

Estimation of Furrow Irrigation Sediment Loss Using an Artificial Neural Network

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Abstract: The area irrigated by furrow irrigation in the United States has been steadily decreasing but still represents about 20% of the total irrigated area in the United States. Furrow irrigation sediment loss is a major water quality issue, and a method for estimating sediment loss is needed to quantify the environmental effects and estimate effectiveness and economic value of conservation practices. Artificial neural network (NN) modeling was applied to furrow irrigation to predict sediment loss as a function of hydraulic and soil conditions. A data set consisting of 1,926 furrow evaluations, spanning three continents and a wide range of hydraulic and soil conditions, was used to train and test a multilayer perceptron feed forward NN model. The final NN model consisted of 16 inputs, 19 hidden nodes in a single hidden layer, and 1 output node. Model efficiency (ME) of the NN model was ME = 0.66 for the training data set and ME = 0.80 for the test data set. The prediction performance for the complete data set of 1,926 furrow evaluations was ME = 0.70 with an absolute sediment loss prediction error of less than ± 5 , ± 10 , ± 20 , and ± 30 kg per furrow for 35, 53, 72, and 85% of the data set values, respectively. The NN model is applicable to predicting sediment loss rates between 1 and 300 kg per furrow for furrow lengths between 30 and 400 m, slopes between 0.1 and 4%, flow rates between 5 and 75 L min⁻¹, and silt or sand particle-sized fractions between 0.1 and 0.75. DOI: 10.1061/(ASCE)IR.1943-4774.0000932. © 2015 American Society of Civil Engineers.

Introduction

The area irrigated by furrow irrigation in the United States has been steadily decreasing but still represents about 20% of the total irrigated area or 4,400,000 ha (USDA NASS 2009). In furrow irrigation, water is introduced into small, equally spaced, human-made channels at the upslope end of a field and allowed to flow downslope and infiltrate, storing water in the root zone for crop growth. Water flow rate must be sufficient to ensure water advances to the end of the field in a reasonable amount of time to allow sufficient time for water to infiltrate along the full length of the field. Water in excess of infiltration flows off the field and often enters nearby water bodies. As water flows in furrows it detaches soil particles which are transported downslope. Furrow flow rate decreases

downslope due to infiltration such that suspended soil particles can no longer be transported and are deposited in the furrow. Water leaving the field carries sediment along with absorbed chemicals which degrades the quality of receiving water bodies. Soil loss from furrow irrigation often exceeds 2–11 Mg ha⁻¹ (Koluvec et al. 1993) and rates of up to 100 Mg ha⁻¹ have been measured in experimental studies (Berg and Carter 1980; Evans et al. 1995; Trout 1996; Fernández-Gómez et al. 2004). Crop yield reductions up to 25% have been documented at furrow inflow ends of fields due to soil loss from 80 years of furrow irrigation erosion (Berg and Carter 1980; Carter et al. 1985; Carter 1993). Furrow irrigation sediment loss is a major water quality issue, and a method for estimating sediment loss is needed to quantify the environmental effects and estimate effectiveness and economic value of conservation practices.

Acquiring field data for developing process-based furrow erosion models is challenging (Mateos and Giraldez 2005). Physical models used to predict furrow erosion are based on predominantly empirical equations used to model rainfall-induced rill erosion (Bjorneberg et al. 2000). The conditions used during experimental development of governing equations limit use of the equations to field conditions similar to experimental conditions. The physical conditions used to define the functional relationships of rill erosion under rainfall runoff differ from furrow irrigation in several aspects (Bjorneberg et al. 2000). For example, water initially flows on dry soil during furrow irrigation, but rainfall wets the soil before water begins to flow in rills. Instantaneous wetting of soil aggregates replaces air absorbed on internal soil particle surfaces which can actually break apart soil aggregates (Carter 1990), increasing soil erodibility. This is a possible reason why furrow erosion often occurs with less than critical hydraulic shear (Kemper et al. 1985). Relatively clean water is introduced into furrows while sediment-laden water enters rills under rainfall erosion. Furrow flow rate decreases with distance, which is not typically the case for rainfall runoff. Flow in furrows usually lasts 12–24 h, considerably longer than a rainfall-runoff event. Initially, sediment detachment during

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furrow irrigation may be similar to rill erosion, but after several hours head cuts and side cuts become important mechanisms for sediment detachment (Bjorneberg et al. 2000) which are not considered in rainfall-induced rill erosion.

