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DETERMINATION OF SOIL PROPERTIES USING OF SPECTROSCOPIC METHOD

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ABSTRACT

As a non-destructive, fast, low-cost technique with the minimum preparation of samples and no risk for ecosystem, visible near infra-red spectroscopy may be replaced with methods using *in vitro*. The current research aims to assess reflective spectroscopy in estimation of properties of soils locating ion farming plains at Tehran, Khuzestan and Yazd provinces. To this end, 88 soil samples were collected from the studied zones and their basic properties were calibrated using standard techniques *in vitro*. The spectral analysis of soils was done using land spectroscopic device at wavelengths (240-400 nm). The types of preprocessing techniques were assessed after recording of spectra and PCA and PLSR models were utilized to determine main properties of soil. The best method was used for estimation of regressive functions to predict studied parameters after linear regression. The findings showed that both PCA and PLSR models had high precision for determination of parameters of soil properties and they could interpret high variances of soil properties and PLSR model was more precise than PCA model. With respect to RPD statistic the best estimation of the offered regressive functions was calculated for minerals (RPD=9.34), pH (RPD=4.45), and nitrogen (RPD>2) each of these three factors were classified in series-A and the lower estimations were computed for clay, silt, gravel, quantities of phosphorus, potassium, calcium, and magnesium, and gypsum within the range of (RPD=0.01-0.28). These numbers denote reasonable precision of spectral regressive functions in prediction of studied basic properties. Overall, results of this study indicate that both PCA and PLSR models have appropriate precision in determination of main parameters of soil properties and also the soil spectral data may be utilized as an indirect technique for estimation of soil physical and chemical properties and in comparison with laboratory methods this technique is more economical to determine chemical and physical properties in terms of time and cost-effectiveness with higher precision.

Keywords: *Soil spectral reflectance, Spectral preprocessing, Soil properties, Reflective spectroscopy, PCA and PLSR linear regressions*

Introduction

Today, the world very remarkably needs to soil spatial information to survey environment, modeling and soil spatial management. The soil includes a heterogeneous and dynamic system with very complex processes and mechanisms. As a perfect system and important natural source, study on soil requires for developing of analytical techniques. In many cases, analytical methods are proposed for establishing of relationship between physical and chemical properties of soil individual components, but the mutual effects have not been addressed on each other in most of them (Arnedo et al., 2017). Therefore, soil spatial data collection from wide area needs to new techniques which can easily and cheaply record information from several soil properties at minimum possible period of time (Stenberg et al., 2020). The necessity for more development in time and cost saving is increased for soil analysis and there are many demands for fast and predicted soil data in monitoring of environment, assessment of soil quality, and agricultural and afforestation precision (Viscarra Rossel et al., 2006). For this reason, the reflective spectroscopy is considered as an alternative for completion (or even replacement) of ordinary analytical methods (Cohen et al., 2005). Utilization from visible- near infrared reflective spectroscopy has drawn more attentions during two recent decades. This noticeable growth is due to a lot of reasons which are followed by spectra. In addition, developing of multivariate statistics and data-mining techniques has increased

application of this technique in pedological and agricultural sciences. One of the foremost advantages of visible-near infrared reflective spectroscopy is in that this is a non-destructive technique with no hazard and destruction for the environment (Guerrero et al., 2010). Whereas direct calibration of soil chemical and physical properties is time- and cost-consuming and at the same time it needs to field studies and a lot of samplings in determination of such properties due to temporal and spatial variability thus looking for finding of indirect, low-cost, fast, and easily available techniques has been converted into one of the important research preferences in pedological sciences in recent decades (Canbazoglu et al., 2013). During recent years, telemetric techniques have been utilized for improving of efficiency in analysis of soil behavior and or replacement of laboratory difficult and high-cost methods. One of the physical telemetric techniques is soil spectroscopic technology. Preparation of reflective curve of the given phenomenon or phenomena within ranges of certain wavelengths is called spectroscopy (Schneider et al., 2011). The near-infrared reflective spectroscopy has been funded on basis of sensitivity of soil organic and mineral compounds to reflectance of visible and infrared waves and this property is utilized for farming and environmental studies on soils. During two recent decades, studies have been increased on reflective spectroscopy of visible and infrared waves in pedological sciences within two visible and infrared ranges. Most of studies have been more focused on soil principal components e.g.

