Remote sensing of 10 years changes in the vegetation cover of the northwestern coastal land of Red Sea, Saudi Arabia

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Abstract
Accurate and up to date land use and land cover (LU/LC) changes information is the main source to understanding and assessing the environmental outcomes of such changes and is important for development plans. Thus, this study quantified the outlines of land cover variation of 10-years in the northwestern coastal land of the Red Sea, Saudi Arabia. Two different supervised classification algorithms are visualized and evaluated to preparing a policy recommendation for the proper improvements towards better determining the tendency and the proportion of the vegetation cover changes. Firstly, to determine present vegetation structure of study area, 78 stands with a size of 50 × 50 m were analysed. Secondly, to obtain the vegetation dynamics in this area, two satellite images of temporal data sets were used; therefore, SPOT-5 images were obtained in 2004 and 2013. For each data set, four SPOT-5 scenes were placed into approximately 250-km intervals to cover the northwestern coastal land of the Red Sea. Both supervised and non-supervised cataloguing methods were attained towards organise the study area in 4-major land cover classes through using 5 various organizations algorithms. Approximately 900 points were evenly distributed within each SPOT-5 image and used for assessment accuracy. The floristic composition exhibits high diversity with 142 species and seven vegetation types were identified after multivariate analysis (VG I: Acacia tortilis-Acacia ehrenbergiana, VG II: Acacia tortilis-Stipagrostis plumosa, VG III: Zygophyllum coccineum-Zygophyllum simplex, VG IV: Acacia raddiana-Lycium shawii-Anabasis setifera, VG V: Tamarix aucheriana-Juncus rigidus, VG VI: Capparis decidua-Zygophyllum simplex and VG VII: Avicennia marina-Aristida adscensionis) and ranged between halophytic vegetation on the coast to xerophytic vegetation with scattered Acacia trees inland. The dynamic results showed rapid, imbalanced variations arises between 3-land cover classes (areas as urban, vegetation and desert). However, these findings shall serve as the baseline data for the design of rehabilitation programs that conserve biodiversity in arid regions and form treasured resources for an urban planner and decision makers to device bearable usage of land and environmental planning.

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1. Introduction
Distribution and structure of vegetations are major components in the function of coastal ecosystems that offer numerous important ecosystem services in many regions of the globe (Arshad et al., 2018). In the recent years of Saudi Arabia at the Red Sea, the costal vegetation degradation has been increased in the last years. The current vegetation is affected by the increasing aridity due to climate change and anthropogenic factors such as urbanization (El-Sheikh et al., 2019). The consideration in present trend of
vegetation alterations will lead to the potential necessity of sustainable management of natural habitats in the coastal lands. In addition to the increasing aridity, the urbanization in Saudi Arabia represents a major land type of land transformation, which has been regarded as one of most important challenges for the conservation of natural vegetation lands from urban lands (El-Sheikh et al., 2019). The applications of change detection and the monitoring of land-use/land-cover (LU/LC) varies and applied in multiple fields associated with (i) land degradation and also desertification (Adamo and Crews-Meyer, 2006; Gao and Liu, 2010) (ii) urban sprawl (Shalaby and Tateishi, 2007), (iii) urban landscape of outlined changes (Dewan and Yamaguchi, 2008; Batisani and Yarnal, 2009; Elhag et al., 2013).

The common practice of remote sensing data analyses are anomaly detection, quantification and the mapping of LU/LC patterns and changes due to its availability and high degree of accuracy (Lu et al., 2004; Chen et al., 2005; Geymen and Baz, 2008; Abd El-Kawy et al., 2011). Numerous techniques have been accomplished for change detection which have been formulated, applied and estimated. The common principle method for the detection of LU/LC change is to compare two or more successive imagerys covering the same area at different dates of acquisition (Lu et al., 2004). The detection of change is basically employing one of two basic methods (i) pixel-to-pixel comparison and (ii) post-classification comparison (PCC) (Lu et al., 2004). The PCC method is the highly accurate used for altering detection technique which identifies LC “land cover” changes through independently comparing the classification maps from different dates (Singh, 1989; Yuan et al., 1998). Temporal data are independently classified; therefore, direct comparability does not require any further adjustment (Singh, 1989; Coppin et al., 2004; Rivera, 2005; Zhou et al., 2008; Green, 2011). The PCC method has an additional advantage of indicating the nature of changes thematically (Mas, 1999; Yuan et al., 2005).

