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Testing the Potential Application of Simulated Multispectral Data in Discriminating Tree Species in Taita Hills

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Abstract Hyperspectral data is gaining tremendous popularity in mapping tree species in the recent past. This is due to its ability to distinguish between individual tree species. However, its cost is prohibitive especially for developing economies. This paper focuses on the possibility of using the recently launched free optical sensors for mapping tree species in the Ngangao Forest of Taita Hills in Kenya. The AISA Eagle hyperspectral data was used to 10 tree species (six indigenous and four exotic species). The hyperspectral data reflectance was then used to derive Worldview 2 and Sentinel 2 data. A total 2504 training sites were used for the classification AISA Eagle data. The same training sites were used for the classification of the Worldview 2 and Sentinel 2 but after downscaling due to coarse resolution of the two sensors resulting into 638 and 23 training sites respectively. Spectral angle mapper, neural network and support vector machine classification algorithms were tested in this study. The three algorithms resulted into accuracies 49.24%, 79.47% and 80.15% respectively for the AISA Eagle data. However, only neural network algorithm was able to classify Worldview 2 and Sentinel 2 images resulting into overall accuracies of 56.43% and 47.22% with Kappa coefficient of 0.48 and 0.33 respectively.

Keywords: *AISA Eagle, hyperspectral data, Worldview 2, Sentinel 2, tree species, Ngangao forest*

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1. Introduction

Remote sensing of species identification assumes that each species has a unique spectral niche that is defined by the species biophysical and biochemical make-up [2,7,9]. In theory therefore, it is possible to identify and separate every tree species using images obtained in the field. In this regard, a rich spectral library that provides the ability to divide the entire or part of the spectrum into separable units is paramount. However, mapping of trees species is hampered by low spectral resolution in multispectral images and the high cost of acquisition of hyperspectral images. Despite the cost, hyperspectral data is important in the determination of spectral separability between species when building a spectral library. The improved division of the electromagnetic spectrum in hyperspectral data gives narrow band data the ability to resolve subtle spectral canopy features such as carotenoid and chlorophyll content and foliar nutrients [7,22,36].

In spite of the good characteristics about narrow band data, it has the disadvantage of high dimensionality, especially when using conventional classification techniques. The Hughes effect in hyperspectral data [11,31] and high redundancy rates of some bands [33,43] in particular applications is problematic. This is because a classifier’s ability to generalize accurately is reduced [5,8] leading to the need for very large samples to achieve good description of data distribution [12]. In addition, multicollinearity is experienced which is introduced by the use of highly correlated predictor variables [19,25]. Multicollinearity becomes a challenge when discriminating between vegetation species with reflectance similarities in hyperspectral data [14,44]. Moreover, when the training data is insufficient, parameterization may not be reliable for feature selection [6].

In such cases, working with scaled data or with few narrow bands become optimal for species discrimination while minimizing the headache of the curse of dimensionality [7]. The physical or spectroscopic meaning of wave bands is analysed to identify important bands which are in turn resampled from the high-dimensional spectra to wider bandwidth intervals [3,34]. There are operational multispectral sensors with few narrow bands such as Worldview 2 & 3, and Sentinel 2 [15,16]. They are designed to capture specific wavelengths such as the red-edge and yellow spectrum in addition to the wavelengths in the conventional multispectral images.

2. Materials and Methods

2.1. Study Area

Ngangao forest (38°20'E, 3°21'S) is one of the remaining forest patches in Taita Hills. Taita Hills are located approximately 100 km east of Kilimanjaro and 175 km inland of Indian Ocean. The area receives a bimodal pattern of rainfall with the long rains occurring from March to May and the short rains from November to December, but the mist and cloud precipitation occurs throughout the year in hilltops [29,32]. The mean annual rainfall in the hills is approximately 1500 mm [30]. Ngangao forest is located on an eastern slope of a north-south oriented mountain ridge with the western slope covered mainly with open rock and some patches of *Acacia mearnsii* and *Pinus patula* plantations. It covers an area of about 120 ha and the elevation ranges between 1700-1952 m [27].

