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Predicting soil map using Jenny equation

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Abstract

Today, with rapid advancement of technology, many methods have been developed to soil mapping that now we know them as digital soil mapping (DSM). Each of these methods is based on mapping rules and specific characterizations of region that can distinguishe the different soils. Soil forming factors that control the direction and speed of soil formation have been expressed in Jenny's equation. These are climate, organism, topography, parent material and time. These factors do not act in isolation but always together which set limits to the operation as a whole. The aim of this study is predicting the soil map using this equation. So, the factors in the Jenny equation converted as a data layer in GIS and then used to predict the soil map using ENVI (4.7) software. To estimate the correct selection of soil forming factors as data layer, other parameters derived of DEM were selected and then were used to predict the soil map. Results showed that the highest accuracy of predicted soil map is when the soil forming factors are used.

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Introduction

Traditional soil survey techniques require a large number of field observations (1–2 observations/cm on the printed map). With the development of computers and information technology and an increased availability of new types of remote sensors and data sources, a more quantitative approach has been developed that may supplement traditional, qualitative survey techniques in cases where significant auxiliary information is available. Increasing environmental concern has grown the demand for regional land use analysis. While in the past regional land use analysis was often based on qualitative procedures, currently more quantitative methods are required and become available (Stoorvogel and Antle, 2001; Bouma *et al*, 2007). Soil information is important for many regional land use analysis models. This is especially true in models that deal with processes of land productivity and degradation. However, traditional soil surveys do not provide quantitative data at the detailed scale level that is required (McBratney *et al*, 2000; Ziadat, 2005; Kravchenko *et al*., 2006) and new methods of soil mapping are needed. Standard soil surveying techniques (USDA, 1984; Soil Survey Staff, 1993; USDA, 2007) have had great importance in pedology. The traditional methods are expensive and time consuming due to the large number of observations and the limited use of auxiliary information. Recently, with the high development of computers and information technology, together with the availability of new types of remote sensors, a more quantitative approach has been developed that may replace the traditional techniques. In digital soil mapping a limited number of soil observations can be used. These observations are then related to auxiliary information representing important soil forming factors: digital elevation models representing topography, satellite images representing land cover and climate, and geological maps representing parent material and possibly age. These relationships can now be used to predict soil properties for the entire area for which auxiliary information is available. In early applications, soil observations were related only to terrain attribute maps using simple regression models, but later the predictors were spread to an array of environmental variables giving origin to the terms "environmental correlation" (McKenzie and Ryan, 1999) or the "CLORPT techniques" (McBratney *et al*, 2000). Alternatively, hybrid methods have been developed from the combination of geostatistics and environmental correlation, where the observations or the residuals of the regression are interpolated using co-kriging or regression kriging (Hengl *et al*, 2004).

Predictive soil mapping (PSM) can be defined as the development of a numerical or statistical model of the relationship among environmental variables and soil properties, which is then applied to a geographic data base to create a predictive map (Scull *et al*, 2003). Model for predicting soil landscape distribution relates soil/soil classes to topographic position in certain landforms, geology, vegetation communities, and/or land use (Cook *et al*, 1996). Thus, it should be theoretically possible to integrate these data types within a small mapped areas used as a training or reference dataset to develop predictive rules for mapping in a broad region (Bui *et al*, 1999). In digital mapping, soil cover is generally predicted first by elaborating relations between soil attributes (or even soil types) and soil forming factors and second, by spatially predicting the relations with landscape on a continuous spatial support (McBratney *et al*, 2003). Landscape is usually considered as the principal factor for delineating and for taxonomically allocating soil types. There is a stratification of soil mapping unit according to landscape, particularly land-systems for physiographic units, landform for terrain units and geomorphology unit (Carre and McBratney, 2005). This study is based on relation between landscape and essential factors to predict the soil map. We considered the soil forming factors as the best factors for prediction.

