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The use of spatial empirical models to estimate soil erosion in arid ecosystems

Meshal Abdullah ⓘ · Rusty Feagin · Layla Musawi

Abstract The central objective of this project was to utilize geographical information systems and remote sensing to compare soil erosion models, including Modified Pacific South-west Inter Agency Committee (MPSIAC), Erosion Potential Method (EPM), and Revised Universal Soil Loss Equation (RUSLE), and to determine their applicability for arid regions such as Kuwait. The northern portion of Umm Nigga, containing both coastal and desert ecosystems, falls within the boundaries of the de-militarized zone (DMZ) adjacent to Iraq and has been fenced off to restrict public access since 1994. Results showed that the MPSIAC and EPM models were similar in spatial distribution of erosion, though the MPSIAC had a more realistic spatial distribution of erosion and presented finer level details. The RUSLE presented unrealistic results. We then predicted the amount of soil loss between coastal and desert areas and fenced and unfenced sites for each model. In the MPSIAC and EPM models, soil loss was different between fenced and unfenced sites at the desert areas, which was higher at the unfenced due to the low vegetation cover. The overall results implied that vegetation cover played an important role in reducing soil erosion and that fencing is much more important in the desert ecosystems to protect against human activities such as overgrazing. We conclude that the MPSIAC model is best for predicting soil erosion for arid regions such as Kuwait. We also recommend the integration of field-based experiments with lab-based spatial analysis and modeling in future research.

Keywords Soil erosion · GIS · Remote sensing · MPSIAC model · EPM model · USLE · Arid ecosystem

Introduction

Soil erosion is a major issue in most arid and semi-arid regions, greatly affecting soil quality and productivity, as most of arid and semi-arid soils are generally shallow in depth. Soil erosion is also considered one of the principle mechanisms of desertification processes at national and regional levels (Kairis, Karavitis, Kounalaki, Salvati, & Kosmas, 2013; Martín-Fernández & Martínez-Núñez, 2011; Sun, Dawson, Li, & Li, 2005). The common consequences of desertification involve vegetation and soil loss, reduction in soil fertility and biodiversity, and reduction in rainfall infiltration rates (Vásquez-Méndez, Ventura-Ramos, Oleschko, Hernández-Sandoval, & Domínguez-Cortázar, 2011; Sun et al., 2005). According to the United Nations Convention to Combat Desertification (UNEP, 1994), desertification was defined as "land degradation in arid, semi-arid and dry sub-humid areas, resulting from various factors, including climatic variations and human activities." However, erosion is difficult to estimate and

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expensive to measure, especially when dealing with large landscapes. Therefore, it is important to use erosion indicators and modeling to estimate potential soil loss (Rostagno & Degorgue, 2011).

Modeling soil erosion by water involves the process of detachment, transport, and deposition of soil particles. Erosion rates are measured based on the combination of several physical and management variables. Many empirical models are proposed to predict soil erosion by water and associated sediment yield. Most of these models are not well tested and require several parameters, but they are used due to their simplicity (Mahmoodabadi, 2011). These models are also limited to the specific site of origin since they were designed according to the correlation of multiple parameters performed using site-specific empirical data. Therefore, many researchers have tried to overcome these limitations by producing numerical models of erosion. Often, these models are classified as semi-quantitative models due to the combination of descriptive and quantitative procedures, which result in a quantitative or qualitative estimate for soil erosion (is the displacement of solids such as soils, rocks, and other particles) and sedimentation (which is also called deposition is the geological process in where materials are added to the landform) (Mohamadiha, Peyrovan, Harami, & Feiznia, 2011). Geographical information systems (GIS) and remote sensing (RS) technologies can be innovative tools in the estimation of soil erosion (Pradhan, Chaudhari, Adinarayana, & Buchroithner, 2012). GIS and RS modeling are widely used for the derivation of variables required to estimate soil erosion, and they have the capability to analyze a large amount of data for arid and semi-arid landscapes (Ahmad & Verma, 2013; Amini, Rafiri, Khodabakhsh, & Heydari, 2010; Taheri, Landi, & Archangi, 2013; Yue-Qing, Xiao-Mei, Xiang-Bin, Jian, & Yun-Long, 2008).

The Universal Soil Loss Equation Method (USLE) is the most widely used empirical model in soil erosion investigations due to its simplicity, though it was designed for agriculture practices (Harmon & Doe, 2001). It is used for planning soil conservation measures, especially in developing countries (Breiby, 2006; Csáfordi, Pődör, Bug, & Gribovsyki, 2012; Kamaludin et al., 2013; Meusburger, Mabit, Park, Sandor, & Alewell, 2013). The major variables that are covered by this model include rainfall, crop and cover management, soil erodibility, slope length and steepness, and conservation practice factor. The major disadvantage of empirical

models is that they are applicable only for the database from which they have been derived. Therefore, in 1987, the USLE was modified to into the Revised Universal Soil Loss Equation (RUSLE) to compute the average annual erosion (Duarte, Teodoro, Gonçalves, Soares, & Cunha, 2016; Renard, Foster, Weesies, McCool, & Yoder, 1997). Several changes occurred with RUSLE including new rainfall-runoff erosivity values, a sub-factor approach for calculating land cover, and new slope and soil erodibility algorithm. The Erosion Potential Method (EPM) model is also an empirical model, which was developed for Yugoslavia for estimating the quantity and quality of soil erosion and sedimentation (Amiri, 2010). This model covers several variables such as soils and geology, land use, present erosion type, and land slope. This model was tested in several agriculture locations in Iran, as the output results of this model were compatible with field observations (Amini et al., 2010; Daneshvar & Bagherzadeh, 2012). However, the Modified Pacific South-west Inter Agency Committee (MPSIAC) model was designed for arid and semi-arid lands in the USA (Adib, Jahani, & Zareh, 2012; Belete, 2013; Ilanloo, 2012). The original MPSIAC model was developed by Johnson and Gebhardt (1982). The newer enhanced MPSIAC model is more quantitative than earlier versions which makes it more accurate when used in regions for where the model was not designed (Najm, Keyhani, Rezaei, Nezamabad, & Vaziri, 2013). This model covers the highest number of variables that includes most erosional processes, which include geology, soils, climate, runoff, topography, vegetation, land use, surface erosion, and channel erosion. This model has been used in several arid and semi-arid agriculture areas in Iran, and these studies also illustrate that the output was compatible with field observation (Rostamizad & Khanbabaei, 2012; Shahzeidi, Entezari, Gholami, & Dadashzadah, 2012; Taheri et al., 2013).

A few studies have compared the EPM and MPSIAC models in agricultural areas in Iran. According to Baqerzadeh-Karimi (1993), Bayat (1999), and Taheri et al. (2013), field data were compared with the model results, and it was illustrated that the MPSIAC model showed more appropriate results when compared with EPM. Mahmoodabadi (2011) concluded that the MPSIAC model showed a maximum value for erosion when compared with field data, and he stated that it was not accurate and needed modification. Eisazadeh et al. (2012) compared the MPSIAC and USLE, with results

showing that both models had reasonable results, though the MPSIAC was the superior model according to the accuracy of the results. One issue with all these studies is that they were conducted for agricultural areas in Iran; none were tested or compared for native desert ecosystems which play a major role in controlling and minimizing soil erosion (Ahmed, Al-Dousari, & Al-Dousari, 2016). Therefore, our central objective was to test and compare the MPSIAC, EPM, and USLE models for arid natural ecosystems by utilizing remote sensing and GIS. We used Umm Nigga, Kuwait, as an example of an arid landscape and discuss soil loss as a function of land degradation, management, and restoration for this region.