2.2. Data

2.2.1. Acquisition of Hyperspectral Data and Training Sites

The hyperspectral images were acquired using Airborne Imaging Spectrometer for Applications (AISA) Eagle VNIR sensor on 4th February 2013 at a mean flying height of approximately 2300 m. above sea level. The sensor covers the spectral range of 400-1000 nm with 129 spectral bands that have bandwidth of approximately 4.6 nm. Ngangao forest was covered by 11 flight lines running across the mountain range with swath width of approximately 500 m. The images were radiometrically and atmospherically corrected using CaliGeo Pro and ATCOR-4 software, respectively. A DEM of 20 m spatial resolution was resampled to 1 m resolution and used to orthorectify the images. The atmospherically corrected images were then geometrically corrected in ENVI software using the GLT files generated by the CaliGeo Pro software.

High resolution aerial photographs, taken in January 2012 using Nikon D3X digital camera were used in the field to delineate subsets of the tree crowns which were identifiable both on the photographs and on the ground. The crowns were then on-screen digitized on the true colour composites of the AISA Eagle images. The reflectance values of pixels within the digitized crowns were derived and used for the classification of the images. The classification was done using the ENVI 5.3 software.

2.2.2. Worldview 2

Worldview 2 is a multispectral image that was launched in the year 2009 by DigitalGlobe with 8 spectral bands and a spatial resolution of 1.84m & 0.5m panchromatic band, with a spectral range from 400nm to 1,050nm [16,28]. The spectral bands range from blue, green red, near-infrared, coastal band, yellow, red edge to the longer wavelength near infrared band. The wavelength range of the Wordview-2 Sensor and the number of spectral bands from the AISA Eagle image used to derive the former and consequently used to map the tree species is represented in Table 1 below.

Table 1. Woldview 2 Wavelength Range and the Number of Spectral Bands from AISA Eagle Image

	Bands	Wavelength range (nm)	No. of spectral bands
1	Coastal	400 - 450	12
2	Blue	450 - 510	13
3	Green	510 - 580	16
4	Yellow	585 - 625	10
5	Red	630 - 690	15
6	Red Edge	705 - 745	10
7	Near-IR1	770 - 895	26
8	Near-IR2	860 - 1,040	30

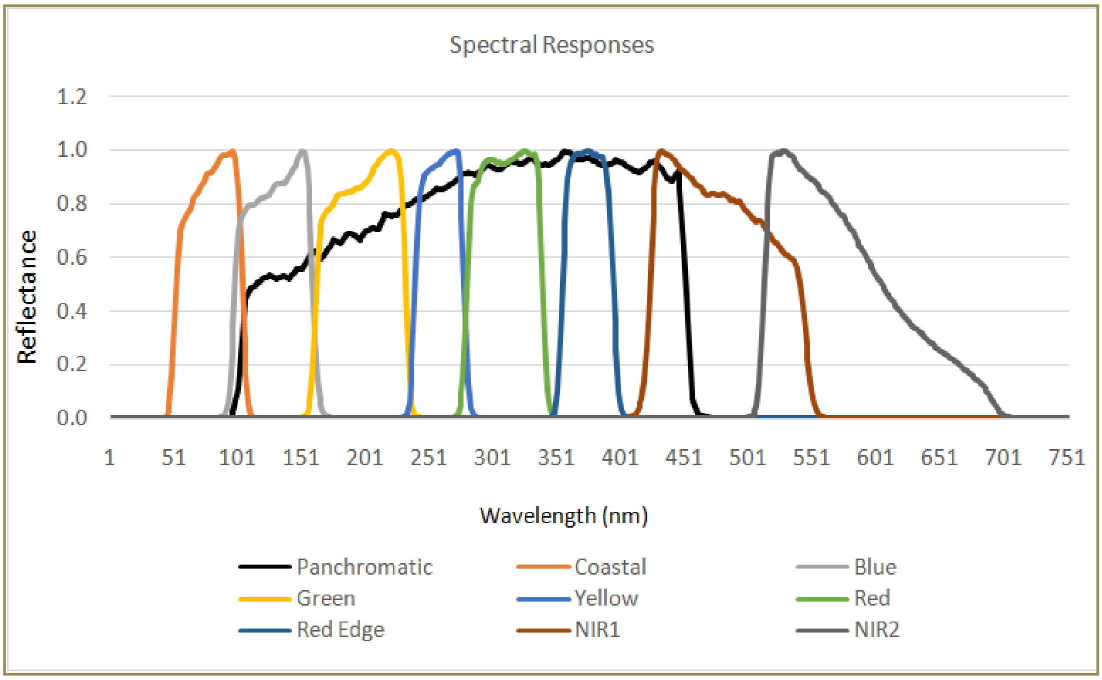

Figure 1. Spectral responses for the spectral bands found in Worldview 2

The spectral response of individual bands is shown in Figure 1. The separation of individual spectral responses to map tree species indicate that it has a high potential in tree species mapping [16] with bands that are strongly related to vegetation. The yellow band is used to detect the senesce stage of vegetation, red-edge to discriminate healthy from unhealthy plants and vegetation age differences, and NIR 1 and 2 are mainly used for vegetation analysis since they are less affected by the atmosphere [16].