soil organic matters, texture, mineralogy, and also access to soil nutritional elements, structure, and the related microbial functions (Hassani et al., 2014). The spectroscopy may be done in two forms i.e. field and imaging. In both spectroscopic modes, the emitted electromagnetic energy from a light source is collided with the given phenomenon out of which some part is reflected, some is absorbed and the other part is passed through it. Therefore, spectroscopy is a type of quantitative calibration of reflection, absorption or passing. Spectroradiometers are utilized for calibration (Summers et al., 2011). The soil spectral reflectance is used within visible (Vis) and near infrared (NIR) ranges at wavelengths (350-2500 nm). (Iurian & Cosma, 2014) In addition, spectroscopy and particularly infrared spectroscopy may also provide for specifying of various soil components. At the same time, one can estimate more than 20 soil properties simultaneously with single calibration in the farm and or in vitro using this technology. The various studies have shown the soil spectral reflectance is affected by some of soil properties e.g. humidity, texture, structure, and quantity of organic matter (Soriano-Disla et al., 2014). Of other important soil properties, which affect quantity of the given spectral reflection, one can refer to type and frequency of clay minerals (kaolinite, smectite and illite), carbonates, hydroxyl groups in water and soil, organic compounds, and iron and aluminum oxides. This means the reflective spectra may act as an efficient tool in assessment of many soil properties. The organic carbon is one of the foremost soil

properties that are estimated by satellite images and spectroscopic technologies with high precision because the organic carbon is accumulated in surface layer of soil. This property has various spectral behaviors because of the existing complexity in chemistry of organic matters (Turhan et al., 2012). The strong absorbent characteristics resulting from organic carbon often occur at the wavelengths about 1730 nm (because of presence of C-H) and 2330 nm (due to existing O-H groups) while the weaker absorbent characteristics are also observed at wavelengths about 1150, 1670, 1765, 2070, 2110, 2140, 2190, 2280, 2310, and 2390 nm. The absorbent bands adjacent to 1400 and 1900 nm may be due to the existing water in organic compounds (Babaeian et al., 2015). Moreover, rise of organic carbon in soil affects spectral curve of soil and reduces reflectance quantity especially in visible and near infrared areas (due to the existing dark humic acid). The dominant carbonate minerals in soil including calcite and dolomite of soil absorb or release some levels of pH by affecting elements in soil. The carbonate minerals often possess strong absorbent characteristics near to 2345 nm (due to existing CO₂) and relatively weaker adjacent to 1860, 1990 and 2140 nm (Hunt et al., 1997). Also distribution of size of soil particles noticeably affects soil spectral behavior. Generally, as size of particles becomes greater and by increase in light path through soil particles, the light is more absorbed by the soil and reflectance quantity is reduced. Under this condition, absorbent characteristics are more clearly revealed on spectral curves. Reduction in

size of soil particles increases soil reflectance with the presence of light color minerals e.g. silicates and carbonates. Regarding oxide and hydroxide minerals which have often small spectral reflectance, the level of soil spectral reflectance is decreased as size of soil particles is reduced (Summers et al., 2011). Overall, spectral behavior of soil is a function of its constituent elements. The chemical components of soil minerals include oxygen, silica and aluminum that lack strong absorbent characteristics within visible and near infrared range. However the soil important components such as iron oxides, clay and organic carbon may highly affect spectral curves and absorbent characteristics. The iron oxides influence in rate of reflectance in visible zone and organic carbon and clay as well as level of reflectance in infrared zone.

Due to presence of overlapping of soil absorbent waves and also because of similarity and close adjustment of these waves together, it is necessary to employ statistical techniques and efficient modeling approaches for extraction of soil spectral information. Several methods have been so far utilized for creation of relationship between soil basic properties and the related spectral characteristics out of which one can imply Artificial Neural Network (ANN), Partial Least Square Regression (PLSR), and Principal Components Regression (PCR), and Multiplicative Linear (and nonlinear) Regressions (MLR) (Viscarra Rossel & Behrens, 2010). Different reports have been reported about exploitation from spectral curves to estimate soil physical and

chemical properties (Lagacheri et al., 2008).