Materials and methods

Study area

Kuwait is located in Asia, has a total area of 17,820 km^2, and a latitude and longitude of 29.3286° N, 48.0034° E. Umm Nigga is situated on the northern edge of Kuwait with a total area of 246 km^2 (Fig. 1a). The study area is distant from residential areas at approximately 50 km from Kuwait City. It is considered an open rangeland,

which is used for camping and grazing, with several private farms in the northeastern section. Currently, restoration is planned for the site and it has been selected as a future protected area. The de-militarized zone (DMZ) lies immediately north and was created as a buffer between Kuwait and Iraq by the United Nations Security Council Resolution 689. The restoration area includes this area but was further extended by the Kuwait Supreme Council for Environment through annexation. The DMZ extends along the Kuwait-Iraq border and the Khawr 'Abd Allah waterway; it is approximately 200 km long, extending 10 km into Iraq and 5 km into Kuwait. Umm Nigga contains a coastal ecosystem type and two desert ecosystem types (Fig. 1b). The coastal area is covered with sabkha, salt marshes and saline depressions, sand dunes, and ridges and terraces. It is also covered with the *Halophyletum* vegetation community unit. The other two desert ecosystems are composed of four soil groups including *Calcigypsids* and *Haplocalcids* (sandy to loamy soils) and *Torripsamments* and *Calcigypsids* (mostly sand and gravel). *Haloxyletum* and *Rhanterietum* are the major vegetation units in the desert ecosystems (Abdullah, Feagin, Musawi, Whisenant, & Popescu, 2016).
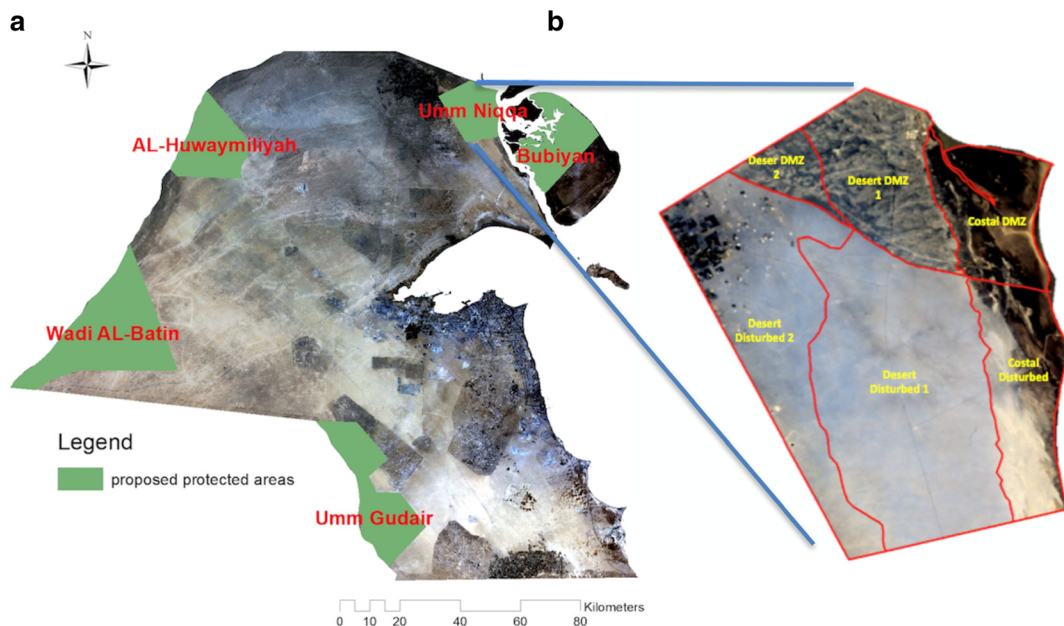

Fig. 1 **a** Suggested protected areas in the State of Kuwait according to the master plan. **b** Study area (Umm Nigga), which is divided into three ecosystems including DMZ (fenced) at the north portion of the study area and unfenced areas (Abdullah et al., 2016)

Potential soil loss estimation using the MPSIAC model

The MPSIAC model requires nine variables: surface geology, topography, land cover, soil characteristics, climate (rainfall), runoff, land use, present erosion, and channel erosion. The channel erosion factor was excluded from our work, as the study area does not include any channels. GIS and remote sensing products were used to generate each variable. GIS data layers were collected from Kuwait University (KU) and Kuwait Institute of Scientific Research (KISR): these layers include a geological map, soil survey, vegetation communities, elevation points, and contour lines with a scale of 1:250,000. Geo-referenced Landsat imagery was also obtained from the United States Geological Survey (USGS) to generate a land use layer. Then, each variable was generated and calculated individually based on the MPSIAC equations (Table 1). Finally, the soil erosion and sedimentation layer was estimated using the following equations:

$$Qs = 38.77e^{0.0353R} \qquad (1)$$

Table 1 Effective factors on soil erosion for the MPSIAC model

Effective factors	Equations	Parameters
Surface geology	Y1 = X1	X1 = geological erosion index
Soil	Y2 = 16.67X2	X2 = soil erodibility factor
Climate	Y3 = 0.2X3	X3 = 6-h rainfall with a 2-year return period
Runoff	Y4 = 0.006R + 10Qp	Q_p = annual specific DEBI (m^3/skm^2) R = annual runoff height (mm^3)
Topography	Y5 = 0.33X5	X5 = percentage of the average basin slope
Vegetation	Y6 = 0.2X6	X6 = percentage of land without vegetation
Land use	Y7 = 20 − 0.2X7	X7 = percentage of vegetation cover
Surface erosion	Y8 = 0.25X8	X8 = total surface soil factor scoring in BLM
Channel erosion	Y9 = 1.67X9	X9 = gully scoring in BLM

BLM Bureau of Land Management

where Qs = total sediment yield in m^3/km^2/year, e = 2.718, and R is the sum of the nine factors. In order to predict the total eroded soil loss, we followed Bagherzadeh and Daneshvar (2013); the sediment delivery ratio (SDR) is obtained from the following equation:

$$SDR = \left(46.7 \times \frac{A}{2.58}\right)^{-0.2071} \qquad (2)$$

where SDR is the sediment delivery ratio and A is the sub-basin surface area. SDR is defined as the ratio of sediment yield to total soil losses. The equation can be expressed in non-dimensional terms as

$$SDR = \frac{SY}{T} \qquad (3)$$

where SY is the sediment yield (m^3/km^2/year) and T is the total eroded soil loss (m^3/km^2/year).

Data collection and preparation

Surface geology (y1)

The surface geology was obtained from the geological map of Kuwait and other previous studies. The study area was covered with aeolian sand, desert floor deposits, Dibdiba formation, intertidal and shoaling sand, silt and mud sabkha deposits, and strand-line deposits (Al-Sulaimi & Al-Ruwaih, 2004). Aeolian sands are mostly sandy with high infiltration rates and low runoff. The desert floor deposits were generated from slopes, and Dibdiba formation is a white fine-grained cherty limestone and sand and gravel, with high infiltration rates. In contrast, the intertidal and shoaling sand, silt and mud sabkha deposits, and strand-line deposits are muddy and contain clay soils with low infiltration rates and high runoff rates (Abdal, Suleiman, & Al-Ghawas, 2002; Al-Sulaimi & Al-Ruwaih, 2004). Based on these characteristics, each unit within the geological layer was ranked from 0 (less sensitivity to erosion) to 10 (high sensitivity to erosion) following the MPSIAC model (Fig. 2a).