Materials and methods

Study area

The study area is located between 36^{o} 22' 14" and 36^{o} 22' 51" N, and 49^{o} 34' 58" and 49^{o} 37' 13" E, approximately 500 ha, in the Kouhin area, Qazvin Province, Iran (Fig.1). The dominant landscapes of study area are plateaus and valleys. Plateau is the major landscape which is included eight different lithologies. Alluvium and then congelomerate and sandstone are the dominant lithology of the study area. Valleys cover the elongated parts among the plateaus and all of their lithology are alluvium that transferred from the highest part of region. The mean annual precipitation and temperature in Kouhin are 327 mm and 11.20 ^{o}C , respectively. The main local vegetation species are Boraginaceae, Asteraceae, Cruciferae, Poaceae, Lamiaceae and Fabaceae. Based on soil survey staff (2010), soil moisture and temperature regimes of the area are Xeric and Mesic, respectively. Dry farming and grassland are the major land uses in this area.

Soil sampling and laboratory studies

A number of twenty four soil profiles were described in different position of landscape and then were classified according to Soil Taxonomy (Soil Survey Staff, 2010). Necessary tests to gather the data including texture, $CaCO_3$, OC, pH, EC, N, P and K were performed according to current methods.

Data preparation for predictive soil mapping

Jenny's equation (1941) was used to predict soil map. The equation consists of five factors (cl=climate, o=organism, r=relief, p=parent material and t=time or development). The factors involved in the formation of soils at a given point. Such as equation is classically used to discuss soil genesis, but in the time of automation the essential question is: how to parameterize this equation in order to predict soils in a given areas? To achieve the purpose (predictive soil mapping), different GIS layers (soil forming factor maps), known as equation. The necessary layers are given as follows: climate, organism, relief (landform and slope steepness), lithology and time (development).

Climate

For climatic map, soil moisture regime was used as the indicator. The term "soil moisture regime" refers to the presence or absence either of ground water or of water held at a tension of less than 1500 kPa in the soil or in specific horizons during periods of the year. The moisture regime of a soil is an important property of the soil as well as a determinant of processes that can occur in the soil. The climate of the study area is defined only as xeric soil moisture regime.

Organism (biotic factor)

The biotic factor in pedogenesis is difficult to assess because of the dependence of both vegetation and soil on climate and the interaction of soil and vegetation includes flora, fauna and human activities (Zinck, 1986/87). It is very difficult to state what kind of vegetation is the native plant of the study areas in particular when soils were forming and also since there was no vegetation map for study area, we considered the land use map as an indicator for organism map.

Relief

To parameterize relief, landform and slope classes which extract from DEM were taken as the indicator. The landforms of study area were separated using SAGA (2.0.8) software based on TPI (topographic position index) classification. The topographic position index compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell (Fig. 2). Positive TPI values represent locations that are higher than the average of their surroundings, as defined by the neighborhood (ridges). Negative TPI values represent locations that are lower than their surroundings (valleys). TPI values near zero are either flat areas (where the slope is near zero) or areas of constant slope (where the slope of the point is significantly greater than zero).

Parent material (lithology)

Parent material refers to organic and mineral material in which soil formation begins. Difference in parent material may be inferred from differences in relief type, a break in slope or difference in drainage pattern. To parameterize parent material, lithology which obtain from geological map and field observation was taken as the indicator.

Time (development)

Time is very relative factor. Time can better be considered in term of stage of development or of maturity (Van Reeuwijk,1997). Studying soil morphology in the field is the way to know about the development of the soil. We can conclude the development of the soil (time) in the study area with related to landscape, relief-type and parent material using soil order in soil Taxonomy. In general soil acquires their properties over a long period of time, measured in hundreds and thousands of years. Soil features or diagnostic characteristics develop and change at variable rates. Counting years is of little use and time can better be considered in terms of stage of development or of maturity (Van Reeuwijk, 1997). In Soil Taxonomy system, they developed term which used to classify and identify the soil properties and soil profile development with related to time scale (Table 1) (Soil Survey Staff).

