STRATIFICATION: A PROBLEM IN RANGELAND MONITORING

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ABSTRACT:

Resource stratification for ground-based and remotely-sensed methods of rangeland assessment is essential for locating appropriate sampling sites. This is particularly the case when site comparisons are required, as in the case of grazing gradient analysis, wherein the objective is to limit the number of environmental variables. This study compared stratified units derived from supervised, unsupervised and object-based classification with pre-defined sites from visual interpretation of satellite imagery and discusses the advantages and disadvantages of these technologies for stratification as pre-consideration in ground-based and remotely-sensed studies. Landsat Thematic Mapper (TM) images have been used for this study. Derived strata were controlled by the collected data prior to image interpretation from 30 systematic sampling sites (5 paddocks and 6 distances from water points) at Middleback Field Center in South Australia. Allocated time for pixel- and object-based stratification is very low compared with the manual interpretation. Overall accuracy and Kappa statistics for pixel-based classification was very low (<33%). Overall, the object-oriented method provided results with more accuracy (50%) in comparison with pixel-based classification, indicating that object-oriented image analysis has more potential for stratification of arid rangelands. However, results from an ecological perspective need further investigation using high spatial resolution imagery and with more samples for ground-truthing. This may create more reliable and robust results.

1. INTRODUCTION

Natural ecosystems are complex and dynamic, and interact with each other. For monitoring these ecosystems, decisions about where to measure (Friedel, 1991; Wright *et al.*, 2003) to overcome the difficulty of patchy distribution of vascular plant and soil components are important (Brook *et al.*, 2001; Edwards *et al.*, 2005). These ecosystems/communities do not have discrete boundaries, and they usually have an ecoton zone where the magnitude depends on ecological factors. These ecosystems can range from intact or natural systems through to those heavily modified by human activity, such as high grazing pressure (Bastin *et al.*, 1993; Pickup & Chewings, 1994). Human activities can influence character and the delineation of some types of ecosystem characteristics. In some situations human activities have historically been persistent, considerably influencing the ecological processes and character of a landscape. The permanent influence of grazing pressure around watering points is one of these well defined significant characteristics in rangelands of Australia (Bastin *et al.*, 1993; Pickup & Chewings, 1994). Ideally, the boundaries reflect factors that control landscape distribution at various scales, such that they can be recognized, compared and applied according to the human activities and other natural disturbances. For example, the boundary between the shrubland and the adjacent woodland dominated eco-district may be due primarily to the lack of vegetation caused by exposure to extreme soil texture conditions and grazing pressure, particularly in the early stages of regeneration of woodland components. Landform pattern with its geologic substrate, surface shape and relief are also important criteria for establishing boundaries. The challenge is to depict the complexity of ecosystems through appropriate map units in the process of stratification. Stratification is a way of identifying and classifying heterogeneity according to the objectives, tools and financial limitations. A number of studies have emphasized that stratification can improve precision and accuracy of spatial sample collection in ground-based and remotely-sensed methods (Bastin *et al.*, 1998; Brook *et al.*, 2001; Wright *et al.*, 2003; Edwards *et al.*, 2005). Spatial data collection can contribute up to 80% of the cost of deploying a monitoring system (Wright *et al.*, 2003). Stratification ensures that the relative contribution of a particular vegetation community or soil/geomorphology type to a study area is (is not) taken into consideration when the total area is measured. In ground-based methods air-photo or satellite imagery is visually interpreted and stratified as pre-typing of rangeland ecosystem for sampling different objectives (Poulton, 1975). Bastin *et al.* (1998), when using a remotely-sensed-based grazing gradient method, concluded that large paddocks generally contain several landscape types which vary in the palatability of forage available to livestock, and these must be identified and mapped before using a grazing gradient method. Brook *et al.* (2001) concluded that stratification is essential for obtaining meaningful results using the grazing gradient method. Overall in ground-based and remotely-sensed approaches to site comparison there is a need to undertake stratification regardless of the type of indicator being utilized. This project was a part of a major project with the aim of stratifying the study area to define shrubland dominant communities for Biological Soil Crusts (BSC/ small soil surface organisms such as lichens and mosses) monitoring under grazing pressure in the framework of grazing gradient using site comparison in different distances of water points by avoiding woodland dominant communities, sandy soils, and water course and crest land forms. For that purpose pre-field visits, visual interpretation of Landsat 5 TM imagery and post field checks were considered. Visual interpretation and digitizing point by point, regardless of its reliability and robustness is a difficult task, time consuming and cost ineffective, particularly for a rangeland ecosystem with low economic value. Thus, a case study with the aim of examining and comparing pixel-based (supervised and unsupervised) classification, and object-based classification for defining sample locations for later use in ground-based and remotely-sensed ecological studies such as

