On the prediction of threshold friction velocity of wind erosion using soil reflectance spectroscopy

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Abstract

Current approaches to estimate threshold friction velocity (TFV) of soil particle movement, including both experimental and empirical methods, suffer from various disadvantages, and they are particularly not effective to estimate TFVs at regional to global scales. Reflectance spectroscopy has been widely used to obtain TFV-related soil properties (e.g., moisture, texture, crust etc.), however, no studies have attempted to directly relate soil TFV to their spectral reflectance. The objective of this study was to investigate the relationship between soil TFV and soil reflectance in the visible and near infrared (VIS-NIR, 350-2500 nm) spectral region, and to identify the best range of wavelengths or combinations of wavelengths to predict TFV. Threshold friction velocity of 31 soils, along with their reflectance spectra and texture were measured in the Mojave Desert, California and Moab, Utah. A correlation analysis between TFV and soil reflectance identified a number of isolated, narrow spectral domains that largely fell into two spectral regions, the VIS area (400-700 nm) and the short-wavelength infrared (SWIR) area (1100-2500 nm). A partial least squares regression analysis (PLSR) confirmed the significant bands that were identified by correlation analysis. The PLSR further identified the strong relationship between the first-difference transformation and TFV at several narrow regions around 1400, 1900, and 2200 nm. The use of PLSR allowed us to identify a total of 17 key wavelengths in the investigated spectrum range, which may be used as the optimal spectral settings [for estimating TFV in the laboratory and field, or mapping of TFV using airborne/satellite sensors.](#)

Keywords: Dust, Wind erosion, Remote sensing, Partial least squares regression

1. Introduction

Threshold friction velocity (TFV) of the soil is a key parameter in quantifying soil particle movement in aeolian research, as it represents the minimum friction velocity required to initiate particle movement. For a bare soil, TFV depends on soil particle size, soil moisture, and surface crusts (Marticorena and Bergametti, 1995; Marticorena et al., 1997; Shao and Lu, 2000; Lu and Shao, 2001; Dong et al., 2002). Conventionally, TFV is estimated by experimental (e.g., wind tunnel) or modeling (e.g., empirical or theoretical) approaches. Wind tunnel can be applied *in situ* or in the laboratory, and it is able to provide a benchmark of TFV against which other methods can be compared. Depending on the soil characteristics of the study area, TFV can be quite variable over the land surface. It is difficult to estimate the spatial heterogeneity of TFV with the wind tunnel approach, as it is both time and resource intensive. These disadvantages are often more manifest at large landscape or regional scales, where extreme values for TFV have the largest impacts on aeolian sediment transport (Okin, 2005).

Alternatively, TFV may be estimated by empirical or theoretical models. A number of studies have showed that soil TFV may be parameterized as a function of the size of the in-place erodible particles (e.g., Shao and Lu, 2000; Dong et al., 2002; Cornelis et al., 2004). The particle size-based models, however, are not appropriate for field conditions as soils are a heterogeneous mixture of multiple grain size and shapes. In addition, these models fail to account for the difference between disturbed and undisturbed soils, as the disturbed soils may have the same soil texture or particle size compared to those of the undisturbed soils but much lower TFVs (Belnap et al., 2007).

Li et al. (2010) developed an empirical method that related TFV to the resistance of the soil surface to the force of external disturbance. This approach is easy-to-use, sensitive to disturbed soil, and is able to account for the high heterogeneity of TFV. However, this approach suffers from similar disadvantage as the wind tunnel and many of the theoretical models - it is not effective for regional- to global-scale studies. Thus, a new TFV estimating method, which is able to account for the spatial heterogeneity of soil surface at appropriate spatial and temporal scales without exhaustive manual measurements, is needed.

Several studies have illustrated that soil properties, including soil texture, soil moisture, and soil crust can be quantified using reflectance spectroscopy in the visible and near infrared (VIS-NIR, 350-2500 nm) spectral regions (e.g., Okin and Painter, 2004; Kaleita et al., 2005; Xiao et al., 2006; Viscarra Rossel et al., 2006; Ben-Dor et al., 2009; Chamizo et al., 2012). For bare soils, the total reflectance increases with decreasing particle size, owing to decreased absorption and greater scattering in smaller particles (e.g., Matteikalli, 1997; Thomasson et al., 2001). More studies have shown that the presence of physical soil crust tends to increase reflectance whereas biological crust generally decreases reflectance (Goldshleger et al., 2004; Levin et al., 2007), and the moisture content of soil also plays an important role in the measured reflectance from the soil surface (Kaleita et al., 2005).

