GIScience & Remote Sensing, 2019
Vol. 56, No. 3, 362–387, https://doi.org/10.1080/15481603.2018.1519093

Time series analysis of vegetation-cover response to environmental factors and residential development in a dryland region

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(*Received 10 January 2018; accepted 30 August 2018*)

Land-use changes as a result of residential development often lead to degradation and alter vegetation cover (VC). Although these are worldwide phenomena, sufficient knowledge about anthropogenic effects caused by various populated areas in dryland ecosystems is lacking. This study explored anthropogenic development in rural areas and its effects on the conservation of protected areas in drylands, focusing on the change in VC, the reasons, extent, and the drivers of change. We propose a novel framework for exploring VC change (VCC) as a function of environmental and human-driven factors including different types of populated areas in drylands. As a case study, we used a 30-year time series of Landsat satellite images over the arid region of Israel to analyze spatiotemporal VCC. The temporal analysis involved the Contextual Mann-Kendall significance test and spatial analysis to model clustering of VCC. A Gradient Boosted Regression machine learning algorithm was applied to study the relative influence of environmental and human-driven factors on VCC. In addition, we used ANOVA to examine differences between the effects of three types of populated areas on the spatiotemporal trends of VC. The results show that the most influential environmental variable on VCC was elevation (relative contribution of 17%), followed by slope (14.8%) and distance from populated areas (14.6%). Moreover, different types of populated areas affected VC differently with varying distances from residential centroids. The nature reserves increased VC positively and significantly, while livestock settlements had a negative effect. Change in vegetation was mostly confined to the stream network and occurred in lower elevations. The study demonstrates how different land-use practices alter the landscape in terms of VC and differ in their extents, patterns, and effects. With the expected growth in population and residential development worldwide, the proposed framework may assist conservation managements and policy makers in minimizing environmental degradation in drylands.

Keywords: drylands; protected area; grazing; agricultural settlements; remote sensing; spatial analysis

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1. Introduction

In recent decades, the Earth's land surface has experienced extensive land-use change (LUC), causing modification of ecosystems worldwide (Newbold et al. 2016; Vitousek et al. 1997). These LUCs are known to affect alteration in vegetation cover (VC), species diversity, biomass alteration, and soil quality and quantity modification (Akhzari, Pessarakli, and Ahandani 2015), thereby influencing ecosystem structure and functioning (Tilman and Lehman 2001). Although LU practices vary greatly across the globe, their general purpose includes acquiring natural resources for human needs that may cause degradation in environmental conditions (Crist, Mora, and Engelman 2017). LU transformations, as a result of population growth and food production, have frequently caused intensified pressure on nearby protected areas with high conservation value. Concurrently, conservation attempts have been made in specific areas that provide valuable ecological and cultural services to minimize the effects of these transformations (Buisson and Dutoit 2006).

Dryland ecosystems are facing adaptation and reorganization challenges in response to anthropogenic climate and LU changes worldwide (Wilcox, Sorice, and Young 2011). These areas are prone to changes in VC given their limited, highly variable rainfall regime, and low soil fertility. The changing ecosystem attributes are often unclear, as are the reasons, the extent, the timescale, and the drivers of change (Bestelmeyer et al. 2015). Small residential settlements may affect their surrounding environment, including adjacent protected areas, through land cultivation for agricultural and livestock production (Amiri et al. 2008). Also, areas characterized by low population densities are often used for military purposes, exposing them to disturbances due to military maneuvers (Milchunas, Schulz, and Shaw 2000) and training. Continuous anthropogenic intervention in an area consisting of natural habitats promotes the system's fragmentation and reduces its ability to support the conditions and surroundings that are essential for their sustainability (Visscher 2006).

Remote sensing is a common tool for quantifying temporal and spatial trends of LUC and VC change (VCC), and is most efficient for conducting VC time-series analysis (Mondal et al. 2017; Liu et al. 2011). VCC may be caused by various aspects of residential development, such as increased agricultural activities, livestock production, and military activities that have varying effects on adjacent protected nature reserves (Hutchinson et al. 2015; Paudel and Andersen 2010).

While various studies have explored the effects of land-cover changes on the surrounding environment in densely populated and urban areas using remote sensing techniques and spatial modeling (Ohana-Levi et al. 2015; Rawat and Kumar 2015), fewer studies have focused on residential activities in rural areas and their effects on protected areas in drylands (Bestelmeyer et al. 2015; Collado, Chuvieco, and Camarasa 2002; Nielsen-Pincus et al. 2010). Together with spatial analysis and advanced spatial statistics techniques, it is possible to assess both the impact of environmental factors and the influence of different anthropogenic practices on VCC at the landscape scale (Paz-Kagan et al. 2014).

Israel is one of the most densely populated countries in the world, with the highest birth rate among developed countries (Shoshany and Goldshleger 2002). The country's rapidly increasing population growth rate is driving the pressure for residential development. The arid southern part of Israel, the Negev Desert, is the country's largest land resource, and government policy encourages redirecting growth to this region (Orenstein and Hamburg 2009). Therefore, residential development is predicted to expand in this area, making it crucial to understand its effects on the surrounding environment, in general, and on protected areas and nature reserves, in particular.

We propose a framework that includes satellite-derived time series of VC to study the effects of residential development on VCC in rural and protected areas in a dryland region, and environmental and human-driven factors that modify VCC on a landscape scale. Rather than monitoring, we focused on characterizing the trend of VCC through time and targeting the causes for these transformations. The main aim of this research was to assess the impacts of environmental factors and populated areas on VCC through a multi-decadal time period in a dryland area that includes protected nature reserves. In order to fulfill this aim, three specific objectives were defined: (1) to produce a spatiotemporal trend map of VCC using a time series of 30 years (1987–2016) of high resolution spaceborne imagery; (2) to analyze the main environmental and human-driven factors that influence the VC trends; and (3) to determine to what extent and distance each populated area type in the region affects VC.

2. Materials and methods

2.1 Study area

Har HaNegev is a region in southern Israel's arid Negev Desert (Figure 1a). The specific study area is a domain within Har HaNegev, covering an area of 445 km^2, and will be referred to as "Har HaNegev study area" hereinafter. The study area was chosen to represent high land-use variability that includes five protected areas and a significant amount of settlements (Figure 1b) of various types and effects. The climate in this arid region is characterized by infrequent rainfall events between October and May, with mean annual rainfall of 80–100 mm (Ziv et al. 2014) and high spatial and inter-annual variations (Kahana et al. 2002). The mean maximum summer temperature is 32°C, and the mean minimum winter temperature is 5°C (Olsvig-Whittaker et al. 2012). The elevation ranges between 290 and 860 m, with the southern part reaching higher elevations and gradually declining towards the north. The area's lithology is dominated by limestone, frequently mixed with dolomite, chalk, and marl. The ephemeral stream channels are loessial and composed of clay, silt, and gravel alluvial soil. The vegetation is patchy and composed mostly of dwarf shrubs with an average areal cover of about 25% (Shelef and Groner 2011), while most of the VC occupies the stream network (Mazor 2001).

The Negev Desert has a very long history of anthropogenic land use, such as agricultural practices (e.g., water-harvesting systems based on terraces) and grazing, often resulting in an equilibrium state of semi-natural ecosystems (Röder et al. 2007). Many ancient agricultural terraces are still abundant in this area, occupying the stream network, retaining rainfall water, and allowing for rich ephemeral flora to become established (Olsvig-Whittaker et al. 2012). Livestock grazing has taken place in this area for thousands of years and has shaped the surrounding desert's vegetation composition and structure.

