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Original Research

A Region-Specific Predictive Model for the Determination of the Wind-Erodible Soil Fraction

Petr Zalesak°*, Jana Kozlovsky Dufkova, Dominik Majkus, Tomas Masicek, Sabina Zalesakova

Department of Applied and Landscape Ecology, Faculty of AgriSciences, Mendel University in Brno, Zemědělská 1, 613 00 Brno, Czech Republic

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Abstract

Purpose: Accurate estimation of the wind-erodible fraction (EF), defined as the proportion of soil particles smaller than 0.84 mm, is essential for wind erosion models such as WEQ, RWEQ, WEPS, EPIC, or APEX. Conventional rotary sieving is often impractical, which has led to the use of predictive equations. This study evaluated the equation [30] for Czech soils and developed a region-specific model.

Methods: Seventy-eight soil samples representing major soil units across the Czech Republic were analyzed for particle-size distribution, organic carbon, and carbonate content. EF was determined using the flat sieve dry-sieving method. Multiple regression analysis was applied to assess the equation [30] and construct an improved model.

Results: The equation [30] exhibited substantial bias under local conditions. The refined model identified key predictors, including sand (r = 0.58), silt (r = –0.50), clay (r = –0.43), and particularly the sand-to-clay ratio (r = 0.65), while organic carbon and calcium carbonate ($CaCO_3$) were insignificant. The model demonstrated high predictive performance ($R^2 = 0.90$; adjusted $R^2 = 0.89$).

Conclusion: The proposed equation provides a robust, region-specific alternative for EF estimation, significantly improving wind erosion risk assessment for Central European soils and underscoring the necessity of localized parameterization in wind erosion modeling.

Keywords: calculation, equation, erosion, regression, sieve, soil aggregate

Introduction

Wind erosion contributes to soil degradation by modifying soil texture and disrupting nutrient dynamics, particularly through the depletion of soil organic carbon and essential nutrients, ultimately reducing soil fertility and ecosystem productivity [1-7]. Wind erosion is governed by complex interactions among atmospheric conditions, surface characteristics, and soil properties [8-10]. Wind-driven particle dynamics have been described as a multi-stage process involving particle detachment, transport (via suspension, saltation, and surface creep), abrasion, sorting, and final deposition of soil materials [11, 12].

*e-mail: petr.zalesak@mendelu.cz
Tel.: +420 545 132 406
°ORCID iD: 0009-0009-3033-5702

Wind erodibility refers to the propensity of soil to undergo detachment and subsequent displacement by aeolian forces, influenced by the complex interplay of soil properties and plant factors [13-15]. In conditions where protective elements such as plant residues, crop cover, surface roughness, or moisture are minimal, wind erodibility primarily depends on the intrinsic, non-structural properties of the soil surface, termed soil-inherent wind erodibility (also referred to as soil erodibility) [13]. This soil-inherent wind erodibility is fundamentally determined by two closely related factors: the distribution of soil aggregate sizes and the stability of these aggregates [13]. The aggregate size distribution is typically quantified using either the erodible fraction (EF) or the geometric mean diameter (GMD), as originally proposed by [13, 16, 17].

The EF of soil represents aggregates and particles susceptible to wind erosion, specifically those with a diameter not exceeding 0.84 mm. This threshold was established through wind tunnel experiments conducted by [18]. The proportion of EF serves as a key input parameter in widely used wind erosion prediction equations, including the Wind Erosion Equation (WEQ) [19], the Revised Wind Erosion Equation (RWEQ) [20], and process-based models such as the Wind Erosion Prediction System (WEPS) [21].

Given its critical role in wind erosion dynamics, EF also serves as a basis for classifying soil erodibility levels. Furthermore, soil can be classified based on its EF content to determine its susceptibility to wind erosion. A soil is considered highly erodible if its EF exceeds 50%, moderately erodible if EF ranges between 40-50%, and slightly erodible if EF remains below 40% [22]. This classification provides a fundamental framework for evaluating soil stability and the potential risk of degradation under aeolian processes.

