Spatial analysis of rangeland's vegetation intensity as related to selected physical soil variables over ABQAIQ municipality of Saudi Arabia

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Through most of the natural rangelands of Saudi Arabia, overgrazing, sand drifting, and off-road vehicles driving are almost the major contributing factors that lead to vegetation damage and land degradation in natural landscapes. The current study aimed at examining the dynamic nature of Abqaiq rangelands’ vegetation, generating a vegetation intensity map, and investigating possible impacts caused by the spatial variability of obtained soil texture, sand content (%), and the derived available water capacity (DAW capacity (%)) on the intensity distribution of vegetation cover. Ordinal-nominal correlation type and spatial autocorrelation processes were adopted throughout the study to analyze the spatial correspondences as well as the interrelated patterns of the given variables. The resultant correlation between vegetation and soil texture (ordinal versus nominal variables) has yielded a significant (p-value < 0.001) relevancies, where, silt loam texture class, in particular, has proven to have the most correlated values to the most intensive vegetation habitats, where 5%, 35%, and 28% of the silt loam class were occupied by 80%, 60%, and 40% of vegetation intensities, respectively. Whereas, for the continuous variables, correlation outcomes have achieved a substantial negative spatial autocorrelation concerning vegetation intensity and sand content percentage, revealing a total absence of green biomass over the sandy soils. Additionally, vegetation intensity versus DAW capacity percentage significantly yielded a positive autocorrelation, revealing a high clustering of green biomass cover that associates with high clustering of high-water capacity soils. The autocorrelation strength identifier (Morn’s $I$), produced an approximate value of 0.3 with a pseudo p-value of 0.001, for both relationships. The findings of this study would help researchers and relative authorities to grasp the reasons, consequences and behaviors of rangeland flora, considering Abqaiq’s area as an example.

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1. Introduction

Rangelands are indeed an important type of the managed-grasslands categories, in which grasslands were assessed to cover 31.5% of the landmass worldwide, and play a massive role in controlling the global cycle of carbon (Franzluebbers, 2010), in addition to encouraging plant-animal biodiversity (Pokluda et al., 2012; Punjabi et al., 2013). According to species structure, rangelands are populated by native herbaceous/shrubbery vegetation that is a feed supply equally for domestic and wild herbivores, available in terms of desert shrublands, steppes, shrub woodlands and savannas (Ali et al., 2016). Forage availability for herbivores relies on the efficient functioning of various environmental, hydrological, as well as soil circumstances (Svoray et al., 2008). Vigorous rangelands certainly are a national source which sustains soil quality, improve the use of clean water, sequester excessive CO2, preserve plant-animal diverseness, and support many additional non-agricultural uses (Wessels et al., 2007; Teague et al., 2009, 2011).

The kingdom of Saudi Arabia is categorized as an arid country with some unique sub-humid regions southwestern the escarpments. Flora in Saudi Arabia entails 2250 varieties that belong to132 families in addition to 837 general species inhabit sand
The principal force causing rangeland degradation is usually related to anthropogenic impacts, e.g., overgrazing and mismanagement of resources through pastoralists (Al-Bukhari et al., 2018; Squires, 2010). The deterioration of biophysical rangeland resources has significant effects for pastoral ecosystems, livelihoods as well as livestock production (AU-IBAR, 2012). Degraded spots over a rangeland usually encounter higher rates of soil erosion as well as compaction in comparison to uninterrupted or perfect conditions, which may have much more dense forage cover (Kassahun et al., 2008). Rangeland degradation might influence soil organic matter (SOM), leading to reduced soil organic carbon (SOC) amounts (Dlaminii et al., 2014), elevated losses of soil moisture and also nutrient because of increased leaching situations (Lal, 2015). Positive relationships have been documented for an average net primary productivity (NPP) and the SOC (Peterson and Lajtha, 2018).

Researches revealing decreased SOC and NPP followed by decreasing rangeland conditions are well established in Africa (Kassahun et al., 2012), United States (Noojiipady et al., 2015), and Asia (Xie and Wu, 2016). Further, rangeland degradation variably influences equally flora and fauna. Increased degradation can further restrict the availability of forage and water resources, minimizes biodiversity at various levels and scales. From another perspective, an increase in soil pH along with increasing rangeland, positive relationships have been documented for an average net primary productivity (NPP) and the SOC (Peterson and Lajtha, 2018).

The deterioration of biophysical rangeland resources has significant effects for pastoral ecosystems, livelihoods as well as livestock production (AU-IBAR, 2012). Degraded spots over a rangeland usually encounter higher rates of soil erosion as well as compaction in comparison to uninterrupted or perfect conditions, which may have much more dense forage cover (Kassahun et al., 2008). Rangeland degradation might influence soil organic matter (SOM), leading to reduced soil organic carbon (SOC) amounts (Dlaminii et al., 2014), elevated losses of soil moisture and also nutrient because of increased leaching situations (Lal, 2015). Positive relationships have been documented for an average net primary productivity (NPP) and the SOC (Peterson and Lajtha, 2013). Researches revealing decreased SOC and NPP followed by decreasing rangeland conditions are well established in Africa (Kassahun et al., 2012), United States (Noojiipady et al., 2015), and Asia (Xie and Wu, 2016). Further, rangeland degradation variably influences equally flora and fauna. Increased degradation can further restrict the availability of forage and water resources, minimizes biodiversity at various levels and scales. From another perspective, an increase in soil pH along with increasing rangeland degradation had been reported (Gebrerkidan and Negassa, 2006).

