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Earth Surface Dynamics Discussions

# Development of a machine learning model for river bedload

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**Abstract.** Prediction of bedload sediment transport rates in rivers is a notoriously challenging problem due to inherent variability in river hydraulics and channel morphology. Machine learning offers a compelling approach to leverage the growing wealth of bedload transport observations towards the development of a data driven predictive model. We present an artificial neural network (ANN) model for predicting bedload transport rates informed by 8,117 measurements from 134 rivers. Inputs to the model were river discharge, flow width, bed slope, and four bed surface sediment sizes. A sensitivity analysis showed that all inputs to the ANN model contributed to a reasonable estimate of bedload flux. At individual sites, the ANN model was able to reproduce observed sediment rating curves with a variety of shapes and outperformed four standard bedload models. This ANN model has the potential to be broadly applied to predict bedload fluxes based on discharge and reach properties alone.

## 1 Introduction

Sediment transport in rivers is a stochastic (Ancey, 2010; Paintal, 1971), nonlinear (Meyer-Peter & Müller, 1948; Wong & Parker, 2006), phenomenon with high dimensionality (Goldstein et al., 2019). Thus, predicting rates of bedload sediment transport has been a persistent challenge, with predictions within an order of magnitude of direct measurements generally considered reasonable model performance (Recking, 2013a; Recking et al., 2012). Models of fluvial sediment transport have been developed based on semi-empirical regressions fit to flume (Meyer-Peter & Müller, 1948; Wong & Parker, 2006) and field (Recking, 2010, 2013b; Rickenmann, 1991) data, probabilistic approaches (Einstein, 1950; Furbish et al., 2012), and physics-based models (Lajeunesse et al., 2010; G Parker, 1990; Wilcock & Crowe, 2003). Multi-model comparisons demonstrate that few models consistently perform well for large, multi-region datasets in part due to limitations in addressing site specific variability or due to temporal and spatial averaging (Barry et al., 2008; Gomez & Church, 1989; Recking, 2010, 2013a). As such, existing bedload flux models are not versatile enough to be applied across the range of observed river reaches without extensive calibration (Goldstein et al., 2019; Kitsikoudis et al., 2015).

The complexity of natural river processes across sites combined with the amount of bedload data in aggregate (Hinton et al., 2017; King et al., 2004; Recking, 2019) suggests that this process may be understood from a data science approach (Geron, 2019). Machine learning (ML) approaches leverage available data to train computers to, through an automated process, determine the relative contribution of individual input variables to a measured output (Geron, 2019). In the learning process, the ML algorithm iteratively discovers patterns and relations within the data and uses them for future predictions given similar input data. Many ML approaches do not consider the physics behind any specified problem directly, but excel at predicting problems with high dimensional nonlinearity given sufficient training data. ML approaches can leverage variability aggregated from many existing datasets in order to improve site-specific bedload transport predictions across a range of fluvial environments. ML approaches have been previously exploited in a variety of geoscience problems including identifying vulnerability in Antarctica's ice sheet (Lai et al., 2020), global-scale soil salinization predictions (Hassani et al., 2021), and landslide susceptibility mapping (Zhou et al., 2021). Artificial neural networks (ANN) may be particularly well-suited for bedload prediction. The ability of ANN to parse nonlinear relations makes it a flexible tool for solving a wide range of problems, including optimization (Haykin, 2001), data classification (Saravanan & Sasithra, 2014), and flood prediction (Hosseiny et al., 2020).

Despite significant improvement in data availability, the application of ML tools to sediment transport in rivers has, to our knowledge, been fairly limited. Kitsikoudis et al. (2015) used sediment concentration data from flume and field studies, for sand (median grain size, $D_{50}$ = 0.062 mm-2.0 mm) bed rivers (Brownlie, 1981), to evaluate the performance of ML approaches: (a) ANN, (b) symbolic regression (SR), and (c) adaptive-network-based fuzzy inference (ANFIS) models. Their results show that models trained solely on flume data perform worse than those trained on field data with root mean squared errors (RMSE) of flume-trained predictions between 85% to 97% more than field-trained models. This study also found that the ANN model trained on field data performed best, with RMSE values 7.5% and 11.1% less than ANFIS and SR, respectively. Bhattacharya (2007) used an ANN approach using the Gomez and Church (1989) sediment flux database for sand and gravel ($D_{50}$ = 0.062 mm-64 mm) bed rivers in subcritical flow to predict bedload and total load transport rates as a function of velocity, depth, particle diameter, slope, non-dimensional shear stress, critical shear stress, and stream power. They concluded that the RMSE of the model trained based on field data was on average 33.6% less than the ones obtained from flume data. When compared with previous empirical and physically based models, the RMSE of the ANN model was less by 16.4% to 249.6% based on 407 observations (Bhattacharya, 2007).

