Remote Detection of Cannabis Plantations in Idanre Forest Reserve, Nigeria using Multispectral Landsat Imagery

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Keywords: Remote Sensing, Cannabis, Spectroradiometer, Landsat Imagery, ANOVA Analysis.

SUMMARY

Cannabis remains the most widely used illicit drug substance in the world. Globally, the number of people who used cannabis at least once in 2008 was estimated at between 129 and 191 million or between 2.9% and 4.3% of the world population aged 15–64. Drug prevention calls for accurate and updated information on cannabis fields as well as monitoring and detection tools that can cover large areas of drug-oriented plants. Hence, the aim of this study is to support the efforts of Nigeria's National Drug Law Enforcement Agency (NDLEA) in tackling the menace from its source through detection of these fields using multispectral remote sensing imagery. By combining spectral measurements of cannabis samples with multispectral Landsat 8 imagery, this study presents a simplified workflow for detecting cannabis plantations in the Idanre Forest Reserve of Ondo State, Nigeria. The spectral measurements of cannabis and other related plants were recorded with a spectroradiometer. Spectral analysis was carried out on the Landsat imagery using the Orthogonal Subspace Projection algorithm of Target Detection in Erdas Imagine software. The results show a consonance in the surface reflectances of cannabis with cassava and maize plants which are usually cultivated on the same plots. Although there is some inter-class spectral variation, the closeness in spectral profile hampers a precise separation of cannabis from the surrounding plants. This is evident in the overall accuracy of 60% in the target identification of cannabis. This study shows that multispectral Landsat imagery offers a viable solution to conduct preliminary studies on known or suspected cannabis plantations before committing human resources and logistics to a field inspection. Hence, it is a good reconnaissance tool in the fight against the illicit drug trade.

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1. INTRODUCTION

Cannabis is produced in nearly every country worldwide and it is the most widely used illicit drug. Globally, the number of people who used cannabis at least once in 2008 was estimated at between 129 and 191 million or between 2.9% and 4.3% of the world population aged 15–64 (Azaria et al., 2012). According to USAID (2013) in Ukwayi et al. (2019), illicit drug trade, like other types of transnational organised crime, portends danger to political and socio-economic development, fosters corruption, and violence, undermines the rule of law and good governance, and poses serious health challenges. The highest levels of cannabis production in the world take place on the African continent (UNODC, 2007). The drug is grown illegally in significant quantities on the African continent and the United Nations estimates that over 38,000 tonnes of cannabis are produced across Africa each year (The African Cannabis Report, 2019).

The African Cannabis Report (2019) states that Nigeria boasts of the world's third highest recreational cannabis prevalence rate according to figures by the United Nations Office on Drug and Crime (UNODC), at 14.3% amongst 15-64 year-olds, the equivalent to almost 15 million users. Despite being illegal in Nigeria, cannabis is widely grown across the country in areas including Ondo State, Edo State, Delta State, Osun State, Oyo State and Ogun State. Cannabis plantations, introduced to Nigeria by foreign drug barons have grown over the years; there are several damning reports of the negative effects on the citizens and of course the image of the country in the face of the international community (Sensi, 2013). To stem these ugly trends, the Federal Military Government of Nigeria set up the National Drug Law Enforcement Agency (NDLEA) through the promulgation of Decree Number 48 of 1989. This measure was aimed at exterminating illicit drug trafficking and consumption in the nigerian society. The NDLEA is present in international airports, seaports and border crossings of Nigeria trying to check the activities of drug traffickers. Due to the covert operation of cannabis production and consumption within the country, the NDLEA has been relying on tip-offs to locate cannabis plantations. The Agency tries to eradicate cannabis by destroying such plantations (Sensi, 2013). However, this is very tedious with most tip-offs not yielding good results or efforts meeting stiff resistance from drug barons who prey on the inability of NDLEA agents to directly identify plantation spots which are usually hidden in between other plants or deep in forest reserves.

