

## Modelling Soil Degradation in Libya

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### Abstract

Soil degradation is considered one of the most important factors limiting agricultural development in Libya, however little effort has been taken to identify the distribution of soil degradation occurrence and type for the country. While the soil degradation for the primary agriculture regions (PAR) has been previously determined as thirty-three percent (33%), the degradation for the rest of the country was still unknown. For this reason, polygons representing soil and climate characteristics, landscape feature and soil degradation from the PAR were converted to raster using ArcGIS (at a resolution of 1000 m<sup>2</sup>) resulting in 850 points which were then exported as a table for modelling purposes. The data set was subjected to logistic regression to model the binomial outcome of soil degradation occurrence (occurrence, no occurrence). A multinomial logistic regression was used to relate predictor variables to the type of soil degradation since there was more than two outcome options (salinization, water erosion, and wind erosion). Finally, the prediction models were used to determine the remainder of the country's degradation occurrence and type. Results indicated that slope, texture and wind speed are the most important variables for soil degradation occurrence and type in PAR. When these models are applied to the remainder of the country, they show that salinization was the primary type of soil degradation (30 %), with water erosion and wind erosion causing 10 % and 15 % of soil degradation, respectively. The intention is for these models to assist stakeholders in identifying areas where agriculture is most likely to be successful, while also applicable to countries with similar climate and soils in North Africa.

**Keywords:** Agriculture, GIS, Libya, Logistic regression, Soil degradation.

### 1. Introduction

The primary issue hindering agricultural development in Libya is soil degradation, a condition caused by salinization, water erosion and wind erosion due to the geology and climate (Nwer et al., 2013; Saad et al., 2013), and improper use of natural resources (Gebril and Saeid 2012). The low rainfall and high evaporation promotes soil salinity and subsequently leads to soil instability (Habel, 2013). Approximately 700799 hectares of Primary Agriculture Regions (PAR) (identified as the Kufrah, Murzuq, Jabal Nafusah, Jabal al Akhdar, and Jifarah) regions of Libya, regardless of irrigation, are degraded due to salinity (Hachicha and Abdegawed, 2003), with 12 % of the northwestern areas and 23 % of the northeastern areas considered salt-affected (Nwer, 2013). Increased use of fresh groundwater as a potable water source for a growing population and extensive agriculture activities increased seawater intrusion into groundwater wells (Nwer et al., 2013) further increasing the soil salinity problem. Extensive irrigation with this contaminated water source, coupled with poor drainage, resulted in the proliferation of salt affected soils in the western part of Jifarah (Atman and Habibah, 2013) and in Jabal Nafusah (Laytimi, 2005).

Rainfall in Libya is spatially and temporally unevenly distributed with deleterious effects. The occasional heavy showers (Nwer, 2013) accelerates soil erosion by detaching and transporting vulnerable soil either by rain splash or rill and gully erosion (Pang et al., 2015). Water erosion has degraded 797 ha of the Jabal Nafusah soils and Jabal al Akhdar soils, collectively (Mahmud, 1995; Ben-Mahmoud et al., 2000). Loss of vegetation covers from over-grazing and over-cultivation of Libya's two primarily rain-fed agriculture areas (Jabal Nafusah and Jabal al Akhdar) resulted in bare soil further exasperating erosion by storm water (Gebril and Saeid, 2012).

Soils of the Jabal al Akhdar region has been degraded the most by wind erosion (Aburas, 2014) since there is minimal plant vegetative cover protecting the soil (Laytimi, 2005). The soils of Jifarah, one of the most cultivable areas of the country due to the availability of groundwater experiences both water and wind erosion due to aridity, poor vegetation cover, and poor landuse decisions during the last half of the 20th century (El-Tantawi, 2005).

While new strategies may address soil degradation issues (Ben-Mahmoud et al., 2000), more complete baseline data and information infrastructure to determine the best management strategy are lacking (Khaled, 2001). Over the past 30 years, numerous soil surveys have been conducted in Libya (primarily in Jabal Nafusah, Jifarah Plain and Jabal al Akhdar in addition to scattered areas in the south) (Nwer et al, 2013). Different agencies and their interests resulted in varied parameters and geographic extent (Khaled, 2001), thereby limiting

its practical use (Nwer et al., 2013) beyond the conclusions made in the previous paragraphs. An alternative, remote approach to classify soil and type degradation across the country must be considered since field determinations are resource intensive (Mueller et al., 2005). Since soil and climate characteristics are linked to the development of the soil degradation, empirical models can be developed to identify areas most susceptible to soil degradation. This empirical model can help identify areas that are either already degraded or most prone to soil degradation, and protect Libya's most viable areas for sustainable agriculture development.