In most of studies, soil chemical properties have been estimated by means of spectral reflectance and also favorable results have been achieved where the findings of these studies suggest that the soil properties are related to solid structure of soil and the related levels (e.g. quantities of clay, silt, organic matter, electrical conductance and pH) and one can estimate it by soil spectral data with very high precision. The findings have indicated that it is not possible to predict properties under influence of soil porosities (e.g. apparent specific mass, saturation humidity and soil saturation water-permeation coefficient) by means of spectral data of soil at high precision (Warren, 2013a). Whereas few studies have been so far conducted about using of spectral data in estimation of basic properties of soils in Iran thus it has been tried in this study to evaluate possible use of visible near infrared spectroscopy to predict some of physical and chemical properties of soils in Tehran, Khuzestan and Yazd provinces.

Materials and methods

Soil sampling and calibration of the related physical and chemical properties:

The studied zone included the lands on farming plains locating in Tehran, Khuzestan and Yazd provinces. This area was located averagely 1550-1600 m higher than sea level. The maximum and minimum annual temperatures of this zone was 50.5°C and -30°C respectively and

also the mean annual precipitations level was also 250-500mm. The humidity and thermal regime of this area is mesic and xeric habitats. In terms of soil textural class, most of soils in this zone were clay and clay loamy and they were classified under typic, vertic typic calcixerepts, calcixerepts, and haploxere groups. The 88 manipulated soil samples were randomly extracted from the studied zone of 0-150 cm depth. The soil samples were dried under air and passed through screen (2mm). After preparation of these samples, some of soil physical and chemical characteristics were calibrated such as percent of clay, silt, sand, organic matter, nitrogen, gypsum, exchangeable, potassium, sodium, calcium, magnesium, and available phosphorus and potassium according to standard technique of water and soil analysis.

Spectral behavior of soil and spectral preprocessing:

The spectral reflectance of the studied soil samples was calibrated by means of spectroscopic device. For this purpose, 88 air-dried soil samples were passed through screen (2mm) and their curves were calibrated within visible- near infrared ranges (250-400nm) using standard spectrometric techniques (Viscarra Rossel, 2008).

The spectral calibrations were implemented using a pistol equipped with lens (8.4°) which created vision field with 2cm diameter. The light source included a halogen lamp (150Watt) with location angle of 45 degrees in respective of vertical axis. In order to increase precision

in calibration of reflectance level and deletion of spectral disturbances (noises) and calibration of device during measurement, one reading was executed for all three soil samples from blank standard page (reflectance: 100%) located in a status similar to calibration of the given soil samples. The given curves existing on portable computer were recorded by means of software RS3 connected to the device. Five scanned items were prepared for any soil sample and 600 spectral curves were totally recorded. The soil sample was calculated by the id of a mean value of spectral curves for each of them by View-Spec software. Then these spectral curves were saved as spectral libraries and in text files format and used in analyses. Any recorded spectral curve included spectral resolution (1nm) so that any spectral curve comprises of 2050 spectral reflectance (2050 wavelengths) within range (400-2450nm). (Dematte et al. 2017)

Preprocessing of spectral data

The preprocessing of spectral data mainly aim to delete external factors and optimal use of spectral data in approximation process. Due to presence of a lot of spectral distortions (noise) in wavelengths at this range, all spectra at wavelengths (350-399 and 2451-2500nm) were deleted and not used in modeling (Terra et al., 2015). Similarly, in order to delete noise in soil spectra (e.g. nonlinear behavior of bands, normalization of spectra, filter, and spectral detection) and for improving of data quality, various preprocessing techniques were adapted to spectral data

using software Parles 3.1 and Unschambler 10.3. It is noteworthy in this study different types of preprocessing were employed e.g. (Savitzky- Golay) normalization filter based on mean, variable, Multiplicative Signal Correction (MSC), Standard Normal Variable (SNV), first derivative of Savitzky- Golay filter, and the second derivative along with Savitzky- Golay filter. Based on the results came from mutual validation technique and evaluation of precision in the given results, the deletion curves were identified in forms of multinomial Savitzky- Golay function, continuum and first-order filter as the most appropriate technique for preprocessing of spectral data. The figure indicates diagram of visible- near infrared spectra for soil samples after conducting of preprocessing (first derivative + Savitzky- Golay filter). It is noteworthy that continuum deletion curve is a curve which is quantized according to an assumed and convex line that connects two ends of a spectral absorption characteristic to each other. Using of this formula, one can calculate continuum deletion curve.

