Predicting soil wind erosion potential under different corn residue management scenarios in the central Great Plains

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Predicting soil wind erosion potential under different corn residue management scenarios in the central Great Plains

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ABSTRACT

Various models and simplified equations are available to predict wind erosion potential. However, their performance can be often site-specific, depending on soil characteristics and agronomic practices, warranting site-specific model validations. Thus, in this study, we 1) validated the wind erodible fraction (WEF) predictive equations by Fryrear et al. (1994) and López et al. (2007) and 2) estimated the total soil loss with the Single-event Wind Erosion Evaluation Program (SWEEP) using 3-yr measured data from six experiments located across a precipitation gradient in the central Great Plains. Each site had three corn (*Zea mays* L.) residue removal treatments: control (no removal), grazed, and baled. The measured and predicted WEF were significantly correlated. While the Fryrear et al. (1994) equation performed better than the López et al. (2007) equation, it underestimated WEF with 59% uncertainty across site-years. To reduce this underestimation and uncertainty, we developed a new statistical equation (WEF% = 84.3 + 2.64 × % silt-0.30 × % clay-7.43 × % organic matter-0.15 × % residue cover; r^2 = 0.56). The predictive ability of the new equation was, however, no better than that of the existing predictive equations, suggesting the need for further refinement of WEF equations for the region. Simulated total soil loss by wind using the SWEEP model indicated that corn residue baling may increase soil loss if residue cover drops below 20% in the study region. Overall, the existing WEF equations could under- or overestimate WEF based on site-specific residue management, warranting further model refinement and site-specific validation, whereas the SWEEP estimated soil loss corroborates the critical importance of maintaining sufficient residue cover (> 20%) to reduce wind erosion.

1. Introduction

Soil models are important tools to integrate existing soil data and predict soil response to management practices including crop residue removal. Removing crop residues such as from corn through baling and grazing is a common practice for livestock production in the central Great Plains. Such practice can reduce soil aggregate stability and organic C concentration, and alter micro-climatic conditions, potentially increasing risks of wind erosion (Blanco-Canqui and Wortmann, 2017). Predicting wind erosion potential using measured data from representative soils can be key to assess how crop residue removal affects wind erosion potential in wind erosion-prone environments including the central Great Plains.

One of the most sensitive indicators of wind erosion potential is the wind erodible fraction (WEF). The WEF includes soil particles or dry soil aggregates < 0.84 mm in diameter. It is frequently used to predict soil wind erodibility in empirical models such as the Wind Erosion Equation (WEQ; Woodruff and Siddoway, 1965) and process-based models such as the Wind Erosion Prediction System (WEPS; Tatarko et al., 2018). Wind erodible fraction can be determined using a rotary sieve (Lyles et al., 1970), flat sieve (López et al., 2007) or empirical equations (Fryrear et al., 1994). Fryrear et al. (1994) developed a WEF equation based on 3000 samples in the US and included sand content, silt content, ratio of sand to clay, organic matter content, and $CaCO_3$ concentration as main predictors. The equation explained 67% of the variability in WEF for the US soils. López et al. (2007) showed that the equation developed by Fryrear et al. (1994) failed to predict WEF for soils in Spain and Argentina. The lack of predictability was mainly due to higher $CaCO_3$ concentration and organic matter content and lower sand to clay ratio in their soils compared to the US soils. Recently, Guo

Abbreviations: SWEEP, single-event wind erosion evaluation program; WEF, wind erodible fraction

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et al. (2017) observed no correlation of WEF with soil texture, organic matter content and $CaCO_3$ concentration for different croplands. The above literature review indicates that the performance of WEF may vary with region and management practice. Furthermore, it suggests the need to validate and refine the existing WEF prediction equations on a site- or region-specific basis and different management practices such as crop residue baling and grazing.

In addition to using simplified or statistical equations, soil loss due to wind erosion can be simulated using process-based models such as Single-event Wind Erosion Evaluation Program (SWEEP). The SWEEP model is a sub-model of the Wind Erosion Prediction System and is designed to estimate soil loss for single-day storm event given site specific surface inputs. In addition, the SWEEP model can estimate the threshold wind velocity to initiate wind erosion for a given site. Only one study is available in Nebraska that simulated soil loss, which used the SWEEP model under residue grazing and baling at a single site on a loamy soil (Blanco-Canqui et al., 2016). However, total soil loss may vary based on soil texture, climate, and residue cover (Blanco-Canqui and Wortmann, 2017). Thus, modeling of wind erosion using measured data from a wide range of soil textural classes, climates, and residue management strategies is needed to better understand how management practices such as crop residue baling and grazing can affect soil loss across a precipitation gradient in the central Great Plains. Thus, the objectives of this study were to: 1) validate the wind erodible fraction (WEF) predictive equations by Fryrear et al. (1994) and López et al. (2007) and 2) estimate the total soil loss with the Single-event Wind Erosion Evaluation Program (SWEEP) using 3-yr measured data from six experiments located across a precipitation gradient in the central Great Plains.

2. Material and methods

The objectives of this study were accomplished by using 3-yr data collected from six sites located across a precipitation gradient in Nebraska. The study sites were located near Nebraska City, Norfolk, Clay Center, Ainsworth, Odessa, and Scottsbluff, NE. The experiment had three corn residue treatments: control, grazed, and baled. No residue was removed after corn harvesting for the control treatment. For the grazed treatment, cattle grazed residues to remove about 12% of the total corn residue produced. The stocking rate ranged from 3.5 to 11 animal unit months (AUM ha^{-1}) across site-years. Baling treatment was applied by the farm cooperators by mechanically cutting the corn residue to height of 5- to 30-cm, raking and then removing residue out of plot as round bales. Additional details about the experimental site, management, soil properties, and residue cover are given in Table S1 and S2.

2.1. Data collection

In the first year, six sites were sampled with three treatments, replicated thrice at three sites and twice at other sites. Thus, we had $(3 \times 3 \times 3) + (3 \times 3 \times 2) = 45$ data points for the first year. In the second year, four sites were sampled with three treatments replicated thrice at two sites and twice at other two sites, resulting in $(2 \times 3 \times 2) + (2 \times 3 \times 3) = 30$ data points. In the third year, three sites were sampled with three treatments, replicated thrice at two sites and twice at one site, resulting in $(1 \times 3 \times 2) + (2 \times 3 \times 3) = 24$ points. In total, we had 99 data observation points for analysis. Field and lab analysis of relevant soil surface properties were conducted following standard protocols. We determined particle size distribution by hydrometer method (Gee and Or, 2002), organic matter content by loss on ignition method (Combs and Nathan, 1998), $CaCO_3$ concentration using Helrich (1990) method, gravimetric water content using Gardner (1986) method, and residue cover by line transect method (USDA-NRCS, 2002). Summary statistics of the dataset used in this study are given in Table 1. Data collected from six sites were representative of a range of soil particle size distribution, organic matter, precipitation, and cropping systems prevalent in Nebraska (Table S1). Our dataset was well within the range of dataset used by Fryrear et al. (1994) but had some differences compared to the López et al. (2007) dataset. For example, the highest amount of $CaCO_3$ concentration in López et al. (2007) study was 40.7%, whereas our dataset had relatively low $CaCO_3$ concentration with maximum of 6.9%.