The objectives of this study are to:

1. To create a database of soil resources and soil degradation using ArcGIS 10.3 software (ESRI, Redlands, California). This step will result in a more efficient and economical method for updating soil information and making it available to a wide variety of stakeholders.
2. To model soil degradation occurrence as a function of soil and climate characteristics within the PAR using logistic and multinomial logistic regression models.
3. To apply these models to the remainder of the country to predict degradation occurrence and type for the entire country.

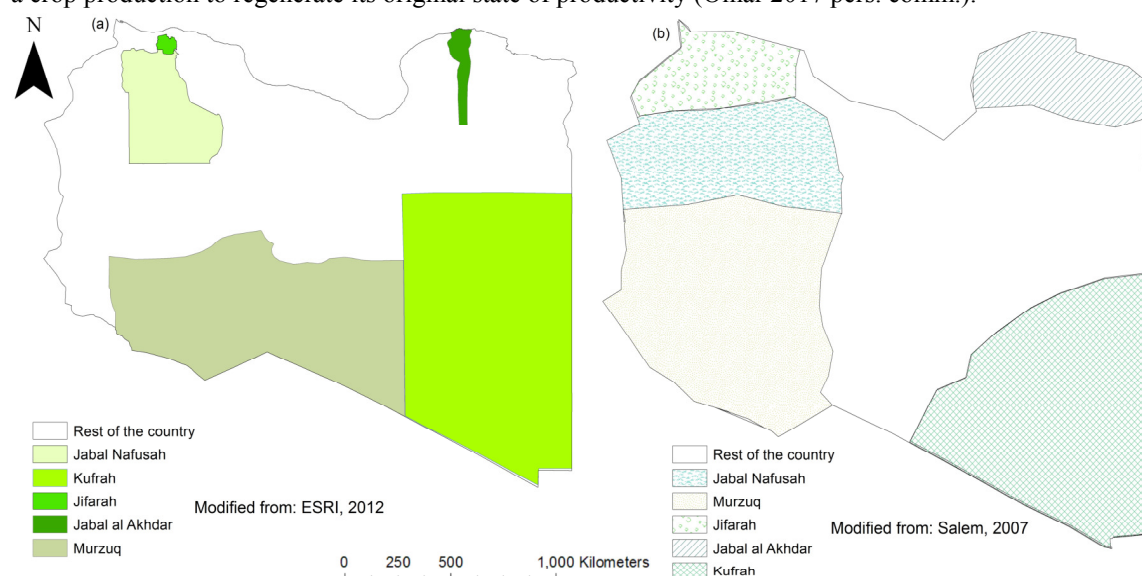
## 2. Methodology

The paper reported here had three approaches:

- 1- Because the existing soil data for the country is from different classification systems and no complete data set was found, creating a baseline data set of soil coverage and degraded areas was the first approach.
- 2- Develop PAR soil degradation occurrence and type models using the baseline data set of soil and climate properties.
- 3- Applying these models to the rest of the country in order to predict the degradation for all Libya.

### 2.1 Assessment of the Primarily Agriculture Regions 2.1.1 Study Area Description

The study was conducted for the PAR in the country of Libya: Kufrah, Murzuq, Jabal Nafusah, Jabal al Akhdar, and Jifarah covering 846126 km<sup>2</sup> or 52.4 % (Fig. 1a), of the total area of the country. Yields from rainfed agriculture in Libya are generally low due to the climate, thus the PAR were primarily selected due to the availability of groundwater aquifers for irrigation (Fig. 1b). In 2005, approximately 22 % of the country's PAR depends on groundwater fed irrigation (Food and Agriculture Organization (FAO), 2005). According to Abagandura and Park (2016), the seasonal rainfall distribution for each PAR varies. Jifarah experiences dry summers and relatively wet winters. Both Jabal al Akhdar and Jabal Nafusah has a plateau type climate with greater rainfall (approximately 500 mm in Jabal al Akhdar and 400 mm in the Jabal Nafusah, annually). Murzuq experiences pre-desert and desert climatic conditions and Kufrah is characterized as an area with little annual rainfall (50 to 150 mm). Wind storms occur all year (Libyan Research Center, 2012). The main productions of PAR are wheat, barley, and the main non-grain agricultural crops include potatoes, onions, tomatoes, watermelons, oranges, dates, and olives (Abagandura and Park, 2016). Traditionally, a fallow period is used after a crop production to regenerate its original state of productivity (Omar 2017 pers. comm.).



**Fig. 1** The Location of (a) the primary agriculture regions, Kufrah, Murzuq, Jabal Nafusah, Jabal al Akhdar, and Jifarah; and (b) groundwater aquifers in Libya.