Drug prevention calls for accurate and updated information on cannabis fields, and the demand for monitoring and detection tools that can cover large areas of drug-oriented plants (e.g., cannabis) has increased accordingly. Today, advancements in Remote Sensing and Geographic Information Systems (GIS) have paved the way for remote detection of cannabis plantations over large areas. Remotely sensed satellite imageries have advantages that include the wide data availability, synoptic surface coverage, and suitability for remote or hazardous areas where field observations might pose a security challenge. It has been shown that remote sensing procedures can quantitatively recognise plant species over broad areas (e.g. Acharya and Thapa, 2015; Peerbhay et al., 2016).

Recently, high spatial resolution aerial photographs have been used to identify plant species (e.g. Jones et al., 2011 in Peerbhay et al., 2016). However, it has been shown that aerial photographs only work best when plants have unique growth patterns distinct from surrounding vegetation (Huang and Asner, 2009). Also, aerial photography is limited to small spatial extents (Mundt et al., 2005). Another approach lies in the use of hyperspectral remote sensing which has an improved resolution (e.g. Lowe et al., 2017). However, the limited availability of free hyperspectral imagery with near-global coverage and the high cost of the available products is a severe limitation in its adoption by researchers for use in plant species identification. Therefore, an alternative is to use multispectral remote sensing (Huang and Asner, 2009). Multispectral sensing is a method of data acquisition in remote sensing whereby data are acquired simultaneously in several spectral bands. Jensen (2005) defined multispectral remote sensing as the collection and analysis of reflected, emitted, or back-scattered energy from an object or an area of interest in multiple bands of regions of the electromagnetic spectrum. Multispectral imagery, with low spectral resolution can be used for cannabis discrimination (World Drug Report, 2007).

Multispectral remote sensing improves on aerial photography by recording spectral information in a number of different wavelengths across the electromagnetic spectrum (Mundt et al., 2005; Peerbhay et al., 2014). Although multispectral remote sensing has the capability of detecting and mapping plant species, the target plants might be obscured in the backdrop of natural vegetation making it difficult to detect (Mundt et al., 2005 in Peerbhay et al., 2016). As such, multispectral data may therefore only be effective to detect plant species in broad areas whose identification depends heavily on the phenological period during which the imageries are acquired (Huang and Asner, 2009). The existing literature is replete with example applications of multispectral imagery for plant species detection and identification. For example, Fuller (2005) used a back-propagation neural network (NN) classifier coupled with landscape fragmentation analysis on IKONOS imagery (4m) to produce a highly distinctive pattern of the invasive Melaleuca quinquenervia tree distinct from woody plants. In another study, Laba et al. (2008) estimated the presence of three alien plants, Lythrum salicaria, Phragmites australis and Trapa natans in a wetland environment using Quickbird imagery (2.4m). More recently, Somodi et al. (2012) combined Landsat Enhanced Thematic Mapper (30m), orthophotography (0.5m and 0.25m) and Geographic Information System (GIS) layers to detect Robinia pseudacacia. Other studies on the use of multispectral imagery for plant species monitoring include Rocchini et al. (2007); Pourazar et al. (2019); and Salik and Karacabey (2019). Consequently, this study tests the use of Landsat 8 multispectral imagery for detecting cannabis (Cannabis sativa) in the Idanre Forest Reserve of Ondo State, Nigeria.

1.1 Study Area

Idanre Forest Reserve is located in Idanre Local Government Area (LGA) of Ondo State in the southwestern part of Nigeria. This International Union for Conservation of Nature designated nature reserve covers 561km^2 (World Database on Protected Areas, 2016). Idanre is bound by longitudes 4°59' E - 5°40' E and latitudes 6°42' N - 7°15' N. The general terrain of Idanre stands at a height of between 286 - 500 m above sea level. It is elevated in relation to the surrounding rainforest zone of southwestern Nigeria and for which average temperatures have been recorded between 24 - 34°C and rainfall up to 2000mm. Ondo state is a state in the southern part of Nigeria geographically located between longitudes 4°01'E - 6°05'E and latitudes 5°51' - 7°55'N. The state has an approximate area of 14,788 km². It borders Ekiti state to the north, Kogi State to the northeast, Edo State to the east, Delta State to the southeast, Ogun State to the southwest, and Osun State to the northwest. Ondo State consists of eighteen (18) LGAs. The tropical coastal climate of Ondo State favours the growth of cannabis and the plant thrives especially in the forest reserves. Idanre Forest Reserve has one of the highest plantations of cannabis (Sensi, 2013). Figure 1 shows a map of the study area while Figure 2 shows a view of cannabis plantations in Ondo State.