Despite the fact that all these TFV-related soil properties have been individually studied with respect to their spectral signatures, no studies, to the best of our knowledge, have attempted to directly relate soil TFV and reflectance. Should such a relationship exist, it may be possible to use remote sensing to directly estimate TFV over large areas

with high spatial and temporal resolutions. The objective of this study was to investigate the relationship between soil TFV and its spectral reflectance for a variety of soils, and to identify the best range of wavelengths or combinations of wavelengths to predict TFVs. Satellite or airborne remote sensing imagery generally consists of mixed pixels that include soil with other elements (e.g., plants, litter, etc.) that confound the direct use of remotely-sensed reflectance for observation of the soil surface. However, a critical first step in the use of remote sensing in support of aeolian studies is to show that a relationship between the governing aeolian transport parameter, TFV, has spectral correlates that can be exploited.

2. Experiment and methods

2.1. Description of the study area

The field measurements in this study were conducted at two primary locations, one is located in the Mojave Desert near Barstow, California, and the other one is located on the Colorado Plateau on lands adjacent to Moab, Utah. Field measurements were conducted during February to June 2013 when the soil surface was dry and free of snow cover. A total of 31 experimental sites were identified with 17 in the Mojave Desert and 14 in the Moab area. These experimental sites represent a range of soils, topography, and vegetation in both study areas. In this study, soils with strong physical or biological crust were not measured as these surfaces are highly resistant to erosion, and the non-spectral method used to estimate TFVs (Li et al., 2010) has not been validated on these soils.

Average annual precipitation in the Mojave Desert study area is 101 mm. An association of *Larrea tridentata* and *Ambrosia dumosa* dominates the vegetation, with minor occurrence of perennial grasses in the shrub interspaces. Soil in this location is

generally sandy with high content of gravels and stones. The Moab study area has an arid climate with average annual precipitation of 229 mm. This area has a dominant shrub cover of *Sarcobatus vermiculatus* and *Atriplex canescens*, with perennial grasses of *Stipa comata* and *Hilaria jamesii* found in the shrub interspaces. Soils in this study area are dominated by sandy loam but a variety of soil textures may be found. Soils with biological or physical crusts are widely distributed in this area.

2.2. Field experiment

Field measurements were conducted at the experimental sites with relatively uniform distributions of soil and vegetation. On each of the sites, 10-15 randomly-distributed sampling locations, each has the size of approximately $5 \times 5 \text{ cm}^2$, were marked out using small flags to measure soil reflectance spectra. These sampling locations were free of vegetation and rocks (diameters $>5 \text{ mm}$). In the Mojave Desert, these sampling locations were distributed along two crossing transects (30-50 m long), with two neighboring spots separated by 2-3 m. In the Moab area, the reflectance spectra and TFVs were measured at the sampling locations located about 25 m away from the unpaved roads, and distributed parallel to the road.

Soil reflectance spectra (R) were measured with an ASD FieldSpec 3 portable spectroradiometer (ASD, Inc., Boulder, Colorado). All soil spectra were measured using a contact probe with a halogen light source. The spectroradiometer has a spectral resolution of 1 nm and a sampling rate of 10 Hz, with a spectral range of 350-2500 nm. A $0.30 \times 0.30 \text{ m}^2$ white SpectralonTM panel (Labsphere, North Sutton, New Hampshire) was used as a 100% reflectance standard. The reflectance of the soil was calculated as the ratio of the reflected radiance of the soil to the reflected radiance of the SpectralonTM

panel. On each of the $5 \times 5 \text{ cm}^2$ spectral measurement locations, 10 replicated spectra readings were collected over the same target, and a total of 100-150 spectra were acquired on each of the experimental sites. The spectral measurements were conducted carefully to minimize the disturbance by the contact probe of the soil surface.

