Modeling Topographic Effects in Satellite Imagery

A. Mazimwe, A. Gidudu

Abstract

The ability to extract accurate land cover information from satellite imagery depends on the quality of satellite data. Thus a study was made to assess the impact of topographic correction on satellite imagery where illumination effects were modelled with a DEM to quantitatively assess the classification accuracy. During the study, false colour composites were created using raw bands, and radiance band images which were a result of applying correct scene date, and varied sun's Zenith and Azimuth angles in the intensity formula. Supervised and unsupervised classification algorithms were used to classify the composites followed by quantitative accuracy assessment to compare classification accuracy. Following the application of topographic correction, results at a 95% confidence level showed that 1) supervised classification was significantly better than unsupervised classification, 2) the true radiance composite classification had a significantly better overall accuracy than radiance classifications where azimuth was varied or the Zenith was increased, and 3) accuracy seems to increase significantly when the Zenith angle is lowered from true Zenith while maintaining the true Azimuth. This paper demonstrates that correcting slope-aspect effects significantly improves classification accuracy of satellite imagery necessitating corrections for geometric errors in remotely sensed data.

Keywords: Azimuth Angle, Zenith Angle, Slope, Aspect, Insolation Intensity, Classification Accuracy

1. Introduction

Vegetative land cover such as forests, shrubs, grassland, crops and wetlands are scarce and yet valuable resources, therefore allocating and managing them requires accurate knowledge about their distribution on the earth's surface (Congalton and Green, 2009).The ability to accurately, reliably extract and interpret land cover information from a remotely sensed imagery is of benefit to many environmental applications such as global environmental modeling and policy formulation, natural resource management such as forestry management, wetlands monitoring and precision farming.

However, during the data acquisition process, radiometric errors due to atmospheric and topographical attenuation are introduced in remotely sensed data, making it difficult to yield accurate classification alone with single-date multispectral data. This paper seeks to assess the impact of correcting for topographic attenuation on classification accuracy of satellite imagery for vegetation identification and landform visualization by:-Using radiance imagery in which illumination effects are modelled

using a DEM to assess classification accuracy. This paper is summarized in an abstract and consists of an introduction, a brief literature review, a methodology, results and discussion, and finally conclusions regarding the study.

2. Modelling Topographic effects

According to Jensen (2005), the two most important sources of environmental attenuation are 1) atmospheric attenuation caused by scattering and absorption in the atmosphere and 2) topographic attenuation. Jensen (2005) further adds that topographic slope and aspect cause radiometric distortion of recorded signal. Topographic effect is the difference in radiance values from inclined surfaces compared to horizontal ones (Schneider and Robbins, 1995). The interaction of the zenith angle and azimuth of the sun's rays with slopes and aspects produce topographic effects resulting in variable illumination. In extreme terrain conditions some areas may be shadowed to the extent that meaningful information is lost altogether (Eastman, 2001).

Jensen (2005) re-affirms that it is for this reason that research has been directed towards removal of topographic effects especially in mountainous regions:- since the objective of topographic correction is to equalize the radiance between the shady and sunny slopes (Nichol *et al.* 2005). Shadowing effects exaggerate the difference in reflectance information coming from similar earth materials (Schneider and Robbins, 1995). In the classification process, the highly variable relationship between slope, land cover, and sun angle can lead to a highly exaggerated number of reflectance groups that make final interpretation of data layers more costly, difficult, and time consuming. According to Eastman (2001), illumination modeling based on a DEM is one of the most accessible techniques for mitigating topographic effects.

The modeling of illumination effects using a DEM can be done using the insolation intensity formula described in spherical trigonometry (Smith et al 1980) based upon a Lambertian assumption that "the portion of radiance reflected off the surface of a plane is a function of the slope and azimuth angle of the sun's radiance at a given moment". The formula is as follows (Tillet *et al.*1982; Kohei Arai, 1996;Ekstrand, 1996);

$$\mathrm{Cos}\ v = \mathrm{Cos}\theta\ \mathrm{Cos}\alpha + \mathrm{Sin}\theta\ \mathrm{Sin}\alpha\ \mathrm{Cos}\ (\emptyset - \delta) \qquad (1)$$