The Negev Desert is the largest land resource of Israel, making it a preferred target for the country's policy makers' solutions for demographic growth and residential development (Orenstein et al. 2009). The selected study area contains protected nature reserves (Figure 1c), two small agricultural towns (hereinafter agricultural settlements), 11 individual family farms (hereinafter agricultural settlements) (Figure 1d), 10 government facilities, mostly military bases and a jailing facility (Figure 1e), and 10 livestock settlements (Figure 1f), as monitored from satellite imagery. The population concentration is rather sparse, and the developed areas, as computed using very high-resolution satellite imagery, occupy about 0.3% of the study area. Military training is allowed only in designated military firing zones that constitute about 60% of the study area, according to official maps of Survey of Israel. These firing zones are used for basic training and maneuvering. Nature reserves are managed and controlled by the Israel Nature and Parks Authority (NPA), and according to official data provided by NPA, occupy about 24% of the study area, occasionally intersecting with the military firing zones. Aside from

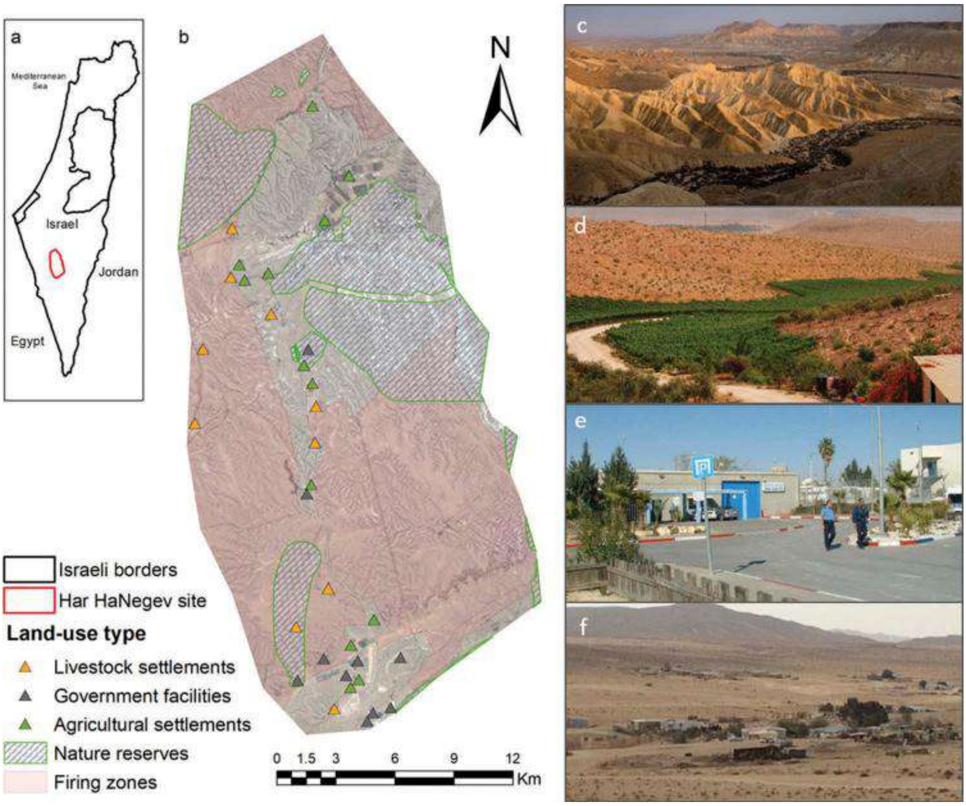

Figure 1. Har HaNegev study area. (a) Location within the Israeli borders; (b) land-use type; (c) the Zin Nature Reserve (photograph by Silvia Giamberini); (d) agricultural farm (photograph by Eyal Israeli); (e) jailing (government) facility (photograph by Ilan Borreda); (f) livestock settlement (photograph by Gal Bismuth).

tourism and hiking purposes in defined and confined paths, anthropogenic activity is limited and minimized in these reserves. These reserves were designated as such for their unique and endemic fauna and flora, as well as their water resources, geological features, and archeological sites.

2.2 The study framework

The following parts of the Methodology section describe the analyses conducted in this work (Figure 2) that included (a) preprocessing of 27 Landsat satellite images along a 30-year timeframe and conducting the soil-adjusted vegetation index (SAVI) for each one. Then, these images were analyzed for spatiotemporal VCC trends using Contextual Mann-Kendall (CMK) significance test; (b) a spatial statistics cluster analysis was performed to evaluate spatial patterns of the vegetation trend; (c) a gradient boosted regression trees (BRT) algorithm was used to assess the relative influence of ten environmental and human-driven predictor variables on VCC; (d) a statistical test to compare the influence of different populated area types on VCC.

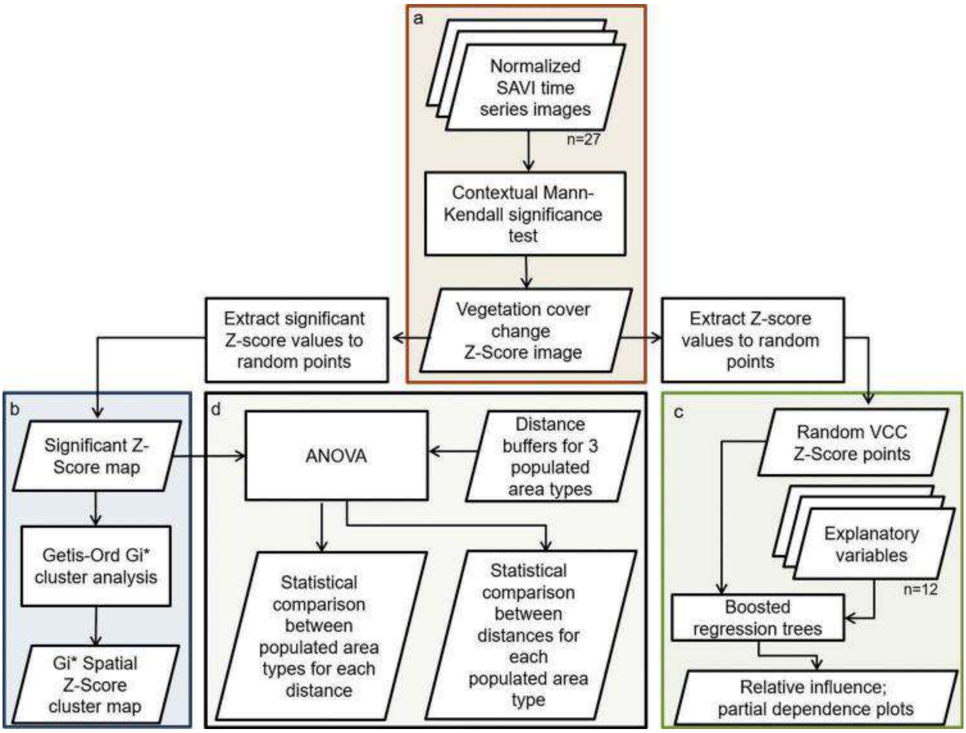

Figure 2. Flowchart of the study framework: (a) time series of Normalized SAVI; (b) cluster analysis of spatial Z-score; (c) environmental factors and human-derived factors; and (d) distance from populated areas effect on vegetation cover.

2.3 Time series analysis of normalized SAVI

We composed a series of Landsat images for a period of 30 years between 1987 and 2016 (excluding images for 1988, 1998, and 2012), all acquired during the summer (Appendix 1). The focus of the analysis was on woody vegetation, since annual vegetation variates greatly along the year and between years, relative to the variability in rainfall (Schmidt and Karnieli 2000). We, therefore, included only images from the summer, when the green annuals are dry and could be disregarded from the VC time series. Each of these images went through a pre-processing procedure that included atmospheric and topographic corrections using the ATCOR-3 model (Richter 2010). To analyze VCC and its related temporal phenomena, we selected SAVI (Huete 1988) (equation 1) and applied it to every image. Unlike other vegetation indices, this index was designed to minimize the soil background influence, which has a significant effect in drylands (Sonnenschein et al. 2011)

$$SAVI = ((\rho NIR - \rho R))/((\rho NIR + \rho R + L) * (1 + L)) \tag{1}$$

where ρNIR and ρR are the reflectance values in the near infrared and red spectral bands of the sensor, respectively. The study area is characterized by sparse vegetation along the slopes and a denser vegetation pattern along the streams. Therefore, we chose an adjustment factor (L = 0.5) for reducing soil noise that describes intermediate-sparse vegetation densities (Huete 1988). A standardization approach was applied to allow comparisons between all SAVI images, with a mean value of 0 and standard deviation of 1 to rescale all of the SAVI images to the same value range, enabling comparison and further analysis (Bayarjargal et al. 2006). The normalized scale ranged overall between −6 and 32, while each of the SAVI images resulted in a slightly different SAVI range, depending on the vegetation status.