Rangeland degradation can cumulatively impact livestock efficiency and instigate severe economical losses that not just endanger national economies, however, it influences the livelihood of the people. In Ethiopia, Yusuf et al. (2008) revealed about USD106 million yearly costs of land degradation associated with soil erosion and nutrient losses from arable and grazing lands.

In Saudi Arabia, off-road vehicles driving is amongst the major contributing factors that lead to vegetation damage and land degradation in natural landscapes including rangelands and nature reserves (Al-Nafie, 2007; Assaeed et al., 2019). Off-road traffic may also alter the physical features of the soil in a manner that may

dunes; and also 90 are considered as halophytes (a plant adapted to growing in saline soil); 75 are trees; and 12 are aquatic plants. Beyond these species, 40 are believed to be endemic (Abuzinada et al., 2005; Dhar et al., 2015; Abd El-Salam and Elhakem, 2016). The natural rangelands in Saudi Arabia are estimated to cover nearly 170,000,000 ha which are equal to 76% of the total land area of Saudi Arabia, situated mostly within arid and hyper-arid regions (Abuzinada et al., 2005). These rangelands vary functionally because of the differences in the spatio-temporal distribution of the structure of vegetation, soil and climate of every region. (Chaudhary and Le Houérou, 2006). Despite the fairly low productivity, positive aspects of ecosystems over rangelands are usually becoming increasingly recognized (Al-Rowaily et al., 2018).

As an important element of the agro-grassland ecosystem, soil plays an integral role in nearly all remote observations targeting at monitoring grassland productivity and production as well (Nan, 2001). However, Saudi Arabian’s soils are generally poorly developed, with large areas are covered with pebbles of various sizes and aeolian dune field (patches) with various sizes of area form and type. Alluvial deposits are found in wadis (valleys), basins, and oases. Salt flats are specifically popular in the east (Abuzinada et al., 2005). Due to the severe climate and soil conditions as well as the intensive human activities, heterogeneity of soil resources in arid and semi-arid grassland ecosystems has gradually increased over the past century (Chen et al., 2003).

Remote-sensing methods comprise a robust tool and present the most valuable information source for the assessment of land surface processes since they provide dynamic, multi-temporal and time-series information (Wu, 2009) and also provide a viable source of data from which updated land-cover information can be extracted efficiently and cheaply in to monitor changes effectively (Louhai chi et al., 2010; Khiralla, 2013). The application of GIS and remote sensing in examining temporal changes in land degradation and desertification, mapping landscape-based vegetation, in addition to monitoring and assessing changes in land cover characteristics is properly reported (Miehe et al., 2010; Vanderpost et al., 2011). Within the semi-arid rangelands of Iran, Amiri and Sharif f (2010) examined the vegetation cover attributes utilizing satellite data and data from the entire vegetation indices, and proved the Normalized Difference Vegetation Index (NDVI) for its accuracy and reliability in predicting land degradation, particularly in rangelands. Bai et al. (2008) observed that the tendencies exhibited by the NDVI/net primary production (NPP) outcomes had the possibilities to produce consistent worldwide standard information regarding areas vulnerable to substantial biological changes assigned to land degradation. Local NPP Scaling (LNS) and NDVI were also employed to observe land degradation. In Kenya, Bai and Dent (2006) employed NPP and rain-use efficiency to identify the possible areas vulnerable to land degradation. By utilizing NDVI results from Khuzestan province of Iran, Masoudi et al. (2018) found out that the degradation in the rangeland locations exceeded that of forests and dry cultivated areas. Symeonakis and Drake (2004) employed NDVI to observe land degradation as well as desertification in sub-Saharan Africa. They verified it is a great approach to assess the present circumstances of land degradation. Vogelmann et al. (2012) carried out a research over a US rangeland area during the period 1984 to 2010 to examine the progressive change in rangeland landscape using time-series information, produced from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+). The results revealed that Landsat time-series data tend to be suitable for deriving change in landscape information of rangeland. Landsat images have also been employed for tracking and evaluating rangeland deterioration in Australia through relating vegetation cover and biomass with a field observed approach (Graetz et al., 1988). At a regional scale, Tucker et al. (1983) employed both a direct and logarithmic regression between the ground assessed biomass data within the Sahel area and AVHRR NDVI to predict biomass. Similarly, Yu et al. (2010) employed the 250-m resolution MODIS NDVI in the Tibetan Autonomous Prefecture of Golog, Qinghai, China, to calculate over ground green biomass making use of regression relationships between derived NDVI and ground-observed biomass from sites throughout the location with an r² correlation of 0.51. Al-Bakri and Taylor (2003) also applied a linear regression approach to assess rangeland shrub biomass in Jordan utilizing AVHRR NDVI in which a substantial correlation (r = 0.75) with observed ground biomass was discovered. Nevertheless, using remote-sensing information with a coarse spatial resolution has its constraints particularly in areas with high fragmentation and heterogeneity of rangelands (Cohen and Shoshany, 2002).

The quantitative decline in rangelands worldwide has accelerated in recent years and has reached a critical level in which the rangelands can no longer support the demands being made on them by herders with increasing numbers of livestock. Periodic drought has also shared in the violent land practices to upset the sensitive ecological balance (Abuzinada et al., 2005). Mostly, processes of intensified soil erosion and/or over-grazing lead to a significant reduction in production (Svoray et al., 2013). Overgrazing, in particular, is broadly considered as a key source of desertification (Goudies, 1998). In the event that grazing control on arid and semi-arid areas is actually improper, then land degradation can certainly take place (Tueller, 1998). Lack of spatially comprehensive data is another factor that contributes to vegetation mismanagement, such as spatial and temporal variability/ fluctuation of rainfall, and landscape variables like soil types and vegetation communities (Kilpatrick et al., 2011; Gibbs and Salmon, 2015).

