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Detection of subtle deforestation due to logging using satellite remote sensing in wet and dry savanna woodlands of Southern Africa

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1. Introduction

Tropical deforestation through logging is the second largest source of carbon dioxide (CO_2) emitted into the atmosphere after fossil combustion (Werf. et al. 2009) and is also one of the biggest threats to biodiversity. Several studies have demonstrated that the removal of forest cover through deforestation has contributed to the reduction in tree diversity (Gibbs et al. 2007, Shvidenko 2008, Umemiya et al. 2010). Deforestation takes the form of clear-cut logging and selective logging (Asner et al. 2004) (hereinafter, subtle deforestation). Understanding how each of these two forms of logging influences the final rate of deforestation is critical for the management of forest ecosystems. In particular, the detection of subtle logging is important even before its effects on forest ecosystems are understood. Thus, the development of techniques to monitor and measure deforestation particularly subtle deforestation is imperative.

The development of remote sensing and Geographical Information Systems (GIS) has enabled the monitoring and quantification of logging across large spatial scales. This has largely complemented field-based methods which are often costly and time consuming (Jin et al. 2014). Remote sensing techniques used in deforestation studies have included methods such as wall-to-wall mapping based on visual interpretation or digital analysis of satellite imagery through use of vegetation indices and hot-spot analysis. Although remote sensing techniques such as simple visual interpretation of the satellite imagery, texture and technical spectral mixture modelling have been successfully implemented for the detection and quantification of clear-cut logging, the detection of subtle logging has remained a challenge, particularly using coarse and moderate spatial resolution satellite data (Anwar and Stein 2012).

Traditionally, remote sensing methods have successfully been applied to detect clear-cut deforestation resulting from land clearance for agriculture or cattle ranching (Cohen et al. 1998, Shimabukuro et al. 2014). However, subtle deforestation resulting from such activities as selective logging which targets individual tree species is an important component of deforestation and has largely remained unquantified particularly using remotely sensed methods (Chambers et al. 2007, Mayes et al. 2014). Figure 1 illustrates the cases of clear-cut logging and subtle deforestation. It can be observed that conversion of woodland to cropland or bare (figure 1a) constitutes clear-cut logging and is thus easily detected using remote sensing. Conversely, removal of few individual tree species within a forest stand (figure 1b) or selective logging which constitutes subtle deforestation is difficult to detect from remote sensing. To this end, developing a method that can detect subtle deforestation is critical for accurately estimating deforestation rates.

Insert figure 1

The development of remotely sensed vegetation indices (VIs) derived from multispectral reflectance has enhanced chances of detecting deforestation. To this end, the development of VIs such as the Normalised Difference Vegetation Index (NDVI) has provided an effective measure of photosynthetically active biomass and has thus been used to successfully detect deforestation (Tucker and Sellers 1986, Thiollay 1997, Shimabukuro et al. 1998, Loboda et al. 2013). Although NDVI has been widely used to monitor deforestation, particularly clear-cut deforestation (Thiollay 1997, Acheson and McCloskey 2008, Getahun et al. 2013, Lambert et al. 2015), we assert that an index that can also indicate underlying tree species diversity within an ecosystem (Arnall et al. 2006) could complement VIs such as NDVI to enhance the detection of subtle deforestation. Such indices include the Coefficient of Variation in NDVI which has been used successfully to characterise tree species diversity (Mutowo and Murwira, 2012). However, to the best of our knowledge, little has been tested combining NDVI and CVNDVI to detect subtle deforestation.

In this study, we used NDVI and CVNDVI derived from medium (Landsat 8) and high (WorldView-2) spatial resolution satellite images to test whether subtle deforestation in miombo woodlands sites in Zimbabwe and Zambia can be detected, as well as predicted. We concurrently tested whether subtle deforestation could better be detected from high spatial resolution WorldView-2 data than from medium resolution data based on Landsat 8. We selected four study sites that experience selective logging, two in Zambia and two in Zimbabwe. In Zambia, the selectively logged tree species are of commercial timber value (Asanzi et al. 2014) while in Zimbabwe, timber extraction is mainly influenced by illegal mining and tobacco curing (Matsa and Kudakwashe 2010, Munanga et al. 2014).

2. Materials and methods

2.1 Study Area

The study was carried out in 4 study sites (Figure.2), in the dry miombo woodlands of Zimbabwe in Kutsaga and Shurugwi and wet miombo woodlands of Zambia in Kaoma, and Sesheke Simungoma (Table 1). Dry miombo woodlands receive an annual rainfall below1000 mm while wet miombo woodlands receive an annual rainfall above 1000 mm. Each of the four study sites covered 100 km^2 in area. These study sites were chosen because they experience logging at different spatial scales. Kutsaga site is an area where logging is facilitated by tobacco farmers; Shurugwi is located along the Great Dyke where minerals such as gold, nickel, chrome and platinum are mined. Kaoma and Sesheke districts are undergoing logging by Chinese and non-Chinese logging companies. Therefore, bulk of timber harvested in Zambia is sourced from these two provinces.

Insert figure 2

Insert table 1

Savannas in Zimbabwe and Zambia are made up primarily of wet and dry miombo woodlands as well mopane woodland with patches of other fine leafed species such as Terminalia in wet miombo woodlands. Broad-leaved miombo woodlands occur on nutrient-poor soils while fine-leafed miombo occur on nutrient-richer soils (Justice 1994, Chidumayo 1997). The availability of resources such as water and nutrients as well as disturbance regimes is central in regulating woody cover in miombo woodlands (Sankaran et al. 2005a). In dry miombo woodlands, canopy cover is relatively sparse and discontinuous mainly due to lack of moisture availability. On the contrary, high moisture availability is experienced in wet miombo woodlands and tree canopy is dense and closed. The rate at which tree species can resprout after disturbances such as logging is dependent on the nature of the disturbance, the species type and on resource availability (Bond et al. 2003). Therefore, increased logging intensity may increase tree mortality which in turn inhibits resprouting rates, decreasing the rate of recovery especially in dry miombo woodlands (Devine et al. 2015).

The miombo woodlands in this present study are characterised by the coexistence of tree and grasses (Sankaran et al. 2008). The dominant grass species in these miombo woodlands include *Hyparrhenia, Andropogon, Loudetia*, *Digitaria* and *Eragrostis* dominate the groundlayer (Ribeiro et al. 2012). Grasses regulate woody plant recruitment directly through competition for light, water and nutrients (Scholes and Archer 1997). In drier miombo, competition for nutrients and water result in the reduction in the emergence, growth, and survival of woody seedlings (Higgins et al. 2000). While in wet miombo woodlands where competition from grasses is minimal, tree survival rate and establishment is high leading to tress reaching heights above 15m (FAO 2005).

