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Remote sensing technique to monitoring the risk of soil degradation using NDVI

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Abstract.

In order to take measures in controlling soil erosion it is required to estimate soil loss over area of interest. Soil loss due to soil erosion can be estimated using predictive models such as Universal Soil Loss Equation (USLE). The accuracy of these models depends on parameters that are used in equations. One of the most important parameters in equations used in both of models is (C) factor that represents effects of vegetation and other land covers. Estimating land cover by interpretation of remote sensing imagery involves Normalized Difference Vegetation Index (NDVI), an indicator that shows vegetation cover. The aim of this study is estimate (C) factor values for Part of Baghdad city using NDVI derived from satellite Image of Landsat-7 ETM in period 2007, Landsat-٧ ETM in period 2001 and Landsat-5 TM in period 1990. The final (C) factor map was generated using the regression equation in Spatial Analyst tool of ArcGIS V.9.3 software. It is found that north part of study area and the some part of area around the river side has higher(C) factor.

Keyword: *Remote Sensing, soil degradation and NDVI.*

1 Introduction:

The processes of land degradation are complex and variable, a cycle of natural and socioeconomic cause and effect. Deforestation, degraded rangelands, exhausted cultivated fields, salinized irrigated land, depleted groundwater resources, all have terrible consequences for many poverty-stricken people living in the dry lands. With little or no capital or decision-making control over their resources and with scant political support, many have had few available options but to mine their resources or to migrate during times of stress Land degradation is about people. People cause and suffer from it. Unsustainable land management practices caused by either inadequate techniques or increasing population pressure will enhance degradation of land especially in susceptible dry lands. Around 40% of the land surface are dry lands and thus prone to the land degradation process. About 65% of all arable land has lost some of its biological and physical functions. Desertification is the consequence of a set of important processes, which are active in arid and semi-arid environment, where water is the main limiting factor of land use performance in ecosystems [1]. Land degradation processes involve two interlocking, complex systems: the natural ecosystem and the human social system [2]. Natural forces, through periodic stresses of extreme and persistent climatic events, and human use and abuse of sensitive and vulnerable dry land ecosystems, often act in unison, creating feed- back processes. Interactions between the two systems determine the severity of the degradation process. Inclusion of climate, vegetation, and land use into desertification assessment is reviewed by [3]. About 3, 6 billion of the world's 5.2 billion hectares of useful dry land for agriculture has suffered erosion and soil degradation. In more than 100 countries, 1 billion of the 6 billion world population is affected by desertification, forcing people to leave their farms for leave in the cities. The economic impact is horrendous, with a loss of more than $40 billion per year in agricultural goods and an increase in agricultural prices. According to the World Wide Fund for Nature, the world lost about 30% of its natural wealth between 1970 and 1995. Desertification takes place in dry land areas where the earth is especially fragile, where rainfall is nil and the climate harsh. The result is the destruction of topsoil followed by loss of the land's ability to sustain crops, livestock or human activity. But the deserts are not necessarily only the product of external forces like dryness and decreasing rainfall, rather, it is the internal ecology of the desert region itself - its habitat of plants, animals, and soil, - that drives its development. Climatic changes can trigger the desertification process, but human activities frequently are the proximate cause. Attending to the historical evolution of some deserts, it has been found that internal arrangements drive the ecosystems from smooth to patchy, and to find the driving forces of that movement means the explanation of desertification. In the last 25 years, satellites have begun to provide the global monitoring necessary for improving our understanding of desertification. Landsat images of the same area, taken several years apart but during the same point in the growing season, may indicate changes in the susceptibility of land to desertification. Studies using Landsat data help demonstrate the impact of people and animals on the Earth. Spatial heterogeneity is assumed as an environmental system property, essential to understand both the environmental gradients and the systems functioning. Heterogeneity refers to some pattern of variation, both in space and time, but within some range. Usually the pattern and the range are physically adequate for the ecosystem it occurs, defining the system resiliency. A change of spatial heterogeneity can be viewed as an indicator of environmental changes, and a clue of some process. We aim to test the usefulness of spatial analysis methodologies to capture spatial-temporal heterogeneity from environmental gradients, for the assessment of desertification process at Remote sensing data [4].

