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Radiometric Compensation for Occluded Crops Imaged Using High-Spatial-Resolution Unmanned Aerial Vehicle System

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Structure of Presentation

- Introduction
- Experimental Site
- Methodology
- Results
- Discussion
- Conclusion

Introduction

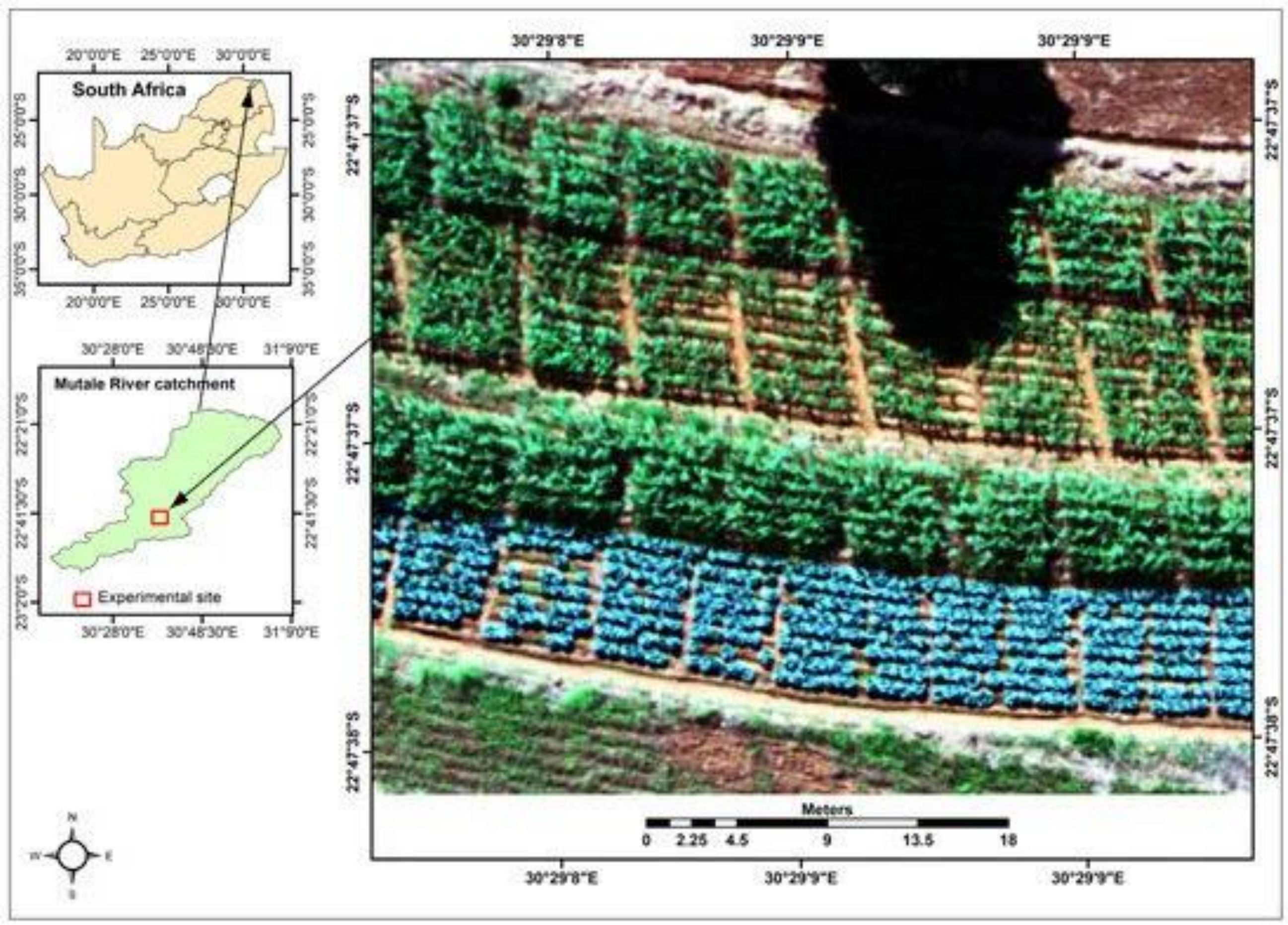
- The progression in remote sensing technology has presented the world with invaluable sources of crop-related information.
- Through this technology, crops can be better quantified for their management and yield estimation
- UAV systems are increasingly developing to be an effective way to complement satellite remote sensing
- The quality of the UAV photogrammetric end products still requires serious attention if accurate spectral characterization of crops is to be achieved with these products
- The presence of shadows on croplands tends to play a role in the alteration of radiometric properties of crops
- The occluded crops may subsequently be subjected to spectral confusion and misclassification

Introduction (Cont'd)