3. Field data

3.1 Tree species data

In each study site, we randomly selected six transects in ArcView GIS 3.2 (ESRI 2002). Each transect had a minimum length of 3 km and a maximum length of 6 km. We navigated from the starting point to the ending point of each transect with the aid of handheld Global Positioning System (GPS) receiver at an accuracy between 3m and 5m. Along each transect, we defined sample plots of 15 m × 15 m at 500 m distances. In each sample plot, species names and the status of the tree as logged and unlogged were recorded. Tree species that could not be identified in the field were taken for identification at the Herbariums in Lusaka for the Zambian sites and in Harare for the Zimbabwean sites respectively. Tree species data were collected in February 2012 and October 2012 in Shurugwi and Kutsaga respectively, in October 2013 in Sesheke Simungoma and Kaoma.

3.2 Remote sensed data

In this study, we used Landsat 8 as well as Worldview -2 imagery as source of remotely sensed data. Landsat 8 imageries used in this study are made freely available by the United

States Geological Survey (USGS) and were downloaded from http://glovis.usgs.gov/ . Landsat 8 data (figure 3) were acquired on7 July 2013 for Sesheke Simungoma and Kaoma, 11 July 2013 for Kutsaga and Shurugwi.

Insert figure 3

Worldview-2 satellite imagery used in this study (figure 4) was acquired on 30 June 2013 for Sesheke Simungoma, 16 July 2012 for Kaoma, 24 July 2012 for Kutsaga and Shurugwi. The multispectral high resolution Worldview-2 has a swath width of 16.4km and a spatial resolution of 2 m and 0.50 m for m multispectral and panchromatic bands. Digital numbers (DN) of Landsat 8 satellite imagery were converted to top-of-atmosphere spectral reflectance in ENVI 5.1 image processing software (ITT 2013) using the reflectance rescaling coefficients provided in the metadata files of the images while the Quick Atmospheric Correction (QUAC) algorithm was applied in ENVI 4.8 (ITT 2008) for Worlview-2.

Insert figure 4

The NDVI derived from Landsat 8 and Worldview-2 was calculated in GIS using the Near Infrared band (NIR) and Red band as,

$$\mathbf{NDVI} = \frac{NIR - RED}{NIR + RED} \qquad \textbf{Equation (1)}$$

Where NIR is the reflectance in the near infrared band and the Red is the reflectance in the Red band. The NDVI has a range of -1 to +1.

Next, we calculated the Coefficient of variation in the NDVI (CVNDVI) derived from Landsat 8 and Worldview 2 images which was computed using a window size of 3pixels by 3 pixels as follows,

$$\mathbf{CV} = \frac{\sigma}{\mu} * 100 \qquad \text{Equation (2)}$$

Where is the standard deviation and μ is the mean of the NDVI.

4. Data Analysis

We plotted a point map of logging status, i.e. logged/not logged in ILWIS GIS 3.3. Next, we used an overlay function in ILWIS GIS 3.3 (ITC 2002) to extract NDVI and CVNDVI to the point map from the satellite images in order to associate a logging status with the NDVI and CVNDVI values. Next, we tested whether the median NDVI and CVNDVI derived from both WorldView-2 and Landsat 8 differed significantly between logged and unlogged areas using a Mann-Whitney U test after the data were found deviating from a normal distribution following a Kolmogorov-Smirnov test. The Mann-Whitney test statistic "U" reflects the difference between the two rank totals. The smaller the U test statistic then the less likely it is to have occurred by chance and the bigger the U test statistic, the less likely it is to have occurred by chance.

Logistic regression is used as a function which relates presence and absence data and it works with the odds which are the ratio of the proportions for the two possible outcomes (Ludeke et al. 1990). It models the median of the response variable in terms of the explanatory variable, thereby enabling the probability of occurrence of an event to be predicted at unsurveyed sites. In logistic regression, a dependent variable transforms into a logit variable (the natural log of the odds of the dependent variable occurring or not (Rueda 2010). To achieve this, we first coded the presence of logging in sampled plots as 1 and 0 otherwise. We then extracted NDVI and CVNDVI from Landsat 8 and Worldview-2 for both logged and unlogged plots using an overlay function in ILWIS GIS 3.2. The logging status of plots data were treated as dependent variables while the NDVI and CVNDVI derived from both Landsat 8 and Worldview-2 were separately treated as independent variables. Logistic regression was calculated as follows,

$$p = \frac{e^{(\beta 0 + \beta 1X)}}{1 + e^{(\beta 0 + \beta 1X)}}$$ **Equation (3)**

p - probabity of logging in a plot, B0 - constant to be estimated and B1-predicted coefficient of the independent variable.

The resulting equations were used as the basis for predicting logging from remotely sensed data using the above logistic equation. We conducted separate analyses for Zambian and Zimbabwe study sites. This enabled us to compare whether we can significantly predict logging in the dry miombo woodlands of Zimbabwe and the wet miombo woodlands of Zambia respectively. We then used the ROC (Receiver Operating Characteristic) curve to test the goodness of fit of the models used to predict logging in wet and dry miombo woodlands. The fitness of the models was assessed by AUC test (Area Under the ROC Curve). The ROC curve determines sensitivity of the model by plotting the prediction of logging occurrence versus false positives in the model. The higher the AUC score, the better the model predicts an event occurring (Van Linn et al. 2013). An ideal model presents an AUC value close to 1.0, whereas a value close to 0.5 indicates inaccuracy in the model (Akgun et al. 2012).

Concurrently, we tested whether and in what way WorldView-2 derived CVNDVI, as well as NDVI predicted logging better than CVNDVI and NDVI derived from Landsat 8 based on the level of statistical significance. Finally, we plotted the logistic functions derived from both CNDVI and NDVI derived from Landsat 8 and Worldview-2.

5. Results

Comparison of NDVI and CVNDVI differences across the four study sites in Zimbabwe and Zambia

In this study, the dominant Brachystegia spiciformis covers 43% and 56% of the trees sampled in Kutsaga and Shurugwi respectively. In the wet miombo woodlands of Zambia, Brachystegia spiciformis and Cryptosepalum covers 58% and 54% of the trees sampled in Kaoma and Simungoma respectively. Based on Landsat 8 derived NDVI (Table 2a), we observed no significant differences (figure 5) in NDVI between logged and unlogged plots in the study sites of Kutsaga, Shurugwi, Kaoma and Simungoma . Similarly, we also observed no significant differences in NDVI using Worldview-2 derived NDVI between logged and unlogged plots in Kutsaga, Shurugwi, Kaoma and Simungoma. Nevertheless, we observed that NDVI was generally higher on logged areas compared with unlogged areas. Next, we observed no significant differences (Table 2b) between logged and unlogged areas using CVNDVI derived from Landsat 8 in Kutsaga, Shurugwi, Kaoma and Simungoma .In addition, we also observe no significant differences ($p > 0.05$) in CVNDVI derived from Worldview-2 between logged and unlogged areas in Kaoma and Simungoma sites. From the results derived from Worldview-2, however the results indicate significant differences ($p < 0.05$) in CVNDVI between logged and unlogged plots in the miombo woodlands of Kutsaga and Shurugwi.