2 Methodology.

2.1 Study Area.

The study site is located at central-west of Baghdad City (Iraq), with geographical coordinates longitude (38º33) to (36º91) northwards and latitude (44º18) to (36º37) eastwards, Geographically within coordinates (Path 169 and Row 37) has area of (318846.8) hectare Studied area has been dominated by agriculture, Irrigation channels, drainage, besides bare land influenced by salts (salt affected soils). The climate of this region is semi arid, with an average yearly rainfall of 2.00 mm. see Figure (1).

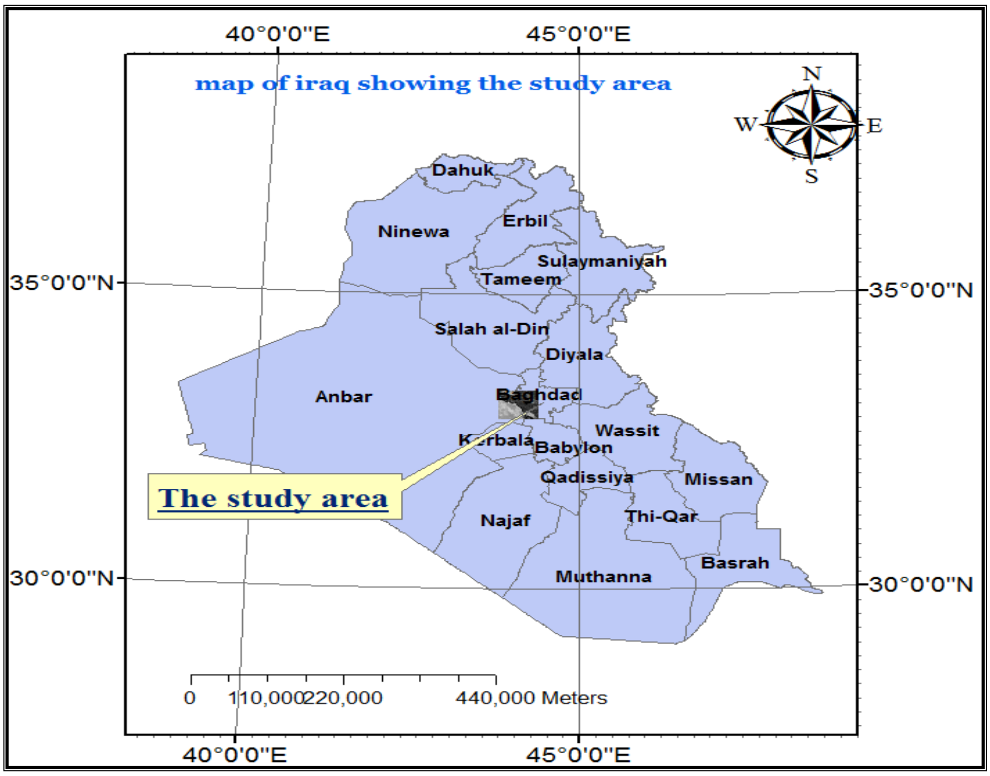

Figure (1): study area.

2.2 Data resources and properties:

Satellite image captured from Landsat-5(TM) in march (1990) ,Landsat-7(ETM) in march (2001) and Landsat-7 (ETM+) in march (2007) respectively with six bands ranging from first to the seventh except the sixth band in following wave length (0.45-0.515 (0.525-0.605), (0.63-0.69), (0.76-0.90), (1.55-1.75), (2.09-3.35) Micrometer, with pixel size (28.5 × 28.5) m. were used to monitor the patterns of annual changes in plant cover using ArcGIS V.9.3 software package was used, shown in Figure (2), Table (1).

Table (1): satellite image properties.

Property	Value
Satellite image	Landsat
Raster Information	
Path and Row	169-37
Columns and Rows	1952,1821
Cell size(X.Y)	28.5,28.5m
Format	Imagine image
Extent	
Top	٣٦٩١٨٤٥
Left	٣٨٣٣٢٥
Right	٤٤١٨٨٥
Bottom	٣٦٣٧٢١٥
Special reference	
Linear unit	Meter (1.00000)
Angular unit	Degree (0.0174533)
Datum	D_WGS_1984