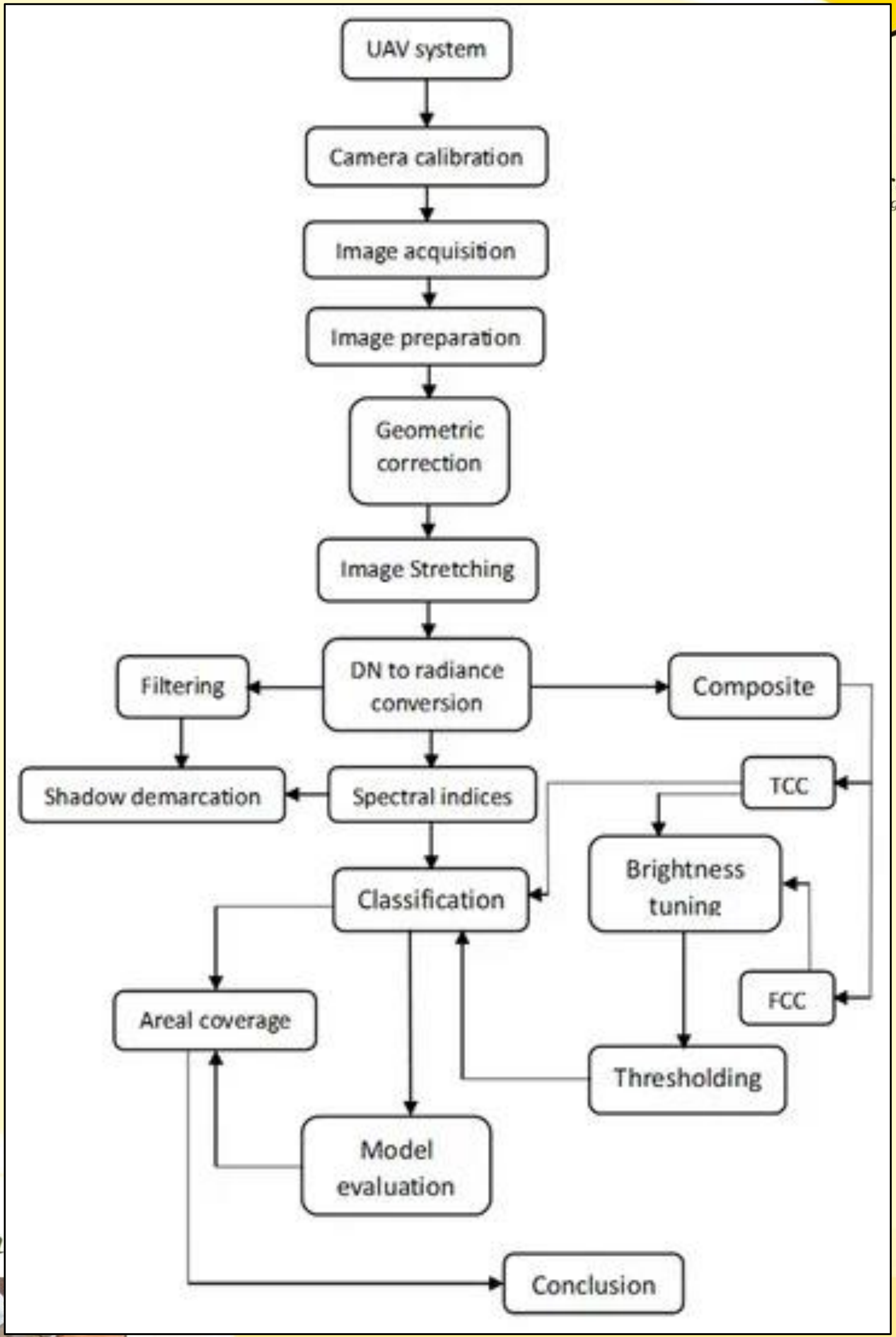
- Radiometric compensation of crops under occlusion can be accomplished using a thresholding algorithm, modeling, or object-oriented techniques.
- Studies on radiometric restoration have extensively focused on built-up environments, neglecting other environmental disciplines
- We envisage that, when used in conjunction with a brightness-tuning approach, thresholding can aid in the restoration of radiometric properties of crops under total occlusion.
- Owing to the limited ability to effectively handle total occlusion scenarios and the lack of simplicity and reliability of these radiometric compensation techniques, this study proposes a simple and reliable approach for radiometrically compensating crops under total occlusion by integrating brightness-based compensation and thresholding techniques

Experimental Site

- The experimental site was situated within the Mutale River catchment in the Limpopo province of South Africa, which is well known for its agricultural practices.
- Small-scale crop farming for supporting local livelihoods and the rural economy is dominant in this area.
- The small-scale farms of the study area were found at 22°47′37.22″ S, 30°29′08.41″ E absolute location of the Earth
- The selection of the experimental site was prompted by the presence of a shadow, which appears as large black spot in the image, created by an adjacent tree.