Immediately following the spectral measurement, TFVs were estimated by using a method developed by Li et al. (2010). In this method, TFV of bare soil is related to the resistance of the soil surface to the disturbance produced from an air gun and a pocket penetrometer. The TFV measurements were conducted within the $5 \times 5 \text{ cm}^2$ area but not overlapped with the footprints of the spectra measurement, as the application of the spectrometer might have caused slight disturbance to the soil surface.

Finally, a soil sample from the top 1-cm was collected from within each of the $5 \times 5 \text{ cm}^2$ areas. These soil samples were mixed together to form a single soil sample for an experimental site, and sent to a laboratory for texture analysis.

2.3. Soil texture analysis

In the laboratory, each soil sample was air dried and then gently crushed to break up large aggregates. Each sample was sieved using a 2-mm sieve to remove gravels and other non-soil ingredients. The relative proportion of sand (0.05-2 mm), silt (0.05-0.002 mm) and clay ($< 0.002 \text{ mm}$) content was determined using a standard hydrometer method.

2.4. Spectral data pretreatment

Spectra from each of the $5 \times 5 \text{ cm}^2$ sampling locations were averaged to represent the spectra at that location, and the spectrum for an individual study site was obtained by taking the average of all spectra from all $5 \times 5 \text{ cm}^2$ sampling locations. This processing resulted in one final reflectance spectrum for each experimental site.

Excessive noise was found in the wavelength from 350 to 400 nm, and these wavelengths were not subject to further analysis. In addition, two stepwise changes, one located at wavelengths 1000-1001 nm and the other located at 1830-1831 nm, were detected in some spectra. These spectral discontinuities were artifacts of the ASD FieldSpec spectroradiometer, which has an anisotropic distribution of the wavelength-dependent fibers that use different areas of the surface to observe different parts of the spectrum (Painter, 2011). A linear scale method, using the ratio of the stepwise drops between 1000-1001 nm (for wavelengths 401-1000 nm) and 1830-1831 nm (for wavelengths 1831-2500 nm), was conducted to correct the spectra according to Painter (2011).

The discontinuity-corrected reflectance spectra were then smoothed with moving averages, which were calculated from plus and minus four nanometers (λ , in nanometer varying from 401-2500), following the method of Wang et al. (2007):

$$R_s = \frac{1}{9} \sum_{i=-4}^4 R_{\lambda \pm i} \quad (1)$$

where R_s and R are smoothed and original reflectance, respectively.

We further calculated the inverse-log spectra ($\log 1/R_s$) from the smoothed reflectance spectra. The first-derivative of the inverse-log spectra $[(\log 1/R_s)']$ was estimated from the differences, plus and minus four bands, divided by the range of wavelength, according to Yoder and Pettigrew-crosby (1995):

$$(\log 1/R_s)' = [\log 1/R_{s,(\lambda+4)} - \log 1/R_{s,(\lambda-4)}]/8 \quad (2)$$

The first-derivative inverse-log amplifies spectral peaks due to absorption features (Curcio et al., 2013). In addition, first-derivative inverse-log spectra are less impacted by

environmental or analytical conditions (including instrument-related spectral discontinuities discussed above), and have been traditionally used to resolve fine-scale spectra from background noise (Yoder and Pettigrew-Crosby, 1995; Wang et al., 2007). Therefore, the following analyses only focused on the first-derivative of spectra $[(\log I / R_s)']$.

2.5. Statistical analyses

2.5.1. Correlation analysis

Following the post-processing and transformation of spectra, the Pearson correlation coefficients were calculated between TFV and $(\log I / R_s)'$ for each individual wavelength for all the study sites. The significance of these correlation coefficients was assessed at levels of $p < 0.05$ and $p < 0.01$.

2.5.2. Partial least squares regression (PLSR)

While the correlation analysis is able to identify wavelengths that are significantly correlated to TFV, it is not able to determine a quantitative relationship between TFV and the significant wavelengths. Here, we used correlation analysis in combination with a partial least squares regression (PLSR) on the spectral data to assess the extent to which it is possible to predict TFVs on various soil surfaces.