The normalized SAVI time series was analyzed for assessing significant trends using the CMK significance test (Figure 1a). This analysis assumes that conditions at a certain location that experienced a trend over time will be similar to neighboring locations, thereby allowing for the application of contextual spatial information (Neeti and Eastman 2011). The CMK test relies on the Theil-Sen (TS) slope estimator, which is the median of the slopes calculated between observation values at all pair-wise time steps, with a total of n(n-1)/2 slopes (Sen 1968). In this test, the data are ranked according to time, which relates to the 27 Landsat images time series (Appendix 1), and each point is treated as the reference for the data points in successive time periods. This test is non-parametric, robust against outliers, and suitable for quantifying non-linear phenomena. To avoid biases resulting in specific trends in isolated pixels, the CMK test was used, taking into account spatial autocorrelation as a line of evidence and including contextual geographical information. Each pixel was evaluated according to a 3 × 3 neighborhood. The resulting statistic was then computed for a Z-score test statistic (VCC Z-Score) that follows a normal distribution with a mean of 0 and standard-deviation (SD) of 1 (Neeti and Eastman 2011). There are several advantages and limitations to using a standardizing and normalizing statistic such as Z-Score. The relationship between scores is more clear and comparable. Moreover, it enables learning about the statistical significance (probability of occurrence) of the original data, which in our study reflects on magnitude of change. Z-Scores follows a normal distribution with negative and positive values, enabling to learn about the direction of the phenomenon. In the case of the CMK test, VCC Z-Score provides a singular result for a large set of data. The limitations of applying this statistic are that it is standardized, with a mean of 0 and SD of 1, therefore limiting the knowledge about the original variance of the data. Moreover, this test tends to magnify small differences.

In the resulting VCC map, a pixel with a positive VCC Z-score indicates an increasing trend, whereas negative scores suggest a decreasing trend. The *p-value* of the CMK was used to determine the significance level of the trend and was determined using the normal cumulative distribution function. We considered p-values ≤ 0.05 (confidence limit of 95%) to represent a significant trend. According to the cumulative distribution function, this means that VCC Z-scores < -1.96 and > 1.96 were considered statistically significant and represented a high magnitude of VCC (Teferi, Uhlenbrook, and Bewket 2015). The resulting map provided a VCC Z-scores, indicating the magnitude and direction of the VC trend with respect to neighbors. This procedure was implemented in IDRISI's TerrSet 18.3, using the Earth Trend Modeler (Eastman 2016), with the Mann-Kendall trend significance tool. The VCC Z-score map was the basis for further analyses. It enabled us to study spatial trends regionally.

2.4 Cluster analysis of spatial z-score

The VCC Z-score map was used to extract values for a sample size of 50,000 randomly generated points. From these random points, only those with significant values ($p \leq 0.05$, confidence limit of 95%) were selected. Quantifying the spatial interactions among these features was conducted using the spatial Getis-Ord Gi* statistic (Getis and Ord 1992)

(Figure 1b). This test is also known as a hot spot analysis and was designed to analyze the location-related tendency in point feature class (Peeters et al. 2015). The Gi* Z-Score statistic provides an indication of the local autocorrelation for each VCC Z-score feature. This enables evaluation of the similarity (high or low) between each point and its surrounding features. This analysis was conducted using the Hot Spot Analysis (Getis-Ord Gi*) tool in ArcGIS 10.5. Positive Gi* Z-scores denoted the spatial dependence of high values, while negative Gi* Z-scores indicated the spatial dependence of low values.

A spatial correlation analysis was conducted for the Getis-Ord Gi* results with distance from streams and elevation gradient, using a geographically weighted regression. This spatial statistics test was applied through a tool in ArcGIS 10.5, and is designed to consider non-stationarity of spatial data, whose values vary locally, to explore spatially varying relationships (Ohana-Levi et al. 2015). Its output is an adjusted regression (R) value that denotes the relationships between the spatial pattern of clustering and the two environmental factors.

2.5 Environmental and human-derived factors

The VCC Z-score raster described in section 2.2 was used as a basis for extracting the values of 16,000 randomly distributed points (Figure 1c) that served as an adequate sample size with a confidence level of 99% and a confidence interval of 1. The VCC Z-score layer was considered the response variable. The predictor variables selected for studying their effect on VCC were both environmental (elevation, slope, aspect, distance from streams, lithology, soils, land-surface temperature (LST),), and human-derived (military firing zones, nature reserves, distance from populated areas) and land cover predictor, which represents environmental and human-derived effects (Figure 3). A detailed review of these variables is provided in Appendix 2. A correlation matrix was computed for these variables to check for multicollinearity; variables with high correlations were removed from the analysis to avoid redundancy and over-fitting. These variables were then analyzed for their relative contribution to VCC using BRT algorithm with R software, using "dismo" package (Elith, Leathwick, and Hastie 2008). The BRT model enables to incorporate different types of predictor variables (continuous, categorical) and does not require prior data transformation or adaptation. It accounts for non-linear relationships and calculates the interaction effects between predictors. The input included a tabulated file with per-point values of all variables that were considered in the model – the environmental predictor variables and the response VCC Z-Score variable. The model then required modifying arguments for optimization such of number of trees, the learning rate of the model, tree complexity and more, for purposes thoroughly described in Elith et al. (2008). The outputs of the model included the relative influence of the predictor variables on the response VCC variable (in %). Also, the non-linear interactions between the predictor variables were computed, and if large interaction sizes were found, one of the variables would be removed from the analysis. Additionally, we considered partial dependence plots (PDPs) that graphically characterize relationships between a specific predictor variable and predicted probabilities of VCC, after averaging out the effects of the other predictor variables in the model (Cutler et al. 2007). PDPs may assist in explaining the pattern of effect for each predictor variable, and whether a specific variable has a negative or positive (or none) effect on the model. All predictors except for the one being examined are held constant, therefore PDPs do not highlight the nonlinear interactions between predictor variables. Finally, to assess the performance of the model, BRT provided statistics for training data correlation and cross-validation correlation.