The exact and updated LU/LC variation data is required for understanding and evaluating the environmental consequences of specific changes (Giri et al., 2005) and is tremendously important for any kind of sustainable development program in which LU/LC serves as one of the important input criteria (Abd El-Kawy et al., 2011). Moreover, analysis and mapping over for both the current LU/LC situations and the changes in LU/LC over time is considered a major to better understand and provides solutions for specific problems such as economic, environment and social issues (Lu et al., 2004; Pelorosso et al., 2009). The valuation of the magnitude and pattern of different land cover types is a necessity for projecting the future of vegetation cover and land development, especially when the major land cover in the study area is rainwater dependent natural vegetation (Jensen et al., 1995). The remote sensing data is in the form of satellite images, in conjunction with Geographic information system (GIS), which has been widely applied and recognized as a powerful tool in detecting land cover changes (Jensen et al., 1995; Lu et al., 2004; Chen et al., 2005; Geymen and Baz, 2008; Wang and Xu, 2010).

In general, the current study enumerated the LU/LC patterns of the last decade in northwestern coastal region of Red Sea. The objectives are set primarily to evaluate and visualize couple of various supervised classification algorithms and to supply the recommended policies for an accurate enhancement towards better determining the tendency and the proportion of vegetation cover changes. This current study results would be relevant globally due to the extrapolated to comparable ecosystems in another planets. Moreover, the findings of the present study form valuable resources for an urban planners and decision makers to devise sustainable usage of land and environment planning for designing of rehabilitation programs that converse biodiversity in arid regions.

2. Materials and methods

2.1. Study area

The study area extends from Jeddah (N 21°46'41.4" E 39°08'36.8") to Haql (N 29°16'39.5" E 34°56'17.8") covering a distance of roughly 1174 km along the Hijaz mountains which located on the Arabian shield and encompass the mountain range at the northwestern part of Saudi Arabia, stretching out along the Red Sea coast. At the east, the mountain range is bordered through the Tihamah i.e., coastal region, which consists majorly of sand plains with varying soil depths and salts concentration. This area was selected because of its high importance in biodiversity conservation resulted from the presence of different unique habitats (coastal wetted habitats, sandy plains, inland desert, alluvial wadis, networks, and rocky foothills) and plant species.

2.2. Data sampling of current vegetation

Seventy-eight stands with a size of 50 × 50 m at the coastal area from Jeddah to Haql (~1174 km) were selected at spring of 2014 to represent all habitat variations and analyse the vegetation structure of the study area. In each stand, species were listed and identified according to Chaudhary (1999–2001), and their life forms were classified. The plant cover value of all species in each stand was estimated as abundance cover % according to Kent (2012). To obtain the vegetation groups; the two-way indicator species analysis (TWINSPAN) and the detrended correspondence analysis (DECORANA) programs (Hill, 1979a,b) of multivariate analysis was applied on the matrix data-set (78 stands × 142 species cover values).

2.3. Field survey for vegetation cover changes

The current study area was surveyed with the aim of mapping the existing natural vegetation cover changes. Two transects were laid out: one between the Hijaz Mountains and the coast and one at the eastern side of the Hijaz Mountains. The western transect was laid out along the Saudi Arabian highway 5 between Jeddah and Haql. The eastern transect followed highway 15 and highway 328, starting between Makkah and Medina and ending before Al-Ula. The stand locations were chosen to cover most of the apparent variation in vegetation and habitat (Elhag and Bahrawi, 2014a,b). Stands were selected through subjective judgement. The upper sectors of the mountains represent a translational zone between the monsoon and Mediterranean climates, which is influenced by the proximity to the Red Sea and the mountain range (Abd El-Ghani, 1997). In the lowlands, the climate is dry, with rainfall not exceeding 100 mm each year. This leads to the lowlands generally having more scarce vegetation, except for wadis, which have traditionally represented a richer ecosystem than the surrounding desert plains (Kassas and Imam, 1954).