### 2.1.2 Creation of Baseline Data (Objective 1)

To complete objective one, ArcGIS was used to integrate data from three existing maps: the African Soil Classification Map created by the FAO in 2005, the Libyan Primary Agricultural Regions Degradation Map created by Libyan Government in 2010, and the Libyan Regional Map created by Environmental Systems Research Institute (ESRI) in 2012.

#### 1. *African Soil Classification Map*

The FAO generated the Libyan GIS portion of the African Soil Classification Map from Russian and American topsoil (1 to 5 cm) surveys (Nwer, 2006). However, the governments used different classification systems and methods of soil analyses: The American surveys were conducted in the northwestern, central, northeastern, and southern zones over an area of 9 to 4 000 km<sup>2</sup>, and used the hydrometer method at a scale of 1:200000 and 1:500000, while the Russian surveys of the northwest and west zone, determined texture by the feel test at a scale of 1:300000 and 1:500000. The clip and export data tools in ArcGIS were used to export data from this map to create the Libyan Soil Classification Map.

#### 2. *Libyan Primary Agricultural Regions Degradation Map*

In 2010 the Libyan government published the map from assessing soil degradation by the following methods. Some of the surveys that identified soil texture also measured soil salinity. Electrical conductivity was determined by laboratory analysis from 1:2.5 soil–water suspensions. Wind and water erosion deterioration were determined from Landsat satellite imagery between 1960 and 1980 at 1:25000 to 1:60000 scale. The Satellite imagery were used to define the spatial extent of soil erosion. Segmentation techniques combined with graphic mask were applied over these imageries in order to obtain the extent of eroded areas for the previous years (Libyan Research Center, 2000).

#### 3. *Libyan Region Map*

In 2012, ESRI created a map of education infrastructure in the 24 Libyan regions including the five within the PAR. The layer of the PAR was clipped creating the Libyan Regions Data Map.

To achieve objective one and two, the Libyan Soil Classification Map, Libyan PAR degradation Map and Libyan Regions map were projected in the same reference system (Africa\_Albers\_Equal\_Area Conic), then intersected in ArcGIS to relate the soil degradation of the PAR to soil texture. Also intersected were shapefiles of average annual rainfall, temperature and wind speed derived from twenty observation stations covering Libya from 2000 to 2008 (maintained by the Libyan Meteorological Administration). New polygons were created by the intersection of the input polygons and were converted from polygon shapefile to a raster (gridded) data set with a resolution of 1000 m<sup>2</sup>. The result was a table of 850 points which was exported to JMP® Pro 12.0.1 software (product of SAS Institute Inc., Cary, NC) for the calculations of the predictive models discussed later in the paper. The predictive dataset was imported back into ArcMap as a raster and finally converted back to a polygon dataset.

To study the relationship between soil texture and soil degradation type, Pearson's Chi-squared test was used to determine how proportions of the degradation types change across texture levels. The distribution of soil degradation and each texture is illustrated using a mosaic plot. The vertical length of each rectangle is proportional to the proportions of the soil degradation in each texture level.

## 2.2 Modelling Climatic and Soil Characteristics to the Occurrence and Type of Soil Degradation Within PAR (Objective 2)

### 2.2.1 Modelling PAR Soil Degradation Occurrence

Logistic Regression (LR), which is commonly used in environmental and ecological studies (Dai et al., 2001; Lee and Min, 2001; Lee et al., 2013), is a statistical model that is used to predict the binomial (Yes/No) outcome of a response (dependent) variable using one or several predictor (independent) variables (Bennett, et al., 2008; Hagan et al 2014). Several factors must be considered for soil degradation including topography (Liu et al., 1994; Liu et al., 2015), soil temperature and moisture (Wei et al., 2014), and soil texture (Fecan et al., 1998; Li et al., 2013). Rainfall and air temperature also affects degradation. For example, the greater the intensity and duration of a rainfall, the higher the soil degradation potential (Wang et al., 2013). In addition, wind intensity is one of the factors inducing movement of soil (Borrelli et al., 2014).

The relationship between soil degradation (y) (occurrence, no occurrence) and the seven independent variables (soil texture, soil moisture, soil temperature, slope, rainfall, air temperature and wind speed) was evaluated using LR model.

The form of the LR model was

$$PY=1/1+\exp(-(\beta_0+i=1n\beta-iXi)$$

where

P(y) is probability of soil degradation being 1,  $\beta_0$  is an intercept of the model,

$\beta_i$  (with  $1 < i < 7$ ) are the model coefficient to associated with the independent variables used in the specific

model evaluated. A positive regression coefficient means that the variable increases the probability of the outcome, while a negative regression coefficient decreases the probability (Agresti, 2002). The variables (denoted independent variables,  $X_i$ ) related to the probability of soil degradation are listed in Table 1. All possible combinations of including and excluding the seven independent variables resulted in 128 different models to evaluate in JMP.