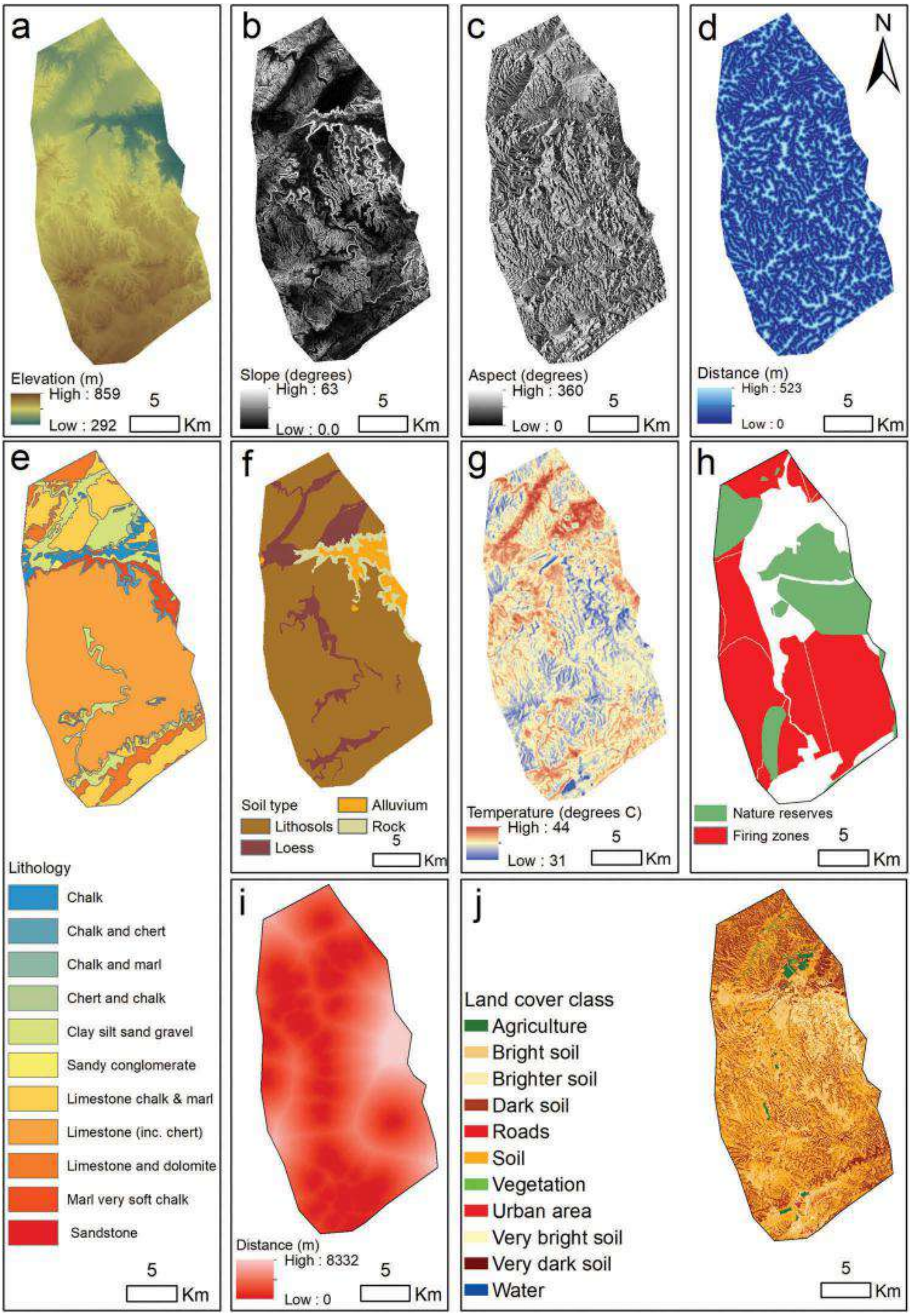

Figure 3. Boosted regression trees explanatory variables: (a) Elevation (m); (b) Slope (degrees); (c) Aspect (degrees); (d) Distance from streams (m); (e) Lithology; (f) Soils; (g) Land surface temperature (°C); (h) Military firing zones and nature reserves; (i) Distance from Populated locations; and (j) Land cover.

Cross-validation tests the model on withheld portion of the data, while using all data to fit the model (Momparler, Carmona, and Climent 2016). If the training data correlation is much higher than the cross-validation correlation, the model is over-fitted (the learning algorithm fits esoteric aspects of the training data that do not result in improvement to the model).

2.6 Distances from populated areas effect on vegetation cover

The populated areas were divided into three types to evaluate to what extent each type affects VCC at various distances. The populated areas were agricultural settlements, livestock settlements, and government facilities (mainly military bases). For each populated area, a centroid was computed to represent its location. Then, buffers were generated for the following distances from centroids: 100, 150, 200, 250, 500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, and 4500 m to represent both the residential development effects within the settlements and the ongoing effects further away from the settlements. The 50 m increments between 100 and 250 m capture the rapid change and slight differences in VCC within the populated areas; further away from the centroids VC changes in larger distance increments and could be represented by 500 m intervals.

The next step involved analyzing the VCC Z-score points, as specified in section 2.3 (Figure 1d). These data included 12,788 points across the study area, with significant VCC Z-scores. For each distance from the centroids of each populated location, the numbers of positive and negative Z-score values were extracted, and the ratio between positive and negative values was computed. These ratios were compared between the three populated areas types and for all of them combined. Negative values denoted more negative Z-score points than positive and vice versa. In addition, the mean and standard error values for each distance of each populated area type were computed and compared. The analysis of variance (ANOVA) statistical test was calculated for the significant Z-score values. We then performed a post-hoc Tukey test in order to establish the differences of specific groups. These tests were performed in order: (1) to study the differences between the various distances for each populated area type; and (2) to study the differences between the various populated area types for each distance (Figure 1d). This analysis excluded the distances 150 and 250 m.

3. Results

3.1 Time series analysis of normalized SAVI

The CMK time series analysis resulted in a map of VCC Z-score values, representing the temporal trend of each pixel (Figure 4). Three major patterns were spatially explicit: (1) the areas of the NPA nature reserves, especially the Zin area, had the highest concentration of positive, significant VCC Z-score values; (2) areas that experienced grazing during this period, such as the Bsor area, showed very low, significantly negative VCC Z-score values; and (3) agricultural activities, such as those in Sede Boker area, were indicated by significantly high VCC Z-score values.

3.2 Cluster analysis of spatial z-score

The cluster analysis results were indicated by Gi* Z-scores with a range between −6.4 and 12.7 (Figure 5a). The Gi* Z-score values relate to the extent of similarity that each

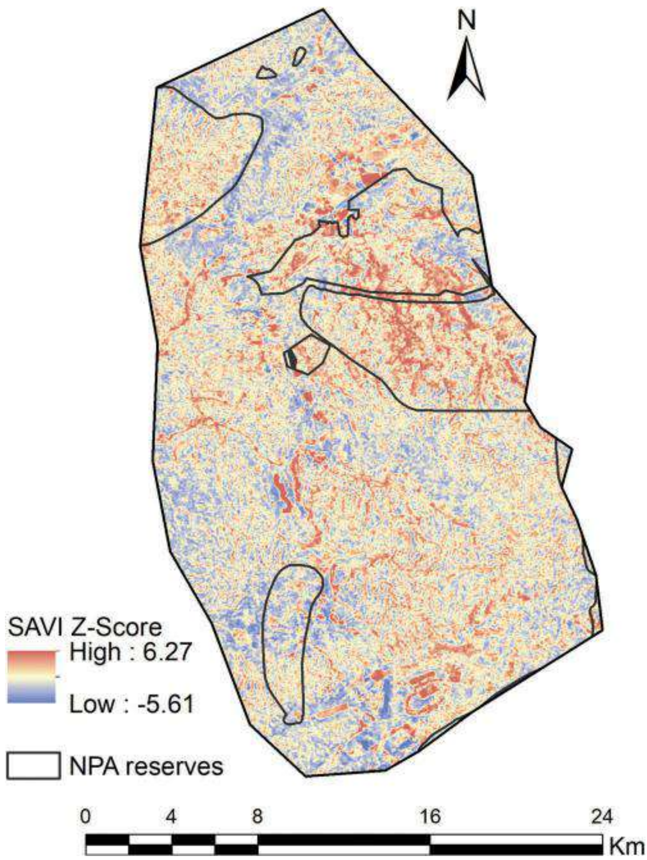

Figure 4. Temporal Z-score map of vegetation cover trends calculated using the Contextual Mann-Kendall statistical test.

VCC Z-score pixel had to its neighbors to analyze the spatial patterns of temporal trends. The spatial extents of the VCC Z-scores showed high positive clustering in the Zin NPA reserve, for example, and high negative clustering in areas with livestock activities. Most of the clustering patterns (both positive and negative) were confined to the stream network, and were correlated to distance from streams with $R_{adjusted} = 0.93$. The spatial clustering was also responsive to the elevation gradient, and had a correlation of $R_{adjusted} = 0.98$ with elevation (Figure 5).