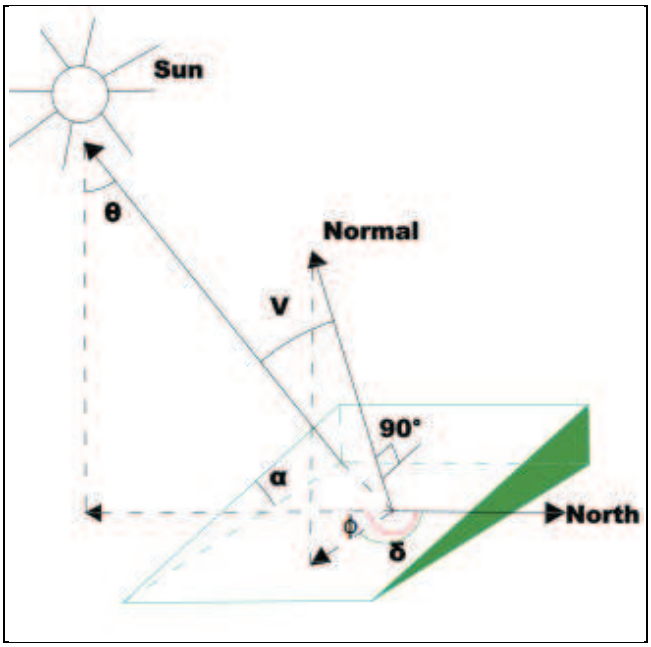


Figure 1: Relationship between slope of a plane and angle of the sun's Rays(Riañoet al., 2003)

θ= zenith angle of the sun which is a measurement of height of the sun in the sky, described in degrees away from the point overhead.

α= slope of the plane.

δ= azimuth of plane (aspect).

ϕ=azimuth of the sun. The azimuth coordinate is the point on a 360 degree arc where the plane/sun's line of illumination intersects with the horizon.

Cos v is the insolation intensity (i.e. the proportion of real reflectance coming off a slope face) determined by the angle of the surface slope being struck by sunlight as well as the angle of the sun at the time of illumination. In Figure 1, the angle of the sun's rays (v) is a function of α and the horizontal position of the sun in the sky relative to the direction in which the slope is facing. To solve for v, the position of the sun in the sky is required as it casts its rays and a description of plane's slope relative to that position.

By using a DEM to derive slope and aspect, equation (1) can be solved using map algebra in GIS to create an output image of Cos v. Smith *et al* (1980) indicates that in theory a "true" radiance image can be created by dividing band images by Cos v. These "corrected" bands may be used to create composites and are used for classification.

3. Methodology

Modeling illumination effects using a DEM was applied on Landsat ETM images in bands 2, 3 and 4 (spatial resolution 30m) acquired on 5th February 2001 for Mt. Elgon region. This method involved comparing classification accuracies for the true radiance composite with the raw false colour composite and other radiance false colour

composites in which the zenith and azimuth angle were varied in the insolation intensity formula.

3.1 Correction for Illumination Effects

The Correction for illumination effects was performed using *Shuttle* Radar Topography Mission (SRTM90) DEM for Mt. Elgon with the help of formula 1. To solve formula 1, the sun's azimuth and zenith (for the correct scene date) together with slope and aspect were used to obtain insolation intensity. Similarly, other combinations like; 1) varying the azimuth while maintaining the correct zenith angle, 2) varying the zenith while maintaining the correct azimuth, and 3) using azimuth and zenith for a distorted scene date, as illustrated in Table 1 were used to calculate the insolation intensity. The Azimuth and Zenith angles, the slope ($\propto$) and aspect (∂) images derived from the DEM were converted from degrees to radians so as to be applied in equation 1.

Table 1: Variations in Azimuth and Zenith angles of the Sun

	Zenith varied			**Correct Scene Date**	**Azimuth varied**						**Distorted Scene Date**
Azimuth (Ø ◦)	119.52	119.52	119.52	**119.52**	103	110	115	125	130	135	**135**
Zenith (θ ◦)	45	50	61	**53.40**	53.40	53.40	53.40	53.40	53.40	53.40	**45**

The radiance images were obtained by dividing the respective raw bands with the insolation intensity (Cos v), for a particular angle combination. The corresponding images generated were stretched using a "linear with saturation at 5%" stretch so as rescale them to 256 levels.

3.2 Composite Creation

8 bit false colour composites for both raw and radiance band images of a 1% linear saturation stretch while maintaining zeros in calculation of the stretch were created; where Landsat ETM images in bands 2, 3 and 4 were specified as Blue, Green and Red band images respectively.

3.3 Classification and Accuracy Assessment

Unsupervised classification was performed on both the raw and radiance false colour composites to five clusters using the CLUSTER module of IDRISI 32 with the fine generalization level. Supervised classification was performed on the raw and radiance composites using the Maximum likelihood algorithm with equal priori probability for each signature while classifying all pixels. Ground truthing was done from a SPOT imagery in the panchromatic band (spatial resolution of 2.5m) in which sseveral distinct land covers were identified.