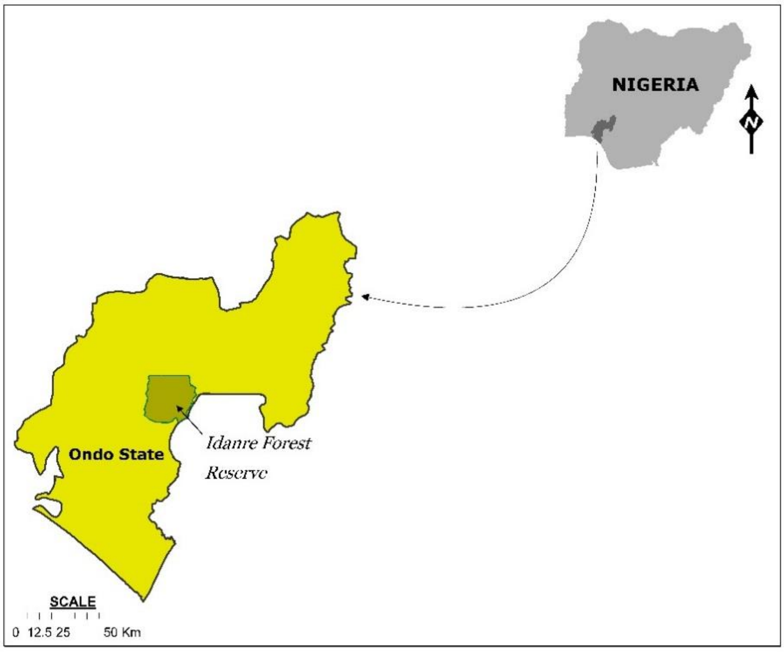

Figure 1: Map showing the location of Idanre Forest Reserve in Ondo State, Nigeria

Figure 2: Cannabis Plantation in Ondo State
(Image courtesy of National Drug Law and Enforcement Agency, Lagos)

2. MATERIALS AND METHODS

Spectral measurement of cannabis and other plant samples were done with a spectroradiometer to acquire their respective surface reflectance which would be used for the processing and spectral analysis of the multispectral Landsat imageries so as to achieve the objective of the study. Specialist software used include Erdas Imagine, ArcGIS, QGIS, SPSS and ViewSpec Pro. Figure 3 presents the workflow for the methodology.

