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Estimation of Wind Erosion Threshold Velocity Based on Spectroscopy Data Using Random Forest Algorithm

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Abstract

Threshold Velocity (TV) of soil is considered a great indicator in order to assess Potential wind erosion (PWE). However, TV is difficult to measure and some techniques such as wind tunnels can be quite time-consuming and hard. To deal with this challenge, spectroscopy could be considered as an advantageous method to estimate TV. In the current research, the potential of Vis-NIR spectroscopy in TV estimation with the help of machine learning algorithm namely Random Forest (RF) was assessed. for this reason, in the Fars Province, Iran, 100 in-situ wind tunnel tests were executed, and soil samples spectral reflectance were examined with the help of spectroscopy apparatus. Results Showed that outputs of TV estimation with the aid of RF model were (R2 = 0.74, RMSE = 0.65 m s-1, RPD = 1.78, and RPIQ = 2.83 m s-1). This study has shown the utilization of the reflectance spectroscopy with the assist of machine learning algorithm is a reassuring method for worldwide evaluation of wind erosion phenomena.

1. Introduction

Alarming danger of Wind erosion is considered as one of the primary sources of deterioration of lands especially in arid also in semi-arid areas (Chappell et al., 2018). This particular issue is a concerning one worldwide (Pásztor et al., 2016). The occurrence of wind erosion happens when intense winds and surface of soil, which has already been exposed to erosion, exist at the same time (Chappell et al., 2018). Determining the threshold velocity parameter (TV) is known to be a critical part for assessing wind erosion because wind velocity ought to be immense to a degree that carries a considerable amount of soil particles.

TV is used as an important hallmark for assessing wind erosion risk and determining soil susceptibility and it is frequently used in many researches (Kouchami-Sardoo et al., 2019). TV is remarkably associated with soil properties (Mina et al., 2022) and the intensity of wind erosion (Visser et al., 2004). In some research, attention was drowning to the distribution of fundamental (textural) particles (Pasztor et al., 2016; Van Pelt et al., 2017) and secondary (aggregate) ones (Rezaei et al., 2022). Also, some focused-on roughness of the surface (Yan et al., 2015), calcium carbonate substance (Kheirabadi et al., 2018), gypsum content (Kouchami-Sardoo et al., 2019), and soil moisture (Sirjani et al., 2019). These factors are reported as the highest rank in terms of influence in soil erosion assessment repeatedly. One of the important obstacles in wind erosion management is the issue of measuring or predicting the TV accurately in arid and in semi-arid regions (Okin, 2005). During the past half century, some researches take advantage of portable wind tunnel method in order to compute wind erosion in natural environment for different reasons (Zobeck and Van Pelt., 2014).

Estimating TV indirectly would be quite beneficial because of the many difficulties in measuring this parameter directly. Significant wind erosion needs to be deal with especially in vast areas which are susceptible to wind erosion for example, in aeolian sediment transport (Li et al., 2015). The technique of Visible-near infrared spectroscopy (Vis-NIRS) has a great capability for soil analysis, and it can be used alternatively in such matter (de Santana et al., 2018).

Detecting the most Significant wavelengths which are highly linked to the desired variables obtained from the wavelengths of each spectral curve, is determined by this

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method. This technology is a promising, fast, non-destructive soil sensing technique that made the estimation of various properties of soil possible by field or laboratory measurement (Kim et al., 2014). Selecting the proper calibration method and its performance is directly linked to the calibration ultimate successful outcome (Mouazen et al., 2010). In most researches, Partial Least Square Regression (PLSR) method has been implemented for linear multivariate calibration. However, the complication in the link between the spectra and wind erosion soil characteristics cannot be denied and considering PLSR method may be insufficient. Therefore, employing other chemometric methods, which follow the principles of non-linear procedures, is extremely important. Complex non-linear systems apply Random Forest (RF), which is an impressive yet commonly-used machine learning method for modelling data (Nawar et al., 2016; de Santana et al., 2018). The only literature investigated the relationship between threshold velocity of wind and near and infrared spectral reflectance (350-2500nm) was practiced by Li et al. in 2015. They have employed PLSR method for TV estimation. Despite the fact that they used 31 samples ($R2 = 0.76$, $RMSE = 0.12$), Their outcome indicated that the visible range (400–700 nm) and near infrared (1100–2500 nm) could be used as indicative wavelengths for TV estimation. Ostovari et al. (2018) investigated the performance of PLSR method in estimating soil erodibility (K) in lands which were affected by water erosion and they used 40 samples. Their results demonstrated a successful prediction for K-factor with $R2 = 0.56$. Some researchers have used soil reflectance spectra for predicting soil properties which were affected by erosion as well as using this method for investigating the link between soil erosion and soil spectra. Wang et al. (2016) discovered that some factors including Soil Organic Matter (SOM), water-stable aggregates (WSA), and geometric mean diameter can have a noticeable effect on erodibility of soil.