Table 1
Summary statistics of soil and corn residue variables used for validation, development of new predictive equation, and SWEEP simulations.

Variable (%)	No. of data points	Mean	Std. Deviation	Minimum	Maximum
Wind erodible fraction	99	55.6	26.4	11.1	98.1
Sand	99	43.7	26.3	15.3	86.6
Silt	99	7.4	3.5	1.4	15.8
Clay	99	48.9	26.7	3.9	73.9
Sand to clay ratio	99	3.3	5.2	0.2	22.2
Organic matter	99	3.1	1.4	0.6	6.0
Water content	99	20.0	10.0	10.0	50.0
Residue cover	99	62.9	25.1	9.0	98.7
$CaCO_3$	99	2.2	1.6	0.5	6.9

2.2. Validation of existing equations

We used measured soil properties to predict WEF by the equations developed by Fryrear et al. (1994); Eq. (1), López et al. (2007) using rotary sieve WEF data (Eq. (2)), and López et al. (2007) using flat sieve WEF data (Eq. (3)).

$$\text{WEF} = 29.09 + 0.31\ \text{sand} + 0.17\ \text{silt} + 0.33\ \text{sand/clay} - 2.59\ \text{organic matter} - 0.95\ CaCO_3 \tag{1}$$

$$\text{WEF} = 9.98 + 6.91\ \text{sand/clay} + 14.1/\text{organic matter} \tag{2}$$

$$\text{WEF} = 4.77 + 7.43\ \text{sand/clay} + 27.6/\text{organic matter} \tag{3}$$

All variables in the above Eqs. (1)-(3) are listed in terms of percentage (%).

Our measured WEF was determined using the flat sieving method (Nimmo and Perkins, 2002; López et al., 2007; Blanco-Canqui et al., 2016). Briefly, soil samples were collected from the 0- to 5-cm soil depth using a flat base shovel and placed in two rectangular trays. The samples were air-dried for 72 h and placed on top of a stack of sieves with openings of 45-, 14-, 6.3-, 2-, 0.84-, and 0.425-mm arranged in a descending order. The samples were mechanically sieved for 5 min at 278 oscillations min^{-1} using a Ro-Tap sieve shaker (RX-29 model, W·S Tyler, Ohio, US). The aggregates remaining on each sieve were weighed to determine the fraction of aggregates within each aggregate-size class (< 0.425, 0.425–0.84, 0.84–2, 2–6.3, 6.3–14, 14–45, and > 45 mm). Wind erodible fraction (%) was calculated by dividing the amount of soil with < 0.84 mm diameter aggregates by the total amount of soil sample (Chepil, 1953).

The model fit was evaluated by plotting predicted WEF versus measured WEF along with 1:1 line. We also checked the performance of each equation for whole dataset, by treatment, and by site dataset across years using root mean square error, coefficient of variation and determination, and absolute relative error.

2.3. Development of a new predictive equation

After examining the performance of existing WEF equations (Eq. (1)-(3), we developed a new WEF equation based on data collected from our study sites. Data collected in 2015 and 2016 was used to develop the prediction equation (total data points = 75), while the data collected in 2017 (total data points = 24) was used to check the equation fit. The soil properties that were significantly correlated ($p < 0.05$) in the dataset were used for developing the new WEF prediction equation. Specifically, we used organic matter content, particle size distribution, $CaCO_3$ concentration, gravimetric soil water content, and percent residue cover to develop new WEF predictive equation using correlation and step-wise regression analysis. The intrinsic soil properties such as particle size distribution and $CaCO_3$ concentration were kept constant for each site in validation. The prediction equation dataset, organic matter and percent residue cover were relatively similar among site-years whereas gravimetric water content, being a highly dynamics soil property had some inevitable variation from year to year (Rakkar et al., 2019).

2.4. Predicting soil loss using the SWEEP model

The SWEEP model (version 1.3.9) was used to simulate wind erosion for an 805 m × 805 m field area with no wind barriers, no crust on the soil surface, and a random roughness of 6 mm for the three residue treatments. We used measured particle size distribution, bulk density, geometric mean diameter and geometric standard deviation of dry aggregates, and percent crop residue cover as model inputs. Other relevant soil parameters were calculated by the model based on site-specific soil series. Corn residue characteristics such as residue height, stem area index, row spacing, and stalk location (seed placement) were assumed and kept constant for all sites. Simulations assumed no growing crop. A summary of inputs for SWEEP modeling is presented in Table 2. Air density was estimated based on elevation and average temperature of each site. Using above given inputs, total soil loss was simulated for two conditions: 1) bare soil using residue cover as zero and 2) residue covered soil using residue cover of each treatment plot. The SWEEP model was programmed to estimate total soil loss at 13 m s^{-1} of wind velocity for three hours for March (soil sampling period) month. March also represents the typical high wind erosion season of February through May in the U.S. Great Plains. During March, in a typical continuous corn or corn-soybean rotation prevalent in Nebraska, soils are commonly without growing vegetation and may have limited or no residue cover based on site-specific residue management scenarios. In addition, threshold velocity to initiate erosion was determined based on measured soil surface conditions. Historical wind data was retrieved by the SWEEP model from the SWEEP weather database for each site. The retrieved dataset was then used to calculate probability of threshold wind velocity to occur in given month by the SWEEP software given the measured surface conditions for each replication.

Table 2
Parameters used for simulating soil wind erosion in the SWEEP model.