3.3 Environmental and human-derived factors

Table 1 shows the arguments that were used for running the BRT algorithm. The relative influence analysis results are presented in Figure 6. After removing the LST variable from the analysis due to strong interactions with elevation, the four most influential predictor variables on VCC were elevation (17%), slope (14.8%), distance from populated areas (14.6%), and aspect (13.6%). Their PDPs show that for elevation (Figure 7a), the range of 290–330 m above sea level, contributed greatest to the model, and the values sharply dropped with increasing altitudes. Above 830 m, the negative influence is

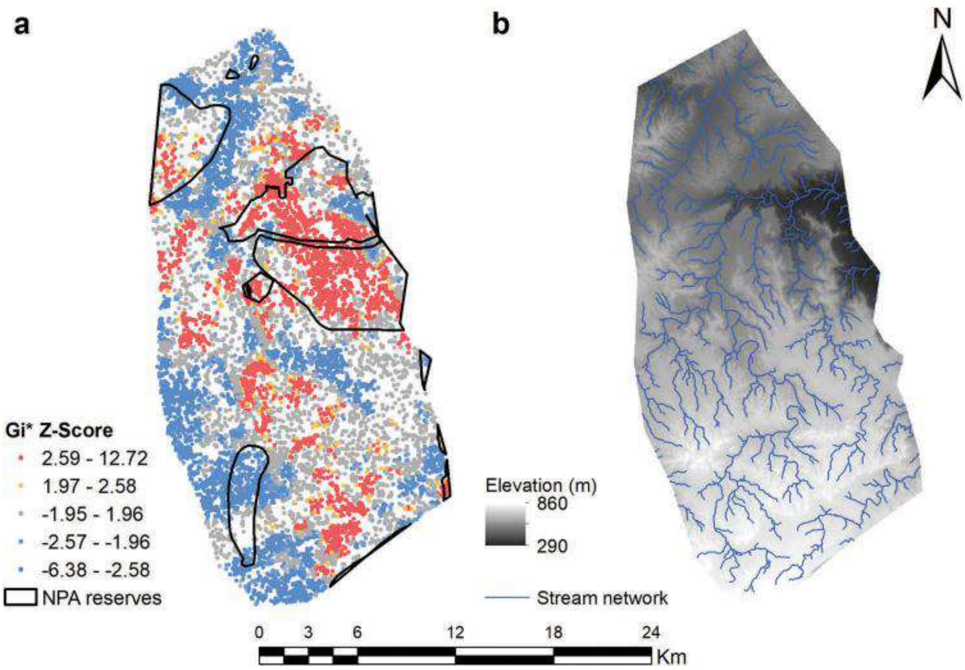

Figure 5. Spatial Z-score map, indicating (a) the clustering features (Getis-Ord Gi*) of temporal trends in vegetation cover; and (b) the elevation and stream network of the study area.

Table 1. Arguments used for running the optimal boosted regression trees model, in order to derive the relative influence of predictor variables on vegetation cover change.

Argument	Input
X	Predictor variables, excluding elevation
Y	Response variable – VCC
Number of trees	1000
Family	Gaussian
Tree complexity	5
Learning rate	0.03
Bag fraction	0.5
Maximum number of trees	4000

sharper. Lower slopes (Figure 7b) were related to a negative impact on the model. As the slope values increased, this variable contributed more. Distance from populated areas (Figure 7c) provided a positive contribution to the model in closer ranges to the populated area (up to 80 m) and sharply decreased into negative values. At a distance of 4500 m the influence reaches a negative peak, but only at a distance of 6500 m its contribution turned positive again. North aspect (Figure 7d) was related to higher performance of the model, along with a moderate positive influence of west and north-west aspects. East and south aspects had a negative impact. The validation results showed that the training data correlation and cross-validation correlation were 0.76 and 0.55, respectively.

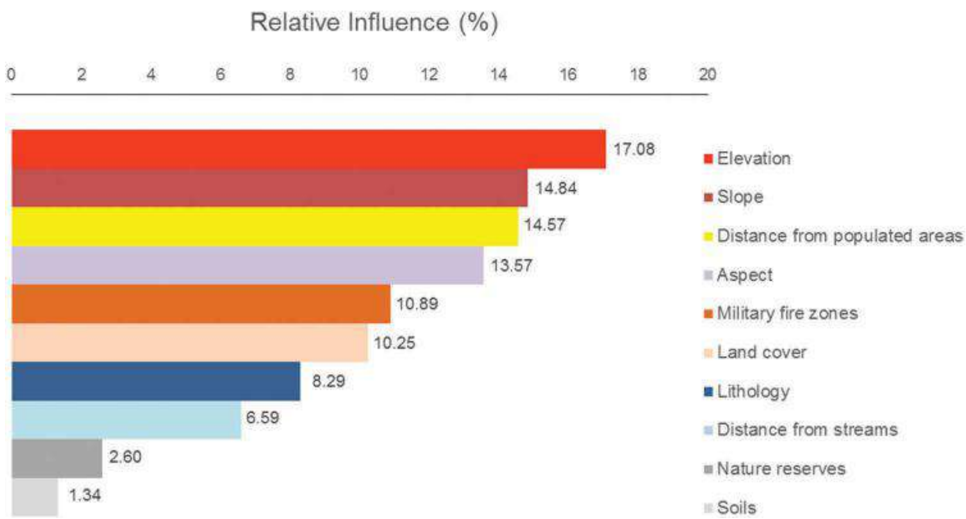

Figure 6. Relative influence (in %) of each environmental variable on vegetation cover change.

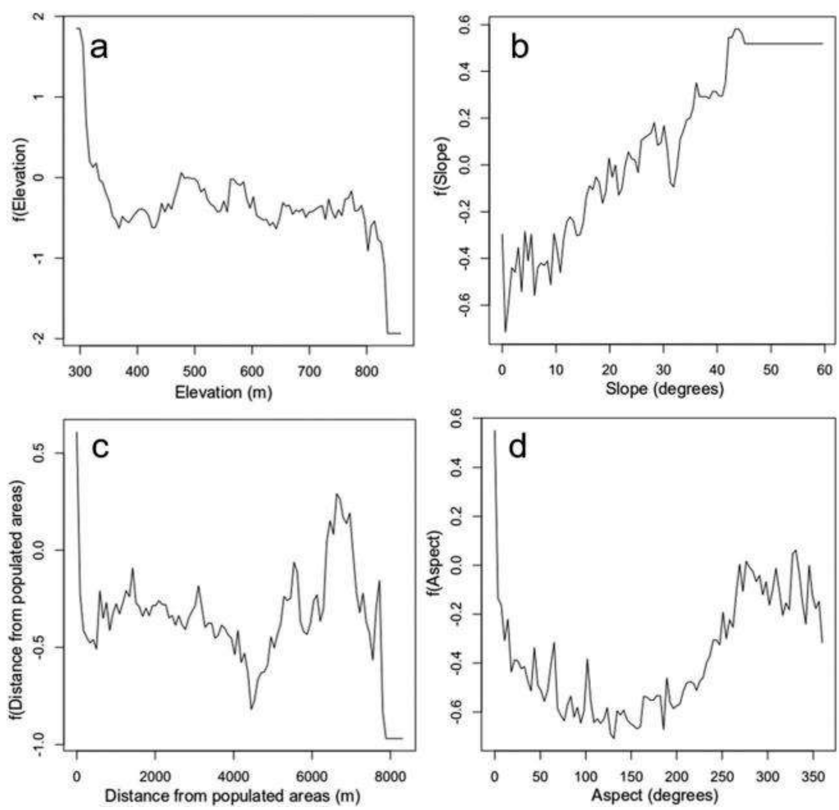

Figure 7. Partial dependence plots of the four most influential variables: (a) elevation; (b) slope; (c) distance from populated locations; and (d) aspect.

3.4 Distances from populated areas effect on vegetation cover

The VCC Z-score ratio values that were calculated for each distance from the populated centroids were plotted in Figure 8a. The ratio for the entire study area was composed of 4502 positive and 8286 negative points, situating the overall ratio at −0.84, reflecting a generally negative VCC trend. The ratio for the NPA nature reserves was 0.17. The ratio for the combined populated areas started as positive at short distances from the centroids, and gradually declined with distance; after about 250 m, the ratio was negative (more significantly negative VCC Z-score points than positive). After 1000 m, the ratio reached the point of the overall ratio (Figure 8b) and kept declining until reaching stability at 1500 m. For agricultural settlements, the trend was similar; however, the ratio values were higher than for all other settlement types. At around 3000 m, the ratio merged with the overall area's ratio (Figure 8b). For livestock settlements, the ratio was positive at