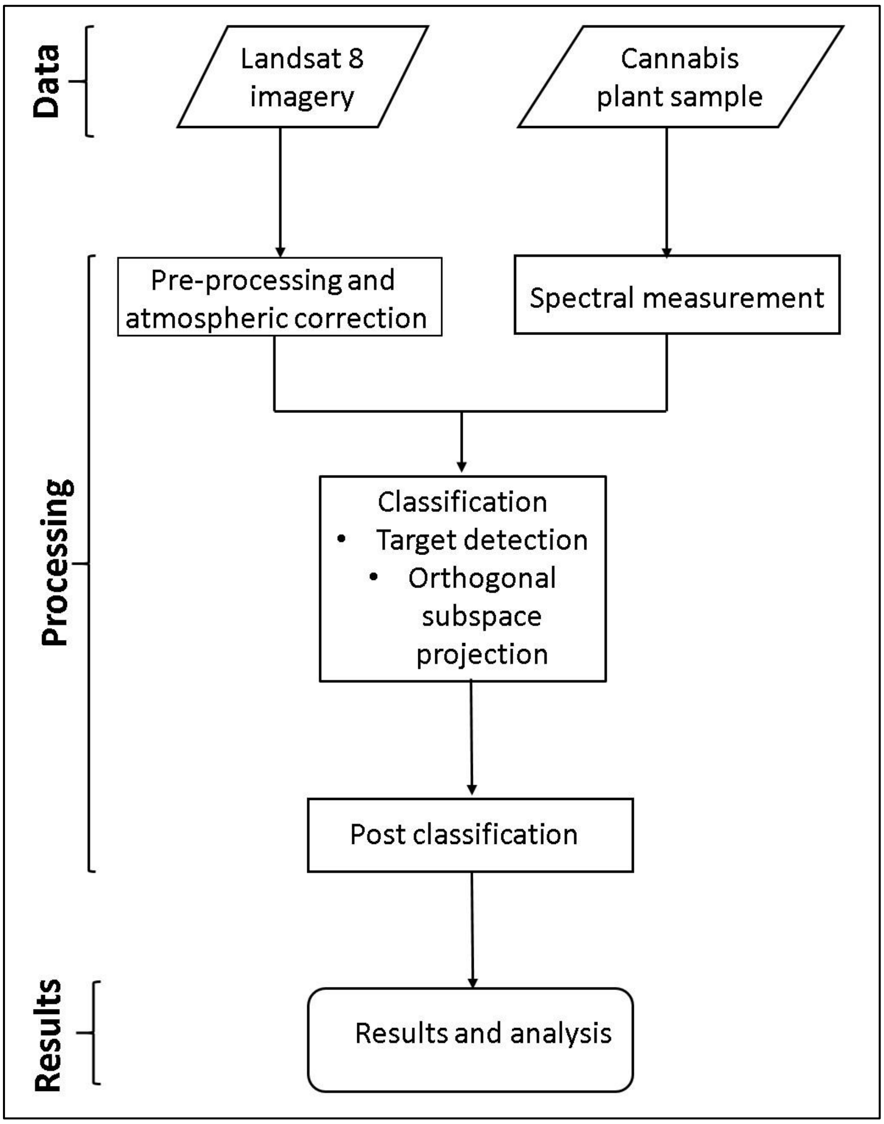

Figure 3: Methodology workflow

2.1 Data Collection

The main datasets used for this study include cannabis plant samples obtained from the Ondo State Command of the NDLEA and Landsat 8 multispectral imagery. In interviews with NDLEA agents, it was disclosed that it is a common practice for cannabis to be cultivated alongside crops like maize and cassava. As such, maize and cassava plant samples were also obtained for spectral analysis. The full list of datasets is presented in Table 1.

Table 1: List of datasets used

Data	Source / Publisher	Year
Cannabis plant sample	National Drug Law Enforcement Agency (NDLEA), Ondo State Command, Nigeria	2018
Digitised administrative map of Ondo state	Office of the Surveyor-General of the Federation	2016
Landsat 8 Imagery (Path/row no. – 190/55)	US Geological Surveys (USGS)	2018
Map of forest reserves in Nigeria	Forest Research Institute of Nigeria	2016
GPS coordinates of detected cannabis sites	National Drug Law Enforcement Agency, Lagos State Command, Nigeria	2018

2.2 Laboratory - Spectroradiometer Measurements

The spectral measurement of the cannabis, maize and cassava samples were recorded with the Handheld2 (HH2) Portable Spectroradiometer which has spectral range of 325 to 1075nm. The spectroradiometer is a passive sensor i.e. operated during the day and depends on the sun; thus, it was properly calibrated using the white reference plane before the measurements were taken. For each sample, 50-150 spectral measurements were recorded. The spectral measurement files were downloaded and imported from the spectrometer using the HH2 Sync software and the downloaded files are in .asd format.

2.3 Data Processing

2.3.1 Spectral Data Processing

The spectral measurements were processed, analysed and visualized using the ViewSpec Pro software. The ViewSpec™ application developed by ASD Inc. is a program used for post-processing spectra files saved with a spectroradiometer. Within the software, the spectral measurements of the samples recorded were viewed, and through visual inspection, the outlying points were eliminated. Next, the averages of the acceptable values were taken and the spectral values were exported for the creation of spectral libraries.

2.3.2 Landsat Image Pre-processing

Pre-processing of the Landsat imagery is necessary in order to perform necessary corrections in preparation for the spectral analysis. This study relied on the surface reflectance of Landsat 8 bands. Firstly, a standard false colour near-infrared composite was created using bands 5, 4 and 3. Next, the digital number values were converted to radiance at the sensor's aperture, then to the top of atmosphere reflectance, then to surface reflectance after the Dark Object Subtraction 1 (DOS 1) had been done. These aspects of the processing were done with the Semi-Automatic Processing in QGIS software.