Table 1. Independent and dependent variables used in logistic regression model for the primary agricultural regions in the Libya.

Variable	Description
<b>I Dependent</b>	
Soil degradation <sup>a</sup>	Degraded soil (1—degraded, 0—not) <sup>c</sup>
	Salinization
	Water erosion
	Wind erosion
<b>II Independent</b>	
Soil moisture <sup>b</sup> I	Class I “dry” (1—class I, 0—other classes) <sup>d</sup>
Soil moisture <sup>b</sup> II	Class II “xeric” (1—class II, 0—other classes) <sup>d</sup>
Soil temperature <sup>b</sup> I	Class I “aridic” (1—class I, 0—other classes) <sup>d</sup>
Soil temperature <sup>b</sup> II	Class II “thermic” (1—class II, 0—other classes) <sup>d</sup>
Soil temperature <sup>b</sup> III	Class III “moderate” (1—class III, 0—other classes) <sup>d</sup>
Soil temperature <sup>b</sup> IV	Class IV “warm” (1—class IV, 0—other classes) <sup>d</sup>
Soil texture <sup>b</sup> I	Class I “coarse loamy” (1—class I, 0—other classes) <sup>d</sup>
Soil texture <sup>b</sup> II	Class II “loamy” (1—class II, 0—other classes) <sup>d</sup>
Soil texture <sup>b</sup> III	Class III “silty loam” (1—class III, 0—other classes) <sup>d</sup>
Soil texture <sup>b</sup> IV	Class IV “sand” (1—class IV, 0—other classes) <sup>d</sup>
Soil texture <sup>b</sup> V	Class V “loamy very fine sand” (1—class V, 0—other classes) <sup>d</sup>
Slope <sup>c</sup>	Slope <sup>c</sup> (%)
Climate (temperature) <sup>c</sup>	Temperature <sup>c</sup> (c°)
Climate (rainfall) <sup>c</sup>	Rainfall <sup>c</sup> (cm)
Wind speed <sup>a</sup>	Wind speed <sup>c</sup> (m s <sup>-1</sup> )

<sup>a</sup> Libyan Government (2010)

<sup>b</sup> FAO (2005)

<sup>c</sup> ESRI Landscape (2014)

<sup>d</sup> categorical variable

<sup>e</sup> continuous variable

### 2.2.1.1 Logistic Regression Statistical Analysis

The LR model development approach included:

- 1- Examining the overall significance of the 128 LR models using the overall Chi-square test and p-values. When the p-value of the LR was  $\leq 0.05$ , the model was kept.
- 2- The goodness-of-fit was determined for each kept LR model using the Akaike Information Criterion (AIC), where the optimal fitted model is identified by the minimum AIC value.
- 3- Fisher’s F-tests (with associated p-values) tested each independent variable considered in the optimal fitted model.

To further validate the LR model developed in this study, the Leave-One-Field-Out Validation approach was used (Pike et al., 2009). A series of analyses were performed in which one PAR was left out and used as a test case. The coefficients for the LR model were used to estimate the probability of a degradation occurrence in the test case (Bishop, 2002). If the probability of degradation for a test case was  $< 0.5$ , it assumed to have no degradation and if the probability was  $\geq 0.5$  it was assumed to have degradation. (Mueller et al., 2005; Pike et al., 2009). The predicted degradation was compared to the actual degradation. This was repeated with each PAR being a test case. Misclassification (disagreement between actual and predicted [degradation] totals were used to examine prediction errors. To display results of the LR validation, data results were imported into ArcMap as a table with respective latitude and longitude, and then converted into polygons using the shapefile tool.

### 2.2.2 Modeling PAR Soil Degradation Type

The LR developed in this study modeled the soil and climate characteristics with the soil degradation occurrence (occurrence or no occurrence) within the PAR. Because the soil degradation had three types (salinization, water erosion and wind erosion) which were determined already for the PAR, the next step was to develop a model to predict the three types. For this step, a Multinomial Logistic Regression (MLR) model was developed. The MLR was used because it is a simple extension of the LR that allows for more than two categories of the dependent variable (Lin et al., 2014; Starkweather and Moske, 2011). Only significant variables in LR became part of the

MLR models. One soil degradation type served as the reference category.