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BSC monitoring was undertaken to test the capability of these technologies to separate shrubland communities from other strata as a substitute for traditional visual image interpretation. Visual interpretation and ground truthing were used as reference source data for accuracy assessment.

2. METHODS

2.1 The Study Area

The study was conducted at Middleback Field Center (MFC), in the pastoral region of the South Australian chenopod shrublands, approximately 400 km north-west of Adelaide and 15 km north-west of Whyalla (Figure 1). Much of the structural geology of the study area has been characterized by fluvial and aeolian deposits of late Tertiary and Quaternary origin (Laut *et al.*, 1977). The soils which are derived from these parent materials were mainly brown calcareous earths with calcium carbonate accumulated at variable depths, usually within the first 50 cm (Laut *et al.*, 1977). The topography of the study area is low and gently undulating (Figure 2), and is characterized by a recurring system of inter fluvial slopes, plains, washes and basins (Laut *et al.*, 1977). The vascular plants are predominantly chenopod shrubland consisting of bushes and woodlands (Wilson & Graetz, 1979). The annual plant community is relatively diverse from year to year. Finally, lichen and moss components are distributed on the interspace of woody plants (Rogers & Lange, 1971). This study was conducted in five replicate paddocks with one watering point including Balah, Billabong, Purpound and Railway paddocks from Roopena lease and Corio from Kutanga lease (Figure1).
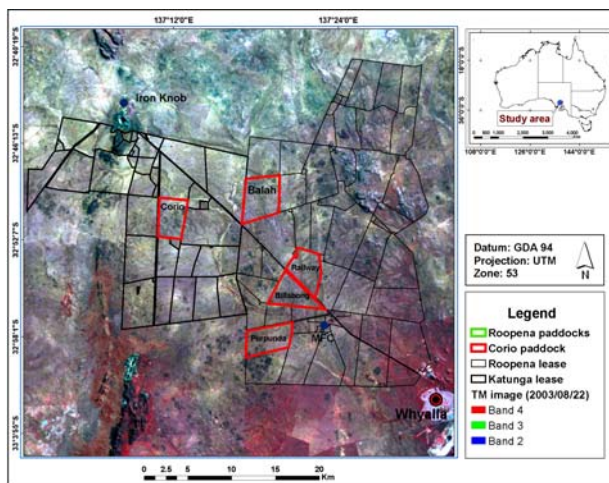

Figure 1 The study area, MFC and study paddocks, 20 km north-west of Whyalla, South Australia

2.2 Existing Stratified Resources at the Study Area

The study area is situated on one land system and three land units (Figure 3) including: 4.2, gently undulating calcrete plains with occasional quartzite or granite hills, low open woodland and mallee scrub; 4.6, calcrete plain with occasional conglomerate hills and tidal flats with low open woodlands; 4.7, conglomerate hills with long dissected foot-slopes, low open woodlands and chenopod understorey (Laut *et al.*, 1977). As can be seen from the map (Figure 3), the extent of the study paddocks in comparison with existing land units are very small with high