Predictive soil mapping

The entire factor layers which were derived from Jenny equation were combined and generated soil map using expert classification of ENVI (4.7) software. The layer maps consist of climate, organism, relief (landform and slope), lithology and time (profile development).

Results and discussion

A total of twenty four soil profile descriptions together with some environmental data were used to generate the soil map. Physicochemical test results of some representative points are shown in TABLE 2.

Table 1. Relationship between soil taxonomy, profile development and related time.

Soil taxonomy			Profile	Related time
Name	Meaning	Order	development	
-ent	Recent	Entisols	Very slight	Young
-ept	L.inceptum, beginning	Inceptisols	Slight to moderate	Young to mature
-ult	L. ultimus,last	Ultisols	High	Old

The Jenny equation was used to predict the soil map. The five factors (cl, o, r, p, t) were parameterized and integrated as follows: Soil moisture regime was taken as the indicator to parameterize the climate. Whole of study area was in Xeric regime, so climate has a same effect on the soils of different map units. Land use was taken as the indicator to parameterize the organism. We had two land uses in the study area: grassland and dry farming. Most parts of the area included dry farming land use and were about 469 ha while grassland was just about 8.5 ha. Despite the variety of land use was low in study area, but it could be effective in soil differentiated and map predicting (Rubio and Escudero, 2005). Soil profile description was taken as the indicator to parameterize the time.

We had just two kinds of soil profile development in the study area named Entisols and Inceptisols. It can be said that Inceptisols covered the whole part of area. Entisol included just a little part of study area, so the soils of study area were young to mature.

Landform and slope classes were taken as the indicator to parameterize the relief. Both of these maps are shown in Fig. 3 and 4. The number of eight landforms were defined in the study area that named high ridge, midslope ridge, upper slope, open slope, midslope drainage, toe slope, stream and plain which open slope and high ridge included the most and the least parts of area respectively.

Slope classes extract from DEM and according to the study area, the number of six slope classes were classified (TABLE 3.

In the study area, landform and slope were the most important agents in differentiating the soils and so in predicting the soil map (Remondo *et al,* 2005; Udomsri, 2006 and Badla *et al,* 2013).

Table 2. Physicochemical results of some sample points.