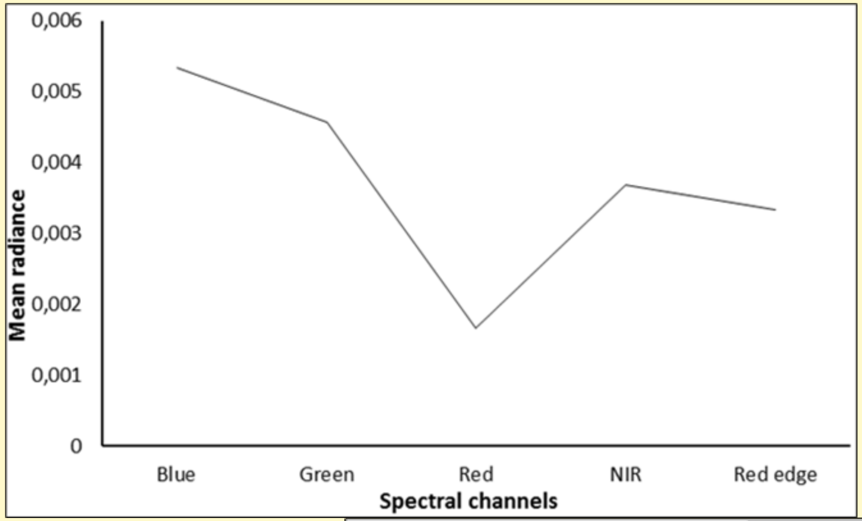


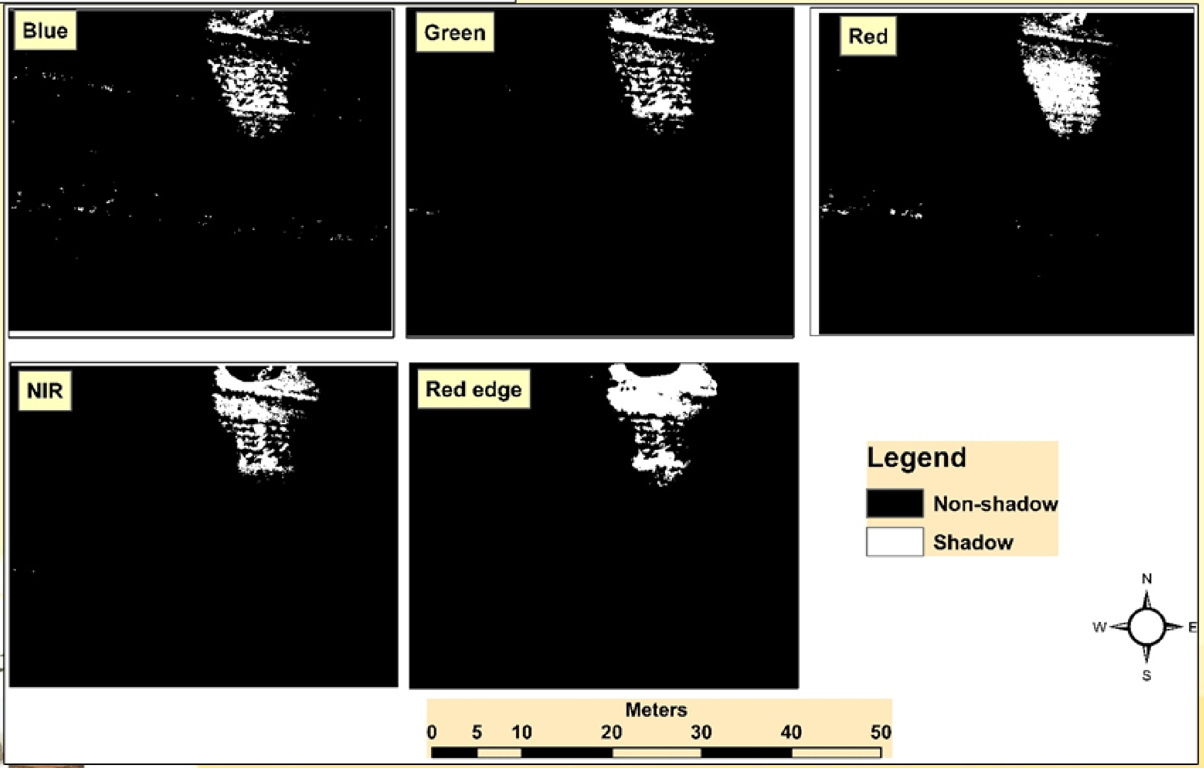
Research Approach



Results

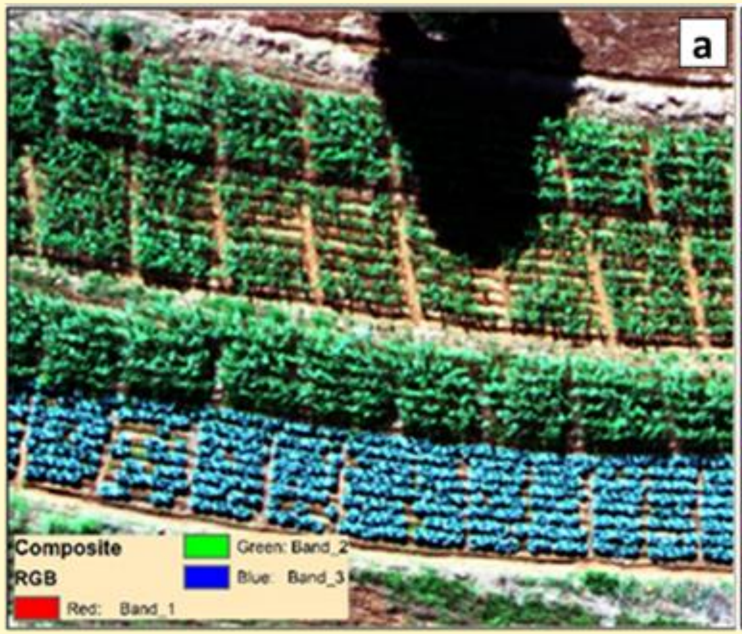
- **Demarcation of Shadow**
  - shadow was demarcated by applying mean radiance values computed from the samples collected from the shaded region of the experimental site.
  - The mean radiance values of shadow as extracted from blue, green, red, NIR and red edge spectral channels were observed to be 0.005, 0.005, 0.002, 0.004 and 0.003 respectively