### 2.2.2.1 Multilogistic Regression Statistical Analysis

The MLR model development approach included:

- 1- Fisher's F tests and p-values were used to determine if the independent variables used in MLR were related to the soil degradation type.
- 2- The coefficients in the MLR were interpreted based on odds ratio (OR). The OR indicated the amount by which the odds of the soil degradation types (with respect to the reference type) changed as the independent variables changed by one unit (with respect to the reference category) (Institute for Digital Research and Education, 2014). Although the magnitude of odds ratio of a category changes with the reference category, its relative trend and the fit of the overall model is not affected. An  $OR \geq 1$  indicated a positive relationship between the independent variable and the probability of soil degradation type existence, while  $< 1$  indicated negative correlation (Debella-Gilo and Etzelmüller, 2009). With wind erosion as the selected reference, a model was developed for soil salinization and water erosion.

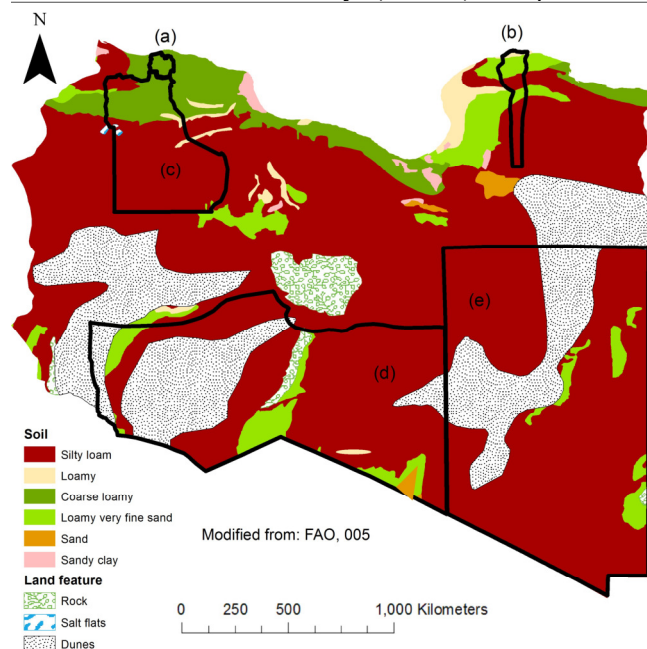
### 2.3 Determining Soil Degradation Occurrence and Type for Libya (Objective 3)

After developing LR and MLR (modelling the soil and climate characteristics with the soil degradation occurrence and type) for the PAR, the next step was applying these models to the areas outside the boundaries of the PAR to predict degradation occurrence and type for the remainder of Libya. Dunes, salt flats and rocks were omitted from the models. Although dunes play a very important role in preventing and delaying intrusion of waters into inland areas (Gómez-Pina et al., 2002), and rocks increase hydraulic roughness and friction, decreasing the overland flow speed and thus decreasing soil erosion (Jomaa et al., 2012), they would not be considered for agriculture purposes. The degradation results were imported into ArcMap and converted to a polygon shapefile to display the results as a degradation map for the entire country.

## 3. Results and Discussions

### 3.1 Baseline Soil Data Map

Intersecting the Libyan soil degradation, classification and region maps in ArcGIS created existing data baseline maps for soil texture and landscape feature distribution (Fig. 2). Calculations included areas ( $\text{km}^2$ ) of each soil texture and land feature present in each PAR (Table 2), and the area ( $\text{km}^2$ ) of the degradation type for each texture within each PAR in Libya (Table 3) were performed.



**Fig.2** Soil and land features of the primary agriculture regions in Libya, (a) Jifara, (b) Jabal al Akhdar, (c) Jabal Nafusah, (d) Murzuq, and (e) Kufrah as created by FAO, 2005.

Table 2. Area (km<sup>2</sup>) of different soil textures and land features for the primary agriculture regions in Libya.

Region	Soil						Land feature		
	Silty loam	Loamy	Coarse loamy	Loamy very fine sand	Sandy clay	Sand	Rock	Salt flats	Dunes
Kufrah	296893	0	0	18289	0	0	825	0	108923
Murzuq	205031	877	0	37566	0	186	5305	0	81376
Jabal Nafusah	59451	1128	15499	461	0	0	0	336	0
Jabal al Akhdar	6568	666	0	4082	0	0	0	0	0
Jifarah	0	0	2664	0	0	0	0	0	0
Total	567943	2671	18163	60398	0	186	6130	336	190299
Libya	1012990	22427	81134	109602	8434	10312	38502	676	330\366

Table 3. Areas (km<sup>2</sup>) of the degraded type for each soil texture in the primary agriculture regions in Libya based of existing data.