Trout and Neibling (1993) provided a review of erosion and sedimentation processes in furrow irrigation along with field study results. They found that the processes of detachment, transport, and deposition occurring in furrow irrigation are not adequately quantified by rill erosion equations based on hydraulic shear. Nearing et al. (1991) investigated particle detachment in rills at low slopes (0–2%) and shear stresses (0.5–2 Pa) and found that detachment rate was not a function of shear stress nor was it related to the existence of a critical shear. They found that the logarithm of detachment rate was well correlated with flow depth, slope, and soil aggregate size ($R^2 = 0.94$). While rill erosion-based equations do not adequately predict erosion for furrow irrigation, they do provide insight into the factors and important relationships (Fernández-Gómez et al. 2004). Trout and Neibling (1993) concluded that while process-based models are important for understanding furrow erosion processes, current models can predict furrow sediment loss no better than empirical models relating sediment loss to measurable hydraulic parameters such as slope, flow rate, and soil characteristics such as texture. Bjorneberg et al. (1999) evaluated furrow irrigation erosion predicted by the water erosion prediction project (WEPP) model (Nearing et al. 1989), a process-based model, and concluded that the steady-state WEPP was not applicable to furrow erosion based on field evaluations for a single soil. Baseline erodibility and critical shear values developed under rainfall-runoff conditions were higher than calibrated values for furrow irrigation. Sediment deposition based on transport capacity also did not match measured deposition in furrows. Bjorneberg et al. (2010) reviewed the current status of furrow sediment loss prediction and concluded that an empirical model may be as good as or better than a process-based model where the parameters cannot be quantified for field conditions.

Development of empirical models for predicting furrow irrigation sediment loss has been a subject of research for over half a century. Koluvek et al. (1993) noted that the first published equation for predicting furrow erosion was based on research in Utah which directly related erosion to exponential functions of furrow flow rate and slope with exponents greater than 1 (Israelson et al. 1946). Regression models have been developed to predict sediment loss with limited success (Fornstrom and Borrelli 1985; O'Donkor 1978). More recently, an empirical surface irrigation soil loss (SISL) model was developed by the Idaho Natural Resources Conservation Service (NRCS) in 1991 to estimate annual soil loss from furrow irrigated fields to assess benefits of conservation practices, such as converting from furrow to sprinkler irrigation (Bjorneberg et al. 2007). A base soil loss value is multiplied by several factors to account for variations in soil erodibility, previous crop, conservation practices, and irrigation management. SISL was based on over 200 field-years of data from southern Idaho. An evaluation of the SISL model with measured furrow irrigation erosion from two studies in Idaho and one in Washington showed that the model predicted the relative effects of conservation tillage practices of straw mulching and surge irrigation reasonably well; however, the absolute differences between measured and predicted soil loss were sometimes large. Number of irrigations per season is embedded in the base soil loss so SISL cannot be applied when irrigation application frequency varies significantly from typical southern Idaho conditions. Bjorneberg et al. (2007) also noted that the baseline soil loss was less than field measured soil loss on occasions, indicating that a different method is needed for calculating baseline soil loss.

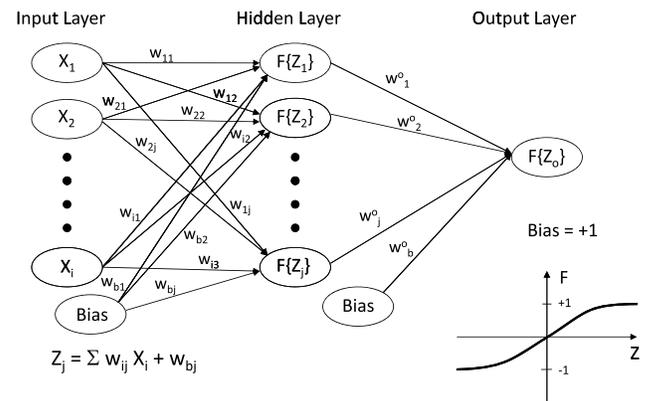


Fig. 1. Schematic structure of the feed-forward neural network used in this study

Artificial neural network (NN) models represent a collection of relatively new modeling approaches that are rapidly finding uses in branches of engineering and science. Initially developed as a means of duplicating the functioning of a biological neuron, NN modeling techniques suitable for predicting physical processes have been developed over the past 50 years. A common basic NN architecture is the multilayer perceptron feed-forward NN which consists of multiple layers of simple computing nodes (neurons) that operate as nonlinear summing devices which are interconnected between layers by weighted links (w_{ij} , Fig. 1), where numerical computation proceeds left to right without feedback to a previous layer. Input values X_i (furrow irrigation field variables, Fig. 1) and interconnection weights are used to calculate Z_j for each hidden layer neuron. Output from the neuron is calculated from the transfer (activation) function F using Z_j (Fig. 1), which becomes the input vector to the output layer where the output from the neural network is calculated in the same manner as for the hidden layer. The functionality of a neuron is to sum the product of the weights and input vectors plus a bias weight (w_{bj} , Fig. 1) and process the sum through a nonlinear transfer (activation) function. Each weight is determined when measured data are presented to the network during a training process. Successful training of a NN results in a numerical model that can perform tasks such as predicting an outcome value, classifying an object, approximating a function, or recognizing a pattern. Artificial neural networks can analyze multisource data sets and are considered to be universal classifiers or approximators (Haykin 2009).