Insert figure 5

Insert table 2

Based on Landsat 8 derived NDVI, the results (Table 3a) show no significant differences between logged and unlogged plots (figure 6) in Zambia. However, the results indicate significant differences between logged and unlogged plots in Zimbabwe using Landsat 8 derived NDVI. In addition, we also observe no significant differences in NDVI derived from Worldview-2 in Zimbabwe and Zambia between logged and unlogged plots. Logged plots significantly have higher NDVI compared to unlogged plots. Next, we also observe no significant differences in CVNDVI (Table 3b) derived from both Landsat 8 and Worldview-2 in Zimbabwe and Zambia between logged and unlogged plots. Logged plots tend to have higher CVNDVI compared to unlogged plots in Zimbabwe and Zambia from both Landsat 8 and Worldview-2.

Insert figure 6

Insert table 3

Predicting the probability of logging across the four study sites in Zimbabwe and Zambia based on CVNDVI and NDVI

Figure 7 show a significant ($p<0.05$) positive relationship between NDVI and the probability that a site is logged. In fact, we observe that the probability of finding a logged site increased with increasing NDVI using both Landsat 8 and Worldview-2 data. It can also be observed that there is a gradual increase in NDVI from the Zimbabwean site compared to the Zambian site which shows a steep increase in NDVI. Again, the gap between these two slopes is wider using NDVI derived from Landsat 8 compared to NDVI derived from Worldview-2.

Insert figure 7

Figure 8 show a negative relationship between CVNDVI and the probability that a site is logged. It is observed that the probability of finding a logged site decreased with increasing CVNDVI using both Landsat 8 and Worldview-2. In addition, the models used in predicting logging are significant ($p<0.05$) for the sites in Zimbabwe but not for sites in Zambia. It can be generally observed that the model for the Zimbabwean sites is steeper compared to the Zambian site using CVNDVI derived from Landsat 8 compared to CVNDVI derived from Worldview-2. Again, the gap between these two slopes is wider using CVNDVI derived from Landsat 8 compared to CVNDVI derived from Worldview-2.

Insert figure 8

Figure 9 shows that NDVI derived from Landsat 8 and Worldview-2 had an AUC >0.5 (Table 4) in the dry miombo woodlands of Zimbabwe compared to that of wet miombo woodlands of Zambia (AUC <0.5). It indicates that the model can be used to predict logging occurrence in dry miombo woodlands of Zimbabwe. Again, the predictive model is significant in Zimbabwe compared to Zambia.

Insert Figure 9

Insert Table 4

Figure 10 show the capability of the model in predicting logging occurrence using CVNDVI derived from Landsat 8 and Worldview-2. We observe that the model can predict logging occurrence (AUC>0.5) in both dry and wet miombo woodlands (Table 5). However the predictve power of the models is not significant across all the landscapes.

Insert Figure 10

Insert Table 5

6. Discussion

Results across the four study sites in the dry miombo woodlands of Zimbabwe with tree densities of 8 and 12 species/m^2 in Kutsaga and Shurugwi respectively and wet miombo woodlands of Zambia with tree densities of 3 and 4 species/m^{2}in Kaoma and Simungoma respectively indicate that there is a consistent positive relationship between NDVI and the probability that a site is logged and a consistent negative relationship between CVNDVI and the probability that a site is logged. Specifically, the same regression trend is observed across all the four study sites. However, results also indicate that we could only significantly predict logging in dry miombo woodlands using both NDVI and CVNDVI derived from both medium spatial resolution (Landsat 8) and high spatial resolution (Worldview-2) satellite data. These results are consistent with the fact that in wet miombo woodlands, vegetation productivity and also that recovery after disturbance is high due to high moisture availability which exceeds 1000mm annually (Cole et al. 2013). In contrast, in the dry miombo woodlands tree regeneration after logging is relatively lower due to limited moisture availability below 1000mm annually (Cole et al. 2013) thereby inhibiting plant growth (Sankaran et al. 2005b, Kambatuku et al. 2013). The differences in slopes in the probability of finding a logged site between Zimbabwean sites and Zambian sites can be attributed to differences in vegetation canopy, soil exposure, tree density and the climatic conditions of the landscape (Sankaran et al. 2008). The results in this present study show that there is high reflectance of vegetation canopy with increased probability of logging plots and low reflectance of vegetation canopy on unlogged plots. Fine leaved tree species such as

Cryptosepalum, Parinari curatellifolia and *Pericopsis angolensis* found in Zambia reflect more in the NIR due to high tree density than that of miombo tree species which are sparse and soil exposure is at maximum. In the dry miombo woodlands of Zimbabwe is dominated by *Julbernadia globiflora*, and *Brachystegia spiciformis,* tree density is low and the disturbances experienced may create open patches which are filled with litter and dry woody material which are significant components of the surface (Ribeiro et al. 2012). In a study conducted in the wet miombo of Ndola in Zambia, there was an increase in tree density and NDVI after logging activities. The steepness of the slope in wet miombo woodlands indicates that the woodland is more productive than the dry miombo woodlands and the vegetation regains the greenness even after logging (Chidumayo and Gumbo 2010).

In this regard, we deduce that remotely sensed data can be used to predict logging especially in dry miombo woodlands while a challenge still remains in wet miombo woodlands. Nevertheless, the consistent relationships between the remotely sensed indices and logging indicate the high potential that remote sensing has in detecting subtle deforestation in both wet and dry miombo woodlands

Results in this study further indicate that logged places have consistently high NDVI and consistently low CVNDVI compared with unlogged places in the dry miombo woodlands of Zimbabwe sites and wet miombo woodlands Zambian sites. Results also indicate no significant differences in NDVI between logged and unlogged sites except for the case of the combined Zimbabwean site data, where there is a significant difference in NDVI between logged and unlogged sites ($p < 0.05$). High NDVI and CVNDVI derived from Landsat 8 and Worldview-2 in unlogged sites indicate high biomass and undisturbed tree species diversity respectively, while low NDVI and CVNDVI on logged sites represents low biomass and diversity resulting from logging in the landscape (Pau et al. 2012). These results are not surprising as CVNDVI has been proven to be related with tree species diversity in dry miombo woodlands (Mutowo and Murwira, 2012) while NDVI is related with biomass (Santin-Janin et al. 2009, Meng et al. 2013, Pena-Yewtukhiw et al. 2015). Although these results are not consistent across wet and dry miombo woodlands in terms of statistical significance, the results overall imply the possibility of detecting evidence of logging using remotely sensed data.