Where, $R_{CR(\lambda_i)}$ denotes rate of reflectance in continuum deletion curve versus wavelength λ_i , and R_{λ_i} is the rate of reflectance of correspondent length in raw spectral curve and $R_{CL(\lambda_i)}$ as rate of reflectance of the given curve at correspondent wavelengths (Babaeian et al., 2015).

$$R_{(\lambda_i)} / R_{CL(\lambda_i)} = R_{CR(\lambda_i)} \quad (\text{Eq. 1})$$

Correlation between variables, derivation of functions and determination of their precision

Most of statistical techniques are based on assumption of normality of data distribution. Therefore, normality status of data was assessed for any soil property by the aid of Kolmogorov- Smirnov test at significance level (5%) after calculation of descriptive statistics. Using appropriate conversion, variables with abnormal distribution were normalized. Then, the rate of relationship was analyzed between values of spectral reflectance at any wavelength with physical and chemical properties of soil using of Pearson's correlation coefficient. In order to provide possibility for proper assessment of precision in the suggested functions, the laboratory and spectral data for calibrated variables were divided into two groups of calibration data ($n=88$) and validation data ($n=88$). Afterwards, the mathematical relations were derived between variables using of regression technique. Some statistics including Normal Mean Square Error (NRMSE), interpretation coefficient (R^2) and Relative Percent Deviation (RPD) to evaluate precision of root (ME) in the given results in which based on Normal Mean Square Error (NRMSE), the smaller amount of this factor showed higher precision in estimation of variable. It should be noted that NRMSE below 10% indicates precision of model, 10-20% indicates appropriate level, 20-30% denote medium precision of model, and higher than 30% level shows poor model. Interpretation coefficient (R^2) denotes correlation between approximated and observed values and parameter of degree adjustment in which prediction of model is free of error (Willmott, 1981). Relative Percent Deviation (RPD) parameter, which

is used often in spectrometric studies, has been classified into three ranges (<1.40, 1.41-2, and >2) that denote poor, reasonable, and strong approximations respectively (Zornoza et al., 2008). Interoperation coefficient and RPD statistic were utilized to analyze precision of models. With respect to their results, R²-value among 0.66 and 0.8 indicates approximated predictions are quantitatively small while R²-value among 0.81 and 0.9 show prediction at favorable level. The calibration models (R²>0.90) are considered as very excellent level. With respect to statistic RPD, the value of RPD>2 is not adequate for programs while RPD-value within range (2-2.5) causes quantitatively approximate predictions. The values of predictions (2.5-3) can be classified at good level and RPD>3 show an excellent prediction. As no precise model is derived, the analytical data for soil properties were changed using of square roots or logarithm. These variance guarantees for data normal distribution that is led to more appropriate PLS regressions. Except from PLS models, correlations were developed for study on relationship between physical, chemical,

and biochemical properties and soil organic matters. This analysis was carried out by SPSS v.13 (for windows) software.

Modeling for soil calibrated properties:

The soil calibrated property in Zone-2 was utilized to model the materials. The Principal Components Analysis (PCA) technique was used for the first model and Partial Least Square Root (PLSR) method was employed for the second model. All operations for these two methods were executed in two software MATLAB and SPSS according to instruction of (Farifteh et al., 2007; Zheng, 2008). Two criteria of R² and RMSE were also utilized to determine precision of models.

Results and discussion

All tested soils included similar and visible near infrared reflective spectra in this study.

Statistical description of soil properties

The results of descriptive statistics for some physical and chemical properties of soil are given in Table 1.

Table 1: Statistical description of soil properties

Standard deviation	Maximum	Minimum	Mean	Quantity	Soil properties
15.91	72.5	0.63	9.19	71	P(Av/)(mg/kg)
0.018	0.08	0	0.017	71	Total N(%)
8.57	48.89	0.18	5.21	71	EC(dS/m)
0.37	9.49	7.33	8.11	71	pH
9.55	44.2	1	18.54	71	TNV(%)
0.28	1.26	0.01	0.25	71	O/C
237.79	1273.70	84.70	340.94	71	K(Av/)(mg/kg)
19	80	1	41.76	71	%Sand
13.96	63	2	32.95	71	%Silt

6.63	46	12	25.30	71	%clay
202.98	1426.32	3.99	102.78	71	Na (mg/l)
7.64	35.27	0.61	10.66	71	K (mg/l)
207.14	1072.61	30.78	221.96	71	Ca (mg/l)
31.48	214.85	2.79	48.29	71	Mg (mg/l)
8.77	33.67	0.02	4.66	71	Gypsum(%)

As it seen in Table 1, the amounts of clay, silt and gavel in the studied soils vary in ranges 12-46, 2-63 and 1-80% respectively. The quantities of organic matter and total salinity were derived for soil samples 0.25 deci-Siemens/ m and 5.21% respectively. The total amounts of nitrogen, phosphorus and potassium were obtained 0.017%, 19.9, and 340.94 ppm respectively. The quantities of calcium, magnesium, sodium and gypsum were derived 221.96, 28.49, 102.78 ppm and 4.66% of amount of gypsum in the soils of zone. Due to presence of carbonates, pH level of studied soils was neutral to alkaline (7.33-9.49) and studied soils were highly various in terms of textural class and they included several textural classes.