2.3.2.1 Conversion of Digital Number (DN) to Spectral Radiance

Landsat imageries are composed of several spectral bands and a metadata file which contains information required for the conversion to reflectance. For Landsat imagery, spectral radiance at the sensor's aperture (L_λ) measured in [watts/(m^2 * ster * μm)] is given by USGS (2015) and Obiefuna et al. (2018):

$$L_\lambda = M_L \times QCAL + A_L \quad (1)$$

Where:

M_L - Radiance multiplicative scaling factor for the band
A_L - Radiance additive scaling factor for the band
$QCAL$ - quantized calibrated pixel value in DN

2.3.2.2 Conversion of Radiance to Top of Atmosphere (TOA) Reflectance

The imagery in radiance was converted to Top of Atmosphere (TOA) reflectance (combined surface and atmospheric reflectance) in order to reduce the in between-scene variability through a normalization for solar irradiance. This TOA reflectance (ρ_p), which is the unitless ratio of reflected versus total power energy (NASA, 2011), is calculated by:

$$\rho_p = (\pi \times L_\lambda \times d^2)/(ESUN_\lambda \times \cos\theta_s) \quad (2)$$

Where:

L_λ - Spectral radiance at the sensor's aperture (at-satellite radiance)
D - Earth-Sun distance in astronomical units (provided with Landsat 8 metadata file)
$ESUN_\lambda$ - Mean solar exo-atmospheric irradiances
θ_s - Solar zenith angle in degrees, which is equal to $\theta_s = 90° - \theta_e$ where θ_e is the Sun elevation

Landsat 8 imageries are provided with band-specific rescaling factors that allow for the direct conversion from DN to TOA reflectance.

2.3.2.3 Conversion of TOA Reflectance to Surface Reflectance

The effects of the atmosphere (i.e. a disturbance on the reflectance that varies with the wavelength) was also considered in order to measure the reflectance at the ground. As given by Fromgistors (2019), the land surface reflectance (ρ) is:

$$\rho = \left[\pi \times \left(L_\lambda - L_p\right) \times d^2\right]/[T_\mathrm{v} \times ((ESUN_\lambda \times \cos\theta_s \times T_\mathrm{z}) + E_{down})] \quad (3)$$

Where:

L_p - path radiance
T_v - atmospheric transmittance in the viewing direction
T_z - atmospheric transmittance in the illumination direction
E_{down} - downwelling diffuse irradiance

The above procedures were the steps taken by the Semi-Automatic Processing in QGIS software to convert the DN values of Landsat 8 to surface reflectance.

2.3.2.4 DOS Correction

The image-based Dark Object Subtraction (DOS) is a family of image-based atmospheric corrections (Cui et al., 2014). The basic assumption in DOS is that within the imagery, some pixels are in complete shadow and their radiances received at the satellite are due to atmospheric scattering (path radiance). This assumption is combined with the fact that very few targets on the earth's surface are absolute black, so an assumed one-percent minimum reflectance is better than zero percent. The DOS correction was implemented using QGIS software. For details on the theoretical background, see Gilmore et al. (2015); Dewa and Danoedoro (2017); and Fromgistors (2019).

2.3.3 Spectral Classification and Cannabis Identification

The spectral library for each sample was created, after which, the Orthogonal Subspace Projection Target Detection Technique in Erdas Imagine was used for the classification of the imagery in order to detect the target (cannabis sativa).

2.3.4 Quantitative Analysis and Accuracy Assessment

With the ViewSpec Pro software, 751 coincident data points of surface reflectance were extracted from the spectral reflectance curves of cannabis, cassava and maize. Using the Statistical Package for the Social Sciences (SPSS) version 20, descriptive statistics of the wavelengths and surface reflectances were calculated. The descriptive statistics calculated include the minimum value (min.), maximum value (max.), mean, standard deviation (SD) and standard error (SE). An ANOVA test was conducted to explore the differences in the surface reflectances of cannabis, cassava and maize. The null hypothesis (H_0) is that there is no significant difference in the surface reflectances of cannabis, cassava and maize. The converse forms the alternative hypothesis (H_1). H_0 is rejected if the *p-value* is less than the significance level of 0.05. If H_0 is rejected, meaning there is a significant difference among the groups, then a Tukey post-hoc analysis will be conducted in order to determine which specific groups differed from each other. In the quantitative analysis, the wavelengths were grouped into four classes: 300 – 500nm, 501 – 700nm, 701 – 900nm, and 901 – 1100nm. The accuracy assessment of the target (cannabis) identification was done by calculating the overall accuracy through comparison of the ground coordinates of known cannabis plots with corresponding areas classified as cannabis in the imagery.