Contrary to what is expected that an area experiencing selective logging might have higher CVNDVI, the results of this study indicate that the probability of finding a logged site decreased with increasing CVNDVI. The negative correlation between rainfall received in an area and soil nutrient-availability is the basis for the distinction between moist-dystrophic miombo woodlands and arid-eutrophic miombo woodlands (Huntley 1982). It is apparent that the dry miombos are found in areas of rainfall less than 1000 mm annually therefore the removal of woody vegetation in these drier miombos results in little tree regeneration. Slow tree recruitment rate from saplings after logging in miombo woodland are dependent on logging frequency and intensity. In addition, a reduction of compensatory recruitment of trees into the canopy to replace logged trees indicates that the probability of finding a logged site decreased with increasing CVNDVI (Chidumayo and Gumbo 2010).

Conclusively the results of this study indicate that NDVI derived from Landsat 8 and Worldview-2 predicts logging occurrence in dry miombo woodlands compared to wet miombo woodlands. The prediction is associated with an area under curve (AUC>0.5). This means that the models can predict about 73% and 75% of logging occurrence using NDVI derived from Landsat 8 and Worldview-2 respectively. The models also indicate that CVNDVI derived from Landsat 8 and Worldview-2 predicts logging occurrence in both dry miombo woodlands and wet miombo woodlands, the predictive model is not significant.

What makes our study innovative is in testing whether subtle deforestation can be detected using remotely sensed data, particularly by complementing NDVI with CVNDVI to detect subtle deforestation across the miombo woodlands wetness gradient, i.e., by considering wet and dry miombo woodlands. The findings of this study could provide insight into improving methods of detecting subtle deforestation using satellite remotely sensed data. Overall, the results of this study indicate that the combined use of remotely sensed data and ground-based validation approaches could provide an effective predictive tool for selective logging in miombo woodlands. However, we caution that further research is needed to test whether these findings would be consistent across a broad range of study sites in the miombo woodlands landscape.

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List of Tables

Table 1

Study site	**Climate data**	**Soils**	**Vegetation data**
Kutsaga lies at latitude 17◦ 55' S and longitude 31◦ 08' E	Mean annual temperature of 18.6◦C and the mean annual rainfall is 850 mm	Ferallic cambisols	Miombo woodlands dominated by *Julbernadia globiflora*, and *Brachystegia spiciformis*
Shurugwi lies at latitude 19◦ 58' S and longitude 29◦ 51' E	Mean annual temperature of 17.6◦C and between 650-800 mm of rainfall annually	Lithic leptosols	Miombo woodlands dominated by *Julbernardia globiflora, Brachystegia spiciformis* and *Terminalia*.
Kaoma lies at 15◦ 70' S latitude and longitude 24◦ 45' E	Mean annual temperature between 5 ^{o}C and 33 ^{o}C and the mean annual	Ferrallic arenosols	Miombo woodlands characterised by *Brachystegia, Isoberlinia Angolensis, Julbenardia paniculta and Marquesia marcroura* with *Erythrophleum africanum, Parinari curatellifolia* and *Pericopsis*

	rainfall between1000 and1100 mm		*angolensis* as frequent associates
Simungoma lies between latitudes 15°30'S and 17°50' S and longitudes 23°00' E and 25°30' E	Mean annual temperature between 13.1° C and 29.3° C the mean annual rainfall is 1000 mm	Ferrallic/ cambic arenosols	The Kalahari woodland dominated by *Cryptosepalum*

Table 2

Site (a)	**NDVI Landsat 8**		**NDVI Worldview-2**	
	U statistic	**p**	**U statistic**	**p**
Kutsaga	67	0.21	84	0.63
Shurugwi	23.5	0.13	31	0.33
Kaoma	20	0.79	15	0.36
Simungma	39	0.9	39.5	0.9
(b)	**CVNDVI Landsat 8**		**CVNDVI Worldview-2**	
Kutsaga	92	0.9	47	0.03*****
Shurugwi	32.5	0.36	9	0.01*****
Kaoma	20	0.79	16	0.43
Simungoma	23	0.19	38	0.88

Significance level: *****$p<0.05$

Table 3

Site (a)	NDVI Landsat 8		NDVI Worldview-2	
	U statistic	**p**	**U statistic**	**p**
Zimbabwe	161	0.01*	232	0.25
Zambia	112.5	0.69	98	0.37
(b)	**CVNDVI Landsat 8**		**CVNDVI Worldview-2**	
Zimbabwe	272	0.68	271	0.66
Zambia	94	0.3	101	0.42

Significance level: *****p<0.05

Table 4

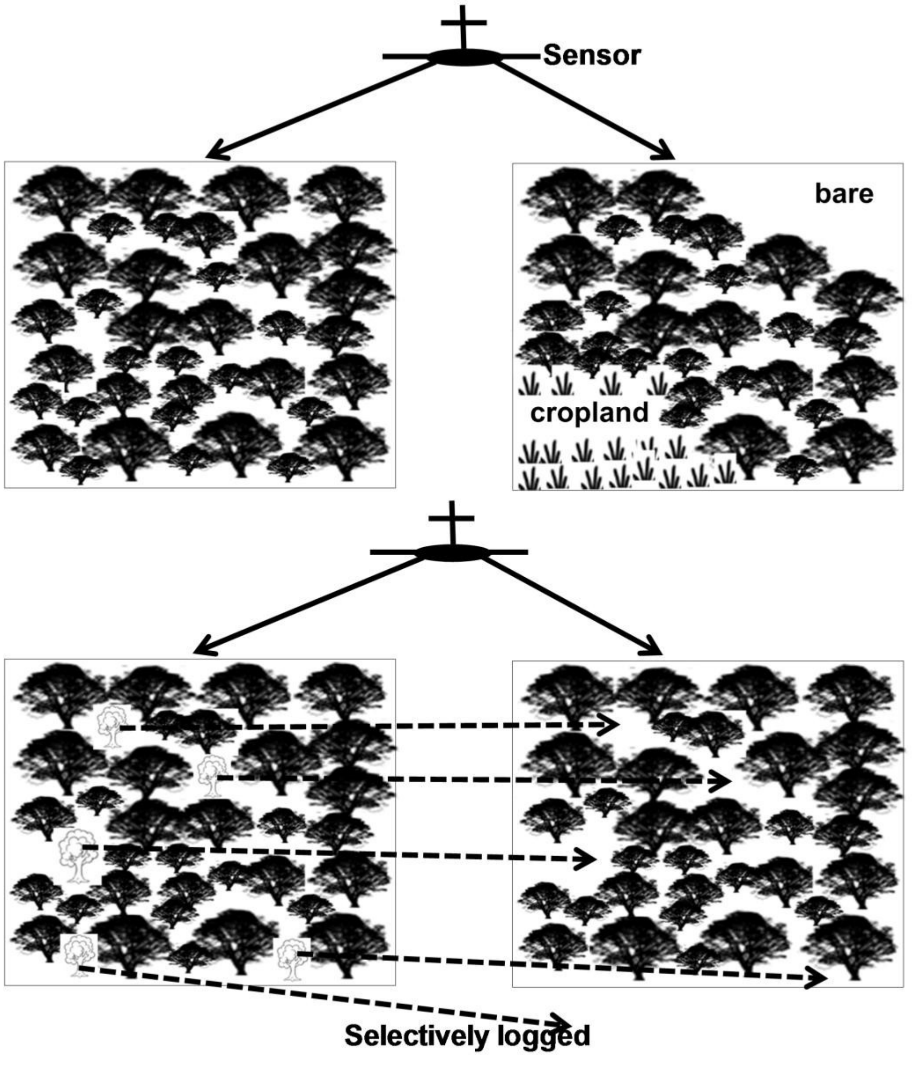
Site	NDVI Landsat 8		NDVI Worldview-2	
	AUC	**p**	**AUC**	**p**
Zimbabwe	0.73	0.01*	0.75	0.02*
Zambia	0.45	0.69	0.60	0.36