The mean of raw curves of spectral reflectance are given for the soils in Fig 1. As it seen in this figure, the raw spectral curves include a protrusion at wavelengths (500-700nm) and also four important absorbent characteristics are placed at

wavelengths 990, 1414, 1915, and 2212 nm. The studies have shown that these absorbent characteristics belong to presence of free water and hygroscopic property (1414nm), hydroxyl groups (O-H factor) existing in clay mineral grid (1915), and bond of these groups with iron, aluminum and magnesium (2212nm) in clay minerals grid (Clark et al., 1990). The soil prevalent properties which influence in amount of their spectral reflectance include soil color, humidity value, content of organic carbon, distribution of particle size and iron and Aluminum oxides. As usual, calcium carbonate increases rate of reflectance from soil and organic carbon and soil humidity reduces it (Stenberg et al., 200).

The studies have indicated that the absorbent characteristics adjacent to wavelength 2341 nm, may be due to existing CO₃ in the present groups on carbonate minerals (Xuemei & Jianshe, 2013).

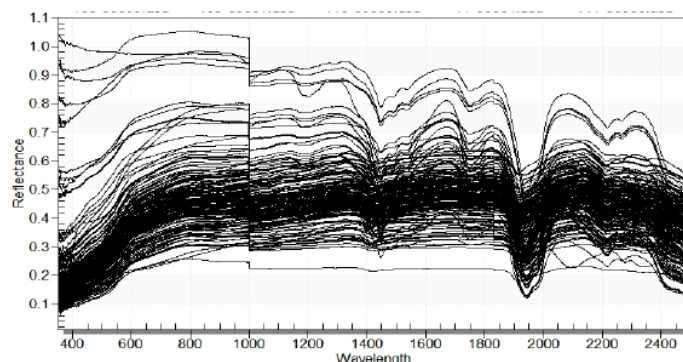


Fig 1: The mean of spectral reflectance of studied soils, position of absorption characteristics at wavelengths 990, 1450, 1946, and 2200 nm have been specified on this figure.

Analysis and correlation between variables

Among (r) parameters in table of Pearson' correlation coefficient, soil physical and chemical properties are given with values of spectral reflectance at any length within range (400-2450nm). With respect to this figure, there is relatively high correlation between calibrated physical and chemical properties and values of spectral reflectance within visible- near infrared range. The results have shown that distribution of soil particle size is positively and negatively correlated at various wavelengths. The results derived from RMSE value and interpretation coefficient (R²) for clay, silt and sand and nutrient elements such as nitrogen, phosphorus, potassium, calcium, and magnesium are shown at wavelengths 990, 1414, 1915, and 2212 nm respectively in Table 2. The values of interpretation values (R²) vary for approximation of physical and chemical properties of studied soil among 0.76 to 0.95 % where the highest value of interpretation

belongs to gypsum and the lowest value is related to contents of phosphorus. It is noteworthy that presence of such high correlations has been also reported between basic physical and chemical properties of soil and rates of spectral reflectance by other researchers (Somers et al., 2010; Bilgili et al., 200). Given RPD statistic, the best approximation for suggested regression functions is designated for organic matters (RPD=9.34) pH (RPD=4.45), and nitrogen (RPD>2) in all three categories of series-A.

The following approximations have been calculated for clay, silt, gravel, contents of phosphorus, potassium, calcium, magnesium and gypsum as (RPD=0.01-0.28) that suggests reasonable precision of spectral regressive functions in prediction of studied basic properties.