3. RESULTS AND ANALYSIS

3.1 Spectral Reflectance Curves

Figure 4 presents the spectral reflectance curves (plot of reflectance as a function of wavelength) of cannabis, cassava and maize superimposed in one graph. For the three samples, the wavelengths range from 325nm – 1075nm. There is a very close consonance in the surface reflectances of cannabis and cassava. The surface reflectances of maize deviate slightly from that of cannabis and are generally higher. From a general perspective, the surface reflectances of all three samples still show some similarities in profile.

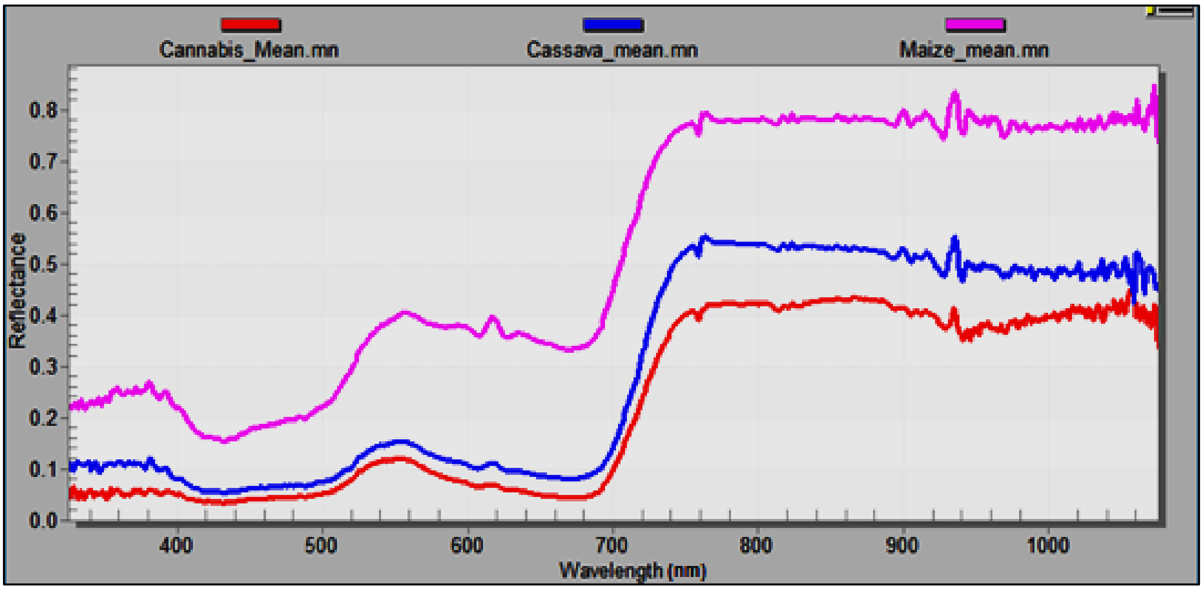

Figure 4: Spectral plots of cannabis, cassava and maize

3.2 Quantitative Analysis

The descriptive statistics of the surface reflectances of the three samples are presented in Table 2. From Table 2, the surface reflectance ranges are as follows: cannabis (0.033 – 0.449), cassava (0.052 – 0.555), and maize (0.152 – 0.848).

Table 2: Descriptive statistics of surface reflectance of cannabis, cassava and maize