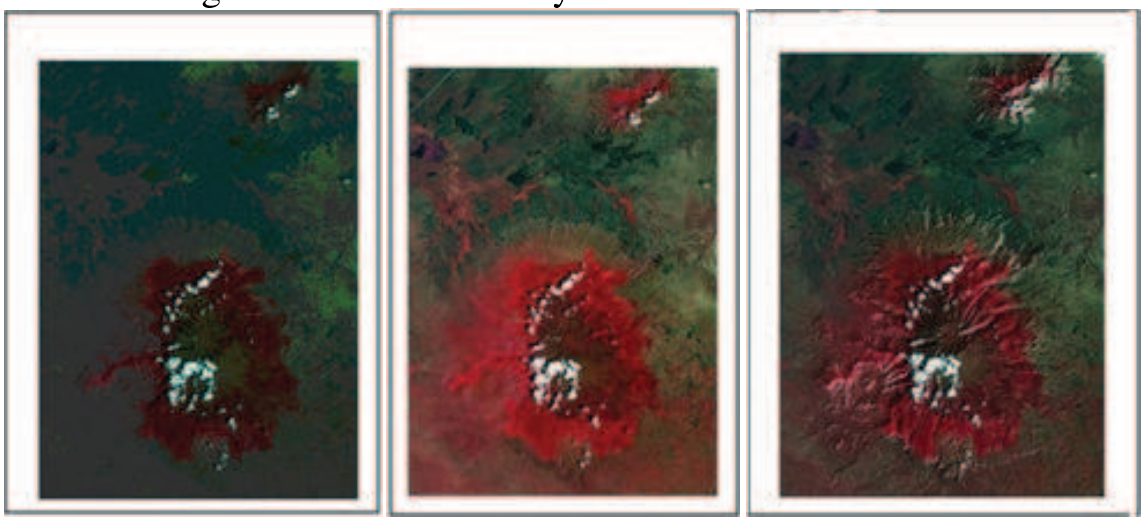
Thematic accuracy assessment was done with an Error matrix supplemented by the Kappa statisticas described byCongalton and Green (2009). The reference data used as a basis for accuracy assessment was the training site data for the true radiance composite. A binomial test of significance was performed to compare the classification algorithms, and classifications for different azimuth and zenith angular combinations.

4. Results and Discussion

4.1 Visual Analysis

4.1. 1 Composites

The true radiance composite in Figure 2b had a bright red colour representing most vegetation with no shadow effects on the slopes of Mt Elgon where terrain variations are intense. The red colour is due to the fact that vegetation reflects strongly in the near infra red band. However, the intensity of the red colour varies with the amount of vegetation available. Therefore, the intensity of red colour in the true radiance image is strong because the image had been corrected by for sun's illumination effects.



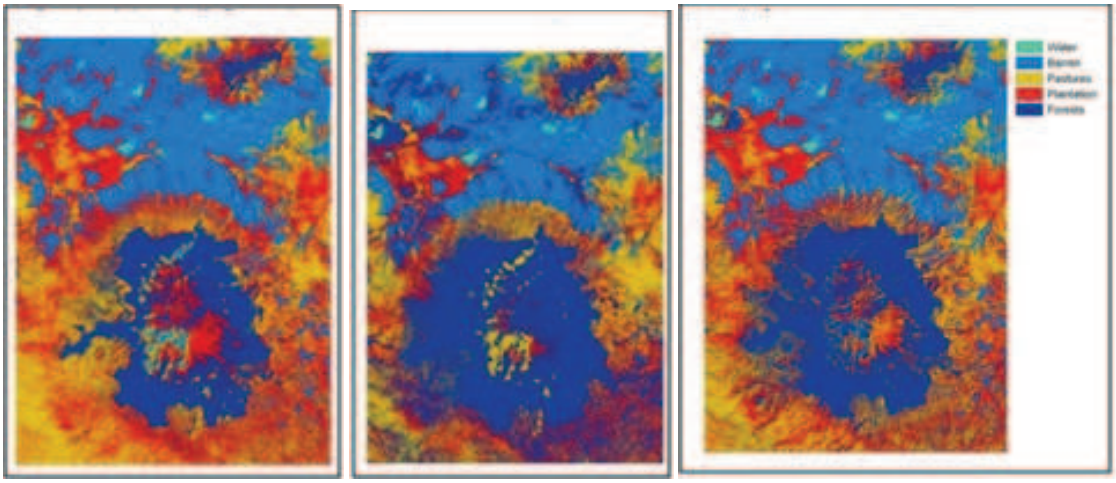
a) Raw band b) True radiance c) Distorted scene date

Figure 2: Raw and Radiance composites

However, there was less vegetation cover and shadowsin the raw and radiance composites where angles for a distorted scene date had been used (Figures 2a and c respectively) or where the sun's zenith and azimuth were varied. This was because the raw image was not corrected or distorted zenith and azimuth angle combinations of the sun for a particular scene date were used in the insolation intensity formula.