Region	Silty loam			Loamy			Loamy very fine sand			Coarse loamy			Sand		
	SA	WA	WI	SA	WA	WI	SA	WA	WI	SA	WA	WI	SA	WA	WI
Kufrah	53964	0	10000	0	0	0	0	0	0	0	0	0	0	0	0
Murzuq	49627	0	2057	0	0	0	7851	0	6064	0	0	0	0	0	187
Jabal Nafusah	50261	3028	4800	671	457	0	254	206	0	381	15118	0	0	0	0
Jabal al Akhdar	5173	0	1000	0	0	0	1607	0	0	0	0	0	0	0	0
Jifarah	0	0	0	0	0	0	0	0	0	562	2102	0	0	0	0
Total	159025	3028	17857	671	457	0	9712	206	6064	943	17220	0	0	0	187

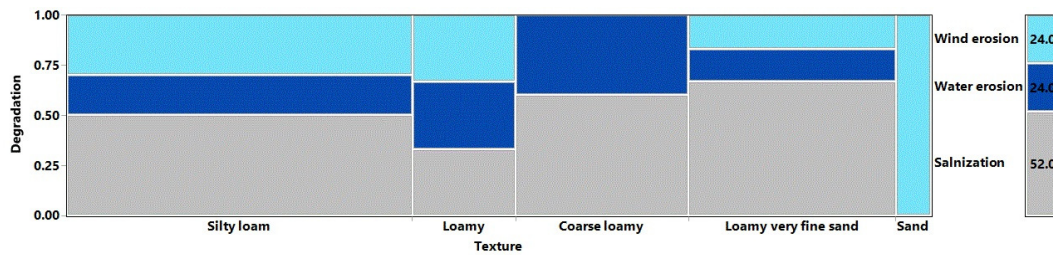
SA refers to salinization, WA refers to water erosion and WI refers to wind erosion.

Silty loam soils dominated in all the regions except for Jifarah, which is dominated by coarse loamy soils (Fig. 2 and Table. 2). Dunes and rocks covered 25.6 % of Kufrah and 24.6 % of Murzuq. Salt flats, which developed from groundwater evaporating and developing a salt pan (Schulz et al. 2015), covers 0.55 % of Jabal Nafusah.

The quantity of degradation measured at 215370 km<sup>2</sup> (33.16 %) of the total area of the PAR (Table 3). Jabal Nafusah, Jabal al Akhdar, and Jifarah are the most degraded regions (98.2 %, 68.5 % and 99.4). Salinization is the greatest type of degradation in all the PAR with exception of Jifarah which has soils degraded primarily from water erosion (Table 3). Laytimi (2005) reported that irrigation with saline groundwater led to soil salinization in some areas of the PAR. Water erosion is also a significant source of degradation in the Jabal Nafusah region, probably because the terrain includes steep slopes coupled with a very high content of very fine sand particles and very low clay content. Sandy soils lack the ability to aggregate leading to weaker physical resistance to water erosion (Khaled, 2001; Aboufayed, 2013). The wind erosion affected Murzuq, Jabal Nafusah, Jabal al Akhdar and Kufrah soils (Table 3).

### 3.1.1 Relationship of Climatic and Soil Characteristics to Soil Degradation Occurrence and Type

The proportions of degraded type (salinization, water, and wind erosion) changes across soil texture ( $p < 0.001$ ) (Fig. 3) and reflected what is found in each region (Obj. 2). For example, salinization occurs in all soil textures except sand. Water drains freely from sand soils with very little to no capillary rise to be expected (Li et al., 2013). In comparison, the other finer textured soils have micropores in which capillarity resulted in evaporation of the water from the soil surface and concentrated dissolved salts precipitated at the soil surface (Osman, 2014). No degradation existed from water erosion and salinity in the sandy texture, most likely because sands contain macropores that allow water to drain freely producing little runoff (Adekalu et al., 2007). Weakly cohesive soils (dominated by sand and silt) are more susceptible to wind erosion, especially when desiccated (Geological Society of London, 2012). In this study soil degradation from wind erosion occurred in all sand dominated areas, as well as associated with silty loam, loamy, and very fine sand textures. The Libyan desert is a significant source of mineral dust due to sandblasting from intense (yet not so frequent) wind storms (Laurent et al., 2008). However, without more sophisticated equipment to collect more complex and detailed wind data, it is most likely that the predictions of wind erosion found in the present model are low.



**Fig.3** Soil degradation type's proportions across texture levels in the primary agriculture regions in Libya. The thickness of each texture represents the percentage of observations for each texture compared to the total data.