PLSR was selected because spectral datasets are usually multi-collinear, e.g., they often consist of a large number of highly correlated wavelengths and a small number of samples (31, in this study). In addition, the hundreds of wavelengths available as potential predictors make the probability of overfitting models high (Yoder and Pettigrew-Crosby, 1995). In such cases, neither the standard regression nor the step-wise regression is appropriate. The idea behind PLSR is to compress information contained in

the independent variables to a smaller number of non-collinear variables (termed principal components, PCs), and to use only these non-collinear variables in the regression equation (Curcio et al., 2013). Briefly, PLSR decomposes independent variables, X , and dependent variables, Y into PC scores (T, U) and PC loadings (P', Q') according to:

$$X = TP' + E \quad (3)$$

$$Y = UQ' + F \quad (4)$$

where E and F are the error terms. The PLSR is performed in such a way that the first few PCs explain most of the variations in X and Y . The choice of best PCs was determined by the loading weights implemented in the PLSR to optimize for predicting the dependent variable (i.e., TFV in this study).

Given a new spectra X , the TFV can be estimated as a bilinear combination of the PC scores and PC loadings of X . Further information on this technique, including the algorithm, can be found in many papers (e.g., Mevik and Wehrens, 2007; Chamizo et al., 2012).

2.5.3. Model validation

The optimal number of PCs (with a maximum of 10) in the PLSR was determined using leave-one-out cross-validation (LOOCV) method (Mevik and Wehrens, 2007). In this procedure, the root mean squared error (RMSE) of validation and the percent of variance explained in the independent variables (i.e., spectra in this study) were computed. The number of optimal PCs was determined when the RMSE was not significantly greater than the minimum RMSE (i.e., RMSE of 10 components), along with the requirement that a majority of the variance (e.g., >80%) in the spectral

reflectance was explained.

Once the optimal number of components was determined, the validation predictions involved computing each PLSR model using spectral reflectance and TFV data from 30 sites (i.e., each site was left out once) and predicting TFV of the site removed. This iterative process was conducted 31 times. RMSE was then calculated to assess the overall accuracy of the model's prediction. We also calculated the coefficient of determination (R^2) between observed and predicted TFVs.

The statistical analyses of both spectral correlation and PLSR were carried out using R software version 3.1.2 (R Development Core Team, 2010), with the PLSR package of Mevik and Wehrens (2007).

3. Results

3.1. TFV and soil texture

Soils in the Mojave Desert sites were sandy with sand content ranging from 85-99%, whereas soils in the Moab area had a dominant texture of sandy loam with sand content varying from 47-85% (Table 1). In addition, gravels with diameters >2 mm were common in the Mojave sites but these large particles were absent in the Moab sites.

Average TFVs ranged from 0.15 to 1.02 m/s across the study sites, with the lowest found at a sand dune site located in the Mojave Desert (Kelso Dunes, Mojave National Preserve, Mv12, Table 1), and the highest located in a loam soil site in the Moab area (Mb14, Table 1). TFVs in the Mojave Desert tend to have higher coefficient of variations than those of the Moab sites, corresponding to a higher spatial variation (Table 1). When plotted against soil fines (silt and clay), TFVs tend to increase linearly with the content of soil silt and clay (Fig. 1).

Fig. 1. Relationship between threshold friction velocity (TFV) and content of soil fines (silt and clay). Note that sites with hard physical crusts were not included because their TFVs were strongly regulated by physical crust rather than soil texture.

3.2. Characteristics of spectra

Representative soil spectra demonstrate a typical soil reflectance shape in the wavelength domain 400-2500 nm, that is, reflectance is generally lower in the visible range (VIS, 400-700 nm) and higher in the near-infrared (NIR, 700-2500 nm), with dominant absorption bands around 1400, 1900, and 2200 nm (Fig. 2). The overall magnitude of reflectance, however, varies with soils of different texture. For most domains in NIR, surface soils with a texture of loamy sand tend to have high reflectance whereas reflectance for clay loam soils is relatively low. The absorption features due to M-OH modes in the short-wavelength infrared (SWIR, 1100-2500 nm) region are also apparent in the first-difference transformation plot, which also highlights the rapid changes in the visible region for the spectra of most soils (Fig. 3)

Fig. 2. Representative reflectance spectra for soils measured in the study sites. Note the spectra of clay loam soils were measured but were not included in the TFW analysis because of their strong physical crust.

Fig. 3. The first-difference transformation of reflectance spectra $[(\log 1/R_s)']$ for all soils measured in the study sites.