Spectral configuration provides better identification of tree species. Worldview 2 has been shown to map big crown tree species with promising results e.g. [7,11,18,26]. However, studies in the coastal region of Kenya especially the Ngangao forest are still missing.

2.2.3. Sentinel 2

Sentinel 2 is a multispectral image developed by the European Space Agency (ESA) and was launched in June 2015. It has a spatial resolution of 10 metres with 13 spectral bands in the visible, near infrared and shortwave infrared ranges [15,35,37]. It consists of two satellites (A and B) coupled to give a temporal resolution of 5 days. Its purpose is for land observation including soil, vegetation and water. It consists of many bands that are important in vegetation mapping and species identification such as blue, green, red, red edge (which is divided into 4) NIR and SWIR [10,17,35]. Table 2 shows the spectral bands and the central wavelength for each of the bands. Ten bands ranging from B1 to B9 were used in the classification as they were within the spectral range of AISA Eagle data as illustrated by Figure 2.

3. Results

Resampling the images from hyperspectral to multispectral reduced the image size (disk) from 2.25 gigabytes to 21.40 megabytes for Worldview 2 and 1.40 megabytes for the Sentinel 2 image. The processing speed improved as the load on the computer reduced. Three classification methods {i.e. (a) spectral angel mapper, (b) neural network and (c) support vector machine} were used to test the applicability of upscaling of tree species identification in Ngangao Forest from hyperspectral to multispectral images. The hyperspectral image was classified using the three methods and the results are shown in Figure 3 and Table 3. The spectral angel mapper classification method output had the lowest accuracy (below 50%). Therefore, this method was eliminated from further analysis. Support vector machine proved to have the highest accuracy of 80.15% compared to neural network (79.47%). These two methods were used to test the applicability of upscaling species identification in tree species in Ngangao Forest.

Table 2. Sentinel 2 Spectral Band and the Central Wavelengnths

	Bands	Centre wwavelength (nm)
1	B1	443
2	B2	490
3	B3	560
4	B4	665
5	B5	705
6	B6	740
7	B7	783
8	B8	842
9	B8a	865
10	B9	945
11	B10	1375
12	B11	1610
13	B12	2190