### 3.2 Logistic Regression Development for the Distribution of Soil Degradation Occurrence

From the 128 models with all possible combinations of seven independent variables, only ten possible models were found significant for predicting soil degradation occurrence ( $p$ -values  $< 0.05$ ) (data not shown). Of these ten models, the model that had slope, soil texture and wind speed had the lowest AIC values, (AIC = 28.13,  $p$ -value  $< 0.001$ ). The equation for this model is:

$$\text{Logit (Soil degradation)} = 11.4 + (0.22 * \text{Slope}) + (2.63 * \text{Texture [loamy very fine sand]}) + (-3.12 * \text{Texture [Coarse loamy]}) + (-7.03 * \text{Texture [Loamy]}) + (-15.2 * \text{Texture [Sand]}) + 0.42 * \text{Wind speed}.$$

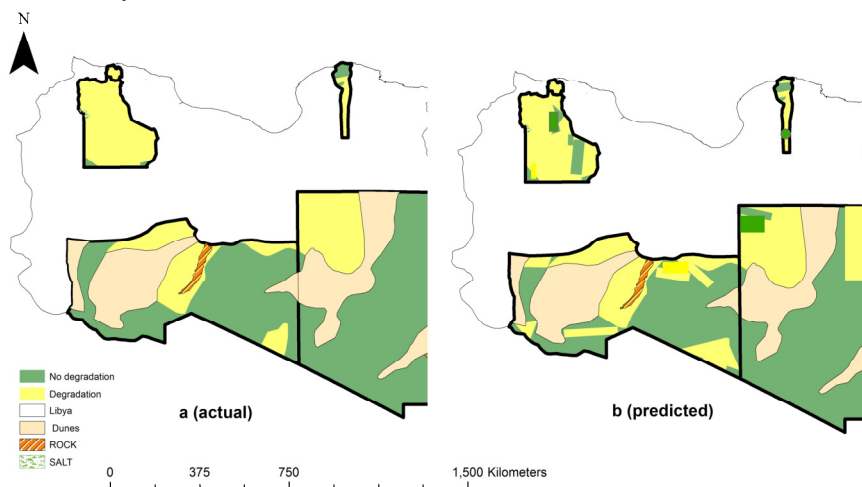
The F-tests with associated  $p$ -values of this model variables suggested that slope ( $p = 0.0142$ ), soil texture ( $p < 0.0001$  for all texture categories), and wind speed ( $p = 0.0321$ ) had significant relationships with soil degradation.

The influence of slope on soil degradation, especially from water erosion is well documented (Liu et al., 1994; Liu et al., 2014; Sensoy and Kara, 2014). In the present study, slope exhibited a positive relationship with the extent of soil degradation. One-degree increase in slope results in a 0.22 increase in the logit of soil degradation. This relationship is best seen in the degradation map of the Jabal Nafusah region with slopes ranging from 4 % to 28 % and having the largest degraded area due to water erosion (30 %). This result supports Liu et al. (2014) who documented that variations in slope can affect soil erosion.

Salako (2003) reported that soil susceptibility to degradation is influenced by small differences in texture. The chance of soil degradation increases most when a silty loam soil is present compared to other textures. The present regression model agreed with the existing degradation data of the PAR, showing that silty texture soil had the highest degradation occurrence compared to other textures (Table 3).

Wind speed had a positive relationship with soil degradation. One-degree increase in wind speed results in a 0.42 increase in the logit of soil degradation. That agrees with Nwer (2015), who reported that wind erosion is one of the most important threats to agriculture development in Libya.

Model performance tests included the leave-one-field-out validation analyses and completed by utilizing the existing data in the PAR (Fig.4, Table 4). Jifarah has no previously determined non-degraded areas so it was not included in the validation. The validation identified that 66 % to 76 % of the model degradation occurrence predictions as correct (Table 4) and thus this model was used to predict degradation occurrence in the remaining areas of Libya.



**Fig. 4** Soil degradation occurrence in the primary agriculture regions in Libya as (a) previously determined (existing), and (b) predicted by LR model using the combination of slope, texture and wind speed.

Table 4. Actual degradation, frequency of correctly determining degradation occurrence, and percent of degradation observations that were correctly classified by model predictions from the leave-one-field-out validation analyses.

Region	Predicted <sup>a</sup>			
	Actual Degradation	Degraded	Not degraded	Percentage correct <sup>b</sup> (%)
		(# of Observations)		
Kufrah	Degraded	70	30	70.0
	Not degraded	32	70	68.8
Murzuq	Degraded	35	18	66.6
	Not degraded	24	77	76.2
Jabal Nafusah	Degraded	45	16	73.7
	Not degraded	9	20	68.0
Jabal al Akhdar	Degraded	44	22	66.6
	Not degraded	13	28	68.2

<sup>a</sup>Degraded if probabilities  $\leq 0.5$  and non-degraded if probabilities were  $> 0.5$ .