While previous studies have demonstrated that ML models appear to improve upon more deterministic sediment transport models, existing ML models have been trained with limited data (less than 500 observations). Despite the increasing availability of bedload datasets, the application of ML in generating a versatile, data-driven model for predicting bedload transport across a wide range of fluvial settings has not been investigated. To fill this gap, this paper develops a new ML model for predicting river bedload. The performance of the proposed model is compared with four existing sediment transport models (Einstein, 1950; Recking, 2013b; Wilcock & Crowe, 2003; Wong & Parker, 2006). The ML model developed here can be implemented over a wide range of commonly measured input variables.

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## 2 Materials and Methods

### 2.1 Data summary and preparation

Data to train the ML model developed here was downloaded from BedloadWeb (http://en.bedloadweb.com), a public online platform that hosts both previously published field and laboratory bedload datasets compiled from the scientific literature or official reports and databases (Recking, 2019). Our study focused only on field-collected datasets, as these cover a greater range of variability in terms of the key variables associated with bedload transport (e.g. discharge, grain size, slope). The database includes10,056 individual measurements of bedload transport from more than 134 unique field sites across the globe. Each reported bedload transport data point, $q_s$ (g/s/m), in our study has an associated measurement of river discharge, $Q$ (m$^3$/s), bed slope, $S$ (m/m), flow width, $W$ (m), and the 16$^{th}$, 50$^{th}$, 84$^{th}$, and 90$^{th}$ percentiles of the bed surface grain size distribution ($D_{16}$, $D_{50}$, $D_{84}$, $D_{90}$). Within this database, slope and grain size are largely static variables for each site describing the river reach, while flow width and discharge are dynamic and vary in time at each site. In the initial application of the ML model, all of these variables are used as input parameters to train the model and predict $q_s$, as we expect an ML model informed by all available parameters (knowledge) will have the strongest predictive power (Haykin, 2008).

Prior to model training, data were inspected for overall quality and outliers were removed. The presence of extreme values and outliers generally degrades the overall performance of the resulting model (Geron, 2019). As such, we chose to first remove transport measurements with associated discharge values exceeding the 95$^{th}$ percentile (Dovoedo & Chakraborti, 2013; Kennedy et al., 1992) of all reported discharges ($Q$ > 430 m$^3$/s; a total of 504 points), followed by removing extreme $q_s$ values including those above the 95$^{th}$ percentile of the remaining data ($q_s$ > 401.4 g/s/m; 478 datapoints) as well as those below the 10$^{th}$ percentile (Kennedy et al., 1992) of remaining data ($q_s$ < 0.1 g/s/m; 957 datapoints). Following removal of these points, the total sample number was reduced from 10,056 to 8,117 measurements across 134 rivers. Data were then log-transformed (base 10) such that each parameter distribution would more closely follow a normal distribution (see Supporting Information). Data were then scaled by minimum and maximum measurement values, such that the transformed range of values for each variable ranged from 0 to 1 (Geron, 2019; Haykin, 2008). Data were shuffled and randomly divided into two populations: a training population (80%) and a test population (20%) with equivalent distributions consistent with the full dataset.

### 2.2 Machine learning structure and implementation

Following previous applications of ML to sediment transport (e.g. (Bhattacharya et al., 2007; Goldstein et al., 2019; Kitsikoudis et al., 2015), we employ an artificial neural network (ANN) approach. The ANN framework is based on a network of connected units (neurons), most commonly comprised of single input and output layers, multiple hidden layers, where each layer contains a set of neurons (Geron, 2019; Haykin, 2008) (Fig. 1a).

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The ANN presented here was developed using Keras (Chollet & others, 2015), an Application Programming Interface in the Python programming language. The structure of the ANN was informed by available bedload transport data and associated measurements of discharge, channel morphology (slope and width), and grain size (4 measurements). The input and output layers of the ANN were set to seven ($Q$, $S$, $W$, $D_{16}$, $D_{50}$, $D_{84}$, $D_{95}$) and one ($q_s$), respectively. The functions that guide the model in identifying nonlinear relations (activations functions), were set to the Rectified Linear Unit (ReLU), except one function associated with the output layer, which was set to be sigmoid function. The ReLU($x$) returns the maximum of (0, $x$) and sigmoid($x$) returns 1/(1+exp(-$x$)). To avoid overfitting in the training process, each input segment was normalized (batch normalization) and a subset of the neurons in each layer were temporarily ignored (dropout) to add additional noise to data (Geron, 2019).