The standard method for determining the EF content in soil involves dry sieving using a rotary sieve [23-26]. This approach assesses dry soil aggregates, providing a more accurate representation of field soil structure compared to primary aggregates analyzed using wet sieving. Dry sieving better reflects the physical disintegration of soil aggregates under natural field conditions, making it a widely accepted methodology for EF determination [26].

A previous study demonstrated a strong correlation ($r = 0.939$, $p<0.001$) between results obtained using a flat sieve and those from a rotary sieve, indicating that a flat sieve can serve as a suitable alternative for EF determination [27]. However, to ensure consistency and reproducibility of results, flat sieve measurements should be conducted using an electromagnetic shaker. This setup provides controlled and uniform sieving conditions, minimizing operator-induced variability and enhancing comparability across different studies. When using a flat sieve with an electromagnetic shaker, it is essential to account for sieving duration, sieving load, and motor shaker frequency, as these factors can influence the results [28, 29].

As an alternative to direct sieving, several predictive equations have been developed to estimate EF content based on soil physicochemical properties. The first widely recognized equation was introduced by [30] using multiple regression analysis. This model integrates key soil parameters, including sand, silt, clay, calcium carbonate ($CaCO_3$), and organic matter content. However, it was calibrated exclusively on a dataset of 3,000 soil samples from the USA, limiting its applicability in regions with distinct soil characteristics [30].

Multiple studies have identified significant limitations in the predictive accuracy of the [30] equation for estimating EF content in soils outside the United States. For instance, [27] reported considerable discrepancies in EF predictions for Argentine and Spanish soils, attributing these deviations primarily to variations in $CaCO_3$ content. Similarly, [31] found that the equation exhibited poor performance for Tunisian soils, particularly Aridisols, where EF values obtained via flat sieving showed a variability of $R^2 = 0.649$.

The correlation between EF predictions based on the [30] equation and values from rotary sieving was examined in a recent study [32]. Their findings revealed that the strength of the correlation varied across different land management practices, including tree windbreaks, conservation tillage farmland, and conventional tillage farmland, suggesting that vegetation cover and land use practices may influence the model's predictive accuracy. The highest correlation ($R^2 = 0.3201$) was observed for grassland soils.

Recent studies on EF prediction models underscore the substantial influence of soil parameters on model accuracy. For instance, [31] demonstrated that incorporating soil texture and $CaCO_3$ content into regression models significantly enhanced predictive performance ($R^2 = 0.723$). Conversely, [33] challenged these findings, reporting no statistically significant effect of $CaCO_3$ content on EF values, thereby suggesting potential methodological or regional variability in EF estimation.

An analysis conducted by [34] using soil samples from Nebraska revealed that the EF equation developed by [30] exhibited better predictive accuracy while still underestimating EF content in 77% of the dataset ($R^2 = 0.41$), whereas the equation proposed by [27] showed a higher underestimation rate (83%) and a lower coefficient of determination ($R^2 = 0.36$), potentially influenced by the low $CaCO_3$ content (<7%) of the analyzed samples. Moreover, a newly developed equation, derived through stepwise regression analysis and incorporating silt content, clay content, organic matter concentration, and percent residue cover, did not outperform the [30] model, as it significantly underestimated EF content in 80% of the dataset, with an R^2 of 0.40 [34].

In a comprehensive review, [33] examined existing equations used for EF content prediction. Their study compiled a dataset integrating rotary and flat sieving data from multiple sources, including [30, 31, 35-42]. The dataset encompasses measurements from various geographic regions, including the USA and Argentina (Americas), the Czech Republic (Europe), Tunisia and Nigeria (Africa), as well as Iran, Türkiye, and China (Asia) [33]. By leveraging a heterogeneous dataset from multiple studies, this analysis enables an objective and methodologically rigorous comparison of existing equations. Such an approach enhances the understanding of equation complexity and supports a robust evaluation of their empirical validity and practical applicability on a global scale.