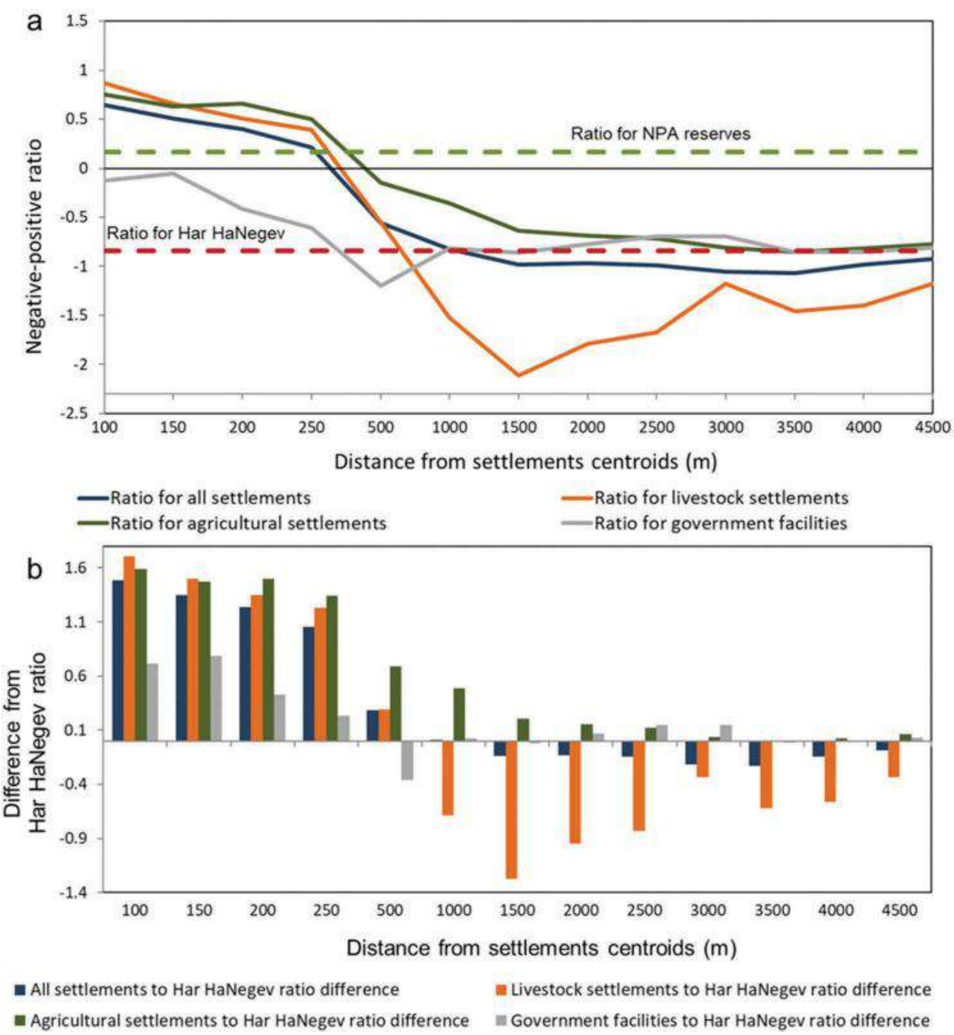

Figure 8. Negative-positive temporal Z-score ratio as a function of distance from the settlements' centroids: (a) ratios relative to 0; and (b) ratios as differences from the overall Har HaNegev study area ratio.

short distances from the centroids, and dropped below 0 at around 500 m. The ratio values at 1000 m were significantly lower than both the average and all settlements ratios, and stayed low for up to 4500 m, moderately increasing at 2000 m and continuing as distance increased. For government facilities, the ratio was always negative, merging with the overall ratio at a distance of 1000 m. The mean VCC Z-score value for the various distances for each settlement type reflects a similar trend as described in the ratio analysis (Figure 9).

Table 2 shows the differences between the populated areas for each distance. For closer distances (of 100 and 200 m), agricultural and livestock settlements were not significantly different; however, both were different from government facilities (as also shown in Figure 8). For distances of 500, 1000, and 1500 m, all settlement types differed significantly from one another, and the longest distances (of 3000 and 4500 m) showed no difference between agricultural settlements and government facilities; however, they were significantly different from livestock settlements that showed much lower VCC Z-score values.

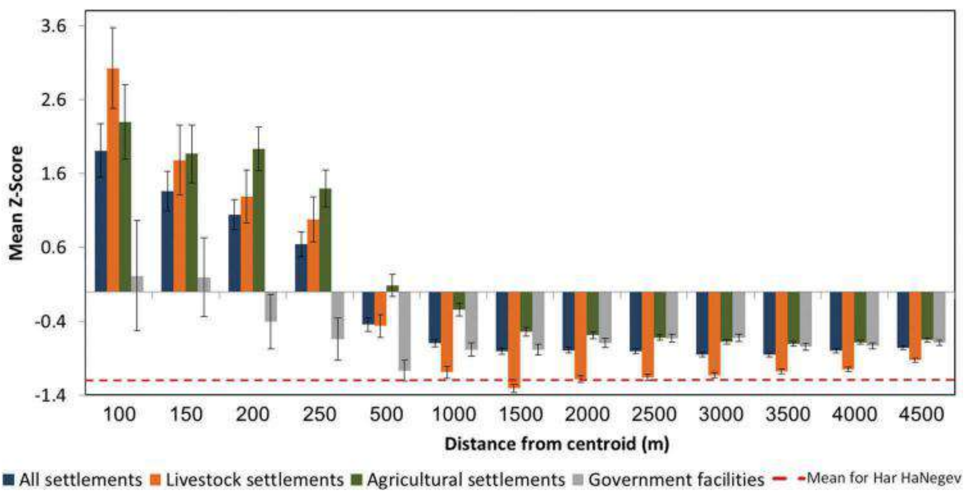

Figure 9. Mean temporal Z-score values for each settlement type and for each distance from the settlements' centroids. Vertical bars indicate standard errors.

Table 2. Significant differences between Z-scores for settlement types for each selected distance from settlements' centroids. The letters a, b, and c denote significant levels of the different population concentration types. Settlement types that receive the same letter, do not show statistically different VCC for the specific distance from the centroid.

Distance from centroid (m)	Agricultural settlements	Livestock settlements	Government facilities
100	a	a	b
200	a	a	b
500	a	b	c
1000	a	b	c
1500	a	b	c
3000	a	b	a
4500	a	b	a

Table 3 shows the differences between Z-score values at different distances for each populated area type. For agricultural settlements, the VCC Z-score values for shorter distances (of 100 and 200 m) were not significantly different, but were different from those for distances of 500 and 1000 m. The Z-scores for longer distances (of 1500, 3000, and 4500 m) were not significantly different either, but differed from those for distances of 1000 m. For livestock settlements, the Z-scores for shorter distances (of 100 and 200 m) showed no significant differences; however, they were different from those for the 500 m range and all of these distances were different from the 1000 m distance. There were no significant differences between the VCC Z-scores for distances of 1000, 1500, and 3000 m. The VCC Z-scores for the distance of 4500 m were significantly different from those of all distances except for the distance of 1000 m. For government facilities, there were no significant differences between the VCC Z-scores for the various distances.

4. Discussion

We evaluated the effects of various types of populated areas on VCC throughout a time series between 1987 and 2016. We examined the environmental and human-induced factors that explained the variation in VCC. The findings show that elevation, slope, distance from populated areas and aspect played dominant roles in shaping VC across the landscape (providing 60% of the overall influence). Spatiotemporal patterns showed that the VC in the stream network responded greatly to residential impacts. The most significant changes in VC were clustered in space, meaning that the impact on vegetation is spatially autocorrelated. We found that the protected areas, where conservation management has been practiced, showed viability in terms of VCC and experienced a significant increase in VC over 30 years. Significant changes in VC were mostly spatially clustered, suggesting that the affected VCC is not location-specific, but is related to a topographical pattern occurring at larger scales.

4.1 Time series analysis of normalized SAVI

The most pronounced and significant changes in VCC occurred along the stream network, since it contains high VC clustering and provides a major source of vegetation in this dryland area (Paz-Kagan et al. 2014). The areas within NPA nature reserves experienced increasing VCC. Most of these areas were declared nature reserves in 1989, minimizing human impacts such as grazing and residential development ever since. Therefore, during a 30-year time span, the VC trends have been significantly positive. The effectiveness of nature reserves and parks is documented in the literature and successful management includes protecting the ecosystems and species within their borders through means of preventing land clearing, logging, grazing, and fire (Bruner

Table 3. Significant differences between the Z-scores for the selected distances of each settlement type. The letters a, b, and c denote significant levels of the different distances. Distances that receive the same letter, do not show statistically different VCC for the specific settlement type.