Artificial neural networks are appropriate where the physical processes are complex, unknown, or difficult to represent mathematically. These three conditions apply in the case of furrow irrigation sediment loss. Artificial neural networks are data-driven models requiring a representative data set for training. Thus, applications where data are limited and/or subject to large variability limit the applicability and success of a NN. Soil erosion data are inherently noisy data as there are many extraneous random factors that can influence soil erosion. Rainfall-runoff erosion data commonly contains a few extreme events that add considerable variability to the data set. In furrow irrigation, gravity can cause sloughing of furrow side walls that have been weakened by wetting and/or undercut by erosion, creating a flush of sediment loss. Compacted subsurface layers such as tillage pans may stop the erosion process. Head cuts and side cuts form when, at points of localized high shear, the surface seal or a resistant soil layer is eroded away and the furrow bed elevation drops. The accelerating water at the drop

erodes a pool that undercuts the resistant layer so the head cut moves upstream, producing large amounts of sediment (Trout and Neibling 1993).

Artificial neural networks have been successfully used for many applications closely related to soil erosion such as rainfall-runoff modeling, stream flow forecasting, groundwater modeling, water quality modeling, water management, precipitation forecasting, hydrological time series, and reservoir operations (ASCE 2000). Licznar and Nearing (2003) developed a NN model to predict soil loss from 2,879 erosion events on plots located at eight sites in the eastern United States. They compared measured erosion with predicted values using the WEPP model and NN models trained using a subset of the erosion events. The NN model provided a better prediction of soil loss than the process-based WEPP model. Kim and Gilley (2008) developed and evaluated NN models for predicting soil erosion and nutrient concentrations in runoff from animal waste land application sites under simulated rainfall. Comparison of predicted versus measured values resulted in coefficient of determination values (R^2) ranging from 0.62 to 0.92. Application of NN modeling to soil erosion prediction has not been extensively studied and does not appear to have been applied to furrow irrigation.

The objective of this project was to investigate development and performance of a multilayer perceptron feed-forward NN to predict sediment loss resulting from furrow irrigation using a large data set representing a variety of soil, crop, and environmental conditions.

Materials and Methods

Furrow irrigation sediment loss data used to develop, train, validate, and test NN models to estimate sediment loss were obtained from a combination of published research reports, theses, and dissertations along with field data collected by the authors over three decades of field studies. Data sources used in this study are listed in Table 1 along with general locations where the data were collected. Collectively 2,257 furrow sediment loss values were obtained covering a wide range of soil, field, and crop conditions spanning three continents, with the majority of the data obtained from Fornstrom and Borrelli (1985) and the authors' past field studies. Nine initial independent variables were considered: freshly cultivated or previously eroded prior to irrigation; compacted by wheel traffic or noncompacted; irrigation duration (T, h); cumulative number of prior irrigations; furrow length (L, m), inflow (Q , $L \text{ min}^{-1}$), and

Table 1. Data Sources Used in This Study along with General Locations Where the Data Were Collected

Data source	General location	Number of furrows
Fornstrom and Borrelli (1985)	Worland, Powell, and Torrington, WY	745
King et al. (1984)	Royal City, WA	190
Fitzsimmons et al. (1978), O'Donkor (1978), and Allen (1977)	Parma, Notus, Nampa, and Kimberly, ID	59
Lou (1994)	Kimberly, ID	32
Tunio (1994)	Ontario, OR	108
Fernández-Gómez (1997)	Córdoba and Seville, Spain	30
Araújo (2014)	Ceará, Brazil	74
Trout (unpublished)	Patterson, CA	318
Bjorneberg and Trout (unpublished)	Kimberly, ID	872

slope (S, %); and soil sand and clay fractions (%). The collective furrow irrigation sediment loss data set represents surface irrigation-induced erosion across a wide range of hydraulic, soil, and cropping practices (Table 2). Average furrow irrigation sediment loss for the data set was 62.8 kg per furrow with a standard deviation of 133.5 kg per furrow, double the average value, which reflects the inherent variability in furrow sediment loss and the wide range of values present in the data set (0–1,879 kg per furrow). Furrow irrigation sediment loss can vary by nearly an order of magnitude (Fig. 2) between adjacent furrows in the same field with the same inflow rates, which makes sediment loss prediction challenging with any model. The data set included 890 values for compacted (wheel) furrows and 1,367 values for noncompacted (nonwheel) furrows. There were 1,075 values for freshly tilled furrows and 1,182 values for previously eroded furrows. There were 1,682 values for silt loam, 20 for sandy clay loam, 68 for clay loam, 203 for loam, and 284 for sandy loam soils.