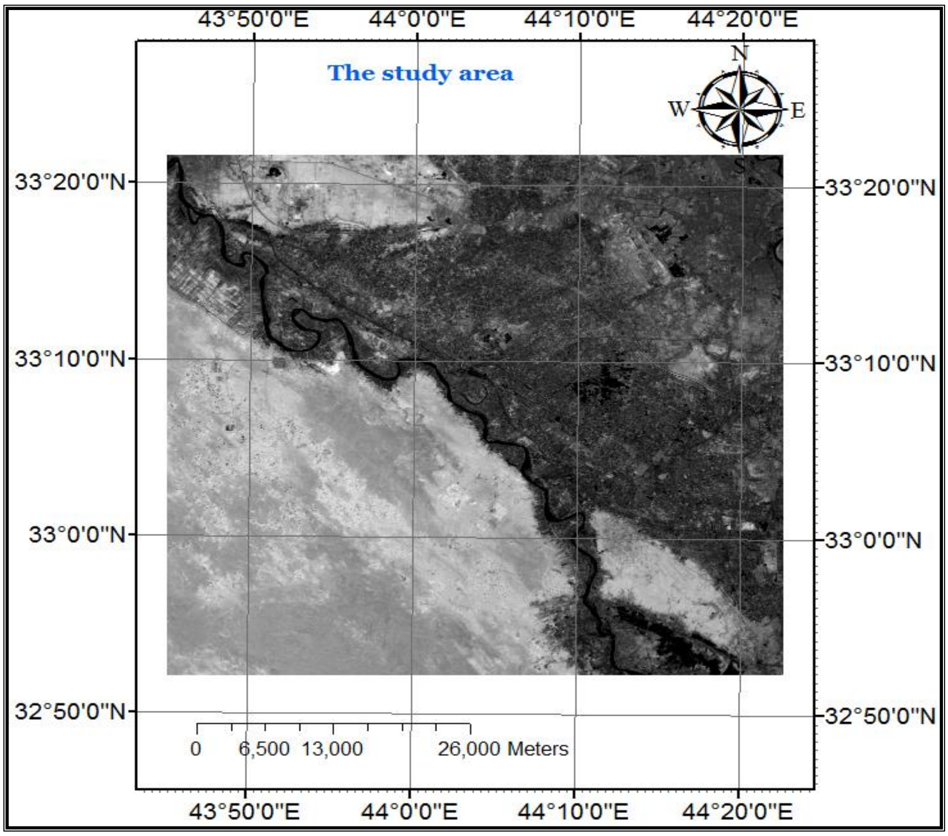

Figure (2): Data resources of study area.

2.3 C-Factor calculation.

The C-factor represents how management affects soil loss. It is mainly related to the vegetation's cover percentage and it is defined as the ratio of soil loss from specific crops to the equivalent loss from tilled, bare test-plots. The value of C depends on vegetation type, stage of growth and cover percentage. For applications on national scale the C-factor can be estimated from mid-resolution satellite images (e.g., Landsat TM) by applying the Normalized Difference Vegetation Index (NDVI). It should be noted that for the scale of 1:100 000 or coarser scales, a link with the CORINE land cover database by means of a lookup-table is suggested when homogenous climatic conditions could be ensured [5]. However, an alternative approach was followed here by replacing the C-factor with the NDVI as a response to the need for seasonal land cover information. The NDVI was generated from satellite images (Landsat-7 ETM+) and the cell size was set at 100 × 100 m^2 (scale 1:100000). The NDVI value was estimated by the following equation:

$$NDVI= \frac{NIR-R}{NIR+R} \text{ .... (1)}$$

Where NIR: the reflection of the near infrared portion of the electromagnetic spectrum and IR: the reflection in the upper visible spectrum. The values lie in the range [-1, +1], but vegetation traces are detected in values bigger than +0.18. Since the original C-factor of USLE ranges from 0 (full cover) to 1 (bare land) and the NDVI values range from 1 (full cover) to 0 (bare land), the calculated NDVI values were inversed using “Raster Calculator” tool of the “Spatial Analyst” extension of “ArcGIS 9.0” software package. More specifically, the C-factor map for each month was produced using the following exponential equation:

$$C=\exp\left[-a \frac{NDVI}{B-NDVI}\right] \text{....... (2)}$$

Where α, β: parameters determining the shape of the NDVI-C curve. A α-value of 2 and a β-value of 1 seem to give reasonable results.

The regression line that describes relationship between C and NDVI values and R shows the correlation coefficient of regression analysis.