The main contributor factors that lead to vegetation damage and land degradation in natural landscapes including rangelands and nature reserves (Al-Nafie, 2007; Assaeed et al., 2019). Off-road traffic may also alter the physical features of the soil in a manner that may...
cause a reduction in infiltration capacity, and consequently elevating the hazard of surface runoff along with inadequacy of soil aeration for ideal seedling growth (Hansson et al., 2018). All of the previously mentioned elements have brought about the deterioration of the desert rangelands and thence led to further desertification.

The assessment of degradation in arid rangelands is challenging due to short-term variations in climatic conditions, landscape diversity and the problems associated with sampling large areas. Moreover, the pastoral systems have been characterized by high mobility, dynamism and a high dependency on local knowledge (SCBD, 2010) to manage a highly diverse and complex environment, given the high spatial and temporal variability of the resources in the drylands (AU-IBAR 2012). Besides, green vegetation cover is an important factor in regard to rangeland status; and is a key sensitivity indicator of land degradation and desertification. Quantitative data (durability, intensity, and spatial distribution) on the green vegetation cover is necessary for numerous environmental change investigations worldwide and at local scale.

In order to contribute in managing and improving decisions towards the natural rangelands of Saudi Arabia taking into account the seasonally distributed biomass, the current study aimed at highlighting the role of selected soil parameters that assumed to impact the quantification and spatial distribution of a rangeland’s green cover. To get to the bottom of the study aim, two distinct objectives were drawn, namely: (a) generating a spatially-ranked vegetation intensity map over the ranges of Abqaiq municipality in the eastern province of Saudi Arabia; then (b) examining and depicting the degrees of spatial association between the green biomass and the distributed classes of soil structure, sand content, and available water capacity. The findings of this study would help researchers and relative authorities to grasp the reasons, consequences and behaviors of rangeland flora, considering Abqaiq’s area as an example.

2. Materials and methods

2.1. Study area

Abqaiq municipality is situated in the desert of the Eastern region of Saudi Arabia, at 60 km southwest of the Dhahran city; and north of the Al-Ahsa province, one of the major parts of the Eastern region with an approximate population number of 44,000. The study area as part of Abqaiq municipality, covering approximately an area of 135,000 ha, extended between longitudes of 49°26′–49°50′ E and latitudes of 25°40′–26°20′ N (Fig. 1), with an approximate elevation of 83 m above sea level. The Abqaiq’s weather is characterized by long summer with extremely hot, and arid climate; while the winter is cool, dry, and windy; and it is regularly clear the year-round. According to Ait (2019), the mean temperature ranges from 26 to 27 °C and exceeds 45 °C throughout the summer season, and reaches 0 °C during winter nights.

Throughout the entire province, the active and mobile dunes define its lands surface. This is because most of the northern, eastern and southern boundaries of the province are situated in Al-Jafurah desert. The mobile sand coming from the north-west as well as north directions is approximated at 3 m³/m width (Ait, 2019). The mobility of sands around the area have for many decades been encroaching against the cultivated areas and endangering the properties. As the area enjoys an arid climate, the average annual rainfall is almost less than 46 mm, and the rainy season normally occurs in winter months from December to April, whilst the maximum mean quantities of rainfall are within January, March, and April, which are estimated as 18, 15.06 and 10.26 mm respectively (Ait, 2019).

2.2. Data and processing

2.2.1. Satellite data

Sentinel-2A satellite (the images provider) which is a global platform for monitoring environment and security (GMES), is committed to planet observation where important aspects of the space components consist the system (Donlon et al., 2012; Torres et al., 2012). This tasks supply continues packages and service based on multi-spectral high spatial resolution (for optical regions) data worldwide (Martimort et al., 2007). Ten Sentinel-2A images (10 m spatial resolution for optical bands) for a period of five years from 2016 to 2020 were downloaded from the USGS portal (https://earthexplorer.usgs.gov/). The downloaded images were selected according to the wet (December-February) and the dry (May-September) periods, where the change in vegetation cover over the ranges of Abqaiq throughout the two periods is always noticeable. Hence, the acquired images were subjected to pre-processing in terms of atmospheric corrections, delineation and clipping of the area of interest, radiometric calibration in addition to reflectance values computation. Throughout the pre-processing phase, image enhancement was carried out using image histogram matching tools to be able to enhance the contrast between features within the image and to boost the visual interpretation of surface characteristics.

2.2.2. Soil data

Three distinctive types of soil physical parameter were used, namely: soil texture, sand content (50–2000 μm) mass fraction, and derived available soil water capacity/content (volumetric fraction). The soil data were acquired from the International Soil Refer-
ence and Information Centre (ISRIC), which is an independent science-based foundation by Dutch law (ISRIC, 2020) that provides a global compilation of soil ground observations, and supplies quality-assessed soil data and interpreted soil information. ISRIC conserves a strong knowledge of soil diagnosis, soil investigation and soil data supply. Also, information on soil classes distribution was obtained according to the World Reference Base (WRB) and the United States Department of Agriculture (USDA) classification systems (Hengl et al., 2017). The illustrative information concerning the used datasets is provided in (Table 1).