SWEEP	Parameter	Source	Value
Field	x length and y length, m	Assumed	805
	Angle, ° from north	Assumed	0
	Wind barriers	Assumed	0
Biomass	Residue average height, m	Assumed	0.0762
	Residue stem area index, m^2 m^{-2}	Calculated	0.0036
	Residue leaf area index, m^2 m^{-2}	Assumed	0
	Residue flat cover, m^2 m^{-2}	Measured	0.09–0.99[a]
	Row spacing, m	Assumed	0.76
	Seed placement	Assumed	Ridge
Soil layers	Number of layers	Assumed	1
	Thickness, mm	Assumed	50
	Sand fraction	Measured	0.15–0.87
	Very fine sand fraction	Calculated	0.09–0.36
	Silt fraction	Measured	0.01–0.16
	Clay fraction	Measured	0.04–0.74
	Rock volume fraction	Assumed	0
	Dry bulk density, Mg m^{-3}	Measured	0.97–1.43
	Average aggregate density, Mg m^{-3}	Calculated	1.8
	Average dry aggregate stability, ln(J kg^{-1})	Calculated	1.50–3.42
	Geometric mean diam. of aggregate sizes	Measured	0.29–13.50
	Geometric SD of aggregate sizes	Measured	1.68–12.6
	Minimum aggregate size, mm	Calculated	0.01
	Maximum aggregate size, mm	Calculated	29.2–43.0
	Soil wilting point water content, Mg Mg^{-1}	Calculated	0.05–0.21
Soil surface	Allmaras random roughness, mm	Assumed	6
	Ridge height, mm	Assumed	0
	Ridge spacing, mm	Assumed	760
	Ridge width, mm	Assumed	0
	Ridge orientation, ° from north	Assumed	0
	Hourly surface water content, Mg Mg^{-1}	Assumed	0
Weather	Air density, kg m^{-3}	Calculated	1.10–1.22
	Wind direction, ° from north	Assumed	–
	Anemometer height, m	Assumed	10
	Aerodynamic roughness, mm	Assumed	10
	Zo location flag	Assumed	Station
	Wind table, m s^{-1}	Assumed	13 for 3 h

[a] Residue flat cover was considered zero for simulating soil loss for bare soil conditions whereas actual residue flat cover was used for simulating soil loss for residue cover scenarios.

2.5. Data analysis

Data were analyzed using SAS version 9.4 (SAS Institute, 2015). PROC REG was used to determine model fit of predicted and measured WEF. Normality of residuals was checked using diagnostic plots of RStudent and predicted value. PROC CORR was used to determine Pearson correlation coefficient between relevant soil properties and WEF. PROC STEPWISE was used to select soil properties and create the new WEF prediction equation at 85% confidence level. The SWEEP model output was mainly non-normally distributed, therefore, mean and standard error were used to determine differences among corn residue treatments.

3. Results and discussion

3.1. Validation of existing WEF prediction equations

Fig. 1 shows the relationship between measured and predicted WEF using Eq. (1) by Fryrear et al., 1994, and Eq. (2) and Eq. (3) by López et al., 2007 across all treatments and site-years. The measured WEF was significantly correlated with the predicted WEF for all three existing equations ($p < 0.001$). Regression analysis indicated that Eq. (1) explained 41% of the variability in the measured WEF. Comparison of WEF with 1:1 line indicated that Eq. (1) under-estimated WEF for 77% of the dataset. In general, the underestimation by Eq. (1) increased as measured WEF increased above 40%. Scatter-plots of measured and predicted WEF indicated that Eq. (1) performed better than Eq. (2) and Eq. (3). The predicted WEF by Eq. (2) explained 36% and Eq. (3) explained 40% of the variability in the measured WEF. The Eq. (2) underestimated WEF for 83% of the dataset whereas Eq. (3) under-estimated WEF for 80% of the dataset. The Eq. (1) output had relatively less absolute relative error and standard deviation compared with Eq. (2) and Eq. (3). Also Eq. (1) showed maximum absolute error of 127% relative to 185% and 204% by Eq. (2) and Eq. (3), respectively. Overall, results show that Eq. (1) performed better than the other two equations (Table 3).

To examine the performance of existing WEF equations under different residue management scenarios, dataset was sorted into three subsets of corn residue baling, grazing, and control. Figs. 2 and 3 show the relation between measured and predicted WEF for three different residue management scenarios. The measured WEF was significantly related to predicted WEF for all three residue treatments for all existing WEF Eqs. (1)-(3). However, the coefficient of determination varied among Eq. (1)-(3) based on the treatments. For baled dataset, the output from Eq. (1) explained only 38% of the variability and under-estimated WEF for 94% of the dataset. The Eq. (1) also under-estimated WEF for 76% of the dataset for the control and 64% for the grazed

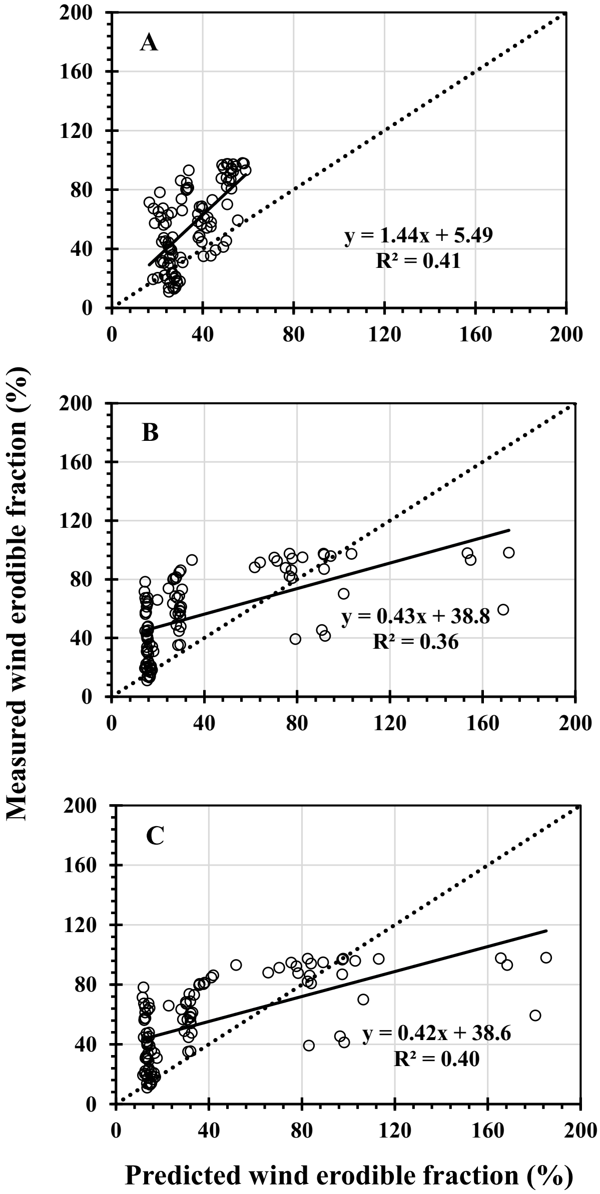

Fig. 1. Relationship between measured and predicted wind erodible fraction by A) Fryrear et al. (1994), B) rotary, and C) flat sieve equation by López et al. (2007) across site-years.

Table 3
Absolute relative error, root mean square error, and coefficient of variation between measured wind erodible fraction (WEF) and predicted WEF across site-years. No. of data points = 99.