[6], [7] The C-factor values for bare soil and forest land cover were set to 1 and 0, respectively in the regression analysis.

The final C-factor map was generated using the regression equation in Spatial Analyst tool of ArcGIS 9.3 software, was estimated by the following equation: The graphs of regression analysis and C-factor are given in Fig. 3 and Fig.4 respectively.

C-factor = 1.02 – 1.21 * NDVI....... (3)

3 Results and Discussion.

As can be seen from table (2), the study area experienced lowest mean NDVI values in the period 2001. Since the study area consists of agricultural areas the mean NDVI values of 1990 and 2007 are close to each other. Mean NVDI values of 2001 are lowest because there is no vegetation on agricultural areas.

Table (2): NDVI value and C-factor of Landsat image.

Image data	Max. NDVI	Min. NDVI	Mean NDVI	value of C-Factor
1990	0.719919	-0.83784	0.058959647	19.283340
2001	0.941311	-0.94737	0.003028539	1.9581204
2007	0.668116	-0.85124	0.090542402	29.066415

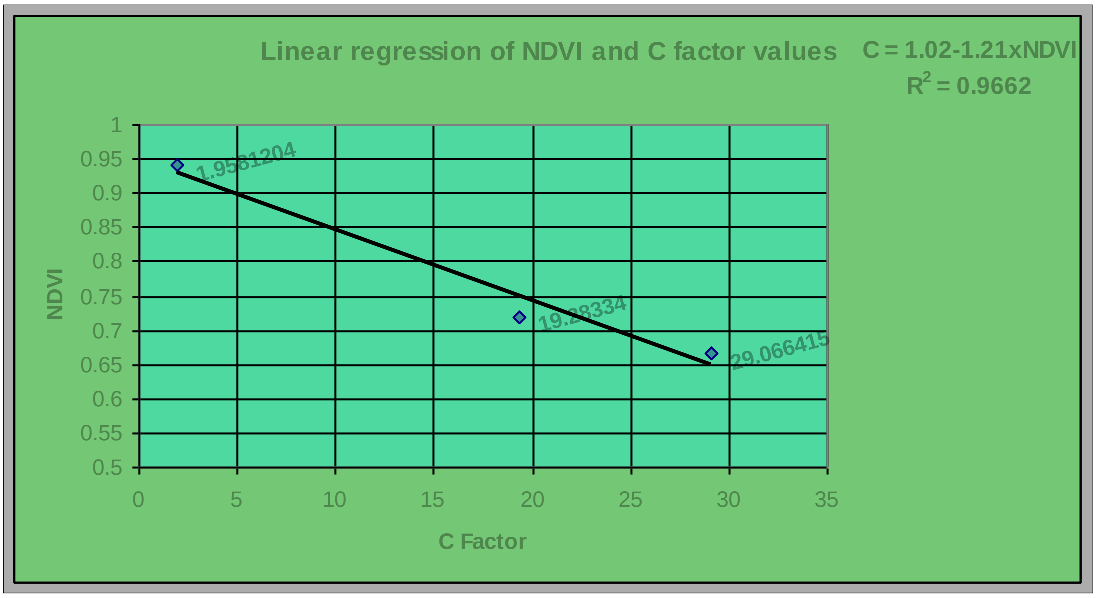

Figure (3): linear regression of NDVI and C-factor values

As seen from Fig.4 the north part of study area is represented by High C-factor class since it is occupied by plants and Grasses. Water bodies are represented by Low C-factor class. The agricultural areas of study area are represented by C-factor classes from intermediate to high.