2.3 Images classification

The obtained Sentinel-2A images were classified using the supervised classification method based on the maximum likelihood algorithm. Convolution filters have been used in order to produce sharp images with enhanced edges between different regions, smooth, and having enhanced high-frequency components. It is worth mentioning that, a binary-based classification criterion was followed, where only two surface class types were originated; namely: vegetation (represented all green cover pixels) and non-vegetation (represented all other features throughout the classified area). Training as well as testing spots have been visually identified to an image differencing procedure using post-processing tools and also the minimum distance classifier is considered to offer greater results in comparison with other forms, like the parallelepiped and also the minimum distance classifier. The kappa coefficient implies a precise classification (Story and Congalton, 1986). As a way to measure the accuracy of classification, classification errors are determined. Hence, errors due to omission and commission are assessed. For each class, errors of the commission take place when a classification method allocates to a certain classes that basically never belong to them. The overall commission errors will then be determined by an indicator referred as producer’s accuracy, which is the overall correctly determined pixels divided by the overall reference image pixels. Omission errors, conversely, occur when pixels that basically fit in with one class, are classified as another class. User’s accuracy is the index that characterizes the sum of the omission errors where the overall number of the accurately determined pixels of a class are divided by the overall pixels of that class (Story and Congalton, 1986).

2.4 Confusion matrix

The confusion/error matrix is usually applied as a numerical strategy for representing the accuracy/precision of the classified image. It is formed in a tabular style that demonstrates the correspondence between the outcome of the classification approach and a reference image. To effort to produce the confusion matrix, ground truth information, for example field data recorded using a GPS, map data, or even a digitized image, are essential.

The kappa coefficient is a crucial indicator of the classification matching. If the kappa coefficient value is 0, this implies no similarity between the classified image and the reference once. While when the value equates to 1, it means the classified image, as well as the reference image are totally identical. Therefore, a greater kappa coefficient implies a precise classification (Story and Congalton, 1986). As a way to measure the accuracy of classification, classification errors are determined. Hence, errors due to omission and commission are assessed. For each class, errors of the commission take place when a classification method allocates pixels to a certain classes that basically never belong to them. The overall commission errors will then be determined by an indicator referred as producer’s accuracy, which is the overall correctly determined pixels divided by the overall reference image pixels. Omission errors, conversely, occur when pixels that basically fit in with one class, are classified as another class. User’s accuracy is the index that characterizes the sum of the omission errors where the overall number of the accurately determined pixels of a class are divided by the overall pixels of that class (Story and Congalton, 1986).

2.5 Vegetation intensity

Monitoring all changes related to vegetation is usually unattainable. Thus, indicators assigned to measure the condition of a target need to include a great deal of data within one particular value (Nordberg and Evertson, 2003). Indicators pertaining to ecological monitoring must provide a distinct and specific signals concerning the environmental condition, and also be simple to separate from unrelated signals (Nordberg and Evertson, 2003). To map the planned 5 years vegetation intensity map over the study land, each year’s wet and dry classified images were subjected to an image differencing procedure using post-

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**Table 1**

Specifications of the obtained Sentinel-2A images and soil data.

| Data type                              | Data acquisition/collection date | Data specifications                                      | Data source                          |
|----------------------------------------|---------------------------------|----------------------------------------------------------|--------------------------------------|
| Satellite images [Sentinel 2A]         | 2016 Jan. 19, 2017 Jan. 03, 2018 Jan. 23, 2019 Jan. 18, 2020 Jan. 08, May 17 | Path/row: 164/42, Spectral bands: 12 channels, Pixel size: 10 m (for RGB bands), Revisit frequency (days): 5 | The European Space Agency (ESA)       |
| Sand content (50–2000 μm) mass fraction | Dec. 01, 2015                   | Format: Geo. Tiff., Resolution: 250 m at 30 cm depth. Coordinate reference system: EPSG: 4326. | The International Soil Reference and Information Centre (ISRIC) |
| Derived available soil water capacity  | June 01, 2017                   |                                                          |                                      |
| (volumetric fraction) with field capacity = pF 2.5 |                                  |                                                          |                                      |
| Texture class (USDA system)            |                                 |                                                          |                                      |
classification approach (Singh, 1989); and comparative analysis (Mas, 1999). Images differencing was applied with the aim of producing an image that was able to quantify the residual vegetation as the season changes from wet to dry. Typical image differencing approaches have been used in detecting vegetation changes through time spans, where vegetation indices (VI) are used (Mas, 1999; Nordberg and Everston, 2003). The concept behind that was to examine how much decrease/increase in vegetation cover could be extracted with change detection techniques of remote sensing, as reported by Singh (1989). The resultant difference image may include both negative and positive values. Positive values indicate how the pixels have increased in green vegetation biomass within the index time period, whilst negative values indicate green biomass decrease. However, zero differences suggest a minimum of or no vegetation change exist between the two dates of image. Pixels without actual change are found concentrating around the mean value, whereas, pixels with actual change are found in the back ends (Singh, 1986). To differentiate between pixels with change and no change, an optimum threshold value is needed.

However, for the current study, all vegetation and non-vegetation’s classified pixels were assigned rank values of 2 and 1, respectively. Hence, all dry season’s classified images were subtracted from their respective wet season ones, as it can be expressed in Equation (1).

\[
\text{Res}_i = C_{wv} - C_{vd} \quad \text{for} \quad \begin{cases} 
    i < 0, & \text{--ive residue} \\
    i = 0, & \text{non-vegetation} \\
    i > 0, & \text{+ive residue} 
\end{cases}
\]

(1)

Where \( \text{Res}_i \) represents the residual value for the \( i \)th classified pixel; \( C_{wv} \) represents the value for the \( i \)th classified pixel for the wet season; and \( C_{vd} \) represents the value for the \( i \)th classified pixel for the dry season.