2.4. Dataset

Two temporal sets of SPOT-5 images were acquired in 2004 and 2013. Each dataset was comprised of four consequent images of Saudi Arabia’s west coast from Haql north to Jeddah south (Fig. 1).

2.5. Image classification process

In a SPOT satellite image, the spectral brightness of each picture elements (pixel) is recorded in four (SPOT-5) different wavelength bands. A pixel is characterized by its spectral signature, which is determined by the relative reflectance in the different wavelength
bands. Multispectral classification is an information extraction process that analyses the spectral signatures and then separates pixels into categories based on similar signatures (Briem et al., 2002). Image classification has become an important part in the fields of remote sensing, image analysis, and pattern recognition (Kloer, 1994; Richards and Richards, 1999).

2.6. Classification methods

Generally, there are two classification methods: the unsupervised classification and the supervised. Unsupervised classification proceeds with only minimal interaction with the analyst. On the other hand, supervised classification procedures require considerable interaction with the analyst, who must guide the classification by identifying small regions on the image that are known to belong to each category.

2.6.1. Unsupervised classification

Unsupervised classification is a computer-implemented process through which each measurement vector is assigned to a class according to a specified decision rule, where in contrast with supervised classification, the possible classes have been defined based on inherent data characteristics rather than on training samples (Swain and Davis, 1981). Based on the calculation of the Optimum Index Factor (OIF), the algorithm used to compute OIF for any subset of channels follows Chavez et al. (1982):

\[
OIF = \frac{\sum_{k=1}^{K} s_k}{\sum_{j=1}^{J} \text{Abs} \left( r_j \right)}
\]

where

- \( s_k \) is the standard deviation from channel \( k \), and \( r_j \) is the absolute value of the correlation coefficient between any of the two channels being evaluated.

2.6.2. Supervised classification

Supervised classification is a computer-implemented process through which each measurement vector is assigned to a class according to a specified decision rule, where the possible class have been defined based on representative training samples of known identity (Swain and Davis, 1981). The first step in the supervised classification is to select training sites for each of the terrain categories. Two different supervised classification algorithms are used in the current research study, namely, Maximum Likelihood - ML and Support Vector Machine - SVM. Maximum Likelihood classification is performed according to the following equation:

\[
g_i(x) = \ln \left( p(o_i) \right) - \frac{1}{2} \ln |\Sigma| - \frac{1}{2} (x - m_i)^T \Sigma^{-1} (x - m_i)
\]

where

- \( i \) is class;
- \( x \) is \( n \)-dimensional data (where \( n \) is the number of bands);
- \( p(o_i) \) is the probability that class \( o_i \) occurs in the image and is assumed the same for all classes;
- \( |\Sigma| \) is the determinant of the covariance matrix of the data in class \( o_i \);
- \( \Sigma^{-1} \) is its inverse matrix; and
- \( m_i \) is mean vector.

Support Vector Machine is performed according to the following equation:

\[
K(x, x_j) = \tanh (g \alpha x_j + r)
\]

where

- \( g \) is the gamma term in the kernel function for all kernel types except linear, and \( r \) is the bias term in the kernel function for the polynomial and sigmoid kernels.

2.7. Classification accuracy assessment

A total number of 900 points of ground truth data were collected from January to March 2014, and the points encompass the major land use/land cover in the study area. The points were evenly distributed along the study area (225 points per scene). The points were converted into 50 m² polygons under the GIS environment for accessibility reasons. Validation points were individually assigned to four different land cover categories: sea, mountain, desert and vegetation. The points were used to calculate user’s, producer’s and overall accuracies. The producer’s accuracy is calculated as follows:
Producer accuracy = \frac{C_{aa}}{C_{ii}} \times 100\% \quad (4)

where

\( C_{aa} \) is the element at position \( a^{th} \) row and \( a^{th} \) column, and \( C_{ii} \) is the column sum.

The user's accuracy is calculated as follows:

User accuracy = \frac{C_{ii}}{C_{ii}} \times 100\% \quad (5)

where

\( C_{ii} \) is the element at position \( a^{th} \) row and \( a^{th} \) column, and \( C_{ii} \) is the row sum.