3.3. Relationships between TFW and spectral reflectance

3.3.1. Correlation analysis

Results of correlation analysis between the first-difference transformation of spectral reflectance and TFV are plotted in Fig. 4. Horizontal bars in the correlograms are the boundary of correlation coefficients, beyond which the results are significant (dash line for $p < 0.05$ and solid line for $p < 0.01$). The significant wavelengths largely fall into two spectral regions, the VIS area and the SWIR area. Table 2 lists all bands with significant relationships that may be used to predict TFVs. A total of 102 and 34 isolated, narrow spectral domains were identified at $p < 0.05$ and $p < 0.01$, respectively.

Fig. 4. Coefficients of correlation between threshold friction velocity (TFV) and the first difference of $\log 1/R_s$ $[(\log 1/R_s)']$ for both study sites. Dash and solid horizontal bars indicate the area of significance with $p < 0.05$ and $p < 0.01$, respectively. The regions of wavelengths with significant coefficients of correlation are listed in Table 2.

3.3.2. PLSR analysis

Fig. 5 shows that an optimum of four PCs may be used to predict TFV, corresponding to a validation RMSE = 0.2 m/s and a cumulative variance of 83% explained in spectral reflectance. PC scores indicate that there is no clear indication of

grouping or outliers for the TFVs measured in this study (See supplemental material 1 for PC scores).

Fig. 5. Performance of the partial least square regression (PLSR) analysis with regard to different number of principal components.

By using four PCs, the PLSR yielded LOOCV performance parameters of $R^2 = 0.76$, RMSE = 0.12 m/s in the prediction of the TFV (Fig. 6). The loadings of the PCs as a function of wavelength are plotted in Fig. 7 (See supplemental material 2 for actual values of the loading). The first PC accounted for a moderate 52% of the total variance in reflectance and the largest absolute loading values peaked in the VIS domain of 401 and 579 nm, and SWIR area around 1900 nm. The second PC accounted for 13% of the variance and the largest absolute loadings occurred also in the VIS area and near 1900 nm. The third and fourth PCs accounted for 17% of the variance together, with largest loadings located in the VIS domain and spectral regions at approximately 1400, 1900, and 2200 nm.

Fig. 6. Measured vs. predicted threshold friction velocity (TFV) using the partial least square regression (PLSR) technique with the full range of wavelength 400-2500 nm.

Fig. 7. Loading weights of the first four principal components (PC) as a function of wavelength (nm) following the application of partial least squares regression (PLSR). In the plot, the wavelengths of the highest loadings for spectral ranges with absolute loading > 0.05 (denoted as dashed lines) are also labeled.

In order to determine specific spectral ranges that may be used for the prediction of TFV, we selected a reduced number of spectral bands characterized by loading weights greater than an arbitrary threshold of ± 0.05 . Fig. 7 shows the wavelengths of the highest loadings and Fig. 8 shows the top-ranked spectral ranges and their mean values of the loadings for each PC, respectively (See supplemental material 3 for the distribution of wavelengths and their loadings). These results clearly show that a majority of the top-ranked spectral ranges are located in the VIS range and in the SWIR range around 1900 and 2200 nm.

Fig. 8. Wavelength ranges (nm) for the top-ranked loadings (threshold of ± 0.05) and their mean values for the first four principal components (PC) following the partial least squares regression (PLSR).

4. Discussion

In this study, we explored the relationship between soil reflectance spectroscopy and TFV for 31 sites located in wind susceptible lands in the Mojave Desert, California, and Moab, Utah. The purpose of this work was to determine, for the first time, whether TFV of bare soils could be predicted from reflectance spectra of the soil, and, if so, whether we can identify the “key wavelengths” of the investigated spectrum range that may be used for the prediction of TFV.