It has been observed that the obtained negative residue values throughout the entire 5 years of the process were very small (--ive residue < 1%), assuring the dominancy of vegetation at the wet seasons. Hence, all negative residual values have been neglected along the process of images differencing, and also at vegetation intensity map generation. For demonstration purposes (Fig. 2), a sample image differencing process was presented for 2019 seasons, where the negative vegetation’s residue is distinguished with a weak presence.

The vegetation intensity map (veg. intensity) was ultimately produced in values between 0 and 1, which was generated as being a pixel-based value averaging for the extracted residual vegetation for the entire 5-years analysis period, as explained by Equation (2). The acquired intensities were segmented into five equal intervals in terms of pixel’s intensity overlay. Pixels having 0 value denoted either a non-vegetation or a perennial plant that existed throughout both the wet and dry seasons (class-ranked 2), hence produced a 0 value when image differencing was applied.

Likewise, pixels having values greater than 0 and up to 1 represented the frequency of residual vegetation occurrences in the same spot throughout the 5 years. The acquired intensity value of 1 denoted that a certain pixel was occupied by a vegetation cover in the wet period/season, however, witnessed a non-vegetation condition at the adjacent dry period/season in the same year, thus, this has been repeated for the 5 designated research years. Making use of such concept, every intensity-pixel with a value of 1 was assumed to have a full intensity or 100% intensity, intensity-pixels with values around 0.8, 0.6, 0.4, and 0.2 had 80%, 60%, 40%, and 20% intensities, respectively; while maintaining the 0 as non-vegetation.

\[
\text{Veg. Intensity} = \frac{1}{9} \sum_{j=1}^{9} \text{(Res}_j\text{)}
\]

(2)

Where Veg. Intensity represents the vegetation intensity map; \( \text{(Res}_j\text{)} \) represents the residual value for the \( i \)th classified pixel for the \( j \)th year.

2.6. Spatial correlation process

Use of ArcGIS software tools, a vectorization procedure was followed in order to extract 1000 stratified random points based on pixels values and pixels adjacency, for a tight correlation between the vegetation intensity and soil parameter’s maps. Two forms of correlation process between the variables have been applied. Firstly, an ordinal vs nominal variables correlation type has been adopted between vegetation intensity (as an ordinal variable) and soil texture (as a nominal variable), where “cross-tabulation” correlation tool in the statistical package for social sciences (SPSS) software program was used. Secondly, a spatial autocorrelation process has been implemented in order to measure the spatial correspondences between the vegetation intensity and the scale/continuous variables of soil, which were sand content (%) and the derived available water capacity (%). The Bivariate Local Indicator of Spatial Autocorrelation (BiLISA) techniques was utilized as a way to determine the correlation, the clustering and also the significance of the pixel-based intensity with regards to the soil continuous variables. It is worth to state that, BiLISA exhibits the extent to what the characteristics of the relationship between every two variables can change within the study region. Moran’s index (I) has also been analyzed to determine the effectiveness of the spatial autocorrelation and also to assess the spatial dependency among the two obtained variables (Moran, 1950). The ultimate finding of BiLISA is normally depicted as a map that can

Fig. 2. Sample residual vegetation map of the years 2019, extracted through images subtraction process.
assist in determining the characteristics of the drawn spatial autocorrelations, which are categorized into four groups. Two groups entail the positive spatial clusters (high-high and low-low), that agree with values surrounded by neighboring pixels having similar values. The opposite two groups entail the spatial outliers (high-low and low-high), which are mostly in an agreement with values whose neighboring pixels include different values. In this work, GeoDa software package (Anselin, 2015) which supplies an exceptionally user-friendly atmosphere to utilize spatial data autocorrelations and examination was used.

The simplified flow chart (Fig. 3) illustrates the tasks implemented for the spatial correlation assessment among the created vegetation intensity map and soil parameter over the ranges of the study area. The process briefly entails satellite (Sentinel-2A series) image acquisition, preprocessing, image processing including classification and images differencing, intensity map generation, and finally the implementation of the spatial correlation process.

3. Results

3.1. Classification performance measurement

The obtained confusion matrix that reviews the testing outcomes of classifiers for further assessment has been obtained using the pre-delineated ground truth region of interest (ROI) tools. The resulting classification accuracy measurement for the wet season’s classified images (determined as an example) is shown in (Table 2).

The given table columns signify the proportions of true (ground truth values) classes, while the rows indicate the percentage of the classifier’s predictions. As it can be noticed from the resultant table that, the overall accuracies of surface cover were determined to be varying from 97 to 99% (with a kappa coefficient of approximately 0.3–0.9) for the analyzed periods from 2016 to 2020. This agreement suggests a very high correspondence between the classifiers and the predictors.

3.2. Variables mapping

The 5 years obtained intensity map for seasonal vegetation cover of Abqaiq area is presented in Fig. 4a, where, the differences in the delineated spatial distribution of the green mass is remarkably distinguished as per the ranked segments. It can be noticed that some locations have been fully covered with green mass during the wet seasons and throughout the whole 5 years (100% veg. intensity). However, a noticeable variation in vegetation intensity was observed along with the presence of abundant non-vegetation cells. Fig. 4b, 4c, and 4d also present the soil compiled parameters as being independent variables; to be able to examine any correspondence in their zonation variability with the generated intensity map. It could be interpreted essentially from the maps that almost all of the variables within the three maps had spatial trends for the distribution of the high and the low values that were resemble to the vegetation intensity ones. What is substantial to mention is that, the high percentages in the sand was the most dominant, where pixel-based sand has reached 97%, cov-
ering considerable spots of the area; while the least pixels that covered with 46% of sands. On the other hand, the DAW capacity (%) was observed to vary between 10 and 17%. For USDA soil texture, 5 distinct classes were existed, namely: silt loam, sandy loam, sandy clay loam, loamy sand, and sand. Even so, texture map has revealed differences in its classes distribution, still positive associations with vegetation could be depicted, which has encouraged the utilization of the spatial correlation between vegetation intensity and soil variables.

