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Predicting the particle size distribution of eroded sediment using artificial neural networks

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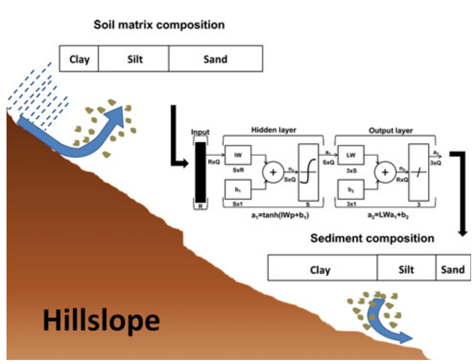
HIGHLIGHTS

- A model for predicting eroded sediment composition was developed.
- Only six input variables are required to estimate sediment composition.
- The model was build based on measured sediment data.
- Sand, silt, and clay were predicted with r^2 of 0.93, 0.95 and 0.85, respectively.
- The model can be coupled with other existing erosion and pollution routines.

GRAPHICAL ABSTRACT



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ABSTRACT

Water erosion causes soil degradation and nonpoint pollution. Pollutants are primarily transported on the surfaces of fine soil and sediment particles. Several soil loss models and empirical equations have been developed for the size distribution estimation of the sediment leaving the field, including the physically-based models and empirical equations. Usually, physically-based models require a large amount of data, sometimes exceeding the amount of available data in the modeled area. Conversely, empirical equations do not always predict the sediment composition associated with individual events and may require data that are not always available. Therefore, the objective of this study was to develop a model to predict the particle size distribution (PSD) of eroded soil. A total of 41 erosion events from 21 soils were used. These data were compiled from previous studies. Correlation and multiple regression analyses were used to identify the main variables controlling sediment PSD. These variables were the particle size distribution in the soil matrix, the antecedent soil moisture condition, soil erodibility, and hillslope geometry. With these variables, an artificial neural network was calibrated using data from 29 events ($r^2 = 0.98$, 0.97, and 0.86; for sand, silt, and clay in the sediment, respectively) and then validated and tested on 12 events ($r^2 = 0.74$, 0.85, and 0.75; for sand, silt, and clay in the sediment, respectively). The artificial neural network was compared with three empirical models. The network presented better performance in predicting sediment PSD and differentiating rain-runoff events in the same soil. In addition to the quality of the particle distribution estimates, this model requires a small number of easily obtained variables, providing a convenient routine for predicting PSD in eroded sediment in other pollutant transport models.

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1. Introduction

Water erosion is one of the major causes of soil degradation (Oldeman, 1992; Morgan, 1995; Lal, 2001; Comino et al., 2016). The consequences of water erosion include soil loss (Morgan, 1995), decline in organic matter and nutrients (Novotny and Chesters, 1989; Morgan, 1995; López et al., 2016), and transport of contaminants such as many pesticides (Foster et al., 1985; Gao et al., 1997; Selbig et al., 2013). The chemical transport capacity by sediment depends on its specific surface area (Young and Onstad, 1976; Deizman et al., 1987; Horowitz and Elrick, 1987), which in turn depends on the sediment particles size distribution. These particles are typically classified as sand, silt, clay, and aggregates (conglomerates of sand, silt and clay).

Using the USDA size classification system (Soil Survey Division Staff, 1993), diameters for sand are between 0.05 and 2.0 mm, between 0.002 and 0.05 mm for silt, <0.002 mm for clay, and between 0.002 and 2.0 mm for aggregates. Particles with diameters <0.02 mm are particularly crucial for chemical transport because of their large surface area. Clay particles have the largest specific surface area, between 20 $m^2\ g^{-1}$ and 800 $m^2\ g^{-1}$ depending on the type of clay (Young and Onstad, 1976; Slattery and Burt, 1997; Boonamnuayvitaya et al., 2004). Therefore, when predicting the transport of soil-absorbed contaminants, it is necessary to use sediment particle size distribution (PSD) with an accurate assessment of the clay content (Meyer et al., 1980; Foster et al., 1985).

Sediment particle size distribution can be estimated using multi-size erosion models, such as the Agricultural Non-Point Source Pollution (AGNPS) model (Young et al., 1989), the Areal Nonpoint Source Watershed Response Simulation (ANSWERS) model (Beasley et al., 1980), the Water Erosion Prediction Project (WEPP) model (Nearing et al., 1989), and the Revised Universal Soil Loss Equation version 2 (RUSLE2) model (Foster, 2008). AGNPS is a conceptual model (Merritt et al., 2003), whereas the others are physical models, but all subdivide eroded soil into five particle size classes: clay, silt, sand, small aggregates and large aggregates. ANSWERS, RUSLE2 and WEPP assume that the detached sediment particle size distribution is the same as the matrix soil, and the deposition of these particles is selective for each. Some of these models require a large amount of input data, which can exceed available data in the modeled area.