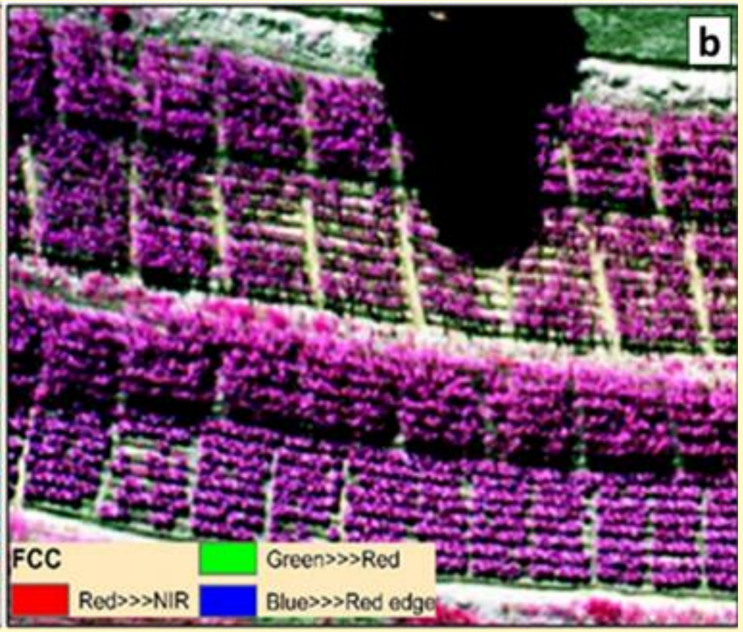




Results

- **Land Cover Types in the Experimental Sites**
- Existing land cover types in these images are cabbage, maize and soils.
- In these images, maize and soils were noted to be subjected to occlusion by adjacent tree.
- Whereas maize was observed to have been only subjected to occlusion by adjacent tree, soils were noted to have been subjected to occlusion by both adjacent trees and above ground maize cover