The training process of the ANN model uses 80% of the bedload transport data to determine the weight coefficients of the neurons' connections that minimize prediction error. The validation of the ML model in each iteration (epoch) is usually carried out by a random subset of the training dataset that was not used in that epoch. For this application, 10% of the training dataset was used within the epoch model validation step.

### 2.3 Comparison of ANN performance with previous bedload models

We selected four bedload transport models with varying approaches and degrees of complexity to compare to and build intuition for the predictions of the ANN model. We selected: (1) a probabilistic model developed by Einstein (1950), (2) a physics-based model developed by Wilcock-Crowe (2003), and (3, 4) two empirical models from Wong-Parker (2006) and Recking (2013).

We compared bedload flux measurements to predictions from these four bedload transport models and the trained ANN model (Fig. 2). All predictions were made using the 20% of data excluded from the ANN training process (test data, $n$ = 1,624). The ANN model utilizes all available data from the bedload database (7 inputs), while the bedload transport models have varying degrees of complexity, ranging from requiring 4 input parameters (Einstein, 1950; Wong & Parker, 2006) to 5 input parameters (Wilcock & Crowe, 2003) (see Table S3). Selected previous models are valid for sand and gravel bed rivers, and therefore, the comparison is restricted to these rivers.

#### 2.3.1. Einstein (1950)

The Einstein model (1950) assumes that bedload flux is related to the probability of a particle being eroded as a function of changes in turbulent intensity, rather than the average fluid forces acting on the particle. As such, the model relates the probability of erosion (as a function of flow intensity) to the intensity of bedload transport (Eq. 1). This method does not require a critical shear stress for incipient motion since the movement of the grain is based on probabilistic estimates. The

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Einstein equation tends to perform well for estimating local bedload in large rivers with uniform sand and gravel (Garcia, 2007). The implicit form of the Einstein equation is described as

$$1 - \frac{1}{\sqrt{\pi}} \int_{-(0.413/\tau^*)-2}^{(0.413/\tau^*)-2} e^{-t^2}\, dt \;=\; \frac{43.5\, q^*}{1+ 43.5\, q^*} \qquad (1)$$

where $\tau^*$ is the dimensionless shear stress for uniform flow (Shields stress), $t$ is the integral parameter, and $q^*$ is the dimensionless bedload transport rate (or Einstein bedload number).

#### 2.3.2. Wong and –Parker (2006)

Wong and Parker (2006) reanalysed the data used to develop the foundational Meyer-Peter and Muller (MPM) equation (Meyer-Peter & Müller, 1948) and found a better fit to data resulting in the following equation:

$$q^* = 3.97(\tau^* - 0.0495)^{3/2} \qquad (2)$$

where the exponent is fixed at 3/2. The MPM equation is similar in form, but tends to overpredict bedload at higher discharges (Barry et al., 2004). Experimentally, bedload flux is well-described by Eq. 5 and similar models employ excess shear stress raised to a 3/2 power (see Lajeunesse et al., 2010), however application within different rivers typically requires that both the coefficient and threshold shear stress be treated as fitting parameters (Mueller et al., 2005; Phillips & Jerolmack, 2019). Here, for the sake of comparison, we have applied this equation using fixed coefficient and thresholds shown in Eq. 5 as it was not possible to estimate these parameters at each site in the database.

#### 2.3.3. Wilcock and Crowe (2003)

Wilcock and Crowe (2003) presented a sophisticated transport model for mixed gravel and sand, based on 48 laboratory experiments with five different sediments sizes. The fractional transport discharge in this model is estimated based on a reference parameter informed by the sediment distribution of the bed surface. This model represents a major advance by incorporating the non-linear effects of sand content on the mobility of gravel and the overall transport rate (Wilcock & Crowe, 2003). We applied this model to the available testing dataset by estimating sand fractions from sediment grain size data, followed by estimating reference shear stress for the geometric mean grain size. More information about this method and the steps undertaken in this study is presented in the supporting document (Text S1).