	Fryrear et al. (1994)	López et al. (2007)	
	Rotary sieve equation	Rotary sieve equation	Flat sieve equation
Absolute relative error (%)			
Mean	43	48	48
Std. deviation	23	29	32
Maximum	127	185	204
Minimum	1	1	0.35
Root mean square error	20.4	21.2	20.5
Coefficient of variation (%)	36.7	38.2	36.9

dataset. The output by Eq. (2) performed better than Eq. (1) for the baled dataset with 48% variability explained. Similar to Eq. (1) output, Eq. (2) also under-estimated WEF ranging from 78% for grazed to 90% for baled dataset. Based on average absolute relative error, Eq. (1) performed better than Eq. (2) for all three residue treatments (Table 4). The relation between measured WEF and predicted WEF using Eq. (3) for each residue treatment across site-years is presented in Fig. 3. Similar to Eq. (2), the relation of measured and predicted WEF by Eq. (3) varied based on treatment. Based on the absolute relative error, root mean square error, and coefficient of variation, Eq. (1) outperformed Eq. (2) and Eq. (3) (Table 4).

To observe the influence of site characteristic on predictive ability of existing WEF equations, regression analysis parameters and absolute relative error were determined between measured WEF and predicted WEF for each site across treatments and years (Table 5). Predicted WEF was significantly correlated with measured WEF only at two of the six sites for all three WEF equations. Sites (Scottsbluff, Ainsworth, and Norfolk) with high sand (> 50%) and low organic matter (< 2%) showed coefficient of determination < 0.15, whereas the Nebraska City and Clay Center sites, with relatively higher clay content showed significant correlation between measured and predicted WEF. Similar to previous results of whole and by treatment dataset, existing equations underestimated WEF for most of the dataset. Based on absolute relative error, root mean square error, and coefficient of variation, the Fryrear et al. (1994) equation performed better than the López et al. (2007) equations for silt loam sites whereas the López et al. (2007) equations performed better for sandy loam sites (Table 5).

The results of regression analysis between measured WEF and predicted WEF indicate that the Fryrear et al. (1994) equation performs better than the López et al. (2007) equations for our study soils. The poor relationship of measured data with predicted WEF using López et al. (2007) equation could be due to low $CaCO_3$ concentration in our soils (< 7%) compared to the soils studied in Spain (30–40%). Also, the values of soil properties in our study were within the range used by Fryrear et al. (1994), which could explain the better predictive ability of the equation by Fryrear et al. (1994) for our study soils than the equations by López et al. (2007).

The existing WEF equations underestimated, however, the actual WEF. One reason for such difference could be the usage of different methodologies to measure WEF between our study and the studies by Fryrear et al. (1994) and López et al. (2007). The existing WEF equations (Eq. (1) and Eq. (2)) were developed based on rotary sieve results whereas, we used a flat sieve to measure WEF in our study. Previous studies found a strong relation between WEF obtained from rotary sieve and flat sieve (López et al., 2007; Guo et al., 2017). However, previous studies also reported an under-estimation of WEF using rotary sieve compared to flat sieve (López et al., 2007, Guo et al., 2017). López et al. (2007) indicated that with rotary sieve procedure, small aggregates do not pass through sieves and are generally, collected with coarser aggregate fraction, resulting in underestimation of WEF.

We observed under-estimation of WEF even with usage of the flat sieve WEF Eq. (3) developed by López et al. (2007). It appears that the flat sieve procedure may need further calibration to standardize the sieving time, oscillation per minute, amplitude, and devices to obtain more reliable WEF results. Also, availability, handling, and operation of flat sieve is easier than the rotary sieve method. Therefore, a new equation based on standardized flat sieve analysis could be helpful to avoid over and underestimation of actual WEF in future studies. In addition, the differences observed in predictability of existing equations under residue grazing, baling, and control (Figs. 2 and 3), warranted including additional parameters such as residue cover, to improve the performance of existing WEF equations. Overall, our results indicate that the Fryrear et al. (1994) equation could be used for soils in Nebraska, however, there is still 45 to 59% uncertainty in prediction along with under-estimation of WEF within a treatment dataset and across site-years.

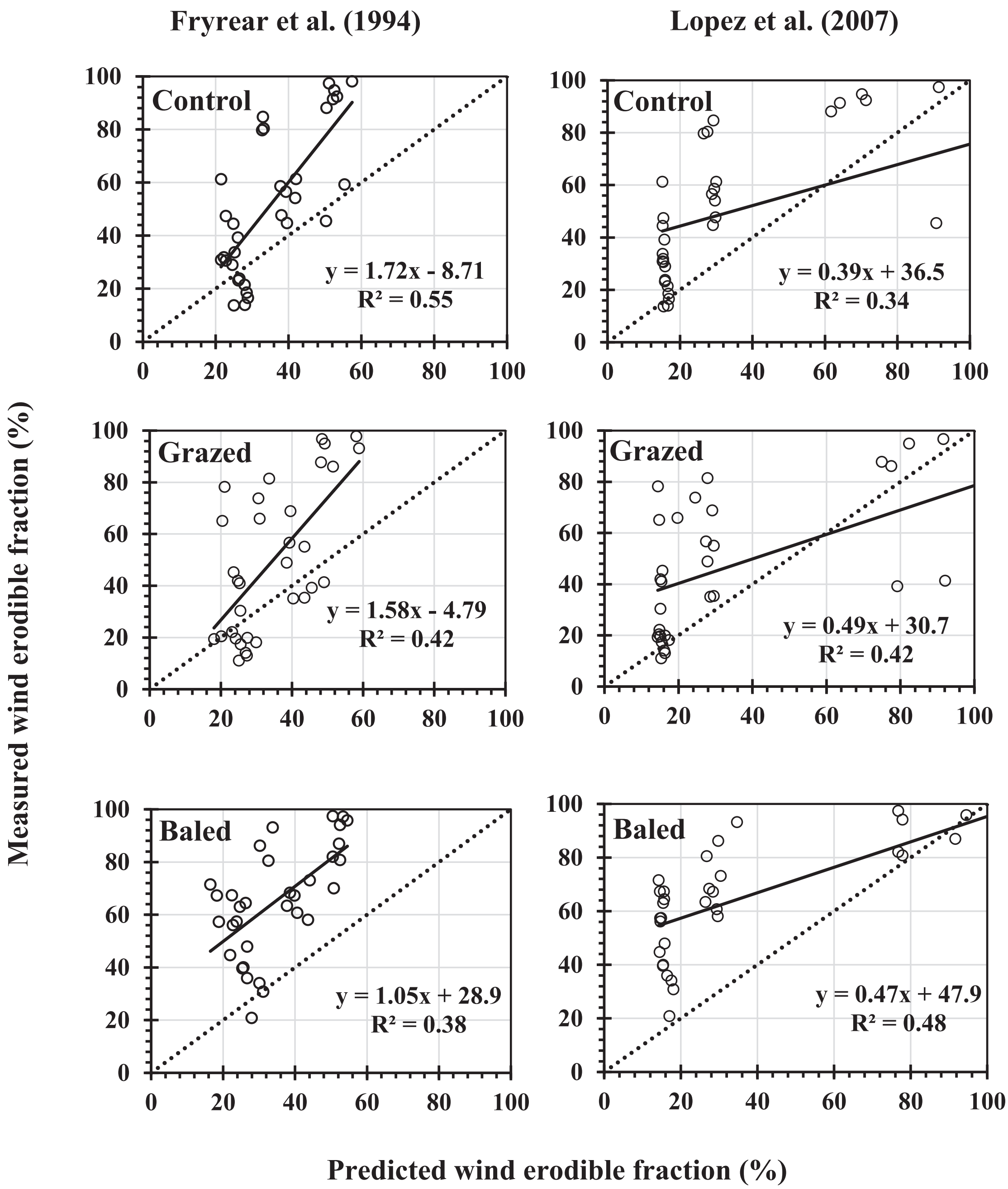

Fig. 2. Relationship between measured and predicted wind erodible fraction (WEF) using rotary sieve WEF equation by Fryrear et al. (1994) and López et al. (2007) within a treatment across site-years.