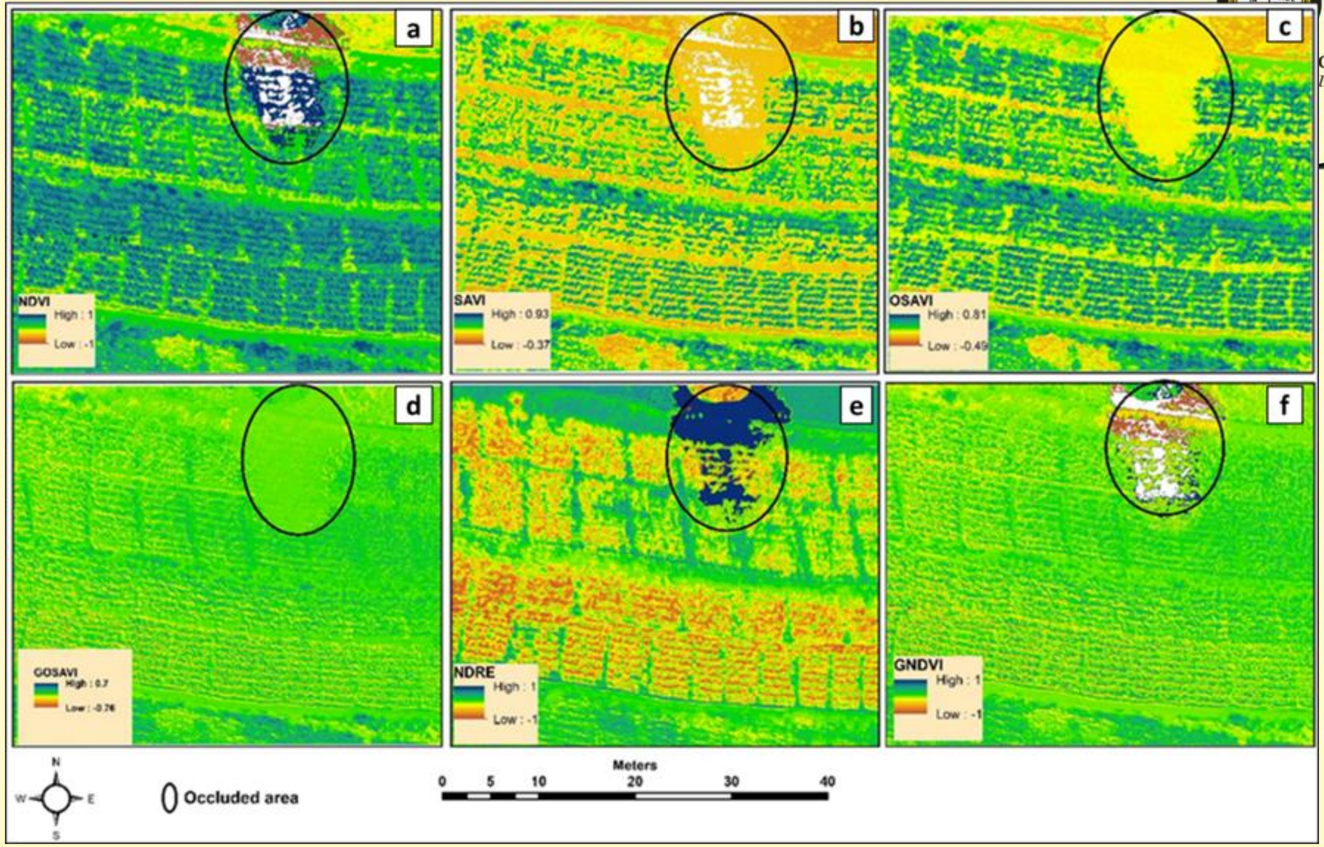
Results

- **Comparative Analysis of Spectral Mean Values of Lit Cover and Occluded Cover**
- A total of 30 pixels from each lit cover and each occluded cover type randomly sampled to determine variations in their spectral radiance values.
- The mean radiance values of various UAV spectral channels were computed for each lit cover type and each occluded cover type to achieve this
- The computed descriptive statistics revealed significant variations in the mean spectral radiance values between lit and occluded land cover types across spectral channels of UAV sensor

	Blue	*Green*	*Red*	*NIR*	*Red edge*
Lit soils	*0.489*	*0.722*	*0.596*	*0.887*	*0.427*
Occluded soils	*0.001*	*0.001*	*0.001*	*0.002*	*0.002*
Occluded maize	*0.014*	*0.023*	*0.002*	*0.017*	*0.027*
Lit maize	*0.336*	*0.733*	*0.109*	*0.791*	*0.940*

Results

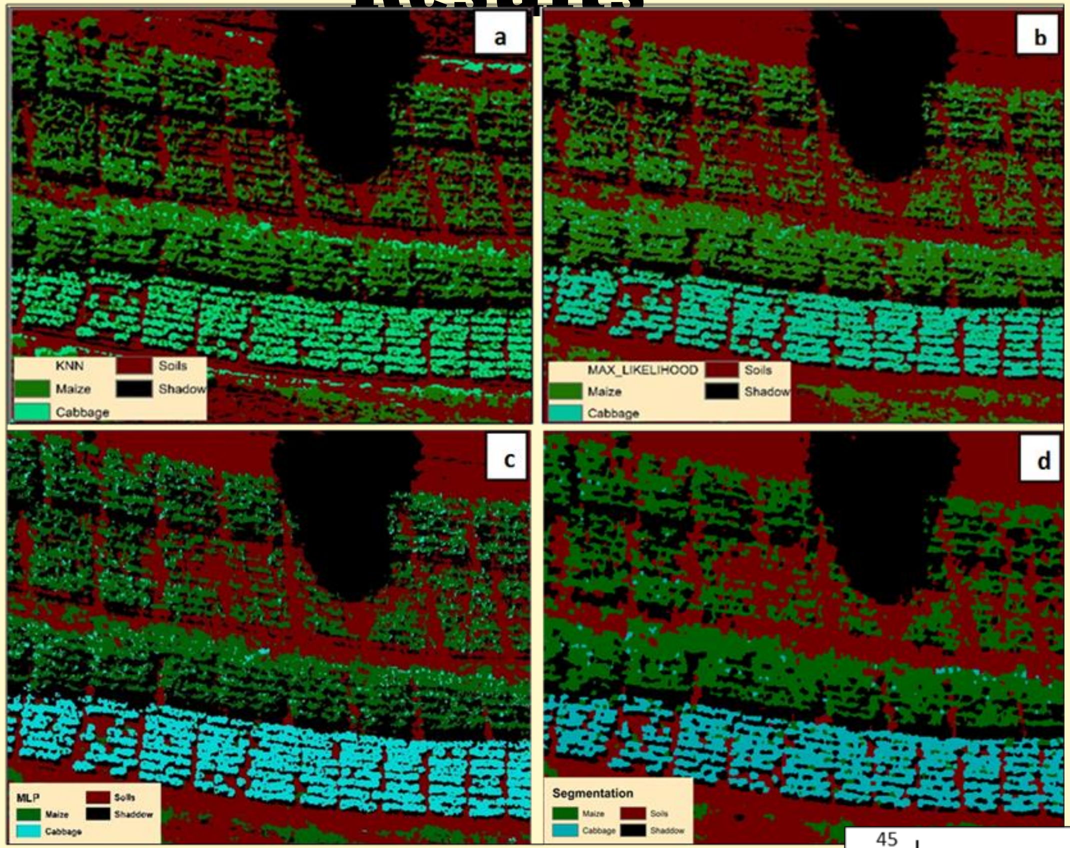
- **Spectral Vegetation Indices for Crop Characterization**
  - Some spectral vegetation indices such as GOSAVI (Figure d) and GNDVI (Figure f) showed inability to clearly distinguish crops from soils,
  - A distinction between crops and soils was clearly visible with spectral vegetation indices NDVI (Figure 6a), SAVI (Figure 6b), OSAVI (Figure 6c) and NDRE (Figure 6).
  - Although OSAVI demonstrated its ability to draw a clear distinction between crops and soils, it generalized crop in the occluded region as soils.
  - Subsequently, the occluded soils was overestimated.