Significance level: *****p<0.05

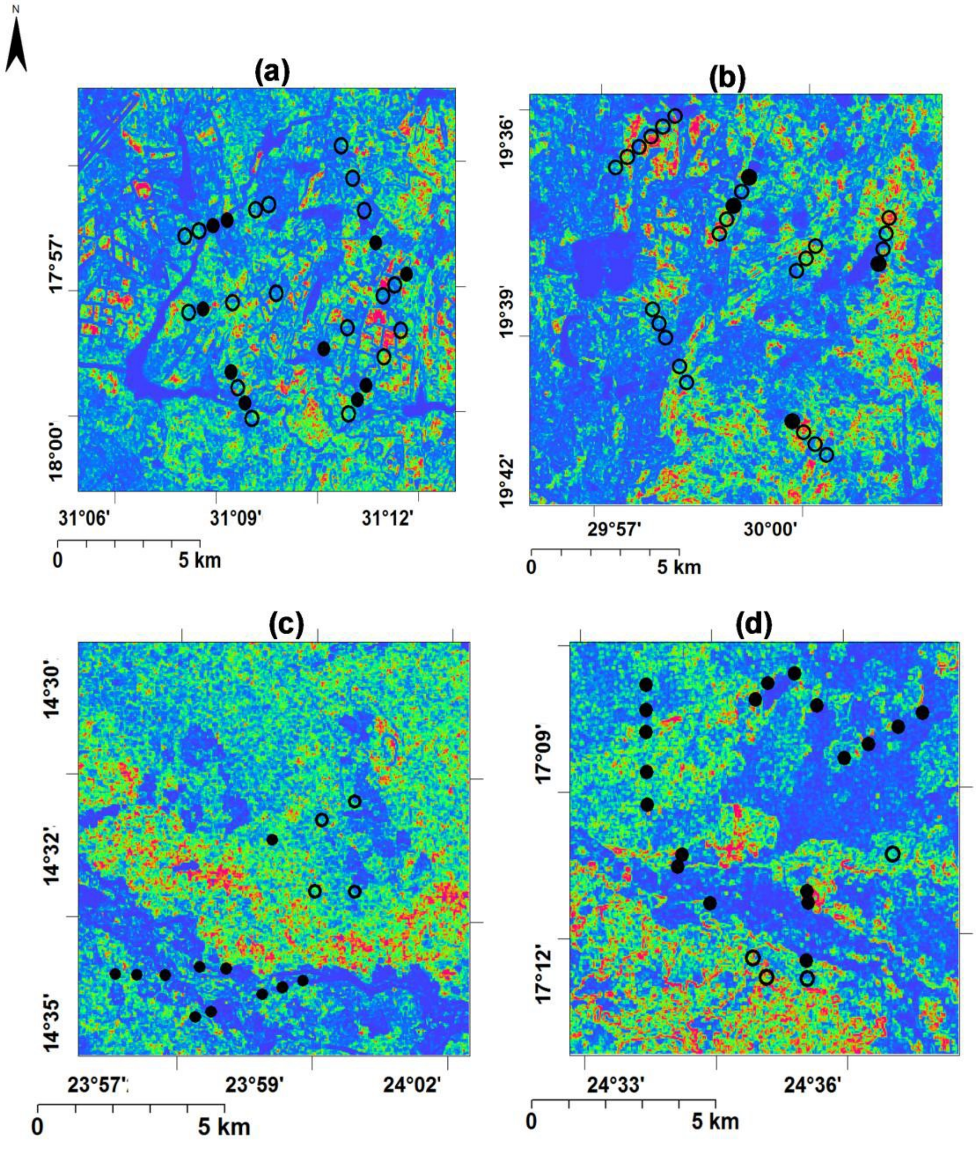
Table 5

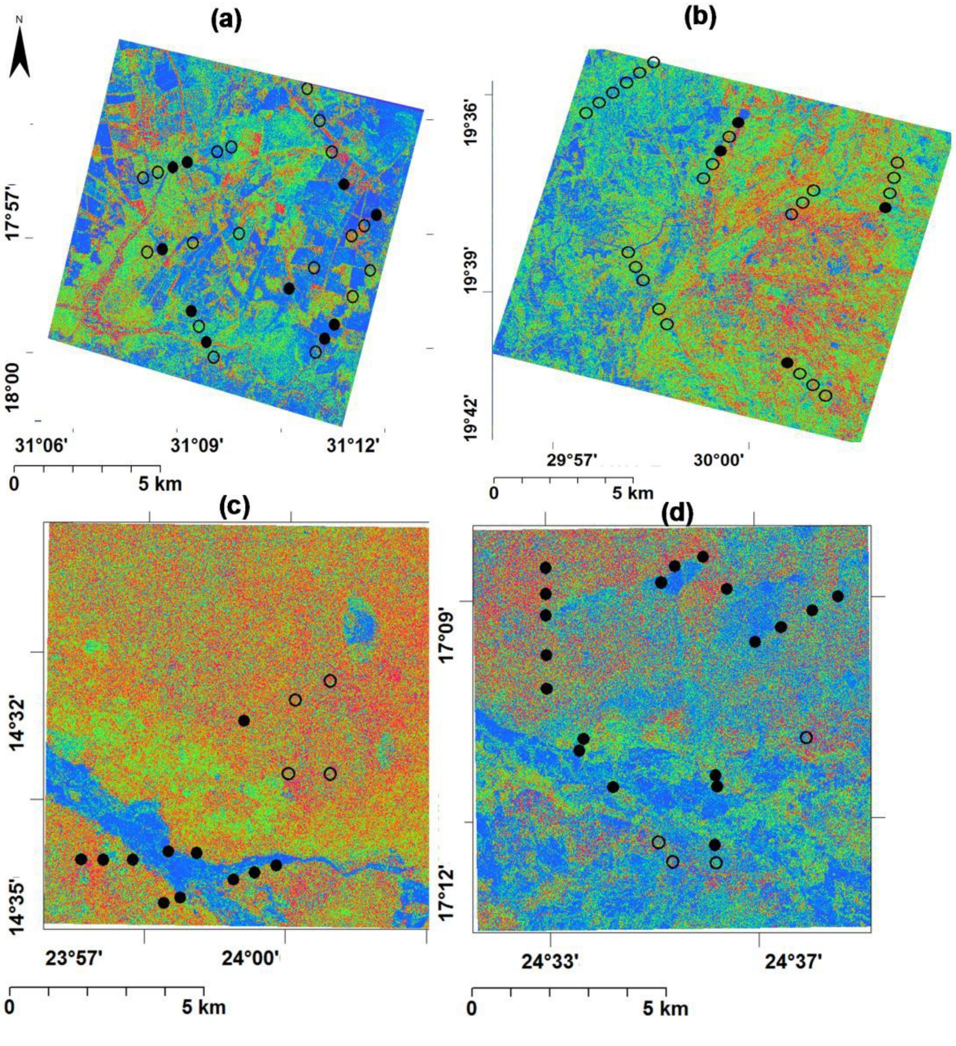
Site	CVNDVI Landsat 8		CVNDVI Worldview-2	
	AUC	**p**	**AUC**	**p**
Zimbabwe	0.54	0.68	0.58	0.38
Zambia	0.62	0.30	0.60	0.42