#### 2.3.4. Recking (2013)

The Recking (2013b) model is a single continuous function from two equations previously developed in Recking (2010). The model can be used for sand and gravel mixtures and was developed based on 6,319 field observations and 1,317 flume measurements (Recking, 2010). The model considers sediment mobility based on $D_{84}$, as this size was observed to impact bed material mobility, flow resistance, hiding, surface armoring, and bed shear stress (Recking, 2013). The critical mobility parameter is set to a constant for sand, and as a function of the ratio of $D_{84}/D_{50}$ and the river slope, $S$.

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## 3 Results

### 3.1 Model training

We found that five hidden layers, each with 600 neurons, could adequately reflect dataset measurements with minimum error (Fig. 1a). The fine-tuning of the ANN model showed that the optimum model had a batch size of 1200, a learning rate of 0.6, a dropout rate of 0.1, incorporated the mean squared error (MSE) as a loss function, and an 'Adadelta' optimizer for minimizing the error in the training process (Chollet & others, 2015; Geron, 2019). The training process began with initial training and validation losses of MSE = 0.098 and MSE = 0.056 (Fig. 1b), and final values of MSE = 0.012 and MSE = 0.013 after 600 iterations (epochs). Minimal improvements in error occurred between 300 and 600 epochs, indicating that the ANN model had captured the relationships between the inputs and output adequately, and further iteration would not improve performance. The ANN model performed similarly on the validation dataset (Fig. 1b), which reveals that overfitting is not an issue since the difference between training and validation errors is relatively constant and minimal (Geron, 2019; Haykin, 2008).

### 3.2 Model performance against observations

Following model training, the model with the weighting coefficients determined during training was applied to the remaining 20% of the dataset (test data) to independently predict bedload transport rates. The ANN prediction resulted in a very close prediction of the mean observed flux ($\overline{q_s}_{\mathrm{ANN}}$ = 39.5 g/s/m compared to $\overline{q_s}_{\ DATA}$ = 42.0 g/s/m) (Fig. 2). We also performed a sensitivity test of the ANN model by training and testing a set of additional models in the same fashion as described for the full ANN model, but removed a single input parameter each time (Fig. 1c). We also trained and tested an ANN model with three grain sizes ($D_{16}$, $D_{84}$, $D_{94}$) removed. We found that the performance of the ANN was most sensitive to removal of discharge leading to a 95% increase in model error (MSE) during training (Fig. 1c) and an associated 65% increase in model error when the trained model was applied to test data.

### 3.3 Comparison of ANN to previous bedload transport models

We calculated the Mean Absolute Error (MAE) for the four previous bedload transport models and the ANN model based on the direct measurements of bedload flux from the Bedloadweb database within the portion of the dataset reserved for the test ($n$ = 1,624). MAE is less sensitive to extreme values and was selected as the primary criteria to assess the average model performance (Willmott & Matsuura, 2005).

In direct comparison, the ANN model outperforms all four previous models, regardless of their complexity. The ANN prediction of bedload transport rates across the test data results in a MAE of 16.5 g/s/m, which is 144-98844% less than the other considered models. Analysis of the ANN model shows that the error for the 50$^{th}$ and 75$^{th}$ percentiles of the river sites are MAE = 5.6 g/s/m and MAE = 25.8 g/s/m, respectively (Fig. S5 in supporting document). In addition, the standard deviation for the test predictions by the ANN model was 60.1 g/s/m and the minimum amongst all models. The skewness in ANN model prediction for the test data was 2.0 and the closest to the one in measured data (skewness = 2.6).

Among four previous bedload equations chosen for comparison, Recking (2013), an empirical model with five input parameters, performed significantly better than all other previous models with an MAE = 40.3 g/s/m when compared to

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measured data (Fig. 2d). Given the standard deviation of 65.8 g/s/m in $q_s$ for measured data (Table S1), the overall MAE of Recking (2013) is low. Einstein (1950), a probabilistic model with four inputs, also performed fairly well, with MAE = 54.9 g/s/m. However, Einstein (1950) underpredicts measured bedload transport rates for more than 82% of observations (Fig. 2a). Further, the distribution of bedload predictions is not reliably reproduced by Einstein (1950) as it generated the highest skewness in the predictions (Table S5 and Fig. S3). Bedload flux predictions made using Wong and Parker (2006) and Wilcock and Crowe (2003), lead to significant overpredictions in bedload flux across sites (Fig. 2b-c). Wong and Parker (2006) resulted in an average $q_s$ = 1044.6 g/s/m with a standard deviation of 1832.1 g/s/m. Despite significant overprediction, with a skewness of 2.9, Wong and Parker (2006) still reflects the skewness in measured data (Table S5). Amongst previous models, Wilcock and Crowe (2003) generated the maximum error in bedload flux prediction with MAE = 16335.6 g/s/m relative to measured values. As such, the 25$^{th}$ percentile of the estimated values for the test data is 1256-fold larger than the 25$^{th}$ percentile of the measured values. In addition, high positive skewness in the predictions (skewness = 5.3) by Wilcock and Crowe (2003) showed that without independent calibration the model could not reflect the distribution of the measured data.