variation in both vascular plant and soil attributes within each paddock, and some previous studies used land system and land units with these heterogeneities as the base for their sample collection and site comparison because of the lack of a suitable map and difficulty of producing a new stratified map for grazing gradient analysis using visual interpretation (Cameron & Lewis, 1996). Therefore stratification within paddocks for BSC monitoring using a suitable method is essential.
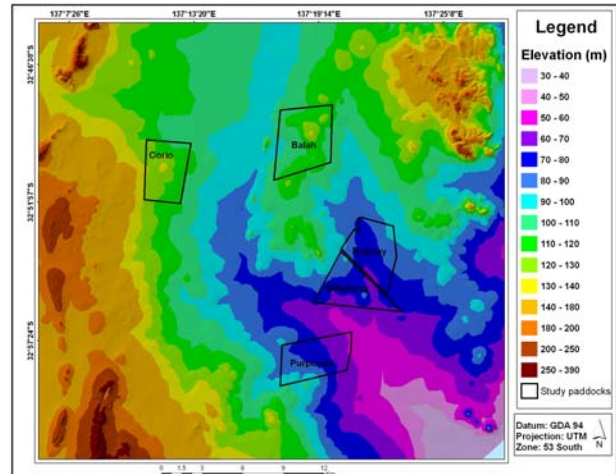

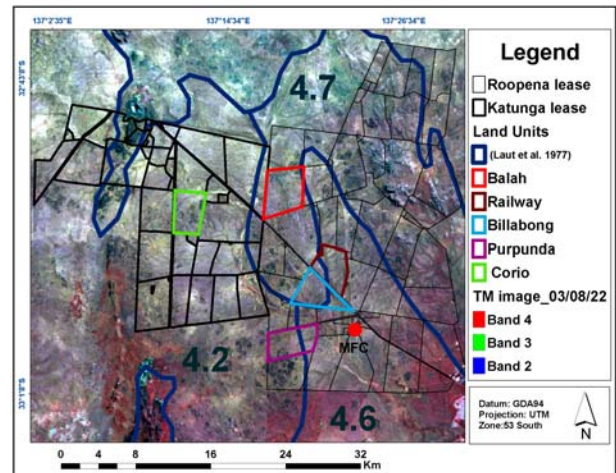Figure 2. Digital elevation model of the study area

Figure 3. The existing stratified map in comparison with the study paddocks

2.3 Spatial Data

A 60 × 60 km © Landsat 5 TM image Copyright (2004) for the study area was acquired on 22 August 2003 providing 6 bands: three in the visible and three in the near infrared, mid and short infrared. Geometric correction of the imagery was undertaken using © ERDAS Imagine v8.7 Copyright (Leica Geosystems GIS & Mapping LLC, 2003) subseted for the study area and placed into a map coordinate system which is the same, that being the Australian Geodetic Datum 1994 (AGD94). Spatial layers such as land unit's map (Laut *et al.*, 1977) (scanned and digitized / Figure 3) and Digital Elevation Model (DEM) (Figure 2), were created

using © ArcGIS Copyright (ESRI, 2004). DEM was constructed using © contours and associated spot heights Copyright (DEHAA, 2004). Drainage enforcement was applied but streams were not used as an input due to their poor definitions and lack of continuity, with attempts to use streams leading to spurious results. In the final stage stream lines were used to check the visual accuracy of the produced DEM.

2.4 Visual Interpretation of Landsat Data

As mentioned the principle objective of the main project was BSC monitoring using ground-based and remotely-sensed methods on the chenopod shrublands. Chenopod shrubland bioregion is diverse and patchy (Wilson & Graetz, 1979) and BSC varying in small areas (Rogers & Lange, 1971). From reconnaissance field visit there was high relationship between BSC distribution and shrubland communities and negative relationship with woodland dominated communities. Moreover, there was negative relationship between BSC and some landform such as crest and water courses, and sandy soil texture. Thus stratification using visual interpretation aimed to separate this diversity and delineate shrubland community for sample locations (Poulton, 1975; Campbell, 2002) using ArcGIS and ground truthing (a 100 m line-intercept method used for ground data collection) by a systematically defined sampling sites in five paddocks and six distances with the priority of shrubland community for site selection. For this paper, pixel-based and object-based techniques were examined for their reliability and robustness for stratification as compared with visual interpretation.

