2.55 Bq/Kg. All but one of the subsoil samples had ^{137}Cs concentrations below the Minimum Detection Limit (MDL).

Background topsoil ^{137}Cs values ($n = 4$) ranged from 6.96 to 9.49 Bq/kg and the mean value was 8.62 Bq/kg. The mean inventory value was used to represent the local fallout input value of ^{137}Cs that remained naturally (no additional cesium input or removal) after original atmospheric deposition.

Non-background samples were collected from areas in which it was believed that the soil surface had been disturbed since ^{137}Cs deposition. It is expected that since non-background sites have been disturbed in some manner, the ^{137}Cs inventory values would be lower than the background. The ^{137}Cs values of these samples ranged from 0.00 to 4.28 Bq/kg, approximately one-half the background level. Cultivation and soil erosion are the dominant processes controlling the magnitude and spatial redistribution of ^{137}Cs . If an individual sampling point has a ^{137}Cs inventory less than the reference value it is indicative of soil redistribution, usually by cultivation and/or erosion. Soil homogenization due to cultivation typically results in a more even vertical distribution of ^{137}Cs throughout the plow layer (0 to 20cm). The lower the inventory value the greater the amount of soil that has been transported. Thus, a low or zero inventory value doesn't signify a poor quality sample but more than likely reveals that the original cesium laden soil has been transported to another location.

Field reconnaissance indicated that 65 percent of the plots showed evidence of topsoil erosion ($n = 17$), while 35 percent ($n = 9$) did not. Eroded plots had a mean ^{137}Cs concentration of 1.68 Bq/kg. Non-Eroded plots had a ^{137}Cs mean concentration of 4.15 Bq/kg. Figure 4 shows the median and quartile distribution of ^{137}Cs concentration by erosion class. ^{137}Cs concentration was also related to slope position (Figure 5). Twenty three percent ($n = 10$) of the samples were collected from the top-slope, 31 percent ($n = 14$) mid-slope and 42 percent ($n = 18$) at the bottom-slope/drainage position. Mean down-slope concentration increased indicating probable soil redistribution.

In this study, soil sample depth intervals were too broad to conduct a detailed soil profile analysis but they did illuminate the general topsoil/subsoil relationship. The mean ^{137}Cs concentration for topsoil ($n = 26$) was 2.63 Bq/kg, while the mean subsoil ($n = 18$) concentration was 0.60 Bq/kg.

Land use impacted the ^{137}Cs inventory. Land disturbance increased the chance of soil redistribution. Of the topsoil samples collected, 42% ($n = 11$) were from cultivated sites, 38% ($n = 10$) were forest and 20% ($n = 5$) pasture. Paired t-tests on primary land use types and ^{137}Cs concentration using forested plots as a reference value indicated a significant difference in ^{137}Cs inventory between primary land-use classes (See Table 2). Forested areas had the greatest mean concentration (4.12 Bq/kg), while pasture and cultivated parcels had lower mean concentrations of 1.70 and 1.55 Bq/kg, respectively. The similarity in the Cs concentrations between pasture and cultivated uses could be due to historic land use practices. Not only had much of the pastured land previously been row-cropped, homogenizing the ^{137}Cs throughout the plow layer, but land owners reported reduced fallow periods. Downward migration of the plow layer, due to tillage, would carry ^{137}Cs deeper into the soil profile.

3.3 CART Analysis

The initial CART analysis, using Gini splitting rules, equal costs and priors and no penalties, resulted in high error cost (0.71), an ROC of 0.62, low overall predictive success (<40%) and 12 primary splitters. Cross-validated results correctly predicted 40% of the non-eroded class and between 38 and 54% of the eroded classes (sheet, rill and gully). Approximately 20% of the eroded cases were misclassified as non-eroded. Whereas predictive confusion of sheet and rill eroded samples occurred between 23% (rill erosion being predicted as sheet erosion) and 28% (sheet erosion being classified as rill erosion). For soil conservation and/or agricultural related interests, predictive differentiation between non-eroded and eroded classes is more important than within-class (sheet, rill and gully) partitioning. Because of the low overall spectral predictive success for the model, the erosion model was “hardened” to two categories: eroded and not eroded.

The modified SEI was retested with CART. The hardened model had improved predictive ability with a lower error cost (0.59), fewer terminal nodes (10), a higher ROC (0.75), and an overall cross-validation predictive success of 72% with fewer (9) primary splitters (wavebands 1950, 770, 2240, 2290, 1890, 520, 1650, 2200, and 1270 nm). Table 1 is a prediction success matrix with rows representing true SEI values and columns showing CART predicted class assignments. The 72% predictive is suitable for predictive purposes and is similar to results by Cohen et al., (2004) and Wolfgramm et al., (2007) where they reported cross-validation accuracies of 77% and 73%, respectively. Cohen et al., (2004) used a decision tree approach to predict soil erosion/degradation status based on “hardened” subjective visual field assessments and remotely sensed data. Field-observed erosion classes were calibrated to soil spectral data using classification trees. Wolfgramm et al., (2007) used VNIR results as part of a data set to identify degraded soil in Tajikistan. In both cases, classification tree models attained levels of accuracy for acceptable for preliminary studies.