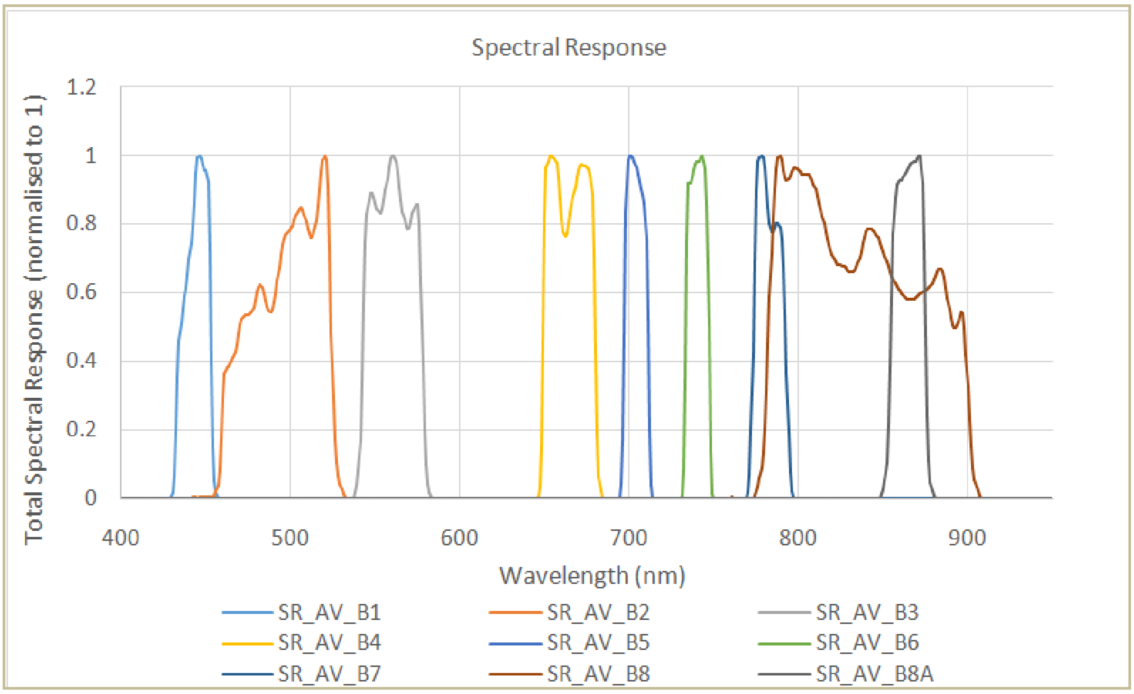

Figure 2. Spectral responses for the spectral bands found in Sentinel 2

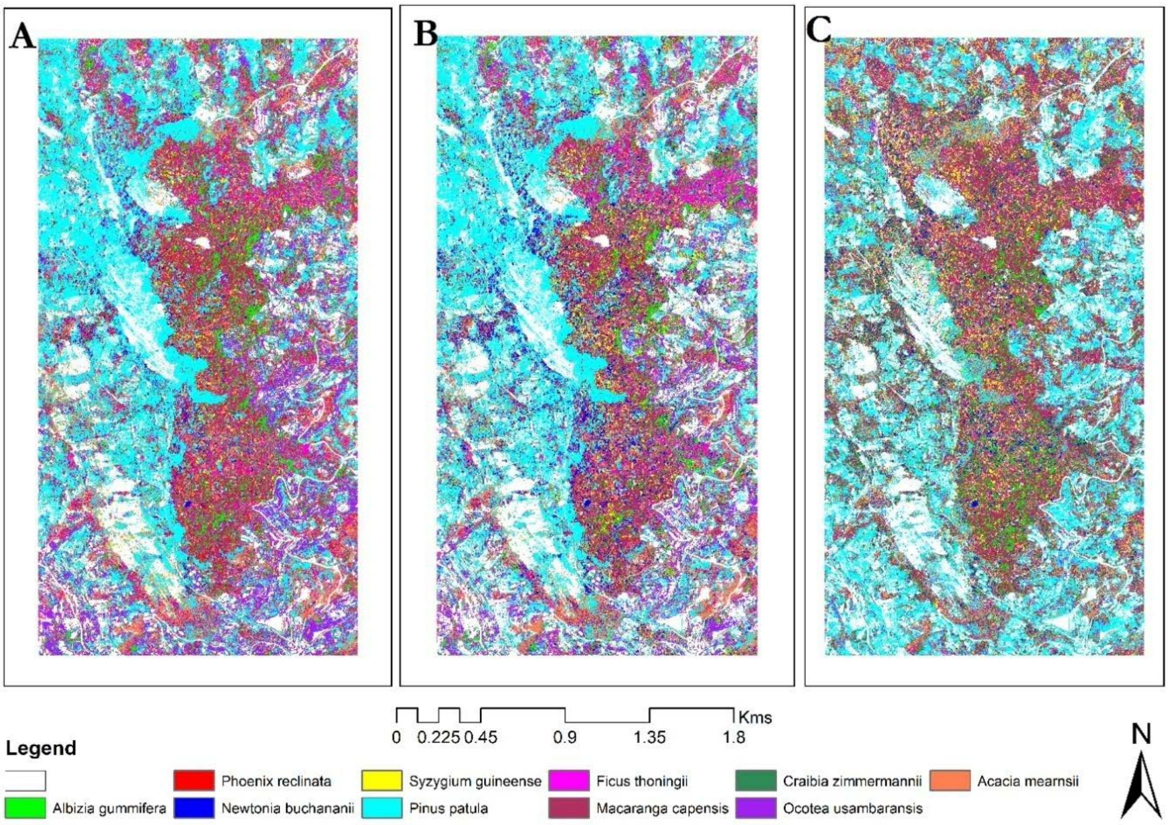

Figure 3. Thematic maps for the classification of tree species in Ngangao forest using hyperspectral data and three different classification algorithms; A. spectral angle mapper, B. neural network, C. support vector machine