Table 2: the coefficient

category	RPD	RMSECV	R ²	Number of main compounds	(n/N)*100	Soil properties
C	0.02	71.67	0.76	20	100	P(Av/)(mg/kg)
A	>2	0	0.92	20	100	Total N(%)
C	0.15	16.43	0.83	20	100	EC(dS/m)
A	4.45	0.03	0.85	20	100	pH
C	0.13	9.12	0.9	13	100	TNV(%)
A	9.34	0.01	0.89	13	100	O/C
C	0.01	51138	0.84	20	100	K(Av/)(mg/kg)
C	0.07	51.8	0.94	20	100	%Sand
C	0.13	33.79	0.9	15	100	%Silt
C	0.17	10.45	0.86	20	100	%clay
C	0.08	26.58	0.88	20	100	Na (mg/l)
C	0.14	16.55	0.78	20	100	K (mg/l)
C	0.01	3274	0.91	20	100	Ca (mg/l)

C	0.06	20.14	0.93	20	100	Mg (mg/l)
C	0.28	7.7	0.95	20	100	Gypsum

The

Results of Principal Components Analysis (PCA) model:

The results of principal components analysis (PCA) model is in fact utilized when quantity of variables is high in modeling. Due to great number of variables, this technique was inevitably employed to reduce number of parameters (Kodaira & Shibusawa, 2013). After execution of PCA analysis on independent variables or bands, 20 principal components remained out of them these five components could embed percent of variance of independent variables or in other words a great number of bands was converted into 20 components and these 20 components have devoted high percent of variance of bands. The results derived from PCA technique are similar to the former methods but the predicted and real value could not acquire suitable regression

coefficients in all zones in Tehran, Khuzestan and Yazd.

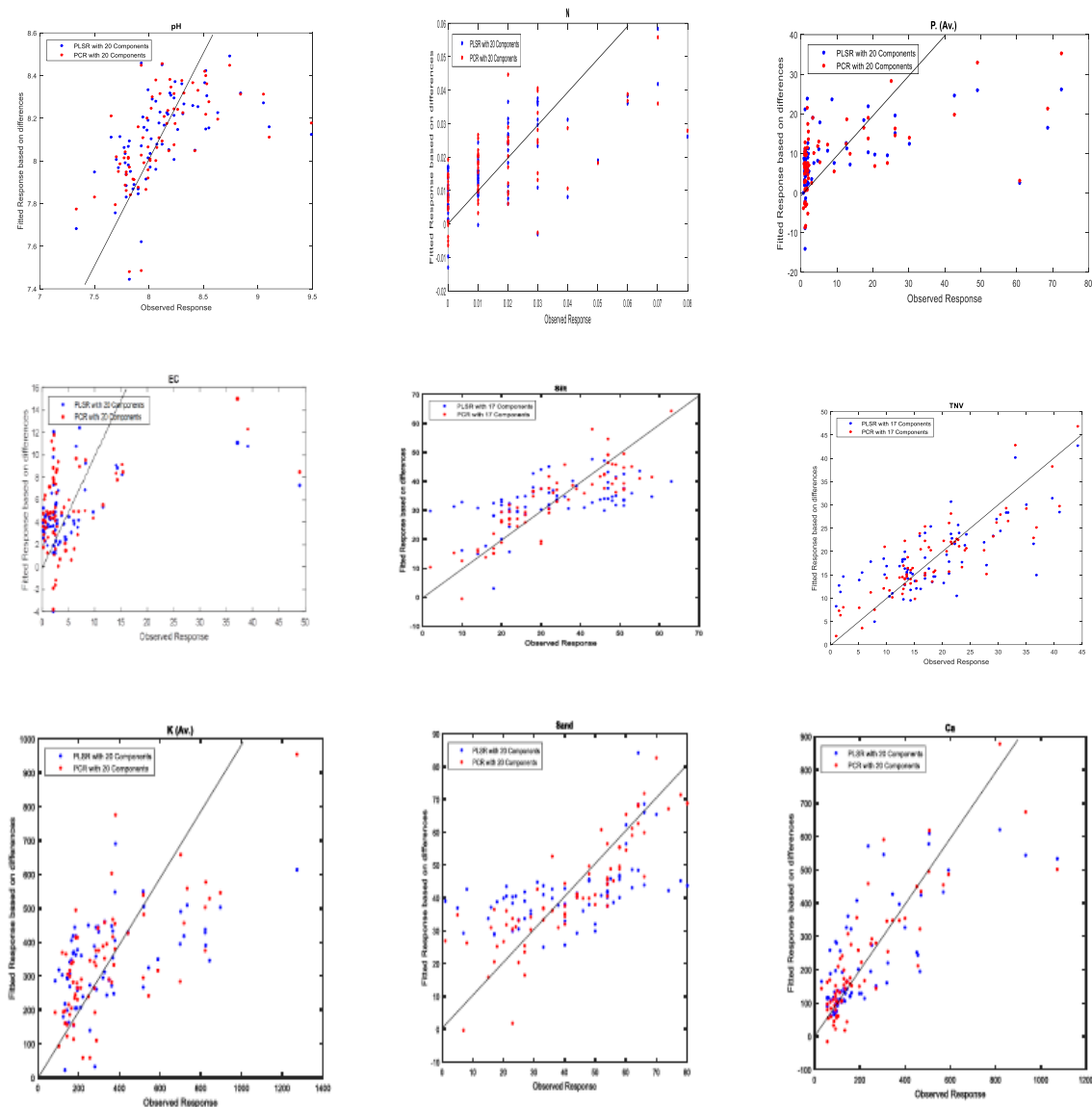
Results of Partial Least Square Root (PLSR) model:

The PLSR models in fact include a technique similar to PCA method but they are different in that they involve dependent variable in classification of factors as well. Thus, it is also expected them to acquire higher precision in estimation of soil properties while the results indicate that a higher percent of total variance of bands can be explained by considering of 20 factors. Likewise, R^2 -value was derived 0.89 at calibration phase. The given results from PLSR regression showed that as it expected, this model has acquired relatively good results among estimation models of soil organic minerals. The reason for this superiority can be attributed to intervention of PCA

dependent variable versus PLSR in categories of bands. These findings are consistent with the results of investigations done by many researchers who have worked on estimation of soil properties either by manual spectrometer or by super-spectral aerial images concerning suitable prediction of variables of soil properties e.g. Chen et al. (2008), He et al. (2007), Zheng et al. (2008) and Wang et al. (2010).

diagrams (1:1) in estimation of some of soil physical and chemical properties versus their calibrated values. As R^2 is observed in this figure and table, among the basic properties, values for statistic of mean tested data is 75 for cation exchange capacity of sand and organic carbon and silt with highest quantity. This means the clay possesses better approximation in the suggested regressive functions for estimation of aforesaid properties.

The values of validation for the offered functions are given in Fig (2) as dispersion



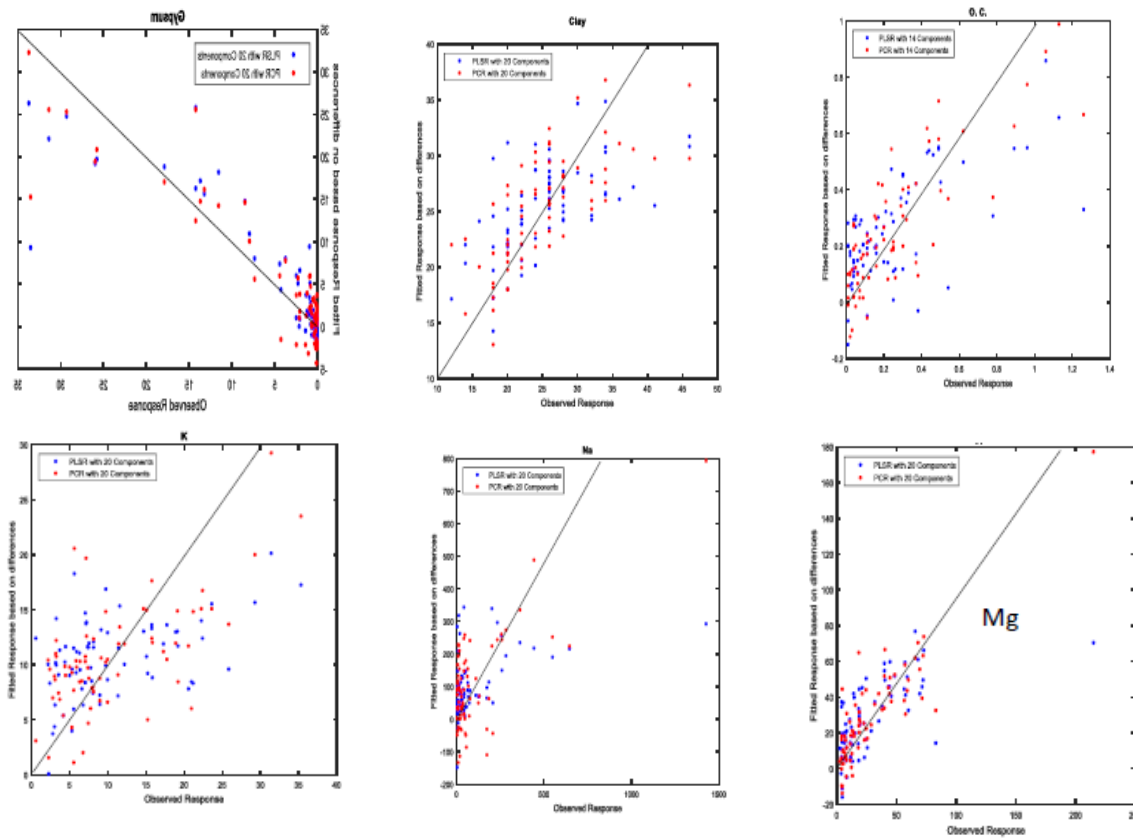


Fig 2: Diagram of precision for results of validation to calibrated and estimated values in two PCA (•) and PLSR (•) models

As it also seen Fig 2, among basic properties, values of R^2 - statistic have the highest data for soil organic carbon (0.89), clay (0.86), sand (0.94), silt (0.9), total nitrogen (0.92), available phosphorus (0.92), exchangeable potassium (0.78), calcium (0.91), magnesium (0.93), sodium (0.88), and gypsum percent (0.95). This means that the suggested regressive functions have better approximation in estimating of the aforesaid properties. In a study, Dematte et al. (2014) observed high compliance between calibrated values in some of basic soil properties and their estimated values using of spectral data. These researchers reported interpretation coefficient (R^2) and Root Mean Square Error of Approximation (RMSEA) for clay (0.83, 4.03), silt (0.32, 5.06), sand (0.7, 5.67),

cation exchange capacity (0.64, 1.94 centi-mol.kg) organic matter (0.73, 0.31%), and for calcium carbonate (0.64, 0.70%) respectively.