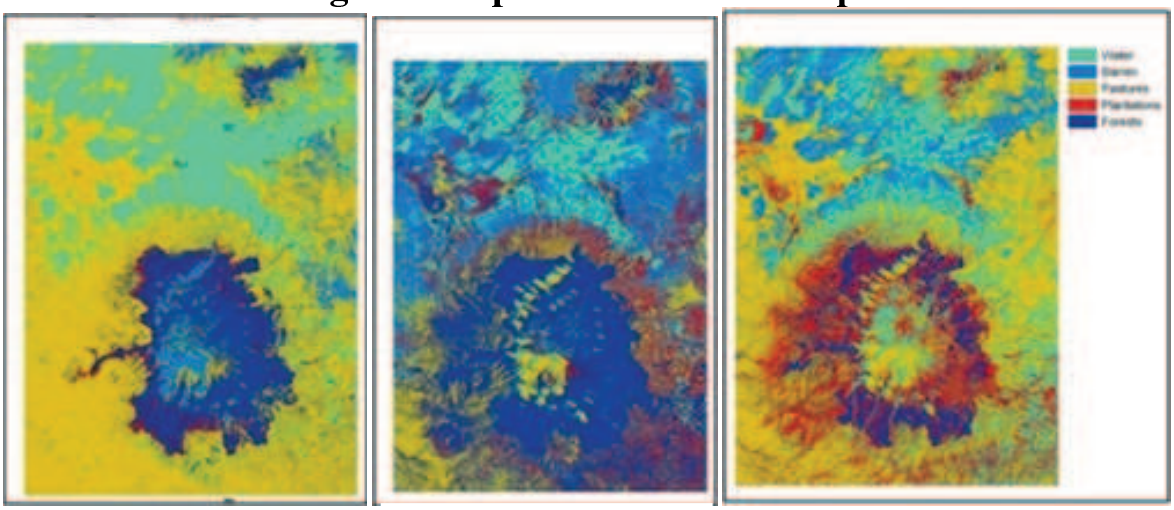
4.1.2 Classified Maps

The true radiance supervised classified map in Figure 3b showed great resemblance to the ground features as indicated in the SPOT imagery with the largest amount of forest cover. Furthermore, all other supervised classifications showed closer resemblance with each others.



a) Raw band b) True radiance c) Distorted scene

Figure 3: Supervised classified maps



a) Raw band b) True radiance c) Distorted scene date

Figure 4: Unsupervised classified maps

Similarly, the unsupervised classified "true" radiance image in Figure 4b showed the greatest forest cover. The classified maps of the composites where distorted scene date angles (Figure 4c) or where the sun's azimuth was varied in the intensity formula showed the least forest coverage. Unsupervised classifications showed land cover misclassifications since it is inaccurate as compared to supervised classification due to the fact that it is a segmentation process.

4.2 Quantitative Accuracy Assessment

From the error matrices, the ability for the producer to extract forest cover from a true radiance image is highest at 99.89% for supervised classification and 99.56% for unsupervised classification with corresponding user accuracies of 99.89% and 99.34% respectively.On the contrary, the raw image classification had a producer accuracy of 97.91% and 89.65% for supervised and unsupervised classification respectively while the user accuracies for corresponding classifications were 100% and 89.85%. Results

from the Table 2 show that the forest area of 14.4% of total land cover extracted from a raw image increases to 29.1% after correcting the raw imagery for slope and aspect effects using correct scene date angles in the intensity formula when supervised classification is used. When unsupervised classification is used a similar trend is observed. This implies that correction for topographic effects increases the forest stand classification as asserted by Civco (1989; Meyer *et al.* 1993).