### 3.3 Multilogistic Regression Development for the Soil Degradation Type

To develop the models of predicting soil degradation type, wind erosion was the reference dependent variable and sand texture was the reference category for the independent variable. JMP software automatically selects the reference category to be the last in alpha-numeric order. Slope and soil texture, which were significant variables in predicting the soil degradation distribution, are again significant (F test = 5.23 to 6.33 for salinization and 6.21 to 7.42 for water erosion, p-values  $< 0.05$  for all variables in salinization and water erosion models) in predicting the soil degradation type. Interpreting the OR identified that silty loam texture (OR= 14.07) resulted in salinization the most and slope (OR= 13.11) is the leading factor in soil degradation from water erosion.

### 3.4 Prediction Distribution of the Soil Degradation Occurrence and Type Throughout Libya

Applying the LR and MLR models developed in this study to the areas outside the boundaries of the PAR created a map (Fig. 5) of the degradation occurrence and type for all Libya. This map identified that 55 % of Libya's soils are degraded, with the greatest type of degradation being salinization (30 %) and the least being water erosion (10 %).

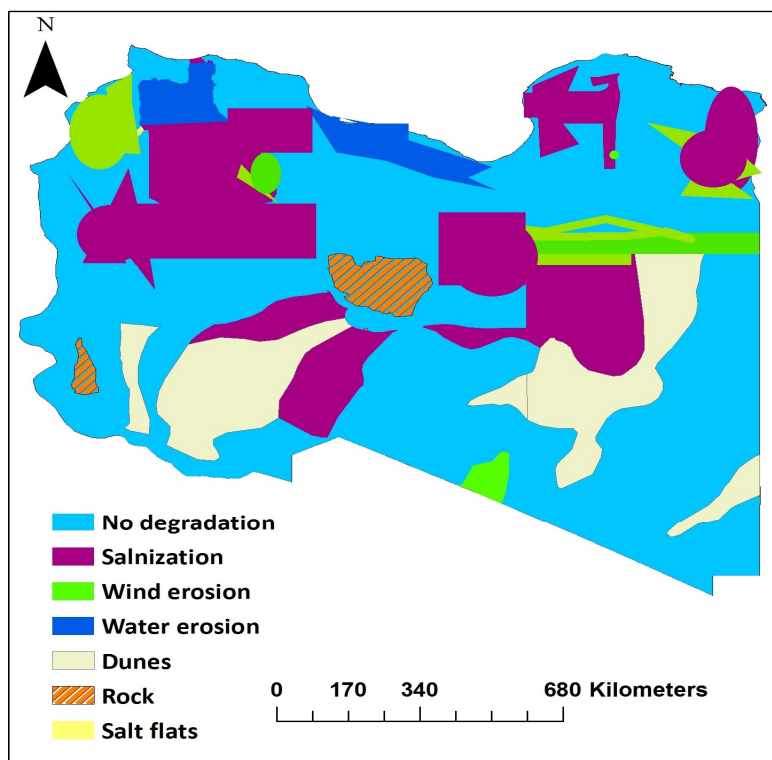


Fig. 5 The probability degradation soil map for all the country developed in this study using LR and MLR models.



#### 4. Conclusions

In Libya, the PAR degradation is a result of salinization, water erosion and wind erosion, with impacts to agricultural development in the country. The combination of slope, soil texture and wind speed (using LR and MLR models) successfully predicted the spatial distribution of soil degradation and the type of degradation. Overall 55 % of Libyan soils are degraded, 30 % due to salinization, 10 % due to water erosion, and 15 % due to wind erosion. However, due to the nature of the wind speed data used, wind erosion is most likely under-predicted in the model. Hopefully this model will assist in substantiating the need for better equipment and data collection to develop more detailed models to predict soil degradation from wind erosion.

Additional parameters, which were not obtainable for this work, may enhance the model performance and allow for other types of soil degradation to be assessed. For example, long term evapotranspiration and drainage data may also influence soil salinization. Long term changes in organic matter (or organic carbon) content, nutrient depletion, and microbial activity can all be considered metrics to gauge soil degradation. Different management practices at the individual farm scale may also affect the occurrence of soil degradation (Garen et al., 1999). Future research is needed to collect data to assist in determining soil erodibility factors, the cropping and land-cover factor, and the support practice factor to integrate the Revised Universal Soil Loss Equation (RUSLE) to estimate soil loss.

Until more detailed data can be collected and organized, the simple models developed in this study can assist stakeholders in management of Libyan soils, and be applied to neighboring countries that have similar geography, climate conditions, and data availability.

#### Acknowledgments

The Libyan Government provided financial support for this research. We are grateful to Brian Ritter, Doctoral Candidate at Clemson University, for his help with using ArcMap software.

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