Significance level: *****p<0.05

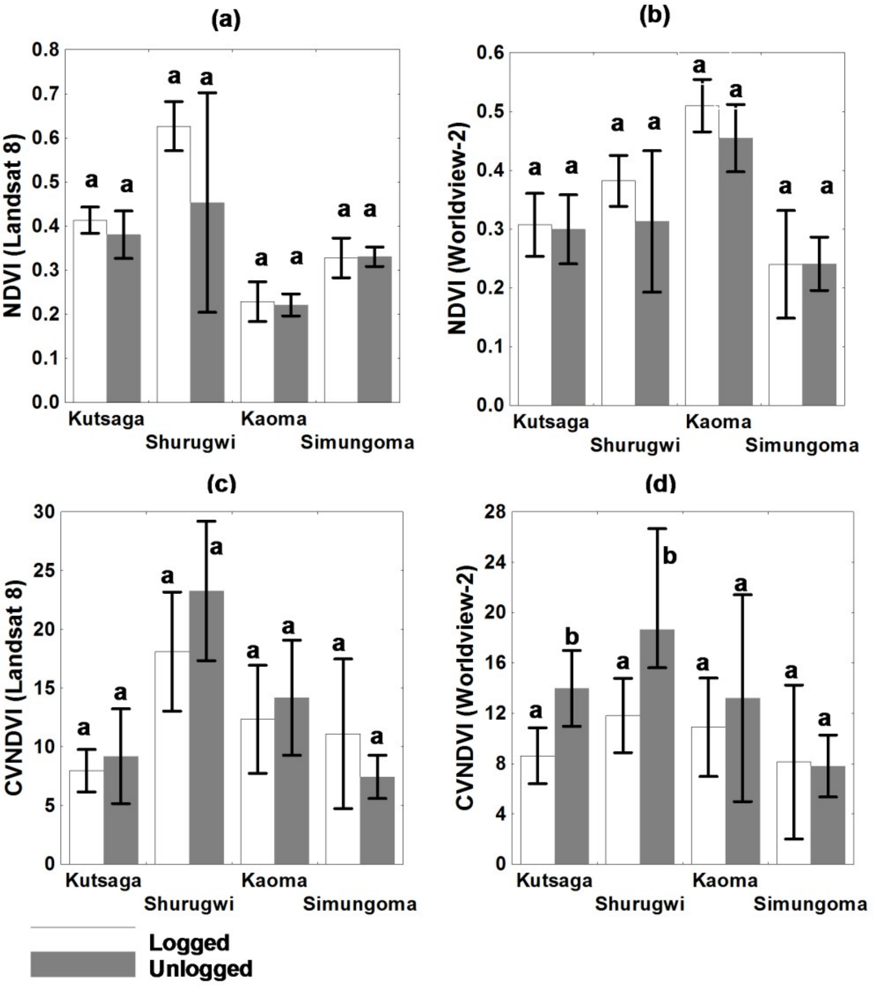

Sensor
bare
cropland
Selectively logged

N
Zambia
Kaoma
Sesheke Simungoma
Zimbabwe
Kutsaga
Shurugwi
500
0
500
1000
1500
Kilometers