Table 2: Comparisons of supervised classification accuracies with % acreage of land cover**.**

	True radiance			Raw classification			Distorted scene date angle		
	% Acreage	produce r acc.	users acc.	% Acreage	produce r acc.	users acc.	% Acreage	producer acc.	users acc.
Water	0.8	100	100	0.6	100	100	0.7	100	100
Barren	25.2	99.9	100	23.6	100	100	29.6	100	100
Pastures	19.5	97.27	97.8	5.7	100	97.34	21.5	89.62	98.8
Plantation	25.5	95	92.68	55.7	95	80.85	23.7	98.75	77.45
Forests	**29.1**	100	99.89	**14.4**	97.91	100	**24.5**	99.45	100

From the raw classification in table 2, vegetation like pastures had a producer accuracy of 100% yet 97.34% was found to exist implying the rest had been classified as plantations which have lower producer accuracy and user accuracy. This is manifested in the higher plantation acreage (i.e. 55.7% of total land cover) than that of pastures (5.7% of total land cover). This anomaly is completely dealt with when the raw image is corrected for illumination effects. This suggests that correction for illumination effects improves vegetation identification in an image. It should also be noted that using distorted scene date angles showed slight changes in acreage ratios of the land covers as compared to the true radiance classification though the producer and user accuracies were lower implying that the ability to extract vegetation from imagery where distorted scene date angles are used is low.

With supervised classification, varying the zenith angle gave an impression that forest stand classification increases as shown by the high forest cover acreages. However, the producer and user accuracies are lower when zenith angles are varied than when the true zenith angle is applied in the intensity formula. This implies that varying the zenith angle doesn't increase forest stand classification as portrayed by areas but it's as a result of lower classification accuracy. Furthermore, when supervised classification was used, varying the azimuth angle lead to lower classification accuracies for vegetation than accuracies achieved when true azimuth is used. Therefore, the high forest cover acreage when azimuth is varied implies some land covers were misclassified. From results it was further realized that variation of azimuth seemed to increase water classification as portrayed by acreage yet this may not be the case since classification accuracies are lower as compared to when true azimuth is used. This could be as a result of shadows being classified as water.

All in all, supervised classification showed superior accuracies with which information about land covers can be extracted from an image as compared to unsupervised classifications since classes to which land covers belonged were accurately known in supervised classification. However, unsupervised classifications showed similar trends as supervised classification except for the poorer classification accuracies.

4. 2.1 Trends in Overall Accuracies

Figure 5 indicates that the overall accuracy for the true radiance classification was significantly better than accuracies for other radiance classifications when azimuth was varied. However, the trend of classification accuracy increased gently as the azimuth angle is increased and gently decreased as the azimuth was decreased away from the correct azimuth while keeping the sun's zenith angle for correct scene date constant.

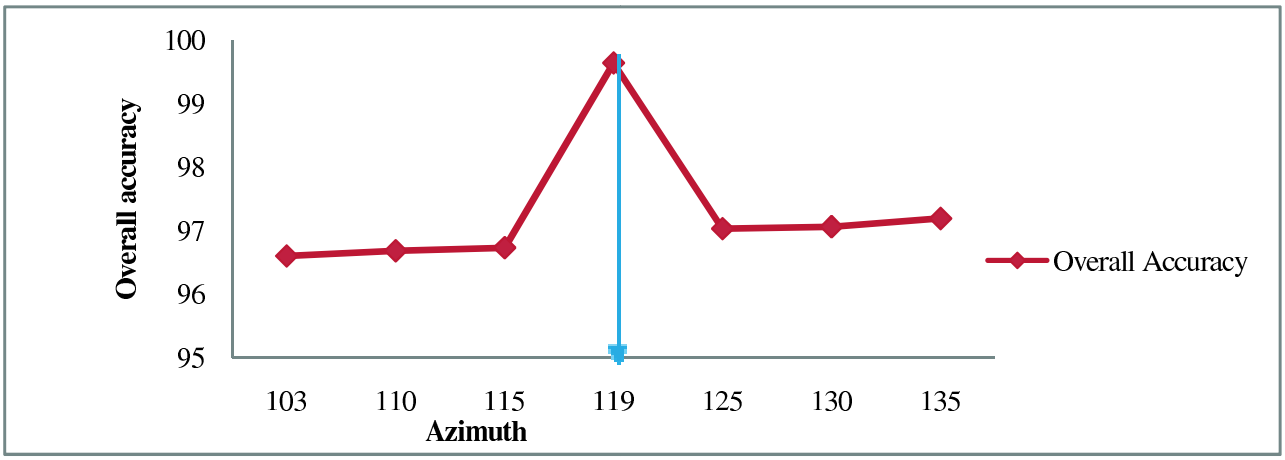


Figure 5: Supervised classifications with varying azimuth

Results in Figure 5 can be explained by the fact that the azimuth is angle measured on a horizontal plane along the 360^0 arc to where the sun's line of illumination intersects the horizon. This implies that variation of azimuth while keeping the true zenith constant has a little impact on position of the sun relative to the overhead position which determines presence of shadow effects in an image. As a result significantly better information from a true radiance image will be extracted regardless of variations in azimuth.