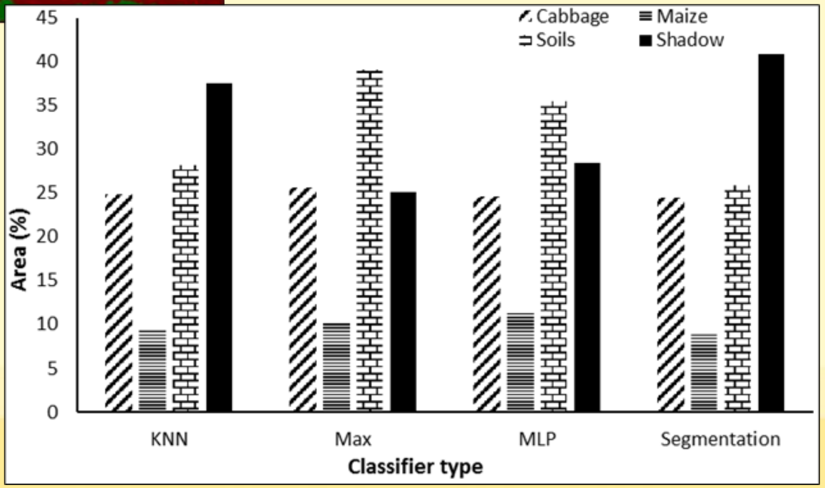


	NDVI	SAVI	OSAVI	GOSAVI	NDRE	GNDVI
Lit maize	0.762	0.706	0.643	0.041	-0.092	0.047
Occluded Maize	0.078	0.023	0.070	-0.026	-0.133	-0.174
Lit soils	0.194	0.243	0.176	0.103	0.371	0.115
Occluded Soils	0.086	0.001	0.004	0.006	0.468	0.157

Results

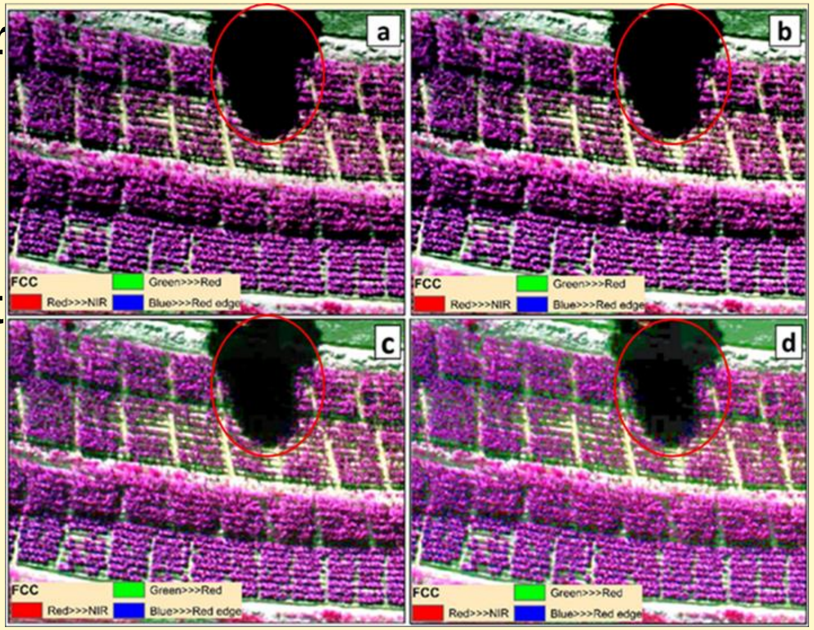
- **Spatial Pattern Analysis of Crops and Soils**
- Crops and soils were classified to determine the area which they cover.
- In this case, a shadow was also included as a land cover class, due to inability of the explored spectral vegetation indices to effectively detect both crops and soils in the occluded region
- Specific index could only effectively detect either crop or soils, or neither show soils nor crops