Overall accuracy is calculated as follows:

User accuracy = \frac{\sum C_{aa} C_{ii}}{Q} \times 100\% \quad (6)

where

\( Q \) and \( U \) are the total number of pixels and classes, respectively. Matching of the user's and producer's accuracies delivers precision to the classification and assures a robust liability of the implemented accuracy assessment (Cohen, 1960; Congalton, 1991). \( K_{\text{hat}} \) statistics is a second measure accuracy agreement. This measure of agreement is based Congalton and Mead (1983) findings. \( K_{\text{hat}} \) was calculated using the following equation:

\[ K_{\text{hat}} = \frac{N \sum x_{ii} - \sum (x_{ii} \cdot x_{ij})}{N^2 - \sum (x_{ij} \cdot x_{ji})} \quad (7) \]

where

\( r \) is the number of rows in the error matrix; \( x_{ii} \) is the number of observations in row \( i \) and column \( i \) (the diagonal cells); \( x_{ij} \) is the total observations of row \( i \); \( x_{ji} \) is the total observations of column \( i \); and \( N \) is the total of observations in the matrix.

2.8. Post-classification comparison

Post-classification comparison takes places after classifying the rectified images separately from two time periods (2004 and 2013) following Mas (1999) and Coppin et al. (2004). Each date of imagery was satisfactorily classified, and then compared and analysed to conduct and change the detection according to Lu et al. (2004) and Huang et al. (2008). Fig. 2 shows the steps of post-classification in the study area.

3. Results and discussion

The floristic composition contains 142 species from 41 families; Fabaceae had the highest percentage (12.5%), followed by Chenopodiaceae (10.2%) and Poaceae (9.2%). The maximum percentage of life-form was characterized by 44% in perennial herbs (or sub-shrubs), followed through 27% in shrubs, 23% in therophytes, and 6% of trees in the total flora (Appendix 1). The prevalence of therophytes is typically the main characteristic feature of arid regions, which are related with unpredictable rainfall, and the dominance of woody sub-shrubs is typical of wetted coastal habitat (Mahmoud et al., 1982; Abbadi and El-Sheikh, 2002; Al-Rowaily et al., 2012). Seven plant communities have been documented after the application of TWINSPAN and DCA techniques (Fig. 3a, b); confirms as these communities are diverse species assemblages. VG I: Acacia tortilis-Acacia ehrenbergiana and VG II: Acacia tortilis-Stipagrostis plumosa are characterized by the presence of trees and grasses which inhabited the inland desert, sandy plains, alluvial wadis networks and rocky foothills of the Red Sea coastal area. On the other hand, the coastal wetted habitats are inhabited by halophytic communities, e.g., VG III: Zygophyllum cocineum-Zygophyllum simplex, VG IV: Acacia raddiana-Lycium shawii-Anabasis setifera, VG V: Tamarix acheriana-Juncus rigidus and VG VI: Capparis decidua-Zygophyllum simplex. The VG VII: Avisenia marina-Aristida adscensions occurred along the muddy banks of the Red Sea coast. The presence of most of these plant communities is more or less comparable to the previous studies on the study area (Vesey-Fitzgerald, 1957; Mahmoud et al., 1982). Therefore, the vegetation type of this area ranges between halophytic vegetation on the coast to xerophytic with scattered Acacia trees inland. In an arid-provinces, the changes in the vegetation composition are determined through the environmental factors and the human impacts as habitat shifting by the construction and modernization which induces heterogeneity concluded in space and time (Whitford, 2002; Jiao et al., 2011; Al-Rowaily et al., 2012).

Numerous algorithm classifications were implemented in supervised classification. Based on the Optimum Index Factor: OIF, unsupervised classification has promoted four various groups of Land Cover: LCs'. The statistical and graphical analysis of featured collections were implemented. The visible and infrared bands were involved in investigation apart from thermal infrared band. The summary in Table 1 indicates the cataloguing results in terms of both accuracy and Kappa statistics of each classification algorithm. Kappa statistics and overall accuracy promotes the Support Vector Machine over Maximum Likelihood classification, which agrees with Elhag et al. (2013). The error matrix was then performed to measure the user and producer's accuracies of the Support Vector Machine classification results as shown in Table 2 and 3 respectively.