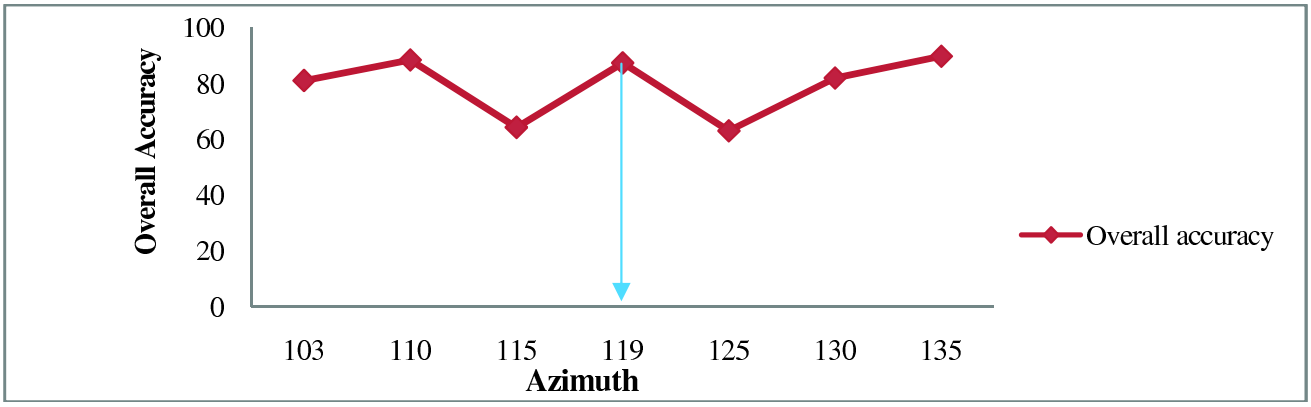


Figure 6: Unsupervised classifications with varying Azimuth

However, unsupervised classification in Figure 6 showed oscillating overall accuracies when azimuth was varied from the true azimuth (119.52^0) while maintaining the correct zenith angle of 53.40^0 though the trend is roughly similar to that for supervised classification where accuracies tend to generally increase with increase in azimuth and the reverse is true. These accuracies are oscillating because unsupervised classification is a less accurate method as it rather a segmentation process. This is further manifested in the low overall accuracies as depicted by the axis in Figure 6.

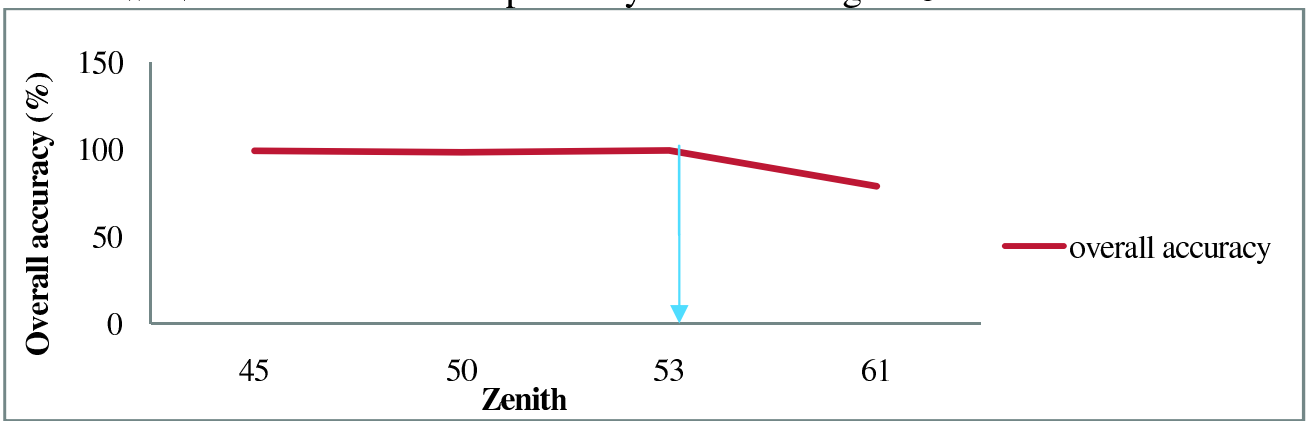


Figure 7: Overall accuracies for supervised classification when zenith varies

From Figure 7, increasing the sun's zenith angle from 53.40^0 resulted into significant reduction in overall accuracy as compared to that of the true radiance image while reduction caused significant increase in overall accuracy. From Figure 7 showing unsupervised classification when zenith is varying, the same trend as indicated in Figure 7 is repeated only that reduction of overall accuracy with increase in zenith angles is very significant while there is a significant increase in overall accuracy with reduction in zenith angles from the true zenith angle of $53.40^{0.}$