Sample	**Wavelength range (nm)**	***N**	**Mean**	**SD**	**SE**	**Min.**	**Max.**
Cannabis	300 - 500	176	0.046	0.008	0.001	0.033	0.066
	501 - 700	200	0.074	0.025	0.002	0.043	0.120
	701 - 900	200	0.383	0.082	0.006	0.104	0.435
	901 - 1100	175	0.395	0.019	0.001	0.336	0.449
	Total	751	0.225	0.170	0.006	0.033	0.449
Cassava	300 - 500	176	0.081	0.022	0.002	0.052	0.121
	501 - 700	200	0.109	0.023	0.002	0.075	0.154
	701 - 900	200	0.490	0.097	0.007	0.150	0.553
	901 - 1100	175	0.491	0.018	0.001	0.422	0.555
	Total	751	0.293	0.204	0.007	0.052	0.555
Maize	300 - 500	176	0.207	0.033	0.002	0.152	0.270
	501 - 700	200	0.356	0.042	0.003	0.223	0.451
	701 - 900	200	0.749	0.074	0.005	0.462	0.799
	901 - 1100	175	0.777	0.017	0.001	0.735	0.848
	Total	751	0.524	0.248	0.009	0.152	0.848

**N – number of measurements*

The mean surface reflectances of cannabis (0.225) and cassava (0.293) are much closer than that of maize (0.524). The practice of mixed cultivation of these crops on the same field, poses a challenge to the detection of cannabis. Still, there are slight differences in spectral variability that can enable separation of the three samples. Table 3 presents the results of the ANOVA test. The results show that there is a significant difference between the surface reflectances of cannabis, cassava and maize. This suggests a rejection of the null hypothesis. Therefore, a Tukey Post-hoc test was conducted to further explore the differences in the surface reflectances under comparison. The results of the Tukey Post-hoc test showed that there is a significant difference in the surface reflectances of cannabis across all wavelength ranges except for the 701 – 900nm and 901 – 1100nm ranges. That is, the surface reflectances in these two wavelength ranges are nearly indistinguishable. The same trend is observed with cassava. That is, there is a significant difference in the surface reflectances of cassava across all wavelength ranges except for the 701 – 900nm and 901 – 1100nm ranges. However, in the surface reflectances of maize, there are significant difference in the surface reflectances across all wavelength ranges.

Table 3: Results of ANOVA test

		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Cannabis	Between Groups	20.222	3	6.741	3309.025	0.000
	Within Groups	1.522	747	0.002		
	Total	21.744	750			
Cassava	Between Groups	29.207	3	9.736	3451.609	0.000
	Within Groups	2.107	747	0.003		
	Total	31.314	750			
Maize	Between Groups	44.563	3	14.854	6613.853	0.000
	Within Groups	1.678	747	0.002		
	Total	46.241	750			

3.3 Cannabis Identification

Based on the orthogonal subspace projection target detection carried out in Erdas Imagine, the scattered distribution of Cannabis in the Idanre Forest Reserve is shown in Figure 5. The total area covered by cannabis was calculated as 727,452.39m^2 (72.75ha). The accuracy assessment, yielded an overall accuracy of 60% in the identification of cannabis. The observed spatial distribution of the plants is an indication of the scattered pattern of cultivation. This suggests that those who cultivate the cannabis prefer to mix it with other crops over broad areas to avoid creating a very large footprint that can expose their activity to ground and aerial surveillance by the NDLEA. The methodology for cannabis identification using Landsat imagery implemented in this study is also applicable to other sites with a caveat that the imagery is appropriately pre-processed to correct for atmospheric effects.