Profile	Depth	Horizon	pH	EC(dS/m)	$CaCO_3$	Clay	Silt	Sand	OC	N	P (mg/Kg)	K (mg/Kg)	Texture
							(%)						
1	0-25	Ap	8.15	0.85	15.00	41	22	37	0.43	0.05	2.8	284.2	C
1	25-60	Bw	8.25	1.49	15.30	41	28	31	0.77	0.08			C
1	60-105	Bk1	8.40	0.69	15.80	45	28	27	0.51	0.05			C
1	105-140	Bk2	8.41	0.68	22.90	47	24	29	0.34	0.03			C
2	0-20	A	7.91	0.89	17.97	32	26	42	0.85	0.09	5.5	203.5	CL
2	20-80	BCK	8.00	0.86	25.01	38	28	34	0.41	0.04			CL
3	0-27	Ap	8.06	0.57	20.97	32	20	48	0.49	0.05	2.8	134.4	SCL
3	27-70	BCK	8.02	0.78	31.03	14	16	70	0.34	0.04			SL
4	0-23	Ap	8.14	0.61	23.88	38	20	42	0.58	0.06	9.8	151.7	CL
4	23-65	BCK	7.90	0.52	31.62	30	26	44	0.41	0.04			CL
5	0-30	Ap	7.96	0.86	13.56	28	18	54	0.85	0.08	9.2	370.7	SCL
5	30-65	Bw	8.00	1.05	11.87	28	16	56	0.51	0.05			SCL
5	65-140	BCK	7.99	0.77	13.56	24	16	60	0.42	0.04			SL
6	0-25	Ap	7.95	1.08	12.21	26	20	54	1.27	0.12	3.52	373.0	SCL
6	25-55	C1	7.96	0.80	16.62	24	16	60	0.51	0.05			SL
6	55- 80	C2	7.97	0.94	16.28	14	10	76	0.34	0.04			SL
7	0-20	A	7.89	0.84	13.55	40	32	28	0.66	0.07	6.7	224.2	CL
7	20-70	BK	8.55	1.68	15.65	28	40	32	0.34	0.03			CL
8	0-25	Ap	7.74	0.62	23.73	43	32	25	0.43	0.04	4.8	224.2	C
8	25-40	Bw	8.00	0.61	23.06	39	30	31	0.25	0.02			CL
8	40-90	BCK	7.87	1.32	25.10	25	36	39	0.25	0.02			L
9	0-20	Ap	7.90	0.65	15.33	44	30	26	0.83	0.09	5.03	356.7	C
9	20-50	BW	8.12	0.70	18.17	44	30	26	0.74	0.07			C
9	50-85	BK	8.14	0.62	28.78	38	24	38	0.49	0.05			CL
9	85-130	BCK	7.88	0.65	29.10	36	26	38	0.34	0.03			CL
10	0-25	Ap	8.13	0.90	10.20	46	20	34	0.99	0.11	2.5	354.3	C
10	25-60	BW	7.98	0.54	19.12	42	32	26	0.66	0.07			C
10	60-150	BK	8.06	0.53	37.16	44	32	24	0.51	0.05			C
11	0-25	Ap	7.78	0.98	10.33	26	22	52	0.83	0.09	23.8	356.7	SCL
11	25-50	Bw	7.97	0.56	11.67	30	18	52	0.59	0.06			SCL
11	50-90	BK	7.90	0.69	18.65	30	20	50	0.34	0.04			SCL
11	90-150	BCK	7.90	0.56	25.03	26	22	52	0.33	0.04			SCL
12	0-20	Ap	7.79	0.79	20.00	47	32	21	0.68	0.07	4.7	338.1	C
12	20-80	bw	7.95	0.59	21.50	47	26	27	0.51	0.05			C
12	80-150	bk	7.99	0.54	28.60	49	32	19	0.34	0.03			C

Table 3. Slope distribution of study area.

class	slope simple slope	steepness(%)
1	level to very gently sloping	0-2
2	gently sloping	2-5
3	sloping	5 - 8
4	strongly sloping	8-12
5	moderately steep	12-25
6	steep	> 25

Table 4. Soil classification of predictive map.

Code	Family
1	Clayey over coarse loamy,mixed,superactive,mesic, Typic Calcixerepts
2	Coarse-loamy over clayey,mixed,active,mesic, Typic Calcixerepts
3	Fine,mixed,semiactive,mesic, Typic Haploxerepts
4	Fine,mixed,superactive,mesic, Typic Calcixerepts
5	Loamy- skeletal,mixed,superactive,mesic, Typic Haploxerepts
6	Fine,mixed,active,mesic, Typic Calcixerepts
7	Coarse- loamy,mixed,superactive,mesic, Typic Calcixerepts
8	Loamy- skeletal,mixed,superactive,mesic, Typic Calcixerepts
9	Fine,mixed,superactive,mesic, Typic Haploxerepts
10	Fine-loamy,mixed,superactive,mesic, Typic Calcixerepts
11	Fine,mixed,semiactive,mesic, Typic Calcixerepts
12	Fine,carbonatic,semiactive,mesic, Typic Calcixerepts
13	Very fine, mixed, semiactive, mesic, Typic Calcixerepts
14	Fine-loamy over loamy-skeletal,mixed,superactive,mesic, Typic Xerofluvents

Lithology was taken as the indicator to parameterize the parent material. There were eight kinds of lithology in the study area. Alluvium covered the most parts of study area. Parent materials greatly influenced soil development and the distribution of soils in the area (Shaw *et al*, 2004; Udomsri, 2006; Vergari *et al*, 2012). Lithology map was the one of the most important maps in predicting of soil map. (Fig. 5).