3.3. Vegetation-texture relationship

Cross tab tool of SPSS which is used to quantitatively examine/review the bond between different variables of categorical data type and assist in presenting the portion of situations in subgroups forms, was used. The outcomes of the applied correlation between vegetation intensity points, produced as ordinal variable and soil texture, given as nominal variables, revealed a big portion of the study area (87.5%) in which vegetation cover was completely nonexistent (Table 3), among this percent, 96.6% and 89.8% of sand and loamy sand were devoid of green biomass, respectively. Conversely, the highest vegetation-texture correspondence was depicted within a 20% vegetation intensity, which covered a half (50%) of the silt loam soil class area, followed by 60% vegetation intensity covering 33.3% of the same texture class.

The only vegetation intensity (100% intensity) that was observed to persist throughout the whole study periods was assessed to represent 0.1% of the study area, which was observed over the loamy sand class. The categorical distribution of the two variables revealed a distinguished distribution of the green biomass over almost all soil types with quantitative and directional variabilities. To assess both goodness of fit and/or the independence of the correlated variables, Pearson’s chi-squared test was applied (Table 4) and found that there was very strong evidence of a relationship between biomass distribution and soil texture, assured by relationship’s significance of P-Value of < 0.001.

An eta coefficient test, which is a process for measuring the strength of association between a categorical variable, was also conducted taking into consideration vegetation intensity as the dependent variable. A moderate degree of association was existed between the green biomass distributed values, and found to be 0.366, which in turn came in line with the expected variability in intensity values, as were pending to the spatio-temporal variability in the residual vegetation cover determined throughout the 5-years period.

| Class 08-01-2020 | Ground Truth (%) | Commission (%) | Omission (%) | Accuracy (%) |
|-----------------|------------------|----------------|--------------|--------------|
| Vegetation      | No-vegetation    |                |              |              |
| 100.00          | 2.05             | 56.96          | 0.00         | 100.00       | 43.05         |
| No-vegetation   |                  | 97.95          | 2.05         | 97.95        | 100.00        |
| Total           |                  | 100.00         | 100.00       |              |              |
| Overall Accuracy (%) = (8157/8325) 97.9820% |
| Kappa Coefficient = 0.5932 |

| Class 19-01-2019 | Ground Truth (%) | Commission (%) | Omission (%) | Accuracy (%) |
|-----------------|------------------|----------------|--------------|--------------|
| Vegetation      | No-vegetation    |                |              |              |
| 100.00          | 1.56             | 46.52          | 0.00         | 100.00       | 53.48         |
| No-vegetation   |                  | 98.44          | 1.56         | 98.44        | 100.00        |
| Total           |                  | 100.00         | 100.00       |              |              |
| Overall Accuracy (%) = (14562/14789) 98.4651% |
| Kappa Coefficient = 0.6898 |

| Class 23-01-2018 | Ground Truth (%) | Commission (%) | Omission (%) | Accuracy (%) |
|-----------------|------------------|----------------|--------------|--------------|
| Vegetation      | No-vegetation    |                |              |              |
| 99.01           | 0.04             | 10.67          | 0.99         | 99.01        | 89.33         |
| No-vegetation   |                  | 99.96          | 0.00         | 99.96        | 100.00        |
| Total           |                  | 100.00         | 100.00       |              |              |
| Overall Accuracy (%) = (68672/68698) 99.9622% |
| Kappa Coefficient = 0.9391 |

| Class 03-01-2017 | Ground Truth (%) | Commission (%) | Omission (%) | Accuracy (%) |
|-----------------|------------------|----------------|--------------|--------------|
| Vegetation      | No-vegetation    |                |              |              |
| 100.00          | 2.43             | 82.63          | 0.00         | 100.00       | 17.37         |
| No-vegetation   |                  | 97.57          | 2.43         | 97.57        | 100.00        |
| Total           |                  | 100.00         | 100.00       |              |              |
| Overall Accuracy (%) = (29328/30056) 97.5779% |
| Kappa Coefficient = 0.2898 |

| Class 19-01-2016 | Ground Truth (%) | Commission (%) | Omission (%) | Accuracy (%) |
|-----------------|------------------|----------------|--------------|--------------|
| Vegetation      | No-vegetation    |                |              |              |
| 100.00          | 0.23             | 50.56          | 0.00         | 100.00       | 49.44         |
| No-vegetation   |                  | 99.77          | 0.23         | 99.77        | 100.00        |
| Total           |                  | 100.00         | 100.00       |              |              |
| Overall Accuracy (%) = (19822/19867) 99.7735% |
| Kappa Coefficient = 0.6606 |

Table 2
Sample confusion/error matrix for the classified images.
variables, bivariate LISA and Moran’s index (I) analysis were utilized. BiLISA and Moran’s I have been examined for the two obtained parameters (sand content % and DAW capacity %) as spatial parameters that assumed to have an effect on vegetation intensity variability. The vertical axis indicates neighboring values for vegetation intensity, sand content %, and DAW capacity %, whereas

Table 3
Cross tab of SPSS statistical analysis for representing the correlated categorical variables.