Settlement type	100 m	200 m	500 m	1000 m	1500 m	3000 m	4500 m
Agricultural settlements	a	a	b	bc	d	d	d
Livestock settlements	a	a	b	cd	d	d	c
Government facilities	a	a	a	a	a	a	a

et al. 2001), thus preventing vegetation loss and fragmentation of natural vegetation (Joppa, Loarie, and Pimm 2008). Segments of the stream network, especially in the lower elevations that have been prone to grazing, were related to significant loss in VC. In addition, edge effects were identified on the borders of protected areas with loss in VC. In some cases, edges of protected areas were shown to be highly vulnerable and at risk when located adjacent to disturbed areas, in terms of changes in plant community, seedling recruitment pattern, distribution of animals, vegetation structure and more (Gascon, Williamson, and Da Fonseca 2000). Therefore, small nature reserves are at a larger risk of suffering edge effects.

4.2 Cluster analysis of spatial z-score

Spatial cluster analysis showed a high spatial autocorrelation, with clustering patterns across large areas. For example, nature reserves and cultivated areas had high significantly positive clustering, and areas that had experienced livestock activities showed high significantly negative clustering (Figure 5). This spatial trend suggests that specific locations were more favorable for grazing activities than others, such as the valleys where vegetation is denser. Significantly positive clustering was also a dominant pattern within military bases and settlements, amplifying the patterns, density and organization of VCC, as documented in various forms of populated areas (Stow et al. 2013). Most of the non-clustered areas were found at higher elevations, and a high clustering pattern was concentrated along and in proximity to the stream network. This spatial phenomenon is related to higher vegetation density in the streams rather than along higher elevation, therefore making the streams more prone to change. Water redistribution by runoff is the primary driver of dryland life-supporting systems (D'Odorico et al. 2007) and changes in the streams' vegetative patterns will possibly influence the hydrological feedback in the area (Descroix et al. 2001).

4.3 Environmental and human-derived factors

Several studies have demonstrated the benefits of using environmental factors as explanatory variables for different spatial phenomena related to vegetation (Goldstein et al. 2018; Ohana-Levi et al. 2015; Paz-Kagan et al. 2014). The analysis in the current research involved eleven different factors that were tested for their impact on VCC. The results of the BRT analysis suggest that elevation had the largest influence on VCC, with 17% (Figure 6) and higher altitudes had a negative impact on the model (Figure 7a). This corresponds with works that established the connection between VC and elevation (Jin et al. 2008; Li et al. 2015), while these interactions vary in their spatial patterns in different climate zones and topographic characteristics. The second and fourth most influential mediators, slope and aspect, were also topography-related, and influenced the pattern of VCC. The third factor was distance from populated areas (14.6%), highlighting the influence of human-driven activities in the landscape. Interpretation of the PDP for elevation predictor (Figure 7a) suggests that in the lowest altitudes (290–330 m above sea level) the contribution to VCC was highly positive. These altitudes are concentrated in the Zin nature reserve, which was characterized by a significantly positive VCC. In the intermediate altitudes (330–800 m), the effect was moderately negative, with high fluctuations that represent the stream network, which was usually characterized by higher VC. Altitudes higher than 800 m showed a highly negative influence on the model. This finding corresponds to the strong cluster analysis relation to elevation (section 3.3), with lower altitudes showing more clustered patterns of VCC, suggesting that sensitivity to change is location-oriented and has geospatial characteristics. The slope variable (Figure 7b) showed higher impact with increasing values, due to the fact that the highest slopes in the study area are located within the Zin nature reserves, which was related to higher values of VCC (Figure 4). The PDP for distance from populated areas (Figure 7c) demonstrated the spatial VCC pattern of increasing values very close to the settlements (50–100 m) and a negative impact with increasing distance. At 6500 m, the settlements' negative impact was reduced and VCC increased, possibly due to maximal range of grazing from livestock settlements. Aspect PDP analysis (Figure 7d) defined the north and north-west aspects as the best contributors to positive VCC. This corresponds to other works in arid areas in Israel that found higher VC in north-facing slopes, due to lower radiation and higher evapotranspiration rates during summer water stress periods (Zaady et al. 2001). The spatial pattern of VCC is attributed to both terrain and human-driven factors. Elevation along with slope and aspect are related to water availability and geo-hydrology of drylands. Although residential development is sparse in the dryland environment, the impact of human-driven factors is strong in forming and changing vegetation structure as well as temporal patterns. Although the BRT results corresponded with our findings in the different analyses (cluster analysis, VCC time-series analysis, ANOVA for different populated area types), the model performance might improve with higher spatial resolution of data (e.g. soil map, lithology).

4.4 Distance from populated areas effect on vegetation cover

The populated area types varied greatly in their influence on VCC in Har HaNegev study area. As the results show (Figure 8, 9), the overall negative-positive VCC Z-score ratio was negative, meaning that on average, the Har HaNegev study area has experienced a decrease in VCC over the last 30 years. Agricultural activities in proximity to the settlements' centroids tended to increase VC, due to intensive cultivation of the areas within and close to the settlements, mostly along the valleys. This effect gradually decreased with distance. This finding is supported by the PDP of the distance from populated areas predictor variable (Figure 7b), that shows very high impact of settlements up to 80 m from the centroid. Modern agriculture relies on high-yield cultivars, chemical fertilizers and pesticides, mechanization and irrigation to increase food production (Foley et al. 2005). Local impacts of land cultivation include an increase in VC; however, this is usually accompanied by environmental damage in the form of degradation of water quality, salinization and loss of arable land, soil erosion, decreased biodiversity and reduced fertility. Moreover, the desert agriculture, often located along the valleys, exploits the increasing runoff for irrigation and accumulate the alluvial sediments (Avni et al. 2006), therefore contributing to deterioration of the stream network's resources. Modern agricultural practices may increase food production in the short term, but increase long-term losses in ecosystem services, some of which are important to agriculture potential (Altieri 1999; Foley et al. 2005).

In many cases, high grazing pressure occurs near population concentrations and watering sites, and gradually decreases with increasing distance from the settlements or watering points (Karnieli et al. 2008). This causes a grazing gradient reduction in VC around livestock settlements (Goirán, Aranibar, and Gomez 2012). The grazing gradient is a function of the grazing intensity and forging pattern of the livestock. Similar to the agricultural settlements, our results show that the livestock settlements had a positive impact on VCC near the settlements' centroids that gradually decreased with distance. They show very low, significant VCC Z-score ratios (more than two times lower than the overall ratio for the Har HaNegev site) at larger distances, and their effect was still present at a distance of 4500 m. This trend is also shown in the PDP analysis of the distance from populated areas predictor variable (Figure 7b), and reflects that up to 6500 m the livestock settlements generally had a negative effect on VCC. This long distance effect lies in the influence of grazing over long periods of time, causing reduced VC and the clearing of streams. The reduction of VC through time may increase the soil erosion risk (Röder et al. 2007) and result in irreversible degradation of the landscape. Moreover, intensive grazing is also responsible for soil compaction that consequently increases runoff and flooding in dryland environments. In drylands, where water is considered to be a limiting factor for vegetation growth, land deterioration due to vegetation removal by grazing pressure has negative effects on the ecosystem (Ravi et al. 2010).

The government facilities had little VC; therefore, their ratio was significantly different from that of agricultural and grazing settlements, and was always negative. They influenced only their nearby surroundings and may have introduced a long-term disturbance to VC (Milchunas, Schulz, and Shaw 2000). A few studies found that tracked vehicles that operate moderately and with high intensity changed soil bulk density, but did not alter species composition or vegetation areal cover, and the impacts on VC were short-termed (Prosser, Sedivec, and Barker 2000). The presence of military activity in many cases does not impact conservation purposes (Gibbes, Havlick, and Robb 2017), and sometimes even modifies anthropogenic influences, since it includes limited civilian presence in restricted and secured areas.