Table 5. Kappa index of data layers to predict the soil map

Data layer	**Kappa index**
Climate, lithology, time, landuse, land form, slope	0.95
Climate, lithology, time, landuse, landform, curvature	0.89
Climate, lithology, time, landuse, landform, aspect	0.37
Climate, lithology, time, landuse, landform, flow direction	0.43
Climate, lithology, time, landuse, landform, flow accumulation	0.49
Landform, DFM	0.47
Lithology, DEM	0.44
Landuse, DEM	0.21

All of six layers (climate, land use, time, lithology, landform and slope map) were combined in the environment of ENVI 4.7 software and classified using minimum distance algorithm and finally the predictive soil map was generated. (Fig. 6).

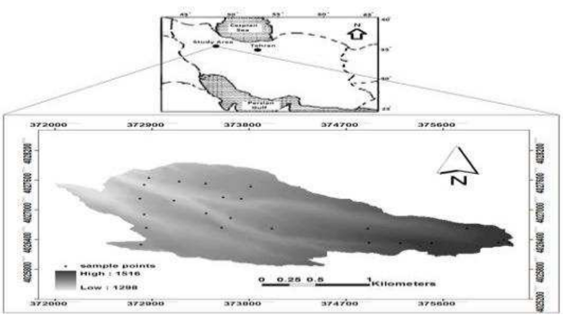

Fig. 1. Location of study area and sample points.

To estimate the correct selection of soil forming factors as data layer, other parameters derived of DEM such as curvature, aspect, flow direction, flow accumulation were selected and then were used to predictie the soil map. Kappa index were calculated for each layer (TABLE 5).

Results showed that the highest kappa index is when soil forming factors are used as data layers to predict the soil map. It is because of all of these factors which can distinguish the different soils, and so can play the main role in production the soil map. Using this method, validation to the same unstudied area is much easier because software predicts and delineates the boundaries according to all of soil forming factors. In this method as kriging, interpolation technique was used to predict the points without any information. Compared with traditional methods, this method such as other digital mapping methods is done with higher speed and precision and lower time and cost.

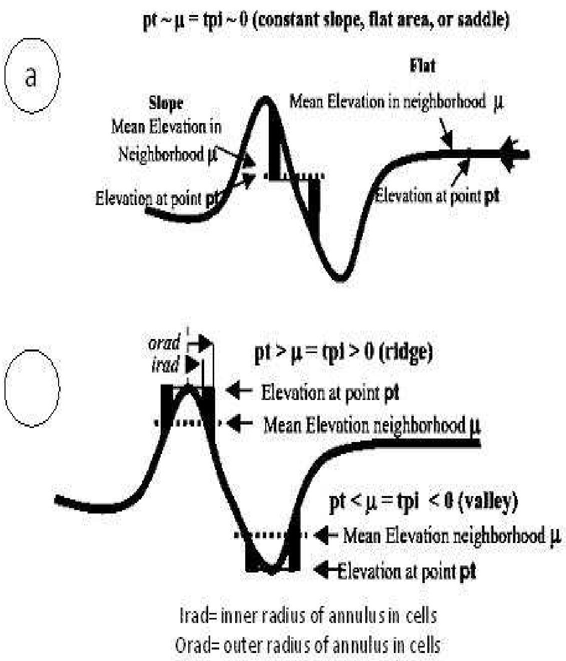

Fig. 2. (a) flat area with zero TPI value. (b) area with negative and positive TPI value.