In general, the output of algorithm classification in both accuracies and kappa statistics were amplified gradually from SPOT-5; early acquisition of 2004 to SPOT-5 late acquisition of 2013. The Maximum Likelihood classifier accuracies also increased towards the late acquisition of 2013. This could be explained because of an acquisition date of the second data-set (SPOT-5, 2013) are moderately close towards the collection date of the training and valida-
a) TWINSPAN:

Fig. 3. Relationship between the seven plant communities after the application of TWINSPAN (a) and DCA (b).

b) DCA:

Table 1
Overall accuracies and Kappa statistics of each classification algorithm.

| Classification algorithm | SPOT 5, 2004 | SPOT 5, 2013 |
|--------------------------|--------------|--------------|
| Year of acquisition      | Overall Kappa | Overall Kappa |
| Maximum Likelihood       | 80.5% 0.75    | 93.5% 0.91    |
| Support Vector Machine   | 90.3% 0.87    | 97.8% 0.97    |

Table 2
Error matrix for 2004 SPOT-5 Support Vector Machine (SVM) classification.

| Item       | Sea   | Mountain | Desert | Vegetation | Sum   | User's Accuracy |
|------------|-------|----------|--------|------------|-------|-----------------|
| Sea        | 208   | 0        | 2      | 1          | 211   | 98.2%           |
| Mountain   | 3     | 204      | 69     | 11         | 287   | 82.3%           |
| Desert     | 7     | 95       | 216    | 15         | 333   | 77.8%           |
| Vegetation | 1     | 11       | 8      | 145        | 165   | 85.1%           |
| Sum        | 219   | 310      | 295    | 172        |       |                 |
| Producer's Accuracy | 97.7% | 57.5% | 82.9% | 88.4% | Overall Accuracy | 90.3% |

| Item       | Sea   | Mountain | Desert | Vegetation | Sum   | User's Accuracy |
|------------|-------|----------|--------|------------|-------|-----------------|
| Sea        | 124   | 0        | 13     | 0          | 137   | 98.3%           |
| Mountain   | 0     | 139      | 45     | 5          | 189   | 78.1%           |
| Desert     | 5     | 84       | 326    | 13         | 428   | 80.4%           |
| Vegetation | 3     | 18       | 21     | 124        | 166   | 78.9%           |
| Sum        | 132   | 241      | 405    | 142        |       |                 |
| Producer's Accuracy | 98.1% | 65.3% | 84.6% | 90.5% | Overall Accuracy | 97.8% |

Table 3
Error matrix for 2013 SPOT-5 Support Vector Machine (SVM) classification.

| Item       | Sea   | Mountain | Desert | Vegetation | Sum   | User's Accuracy |
|------------|-------|----------|--------|------------|-------|-----------------|
| Sea        | 124   | 0        | 13     | 0          | 137   | 98.3%           |
| Mountain   | 0     | 139      | 45     | 5          | 189   | 78.1%           |
| Desert     | 5     | 84       | 326    | 13         | 428   | 80.4%           |
| Vegetation | 3     | 18       | 21     | 124        | 166   | 78.9%           |
| Sum        | 132   | 241      | 405    | 142        |       |                 |
| Producer's Accuracy | 98.1% | 65.3% | 84.6% | 90.5% | Overall Accuracy | 97.8% |
tion points, which were also proved as an adequacy of the Support Vector Machine classifier over the rest of the classifier in the complex areas (Hsu et al., 2003; Batisani and Yarnal, 2009).

Fig. 4 showed each data set with respect to its classification and usage of map in SVM as the supervised classification algorithms. Four classes for LU/LC were detected in each temporal dataset.