According to [33], the equation proposed by [31] (R^2 = 0.067; RMSE = 51.174; MAPE = 0.167) demonstrated greater accuracy compared to that of [34] (R^2 = 0.331; RMSE = 48.805; MAPE = 0.277), which systematically overestimated EF content by more than 100% in most cases. However, both equations exhibited a general tendency to overestimate EF content. Similarly, the equation developed by [27] (R^2 = 0.346; RMSE = 5.798; MAPE = 0.096) overestimated EF content in multiple instances, sometimes exceeding a 100% deviation. Likewise, the equation by [35] significantly overestimated EF content.

The poorest predictive performance was observed for the equation developed by [40] (R^2 = 0.0001; RMSE = 156.632; MAPE = 0.742), which failed to provide reliable estimates. In many cases, the predicted EF content exceeded the plausible range by more than 100%. In samples with low clay content, the equation even produced negative EF values, which are unrealistic outcomes. Conversely, the equation by [30] (R^2 = 0.203; RMSE = 3.080; MAPE = 0.007) demonstrated the highest predictive accuracy among the compared models. However, both this equation and the model by [35] (R^2 = 0.002; RMSE = 36.180; MAPE = 0.205) produced negative EF content values for some samples.

To overcome these limitations, [33] developed an innovative equation based on stepwise regression analysis (R^2 = 0.81; RMSE = 2.487; MAPE = 0.015). This model was calibrated on the compiled dataset and does not produce negative EF values or estimates exceeding 100%, thereby improving the reliability and applicability of EF predictions across diverse soil types and geographic regions.

Materials and Methods

To evaluate the applicability of the first published equation for determining EF content [30] and to develop a new approach for assessing EF in soil, a comprehensive dataset of soil samples was assembled, representing various soil types across the Czech Republic (48.5°N to 51.1°N; 12.1°E to 18.9°E; Fig. 1). The country covers an area of 78,866 km^2 with a median elevation of 430 m above sea level (m a.s.l.), a mean annual temperature of 7.6ºC, and an average annual precipitation of 677 mm (1921-2020) [43]. The average relative air humidity for the period 2021-2022 was 74.2% [44]. This study area was particularly suitable due to the availability of a highly detailed and continuously updated soil mapping system [45].

Soil survey methodologies in the Czech Republic adhere to high standards, with a long-standing tradition dating back to the 18th century, beginning