The findings indicate that in nature reserves, the total VCC Z-score ratio was positive. Reserves are known to be an effective conservation instrument to prevent natural vegetation loss compared to their adjacent environment (Figueroa and Sánchez-Cordero 2008). Successful preservation of the natural landscape and mitigation of vegetation clearing relies on reducing human pressure and applying suitable management strategies (Nagendra 2008). However, grazing activity is still occurring in protected areas in Har HaNegev study area, especially in its southern part (Figure 4). The southern reserve was not fully operative with weak regulation by the authorities. Its proximity to livestock settlements makes this reserve prone to VC decrease as long as conservation practices are not applied. An integrated effect between firing zones and nature reserves was also found, specifically in the northern nature reserve. In parts of this conservation site, the military forces practice cannon fire as part of regular training, driving away human activity.

The suggested framework was unable to distinguish between nearby settlements due to their relative proximity to each other. When examining distances of 1000 m and above, some effects on VCC might have been caused by two or more settlements, sometimes of different types, and their influences on the landscape might have overlapped. However, the results were separated by populated area type, and showed divergent behaviors and significant differences. This framework could be valuable for development, preservation management and policy-making processes. Both the private sector and government bodies can benefit from the methods and results that this study provided for future planning directives and sustainable development of the study area, as well as other rural environments experiencing long-term VCC. High LU pressures, such as grazing and agricultural cultivation, may impact VCC and alter the conservation effort in protected areas, as shown in this current study. Additional effects of development may include species diversity and richness, species composition, and soil nutrient input and erosion (Zhao et al. 2005), as well as the size and composition of seeds in the soil seed bank (Solomon, Snyman, and Smit 2006). Characterization of spatial vegetation patterns may provide an indicator of ecosystem functioning in drylands and assist in indicating hot spots of degradation or improvement in VC (Berdugo et al. 2017) and the effectiveness of conservation practices in protected areas. The time series analysis conducted in this current study reveals a multi-annual degradation in VC, excluding increasing trends in nature reserves. Har HaNegev study area has a very low population density that nevertheless has affected VCCs greatly for several decades. The population is expected to grow and residential development to expand, however a little less than 30% of the study area is available for development; and unless new management practices are undertaken and policy in this region is changed, this VC degradation will progress, possibly affecting protected areas and additional sites will suffer similar spatiotemporal consequences.

5. Conclusions

This study aimed at assessing the impacts of environmental mediators and populated areas on VC through a multi-decadal time frame in a dryland area that includes protected nature reserves. The results show that both environmental and human-induced mediators contributed to VCC while the most affecting variables were elevation, slope, distance from populated locations, and aspect, with a cumulative relative influence of about 60%. Populated area types had different effects on VCC. Due to agricultural activities, VC had increased closer to settlements' centroids. However, as distance increases from livestock settlements, the impact was negative owing to intensive, ongoing, rapid grazing activities. Military activity contributed to loss in VC at specific locations, as a result of continuously occupying the same training sites. The stream network was more sensitive to VC loss, mostly since it is a preferred site for grazing. In protected areas human interference is minimal, therefore there was a higher probability of preserving or increasing VC. The most significant changes in VC were clustered, suggesting that the impacts on vegetation occur in spatial patterns and are location-specific.

After decades of vegetation loss, significant management strategies and measures should be implemented in order to begin a conservation and restoration process. Governmental and municipal regulations are needed before the areas adjacent to nature reserves become more populated and degradation processes correspondingly expand further. Negative VCC in drylands may have irreversible effects that influence the vegetation pattern and organization in space, thus altering the ecosystem structure and function. These changes may have a long-term effect on the ability to protect nature reserves and conserve their unique environment.

Acknowledgements

The project leading to this research was funded by the European Union's Horizon 2020 Research and Innovation Programme under grant agreement no. 641762 "Improving Future Ecosystem Benefits through Earth Observations" (Ecopotential). We wish to thank Gal Bismuth and Boaz Freifeld from the NPA for their assistance and valuable insights. We greatly appreciate the input and advice provided by Moshe Shachak and Shaily Dor-Haim throughout the course of this research.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the European Union's Horizon 2020 Research and Innovation Programme "Improving Future Ecosystem Benefits through Earth Observations" (Ecopotential) [641762].

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Appendix 1. A list of Landsat images chosen to conduct the SAVI time series analysis

Number	Date	Satellite sensor
1	14 August 1987	Landsat 5
2	11 August 1989	Landsat 4
3	30 August 1990	Landsat 4
4	1 August 1991	Landsat 4
5	19 August 1992	Landsat 4
6	14 August 1993	Landsat 5
7	17 August 1994	Landsat 5
8	4 August 1995	Landsat 5
9	6 August 1996	Landsat 5
10	9 August 1997	Landsat 5
11	15 August 1999	Landsat 5
12	25 August 2000	Landsat 7
13	27 July 2001	Landsat 7
14	31 August 2002	Landsat 7
15	10 August 2003	Landsat 5
16	28 August 2004	Landsat 5
17	15 August 2005	Landsat 5
18	18 August 2006	Landsat 5
19	5 August 2007	Landsat 5
20	23 August 2008	Landsat 5
21	26 August 2009	Landsat 5
22	29 August 2010	Landsat 5
23	16 August 2011	Landsat 5
24	5 August 2013	Landsat 8
25	24 August 2014	Landsat 8
26	27 August 2015	Landsat 8
27	13 August 2016	Landsat 8

Appendix 2. A list of environmental variables, their sources and their expected effects on vegetation cover

Variable	Source	Expected effect on vegetation cover
Elevation (environmental)	Digital elevation model (DEM)	Elevation affects the water supply to the stream network that nourishes the vegetation (Paz-Kagan et al. 2017).
Slope (environmental)	Derived from DEM	Slope affects water distribution; steep slopes are related to higher water discharge rates than shallow slopes (Carmel and Kadmon 1999).
Aspect (environmental)	Derived from DEM	Aspect affects the amount of radiation; in the northern hemisphere, south-facing slopes receive more solar radiation than north-facing slopes and are characterized by lower water availability for the vegetation (Paz-Kagan et al. 2017).
Distance from streams (environmental)	Derived from DEM	Streams provide water for vegetation to thrive; longer distance from water is related to lower vegetation cover and a higher risk of mortality (Karnieli 1997).
Firing zones (human-derived)	Official Survey of Israel data	These are military areas where civilian activities are restricted. Changes in vegetation cover and composition in restricted military areas in drylands are well documented (Diamond 1975). 0 is civilian area, while zones 1–14 are firing zones. 9 was excluded since it had a very small area within the study area.
Nature reserves (human-derived)	Israel Nature and Park Authority (NPA) data	Nature reserves are locations where human impact is minimized, therefore preserving the natural characteristics of vegetation cover within a confined area (Rozenstein et al. 2014).
Temperature (environmental)	Land surface temperature (LST), derived from band 10 of Landsat 8 OLI, acquired on 13 August 2016	Temperature is related to surface energy and water balance and is used for estimating evapotranspiration, vegetation water stress, and soil moisture, all affecting vegetation cover (Franz et al. 2011).
Soils (environmental)	Official Survey of Israel data	The spatial distribution of soil texture influences the partitioning and resulting soil moisture distribution patterns that affect vegetation cover and structure (Moore, Lees, and Davey 1991).
Lithology (environmental)	Official Survey of Israel data	Geology affects soil structure and soil chemistry, thereby influencing vegetation cover (Newbold et al. 2016).
Land cover (both environmental and human-derived)	Classification of Landsat 8 OLI image acquired on 13 August 2016, with an overall accuracy of 99.8%	Different land-cover types affect the spatial distribution and pattern of natural and planted vegetation cover (Ohana-Levi et al. 2015).

(*continued*)

(*Continued*).

Variable	Source	Expected effect on vegetation cover
Distance from Populated areas (human-derived)	Euclidean distance measured from manually digitized settlements based on a high-resolution orthophoto and a RapidEye satellite image from 2015	Urbanized environments are known to spatially affect vegetation distribution and patterns, especially during the process of vegetation removal through grazing, urban development and agricultural activities (Schmidt and Karnieli 2000). As distance increases, this effect is expected to decrease.