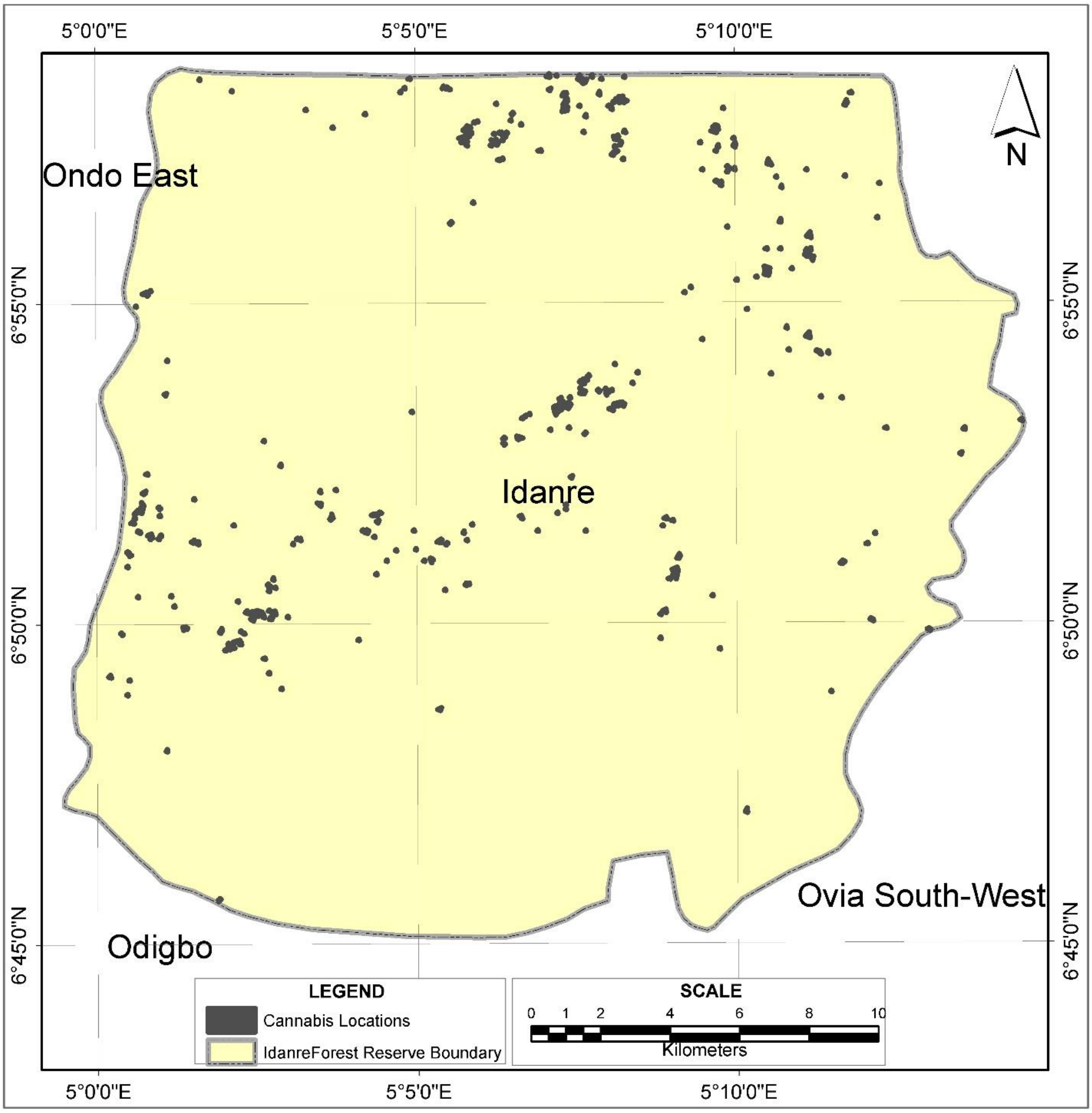

Figure 5: Map showing cannabis locations in Idanre Forest Reserve

4. CONCLUSION AND RECOMMENDATIONS

This study indicates that Landsat multispectral imagery, with medium spatial resolution can be used for cannabis discrimination with up to 60% overall accuracy. Thus, it is a good reconnaissance tool for detecting cannabis plantation locations before embarking on visits or raids on the sites. The presented approach is applicable in the detection of other plant species and the exact workflow may be dependent on factors such as the resolution characteristics of the imaging sensor and pre-processing operations to be run. In conclusion, since the conventional field methods of cannabis detection by NDLEA and law enforcement agents is potentially hazardous, multispectral remote sensing offers a viable solution to conduct preliminary studies on known or suspected cannabis plantations before committing human resources and logistics to a field inspection. It can also serve as an interim solution to help prioritise drug interdiction operations in cases where there are manpower shortages. More importantly, the Landsat-derived data serves to complement and fill in gaps in the existing database of known cannabis sites.

This study shows the utility of multispectral imagery as a useful reconnaissance tool for cannabis identification. To detect cannabis with higher accuracy, hyperspectral remote sensing data offers significant advantages but is not readily available to the worldwide remote sensing user community. However, due to the free availability of multi-spectral data like Landsat, further research into improved classification algorithms for a more precise detection is recommended. It is also recommended that the NDLEA should take advantage of the latest advancements in Remotely Piloted Aircraft (RPA) for supporting their operations.

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