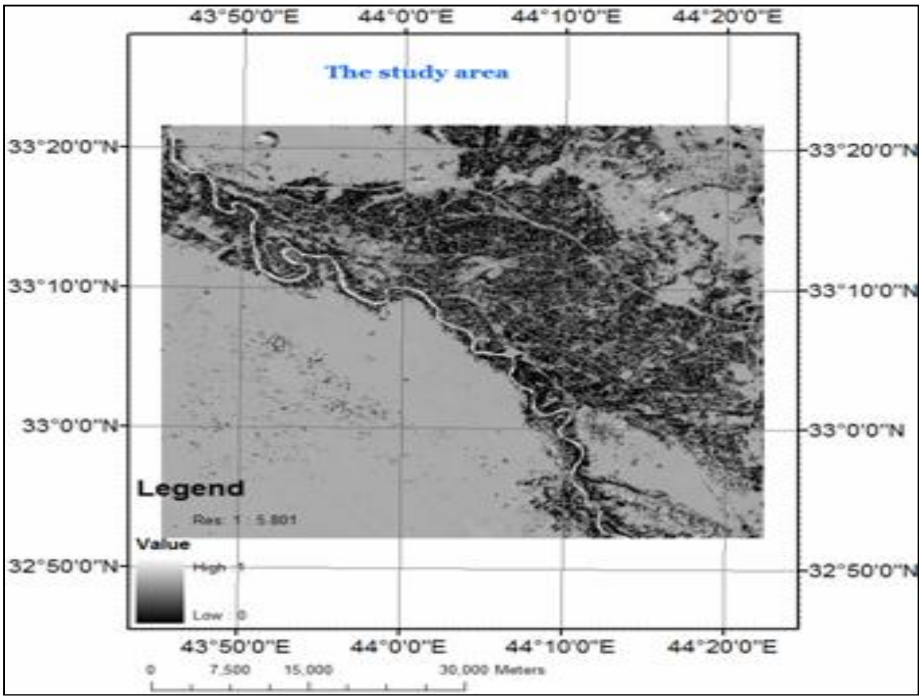

Figure (4):C-factor map of study area.

The estimated C-factor values through regression equation were divided into three categorical classes and those classes vary between 0-0.1 and 70.0. The pixel numbers of those classes are shown in Figure.5. Since agricultural areas cover almost 80% of study area the C-factor classes 40-45 of pixel numbers and 60-62 contain the highest pixel number respectively.

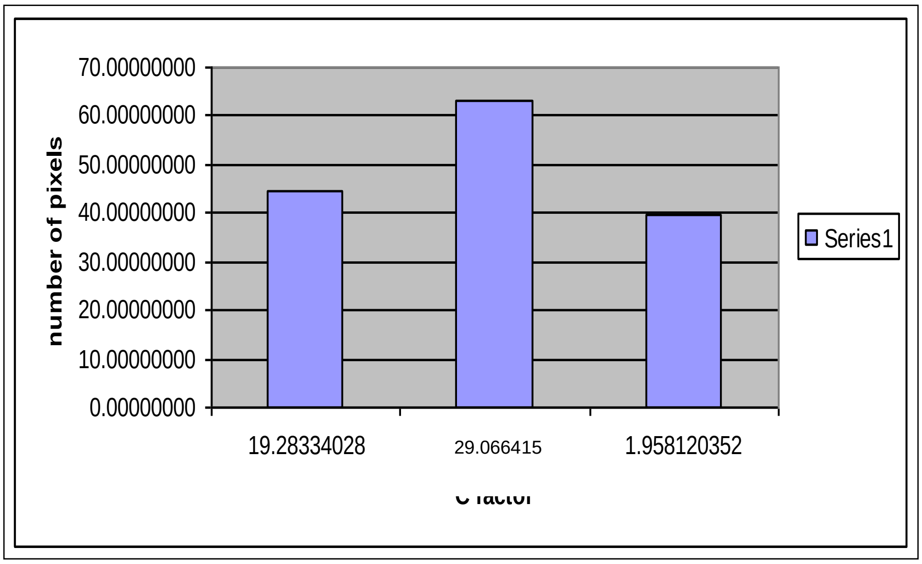

Figure (5): Pixel distribution of the C-factor map based on NDVI

An attempt has been made to estimate C-factor values of land cover classes using NDVI values for modeling soil erosion using ArcGIS 9.3 software. A regression analysis was performed between NDVI and C-factor using an assumption. C-factor values were assigned to pixels of NDVI image through regression equation. Based on an assumption, the C-factor map of study area was produced to use in soil erosion methods such as Universal Soil Loss Equation (USLE) based on an assumption that NDVI and C-factor values are correlated with each other. The results revealed that large parts of areas were assigned to C-factor classes that vary between study area in period 1990 and 2007 were assigned to C-factor classes that vary between 19.283340 and 29.066415 of pixels number. It should be noted that C-factor values can be precisely estimated using empirical equations that contain field measurements of land cover classes. However, this study shows that NDVI based regression method offers an optimal method to estimate C-factor values of land cover classes of large areas in a short time.

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