The wavebands selected as primary splitters are can be associated with water, minerals (especially clay), iron oxides, organic mater and texture in the soil system and absorb incident radiation near these at locations (Malley et al, 2004; Baumgardner et al., 1985).

Iron oxides in soil, even in small amounts, are known to strongly influence soil color and since it is a strong electronic absorber, lead to a decrease in overall reflectance in the VNIR region (Jarmer and Shutt, 1998). It is well documented (Obukov and Orlov, 1964; Baumgardner et al.,1985; Ben-Dor and Bannin, 1994; Clark, 1995) that there is an inverse relationship between iron content and spectral reflectance between 500 and the 900 nm regions. Two of the primary splitters (520 and 770) were located in the visible spectral region influenced by iron oxides and water vapor. Waveband 520 is a primary iron absorption region, whereas waveband 770 is located within regions associated with both iron and water absorption features (Chaplin, 2009). Other primary splitters, 1890, 1950, 2200, 2240 and 2290 nm may be linked to specific overtones and combinations of OH⁻ bonding associated with absorbed and structural water molecules common to clay minerals and organics (Hunt, 1982; Clark, 1999; Ben-Dor et. al., 1999; Shepherd and Walsh, 2002, Ben-Dor et. al., 2003). The OH⁻ bond is the strongest absorber in the NIR region (Malley et al., 2004). Spectral absorption in the 1900, 1950 nm and 2200 nm regions are related to various combination modes of O-H bonding in hygroscopic water and carbon and hydrogen (C-C and C-H) bands generally associated with O-H in the soil-clay crystal lattice (Hunt and Salisbury, 1970, Ben-Dor and Banin, 1995; Ben-Dor et al., 2003; Confalonieri, 2001; ASD, 2006). Palmborg and Nordgren (1993) assigned wavelengths 1880 and 1896 to organic Phosphorus (P). Clark (1999) indicated that spectral features in the 2300nm region are complex and can easily be confused due to the presence of OH overtones and combinations due to carbonates and/or organics. The wavebands located at 2240 and 2290 nm may be attributed to carbonate (CO₃) enriched soils in the 2330 nm region (Gaffey, 1986; Chang and Laird, 2002; Ben-Dor et al., 2003) and/or hydroxyl bands between 2200 and 2600 nm (Hunt and Salisbury, 1970).

Even though CART successfully generated a practical predictive soil condition model from soil VNIR spectra, i.e. one that can be rapidly generated with reasonable results, it generally under predicted the eroded class and over predicted non-eroded class. When used, the potential for error should be taken into account.

4.0 Conclusions

The results supported the concept that VNIR spectroscopy can be used to rapidly and sufficiently accurately evaluate a large and diverse soil data set for initial screening of soil erosion characteristics. The spectral differences reported herein were consistent with expectations that soil erosion altered soil chemistry and texture, and thus could be spectrally classified.

Most of the spectral calibrations showed significant differences between categories of physical/chemical properties commonly associated with soil degradation. The real advantage of spectral identification of soil degradation lies in the rapidity and the integral nature of the analysis, i.e. many soil parameters can be measured with the same sample at the same time

with good precision, and this would be especially beneficial at the landscape scale. Also, this index could be established quickly from effective field observations and soil samples. Once established, the spectral indices could be used in conjunction with, or instead of, additional field observations to estimate the extent of erosion, providing a more objective measure than field observations alone.

CART analysis provided evidence that soils with different physical characteristics have distinct spectral patterns that can be quickly separated and identified to form a reproducible erosion class model. In this case, even though CART analysis was accurate, it underestimated eroded soil and over estimated non-eroded soils. Results of ^{137}Cs analysis validated that the spectral indices effectively identified eroded soil.

Data provided herein established a soil erosion baseline that could be used in future soil condition surveys and remote sensing efforts for the western Kenya or Lake Victoria watershed area. In addition, this information could be used with satellite imagery and or Geographic Information System (GIS) to complete landscape scale soil condition maps to efficiently target problem areas and direct soil conservation interventions. Improved soil quality has many long term benefits, including increased crop production leading to increased on-farm income and food security.

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Figure 1.
site location map.

Figure 2.
Soil Reflectance of Topsoil by Erosion Class.

Figure 3.
Soil Albedo Difference by Erosion Class and Soil Depth

Figure 4. ^{137}Cs concentration by erosion class. The boxes contain 50% of the values and the whiskers show the data range (excluding outliers). The line across the box indicates the median value.

Figure 5.
 ^{137}Cs Concentration by Slope Position.

Table 1

CART Analysis Predictive Success Matrix for Soil Erosion Class

Erosion Class	Total	Correct (%)	Predicted Class	
			Not Eroded	Eroded
Not Eroded	320	68	216	104
Eroded	985	73	266	719
Total (n)	1,305		482	823
Average		70		
Correct %		72		

Table 2

Statistics for ^{137}Cs and Primary Land Use.

Paired Samples Test		
Property	Mean ^{137}Cs (Bq/kg)	Significance (p)
Pasture	1.70	0.004
Cultivated (food)	1.55	0.016
*Forested is reference variable	4.12	*