3.2. Development and testing of a new equation

Prior to developing a new WEF equation, correlations among soil properties for our study were performed across treatments and site-years. Analysis showed significant correlation of WEF with all soil properties that are used in the existing WEF prediction equations Eqs. (1)-(3) except $CaCO_3$ concentration. The results showed that WEF increased as sand ($r = 0.55$) and silt content ($r = 0.35$) increased, whereas it decreased as clay content ($r = -0.58$), organic matter concentration ($r = -0.59$), water content at the time of soil sampling ($r = -0.46$), and percent residue cover ($r = -0.23$) increased. It is well known that an increase in clay content and percent residue cover stabilizes the aggregates whereas increase in sand and silt content may weaken the aggregates due to fewer binding forces among particles (Skidmore and Layton, 1992). The results also indicated that increase in organic matter concentration and water content could decrease WEF. Such results may be related to binding forces of organic matter and water (Colazo and Buschiazzo, 2010; Sirjani et al., 2019). In our study, plots with no residue removal had higher soil water content due to less evaporation losses compared to plots with residues removed (Rakkar et al., 2019). Water content is known to affect soil aggregation through wetting and drying; freezing and thawing; and freeze-drying (Layton et al., 1993; Bullock et al., 2001). The presence of relatively high water content in control plots could have increased the cohesive forces to bind soil particles. During soil sampling and even after air drying, soils from high soil water content plots had intact large clods and macro-aggregates as opposed to baled plots where soils were composed of predominately micro aggregates (powdery), which clearly affected the amount of erodible fraction. Therefore, our results indicate that even though soil water content is highly dynamic in both time and space,

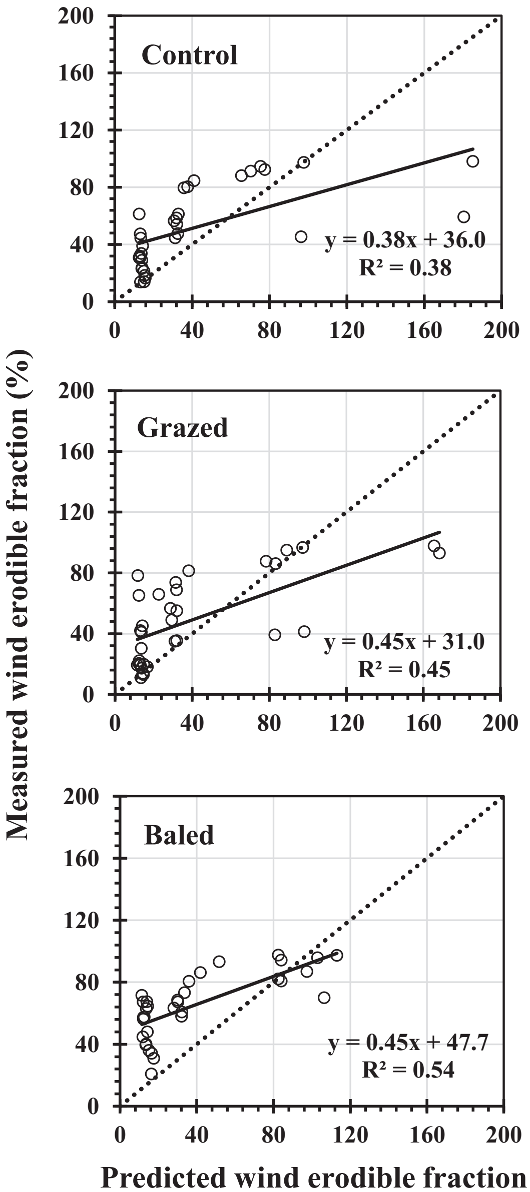

Fig. 3. Relationship between measured wind erodible fraction and predicted wind erodible fraction by López et al. (2007) flat sieve equation for three residue treatments.

determination of soil water content during sampling could be important to explain observed wind erodible fraction. The relation of $CaCO_3$ concentration with WEF is contradictory in literature. Our results agree with the study by López et al. (2007) that showed no correlation whereas contrast with other studies reporting increase or decrease in WEF with an increase in $CaCO_3$ concentration (Chepil, 1954; Fryrear et al., 1994). Our analysis indicates that the measurement of percent residue cover and soil water content, in addition to intrinsic soil properties, may improve the predictability of WEF for soils in Nebraska.

The stepwise regression analysis selected silt content, clay content, organic matter concentration, and percent residue cover as the main predictors of WEF in Eq. (4):

$$\text{WEF\%} = 84.3 + 2.64 \times \text{\%silt} - 0.30 \times \text{\%clay} - 7.43 \times \text{\% organic matter} - 0.15 \times \text{\%residue cover} \tag{4}$$

Organic matter concentration explained 31%, silt content 17%, clay content 6%, and percent residue cover 2% of the variation in the model

Table 4
Absolute relative error, root mean square error, and coefficient of variation between measured wind erodible fraction (WEF) and predicted WEF for each treatment across site-year No. of data points = 33 for each treatment.

	Control	Grazing	Baling
	Fryrear et al. (1994)		
Absolute relative error (%)			
Mean	43	39	45
Std. deviation	29	22	17
Maximum	127	101	77
Minimum	1	7	1
Root mean square error	8.0	9.1	9.7
Coefficient of variation (%)	22.7	26.5	28.0
	Rotary sieve equation by López et al. (2007)		
Absolute relative error (%)			
Mean	44	48	50
Std. deviation	29	33	25
Maximum	123	185	80
Minimum	4	2	1
Root mean square error	22.5	22.0	15.2
Coefficient of variation (%)	43.4	44.5	23.2
	Flat sieve equation by López et al. (2007)		
Absolute relative error (%)			
Mean	45	49	51
Std. deviation	33	38	26
Maximum	138	204	84
Minimum	1	0	1
Root mean square error	21.7	21.5	14.3
Coefficient of variation (%)	41.9	43.4	21.9

with cumulative coefficient of determination of 57%. In our new WEF equation, percent residue cover was the additional parameter over the equation by Fryrear et al. (1994). The negative correlation of residue cover with WEF elucidated the importance of retaining residue cover to reduce WEF. The retention of residue cover is important to protect soil from abrupt fluctuations of temperature and water content (Blanco-Canqui and Wortmann, 2017). Frequent freeze-thaw and wet-dry cycles weaken the aggregates resulting in higher proportion of WEF. It is important to mention that the given equation was developed without using boundary conditions of 0 to 100% (beta-distribution) in stepwise regression analysis because of 1) nearly normal distribution of residuals and 2) none of the predicted WEF showed any value below 0% or above 100% using the new equation. Measured WEF and Eq. (4) output showed significant correlation with explanation of 49% variation in the 2017 measured WEF dataset (Fig. 4).