Data from some sources were incomplete in regards to the selected variables so some were estimated based on existing data and standard cropping practices at the time. For example, the on-farm Washington data set (King et al. 1984) was the most incomplete data set used. They expressed sediment loss in kg ha^{-1} rather than kg per furrow and did not specifically include furrow spacing or irrigation duration. The data set did include Kostiaikov infiltration parameters, infiltrated depth, deep percolation, inflow rate, length, and irrigation efficiency for each furrow evaluation. Sediment loss

Table 2. Range of Hydraulic, Soil, and Cropping Practices in the Data Set Used in This Study

Variable	Mean	Standard deviation	Maximum	Minimum
Length (m)	190	111	549	20
Slope (%)	1.35	1.1	7.0	0.05
Inflow ($L \text{ min}^{-1}$)	31.0	22.6	192	3.2
Time (h)	16.3	8.3	54	0.5
Sand fraction (%)	28.9	18.7	76.8	11.1
Clay fraction (%)	18.2	7.8	48.3	1.9
Silt fraction (%)	52.9	16.9	73.7	14.8
Sediment loss (kg per furrow)	62.8	133.5	1,879	0.0

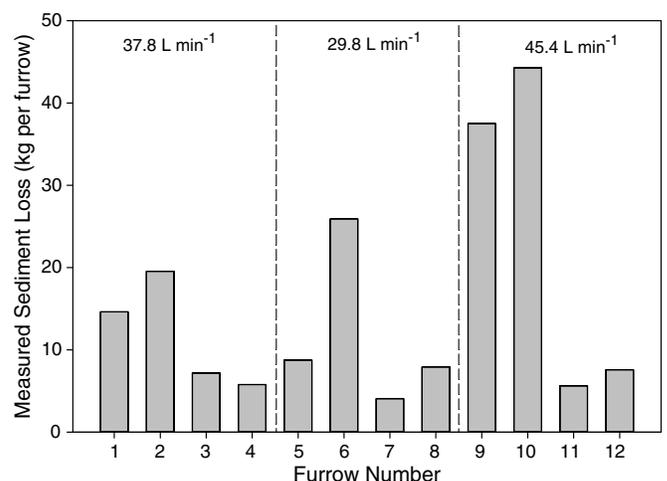


Fig. 2. Furrow irrigation sediment loss measured by Fornstrom and Borrelli (1985) from a block of 12 noncompacted previously eroded furrows irrigated at the same time with three different flow rates

per furrow was estimated for an assumed furrow spacing of 76 cm. Irrigation duration was estimated by volume balance using estimated furrow spacing and given inflow rate, infiltrated depth, and irrigation efficiency provided in the report. The resulting irrigation durations were near multiples of 12 h, usually 24 h, which was described as common irrigation times on commercial farms in the study area, indicating realistic estimates of unknown parameters. Recently tilled furrows have a higher infiltration rate than furrows previously irrigated and eroded, affecting advance times and sediment loss. For the Washington data set, Kostiakov infiltration values for each furrow were used to estimate if the furrow was recently tilled or previously eroded prior to an irrigation event. In other cases, advance time was used to estimate if the furrow was recently tilled or previously irrigated and eroded. The cumulative number of prior irrigation events during the season was estimated when necessary based on estimated planting date and date of the irrigation event. For data sets where wheel traffic furrows were not specified, the data were assumed to be from noncompacted furrows. When not specified in published reports, soil texture was estimated based on study location using USDA soil survey data. Uncertainty added by estimating missing data was considered minimal and less important than securing a data set that represented a wide range of conditions across a diverse geographic area. The primary disadvantage of estimating unknown values is degradation of prediction performance of derived models due to addition of errors in the data set.

Neural network development software *NeuroIntelligence* was used to develop, train, and evaluate NN models. 68% of the data set was used for training, 16% for validation, and 16% for testing. Furrow data records were assigned to the training and testing data sets randomly. Continuous input variables were linearly scaled to a range of -1 to 1 using the maximum and minimum values of measured variables in the composite data set (Table 2), which is a normal procedure for NN modeling to prevent large numbers from suppressing smaller values and premature saturation of hidden neurons impeding the learning algorithm (Kim and Gilley 2008). Binary data values (compacted and cultivated) were assigned -1 for false and $+1$ for true. A multilayer perceptron feed-forward NN architecture was used to estimate furrow irrigation sediment loss. Hidden layer neurons used a hyperbolic tangent activation function and the single output neuron used a logistic activation function. Neural network architectures having only one hidden layer with up to 30 neurons were evaluated. The quasi-Newton method with minimization of sum of square error (Haykin 2009) was used to train the network using the training data set. The best NN architecture (number of hidden layer neurons, input parameters) was selected based on maximizing model efficiency (ME) (Nash and Sutcliffe 1970), while using a minimum number of neurons to reduce risk of overtraining the NN to the data. Model efficiency, which is commonly used for hydrologic model evaluation (Moriasi et al. 2007), is defined as

$$ME = 1 - \frac{\sum (y_i - y_{\text{pred}})^2}{\sum (y_i - y_{\text{ave}})^2} \quad (1)$$

where y_i = i th data value; y_{pred} = model predicted value for y_i ; and y_{ave} = mean of the data values. Model efficiency is similar to the correlation coefficient associated with linear regression in that its value ranges from $-\infty$ to 1 . A value of 1 means the model is a perfect fit to the data, but a negative ME value signifies that the data mean is a better estimate of the data than the model.