Fig. 4. Support Vector Machine (SVM) classification maps of SPOT 5 (a) early acquisition scene 120–291, (b) early acquisition scene 128–301, (c) early acquisition scene 131–304, (d) early acquisition scene 133–307, (e) late acquisition scene 120–291, (f) late acquisition scene 128–301, (g) late acquisition scene 131–304, and (h) late acquisition scene 133–307.
The composition for LU/LC was varied from scene to scene based on the scene morphological features (Elhag et al., 2013). The majority of LU/LC changes exist mainly along the coast indicating that the coastal ecosystem in those regions is highly fragile (Kumar et al., 2010). Sea water intrusion was the keystone LU/LC change detected in scene 131–304. The loss of vegetation was the main finding of temporal change detection subjected to scene 133–307. Urban expansion is the driving force for the loss of the natural vegetation in the study area (Elhag et al., 2013).

Fig. 5 quantifies the temporal changes in the present study. Fig. 5a shows that the majority of LU/LC changes were confined to sea sedimentation deposits (4.86%). Fig. 5b expressed two contradictory processes, sea water intrusion (4.25%) and sedimentation deposits (5.48%). Sea water intrusion was also the major temporal LU/LC changes in Fig. 5c counted for 8.76% of the changes. Fig. 5c demonstrated heterogeneity in the LU/LC temporal changes with major changes in the sea sedimentation deposits (4.63%) and minor changes in the degradation of coastal mangrove forests (0.10%).

Concerning temporal changes in vegetation cover confirmed in Fig. 6, the net vegetation cover changes were varied from one study site to another. In scene 120–291, vegetation loss was three times more than the vegetation gain, which requires immediate and intensive restoration plans. Similarly, the vegetation loss in scene 128–301 showed that the gain in vegetation cover is negligible compared to vegetation loss. Fig. 6b demonstrated that the bulk of the vegetation cover is mostly lost. Regulation procedures were to be adopted in both scene 131–304 and scene 133–307, where the loss of the vegetation cover was nearly equal to the vegetation gain. Regulation procedures are to maintain the existing vegetation cover and to restore degraded ones (Kumar et al., 2010).