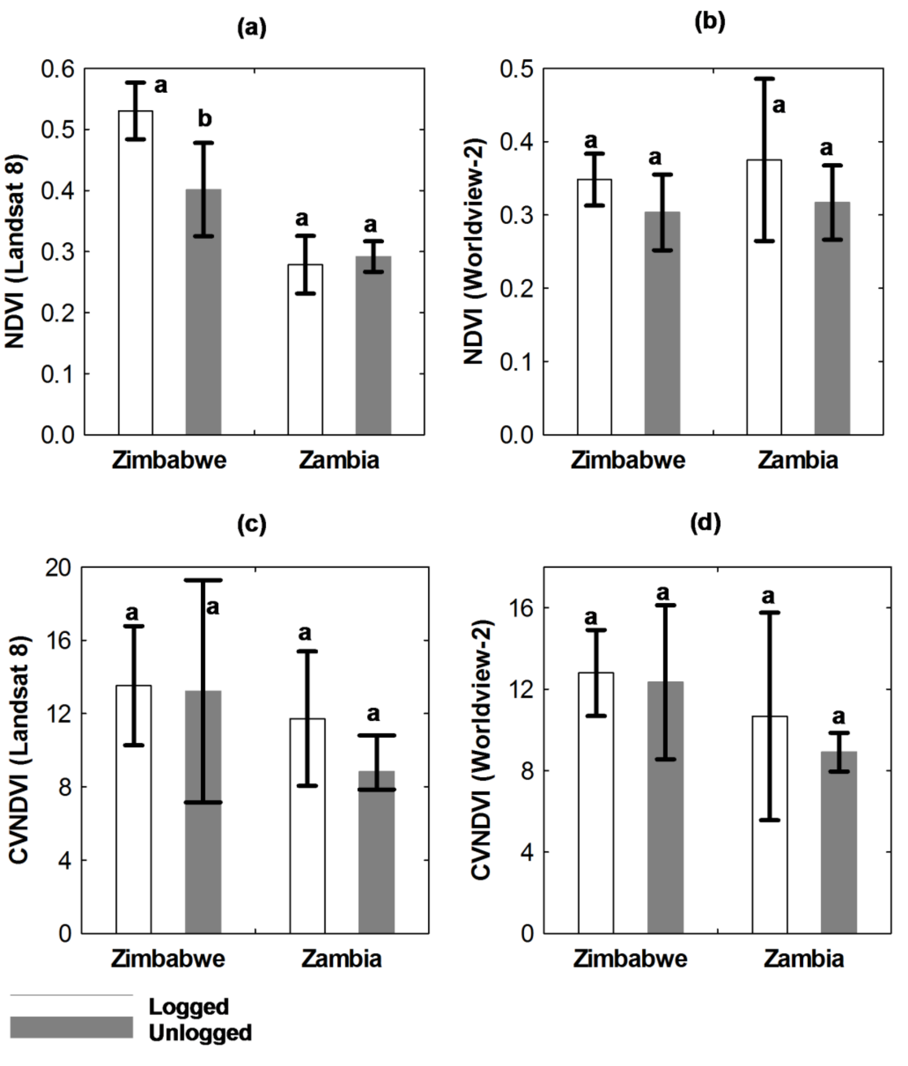

N
(a)
17°57'
18°00'
31°06'
31°09'
31°12'
0
5 km
(b)
19°36'
19°39'
19°42'
29°57'
30°00'
0
5 km
(c)
14°30'
14°32'
14°35'
23°57'
23°59'
24°02'
0
5 km
(d)
17°09'
17°12'
24°33'
24°36'
0
5 km



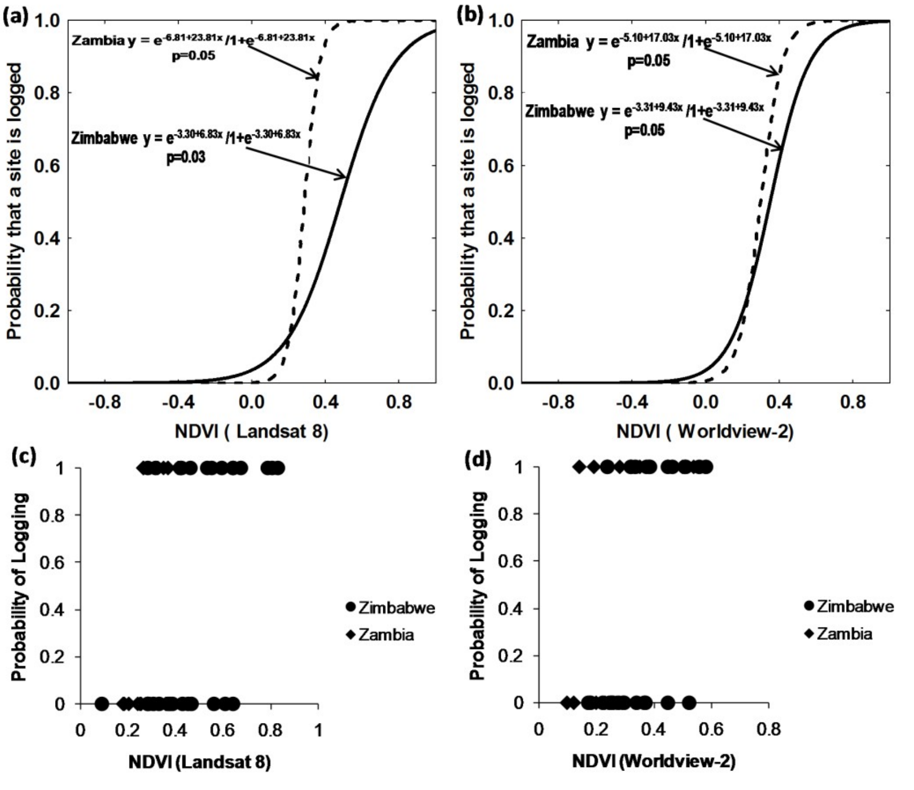
(a)
N
17°57'
18°00
31°06'
31°09'
31°12'
0
5 km
(b)
19°36'
19°39'
19°42'
29°57'
30°00'
0
5 km
(c)
14°32'
14°35'
23°57'
24°00'
0
5 km
(d)
17°09'
17°12'
24°33'
24°37'
0
5 km



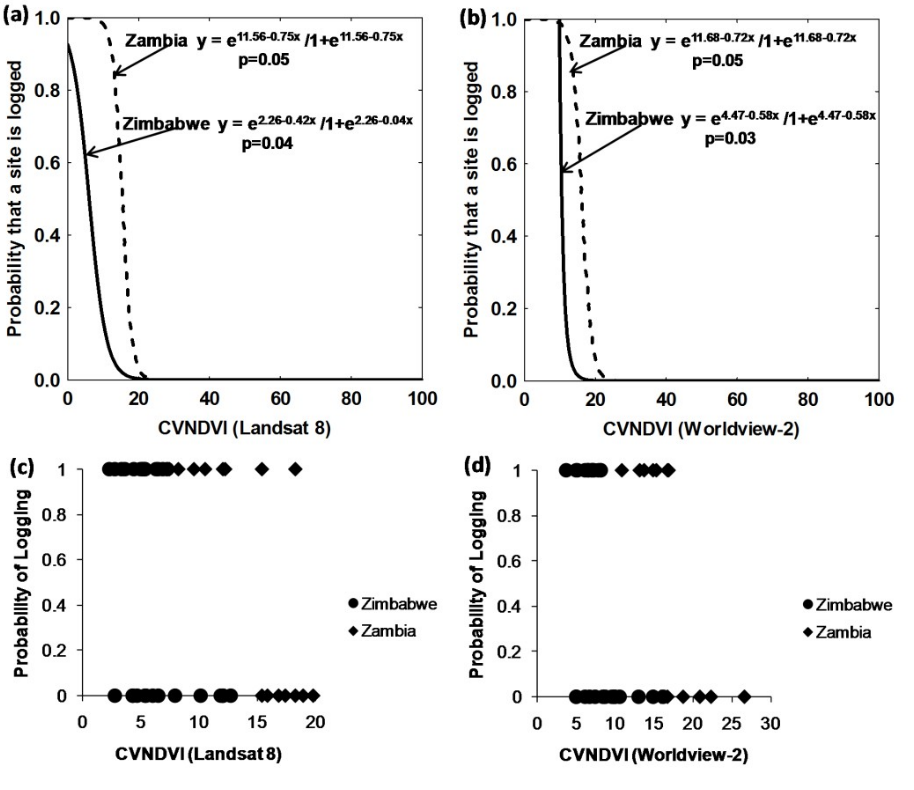
(a)
(b)
(c)
(d)
NDVI (Landsat 8)
NDVI (Worldview-2)
CVNDVI (Landsat 8)
CVNDVI (Worldview-2)
Kutsaga
Shurugwi
Kaoma
Simungoma
Logged
Unlogged