Soil factor (y2)

The soil factor was calculated using data from the soil survey of Kuwait (KISR, 1999). The soil erodibility

Fig. 2 MPSIAC model variables.
a Surface geology (y1). **b** Soils
(y2). **c** Runoff (y4). **d** Topography
(y5). **e** Vegetation and land use
(y6 and y7). **f** Surface erosion (y8)
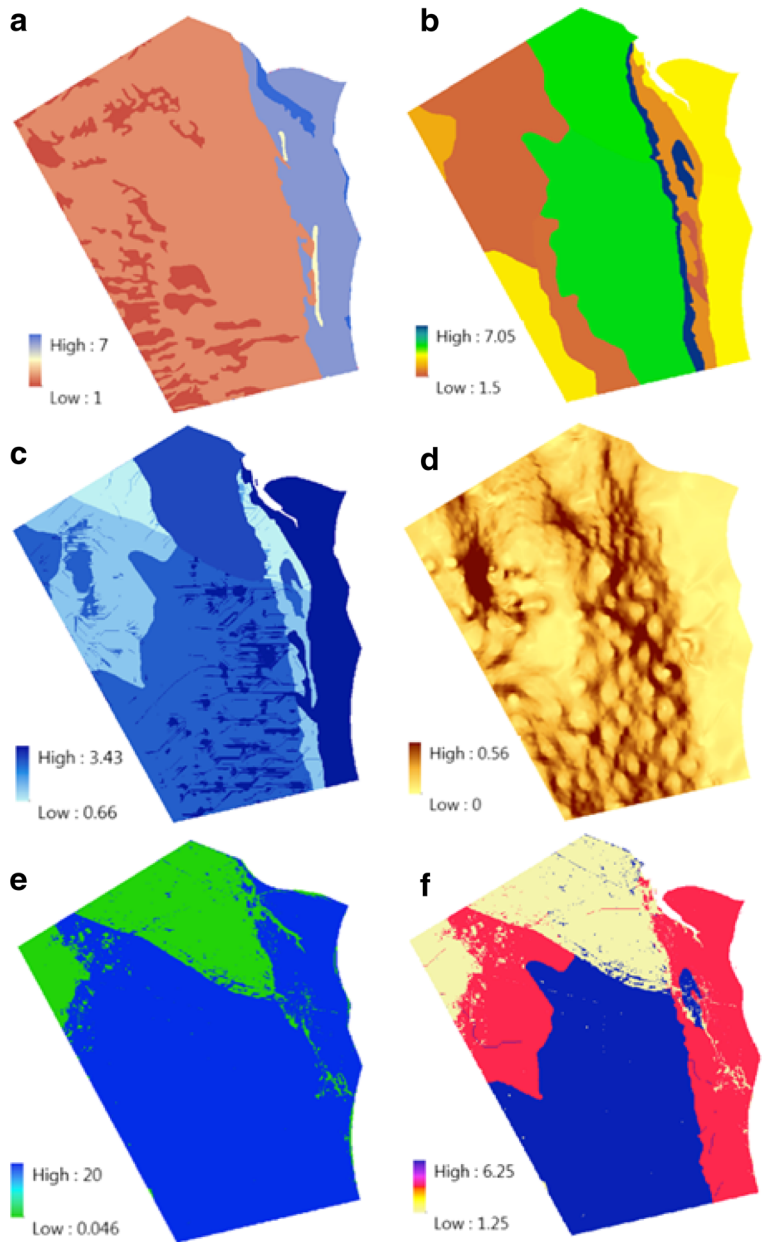
map was generated according to the RUSLE equation for soil erodibility (*K* factor) (Benzer, 2010; Dumas & Printemps, 2010; Gitas, Douros, Minakou, Silleos, & Karydas, 2009):

$$K = 2.8 \times 10^{-7} \times M^{1.4} (1.2{-}a) + 4.3 \times 10^{-3} (b{-}2) + 3.3(c{-}3)$$
(4)

where *M* is the size of soil particles (%silt + % very fine sand) × (100 − % clay), *a* is the

percentage of organic matter, *b* is the code number defining the soil structure (very fine granular = 1, fine granular = 2, coarse granular = 3, lattice or massive = 4), and *c* is the soil drainage class (fast = 1, fast to moderately fast = 2, moderately fast = 3, moderately fast to slow = 4, slow = 5, very slow = 6). Subsequently, the *K* factor was used to calculate the soil factor using the MPSIAC model equation. The final score for the soil factor layer ranged from 1.5 to 7.05 (Fig. 2b).

Climate (y3)

The commonly used index of rainfall aggressiveness, which is significantly correlated with soil erosion, is the ratio of the highest mean monthly precipitation and the mean annual precipitation (Morgan, 1976). Recent work suggests that elevation may also influence erosivity (Daly, Neilson, & Phillips, 1994). Precipitation data were collected from meteorological records from the Kuwait Meteorological Center, Kuwait Airport Station, and Al-Abdaly Station. The climatic factor rating was estimated based on 20 years (1990–2010). The same rating value was given to the entire location since there is no variation with rainfall around the study area.

Runoff (y4)

Surface runoff is a major factor influencing soil erosion. This factor was generated using the Soil Conservation Service Curve Number Equation (SCS-CNE) model, which was developed in the mid-1950s (Beven, 2011; Mockus, 1964). This model is widely used as a simple method for predicting direct runoff volume for a given rainfall event. This model requires rainfall data and soil data including potential maximum retention, soil moisture retention, and infiltration rates. An empirical relationship estimates initial abstraction and runoff as a function of soil type and land use. The rainfall-runoff relationship was calculated using the following equations:

$$Q = (P - I_a)^2 / (P - I_a) + S \qquad (5)$$

where Q = runoff (in),

$\quad P$ = rainfall (in),

$\quad S$ = potential maximum retention after runoff begins (in), and

$\quad I_a$ = initial abstraction (in).

Initial abstraction (I_a) includes water retained in surface depressions and water intercepted by vegetation, evaporation, and infiltration. It is also correlated with soil and cover parameters and was found to be 20% of the potential maximum retention (S) (Ghadiri & Rose, 1992). By assuming that the initial abstraction is equal to 20% of potential maximum retention (I_a 0.2S), the previous equation can be simplified to

$$Q = (P - 0.2S)^2 / (P - 0.2S) \qquad (6)$$

where S is related to the soil and cover conditions through the curve number (CN), which is an empirical parameter used in hydrology for predicting direct runoff or infiltration from rainfall excess (Ghadiri & Rose, 1992). CN has a range of 0 to 100, and S is derived from CN by

$$S = 1000/CN - 10 \qquad (7)$$

The runoff CN parameter values correspond to various soil, land covers, and land management conditions and can be selected from model tables. However, it is preferable to estimate the CN value from measured rainfall and runoff data if available (Soulis & Valiantzas, 2012). Here, the CN value was estimated using soil survey of Kuwait (KISR, 1999) and the Natural Resource Conservation Service (NRCS) curve number, which divides soils into four hydrologic soil groups (HSGs) based on infiltration rates (Ghadiri & Rose, 1992). Soil infiltration data were used to estimate HSGs, which were combined with the land cover factor (y7) to estimate CN. Then, potential maximum retention (S) was calculated from the CN value using Eq. (6), and the potential maximum retention was used in Eq. (7) to estimate runoff (Q). The scoring values ranged from 0.66 to 3.43 (Fig. 2c).