Based on the coefficient of determination and root mean square error, the predictive ability of new WEF equation was, however, similar to the WEF equations developed by Fryrear et al. (1994) and López et al. (2007) (Fig. 4). It is important to highlight that our new equation did not include percent sand, ratio of sand to clay, and $CaCO_3$ content but had percent residue cover as an additional parameter as compared to Fryrear et al. (1994) and López et al. (2007) equation. The new equation showed the highest coefficient of variation of all equations and the data points were scattered more uniformly around the 1:1 line unlike predicted data points by the equations of Fryrear et al. (1994) and López et al. (2007), in which data points were clustered into two separate groups. The differences observed in prediction pattern could be due to the use of different parameters in our new equation compared to the existing WEF equations. Overall, contrary to our expectations, the newly developed equation did not improve prediction of WEF. The existing and the new WEF equations showed nearly 50% of uncertainties in the results. We hypothesize that more data points from a wider range of soil textural classes, organic matter concentrations, and levels of residue cover than those used in this study could be needed to for a better estimation of WEF.

Table 5
Absolute relative error, root mean square error, and coefficient of variation and determination between measured wind erodible fraction (WEF) and predicted WEF for each site across treatment and years.

	Scottsbluff	Ainsworth	Norfolk	Odessa	Clay Center	Nebraska City
No. of data points	18	12	12	12	27	18
	Fryrear et al. (1994)					
Absolute relative error (%)						
Mean	46	23	58	23	54	66
Std. deviation	13	27	56	17	22	7
Maximum	60	102	185	54	82	77
Minimum	16	1	5	2	11	50
Root mean square error	11.1	11.1	21.2	7.8	17.2	12.5
Coefficient of variation (%)	19.7	12.9	26.1	36.4	43.6	19.4
Coefficient of determination (%)	0.001	0.04	0.13	0.11	0.24*	0.63*
	Rotary sieve equation by López et al. (2007)					
Absolute relative error (%)						
Mean	29	40	34	53	47	52
Std. deviation	10	8	15	36	28	14
Maximum	44	48	50	110	127	67
Minimum	12	16	7	1	5	16
Root mean square error	11.1	16.2	22.6	7.3	16.7	9.8
Coefficient of variation (%)	19.6	18.8	27.7	34.3	42.2	15.3
Coefficient of determination (%)	0.008	0	0.02	0.21	0.28*	0.77*
	Flat sieve equation by López et al. (2007)					
Absolute relative error (%)						
Mean	42	21	23	23	58	62
Std. deviation	14	30	19	19	22	10
Maximum	56	112	58	58	85	79
Minimum	9	3	3	3	3	45
Root mean square error	11.1	16.2	22.5	7.4	17	9.9
Coefficient of variation (%)	19.7	18.8	27.7	34.4	42.9	15.4
Coefficient of determination (%)	0	0.01	0.02	0.21	0.26*	0.77*

* numbers followed by asterisk signify significant relation between measured and predicted WEF at 0.05 significance level.

3.3. Simulated soil loss using SWEEP

Corn residue grazing and baling impacted the simulated soil loss for the bare soil condition scenario (Table 6). Averaged across site-years, mean soil loss due to residue baling was $0.2\,kg\,m^{-2}$ more than the control. The increase in soil loss by baling ranged from $0.1\,kg\,m^{-2}$ at Scottsbluff to $1.0\,kg\,m^{-2}$ at Odessa in the first year compared with the control. After considering standard error within a treatment for each site-year, residue baling appeared to increase soil loss at four of the 13 site-years compared with the control. Averaged across site-years, mean soil loss due to residue grazing was $0.1\,kg\,m^{-2}$ less compared with the control. After considering standard error within a treatment for each site-year, residue grazing appeared to decrease soil loss at Clay center in the second year. In general, sites with sandy loam texture (Scottsbluff, Ainsworth, and Norfolk) had greater soil loss ($2.1\,kg\,m^{-2}$) compared with the sites which had silty loam texture (Clay Center, Nebraska City, and Odessa) at $0.7\,kg\,m^{-2}$, indicating more susceptibility of coarse textured soils to wind erosion irrespective of crop residue management. We expected variability in simulated soil loss due to the precipitation gradient of Nebraska. Precipitation could be one of the major factors affecting soil water deficit that could impact soil organic matter and residue production, which could affect wind erodible fraction. However, no specific pattern of simulated soil loss was observed along the precipitation gradient in Nebraska. It appears that intrinsic soil properties such as texture have more impact on soil erosion than precipitation. For example, Scottsbluff (400 mm) receives 1.6 times lower precipitation than Norfolk (706 mm), but both sites had similar total soil loss due to sandy loam textural class (Table 6).

Corn residue treatments also influenced the threshold velocity to initiate soil erosion given measured surface conditions for each replication (Table 6). Averaged across site-years, the mean threshold wind velocity required to initiate erosion was $1.9\,m\,s^{-1}$ less for baled treatment than the control. The results indicate that soils under baled treatment were more prone to wind erosion compared with that under control. The residue grazing treatment had mean threshold wind velocity of $10.8\,m\,s^{-1}$, which was $0.6\,m\,s^{-1}$ less than control but $1.3\,m\,s^{-1}$ more than the baled treatment. Corresponding to the threshold velocity results, the probability of threshold wind velocity to occur in a given month at a site was also higher for the baled treatment compared with the grazed and control treatments. Overall, the SWEEP output indicated that baling could increase the total soil loss in this region.

To determine the importance of retaining residue cover, total soil loss was simulated using residue cover of each treatment along with other soil, biomass, and weather inputs given in Table 1. Corn residue treatments showed no influence on total soil loss except at Scottsbluff (Table 7). At this site, average soil loss due to baling increased to $0.5\,kg\,m^{-2}$ in 2015 and to $0.7\,kg\,m^{-2}$ in 2016 compared to $0.0\,kg\,m^{-2}$ with the control and grazed plots. As expected, a decrease in residue cover decreased the threshold wind velocity needed to initiate soil erosion. Averaged across-site years, baled plots required threshold velocity of $14\,m\,s^{-1}$ to initiate wind erosion followed by grazed ($19\,m\,s^{-1}$) and control ($21\,m\,s^{-1}$) treatments. Similar to bare soil condition results, baling had the highest probability to cause wind erosion in a given month.