| Veg. Intensity * Texture30 Cross-tabulation | Texture          | Silt loam | Sandy clay loam | Loamy sand | Sand | Total |
|-------------------------------------------|------------------|-----------|-----------------|------------|------|-------|
| No Vegetation                             | Count            | 0a        | 41a             | 575a       | 259a | 875   |
| % within Texture                          | 0.0%             | 47.7%     | 89.8%           | 96.6%      | 87.5%|       |
| 20% Intensity                             | Count            | 3a        | 18a             | 28a        | 2a   | 51    |
| % within Texture                          | 50.0%            | 20.9%     | 4.4%            | 0.7%       | 5.1% |       |
| 40% Intensity                             | Count            | 1a        | 9a              | 13b        | 2b   | 25    |
| % within Texture                          | 16.7%            | 10.5%     | 2.0%            | 0.7%       |      |       |
| 60% Intensity                             | Count            | 2a        | 14a             | 15b        | 4a   | 35    |
| % within Texture                          | 33.3%            | 16.3%     | 2.3%            | 1.5%       |      |       |
| 80% Intensity                             | Count            | 0a, b     | 4a              | 8a         | 1a   | 13    |
| % within Texture                          | 0.0%             | 4.7%      | 1.2%            | 0.4%       |      |       |
| 100% Intensity                            | Count            | 0a        | 0a              | 1a         | 0a   | 1     |
| % within Texture                          | 0.0%             | 0.0%      | 0.2%            | 0.0%       |      | 0.1%  |
| Total                                     | Count            | 6         | 86              | 640        | 268  | 1000  |
| % within Texture                          | 100.0%           | 100.0%    | 100.0%          | 100.0%     | 100.0% | 100.0% |

Each subscript letter denotes a subset of Texture categories whose column proportions do not differ significantly from each other at the 0.05 level.

Fig. 4. Maps showing the study-based variables where, (a) shows the generated vegetation intensity, in addition to the obtained (b) DAW capacity %, (c) sand content %, and (d) USDA soil texture maps.
the horizontal axis indicates the average vegetation intensity values. The results of BiLISA clustering and its particular significance for vegetation intensity against sand content % is highlighted (Fig. 5a), along with the resultant bivariate Moran’s \(I\) which is illustrated (Fig. 5b). Likewise, Fig. 5c and 5d present the spatial autocorrelation status of vegetation intensity versus the DAW capacity %, produced in terms of BiLISA clustering significance map and bivariate Moran’s \(I\), respectively.

The applied BiLISA clustering has revealed a significant negative spatial autocorrelation concerning vegetation intensity and sand content % (Fig. 5a), where, the percent of the high sand content area that correlates low vegetation intensity was the most dominating, corresponding to the green mass areas (low-high); while few sporadic areas occupied with low percent of sand content that observed to have correlations with high vegetation intensity (high-low). The obtained Moran’s \(I\) for the vegetation intensity-sand content % (Fig. 5b) process was approximately 0.3, upon 999 permutations with a pseudo \(p\)-value of 0.001. On the other hand, the employed BiLISA method for vegetation intensity and DAW capacity % relationship (Fig. 5c), revealed a significant positive autocorrelation (denoted by high-high and low-low) showing a high clustering of green biomass cover that associates with high clustering of soils distinguished by their high capacity for water content. Likewise, areas covered with low intensity of vegetation cover correlated (utmost) spots of soil that were having the least capacity to water availability (146 pixels). Moran’s \(I\) that was applied to measure the robustness of the relationship has also revealed a value of 0.3 with 999 permutations process, in which the pseudo \(p\)-value was assessed to be 0.001. It is worth to state that, a big portion of non-significant autocorrelation for both relationships (outliers) existed, this can be justified by the spatial incompatibility between green biomass and soil variables, within the areas where sand dunes/sheets were extended utmost against the non-vegetation class.

In the context of soil texture-aided vegetation development, a schematic relationship was developed between the ranks of vegetation intensity and soil texture classes (Fig. 6), where Fig. 6a show the higher occupancy rate for each category of vegetation intensity, excluding the non-vegetation class. Additionally, in order to characterize the percentages of vegetation occupancy within each given texture-class area of the soil, the resultant ranks of the vegetation intensity map were plotted versus texture (Fig. 5b).
4. Discussion

Despite the temporal compatibility between green biomass pixels as well as their spatial adjacency, the analysis revealed that the sand dunes/sheets have been the most dominating surface cover throughout the study area. With reference to Fig. 6a, although the full (100%), as well as the very high vegetation intensity classes, were observed to be obtained by the sandy clay loam and silt loam, respectively, more than half of the green biomass has been covered with only 20% of the vegetation. In comparison, very few spots of the area have witnessed vegetation growth frequented by the 5 successive wet seasons. This could be due to many reasons represented in the possible change in climatic aspects, where spatial and temporal variabilities in precipitation could play a significant role in grass species distribution. A study by Mussa et al. (2016) has confirmed the climate effect by pointing that climate change has an influence on pastoral mobility trends, which is a consequence of substantial droughts in different parts, leading to accelerating decline in vegetation quantity and quality. On the other hand, from Fig. 6b, which highlights the occupancy percentages within soil texture classes of the area soil, it can be figured out that almost all (>97%) of soils with high percentages of sand content reveal a total absence of green biomass. This specifies the nature of region’s rangelands, where deserts that featured with transferring sand dunes is the most distinguished component (Al-Tahir, 1999), showing the influence of Aeolian system on green clans (Rajab, 1990; Gharaibeh et al., 2011). The sand dunes domination over the region was formerly reported by Salih (2018), who likewise revealed that sand dunes were the most dominating land cover when compared to other classes such as bare soil, agricultural lands, water bodies, Sabakha, and urban. Further, a study conducted by Abd El-Salam and Elhakem (2016) in Jazan region of south-western Saudi Arabia to analyze the characteristics of vegetation cover in terms of frequency and abundance corresponding to soil, applied at three locations with different quantitative and descriptive criteria. The results proved that the distribution of plant species was governed by soil characteristics. Another supporting study was achieved by Zare Chahouki et al. (2008), who examined the relationship between patterns in vegetation distribution and soil characteristics within the rangelands of Yazd Province, in Iran. Their outcomes stated that the pattern in vegetation distribution seemed to be mostly correlated to soil parameters such as texture, salinity, soluble potassium, gypsum, and lime. With regards to the impact of soil variables on the variety of vegetation, Munhoz et al. (2008) likewise worked in the species-environment relationship in the herb-subshrub part of a humid Savanna site in central Brazil. They also observed a significant relationship between the soil texture and soil moisture variables with the plant distribution depending on the canonical-correlation analysis. Furthermore, another confirmatory study was carried out by Sala et al. (1997), where they managed to present a conceptual model primarily based on 2 components they assumed to have a significant effect on controlling shrub and grass popularity in semi-arid regions. The applied components were the seasonal connection between monthly temperatures-precipitation and soil texture.