4. Conclusion

The study quantified the patterns of LU/LC changes over ten years in the northwestern coastal land of the Red Sea. The two different supervised classification algorithms are used in the post-classification comparison method. The Support Vector Machine classifier was adopted because it’s higher classification accuracies. Four classes of LU/LC and LC was produced, and both the vegetation and sediments main classes have changed rapidly in the area of the coastal land. The vegetation cover class has decreased almost 19% through the time from 2004 to 2013. Meanwhile, sediments have increased by the same value of percentage (12%), despite of the proportional area in each class. The desert class has decreased because human intervention. Sedimentation deposits are remarkably noticeable along the shoreline of the coastal area. Usage of both multi spectral and temporal images for remote sensing data.
provides the cost-effective tools to obtain valuable information for more efficient monitoring patterns of the developed land and further progress. The knowledge for GIS offers a flexible environment for storing, analysing and visualizing the digital data required for change assessing an improvement for database and also important for urban class investigation in further research. This could provide status of the vegetation cover land analysis, determine the definite restoration techniques that require be adopting, and setting the foundations for the planning policy intended to maximize and sustain of natural resources management. At last, the current study results strongly recommend new strategies for considering into account of the adjacent regions which may or may not be as direct or indirect affect the costal land development in the Saudi Arabia. For example, extension of urban should be strongly prohibited towards vegetation cover land and depositing the sediments towards shoreline, which could be wisely opted for perusing the effective plan of the management. The current study should be relevant globally due to the extrapolated of similar ecosystems in other parts of planet. Moreover, the findings of the present study form valuable resources for urban-planners and decision markers to devise sustainable land use and environmental planning and for the design of rehabilitation programs that conserve biodiversity in arid regions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. Synoptic table of the percentage cover species of 7 vegetation groups: VGI = Acacia tortilis-Acacia ehrenbergiana; VGII = Acacia tortilis-Stipagrostis plumosa; VG III = Zygophyllum coccineum-Zygophyllum simplex; VG IV = Acacia raddiana-Lycium shawii-Anabasis setifera; VG V = Tamarix aucheriana-Juncus rigidus; VG VI = Capparis decidua-Zygophyllum simplex and VG VII = Avicennia marina-Aristida adscensionis. A. = Annual; P. Perennial; Am = American; Eu.Sib = Euro siberian; IT = Irano turanian; Pac = Pacific; Med = Mediterranean; Med-IT = Mediterranean-Irano turanian; SA = Saharo Arabian; SM = Somali masai; SH = Sahel; TR AF = Tropical African.
| Vegetation Group No. | L. form | Chorotype | I  | II | III | IV | V  | VI | VII |
|----------------------|---------|-----------|----|----|-----|----|----|----|-----|
| No. of stands        | 2       | 3         | 39 | 12 | 11  | 2  | 9  |    |     |
| Zygophyllum simplex  | A. Herb | SH-SM     | 1.0| 1.0| 5.1 | 3.0| 5.0 | 3.0| 2.0 |
| Zygophyllum coccineum| P. Herb | SA       | 12.0| 2.0| 5.4 | 8.6| 9.7 | 1.0| 15.0|
| Acacia tortilis      | Shrub   | SH-SM     | 30.0| 30.0| 24.3| 16.1| 1.0 |   |     |
| Acacia ehrenbergiana | Shrub   | SH-SM     | 10.0|    | 19.2| 15.0|     | 10.0| 20.0|
| Senna italica        | P. Herb | SH-SM     |     |    |     |    |     |     |     |
| Haloxylon salicornicum| Shrub  | SH-SM     |     |    |     |    |     |     |     |
| Citrullus colocynthis| P. Herb | SA       |     |    |     |    |     |     |     |
| Calotropis procera   | Shrub   | SH-SM     |     |    |     |    |     |     |     |
| Zygophyllum coccineum| P. Herb | SA       |     |    |     |    |     |     |     |
| Acacia radiana       | Tree    | SH-SM     |     |    |     |    |     |     |     |
| Fagonia ehrenbergiana| P. Herb | SA       |     |    |     |    |     |     |     |
| Panicum turgidum     | P. Grass| SA-SM     |     |    |     |    |     |     |     |
| Salvadora persica    | Shrub   | SH-SM     |     |    |     |    |     |     |     |
| Cadaba gardunosa     | Shrub   | SH-SM     |     |    |     |    |     |     |     |
| Acacia oerfota       | Shrub   | TR-AF     |     |    |     |    |     |     |     |
| Stipagrostis plumosa | P. Grass| SA-IT     |     |    |     |    |     |     |     |
| Anabasis setifera    | P. Herb | SA       |     |    |     |    |     |     |     |