Topography (y5)

The topography factor was generated using elevation contour lines and spot elevation points to create a raster digital elevation model (DEM). Percentage slopes were derived from the DEM using GIS and were used in the MPSIAC equation to compute the scoring value, which ranged from 0 to 0.56 (Fig. 2d).

Vegetation cover and land use (y 6 and y7)

Geo-referenced Landsat 8 was obtained from the USGS for the year 2013 to create a land use and vegetation cover layer. The spatial resolution of the imagery was 30 × 30 m, and the projection was WGS 84 UTM Zone 38N. No atmospheric and geometric corrections were necessary for this region due to the low cloud cover and since the image was classified individually. Supervised classification was used in this study using ENVI 5.2 to identify the land cover; methods are described in detail by Abdullah et al. (2016). The imagery was divided into five land cover types: soil, bare ground, vegetation, wetlands, and water. Then, vegetation cover and land use layers were combined in one layer and were scored

as ranks using the MPSIAC equation. The final ranking ranged from 0.046 (for locations covered with vegetation) to 20 (for bare ground locations) (Fig. 2e).

Surface and channel erosion (y8 and y9)

The surface erosion was estimated based on the surface soil erosion types using Bureau of Land Management (BLM) method. This method is used for monitoring and assessing upland soil surface erosion, other than gully erosion (Ypsilantis, 2011). The layers that were taken into consideration to create surface erosion are geomorphology, land cover, and slopes. Finally, all three factors were combined to establish the surface erosion layer using the MPSIAC equation. The study area includes sheet erosion (as occurs when rain falls on bare or sparsely covered soil) and some rill erosion (as occurs on slopes and streams). Each erosion type was rated from 0 (low sensitivity) to 15 (high sensitivity) based on their level of degree of sensitivity. The final ranking layer ranged from 1.25 (low sensitivity to erosion) to 6.25 (high sensitivity to erosion) (Fig. 2f). However, the channel erosion factor (y9) was not included in this model since channels do not exist in the study area.

MPSIAC model versus RUSLE and EPM models

The MPSIAC model was compared with the EPM and RUSLE models. The majority of the data layers for the MPSIAC model were also used in this step, but the coefficient for the variables was rated and scored according to their respective EPM or RUSLE equations.

EPM model

Soil erosion in the Erosion Potential Method (EPM) model is based on the following four factors:

Y: the coefficient of rock and soil erosion, ranging from 0.25 to 2

Xa: the land use coefficient, ranging from 0.05 to 1

Ψ: the coefficient for present erosion type, ranging from 0.1 to 1

I: average land slope in percentage

The necessary layers and data for these factors were geology and soil types, land use, slope, and erosion type. The required data and GIS layers

were the same as in the MPSIAC model, but they were rated based on the EPM coefficient rating (Fig. 3). The EPM calculates the coefficient of erosion and sediment yield (Z) of an area using the following equation:

$$Z = Y \times Xa \left(\Psi + I^{0.5} \right) \tag{8}$$

In which Y is the coefficient of rock and soil erosion, Xa is the land use coefficient, Ψ is the coefficient for the present erosion type, and I is the average land slope in terms of percentage.

Then, the volume of soil erosion was calculated using the following equation:

$$W_{SP} = T \times H \times \pi \times Z^{1.5} \tag{9}$$

In which, W_{SP} is the volume of soil erosion (m^3/km^2/year), H is the annual rainfall (mm), Z is erosion intensity, and T is the coefficient of temperature which is calculated as shown in the following equation:

$$T = (t/10 + 0.1)^{0.5} \tag{10}$$

where t is the mean annual temperature (°C).

RUSLE model

The RUSLE is the most common used model, as it is considered the most simplistic model for estimating soil erosion. This model covers five variables as shown in the following equation:

$$A = R \times K \times LS \times C \times P \tag{11}$$

where,

A = predicted soil loss (tons/acre/year)

R = rainfall and runoff factor

K = soil erodibility factor

LS = slope factor (length and steepness)

C = crop and cover management factor

P = conservation practice factor

The same vegetation cover and soil erodibility layers (Fig. 4a, b) that were generated for the MPSIAC model were used. An annual rainfall of 129 mm was defined for the entire location. However, the P factor was discounted to one because there were no conservation practices in the study area. The slope length and steepness (LS) factor

Fig. 3 EPM model variables. **a**
Coefficient of rock and soil
erosion (Y). **b** Land use
coefficient (Xa). **c** Coefficient for
present erosion type (Ψ). **d**
Average land slope in percentage
(I)
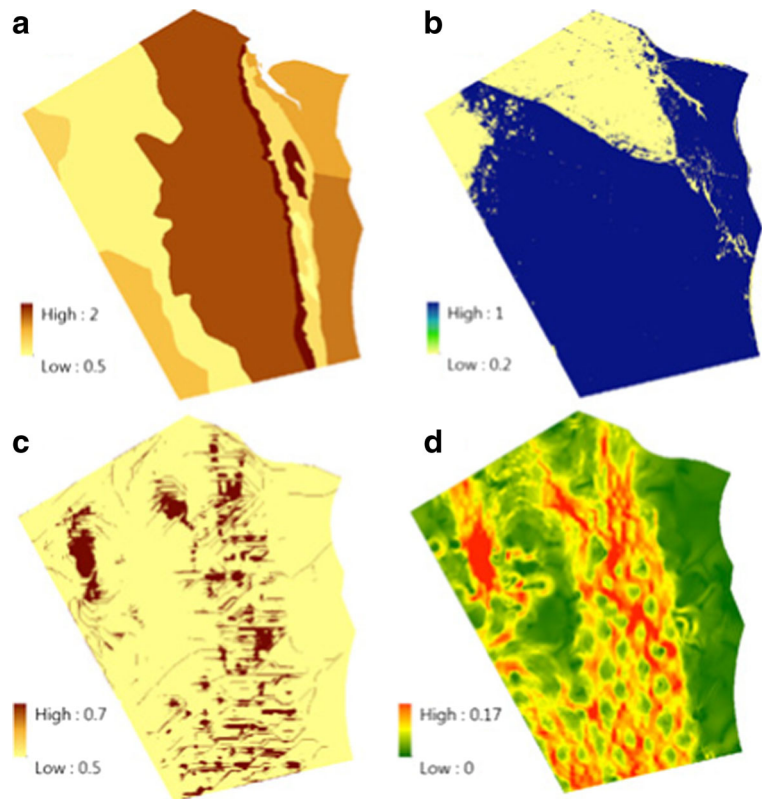
was generated (Fig. 4c), using the DEM and the
following equation:

$$LS = (\text{flow accumulation} \times \text{cell value}/22.1)^m \quad (12)$$

$$\left(0.065 + 0.045\,s + 0.0065\,s^2\right)$$

where LS is the slope length and steepness, s is
the slope percentage, and m is a variable plot
exponent adjustable to match terrain and soil
variants.

Model comparison and testing

To compare the models, results of potential soil loss
maps were classified into five ranked classes (which
ranged from very low to very high) using GIS. Maps
were converted to grid files and analyzed using
FRAGSTATS 4.2 to compute a set of class matrices.
Total area CA (how much of the class is comprised of a
particular patch type), percentage of landscape
(PLAND) (quantifies the proportional abundance of
each patch type in the class), patch number (NP), patch
density (PD), and patch area distribution (PAD) were

selected to provide information on class area and num-
ber. The shape index (measures the complexity of patch
shape compared to a standard shape) was also used to
measure the shape complexity for each class. Then, the
aggregation index (AI) (the percentage of like adjacen-
cies between cells of the same patch type) was used to
analyze patch connectivity within the classes.