## 4 Discussion

We demonstrate that the trained ANN model provides a robust prediction of available test data and outperforms all four of the selected previous models, regardless of model complexity. This is particularly encouraging because the model is trained using a dataset with wide parameter ranges compiled from many sites across the world, suggesting that it may be readily applied to any site which falls within the existing distributions of the training dataset with fairly good results (see Supplementary Information). Caution should be applied in the application of this ANN for input parameters outside of the parameter distributions for which it was trained. Admittedly, the ANN model leverages all seven available inputs from the BedloadWeb database, whereas previous models utilize a subset (Table S3). Thus, it is not entirely surprising that the ANN outperforms existing models. However, it is worth noting that, to our knowledge, there is no available empirical or theoretical bedload model that would similarly leverage all of these input parameters. ANN model sensitivity testing revealed that each of the seven parameters aides in the final prediction, however the removal of discharge produced the largest errors by far. This result is unsurprising, as bedload flux is chiefly a function of the fluid stress applied to the bed in excess of the threshold for motion and thus primarily dependent on how channel discharge maps to stress through the channel cross section (Meyer-Peter & Müller, 1948; Wong & Parker, 2006). It is worth noting, however, that the trained ANN model which does not include discharge only has a MAE = 21.1 g/s/m compared to the full ANN MAE of 16.5 g/s/m, which is still less than those from all previous models (Table S5). It should be noted that all four existing bedload transport models require some form of discharge (or shear stress) data in order to make predictions. All other ANN models trained on only a subset of the input parameters showed an increase in model error (MSE) in the test phase of up to 12% relative to the full ANN model. Across these sensitivity runs, ANN model error was most sensitive to the removal of channel width (MSE increase of 12%) and least sensitive to the removal of $D_{90}$ (MSE increase of 0.8%). However, across all cases, increases in

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total error of this class of ANN models (average MSE = 1546.0 $g^2/s^2/m^2$) is still less than all four previous bedload models (minimum MSE = 6215.1 $g^2/s^2/m^2$).

We suggest that the relative insensitivity of ANN performance reflects the inherent self-organization of alluvial river systems (Leopold et al., 1960; Parker, 1978; Phillips & Jerolmack, 2016). Alluvial rivers evolve towards a stable geometry that reflects a condition at which the bankfull flood will only slightly exceed the threshold for motion and initiate bedload transport (Dunne & Jerolmack, 2020; Parker, 1990). By extension, if a river is at or near this stable state, its width, slope, and surface grain size distribution, all hold information about channel size and therefore discharge required to transport sediment. We suggest that the machine learning approach, which incorporates all of these inputs, better captures the covariation between channel characteristics and their influence on bedload transport rates in natural systems when compared to more deterministic models. This is, in part, due to the model training, which is explicitly aimed at parsing the functional relationships between these covaried input parameters.

Inspection of the model predictions (Fig. 3) shows that the Wong and Parker (2004) and Wilcock and Crowe (2003) models tend to overpredict observed fluxes, but generally, capture the correct shape and therefore could be calibrated to match the observed data. Calibration of bedload transport functions through adjustments to the leading coefficient and/or the threshold term can also generally increase their utility (Hinton et al., 2017). However, these calibration parameters are not always easy to estimate and require measurements of bedload flux. Phillips and Jerolmack (2019) specifically analyzed field sites to investigate channel geometry and the threshold of motion and were only able to reliably calibrate bedload functions for 68 of 132 sites (51.5%). Application of empirical functions can require additional derived or calculated parameters such as shear stress. Shear stress is not necessarily challenging to derive by assuming steady, uniform flow; however, even shear stress data is rarely available at the majority of stream monitoring sites and can require a complicated set of processing routines for gaged sites (see Phillips and Jerolmack, 2016). A primary advantage of this ANN model is that it utilizes either parameters that are directly and consistently measured at stream gages (flow), measured from high-resolution topography (slope, width), or can be measured during low or no flow periods (grain size). For the majority of sites, both slope and grain size are static site variables and this presents a major advantage of this ANN model for predicting bedload transport at gaged sites.