Table 3. Individual Class Accuracy of Tree Species Classification in Ngangao Forest using Three Different Classification Algorithms; A. Spectral Angle Mapper, B. Neural Network, C. Support Vector Machine

		Spectral Angle Mapper		Neural Network		Support Vector Machine	
	Species Name	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
1	*Albizia gummifera*	52.42	42.34	95.17	76.42	89.22	78.18
2	*Phoenix reclinata*	26.09	60.00	55.07	45.78	33.33	69.70
3	*Newtonia buchananii*	69.57	67.69	71.94	93.81	79.45	75.00
4	*Syzygium guineense*	39.76	33.44	71.26	69.35	74.80	72.52
5	*Pinus patula*	72.75	84.90	98.02	89.94	97.72	90.17
6	*Ficus thoningii*	27.38	49.48	77.23	72.63	71.76	80.58
7	*Macaranga capensis*	29.46	33.65	62.24	82.87	66.80	74.54
8	*Acacia mearnsii*	27.94	20.11	72.06	65.33	76.47	63.80
9	*Craibia zimmermannii*	60.00	16.18	29.09	53.33	25.45	63.64
10	*Ocotea usambaransis*	36.77	37.27	70.40	84.86	82.06	86.32
	Overall Accuracy	49.24		79.47		80.15	
	Kappa Coefficient	0.42		0.76		0.77	

Support vector machine crushed during the classification of Sentinel 2 image. Therefore, it was eliminated from further analysis. On the other hand, neural network successfully classified the Worldview 2 and Sentinel 2 images. Generally, the overall classification accuracy and Kappa coefficient of Worldview 2 was higher than that of Sentinel 2 (Table 4). Even though the spatial resolution of Sentinel 2 was lower than Worldview 2 and the training sites were fewer, the interclass accuracies of some species were high in Sentinel 2 than in Worldview 2. On the other hand, some classes had 0% accuracy for both producer and user accuracies in Sentinel 2. Moreover, two classes did not classify in the Sentinel 2 image.

Training sites reduced progressively from the hyperspectral image, Worldview 2 image to the Sentinel 2 image (Table 5). *Albizia gummifera* and *Pinus patula* had the highest accuracies in the Worldview 2 classification while *Phoenix reclinata* had the lowest accuracy. *Acacia mearnsii* and *Crabia zimmermannii* had 0% accuracy in this classification. On the other hand, *Newtonia buchananii*, *Syzygium guineense*, *Ficus thoningi* and *Acacia mearnsii* had 0% accuracy in the Sentinel 2 classification while *Phoenix reclinata* and *Crabia zimmermannii* did not classify because the scaling of the images from AISA Eagle to Sentinel 2 increased the pixel size of the image beyond the training sites the diameter ranges of the training sites.

Table 4. Classification accuracies of tree species in Ngangao forest using Worldview 2 and Sentinel 2

		Worldview 2		Sentinel 2	
	Species Name	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
1	*Albizia gummifera*	95.77	66.67	75.00	75.00
2	*Phoenix reclinata*	5.88	100.00	Did not classify	Did not classify
3	*Newtonia buchananii*	23.81	83.33	0.00	0.00
4	*Syzygium guineense*	59.32	33.02	0.00	0.00
5	*Pinus patula*	94.77	85.34	100.00	71.43
6	*Ficus thoningii*	54.12	29.30	100.00	36.00
7	*Macaranga capensis*	30.88	45.65	0.00	0.00
8	*Acacia mearnsii*	0.00	0.00	0.00	0.00
9	*Craibia zimmermannii*	0.00	0.00	Did not classify	Did not classify
10	*Ocotea usambaransis*	19.30	78.57	0.00	0.00
	Overall Accuracy	56.43		47.22	
	Kappa Accuracy	0.48		0.33	

Table 5. Training sites used to classify tree species in Ngangao forest using AISA Eagle, Worldview 2 and Sentinel 2

	Species Name	RoIs AISA Eagle	RoIs Worldview 2	RoIs Sentinel 2
1	*Albizia gummifera*	269	71	4
2	*Phoenix reclinata*	69	17	0
3	*Newtonia buchananii*	253	63	4
4	*Syzygium guineense*	254	59	2
5	*Pinus patula*	657	172	4
6	*Ficus thoningii*	347	85	5
7	*Macaranga capensis*	241	68	1
8	*Acacia mearnsii*	136	15	1
	Craibia zimmermannii	55	57	0
	Ocotea usambaransis	223	31	2
	Total ROIs	2504	638	23