Simulated SWEEP output for bare soil conditions indicated that residue baling could affect the soil susceptibility to wind erosion whereas grazing impact could be minimal. It appears that residue baling weakens the aggregate stability that results in breakdown of coarse aggregates into smaller aggregates, increasing WEF (< 0.84 mm diameter soil). Previous studies of residue baling and grazing reported 25 to 43% increase in WEF due to residue baling (Blanco-Canqui et al., 2016; Ruis et al., 2018). This could be due to the mechanical action of the baler, such as the raking action of the residue pickup teeth in breaking up aggregates. Decreased threshold velocity to initiate soil erosion also indicated that soil aggregates in baled plots could be weaker than aggregates of control and grazed treatments. It is important to note that irrespective of residue treatment, simulated soil loss obtained for bare soil conditions (Table 6) was much higher than residue cover conditions (Table 7). Our results emphasize the critical

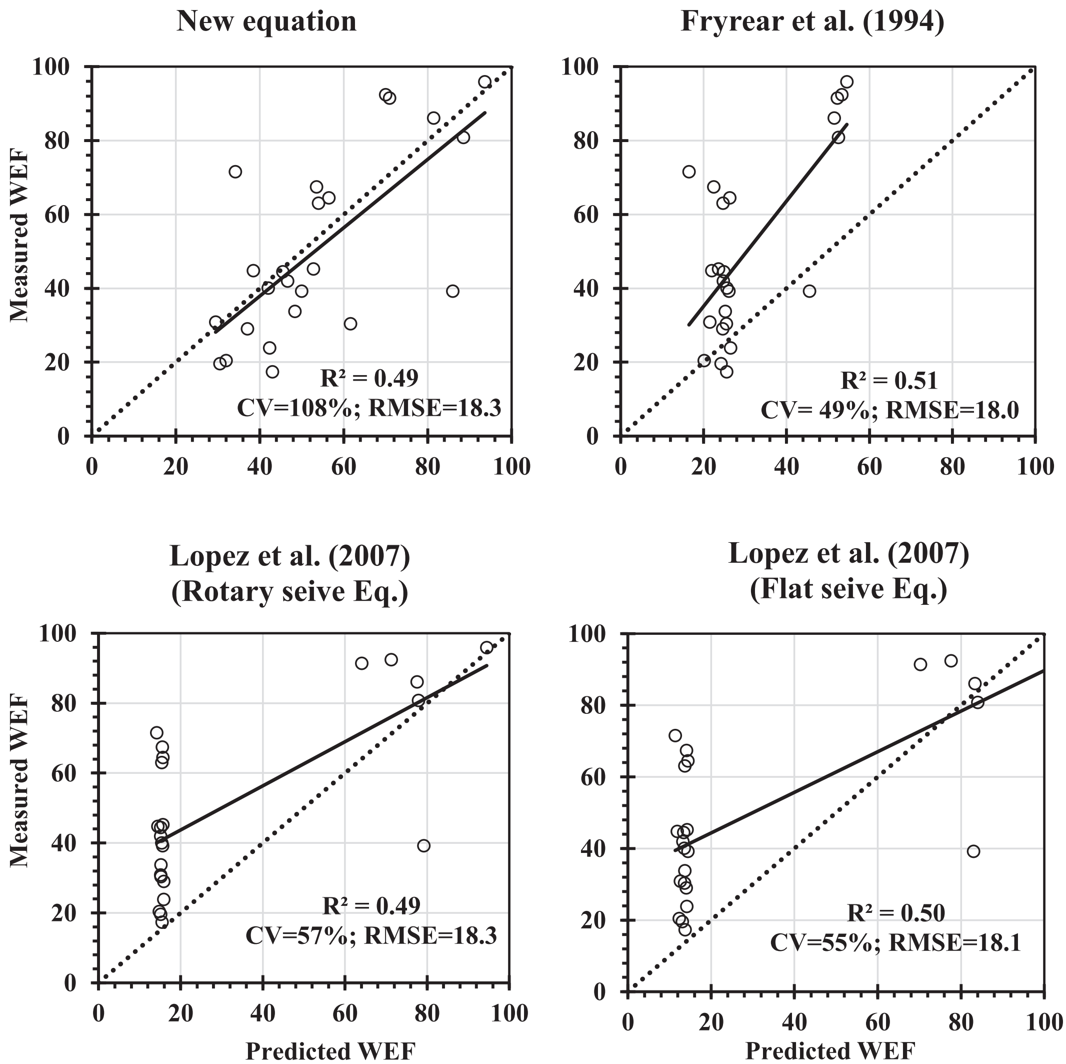

Fig. 4. Relationship between measured and predicted wind erodible fraction (WEF) using new equation and existing prediction equations developed by Fryrear et al. (1994) and López et al. (2007).

Table 6
Amount of soil loss, threshold velocity to initiate erosion, and probability of threshold wind velocity to occur on a given day in March under three residue treatments for study sites in Nebraska as calculated by the SWEEP model under bare soil conditions.