For this purpose, they have implemented hyperspectral visible and near-infrared reflectance spectroscopy method. Moreover, They evidenced that a spectral analytical method is applicable for complex datasets analysis and they shed some light on dynamic variation association to erodibility estimation. There have been many researches in this field, most of which have investigated on soil particle size (Shi et al., 2020), $CaCO3$ (Bilgili et al., 2010), the soil organic matter (Nawar et al., 2016; Ostovari et al., 2018) and soil moisture (Mirzaei et al., 2022) and Cation Exchange Capacity (CEC) (Ng et al., 2019; Mina et al., 2022). In order to discover how soil is resisting to environmental highly erosive forces, some criterions including the stability of soil aggregation and distribution of aggregate soil size were determined and estimated by Vis-NIR spectroscopic technique (Shi et al., 2020). Indeed, in Italy (Conforti et al., 2013) and in Czech Republic (Žížala et al., 2017) have used SOM as an initial indicator for determination of water-induced soil erosion areas. Schmid et al., (2012) classified soil eroded spots in Spain using land surface's spectral properties with the help of important soil features such as physical, chemical, and morphological ones which were all associated with soil loss.

To our understanding, there is no research on the applicability of Vis-NIR spectroscopy coupled to RF model for wind erosion prediction. Conducting such researches are markedly and extremely vital for wind erosion controlling scenarios and conserving of soil in large areas especially the ones which are susceptible to wind erosion and emission of dust for example, Iran. The application of Remote Sensing (RS) techniques in wind erosion field is emphasized in this research and its results can be used for evaluating policies at local and worldwide scales in order to manage soil erosion.

Therefore, some purposes of this study were 1) to measure the TV using extensive wind tunnel test, 2) evaluation of the possibility of employing reflectance spectroscopy method in TV estimation.

2. Method

2.1. Study Area

Fars province, which is an arid and semi- arid region, in Iran is situated in the south-central part of the county and was our study (Abbasi et al., 2021). In most parts of this province, wind erosion happens regularly and one reason is climate condition. In this area, many critical wind erosion regions exist (Mina et al., 2022). The average amount of the annual rainfall is within the range of 100 mm in the south parts and nearly 400 mm in the north parts (Ostovari et al., 2018). There are many seasonal and empty agricultural fields, rangelands, lakes and dried riverbeds. The slope was less than 1% and poor vegetation condition was recognizable in these areas.

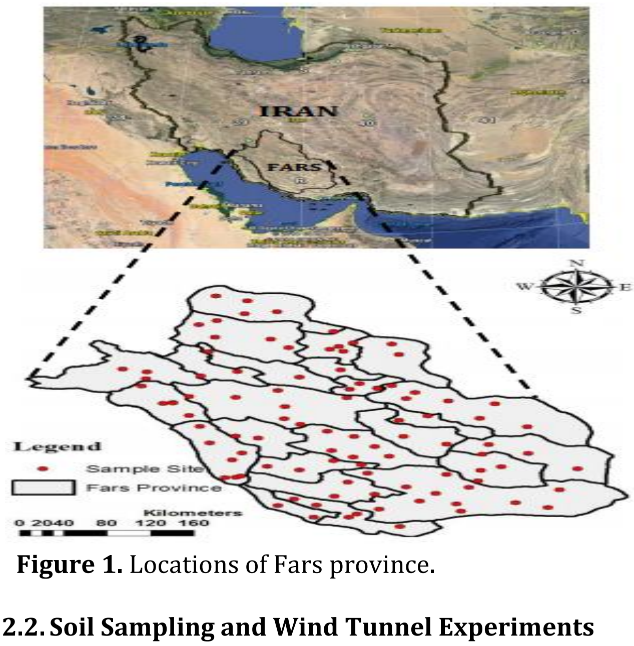

Figure 1. Locations of Fars province.