2.5 Pixel-based Classification

The pixel-based standard supervised and unsupervised classifications (Campbell, 2002) were conducted using ERDAS Imagine. Supervised classification undertaken using the Maximum Likelihood algorithm (Campbell, 2002). The process involved the selection of training areas representative of the seven land cover classes including bare ground, patch-shrub-woodlands, woodland, shrub-woodlands, wood-shrublands and water course as the major strata on the study area. A number of training areas were selected to represent each class. The signature of the training area was then used to determine to which class the pixels were assigned.

2.6 Object-based classification

The object-oriented classification undertaken using © eCognition v4 Copyright (2005). The process can be split into two steps: segmentation and classification.

2.6.1 Multiresolution Segmentation

The subset images were segmented into smaller regions (object primitives) or segments on 2 scale levels (Table 1 & Figure 4) to simplify thematically complex data content. The segmentation of the images into objects was influenced by three parameters: scale, colour/shape ratio and form/spatial properties (smoothness / compactness ratio) (Baatz et al., 2004). The scale parameter set by the operator is influenced by the heterogeneity of the pixels. The colour parameter is a balance between the homogeneity of a segment's colour and the homogeneity of its shape. The form parameter balances the smoothness of an object's border with its compactness (Whiteside & Ahmad, 2004). The homogeneity

criterion for the objects was established in the weighting of these parameters. The image objects were based on parameters such as the spectral characteristics of pixels, the size and shape of the objects determined at each scale level. The homogeneity criterion for the objects is established in the weighting of these parameters. A visual inspection of the objects resulting from variations to parameter weighting was used to determine the overall values for the weighting of the parameters at each scale level.

2.6.2 Classification

Training sample objects were selected as representative of land cover classes from segmented components. A total of seven defined strata for the study paddocks were classified from visual interpretation and field checking based on the structural formation of the biophysical components. Objects were assigned class rules using spectral signatures, shape and contextual relationships. These rules were then used as a basis for classification of image data. The image was classified using fuzzy logic (Baatz et al., 2004). After classification image objects have degree of membership to several classes. The class with the highest membership value was assigned as the best class for each object (Baatz et al., 2004).

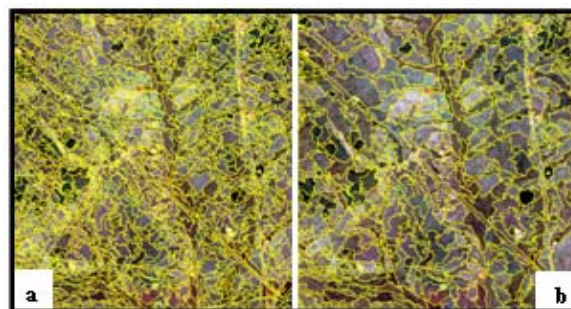| Scale level	Scale parameter	Shape factor	Compactness	Smoothness
2	10	0.05	0.02	0.98
1	5	0.05	0.02	0.98

Table–1. Segmentation parameters

Figure 4. Segmentation, a) Level 1 and b) Level 2 for Billabong and Railway paddocks (see Table 1 for segmentation parameters)

2.7 Accuracy Assessment

Accuracy assessments of both classifications were undertaken using confusion matrices and Kappa statistics (Congalton & Green, 1999). The accuracy of the classified image was assessed using field data collected in the study area over a two- year period and visual interpretation of Landsat 5 TM imagery. Producer and user accuracies for each class were calculated along with the overall accuracies and Kappa statistics. It should be noted that, because of the main project objective, which was to avoid bare ground, sandy soil, woodland community and water courses and crest land forms, accuracy assessment and ground truthing in mentioned communities and landforms was not considered, and ground truth data were not collected for those strata. See Table 2 for number of ground truth samples for each stratum.