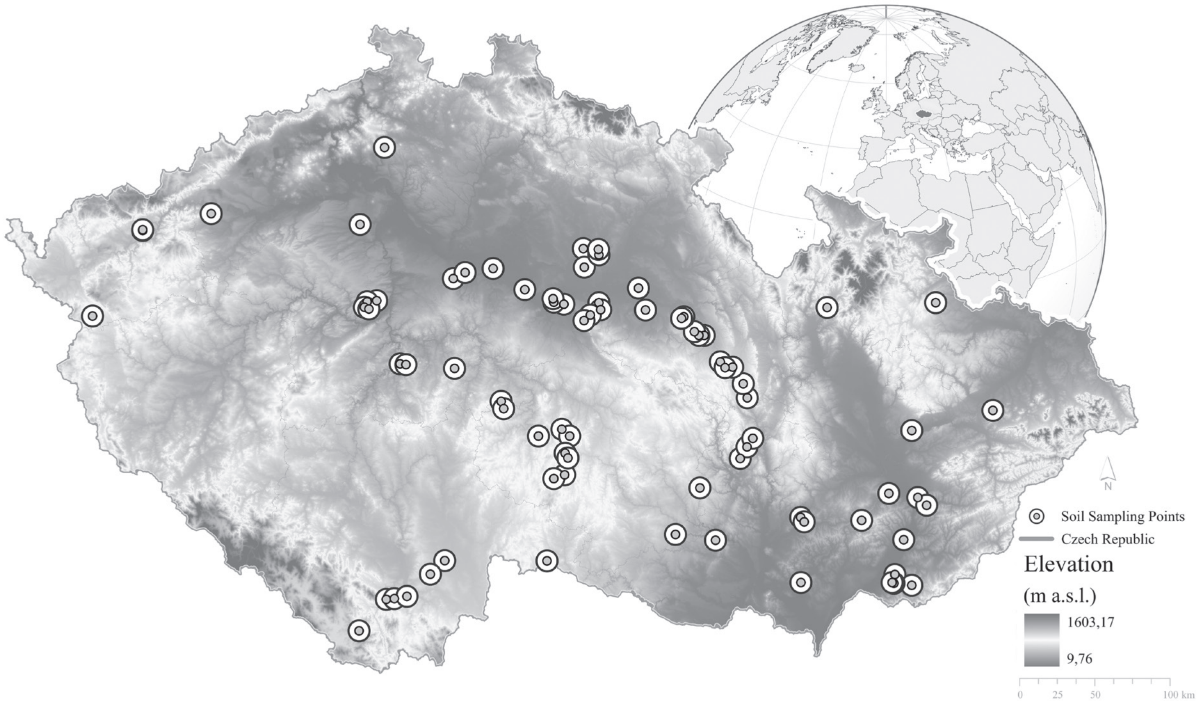

Fig. 1 Geolocation of soil sample collection points based on a digital elevation model. Data source: DMR 5G (ČÚZK).

with the Josefian Cadastre and continuing to the present day [46]. One of the most sophisticated surveys, the Systematic Soil Survey of Agricultural Soils in Czechoslovakia (SSS), was conducted in the 1960s and 1970s [47, 48]. Within the Czech Republic alone, this survey encompassed over 500,000 soil profile observations, with a total of more than 2 million soil samples analyzed [47].

The SSS employed the Genetic-Agronomic Soil Classification System [49] to systematically categorize soils [47]. Building upon the findings of the SSS, the Evaluated Soil-Ecological Unit (ESEU) system was developed as a key tool for land assessment and management [46]. The ESEU classification continues to be updated regularly, with its characteristics and revision procedures formally outlined in [45].

Soil samples were primarily collected from the Main Soil Unit (MSU), a component of the ESEU [45]. The ESEU consists of a five-digit code that provides information about the climatic region, the MSU, inclination, exposure, and skeletal content [45]. The MSU is characterized by a targeted agronomic classification of genetic soil types and subtypes, taking into account soil-forming substrates, particle size distribution, soil depth, hydromorphic properties (type and degree), and the area's relief. The Czech Republic contains 89 different types of MSUs, representing a highly diverse range of soils [45].

A single soil sample was collected from MSU 01-78, while MSU 79-89 are newly established and have not been practically used so far. The GNSS system and GIS software were used for field navigation and location recording during soil sample collection. To select the most suitable sampling sites, publicly available datasets such as SoilGrids, WoSIS, and the LUCAS database were utilized. The soil types of the collected samples,

Table 1. Classification of the collected soil samples according to the WRB.

ESEU	WRB	ESEU	WRB	ESEU	WRB
0.01.00	Haplic luvisols	6.27.01	Cambisols	5.51.11	Stagnosols
3.02.00	Haplic luvisols	5.28.44	Cambisols	7.52.01	Albeluvisols
0.03.00	Chernozems	7.29.14	Cambisols	7.53.01	Stagnosols
2.04.01	Chernozems	7.30.14	Cambisols	3.54.11	Haplic luvisols
1.05.01	Chernozems	2.31.14	Haplic luvisols	3.55.00	Chernozems
0.06.00	Phaeozems	7.32.01	Cambisols	3.56.00	Fluvisols
2.06.10	Chernozems	2.33.01	Cambisols	3.57.00	Fluvisols
2.07.10	Vertisols	8.34.24	Cambisols	5.58.00	Fluvisols
3.08.10	Chernozems	8.35.04	Cambisols	0.59.00	Fluvisols
3.09.00	Greyic phaeozems	9.36.04	Entic podzols	2.61.00	Fluvisols
2.10.10	Haplic luvisols	5.37.16	Cambisols	3.62.00	Phaeozems
4.11.00	Gleysols	7.38.16	Cambisols	0.63.00	Phaeozems
5.12.00	Fluvisols	3.39.19	Haplic luvisols	3.64.01	Fluvisols
3.13.00	Haplic luvisols	5.40.78	Cambisols	8.65.01	Stagnosols
7.14.00	Albeluvisols	5.41.68	Leptosols	8.66.01	Gleyic stagnosols
7.15.12	Haplic luvisols	3.42.00	Haplic luvisols	4.67.01	Gleysols
3.16.02	Albeluvisols	5.43.00	Albeluvisols	7.68.11	Cambisols
4.18.11	Rendzic leptosols	3.44.00	Haplic luvisols	7.69.01	Gleysols
3.19.01	Cambisols	3.44.00	Haplic luvisols	2.70.01	Fluvisols
2.20.01	Leptosols	3.45.01	Haplic luvisols	7.71.01	Cambisols
3.21.10	Fluvisols	7.46.10	Haplic luvisols	8.72.01	Gleysols
3.22.10	Regosols/arenosols	7.47.10	Albeluvisols	7.73.11	Stagnosols
3.23.10	Regosols/arenosols	5.48.11	Albeluvisols	7.74.11	Cambisols
3.24.11	Cambisols	4.49.11	Cambisols	7.75.41	Cambisols
7.25.04	Cambisols	5.49.11	Cambisols	1.77.69	Leptosols
5.26.01	Cambisols	7.50.11	Cambisols	3.78.69	haplic Luvisols