Sensitivity analysis was also conducted to evaluate
the soil erosion models' response to changes in input,
and this was done by collecting 300 random points
using GIS. Sensitivity analysis is a technique for evalu-
ation and calibration models, which helps to understand
the influence of input data on output. For this study, we
used the sensitivity analysis method that was designed
by Lane and Ferreira (1980). Input data variables were
increased by 20% with the aim of calculating Qs and
variation of erosion. Sensitivity for the main factors for
each model was calculated using the following equa-
tion:

$$SI = ((Qs - Qsa)/Qsa)/((P - Pa)/Pa) \quad (13)$$

Where SI is the parameter sensitivity indices, Pa is
the initial first parameter, Qsa is the calculated sediment

Fig. 4 RUSLE model variables.
a Land cover (*C*). **b** Soil
erodibility factor (*K*). **c** Slope
length and steepness (LS)
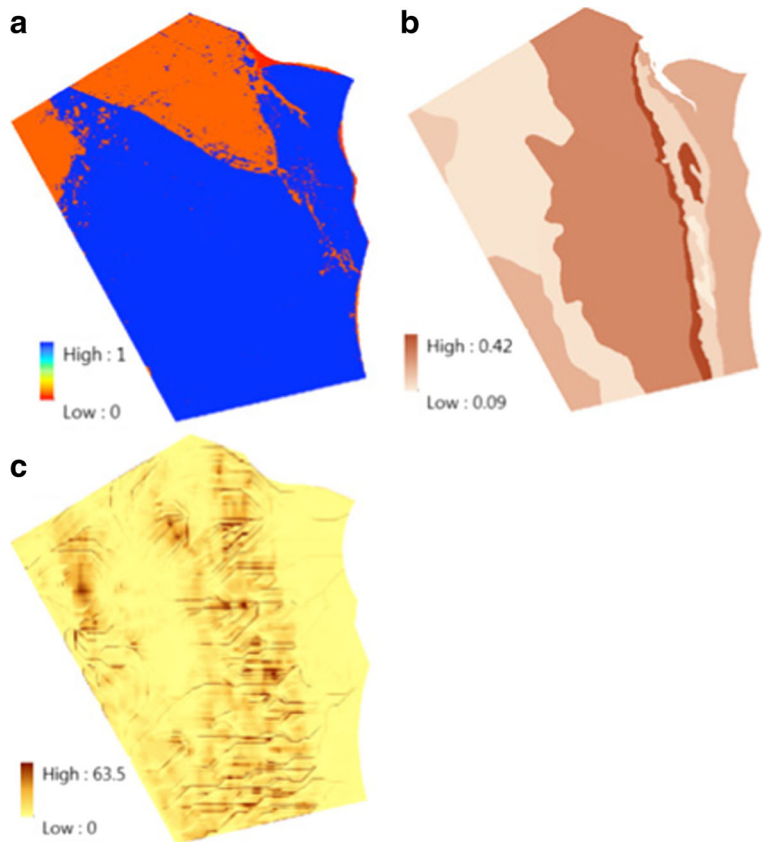
using Pa, P is the increased or decreased input data, and Qs is the calculated sediment using P. Sensitivity index was calculated using Excel.

In addition, a simulation was conducted to assess the effects of increasing vegetation cover on soil loss, as might result from a change in management practices as part of a major restoration effort (for example, fencing to prevent overgrazing or camping). As discussed by Abdullah et al. (2016), the vegetation cover was relatively high at the unfenced area in 1998 (37% in unfenced areas) but then decreased to 3% by 2013, due to overgrazing and spring camping by people; these management practices accelerated vegetation loss after land mines were removed from the area. To simulate the potential vegetation cover after restoration, we assumed that the vegetation cover might reach the percentage of 1998 after it is restored. Therefore, satellite imagery for the year 1998 was classified and the model was re-run using this as input for y6 and y7 in Eqs. (1) and (2).

Results

Potential soil loss

MPSIAC model

A soil erosion risk map was generated based on the attributes of the nine variables and the given scores by the MPSIAC model (Fig. 5a). Modeled soil loss varied from 129 to 1184 $m^3/km^2/year$, which was categorized into five classes ranging from very low to very high. Approximately 24% of the total area ranged between low and very low potential soil loss; of that, 18% of the surface was moderately and 58% was high–very high. The estimated soil loss varied between coastal and desert areas (Table 2): it was higher at the desert area. At the coastal area, the potential soil loss was high, and the amount of erosion was similar between the DMZ (fenced) and the unfenced sites. The average soil loss was 570 $m^3/km^2/year$ for the fenced and 523 $m^3/km^2/$ year for unfenced (Fig. 6a). The high soil erosion levels
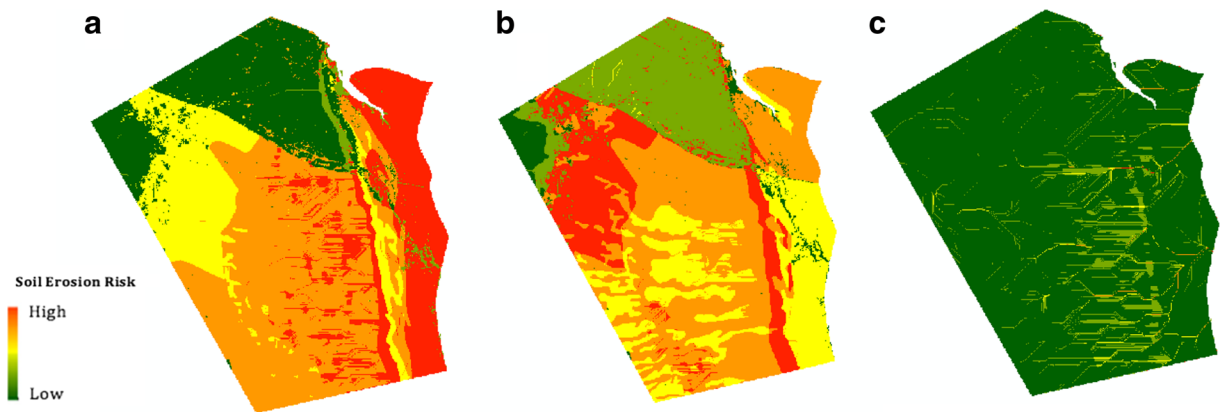
Fig. 5 Potential soil loss map. **a** MPSIAC model. **b** EPM model. **c** USLE model

at the coastal area were likely due to natural geomorphic changes, as opposed to grazing and camping, as these activities are not typically conducted along the tidal flat due to the muddiness, high salinity, and difficulty of access. The erosion rate was still higher at the desert areas, and it varied substantially between unfenced (high to very high, avg. = 703 m³/km²/year) and fenced DMZ sites (very low to low, avg. = 313 m³/km²/year) (Fig. 7a). Vegetation cover greatly influenced the modeled erosion for the desert area unfenced (3% vegetated surface in unfenced versus 88% in fenced).

Sensitivity analysis indices showed that the vegetation cover (y6 and y7) was the most influential factor to the final output with the highest sensitivity index (0.569). Surface geology (y1) comes next with an index of 0.281; soil factor (y2) had a sensitivity index of 0.143 and runoff (y4) had 0.093. However, sheet erosion was the most common erosion type (y8) in the study area, and it was less influential on the output (0.021) as compared with other possible erosion types such as gully erosion. Topography (y5) only slightly affected the output (0.0003), as the study area is mostly flat with low slopes (Fig. 8). The simulation showed that by increasing vegetation cover from 3 to 37% at the

unfenced area, soil loss could decrease from 703 to 478 m³/km²/year (Fig. 7).