One application of the ANN model developed here on a large collection of data from a variety of rivers is that it can be used to construct bedload transport rating curves for a broad range of gaged rivers. We selected a small subset of rivers that cover a wide range of parameters from the dataset used in this study to highlight the ANN model output (Fig. 3). These simple results highlight how the ANN approach can be used for the prediction of bedload transport at gaged sites without additional site-specific calibration. The strength of the ANN model should allow for this approach to be relatively easily be adapted to any gaged catchment with similar parameters or site without prior transport measurements to estimate bedload flux based on a hydrograph and reach scale estimates of bed grain size and slope. Within the US Geological Surveys National Water Information System, there are 1000s of potential gages. Furthermore, this model could be paired with spatially distributed hydrologic models if sufficient grain size measurements could be made and grain size is substantially easier to measure than flux.

## 5 Conclusions

This paper presented an artificial neural network (ANN) model for predicting river bedload. To do that, a large, measured bedload dataset, including 8,117 data points from 134 rivers, was gathered from the BedloadWeb, a free public online platform. The structure of the ANN included an input layer, an output layer, and five hidden layers with 600 neurons. The inputs to the model included temporally variable river discharge and flow width, and static measurements of bed slope, $D_{16}$, $D_{50}$, $D_{84}$, and $D_{90}$. A sensitivity analysis was carried out to show the sensitivity of the model with the input parameters. The results showed that the ANN model was most sensitive to the river discharge and least sensitive to the largest grain size ($D_{90}$). Our analysis suggests that including all available parameters in the ANN model better captures the covariations between the input and output parameters. Further, the ANN model provides robust prediction of the test (unseen) bedload data ($n$ = 1,624) within the bounds of one order of magnitude. We highlight that an advantage of this ANN model is that it was developed on a broad range of rivers and appears to accurately capture the variation in the data, making this model a good candidate for predicting bedload fluxes at gaged sites. The proposed machine learning model in this research lays the foundations for efficient and accurate predictions of river bedload.

## Data availability

Data sets are available at both http://en.bedloadweb.com and https://docs.google.com/spreadsheets/d/1TeGFcRfFqCaD-8keugCDIBftpl0Mxpz5/edit?usp=sharing&ouid=113425085155864679118&rtpof=true&sd=true

## Supplement

The supplement related to this article is available online at

## Author contributions

HH conceptualized the research and led the processing of the data, developing machine learning algorithms, visualizations, and writing the initial draft. CM and CP developed the idea, provided feedback, and contributed to the editing and writing of the manuscript. All authors were responsible for critical contributions and passing the final paper.

## Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

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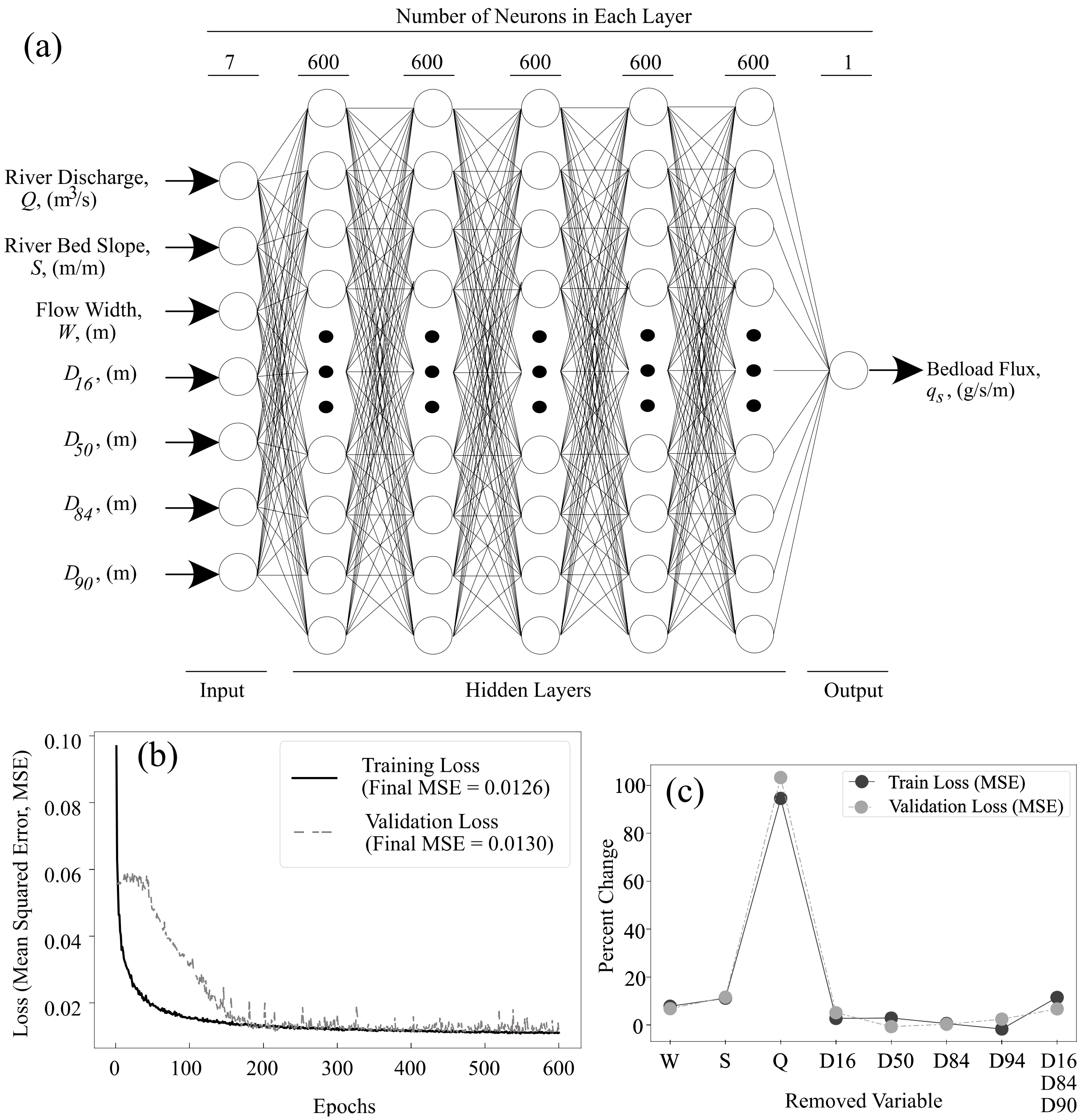


Figure 1. (a) Structure of the ANN model developed in this study with 7 input parameters. (b) Learning curves illustrate the decline in mean squared errors for training and validation. (c) Variations in ML model performance in training and validation due to changes in model input variables.

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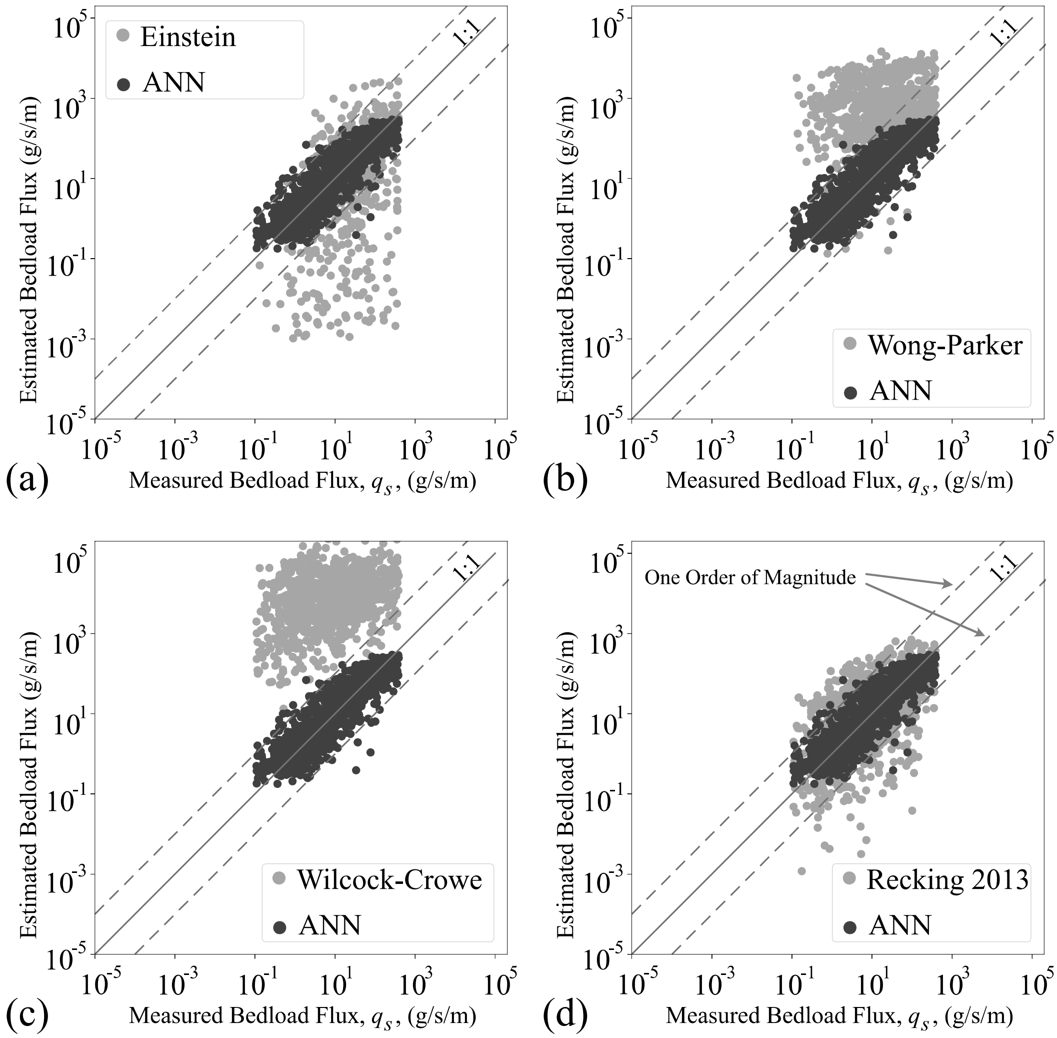