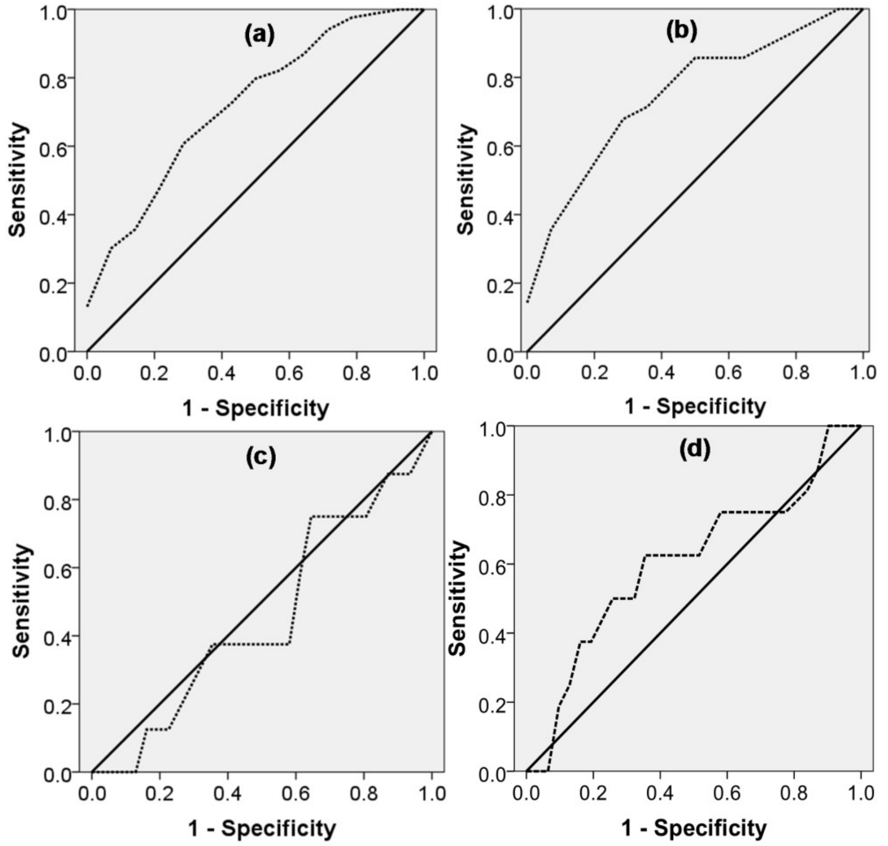


(a)
(b)
(c)
(d)
NDVI (Landsat 8)
NDVI (Worldview-2)
CVNDVI (Landsat 8)
CVNDVI (Worldview-2)
Zimbabwe
Zambia
Logged
Unlogged

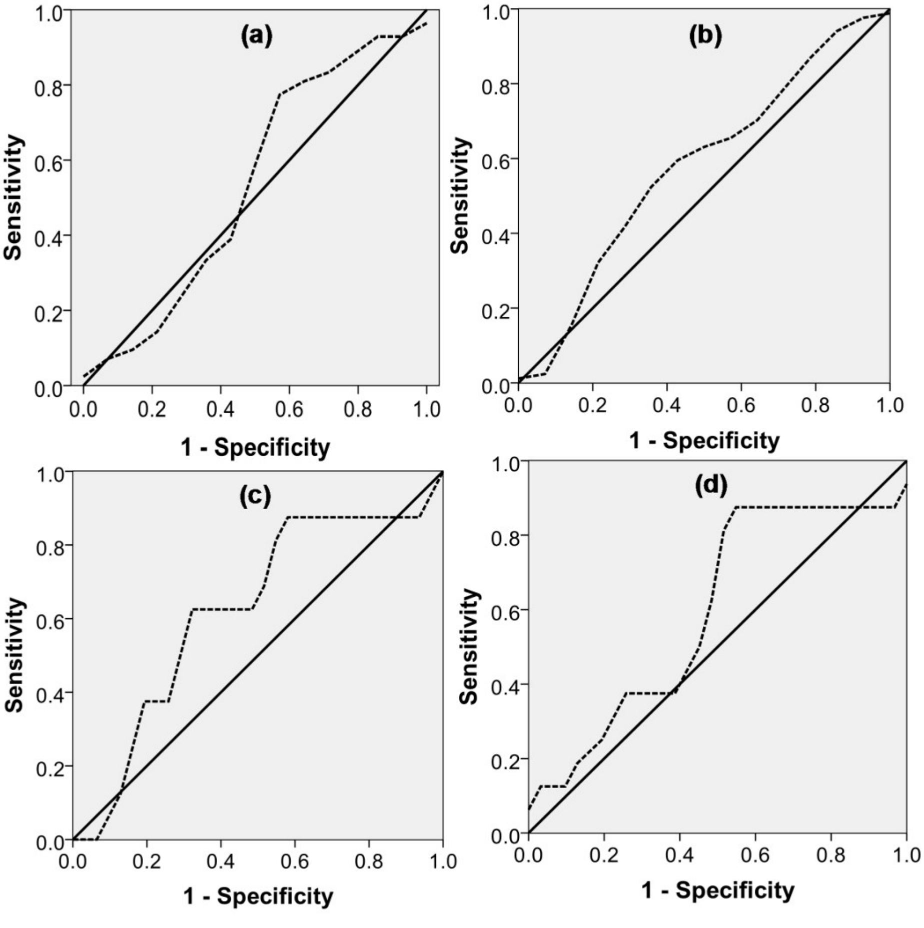


(a)
Zambia y = e-6.81+23.81x /1+e-6.81+23.81x
p=0.05
Zimbabwe y = e-3.30+6.83x /1+e-3.30+6.83x
p=0.03
Probability that a site is logged
NDVI (Landsat 8)
(b)
Zambia y = e-5.10+17.03x /1+e-5.10+17.03x
p=0.05
Zimbabwe y = e-3.31+9.43x /1+e-3.31+9.43x
p=0.05
Probability that a site is logged
NDVI (Worldview-2)
(c)
Probability of Logging
Zimbabwe
Zambia
NDVI (Landsat 8)
(d)
Probability of Logging
Zimbabwe
Zambia
NDVI (Worldview-2)


(a)
Zambia y = e11.56-0.75x /1+e11.56-0.75x
p=0.05
Zimbabwe y = e2.26-0.42x /1+e2.26-0.04x
p=0.04
Probability that a site is logged
CVNDVI (Landsat 8)
(b)
Zambia y = e11.68-0.72x /1+e11.68-0.72x
p=0.05
Zimbabwe y = e4.47-0.58x /1+e4.47-0.58x
p=0.03
Probability that a site is logged
CVNDVI (Worldview-2)
(c)
Probability of Logging
Zimbabwe
Zambia
CVNDVI (Landsat 8)
(d)
Probability of Logging
Zimbabwe
Zambia
CVNDVI (Worldview-2)



(a)
(b)
(c)
(d)
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0



(a)
(b)
(c)
(d)
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0