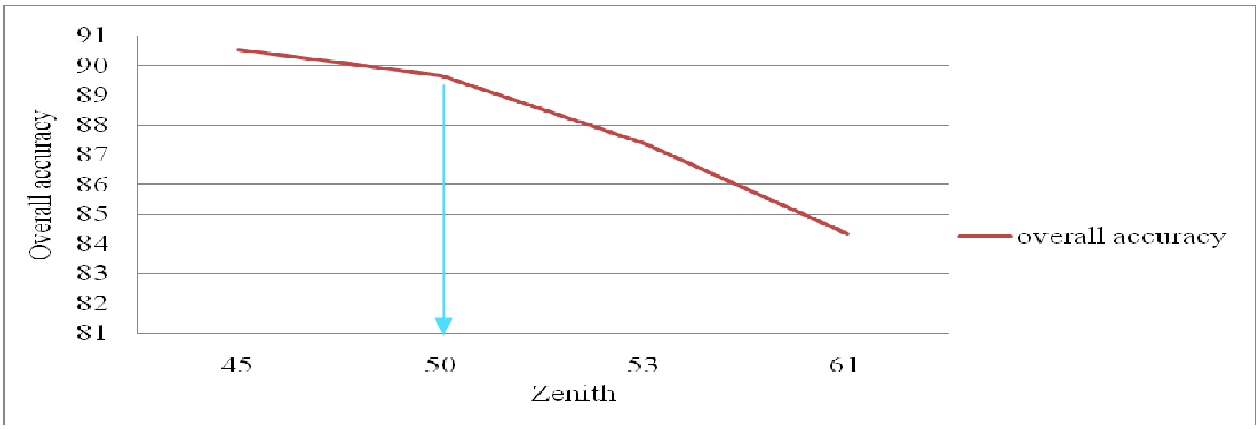


Figure 8: Overall accuracies for unsupervised classification with varying zenith

Results in Figures 7 and 8 are due to the fact that varying the zenith angle supposedly changes the position of the sun above the terrain. Therefore, when the zenith angle is reduced it means that the sun's position is brought nearer the point overhead as indicated in Figure 1. Therefore, there will be less shadow effects as all the sun's rays illuminate terrain directly as a result more information can be extracted from the radiance imagery. On the contrary, increasing the zenith angle varies the position of sun away from the point overhead resulting into extreme effects of the sun angle on slope illumination thus shadows. This yields a lower accuracy with which information can be extracted from imagery.

4. 2.2 Binomial Tests of Significance

Using results from Table 3, statistical tests were carried out to test for the level of significance of accuracies. Therefore, the null hypothesis (H_o) that the accuracy derived from a supervised true radiance is not significantly better than accuracies derived from other supervised classifications will be rejected if $|Z_1| \geq Z_{\alpha/2}$ at 95% confidence level i.e. $|Z_1| \geq 1.96$ (Fitzpatrick-lins, 1986).

$$Z_1 = \frac{|O.A_1 - O.A_2|}{\sqrt{\frac{O.A_1(1-O.A_1)}{No.\ of\ Sample\ Points} + \frac{O.A_2(1-O.A_2)}{No.\ of\ Sample\ Points}}} \qquad (2)$$

Where

$O.A_1$– Overall accuracy of error matrix for supervised true radiance composite classification

$O.A_2$-Overall accuracy of error matrix for supervised radiance classification with varying angles or with angles of a distorted scene date or supervised raw imagery.

From Table 3, generally $|Z_1| > 1.96$ therefore the null hypothesis was rejected implying that accuracy with which information can be derived from a true radiance image with azimuth and zenith angles for a correct scene date is significantly better than accuracies obtained from a raw image, when the distorted scene date angles are used, and when azimuth and zenith are varied while keeping either of them constant when supervised classification is used at 95% confidence level. However, an exception arised when the zenith angle was lowered from 53.40^o to 45^0 while keeping the correct azimuth

constant as indicated in Figure 4 where |Z|<1.96 thus the null hypothesis was accepted. This implies that accuracy with which information can be derived from a true radiance image (with correct angles for a correct scene date) is not significantly better than when zenith angle is lowered away from the correct zenith at 95% confidence level.

Table 3: Z-scores for True Radiance images, Raw images, Radiance images with Distorted scene dates and varying Azimuth and Zenith.