classified according to the World Reference Base for Soil Resources (WRB) based on [50], are summarized in Table 1. Additionally, the particle size distribution of the samples, as determined according to the USDA soil texture classification system, is illustrated in the soil texture triangle (Fig. 2). The collected samples were taken from various elevations across the Czech Republic, spanning locations from 48.72°N, 12.62°E to 50.59°N, 17.99°E, with elevations ranging from 174 to 794 m a.s.l., as illustrated in Fig. 1.

Soil samples were collected during the spring season following primary tillage operations [27]. Sampling was conducted from the uppermost soil layer [51, 52], with a maximum depth of 25 mm [53, 54]. After collecting, the soil samples were air-dried and subsequently analyzed using the dry sieving technique [26-28, 55]. The EF content was determined using a flat sieve in combination with an electromagnetic vibration shaker (Retsch AS 200) to ensure process consistency [29]. The amplitude and time settings of the electromagnetic vibration shaker were consistent for all soil samples. An amplitude of 0.1 mm was applied for a duration of 5 min, following [27]. The sieve load, which is related to the varying weight of the soil, can significantly affect the results and cause distortions. Therefore, the constant weight of the sieved soil must be maintained during sieving [29]. According to [56], the optimal sieve loading should not exceed 30% of its capacity. Based on this criterion, an optimal soil mass of 100-200 g was determined in this study, aligning with the values reported by [27].

According to the original EF equation [30], grain size distribution, organic carbon content, and carbonate content were determined. The grain size distribution was analyzed using the hydrometer method in accordance with [57], following Casagrande's approach. The hydrometer method is based on Stokes' law [58], with principles detailed in [59]. The organic carbon content was determined using the [60] method, which relies on an oxidation-reduction titration. The carbonate content ($CaCO_3$) was quantified using the Scheibler method, a volumetric technique conducted in accordance with ISO 10693 [61, 62].

Data preparation for statistical analyses involved preprocessing in a conventional spreadsheet editor. Statistical analyses were conducted in Python using open-source libraries, including pandas, numpy, statsmodels, scikit-learn, seaborn, scipy, and matplotlib.

Results and Discussion

Characteristics of the Soil Sample Dataset

The dataset comprised a total of 78 soil samples (Fig. 2), each representing an individual MSU. The complexity and variability inherent in the diverse range of soil properties were characterized through statistical analysis, as presented in Table 2, which provides key descriptive statistics, including the median, mean, standard deviation, minimum, maximum, and coefficient of variation (CV) for the parameters EF sieve, sand, silt, clay, sand-to-clay (S/C) ratio, organic carbon, and $CaCO_3$ content.