The TFVs estimated from the study sites are well within the range of TFVs measured in the similar locations by other studies (e.g., Belnap et al., 2007; Li et al., 2013). The correlation analysis provided a clear picture of the relationships between spectral reflectance and TFV. The PLSR further confirmed the significant bands that were identified by the correlation analysis. Collectively, the strong relationship between the first-difference transformation and TFV appeared at several narrow regions, with three major specific bands around 1400, 1900 and 2200 nm. Studies have found that the strong relationships at 1400 and 1900 nm may be associated with the presence of both hydration and mineral-bound water (Sorensen and Dalsgaard, 2005; Curcio et al., 2013). The absorption peak around 2200 nm should be ascribed to the Si-OH bonds and cation-OH bonds in various clays, such as the phyllosilicate minerals (e.g., kaolinite, montmorillonite) (Karnieli et al., 1999; Viscarra Rossel et al., 2006). These findings

agreed with many experimental studies that soil TFVs are sensitive to soil moisture content and soil fines, and consistent with our observed strong correlation between TFV and soil fine content (Fig. 1, Marticorena and Bergametti, 1995; Shao and Lu, 2000).

To further reduce the number of spectral bands that may be used to predict TFVs, we reapplied PLSR using only the peak wavelengths in the spectral ranges with absolute loading weights greater than 0.05. In this way we selected only 17 “key wavelength” labeled in Fig. 7. As can be observed, despite the greatly reduced number of spectral bands, the performance of the PLSR technique in prediction of TFV changed only slightly ($R^2=0.56$, $RMSE=0.17$ m/s, Fig. 9), compared to those obtained using the full spectrum.

Fig. 9. Measured vs. predicted soil threshold friction velocity (TFV) using PLSR technique, with the only 17 highest-loading wavelengths. The highest-loading wavelengths are listed in Fig. 7.

The performance of the PLSR technique in the prediction of TFV (e.g., $R^2 = 0.76$ and $RMSE = 0.12$ m/s using the full spectral range, Fig.7; $R^2 = 0.56$ and $RMSE = 0.17$

m/s for reduced set of wavelengths, Fig. 9) is striking for several reasons. First, soils in the arid and semiarid environment are notoriously heterogeneous in texture, water content, roughness, and nutrient content, all of which give rise to strong variations of soil TFVs, even at a small scale of few centimeters that measured in this study. In addition, soil reflectance spectra may be complicated by the presence of roughness elements such as gravels, which were ruled out of soil texture inputs. This is particularly the case in the Mojave Desert, where errors could occur for both the spectral and TFV measurements. Second, the spectral bands that correlated highly with TFVs are consistent with those of the known variables that strongly impact TFVs found in other studies (e.g., Kaleita et al., 2006 for soil moisture, Curcio et al., 2013 for soil texture). Finally, although TFVs measured in this study are within the range of TFVs measured using wind tunnel method in the nearby locations, these measurements are subject to errors. For example, errors may occur related to different users or the condition of the device (e.g., the air gun) when applying the Li et al. (2010) method to estimate TFVs in the field.

There are several issues that must be considered in applying reflectance spectroscopy to developing TFV data sets for modeling wind erosion and dust emission. The current study intentionally focused on spectra at the soil level to avoid complications arising from the presence of vegetation. In reality, desert environments that are susceptible to wind erosion are rarely bare, and airborne or satellite remote sensing nearly always capture reflectance signals that include vegetation, except for the most barren areas. Fortunately, this issue may be tackled by using a technique like multiple member spectral mixture analysis (MESMA) method (Robert et al., 1997; Robert et al., 1998), which selects the best-fit soil spectrum among a library of candidates. Using

hyperspectral data, Okin et al. (2001) showed that MESMA is capable of choosing the correct soil spectrum in some cases. This suggests that, in the cases where MESMA can be used to estimate the soil reflectance, soil TFV might be inferred as well. Additionally, although both correlation and PLSR analyses showed that visible wavelength regions exhibit strong relationships with TFVs (Figs. 4, 7), the use of these wavelengths to estimate TFV may not be practical for remote sensing application, as variable lighting conditions can cause significant changes in the overall reflected brightness (Wang et al., 2007). While the wavelengths around 1400 and 1900 nm can be relevant for estimating TFV using field or laboratory spectral measurements, they will not be useful in airborne or spaceborne remote sensing due to atmospheric water absorption (Whiting et al., 2004; Wang et al., 2007).

Reflectance spectroscopy provides a non-invasive and non-destructive method for gathering information about soil features. This technology may become a valuable tool for TFV estimation because spectroradiometers are capable of collecting data quickly over an entire field, which could reduce expensive fieldwork procedures. The use of correlation analysis and PLSR technique allowed us to establish the “key wavelengths” for the prediction of TFV. The distribution of these key wavelengths indicated that multispectral, rather than single band data may be used in future remote sensing for TFV estimation.