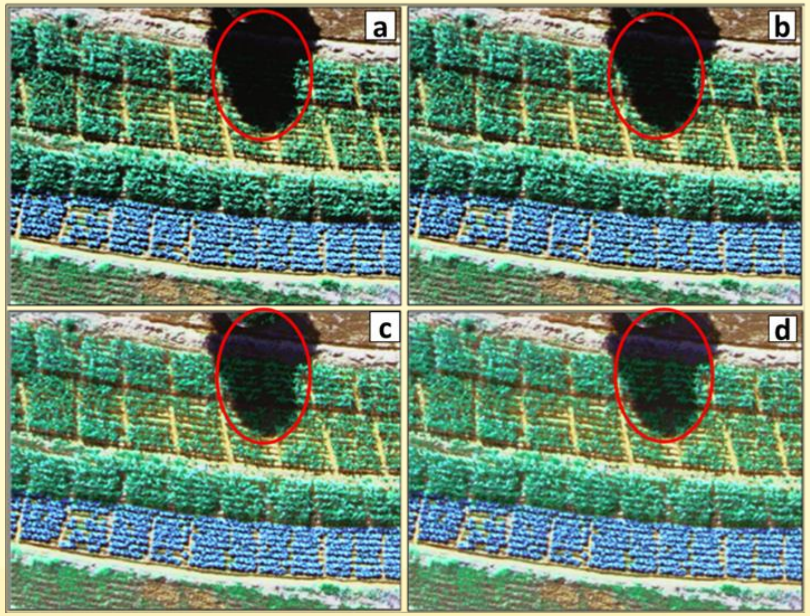




Results

- **Radiometric Compensation**
  - Radiometric compensation analysis of four threshold levels applied on both FCC and TCC
  - The brightness tuning results on FCC showed increased radiance intensity in lit region of the experimental site at T1, T2, T3 and T4 threshold levels
  - There was no radiometric restoration noted in the occluded region as expected
  - The brightness tuning results on TCC revealed gradual increase in radiance intensity in both lit and occluded regions of the experimental site as threshold level increased
  - It was subsequently noted that maize cultivars and soils were the only land feature types subjected to occlusion

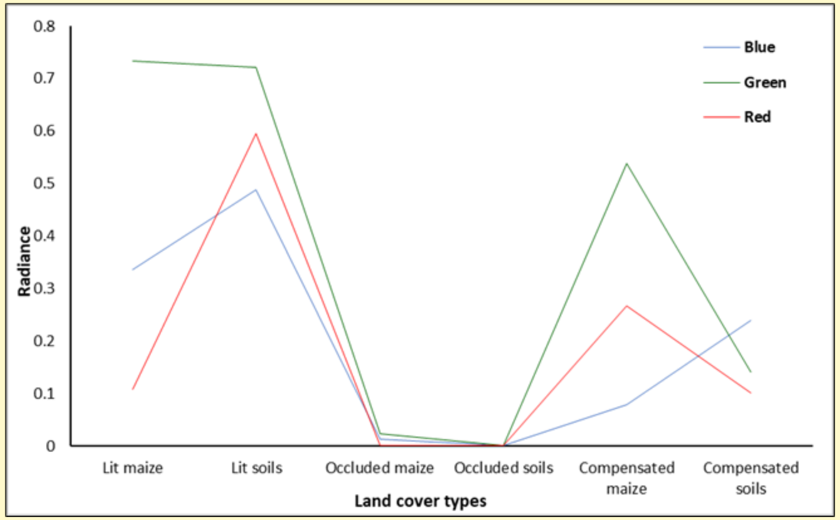




Results

- **Spectral Analysis of Radiometrically Compensated Maize and Soils**
- The restored spectral radiance samples of the occluded land futures were collected through digitization of point shapefile and extracting restored spectral radiance values on which the point shapefile was superimposed.
- The mean spectral radiance value of each occluded land feature was calculated and com-pared with the ones sampled on the lit region, and occluded region prior to radiometric restoration process
- The computed relative error of mean results for radiance comparison between lit and occluded region revealed 26.47% deviation of restored radiance of occluded maize from that of lit maize.