2.2. Soil Sampling and Wind Tunnel Experiments

In 100 study sites soil samples were selected from the topsoil (3 cm) in the summer of 2019. Then, a comprehensive in-situ wind tunnel experiment was done in 100 sites. Three different sites were chosen in order to practice wind tunnel experiment considering local soil variability. After the determination of the proper test points, we have placed wind tunnel on intact soil in the prevailing wind direction. We have implemented observational method to measure TV. The comprehensive detail of the wind tunnel is described in Mina et al. (2022).

2.3. Spectral Reflectance Measurement

We have used spectrophotometer apparatus (Metrohm, NIRS XDS) within the range of Vis-NIR (400-2500 nm) with 0.5 nm spectral resolution for measuring spectral reflectance of samples. Twenty replicates were considered for each sample. Figure. 2. provides the spectral reflectance in detail. Reduction of noise was done and the reflectance spectra range were between 450-2450 nm. For the aim of eliminating turbulence and increasing spectral data quality, various pre-processing techniques have been done. For that matter, firstly, Savitizky and Goly filter (SG) (Savitzky and Golay, 1964) was performed on spectral data. Then, Standard Normal Variate (SNV) technique for each parameter were done. Finally, For spectral data processing we have used Unscrambler X v. 10.4 software (Camo Software AS, Oslo, Norway).

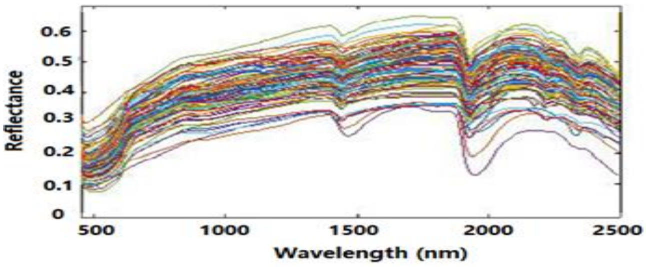

Figure 2. The raw spectral reflectance data of the soil samples.

2.4. Model Evaluation

For the prediction of TV based on soil spectral reflectance, RF model was used. RF regression is famously used for many data analysis and many statistical purposes. Evaluation step contained using four statistical criteria including Ratio of Performance to the Interquartile range (RPIQ), coefficient of determination (R2), the Ratio of Predicted Deviation (RPD), and Root Mean Square Error (RMSE) to examine the accuracy of the model. To perform Statistical analysis and model the data we have used Machine Learning (ML) toolbox in MATLAB 2019b.

In Equations 1-4, P_i and O_i are the estimated and measured values of the parameter, respectively, and n: is the number of observations. SD is the standard deviation of the measured values, Q_1 is the first quartile of the samples, and Q_3 is the third quartile of them. The estimations were categorized in the following order: very poor with RPD <1, weak with RPD=1-1.4, moderate with RPD=1.4-1.8, good with RPD=1.8-2, very good with RPD=2.5-2, and excellent with RPD>2.5 (Lacerda et al., 2016). The same classification principle was applied for RPIQ analysis.

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O}_i\right)\left(P_i - \overline{P}_i\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}_i\right)^2 \sum_{i=1}^{n}\left(P_i - \overline{P}_i\right)^2} \quad (1)$$

$$RMSE = \sqrt{\left(\frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{n}\right)} \quad (2)$$

$$RPD = \frac{SD}{RMSE} \quad (3)$$

$$RPIQ = \frac{IQ}{RMSE} \quad (4)$$
$$IQ = Q_3 - Q_1$$

3. Results and Discussion

Statistical summary for TV is shown in Table 1. Average TV ranged from 1.50 to 12.5 m s-1, presenting a noticeable potential of wind erosion in the region.

Table 1. TV Statistical analysis. Q1: First quartile, Q3: Third quartile, SD: Standard Deviation, CV: Coefficient of Variation

Soil parameter	Threshold Velocity
Unit	m s^{-1}
Range	1.5-12.5
Q_1-Q_3	6 - 8
Mean $_{\pm SD}$	7.21±1.98
CV (%)	28

Represented soil spectra revealed three specific absorption bands at 1414, 1915, and 2212 nm (Figure. 2).