5. Conclusions

We have demonstrated that reflectance spectroscopy potentially provides a promising tool for the estimation of TFV of aeolian soil particle movement. Our analysis highlighted the significance of a number of isolated, narrow bands around 1400, 1900

and 2200 nm in TFV assessment, despite the fact that the 1400 and 1900 nm bands may not be useful for airborne or spaceborne remote sensing due to atmospheric absorption.

This study provided some insights to the relationship between reflectance spectra and TFV, but also raised a few issues. For example, current study focused on spectral reflectance at contact level whereas airborne or satellite-borne remote sensing sensors typically capture reflectance at canopy level. Even though the MESMA has been used to retrieve vegetation information, their application in retrieving soil and therefore TFV of the soil requires more study. Also, this study was based on a limited number of soil types and the scope of this study is intentionally restricted to bare soil and spectral measurements at contact level. It therefore corresponds to a first step in the development of methods for soil TFV estimation from spectral data. This could ultimately open avenues for applications related to dust emission monitoring and the quantification of dust emissions at large scales with high spatial and temporal resolutions. Future studies should focus on obtaining the spatial distributions of TFV using remotely sensed data over larger areas with mixed surfaces.

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Table 1. Threshold friction velocity (TFV) and soil texture data at the study sites.

Sample site*	TFV (m s ⁻¹)		Gravel (>2 mm, %) [#]	Sand (%)	Silt (%)	Clay (%)	Soil Texture ^{##}
	Mean	Coefficient of variation (%)					
Mv1	0.53	23	3	90	9	1	Sand
Mv2	0.77	87	<1	85	12	3	Loamy sand
Mv3	0.46	26	23	94	6	<1	Sand
Mv4	0.47	38	43	94	6	<1	Sand
Mv5	0.29	5	51	93	7	<1	Sand
Mv6	0.22	3	29	91	8	1	Sand
Mv7	0.46	34	39	96	4	<1	Sand
Mv8	0.58	36	40	85	13	2	Loamy sand
Mv9	0.41	32	17	88	11	1	Sand
Mv10	0.33	46	49	90	10	<1	Sand
Mv11	0.21	7	24	93	6	1	Sand
Mv12	0.15	2	<1	99	1	<1	Sand
Mv13	0.41	40	16	94	6	<1	Sand
Mv14	0.27	30	<1	92	5	3	Sand
Mv15	0.27	2	24	96	3	1	Sand
Mv16	0.19	18	21	98	2	<1	Sand
Mv17	0.27	15	1	87	10	3	Sand
Mb1	0.51	18	-	85	7	7	Sand
Mb2	0.51	51	-	83	8	9	Loamy sand
Mb3	0.74	28	-	59	25	17	Sandy loam
Mb4	0.72	24	-	73	15	12	Loamy sand
Mb5	0.49	14	-	69	15	16	Sandy loam
Mb6	0.92	25	-	55	29	15	Sandy loam
Mb7	0.57	10	-	63	21	16	Sandy loam
Mb8	0.76	21	-	75	11	13	Sandy loam
Mb9	0.80	15	-	66	19	15	Sandy loam
Mb10	0.59	32	-	74	9	17	Sandy loam
Mb11	0.71	17	-	61	24	14	Sandy loam
Mb12	0.95	27	-	67	19	14	Sandy loam
Mb13	1.02	11	-	55	27	18	Sandy loam
Mb14	1.02	4	-	47	31	23	Loam

Notes: * “Mv” represents Mojave Desert sites, and “Mb” represents Moab, Utah sites; [#] Percent of gravel was calculated as the mass of gravel over bulk soil samples from the study sites, and no gravels were found in the Moab sites; ^{##} Soil texture determination was based on particles with diameters <2mm, using the US Department of Agriculture soil texture triangle.

Table 2. Distribution of ranges of wavelength (nm) with significant coefficients of correlation that may be useful for predicting threshold friction velocity.

Spectral parameter	Significance level	Spectral range (nm)
(log 1/R _s)'	$p < 0.05$	517-543,1347-1354, 1898-1911, 1936-1943, 1969-2092, 2273-2293
	$p < 0.01$	525-535, 2056-2088