3. RESULTS

3.1 Stratified Results from Visual Interpretation

Results of visual stratification in five paddocks (Figures 5) showed that 44% of the selected sites were established on shrubland communities. A further 30%, 13%, 10% and 3% of total sites were established on shrub-woodland, patch-shrub-woodlands, wood-shrubland and woodland communities respectively. Overall, 87% of the selected sites were established in communities with a dominance of shrub components. There were road accessibility and distances limitations to select all sample locations on shrubland communities. The accuracy of the selected sites by ground truthing was 100% as reference data.

3.2 Stratified Resources from Pixel-based Classification

3.2.1 Unsupervised Classification

Raw results of unsupervised stratification in five paddocks (Figure 6) showed that 34% of the selected sites were established on shrubland communities and a further 13%, 13%, 13%, 10% and 3% of total sites were established on shrub-woodland, patch-shrub-woodlands, wood-shrubland, woodland and water course communities respectively. Overall, accuracy of the selected sites is described in Section 3-4.

3.2.2 Supervised Classification

Raw results of supervised stratification in five paddocks (Figure 7) showed that 60% of the selected sites were established on shrubland communities. A further 20%, 17% and 3% of total sites were established on shrub-patches, water course and woodland communities respectively. However, accuracy of the selected sites was much lower than the presented data for both supervised and unsupervised classifications. See Section 3-4 for accuracy assessment results. It should be noted that, although in advance sample locations were meant to be established on a homogeneous landscape, sample locations along a 100 m line-intercept did not exhibit a completely homogeneous pattern, and in some cases pixel values were different, so in these cases major land cover was considered as the representative of the sites in the accuracy assessment.
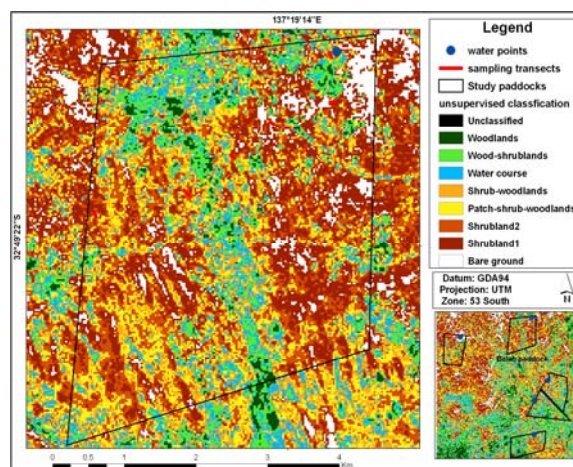

Figure 5. The visual interpretation and stratification: an example Balah paddock

Figure 6. Unsupervised classification: as an example Balah paddock
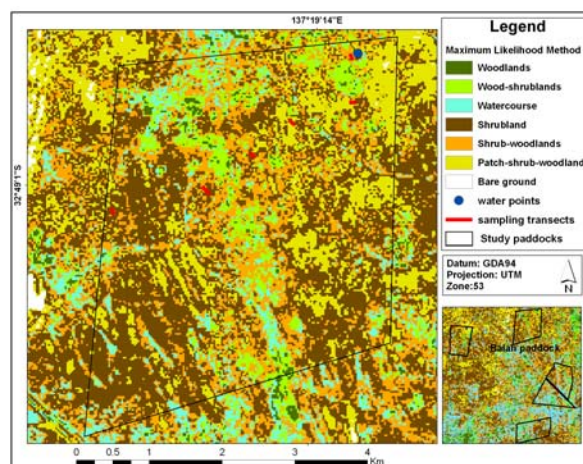
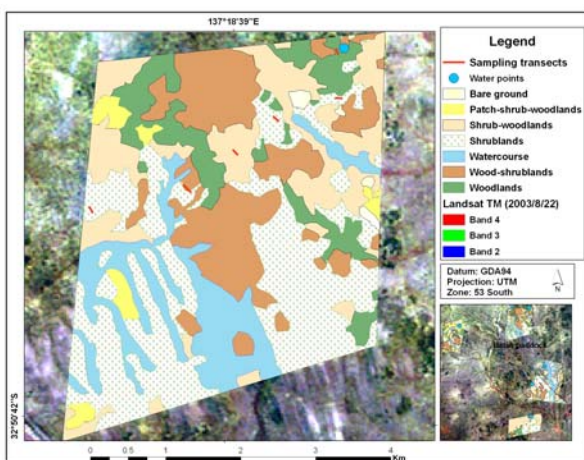Figure 7. Supervised classification as an example Balah paddock