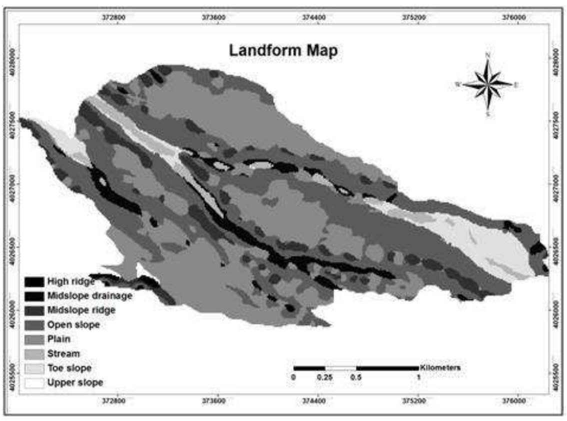

Fig. 3. Landform map.

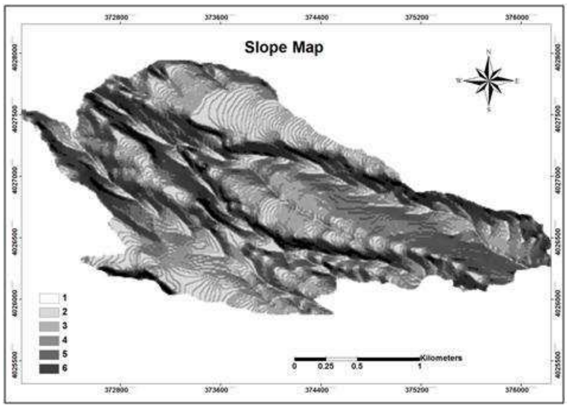

Fig. 4. slope map.

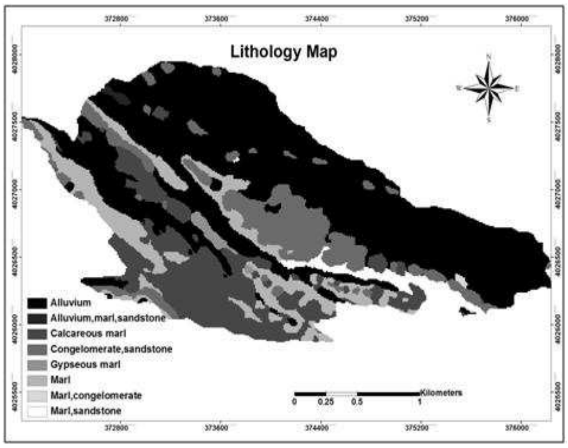

Fig. 5. Lithology map.

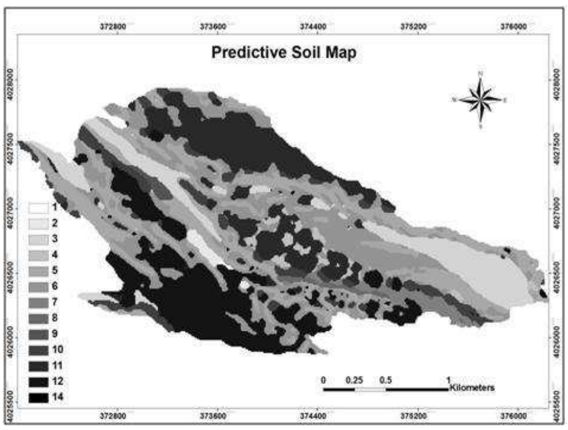

Fig. 6. Predictive soil map.

Conclusions

This paper has attempted to discuss a scheme for digital soil mapping using Jenny equation. Jenny equation includes five soil forming factors that each of these factors can distinguish the soils and thus can separate the map units. We converted the factors as a

GIS layer and combined them for prediction. Also we used some parameters derived of DEM as data layer for prediction. Results showed that the highest kappa index is related to the soil forming factors layer. It should be noted that this method was performed in a region with high correlation between geomorphology and soil, so should also be done in other regions with different geomorphology, maybe better combination of data layers moreover of soil forming factors be formed.

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