Figure 2. Comparison between ANN prediction for the test data (gravel and sand bed rivers) and previous models of (A) Einstein, (B) Wong-Parker, (C) Wilcock-Crowe, and (D) Recking (2013).

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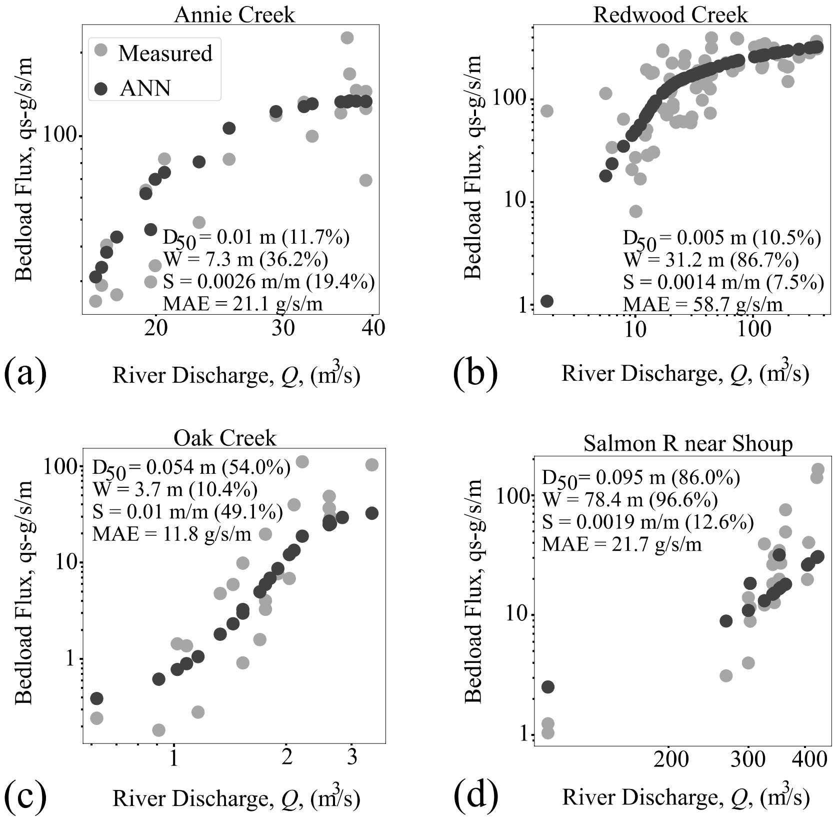


Figure 3. Example of the ANN model developed in this study applied to construct bedload transport rating curves for several sites. The numbers in parenthesis show the percentages in the whole dataset.