In addition to all of that, herbivore grazing could be the principal disturbance influencing the spatial distribution of grassland ecosystems, which includes productivity as well as ecosystem capabilities (An and Li, 2014; Liu et al., 2015). This has been confirmed by Belsky (1992) and Zhou et al. (2010) who stated that, within the soil-plant-herbivore system, herbivore grazing impacts species structure and diversity within the plant community, and also affects soil physical/ chemical properties. Harris (2010) has supported this argument by stating that, overstocking, in addition to related overgrazing, is usually often cited as being the main source of rangeland degradation. It is driven by social prestige and prosperity linked to livestock along with population increase in the rangelands. While Li et al. (2013) confirmed that, extreme removal of green biomass in overgrazing puts plants development at risk and also the associated primary productivity. A report by Abuinada et al. (2005) supporting the dynamic nature of vegetation demonstrated that approximately 60% of the vegetation, generally within the low lying areas, is found in the form of annuals of which inhabitants density differs from year to year, according to the quantity of precipitation and also the quantity of seeds remained from former years.

To sum up, it was observed from the interpretation of the generated vegetation intensity’s distribution, corresponding to the obtained soil physical variables that variability in soil properties was assessed to introduce additional influence on the spatial variability. Silt loam texture class, in particular, has proven to have the most correlated values to the intense vegetation habitats, where 5%, 35%, and 28% of the silt loam class were occupied by 80%, 60%, and 40% of vegetation intensities, respectively. It is also worth to point to that noticeable point’s outlier was observed upon BiLISA autocorrelation, from which insignificant representations were addressed (641 for sand content % and 674 for DAW capacity %), this is attributed to the intensive allocation of sands at the eastern and south-east directions, in addition to small portions located at west of the study area. Such outlier (sand vs non-vegetation) could be considered for a univariate-type Moran’s I so as to be able to measure the presence of spatial clusters/outliers among the assessed values of every single parameter. Hence, the robustness of the spatial association between average values corresponding to the values within the neighboring locations, for the same...
parameter will be examined (Edris et al., 2020). However, the univariate Moran's I was yet considered as part of the current spatial autocorrelation, as the spatial representation of biomass cover along with soil parameters was considered.

5. Conclusion

Based on an established conviction assuring that remote sensing has proven to be a valuable application for depicting spatial and temporal changes in land cover and land use, this study highlighted the dynamic nature of Abqaiq rangelands' vegetation and quantify the degrees to which intensities have spatially categorized. The study also investigated the possible impact caused by the spatial variability of obtained soil texture, sand content (%), and the DAW capacity (%) on the intensity distribution of vegetation cover. Ordinal-nominal correlation type and spatial autocorrelation processes were adopted throughout the study, to analyze the spatial correspondences as well as the interrelated patterns of the given variables. However, the following concluding points are inferred from the study:

- Annual vegetation residual maps were produced with classification accuracies ranged between 97 and 99%, hence, a vegetation intensity map was generated at 5-years bases. The acquired map revealed variability in the intensity of rangeland's vegetation ranged from 20 to 100%.
- The correlation between vegetation and soil texture (ordinal versus nominal variables) has yielded a significant (p-value < 0.001) relevancies, where, silt loam texture class in particular, has proven to have the most correlated values to the intense vegetation habitats, where 5%, 35%, and 28% of the silt loam class were occupied by 80%, 60%, and 40% of vegetation intensities, respectively.
- The applied BiLISA clustering process has achieved a substantial (pseudo p-value of 0.001, for both relationships (intensity measure and/or test the robustness of the relationship has been yet considered as part of the current spatial autocorrelation concerning vegetation intensity and sand content %), revealing a total absence of green biomass over the sandy soils.
- Conversely, the BiLISA applied autocorrelation between vegetation intensity and DAW capacity %, has revealed a significant positive autocorrelation, showing a high clustering of green biomass cover associates with high clustering of soils that have a high intensity for water content. Morn's I, which was applied to measure and/or test the robustness of the relationship has revealed an approximate value of 0.3 with 999 permutations and pseudo p-value of 0.001, for both relationships (intensity vs sand content % and intensity vs DAW capacity %).

As the study has focused on the vegetation intensity and its relationship to soil physical parameters, it is recommended that the future studies should include climatic data (precipitation, temperature, wind, etc.), data on grazing activity, crop phonological data, and surface topography (as examples), for more precise and accurate assessment of rangeland's influential parameters.

Declaration of Interests

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 A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.sjbs.2020.11.060.

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