The dataset compiled by [33], integrating samples from multiple studies and capturing a broader range of soil characteristics, serves as a comprehensive

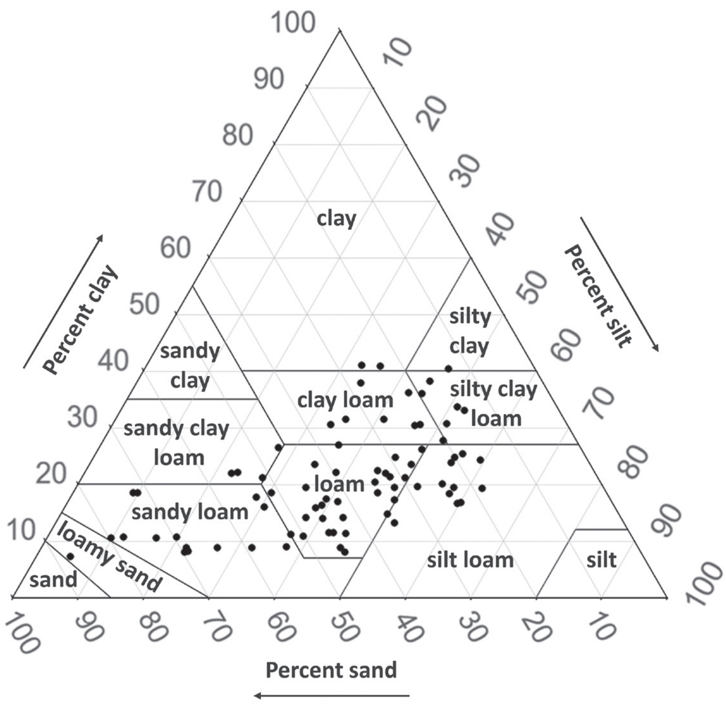

Fig. 2 Distribution of the collected soil samples within the USDA soil texture triangle.

Table 2. Statistical evaluation of the analyzed soil parameters for the examined soil samples.

Parameter	Unit	Median	Mean	Minimum	Maximum	Std. Deviation	CV (%)
EF Sieve	%	21.84	24.21	9.24	89.95	12.33	50.91
Sand	%	35.80	39.74	13.21	87.53	18.00	45.29
Silt	%	42.42	39.68	5.20	62.00	13.24	33.37
Clay	%	19.49	20.57	7.27	41.12	8.89	43.20
S/C Ratio *	-	1.76	2.60	0.18	12.03	2.33	89.76
Organic Carbon	%	1.87	2.32	0.51	7.02	1.33	57.46
$CaCO_3$	%	0.21	2.11	0.03	20.00	4.96	235.19

* calculated value

reference for comparison. Additionally, the dataset from [34], consisting of 99 samples collected near Nebraska City, USA, provides further context for comparative analysis. To enable more robust comparisons in future studies, soil characteristics could also be derived from soil spectral libraries [63-66]. A systematic comparison with the dataset presented in Table 1 reveals significant variations across multiple soil parameters.

The most pronounced discrepancies are observed in sand content, which shows lower absolute variance but slightly higher relative variance in the present study compared to [33]. While the mean sand content is lower than that of [33], its relative variability is slightly greater. Furthermore, the relative variance of organic carbon content in the current dataset is approximately three times lower, while its mean value (2.32) is higher and comparable to the mean organic carbon content reported by [34] (3.1). Notably, the present dataset shows a wider range of organic carbon values, indicating greater variability than in the reference datasets.

In contrast, $CaCO_3$ content exhibits roughly a 0.5-fold increase in relative variance, while its mean value is less than half of that reported by [33], whose dataset spans a broader range (0.00-24.30). The dataset from [34], by comparison, reports a much narrower $CaCO_3$ range (0.5-6.9). Additionally, sand, silt, and clay contents in the present study display higher absolute variance but lower relative variance compared to [33]. The dataset from [34] shows greater absolute variance and higher mean values for EF, sand, clay, and the S/C ratio, whereas silt and $CaCO_3$ contents show lower absolute variance. Interestingly, the absolute variance of organic carbon content is nearly identical across datasets, although its mean value is higher in the present study. The mean silt content reported by [34] is lower, whereas the mean $CaCO_3$ content is nearly identical to that presented in Table 2.