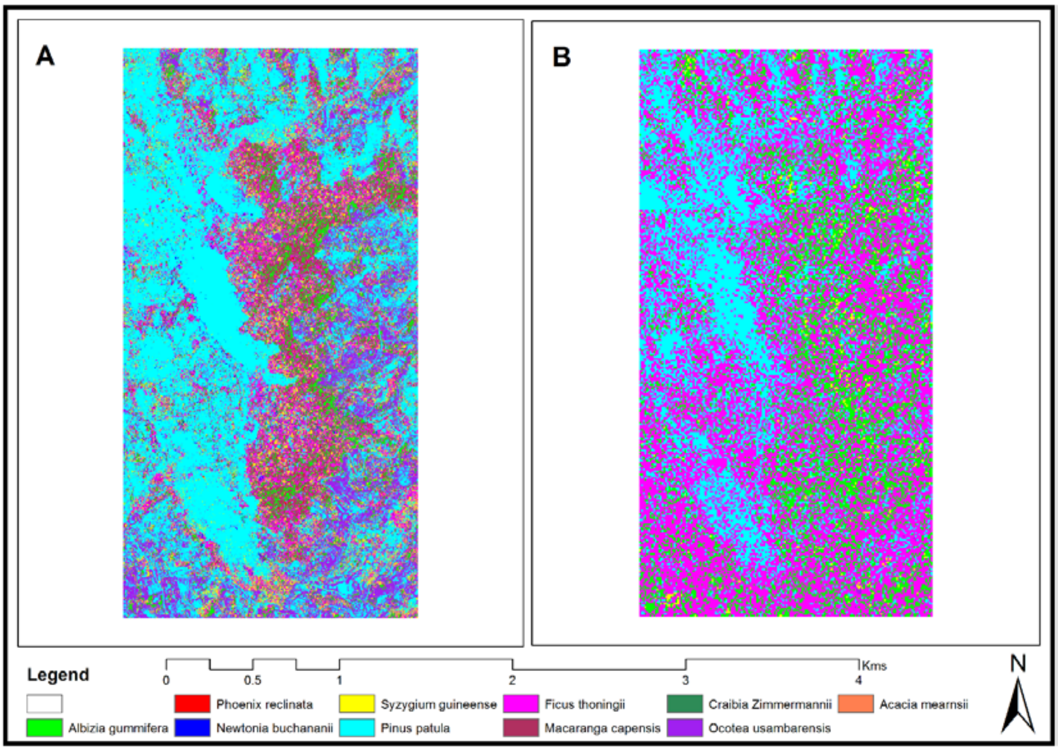

Figure 4. Thematic maps for the classification of tree species in Ngangao forest using different multispectral images; A. Worldview 2 and B, Sentinel 2 using the neural network algorithm

Worldview 2 classification maps show that features were distinguishable and classes separable at that level. On the other hand, the Sentinel 2 classification map did not distinguish between features clearly, while some of the classes were not clearly separable (Figure 4B). This was mainly because the difference between cell resolution canopy sizes of some of the tree species was small.

4. Discussions

4.1. Disk Size and Processing Speed

Resampling transforms the image dimension on various axes. For instance, upscaling introduces more pixels to the image while downscaling leads to pixel reduction [40]. Resampling the Ngangao Forest hyperspectral data to multispectral data involved both spectral and spatial dimensional reduction. The image was downscaled both spatially and spectrally leading to a reduction in image size [38,45]. The number of bands in the simulated data was smaller than bands in hyperspectral data. Most of the bands in the hyperspectral data were redundant, hence when they are resampled the information therein was consolidated into fewer bands. This meant that the smaller simulated images were processed by the classification algorithm with ease compared to the larger hyperspectral images.