3.3 Stratified Recourses from Object-based Classification

At scale level 2, a total of seven land cover classes were classified for the study area. These classes were based upon the vegetation characteristic and knowledge of the area from ground-based studies for BSC monitoring. At scale level 1 also a total of seven land cover classes were classified based on the structural formation of the pre-defined land cover. Class rules for the objects were then developed using spectral signatures, shape, location and the contextual relationships of the objects. Selected image objects were then used as samples for each class to act as training areas for the classification process. The image resulting from the object-based classification is shown in Figure 9. The accuracy of classified strata is presented in Section 3-4.

3.4 Results of Accuracy Assessment

The results of the confusion matrix accuracy assessment are summarized in Table 2. Overall accuracy for pixel-based classification are very low (<33%) and for object-based classification was also low (50%). In object-based classification

Producer's accuracy particularly for shrubland and shrub-woodland strata was low in comparison with user's accuracy. Overall Kappa statistics for object-based classifications were very low and for object-based was also low (0.37). Overall Kappa for different strata was low, but in object-based classification for shrubland and shrub-woodlands strata, which was important from this study perspective were 0.57 and 0.37 respectively, and for woodland was high (1).
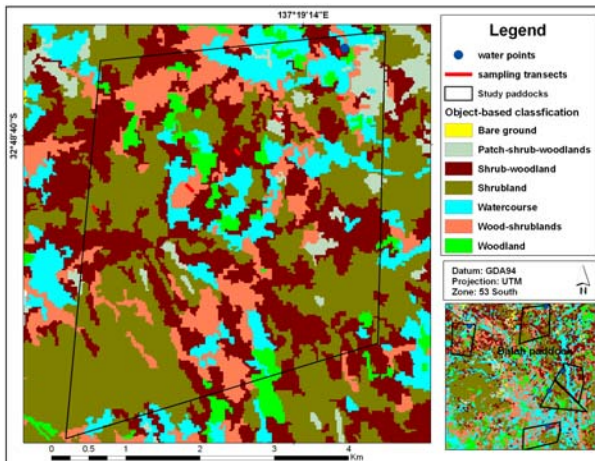

Figure 8. Object-based classification as an example Balah paddock

4. DISCUSION ANS CONCLUSION

4.1 Capability of Pixel and Object-based Stratification as a Surrogate for Visual Interpretation Method

Resource stratification for ground-based and remotely-sensed methods of rangeland assessment is essential for locating appropriate sampling sites. This is particularly the case when site comparisons are required, as in the case of grazing gradient analysis, wherein the objective is to limit the number of environmental variables. Remote sensing offers an opportunity to provide a means by which stratification can be implemented, via the use of image classification. However, despite significant advances in remote sensing technologies over the last 15 years, rangeland stratification still is a problem and needs to be solved (Bastin *et al.*, 1998; Brook *et al.*, 2001). Indeed reliable stratification from imagery is still based on traditional visual interpretation and manual digitizing point by point. In spite of the high reliability and robustness of this method, it is time consuming and can outweigh the financial benefits of monitoring when extensive areas involved, especially where land management goals are primarily environmental (Bastin *et al.*, 1998; Brook *et al.*, 2001; Wright *et al.*, 2003). Our results in support of Whiteside and Ahmad (2004) conclude that pixel-based remote sensing has more limitations for stratification in ground-based and remotely-sensed studies. The object-based technique provided results with more accuracy than the pixel-based classification. This suggests that object-oriented analysis has more potential for extracting strata information from satellite imagery captured over chenopod shrublands in South Australia. This will be the case particularly with the increasing application of higher resolution imagery such as IKONOS and the greater spatial information content it holds to undertake a further level of