Results of predictive model for TV estimation model using spectral reflectance are presented in Table 2. Figure. 3 also shows its scatter plot demonstrating predicted versus measured TV using RF technique. The parameter concentration area is distributed along the adjusted regression line in the validation group. Consequently, results clearly showed the estimation acceptance and it was due to the overall consistency of the predicted and measured values. Overestimation and underestimation predicted values considering RMSE and RPD factors were not great enough to consider the regression model invalid.

For the purpose of assessing model performance, we have used datasets which were not invoved in the calibration as an external validation set. According to Table 2, the RF model showed R2 (0.74) and RMSE (0.65), with RPD of 1.78 and RPIQ = 2.83 stating prediction excellency.

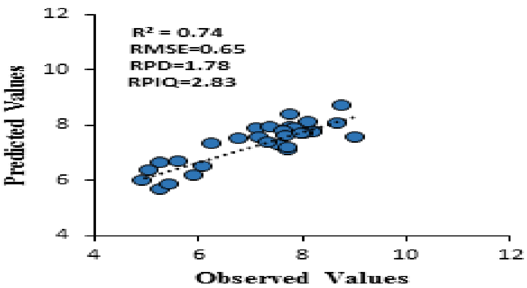

Figure 3. Scatter plot of predicted versus measured TV by RF model

Table 2. Prediction results for TV (m s^{-1}) using RF model

Model	Calibration		Validation			
RF	R^2	RMSE	R^2	RMSE	RPD	RPIQ
	0.91	0.62	0.74	0.65	1.78	2.83

4. Discussion

According to the TV value, the lowest TV was noticed in the southwest part of the province containing sandy texture and it had very poor vegetation cover. Additionally, this area is famous for its susceptibility to wind erosion and it is a critical part of this province (Rezaei et al., 2016). Meanwhile, the highest TV was found in the northwest and north parts of the province and in these regions, soils were largely contained of clay loam texture and they were under rangeland (Sirjani et al. 2019).

They also showed free and hygroscopic water characteristic at 1414 nm, hydroxyl groups at 1915 nm, magnesium and aluminium metals clay minerals networks, the bonding of hydroxides with iron at 2212 nm (Clark et al., 1990). Research has illustrated that the absorption peaks which is around 2341 nm are linked to CO3 groups in minerals which contain carbonate (Lagacherie et al., 2008). Furthermore, spectral curves show a peak at wavelengths in range of 500-700 nm which can be considered as a characteristic of goethite and hematite of soil (de Santana et al., 2018).

PLSR performance in TV prediction was (R^2 = 0.76, RMSE = 0.12) in a research by Li et al. (2015). This difference in accuracy factors might be due to the fact that we have used more samples than them. They examined 31 samples and we had 100 samples.

Our results indicate that the data mining technique (RF) revealed better results compare to the other one. One reason could be its ability to include nonlinear interactions and relationships, and it was mentioned in other researches as well (Brown et al., 2006; Mouazen et al., 2010; Vohland et al., 2011). The superiority of RF performance over PLSR was also reported by de Santana et al (2018), and they have quantified clay content in their research. They also emphasized on this better performance and they associated it to the lower number of outliers excluded from RF in calibration and validation sets in comparison with PLSR.

Generally, the complexity of prediction model has increased with an increase in sample's number and also variability. ML calibration models can improve prediction accuracy assessment. In overall, the TV factor, considered as a soil property, which has no well-known spectral characteristic, ML algorithms can result in better performance in terms of assessment.

5. Conclusion

In the presented research, we examined the utilization of reflection spectroscopy for TV estimation in wind erosion estimation challenges. All in all, the results illustrated that between the TV factor and soil spectral reflectance a clear correlation has been noticed. Representative soil spectra demonstrated specific absorption bands at 1414, 1915, 2212, and 2341 nm. Our results have stated that spectral reflectance is a sufficient tool even in large areas. Hence, soil spectral reflections could be mentioned as an effective method in soil analysis. Other sources including remotely-sensed data can provide these spectra too. Lastly, to have a comprehensive knowledge of its application more studies should be done including the developed PSTD method with the help of satellite imageries for monitoring TV spatial distribution, and data mining techniques such as support vector regression and artificial neural networks could be useful for future projects.

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