	Soil loss, kg m^{-2}			Threshold wind velocity, m s^{-1}			Probability (%)		
	Control	Grazed	Baled	Control	Grazed	Baled	Control	Grazed	Baled
2015									
Scottsbluff	2.2 ± 0.0[a]	2.1 ± 0.1	2.3 ± 0.0	10.7 ± 0.3	12.0 ± 1.0	10.0 ± 0.6	7.0 ± 0.9	4.7 ± 2.1	9.3 ± 2.0
Ainsworth	1.9 ± 0.0	1.9 ± 0.0	1.9 ± 0.1	8.0 ± 0.0	8.0 ± 0.0	8.0 ± 0.0	24.5 ± 0.0	24.5 ± 0.0	24.5 ± 0.0
Norfolk	2.2 ± 0.1	2.2 ± 0.1	2.3 ± 0.1	8.0 ± 0.0	8.0 ± 0.0	8.0 ± 0.0	24.6 ± 0.0	24.6 ± 0.0	24.6 ± 0.0
Odessa	0.0 ± 0.0	0.0 ± 0.0	1.0 ± 0.1	14.5 ± 0.5	15.0 ± 0.0	12.5 ± 0.5	1.1 ± 0.2	0.9 ± 0.0	3.4 ± 0.8
Clay Center	0.9 ± 0.6	1.5 ± 0.2	1.4 ± 0.0	12.0 ± 1.4	10.7 ± 1.5	10.3 ± 0.4	6.6 ± 4.3	11.3 ± 5.3	11.6 ± 2.1
Nebraska City	1.1 ± 0.0	1.1 ± 0.1	1.2 ± 0.1	10.0 ± 0.0	10.7 ± 0.3	9.7 ± 0.3	8.0 ± 0.0	6.1 ± 0.9	9.6 ± 1.6
2016									
Scottsbluff	2.2 ± 0.0	2.2 ± 0.0	2.4 ± 0.1	11.3 ± 0.3	11.0 ± 0.0	9.7 ± 0.3	5.4 ± 0.7	6.1 ± 0.0	10.3 ± 1.4
Norfolk	2.1 ± 0.1	2.3 ± 0.3	2.4 ± 0.1	12.0 ± 1.0	10.5 ± 2.5	10.0 ± 1.0	5.8 ± 2.5	14.0 ± 10.6	12.7 ± 4.4
Odessa	0.0 ± 0.0	0.0 ± 0.0	0.5 ± 0.5	14.0 ± 0.0	15.0 ± 0.0	14.0 ± 1.0	1.4 ± 0.0	0.9 ± 0.0	1.7 ± 0.8
Clay Center	0.6 ± 0.3	0.0 ± 0.0	1.1 ± 0.5	13.7 ± 0.7	14.7 ± 0.3	10.0 ± 0.6	2.3 ± 0.6	1.2 ± 0.2	13.0 ± 2.7
2017									
Ainsworth	2.0 ± 0.1	1.0 ± 1.0	2.2 ± 0.2	8.0 ± 0.0	11.5 ± 3.5	7.5 ± 0.5	24.5 ± 0.0	12.6 ± 11.9	34.2 ± 9.8
Clay Center	0.4 ± 0.4	0.5 ± 0.5	0.9 ± 0.4	14.3 ± 0.9	12.7 ± 1.3	13.3 ± 0.9	1.7 ± 0.7	5.4 ± 3.9	2.9 ± 1.2
Nebraska City	1.0 ± 0.0	1.0 ± 0.0	1.3 ± 0.3	11.3 ± 0.3	11.3 ± 0.3	9.0 ± 0.0	4.5 ± 0.7	4.5 ± 0.7	12.9 ± 0.0
Average across site-years	1.3	1.2	1.5	11.4	10.8	9.5	9.0	8.9	12.5

[a] Numbers followed by ' ± ' refer to standard error within a treatment.

Table 7
Amount of soil loss, threshold velocity to initiate erosion, and probability of threshold wind velocity to occur on a given day in March with residue cover of three residue treatments in March for study sites in Nebraska as calculated by the SWEEP model.

	Soil loss, kg m^{-2}			Threshold wind velocity, m s^{-1}			Probability (%)		
	Control	Grazed	Baled	Control	Grazed	Baled	Control	Grazed	Baled
2015									
Scottsbluff	0.0 ± 0.0[a]	0.0 ± 0.0	0.5 ± 0.2	20.0 ± 0.0	19.0 ± 0.6	12.7 ± 0.3	0.2 ± 0.0	0.2 ± 0.0	3.1 ± 0.5
Ainsworth	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	18.0 ± 0.0	16.0 ± 0.0	13.5 ± 0.4	0.1 ± 0.0	0.5 ± 0.0	2.2 ± 0.5
Norfolk	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	20.0 ± 0.0	19.5 ± 0.5	15.5 ± 0.5	0.1 ± 0.0	0.1 ± 0.0	1.1 ± 0.3
Odessa	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	24.0 ± 0.0	24.0 ± 0.0	19.0 ± 1.0	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1
Clay Center	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	21.7 ± 0.4	18.7 ± 0.8	15.3 ± 0.4	0.0 ± 0.0	0.2 ± 0.1	0.9 ± 0.2
Nebraska City	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	19.0 ± 0.0	18.0 ± 0.7	15.3 ± 0.4	0.1 ± 0.0	0.2 ± 0.1	0.7 ± 0.1
2016									
Scottsbluff	0.0 ± 0.0	0.0 ± 0.0	0.7 ± 0.4	20.7 ± 0.3	20.0 ± 0.0	12.3 ± 0.9	0.1 ± 0.0	0.2 ± 0.0	4.0 ± 1.3
Norfolk	0.0 ± 0.0	0.0 ± 0.0	0.2 ± 0.2	21.0 ± 1.0	19.5 ± 1.5	13.5 ± 0.5	0.1 ± 0.0	0.2 ± 0.1	2.8 ± 0.6
Odessa	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	22.5 ± 0.5	23.0 ± 0.0	18.5 ± 0.5	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.0
Clay Center	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	22.3 ± 0.3	21.3 ± 0.7	14.3 ± 0.7	0.0 ± 0.0	0.0 ± 0.0	1.7 ± 0.6
2017									
Ainsworth	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	19.0 ± 0.0	21.0 ± 2.0	14.0 ± 1.0	0.1 ± 0.0	0.0 ± 0.0	1.8 ± 1.0
Clay Center	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	23.0 ± 1.0	21.7 ± 0.7	16.7 ± 1.2	0.0 ± 0.0	0.0 ± 0.0	0.6 ± 0.3
Nebraska City	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	20.0 ± 0.0	18.7 ± 0.3	15.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.0	0.8 ± 0.0
Average across site-years	0	0	0.1	20.9	18.6	14	0.1	0.1	1.5

[a] numbers followed by ' ± ' refer to standard error within a treatment.

importance of covering soils with residue. The presence of residue on the soil surface buffers the wind erosive forces and could decrease the wind erosion risks (Blanco-Canqui and Wortmann, 2017). In our study, the greatest simulated soil loss was observed at Scottsbluff under the baled treatment. The residue cover at this site was < 20%, whereas other sites had > 20% residue cover even in baled plots (Table S2). It appears that in our study region, retention of at least 20% residue cover has the potential to decrease the wind erosion risks. Overall, the SWEEP model suggests that residue baling may increase wind erosion risks by weakening the soil aggregates, however soil loss can be prevented by having > 20% residue cover in the study region.

4. Summary and conclusion

Comparison of our measured WEF with predicted WEF using the equations by Fryrear et al. (1994) and López et al. (2007), indicated that the equation by Fryrear et al. (1994) predicted WEF more satisfactorily than the equations by López et al. (2007) in our study region. However, all the above WEF equations under-estimated WEF suggesting that their predictive ability could vary based on residue management and site-specific conditions. A new equation (WEF % = 84.3 + 2.64 silt%-0.30 clay%-7.43 organic matter%-0.15 crop residue cover%.) developed using our measured data from multiple sites had no better predictive ability than the existing equations, which suggests the need to further refine the predictive ability of WEF equations for the region.. Additionally, simulation of soil loss with the SWEEP models suggested that wind erosion can be reduced by retaining at least 20% residue cover during times when soils are most susceptible to wind erosion.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2019.05.040.

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