It is noteworthy that Bilgili et al. (2010) have also suggested using of spectral data to estimate some of soil physical and chemical properties. In an investigation done by Babaeian et al. (2015), they also predicted some of soil basic properties using of spectral data in addition to soil hydraulic properties. These researchers indicated that interpretation coefficient (R^2) and Root Mean Square Error of Approximation (RMSEA) were derived in the suggested functions for clay (0.65, 0.39%), silt (0.41, 0.04%), sand (0.70, 0.056%), apparent specific mass (0.57, 0.04 g/cm³),

organic matter (0.69, 0.14%), and for geometric mean of particle size of soil (0.65, 0.04mm). overall, these researcher proposed soil spectral properties for access to indirect and relatively precise estimations of the studied physical and chemical properties.

Conclusion

The results of this study generally indicate that both PCA and PLSR models enjoy suitable precision in determination of main soil parameters in Tehran, Khuzestan and Yazd provinces and also PLSR model is more precise than PCA model. The potential for use of soil spectral data was evaluated in this study within visible- near infrared range (400-2400nm) in this study to estimate some of soil physical and chemical properties. The preprocessing curve was drawn for spectral preprocessing after recording of spectral data and calculation of their mean. The results showed that (first derivative + Savitzky- Golay filter) method was the best technique for preprocessing of spectral data. With respect to high correlation and significance of basic calibrated properties of soil with their spectral reflectance values, the regressive functions were proposed to estimate these properties. Various statistics were utilized to evaluate precision of offered functions such as Root Mean Square of Error (RMSE), interpretation coefficient (R^2) and Relative Percent Deviation (RPD). The results of assessment of these statistics indicated that RMSE value and ME mean were 27 and 56.7 for total studied basic properties respectively. The best approximations of offered

regressive functions are derived for organic matters (RPD=9.34), pH (RPD=4.45), and nitrogen (RPD>2) all of these three factors are classified in series-A. The lower approximations were calculated (RPD=0.01-0.028) for clay, silt, gravel, contents of phosphorus, potassium, calcium, magnesium and gypsum where it denotes reasonable precision of spectral regressive functions in prediction of studied basic properties. In general, findings of this study indicate that using of soil spectral data may be employed as an indirect technique for estimation of physical and chemical properties of soil. Although with respect to empirical nature of spectral regressive functions and spatial and temporal variation of soil properties in other zones (e.g. saline soils, organic soils, limy and gypsum soils with different effects in soil spectral behavior) it is necessary to extract and evaluate these functions for other more diversified zones and soils.

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