4.2. Dimensionality

Dimensionality reduction minimizes the problems of nonlinearity, redundancy of bands and high dimensions in hyperspectral data [39,41], which in turn leads to data sets that are smaller in size compared to the original files, without loss of important information [4]. Resampling the Ngangao forest image reduced it spectrally from 129 bands to 8 bands for Worldview 2. The classified image of the resampled data achieved more than 56% accuracy in species identification compared to the 78% accuracy achieved by the hyperspectral data. This is despite the reduction in spatial resolution of the resampled image which might have contributed to the reduction in accuracy. Reference [23] showed that spatial resolution improves the amount of details an image contains, while [21] demonstrated how this resolution improves within class accuracy. More details improve the algorithms ability to discriminate between classes because the signatures of the different classes are better defined. Contrary, a reduction of the image details that discriminate between species classes will lead to a low ability of the algorithm to identify and differentiate between classes, hence lower accuracy.

4.3. Classification Methods and Machine Learning Algorithms

As a machine learning algorithm, support vector machine [11,13] utilizes signature data provided in the training sample to build separable units that are used in the classification. On the other hand, artificial neural network [1,42] simulate animal brains to progressively build information from signatures provided for by the training samples. Even though support vector machine achieved the highest accuracy when the Worldview 2 image of Ngangao Forest was classified, the algorithm was not able to classify the simulated sentinel 2 image which had more spectral bands than Worldview 2 but less spatial resolution. On the other hand, neural network which was ranked second in this classification, managed to classify the image well with a small reduction in accuracy. Artificial neural network is reputed to optimize training sites to obtain high accuracy without the need for too much information [24]. Therefore, artificial neural network optimized the training sites to classify the Sentinel 2 image better than support vector machine.

4.4. Training Sites

Supervised classification is guided by specific spectral signatures which are representatives of the desired or available landcover classes in an image [6,20]. These representative classes, which are also called training sites, guide the algorithm in the identification of similar pixel throughout the image, which are grouped into one class. In the Ngangao Forest image, the training sites were collected using the hyperspectral image whose spatial resolution was 0.6 metres. These sites were collected based on the pixel properties of the image, and considering that the canopy sizes of most of the trees was less than 10 metres, therefore most sites were less than the canopy sizes of these trees. In fact, to obtain pure pixels, only a subset of the canopy was considered as training sites.

To classify the resampled Worldview 2 image, whose resolution is less than 2 metres, and Sentinel 2 whose resolution is10 metres, the training sites were scaled to these images using the scaling application. Therefore, those training sites whose size was smaller than the resolution of the respective scaled images were automatically eliminated. This resulted to a total of 638 in Worldview 2 and 23 in Sentinel 2, down from 2,504 training sites in AISA Eagle image.

Some of the classes did not have any training sites to classify the Sentinel 2 image such as *Phoenix reclinata*, and *Craibia zimmermannii*, while some, such as *Macaranga capensis* and *Acacia mearnsii* had very few training sites (see Table 5). This affected the overall accuracy of the classification since the training sites that were used in the classification were also used in verification. This led to some of the tree species classes being classified with higher accuracy in Sentinel 2 then in Worldview 2.

Increasing the training sites of these images to achieve better representation was not possible since the pixel sizes were bigger than the canopies of some of the trees used to pick pure pixel. However, some of the classes which had bigger sized tree canopies as training sites gave impressive accuracies. Therefore, it is possible to upscale the tree species identification to Sentinel 2 using big sized tree canopies as training sites.

4.5. Map Description

Moreover, the maps in Figure 3 show that species identification and segregation in Ngangao forest was successfully done using multispectral images. On one hand, the shape of the forest was distinct in Worldview 2 than in Sentinel 2. On the other hand, *Ficus thoningii* and *Albizia gummifera* species was over-classified in Sentinel 2 as compared to other species. This was attributable to the close similarity between the spectral reflectance of these species with farmlands around the forest. Since the training sites were reduced in Sentinel 2 compared to Worldview 2, distinguishing between tree species classes in the forest and crops in the farmlands was not clear. Therefore, they were classed as similar classes. This could however have been improved had the spatial resolution of the Sentinel 2 images been high. It is suspected that resampling the Sentinel 2 images with higher spatial resolution (probably between 2 to 5 metres) would improve the classification accuracy of tree species.

5. Conclusion

This study tested the possibility of using two optical sensors (Worldview 2 and Sentinel 2) in identifying tree species in the tropics. Three methods, namely spectral angel mapper, neural network and support vector machine were tested. The three methods were able to classify the hyperspectral data but only neural network was able to classify data from the two optical sensors. The classification results have shown that Worldview 2 is able to map the tree species but it was not possible with Sentinel 2. However, further research should be done on the two sensors with enough training sites. Other classification methods should also be tested.

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