Compared to [33], the current dataset has a lower mean sand content and a slightly narrower range but higher mean values for silt and clay contents. The proximity of mean and median values suggests a higher risk of soil erosion, particularly in areas with elevated EF content. The maximum silt content in the present dataset (62) exceeds that of [34] but remains slightly lower than the maximum reported by [33] (70.30). Similarly, while the maximum clay content in [33] is 46.00, [34] reports a higher maximum value (73.90), compared to the present study.

Assessment of the Predictive Performance of the [30] Equation for EF

The most comprehensive review of EF estimation equations to date was conducted by [33], who identified the [30] equation as the most accurate. Accordingly, this equation was selected for further validation using the dataset collected in this study.

Its predictive performance was evaluated through regression analysis, comparing EF obtained via the flat sieve method with those predicted by the equation (Fig. 3). The results revealed a positive linear trend; however, the coefficient of determination ($R^2 = 0.1357$) indicates a weak predictive capability, consistent with the findings of [27, 31, 34].

Although the equation does not systematically overestimate values exceeding 100%, as reported by [33], our study confirms that it does not yield negative EF values (Fig. 3). Nonetheless, its applicability to Czech soils remains limited. To improve predictive accuracy, the development of a new model tailored to regional soil properties is necessary.

Development of Prediction Equations for EF Calibrated Using the Czech Soils

A correlation analysis was conducted to illustrate the relationships among individual soil properties (Fig. 4). EF indicates a strong positive correlation with the calculated S/C ratio ($r = 0.65$) and sand content ($r = 0.58$), indicating that higher values of these parameters are associated with increased EF. In contrast, EF shows a strong negative correlation with silt content ($r = -0.50$), suggesting that lower silt content enhances EF. A moderate negative correlation is observed between

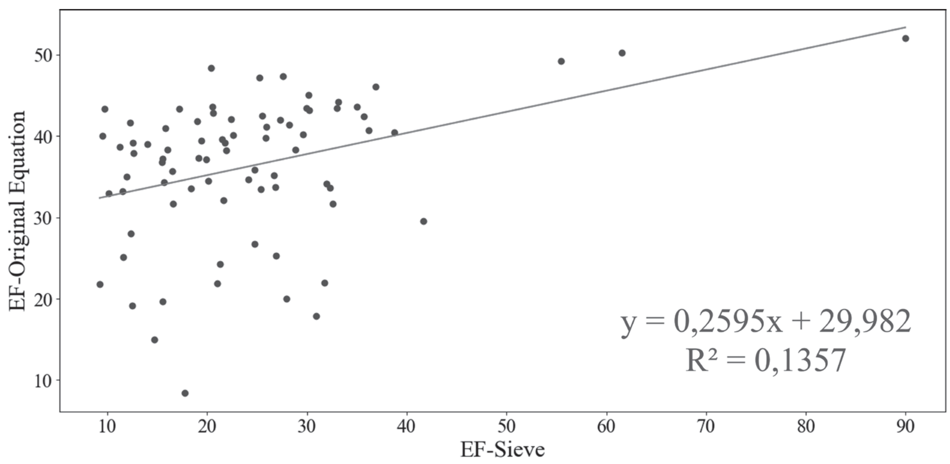

Fig. 3 Relationship between the measured wind-erodible fraction (flat sieve) and the predicted values for the soil surface (0-2.5 cm depth) based on the equation by Fryrear et al. (1994) for USA soils.