	Sunlit			*Occluded*			*Compensated*		
	Blue	*Green*	*Red*	*Blue*	*Green*	*Red*	*Blue*	*Green*	*Red*
Maize	0.336	0.733	0.109	0.014	0.023	0.002	0.079	0.539	0.267
Soils	0.489	0.722	0.596	0.001	0.001	0.001	0.24	0.141	0.102



	Blue	*Green*	*Red*
REM_{Maize}	76.49	26.47	153.21
REM_{Soils}	50.92	80.47	82.89

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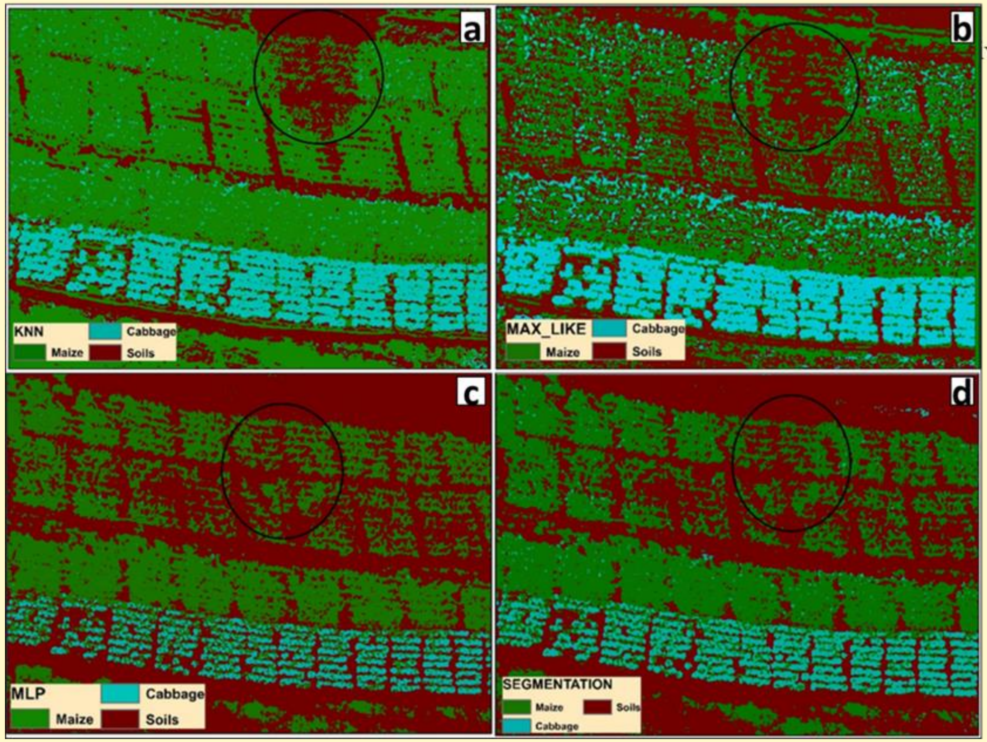
Results

- **Spatial Configuration of Land Feature Types Post Radiometric Compensation**
- land features were classified again, with a view to determine the lost area due to occlusion
- The oval shape in each classified image shows the radiometrically restored land features in the occluded region of the imagery
- areal analysis of different land features were carried out to evaluate the deviation of land feature areas post radiometric compensation process



	Area covered (%) pre-compensation				*Area covered (%) post-compensation*			
	KNN	*Max_Like*	*MLP*	*Segmentation*	*KNN*	*Max_Like*	*MLP*	*Segmentation*
Cabbage	*25.09*	*25.96*	*24.88*	*24.36*	*28.33*	*32.11*	*20.56*	*21.09*
Maize	*8.81*	*10.13*	*12.83*	*7.92*	*49.37*	*28.16*	*35.25*	*38.56*
Soils	*27.36*	*38.27*	*35.14*	*26.06*	*22.3*	*39.73*	*44.19*	*40.35*

Discussion

- Shadows are an unavoidable component of high-resolution remotely sensed imagery, and the impact of shadows will increase as the spatial resolution of the imagery increases
- This is even more difficult if the imagery is to be subjected to image classification process
- Several existing shadow removal methods have evaluated their results quantitatively, as no shadow free ground truth is available
- No technique can deal with a shadow projected in complex texture
- The results from visual and statistical assessments indicated a significant difference be-tween soil/vegetation indices in sunlit and shaded pixels
- This study did not employ field-based measurements to verify the precision of the estimated areal coverage of occluded crop.
- As such, the reliability of the classifiers was evaluated by visual comparison of the classified land cover types with those shown by TCC image.
- However, only ground based knowledge was employed in the recognition of land feature types without measurements

Conclusion

- This study has demonstrated the importance of radiometrically compensating the crops for informed quantification of their areal coverage
- The reliability of the proposed approach was evaluated by analyzing the relative error of mean results, which compared the mean spectral radiance of the compensated land features and those in sunlit area.
- Overall, the results of this study highlighted the significance of radiometrically compensating the occluded crops for their precise quantification.
- Ultimately, this study emphasized the on-going significance of remote sensing technology in addressing agricultural issues which hamper successful attainment of poverty alleviation and food security goals

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