EPM model

The calculated soil loss for the EPM model varied from 9 to 1252 m³/km²/year and was also classified from very low to very high (Fig. 5b). Approximately 65% of the total area ranged between low and very low potential soil losses, 12% of the surface was moderately, and 19% was high–very high. Also similar to MPSIAC, the EPM-based erosion was high at the desert area, with large differences between fenced (223 m³/km²/year) and unfenced sites (1051 m³/km²/year) (Table 3). The potential soil loss at the coastal area was almost similar between the fenced and unfenced sites (Fig. 7b). At the coastal area, the degree of soil loss ranged from moderate to high. The average soil loss was 682 m³/km²/year at the unfenced and 587 m³/km²/year at the fenced site. Vegetation cover highly influenced the modeled erosion at the fenced and at some parts of the unfenced area as well as soil types also influenced the model as areas with clay soils were less affected compared with sandy soils. It

Table 2 Average annual coefficient for effective factors and soil loss for MPSIAC model

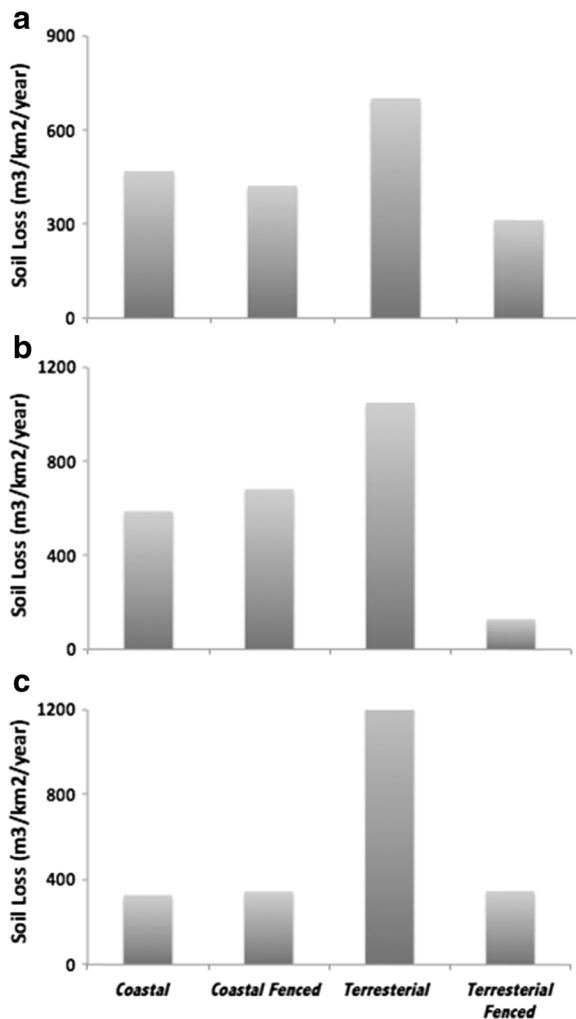| Effective factors	Geology	Soil	Climate	Runoff	Topography	Land use	Erosion type	Total score	Soil loss m³/km²/year
Coastal	3.77	2.76	4.72	3.06	0.03	19.99	2.9	27.2	470
Coastal (fenced)	2.9	2.82	4.72	2.62	0.3	17.25	3.1	36.1	423
Terrestrial	1.4	2.06	4.72	2.61	0.14	18.21	4.2	31.6	703
Terrestrial (fenced)	1.8	3.3	4.72	2.44	0.12	0.046	1.25	13.8	310

Fig. 6 Comparison between soil loss for coastal and desert areas. **a** MPSIAC. **b** EPM. **c** RUSLE

was also seen that erosion rates were not high at the coastal area, which was mostly considered moderate.

Sensitivity analysis (Fig. 8b) showed that land use and vegetation cover (Xa) highly influenced the EPM model output. Also similar, the simulated increase in vegetation decreased the rates of soil erosion at the fenced site. Geology and soils (Y) came next; slopes (I) did not influence the model output as the study area is considered a flat area with slope ranges from 0 to 5%.

RUSLE model

The RUSLE showed different results compared with MPSIAC and EPM (Fig. 5c). Around 94% of the total

area ranged from very low to low erosion rate and 6% ranged from moderate to very high. This model did not show any variation between the classes, and 94% of the total areas were concentrated in the low erosion zone. The degree of soil loss was also similar between the fenced (344 m^3/km^2/year) and unfenced area (327 m^3/km^2/year) at the coastal site (Fig. 7c), but some differences were seen at the desert fenced versus unfenced sites, which had an average of 345 m^3/km^2/year for the fenced and 1560 m^3/km^2/year for the unfenced area (Table 4). The results also showed that each of the four variables had similar influence on the output (Fig. 8c).

FRAGSTATS class matrix analysis for empirical models

Results of FRAGSTATS class metrics showed variation between the three models. The total area for each class was somewhat consistent for the MPSIAC model as 39% of the total area was considered as high potential soil loss, 3% were considered low, but the remaining classes were almost similar at around 20%. The total area for the EPM and RUSLE classes differed more greatly in general, with around 65% of total area of the EPM model was considered very low to low and more than 90% of the total area at the RUSLE was considered very low to low (Fig. 9a).

The MPSIAC model also had the highest patch number and density, and was relatively consistent among the five erosion levels. However, patch number and density varied more greatly between classes in the EPM and RUSLE. The EPM model had a higher patch density among all classes as compared with the RUSLE, except at the moderate erosion level, which was higher for the USLE (Fig. 9b, c).

The results also showed that the erosion classes in the MPSIAC model were more evenly distributed within the five classes, since the patch area distribution was fairly consistent among the five classes. However, the classes within the EPM and RUSLE were mostly concentrated at the low erosion level (Fig. 9d). The MPSIAC and EPM model had similar shape index values among the five classes though with a slightly higher value at the very high level of erosion, which illustrates that all classes had the same shape complexity. However, the shape index varied much more strongly with RUSLE across the classes, though showing the same generally increasing pattern among the classes (Fig. 9e). Overall, the FRAGSTATS results illustrate

Fig. 7 Vegetation cover simulation. **a** Soil erosion map with 3% vegetation cover at the unfenced area. **b** Soil erosion map after increasing vegetation cover at the unfenced area to 37%. **c** Potential soil loss decreased from 703 to 478 m³/km²/year with increase in vegetation cover
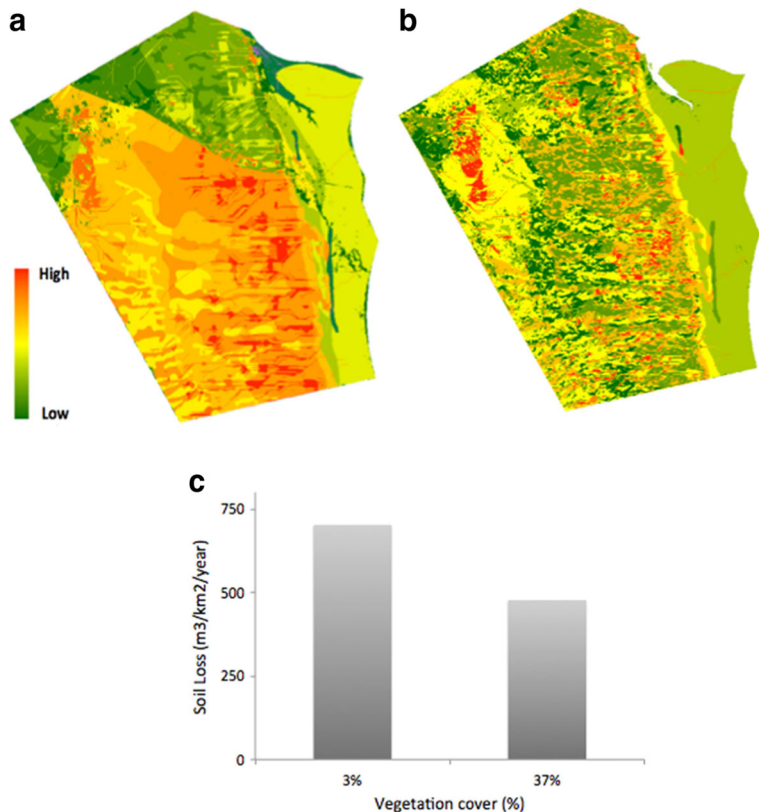
that the MPSIAC model produced output with more evenly distributed classes of erosion, yet within these classes, there were more individual patches and a greater density of them, suggesting that the MPSIAC results were more finely detailed as compared with the other models.