segmentation and to conduct a classification of a much larger area. The visual difference between the classifications is obvious. Pixel-based classifications do misclassify pixels, particularly in land covers that are spectrally heterogeneous, such as water course land forms and mixed vegetation communities such as shrub-woodlands or wood-shrublands. Object-based classification appears to overcome some of the problems encountered using pixel-based methods to classify strata, while there is evident that pixel-based classification is still quite successful in classifying land cover of a homogenous nature (i.e. closed black oak / woodland / Figure7). To improve the accuracies of the object-based classification, further work refining the process should be continued. The use of multispectral and ancillary data, such as DEM layers, is being investigated. The precision of data used for DEM was 10 meter (vertical /horizontal). However, according to the topographic pattern of the study area the constructed DEM does not depict the landscape details such as crest landforms and water courses precisely required at the paddock level. Thus a topo-gird information at least with vertical precision of 1 to 2 m and horizontal precision of 5 to 10 m are required, particularly for strata characterization. There is also to be further development of the contextual information to be applied to objects. While the accuracy of most classes was not reasonable or lower, the classification of some classes was satisfactory. Further research is required to refine the scale parameters used within the segmentation process. Although, our results showed better results for object-based classification in comparison with pixel-based classification, there are some difficulties and results are far behind an acceptable standard stratified units for ecological studies such as BSC monitoring. Because there is high possibility even using object-based classification to obtain bias results, particularly for the landforms such as water courses and mixed vascular plant structure. Time allocation in both pixel-based and object-based stratification is considerably low. However using both techniques for large areas with heterogeneity pattern create difficulties with classifying different land cover with similar spectra. Moreover, ground-truthing of pixel or object-based procedures for large geographical extents and low economic value rangeland ecosystems could still be of concern. The accuracy of stratification, depended on many issues, including the familiarity of the analyst with the pattern and distribution of different land cover components (e.g. woodland, shrubland, water courses), as well as familiarity with their spectral and spatial patterns on the remote sensing imagery. Additionally, further issues affecting accuracy of results included the selection of segmentation parameters such as those for scale and shape. In particular, the classification accuracies of the mixed woodland and shrubland classes were exceptionally low. In the accuracy assessment ground-truth data for bare ground and water course were not collected and for woodland, patch-shrub-woodlands and wood-shrublands were within the confusion matrix is partially attributed to the low number of points selected (only 1 to 4).

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Pre-defined class name	Visual interpretation (reference source)	Unsupervised classification		Supervised classification		Object-based classification		
		Producer (%)	User (%)	Producer (%)	User (%)	Producer (%)	User (%)	Kappa
Bare ground	0	-	-	-	-	-	-	-
Patch-shrub-woodlands	4	33	17	50	33	50	50	0.07
Shrublands	13	40	55	40	55	43	75	0.57
Shrub-woodlands	9	13	25	25	25	50	67	0.37
woodlands	1	0	0	0	0	100	50	1
Wood-shrublands	4	0	0	0	0	67	40	0.22
Water course	0	-	-	-	-	-	-	-
	Overall accuracy = 100%	Overall accuracy =27% Overall Kappa =0.03		Overall accuracy =33% Overall Kappa =0.09		Overall accuracy =50% Overall Kappa =0.37		

Table–2. Summary of confusion matrices for the accuracy of pixel-based (unsupervised & supervised) and object-based stratification /classification (accuracy assessment was not undertaken for bare ground and water course classes)

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