| Abutilon pannosum    | Shrub   | TR-AF     |     |    |     |    |     |     |     |
| Astragalus fatmannis | A. Herb | TR-AF     |     |    |     |    |     |     |     |
| Convolvulus pilosellus| P. Herb| IT       |     |    |     |    |     |     |     |
| Tamarix nilotica     | Tree    | SA-SM     |     |    |     |    |     |     |     |
| Capparis decidua     | Tree    | SH-SM     |     |    |     |    |     |     |     |
| Prosopis juliflora   | Tree    | AM        |     |    |     |    |     |     |     |
| Rhyastra stricta     | Shrub   | SA        |     |    |     |    |     |     |     |
| Paspalidium desertorum| P. Grass| SH-SM     |     |    |     |    |     |     |     |
| Sporobolus spicatus  | P. Grass| TR-AF     |     |    |     |    |     |     |     |
| Suoeda aegyptiaca    | A. Herb | SA-SM     |     |    |     |    |     |     |     |
| Maerua crassifolia   | Tree    | SH-SM     |     |    |     |    |     |     |     |
| Cressa cretica       | P. Herb | Med-IT    |     |    |     |    |     |     |     |
| Salsoa lachnantha    | Shrub   | IT        |     |    |     |    |     |     |     |
| Cenchrus ciliaris     | P. Grass| SA-SM     |     |    |     |    |     |     |     |
| Leptadenia pyrotechnica| Shrub  | SA-SM     |     |    | 1.0 | 1.0|     |     |     |
| Odontanthra radians  | A. Herb | TR-AF     |     |    |     |    |     |     |     |
| Suoeda verniculata   | Shrub   | SA-SM     |     |    | 15.0|    |     |     |     |
| Lasius hirsutus      | P. Grass| SA-SM     |     |    | 15.0|    |     |     |     |
| Zygophyllum qatarense| P. Herb | SA-SM     |     |    | 5.0 |    |     |     |     |
| Indigofera oblongifolia| Shrub  | SA-SM     |     |    | 15.0|    |     |     |     |
| Digera maricata      | A. Herb | TR-AF     |     |    | 5.0 |    |     |     |     |
| Heliotropium europaeum| P. Herb| EU-SI-ME-IT|     |    | 5.0 |    |     |     |     |
| Solanum sepalum      | P. Herb | SA-SM     |     |    | 5.0 |    |     |     |     |
| Taveniangi spartea   | Shrub   | SA-SM     |     |    | 4.0 |    | 16.0|    |     |
| Ochradenus baccatus   | Shrub   | TR-AF     |     |    | 8.0 | 1.0 | 2.0 |    |     |
| Aeluropus lagopoides  | P. Grass| SA-SM     |     |    | 15.0|    |     |     |     |
| Zygophyllum album     | P. Herb | SA-SM     |     |    | 3.5 | 2.0 | 3.3 |    |     |
| Tamarix aicheriana    | Tree    | SA-SM     |     |    | 5.0 |    | 10.3|    |     |
| Nitraria retusa      | Shrub   | SA-SM     |     |    | 4.5 |    | 8.5 | 15.0|     |
| Lycium shawii        | Shrub   | SA-SM     |     |    | 2.0 | 7.3 | 3.5 |    |     |
| Linnimium axillare    | P. Herb | TR-AF     |     |    | 4.0 | 2.0 | 8.0 |    |     |
| Juncus rigidus       | Shrub   | EU-SI-ME-IT|     |    | 15.0|    | 13.5|    |     |
| Hyphaene thebaica    | Shrub   | SA-SM     |     |    | 2.0 | 2.0 | 1.0 |    |     |
| Sehildzia rosmarinus | Shrub   | SA-SM     |     |    | 1.0 |    | 25.0|    |     |
| Aviceinia marina      | Tree    | TR        |     |    | 4.3 | 2.0 | 2.0 | 15.7|     |
| Halopepis perfoliata | Shrub   | SA-SM     |     |    | 5.0 |    | 6.0 | 2.0 |     |
| Halocnemum strobilaceum| Shrub  | SA-MED-IT | 2.0|    |     |    |     |     |     |
| Arthrocnemum macrostachyum| Shrub  | SA-MED-IT | 2.0|    |     | 15.0| 2.0 |     |
| Calligonum comosum    | Shrub   | SA-SM     |     |    |     |    | 7.0 |    |     |
| Euphoria retusa      | P. Herb | SA-SM     |     |    | 1.0 |    |     |     |     |
| Forskoleoa tenacissima| P. Herb| SA-SM     | 1.0 |    | 1.0 |    |     |     |     |
| Asphodelus fistulosus| A. Herb | SA-SM     |     |    | 1.0 |    |     |     |     |
| Pergularia tomentosa  | Shrub   | SH-SM     |     |    |     | 1.0 |    |     |     |
| Pulicaria guestiti   | P. Herb | SA-SM     | 1.0 | 1.0 | 1.0 |    |     |     |     |
| Launaea capitata     | A. Herb | SA-SM     | 1.0 |    | 1.0 |    |     |     |     |
| Fagonia mollis      | P. Herb | SA-SM     | 1.0 |    | 1.0 |    |     |     |     |
| Iphiona scabra      | P. Herb | SA-SM     | 1.0 |    | 1.0 |    |     |     |     |
| Zygophyllum fabago   | Shrub   | IT        |     |    | 1.0 |    | 1.5 |    |     |
| Cocculus pendulus    | Climber | SH-SM     |     |    | 5.0 |    | 2.0 |    |     |
| Cymodocea rotundata  | P. Herb | Indian-Pac| 16.0|    |     |     |     |     |     |
| Cadaba farinosa      | Shrub   | TR-AF     |     |    | 3.0 |    |     |     |     |
| Retama raetam        | Shrub   | SA-SM     |     |    | 3.0 |    |     |     |     |
| Farsetia stylosa     | P. Herb | SA-SM     |     |    | 1.0 |    |     |     |     |

(continued on next page)
Fifty two species are considered rare and their cover represents 3%.

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