Discussion

Response of soil erosion models

The MPSIAC and EPM models produced somewhat similar results, but the MPSIAC model presented more logical and well-resolved spatial results. The soil factor was more effective in the MPSIAC model; it showed that erosion rates were higher at the coastal area, which is indeed the case as it is covered with clay soils with low infiltration rate and high runoff rates. Also in the MPSIAC, the desert areas with low vegetation fell within the high erosion risk class. In contrast, the EPM model produced a low erosion rate in some parts of the

desert area, especially those that were covered with sandy to loam soils with a high runoff rate, which could be unrealistic, especially with the absence of vegetation cover. The MPSIAC model also presented better spatial detail, with a higher patch number and density and higher evenness across all classes for the various FRAGSTATS metrics, when compared with EPM and RUSLE. The reasons for this result are likely that the higher number of input variables covers a higher number of independent erosional processes as well as the fact that the model was designed for arid and semi-arid lands in the USA. The MPSIAC model is also more quantitative compared with the EPM since the EPM depends on tables to estimate the coefficient of the factors, and then these coefficients were used in equations to estimate the potential soil loss. However, the MPSIAC factors were estimated using equations, which provide more accurate results. For these reasons, the MPSIAC model should be considered the superior model to assess and map soil erosion in arid regions such as Umm Nigga. Moreover, the results calculated by the MPSIAC model are in better
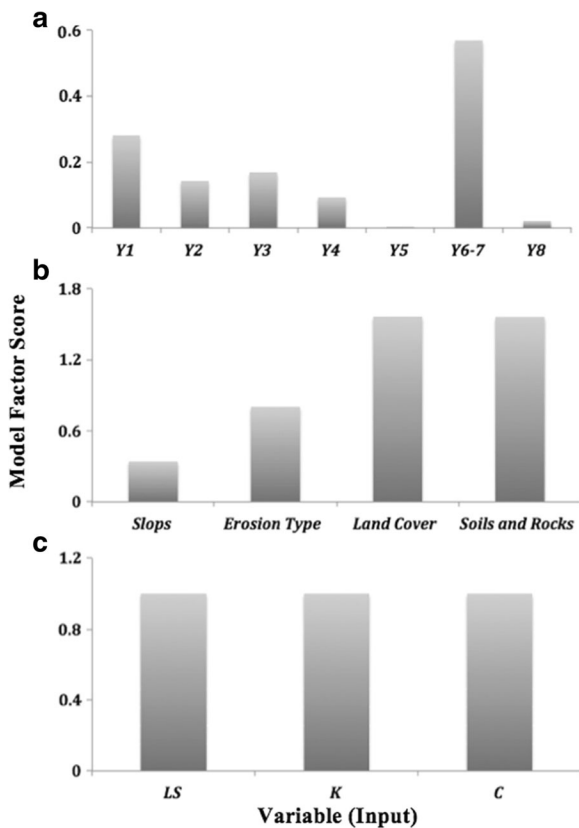
Fig. 8 Results of sensitivity analysis for input variables. **a** MPSIAC. **b** EPM. **c** RUSLE. Higher values indicate a higher sensitivity to an input parameter

accordance with those of the studies of Renard et al. (1997) and Rahmani, Hadian Amri, and Mollaaghajanzadeh (2004) as it showed realistic results in other regions such as arid and semi-arid lands in Iran.

The RUSLE presented unrealistic results, as all four factors had the same sensitivity, but moreover, the locations with high erosion risks were most strongly correlated with slope length and steepness—an unrealistic result since the study area is a flat open landscape. This model was designed for agricultural areas in the USA, and so this conclusion should not be surprising. For these reasons, the RUSLE was deemed an unsuitable model for the Umm Nigga study area and likely for other arid lands such as those found in Kuwait.

Why do the model responses differ?

Our study showed that the MPSIAC model is likely the superior model, when compared with EPM and USLE models. However, this may not always be the case, as it depends on the region and condition in which the model was developed. Empirical models are based on the determination of the significant relationship between model input and model output. The realistic response of the MPSIAC model in our study is likely due to the fact that model was designed for arid and semi-arid lands in the USA (Bagherzadeh & Daneshvar, 2013). However, this does not mean that RUSLE is always unrealistic, as it showed reasonable results when applied for forest regions with high slope percentage (Csáfordi et al., 2012; Terranova, Antronico, Coscarelli, & Iaquinta, 2009) and agriculture areas (Angima, Stott, O'neill, Ong, & Weesies, 2003; Fu, Chen, & McCool, 2006; Meusburger et al., 2013; Ozsoy & Aksoy, 2015).

Differences among model outputs may also be due to the erosional processes dominant at different spatial and temporal scales, with each representing a somewhat different mix of erosional processes. Models that were designed for different regions such as the RUSLE, which was designed for agriculture areas in the USA, differ in the mix of erosional process compared with arid ecosystems. In addition, most empirical models lump a number of processes together and describe them as a signal mathematical or logical relationship, for example,

Table 3 Average coefficient for effective factors and soil loss for EPM model

Effective factor	The coefficient of rock and soil (Y)	The land use coefficient (X_a)	The coefficient for present erosion type (Ψ)	Average- land slope in percentage (I)	Z	Soil loss m^3/km^2/year
Coastal	1.4	1	0.5	0.1	1.07	682
Coastal fenced	1.4	0.8	0.5	0.9	0.9	587
Terrestrial	1.2	0.9	0.56	0.42	1.31	1051
Terrestrial fenced	1.3	0.2	0.56	3.37	0.4	223

Table 4 Average coefficient for effective factors and soil loss for RUSLE model

Effective factors	K factor	LS factor	C factor	R factor	Soil loss m^3/km^2/year
Coastal	0.17	0.49	1	0.92	327
Coastal fenced	0.16	0.40	0.89	0.92	344
Terrestrial	0.18	7.2	0.9	0.92	1560
Terrestrial fenced	0.18	9.25	0.3	0.92	345

the older USLE. The advantages of such models are their simplicity in term of data requirements and computation (Harmon & Doe, 2001). However, the individual modeled processes cannot be disaggregated or changed, which is a problem if the model was designed for a different location or spatial scale. Moreover, empirical relationships are often calibrated for a particular dataset that is only valid for the dataset in which they were derived from (Ghadiri & Rose, 1992; Hudson, 1993). The ideal approach is for each country or region to have their own model, for example, the Soil Loss Estimation Model for Southern Africa (SLEMSA) and the European Soil Erosion Model (EUROSEM) (Hudson, 1993).