The dependent variable, furrow sediment loss, was logarithmic transformed prior to linear scaling to eliminate the prediction of negative sediment loss (Kim and Gilley 2008). In addition to the nine independent input variables, three functional relationships

were individually evaluated as a possible additional input variable to improve neural network prediction performance. The functional relationships evaluated were $Q^{1.5}$, QSL^{-1} , and QTL^{-1} . Trial and error searching was used to determine the best combination of input parameters and number of hidden layer neurons.

Results and Discussion

Neural network models developed using the nine initial input parameters resulted in good ME values (~ 0.6) for logarithm transformed furrow sediment loss, but when back-transformed the resulting ME values were typically less than 0.4 . Neural network models developed without logarithm transformation of furrow sediment loss also resulted in ME values typically less than 0.4 , indicating there was no advantage in logarithm transformation of furrow sediment loss. The use of functional relationships $Q^{1.5}$, QSL^{-1} , and QTL^{-1} as input parameters also did not materially improve prediction performance of NN models. Consequently, logarithm transformation of furrow sediment loss and the functional relationships were abandoned in further development of furrow sediment loss NN models. The large range in measured furrow sediment loss (0.0 – $1,879$ kg per furrow), along with an associated high degree of variability in sediment loss among furrows during the same irrigation (Fig. 2), appeared to limit prediction performance of the NN models.

The potential application of a furrow irrigation sediment loss prediction model is estimating sediment loss reduction from a change in furrow irrigation management practice or more likely conversion from furrow irrigation to sprinkler irrigation or micro-irrigation. In practice, furrow irrigation sediment loss less than 5 kg per furrow per irrigation is uncommon, with the exception of late season irrigations, close growing crops, and sandy soils. Sediment loss greater than 300 kg per furrow per irrigation is excessive and certainly not sustainable due to the negative effects on agricultural production practice and environmental impact on runoff receiving water bodies. Therefore the furrow irrigation sediment loss data set was filtered to include only records with sediment loss in the range of 1 – 300 kg per furrow in an attempt to improve NN model prediction performance. Filtering the sediment loss data set eliminated 331 data records with about $2/3$ being < 1 kg per furrow and $1/3$ being > 300 kg per furrow and had a minor effect on the cumulative distribution of furrow irrigation sediment loss values (Fig. 3) for < 300 kg per furrow sediment loss. Prediction performance of NN models developed using the filtered data set increased ME to 0.55 .

Comparison of NN predicted furrow irrigation sediment loss with measured sediment loss revealed that the number of prior irrigations had minimal influence on predicted sediment loss even though an effect was apparent in the data set. The architecture of the NN model was modified to consider the number of prior irrigations as a categorical rather than a continuous variable. Examination of the number of records for each irrigation event revealed that there were few data values for prior irrigations greater than eight. Consequently, irrigation number values greater than eight were grouped together as a single category (eight). Irrigation number was represented in the revised NN model architecture as a one-of- N categorical value. Thus, eight inputs were added to the NN model, where irrigation number one through eight were separate inputs, with each assigned either a -1 if false or $+1$ if true depending upon irrigation number of the data value. This increased the number of variables in the input layer to 16 . Prediction performance of the modified NN model resulted in $ME > 0.65$. Substituting silt fraction for clay fraction as an input variable along with multiple sequential training

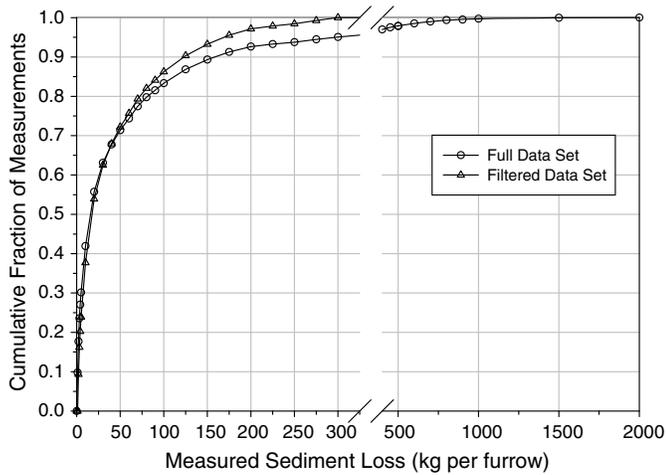


Fig. 3. Cumulative distribution of furrow irrigation sediment loss values for the filtered data set used to develop NN models to predict furrow sediment loss compared to the full data set