Azimuth ($\emptyset$ °) Zenith (θ °)	Overall Accuracy (supervised)	Z_1 – score	Overall KAPPA (supervised)	Overall Accuracy (unsupervised)	Z_2- score	Overall KAPPA (unsupervised)	Z_3- score
$\emptyset$ = 103	96.6	8.8	95.3	81.1	25.8	73.7	19.8
$\emptyset$ = 110	96.7	8.6	95.5	88.5	18.9	84.0	12.3
$\emptyset$ = 115	96.7	8.5	95.4	64.3	40.3	49.3	34.9
Correct scene date; $\emptyset$ =119.52 θ = 53.40	99.6	0.0	99.5	87.4	20.0	82.5	20
$\emptyset$ =125	95.0	11.3	95.9	63.1	41.4	51.8	33.1
$\emptyset$ =130	97.1	7.9	95.9	82.0	25.0	75.4	19.8
$\emptyset$ =135	97.2	7.7	96.1	89.8	17.6	85.8	11.8
θ = 45	99.4	1.2	99.2	90.5	16.8	86.8	16.2
θ = 50	98.6	4.3	98.1	89.7	17.7	85.7	15.1
θ = 61	79.1	27.5	71.0	84.4	22.9	78.0	-5.3
Raw	99.2	2.1	98.9	51.2	53.0	42.2	52.1
Distorted scene date θ =45 $\emptyset$=135	99.2	2.4	98.9	72.2	33.4	63.3	32.4

Using results from Table 3, the null hypothesis (H_o) that the accuracy derived from a supervised true radiance is not significantly better than accuracies derived from all other unsupervised classifications to rejected be if $|Z_2| \geq Z_{\alpha/2}$ at 95% confidence level i.e. $|Z_2| \geq 1.96$.

$$Z_2 = \frac{|O.A_1 - O.A_2|}{\sqrt{\frac{O.A_1(1-O.A_1)}{No.\ of\ Sample\ Points} + \frac{O.A_2(1-O.A_2)}{No.\ of\ Sample\ Points}}} \quad (3)$$

Where

$O.A_1$ – Overall accuracy of error matrix for supervised true radiance classification

$O.A_2$- Overall accuracy of error matrix for unsupervised classification for radiance images with varying angle or with angles of a distorted scene date, raw image.

Since $|Z_2| > 1.96$ in Table 3, the null hypothesis was rejected. This means that the overall accuracy derived from supervised true radiance classification is more

significantly better than any other unsupervised classification at a 95% confidence level.

Finally, the null hypothesis (H_0) that supervised classifications were not significantly better than their corresponding unsupervised classifications would be rejected if $|Z_3| \geq Z_{\alpha/2}$ at 95% confidence level i.e. $|Z_3| \geq 1.96$.

$$Z_3 = \frac{|O.A_1 - O.A_2|}{\sqrt{\frac{O.A_1(1-O.A_1)}{No.\ of\ Sample\ Points} + \frac{O.A_2(1-O.A_2)}{No.\ of\ Sample\ Points}}} \qquad (4)$$

Where

$O.A_1$ – Overall accuracy of error matrix for supervised classification for any image

$O.A_2$ - Overall accuracy of error matrix for unsupervised classification for any image

Since $|Z_3| > 1.96$ in Table 3, the null hypothesis was rejected. Literally, the ability to extract information from composites with supervised classification is significantly higher than when unsupervised classification is used at a 95% confidence level. This is because the classes to which land covers belonged were accurately known in supervised classification yet unsupervised classification is rather a segmentation process. However, an exception was realized when the zenith angle had been varied to 61^0 where $Z_3 < 1.96$ implying that it's a point where unsupervised classification yields significantly better accuracy than supervised classification

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The overall Kappa in Table 3 for all supervised classifications showed that there was a strong agreement between remote sensing-derived classification maps and the reference data i.e. (K>80%). Generally, the individual class Kappa coefficients for supervised classifications showed strong agreement between individual land covers of both classified and reference maps as indicated in error matrices.

5. Conclusions

Results suggest that much more information is accurately extracted from an image when the zenith angle is decreased away from the correct scene sun's Zenith regardless of the classification algorithm. However, this does not necessarily improve the classification accuracies for the individual classes in an image.Also from the results, at a 95% confidence level, the accuracy with which land cover information is derived from a true radiance image is significantly better than that extracted from a raw image, images where distorted scene date angles are used and/or images where azimuth is varied in the intensity formula regardless of the type of classification. Since results show that supervised is significantly better than classification, more accurate information can be derived from true radiance imagery when supervised classification is used.

6. Recommendations

There is need to correct for radiometric errors due to topographical attenuation introduced in remotely sensed data with correct angles for particular scene date so as to yield accurate land cover information alone with single-date multispectral data. Furthermore, research can be done using other methods of correcting topographic effects that based on non- Lambertian Assumptions.

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