Factor models are considered empirical models in that the variables are represented by a quantified factor and are combined together by adding them up or multiplying them together (Hudson, 1993). The MPSIAC and RUSLE could be considered as factor models since the scoring of each factor is created based on equations; then, the scores are used in the final equation to predict the amount of soil loss. However, the EPM model depends on tables when selecting a coefficient score, and then these scores are added in an equation to calculate the amount of soil loss. Moreover, The MPSIAC model contains the highest number of factors influencing the erosion processes.

Can native vegetation control soil erosion?

Our results indicated that vegetation cover plays an important role in controlling soil erosion. In the MPSIAC model, the erosion was most sensitive to this factor, as was demonstrated by the difference between the fenced DMZ and the unfenced portion of the desert areas. The fenced area ranged from low to very low soil loss, as compared with high to very high at the unfenced area. Previous studies have similarly concluded that

vegetation is a major driver for the MPSIAC model (BehnamA, ParehkarB, & PaziraC, 2011; Ilanloo, 2012). For this reason, it is likely important to restore the vegetation in the desert unfenced areas. Somewhat conversely, the high amount of erosion that occurred in the coastal areas could be considered natural (Abdullah et al., 2016) and thus re-vegetation is not a relevant or likely outcome.

Limitations

Judgments on how well the models perform are usually made by comparing the output with observed data from the field (Harmon & Doe, 2001). Since we did not measure soil erosion in the field or lab, we are unable to judge the accuracy of the potential soil loss values for each model. Direct field measurements of surface soil erosion will be required to confirm the results of our model evaluation work. With this verification in mind, it might become necessary to modify or calibrate the MPSIAC model in order to get more accurate results. Lal (1994) discussed the critical nature of continuous simulation modeling in predicting erosion reliably, stating that long-term continuous simulation may be needed in order to quantify erosional responses within 10% of the field values. Therefore, it is highly recommended to integrate field-based experiments with lab-based spatial analysis and modeling in future research.

For Kuwait, it will be important to provide further calibration between winter storms and summer storm conditions. Also, calibration for bare soils may also not be applicable for mature crop stands (Harmon & Doe, 2001). Models cannot fully represent all details in the natural world, but simultaneously, it is not possible to use field samples only to quantify and map soil erosion across a large area, by making assumptions that the landscape is homogenous between each sample. Therefore, models are a critical tool in estimating soil erosion.
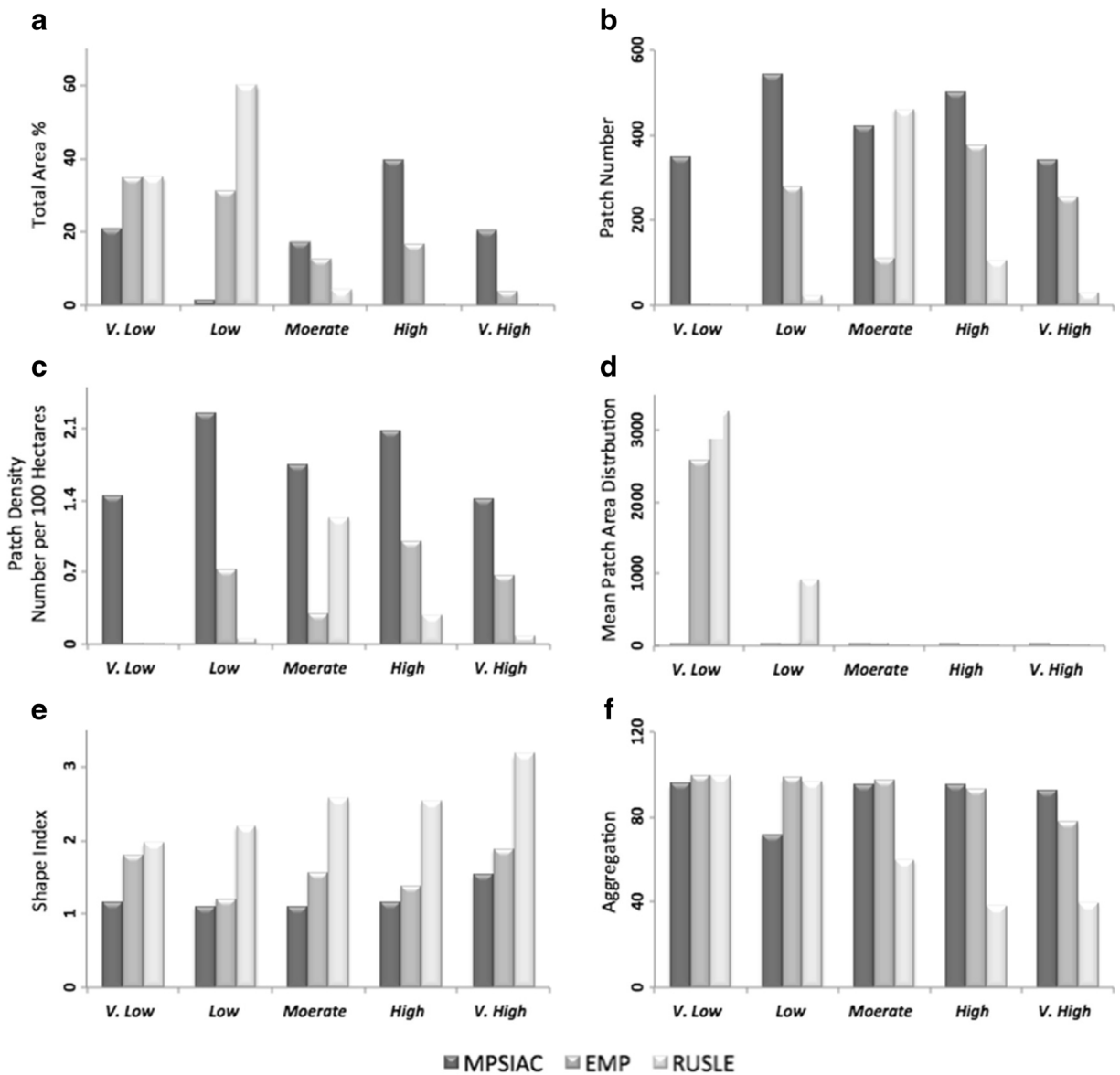
Fig. 9 Class matrix analysis. **a** Total area. **b** Patch number. **c** Patch density. **d** Mean patch area distribution. **e** Shape index. **f** Aggregation percentage

Conclusion

The MPSIAC model was the superior model for our study site and when combined with the findings of other authors suggests that arid regions should avoid use of the EPM and RUSLE when possible. The MPSIAC produced the most even and detailed results, likely because of the greater number of modeled factors that represents the various mechanisms that affect soil erosion as well as the fact that the model was designed for arid and semi-arid lands in the USA. The MPSIAC model is also more quantitative compared with other models. For all of the models, vegetation (ideally native plants) played an important role in decreasing the amount of soil erosion and controlling desertification. Thus, we suggest restoring the unfenced areas at Umm

Nigga, Kuwait, by restricted grazing and access and by protecting native plant species. Practices that limit vegetation loss could potentially lower soil erosion by 32%, as shown by our results. Moreover, the output maps generated by this study could be used to select suitable locations for re-vegetation efforts as based on the rated erosion rates or compounding factors mapped by each independent input factor. In summary, the MPSIAC spatial model is a useful predictive tool for estimating soil erosion across large-extent, arid landscapes.

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