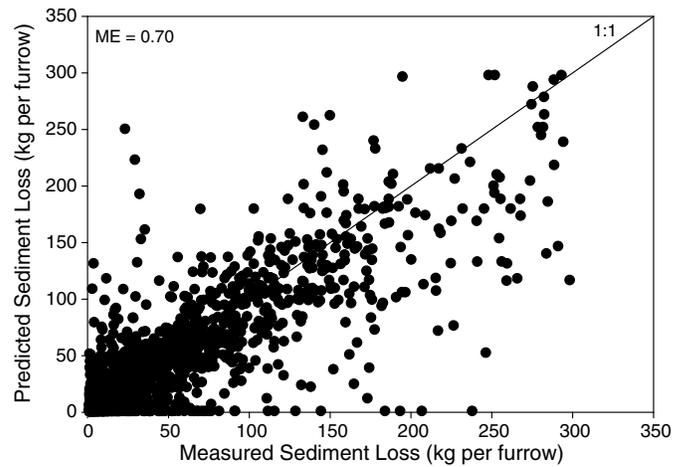


Fig. 5. Furrow irrigation sediment loss neural network model prediction performance for the combined filtered training, validation, and testing data sets

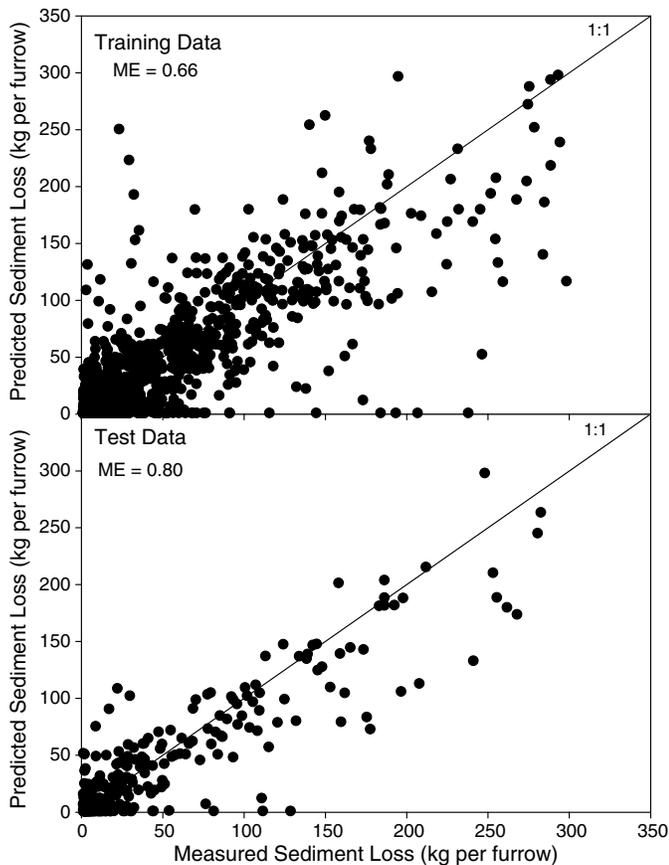


Fig. 4. Furrow irrigation sediment loss neural network model prediction performance on the training and test data sets

sessions increased prediction performance to $ME \sim 0.70$, which likely represents about the best prediction performance that can be expected due to variability in furrow irrigation sediment loss field measurements in diverse regions not captured by the input variables. Additional improvements in NN model prediction performance were not pursued as they were deemed to be incremental at best using the chosen NN architecture.

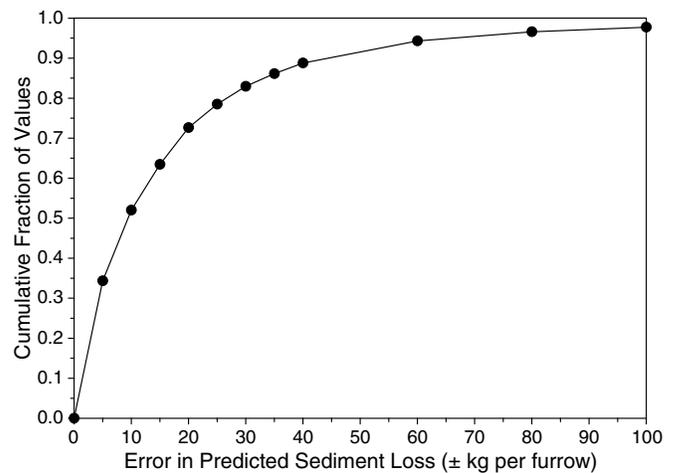


Fig. 6. Cumulative probability distribution of absolute prediction error in neural network model estimated sediment loss