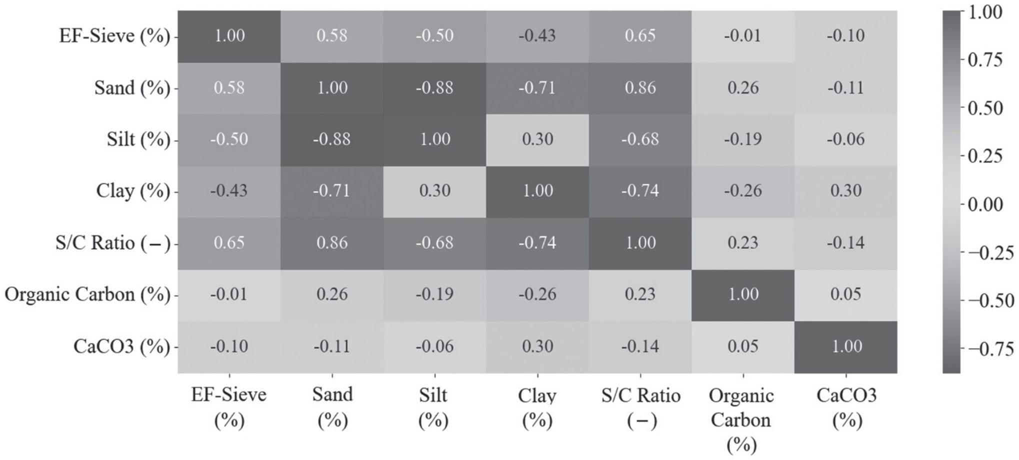

Fig. 4 Correlation (Pearson) coefficients of physical and chemical soil surface properties (0-2.5 cm depth) and wind-erodible fraction obtained with the flat sieve.

EF and clay content (r = -0.43), while weak negative correlations are found with organic carbon (r = -0.013) and $CaCO_3$ content (r = -0.10). These relationships are illustrated in Fig. 4. The observed patterns align with the findings of [33], who also reported the weakest negative correlation between EF and both organic carbon and $CaCO_3$ content in their compiled dataset.

The new equation was derived using stepwise multiple regression with Ordinary Least Squares (OLS) estimation. Predictor selection was based on statistical significance (p-value) and multicollinearity assessment using the variance inflation factor (VIF). The initial model included the contents of sand, silt, clay, the S/C ratio, organic carbon, and $CaCO_3$. To optimize model performance, only the most statistically significant predictors, including the content of sand (%), silt (%), clay (%), and the S/C ratio (-), were retained in the final equation (1). The stepwise regression procedure correctly excluded organic carbon and $CaCO_3$ content, as they were not statistically significant, which was further supported by the correlation analysis (Fig. 4). The exclusion of $CaCO_3$ content aligns with previous findings reported by [27, 33, 34].

$$EF = 0.0530 \times sand \times \frac{S}{C} ratio + 0.0061 \times silt^2 - 0.0719 \times silt \times S/C\ ratio + 0.3069 \times clay \times S/C\ ratio \quad (1)$$

Equation (1) yielded a coefficient of determination (R^2) of 0.8995 ($p<0.001$) and an adjusted R^2 of 0.8940 ($p<0.001$), demonstrating strong explanatory power. To validate the model's performance, the normality of residuals was assessed using graphical methods, including a histogram, a Q-Q plot, and a residual scatter plot. Furthermore, the Shapiro-Wilk and Jarque-Bera tests were conducted at a significance level of $p<0.05$, both confirming the normality of residuals. Homoscedasticity was tested using the Breusch-Pagan test, which indicated significant heteroskedasticity ($p<0.05$).

Conclusions

This study evaluated the predictive accuracy and applicability of the [30] equation for Czech soils and aimed to improve the modeling of the wind-erodible soil fraction by developing a more robust empirical framework. The findings indicate that the [30] equation exhibits significant prediction errors when applied to Czech soils, thereby limiting its applicability across diverse pedological conditions.

To address this limitation, Equation (1) was developed, demonstrating strong predictive performance (R^2 = 0.8995; $p<0.001$; adjusted R^2 = 0.8940; $p<0.001$). The model was calibrated using a comprehensive dataset of Czech soil properties, and the analysis identified sand (r = 0.58), silt (r = -0.50), and clay (r = -0.43) contents, along with the sand-to-clay (S/C) ratio (r = 0.65), as the primary predictors of EF, whereas organic carbon (r = -0.013) and $CaCO_3$ (r = -0.10) exhibited no significant impact.

The substantial variability within this dataset, compared to those used in studies from other regions, suggests that Equation (1) demonstrates strong predictive capabilities and may be applicable to soils in different geographical contexts. However, further validation across diverse environmental conditions is necessary to confirm its broader applicability and ensure its generalizability.

This study advances wind-erodible soil fraction modeling for Central European soils by introducing a region-specific alternative and emphasizing the need for localized calibrations.

Acknowledgments

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Conflict of Interest

The authors declare no conflict of interest.

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