Another way to estimate sediment particle size is by using empirical equations. Frere et al. (1975) used texture information from 56 Midwest soils to develop a relationship between specific surface area and soil texture to estimate the particle size distribution of the eroded sediment. In this study, the author assumed a specific surface area for each particle size. Young and Onstad (1976) used 45 Indiana soils and 30 Minnesota soils in addition to the Frere et al. (1975) data to develop a set of equations considering organic matter content and clay mineralogy. These equations require as input the particle size distribution of the soil matrix, organic matter, and water content at −15 bar pore pressure. Young (1980) built a database of 21 soils and developed three sets of empirical equations to approximate the undispersed particle size distribution of sediment from the dispersed matrix soil depending on the sediment size distribution of the matrix soil. Deizman et al. (1987) conducted 12 field experiments with a Groseclose silt loam soil using a rainfall simulator with an intensity of 50 mm h^{-1} in three runs. The plots were divided into conventional and no-tillage systems with slope from 8.5% to 9.7%. The results of the experiments showed that the rainfall amount, slope, initial soil water content, and undispersed size distributions of the matrix soil explain the behavior of the sediment PSD. Using these variables Deizman et al. (1987) developed empirical equations to describe the undispersed and dispersed size distributions of sediment from no-till and conventional tillage methods.

Some of the empirical equations listed above only consider soil properties, so they are unable to predict sediment particle size distribution based on rainfall, runoff or size of erosion event. The assumptions used in the empirical equations and data arrangement required may limit their applicability to other soils and soil conditions.

Sediment particle size distribution is a function of soil properties, management, cover, slope, and detachment and transport processes (Gabriels and Moldenhauer, 1978; Meyer et al., 1980; Young, 1980; Foster et al., 1985; Deizman et al., 1987; Martinez-Mena et al., 1999; Kinnell, 2009; Zhang et al., 2011a; Zhang et al., 2011b; Defersha and Melesse, 2012; Carkovic et al., 2015). Many studies have been conducted to determine sediment PSD and factors affecting distributions. Gabriels and Moldenhauer (1978) conducted a series of experiments on four soils from Ames, Iowa, and two Belgian soils, A and B, using simulated rainfall of 63.5 mm h^{-1} intensity and a duration of 90 min to assess the effect of soil texture and rainfall intensity on sediment size distribution. They found that the sediment PSD had higher percentages of particles <0.05 mm when the slope was less pronounced. Meyer et al. (1980) conducted a series of field experiments on 10 soils with slopes of 8% to <1% using a simulated rainfall of 67 mm h^{-1} intensity for 1 h in order to compare sediment size distributions. They found that sediment PDS (1) did not vary significantly due to variations in the rainfall intensity and (2) was similar to the PSD of the matrix soil. Foster et al. (1985), based on the analysis of experimental data, concluded that the sediment sand content was directly related to sand in the matrix soil and inversely related to the clay content in the matrix soil. They also developed equations that describe the composition of sediment at its point of detachment.

Martinez-Mena et al. (1999) demonstrated that vegetal cover in natural plots reduces the energy available for water erosion. Similar results were obtained by Zhang et al. (2011a) conducting field experiments on a sandy loam soil under simulated rainfall with three intensities (60, 100, and 140 mm h^{-1}) for 60 min each and three cover percentages (0%, 30% and 80%) with a 15% slope to investigate the effect of rainfall intensity and vegetation cover on sediment PSD. Additionally, they found that with the same cover condition, the fine fraction in the sediment decreased significantly when the rainfall intensity increased.

Defersha and Melesse (2012) conducted laboratory experiments using simulated rainfall of 120, 70, and 55 mm h^{-1} intensity applied sequentially for 90 min with 9%, 25% and 45% slopes for three soil types that varied from clay to sandy clay loam to evaluate the effect of rainfall intensity, slope, soil types and antecedent moisture content on sediment PSD. They found that the effects of slope and rainfall intensity on PSD vary with soil types and moisture contents. Similar results were obtained by Rienzi et al. (2013), indicating that sediment PSD depends on the antecedent moisture content.

Many studies have been developed to identify and understand the factors controlling PSD. Most models developed in these studies use data from soil, slope, management, climate, cover, and irrigation/rainfall to estimate PSD. This information is not always available at the site of interest, precluding the use of these models in many applications. In contrast, the empirical equations assume very specific conditions in the matrix soil, and require that the PSD of the matrix soil is expressed as aggregate. Other tools such as artificial neural networks (ANNs) have been used to predict soil properties and soil related process (Tamari et al., 1996; Koekkoek and Booltink, 1999; Wösten et al., 2001; Licznar and Nearing, 2003; Merdun et al., 2006; Baker and Ellison, 2008). ANNs have several advantages, such as the ability to detect complex nonlinear relationships between dependent and independent variables, as its range of choices of structures of interconnections among components (Wösten et al., 2001). ANNs have a complex formula in the relationship between inputs and output values (Maren et al., 1990) and can be used similar to a regression formula (Wösten et al., 2001).

The goal of this study is to provide an empirical and more comprehensive equation for predicting sediment PSD by using simple and typically measured soil properties. With this purpose, a sediment and soil database was compiled based on existing studies, and correlation and multiple regression analyses were used to identify the main variables controlling sediment PSD. With these variables, an artificial neural network was built to estimate the sand, silt, and clay in the eroded sediment. The effectiveness of the model was evaluated using the constructed database and compared with existing empirical equations.