The final NN model architecture for predicting furrow irrigation sediment loss consisted of 16 input nodes, a single hidden layer with 19 nodes, and 1 output layer node, conventionally denoted as 16-19-1. Prediction performance of the NN model for the filtered training data set was $ME = 0.66$ and $ME = 0.80$ (Fig. 4) for the testing data set. The prediction performance of the NN model for the complete filtered data set (training, testing, validation combined) was $ME = 0.70$ ($R^2 = 0.71$) (Fig. 5). Visually, there appeared to be a slight tendency for the NN model to underpredict furrow irrigation sediment loss, especially for high sediment loss conditions. There were several instances with measured sediment loss for which the NN model predicted zero sediment loss, indicating the furrow erosion processes were not fully represented. These uncaptured processes could include sloughing of furrow sidewalls or presence of head cutting that can contribute substantial amounts of sediment. These high sediment loss events are difficult to predict by any model. Absolute furrow sediment loss prediction of the NN model was ± 5 , ± 10 , ± 20 , and ± 30 kg per furrow for 35, 53, 72, and 85% of the combined filtered data set values, respectively (Fig. 6).

The furrow irrigation sediment loss NN model with 16 inputs, 19 hidden nodes, and 1 output node consists of 20 linear equations with a total of 343 coefficients and 20 nonlinear activation functions to evaluate. Solution of the NN model is impractical for a handheld calculator but could easily be coded into a standalone

program or a procedure added to a hydrological or geographical information system model.

The performance of the NN furrow irrigation sediment loss model surpassed results obtained in other studies using much smaller data sets. For example, Fornstrom and Borrelli (1985) obtained an

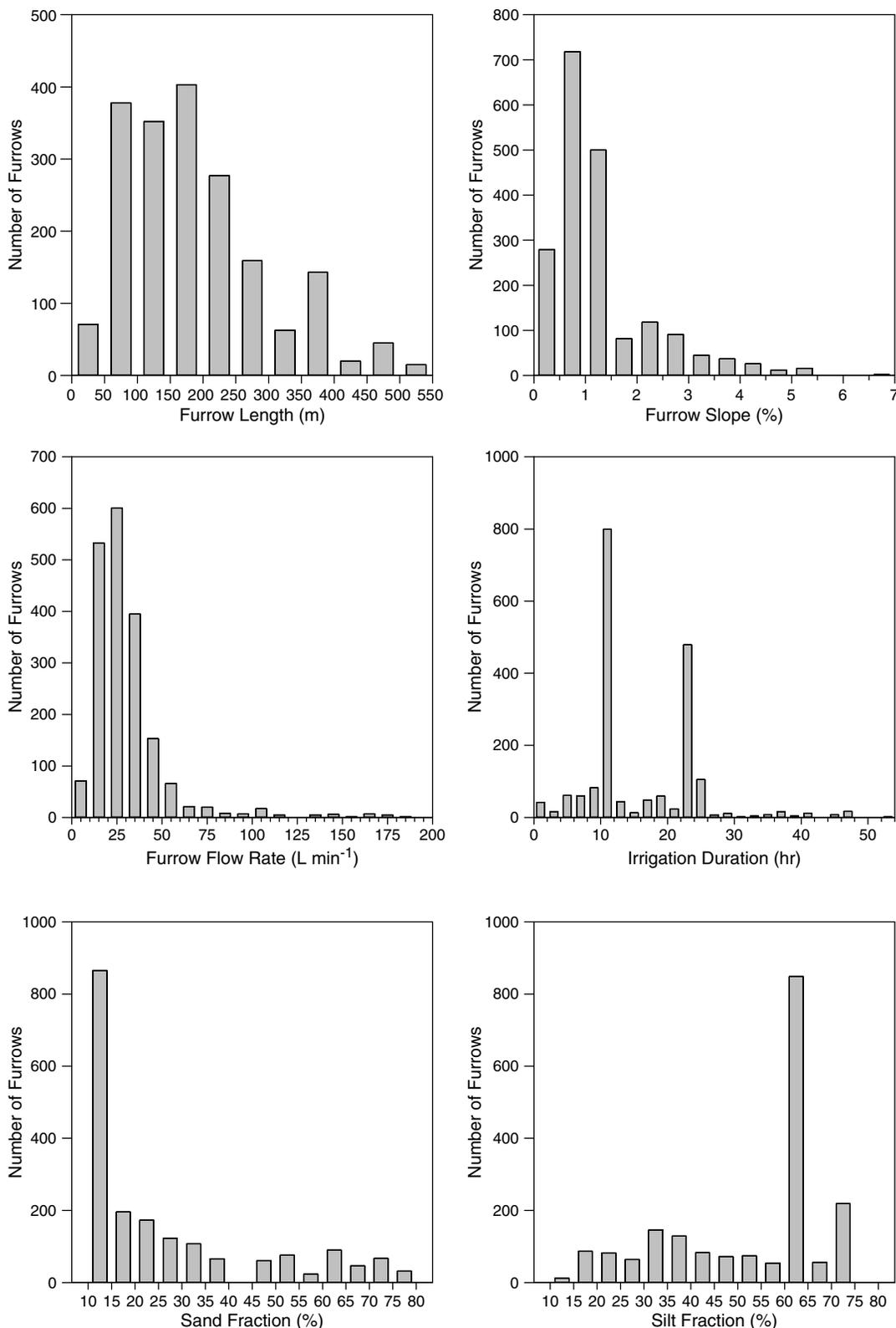


Fig. 7. Histograms of continuous input variables used to develop the neural network model

$R^2 = 0.37$ for predicting seasonal furrow sediment loss using exponential regression on all furrows in their Wyoming study. They obtained R^2 values as great as 0.62 using subsets of the data such as tilled noncompacted furrows. O'Donkor (1978) used multiple linear regressions to predict seasonal sediment loss with an $R^2 > 0.9$ based on a single year's data from 60 furrows on medium textured soils in Idaho. Regression results, however, were not consistent across years or locations, limiting the ability of these regression relationships to predict sediment loss for fields that were not measured in the study. Predicted annual soil loss from the SISL model correlated relatively well with measured soil loss ($R^2 = 0.73$, $ME = 0.62$) for 30 measurements from three different studies (Bjorneberg et al. 2007). These results, however, were skewed by a few high soil loss values from one study and without these high values, $R^2 = 0.40$ and $ME = 0.37$.

The NN furrow sediment loss model is an empirical model and as such will not provide useful estimates of sediment loss for conditions beyond the numerical limits of the data base used to develop the model. Histograms of the continuous variables in the data base used to develop the model (Fig. 7) provide some guidance in regards to practical input value limits that can be used in the NN model to obtain reliable estimates of sediment loss. The largest number of the furrow observations was for furrow lengths less than 300 m (Fig. 7). The limited number of furrow observations with furrow lengths greater 300 m limits training of the NN model to the point that sediment loss predictions for furrow lengths greater than 400 m are likely subject to considerable error. Only about 25% of the furrow observations were for furrow slopes greater than 1.5% with very few observations for furrow slopes greater than 4% (Fig. 7). The limited number of furrow observations for furrow slopes greater than 1.5% resulted in very limited NN training for greater furrow slopes. Approximately 98% of the furrow observations were for flow rates less than 50 L min^{-1} , resulting in very limited NN training for higher furrow flow rates. Irrigation durations on commercial farms are commonly a multiple of 12 h for convenience with longer set times used on longer furrow lengths. There were relatively few furrow observations in the data set with irrigation durations exceeding 24 h (Fig. 7), which further limited training of the NN model for longer irrigation durations. Nearly 50% of the furrow observations were for silt particle size fractions between 65 and 70% (Fig. 7) despite having soil fractions spanning a large range. Similarly, nearly 50% of the furrow observations were for sand particle size fractions between 10 and 15%. From a practical application viewpoint, furrow irrigation sediment loss predictions of the NN model are probably limited to furrow lengths between 30 and 400 m, slopes between 0.1 and 4%, flow rates between 5 and 75 L min^{-1} , and silt or sand particle-sized fractions between 0.1 and 0.75.

In addition to limits on input values based on the data set used for the NN model development, combinations of inputs that are not feasible in the physical world will result in a numerical output from the NN model due to its empirical nature. Input combinations such as a flow rate that will not advance to the end of the field can be input into the NN model and a value for sediment loss will be returned. While limits on input values can be easily imposed in computer code, infeasible combinations of inputs are much more difficult to screen. Inputs to the NN model should be checked for feasibility using a surface irrigation simulation model or be from field data of on-farm irrigation practices.

Conclusions

Artificial neural network modeling was applied to furrow irrigation to predict sediment loss as a function of hydraulic and soil conditions. A data set consisting of 1,926 furrow evaluations, spanning

three continents and a wide range of hydraulic and soil conditions, was used to train and test a multilayer perceptron feed-forward NN model. The final NN model consisted of 16 inputs, 19 hidden nodes in a single hidden layer, and 1 output node. Prediction performance of the NN model for the training data set was $ME = 0.66$ and $ME = 0.80$ for the testing data set. The prediction performance for the complete data set of 1,926 furrow evaluations was $ME = 0.70$ with an absolute sediment loss prediction error of ± 5 , ± 10 , ± 20 , and $\pm 30 \text{ kg per furrow}$ for 35, 53, 72, and 85% of the data set values, respectively. Sediment loss prediction performance of the NN model surpassed the performance of previous sediment loss prediction models, either physical or empirical, for a much larger data set covering a wide range of hydraulic and soil conditions and geographic locations. The resulting furrow irrigation sediment loss prediction model is suitable for inclusion as a component of a water quality model.

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