Heliyon 9 (2023) e18506

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Suspended sediment load prediction modelling based on artificial intelligence methods: The tropical region as a case study

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ARTICLE INFO

Keywords:
Sedimentation
Artificial intelligence
LSTM model
Prediction model
Tropical region

ABSTRACT

The impact of the suspended sediment load (SSL) on environmental health, agricultural operations, and water resources planning, is significant. The deposit of SSL restricts the streamflow region, affecting aquatic life migration and finally causing a river course shift. As a result, data on suspended sediments and their fluctuations are essential for a number of authorities especially for water resources decision makers. SSL prediction is often difficult due to a number of issues such as site-specific data, site-specific models, lack of several substantial components to use in prediction, and complexity its pattern. In the past two decades, many machine learning algorithms have shown huge potential for SSL river prediction. However, these models did not provide very reliable results, which led to the conclusion that the accuracy of SSL prediction should be improved. As a result, in order to solve past concerns, this research proposes a Long Short-Term Memory (LSTM) model for SSL prediction. The proposed model was applied for SSL prediction in Johor River located in Malaysia. The study allocated data for suspended sediment load and river flow for period 2010 to 2020. In the current research, four alternative models—Multi-Layer Perceptron (MLP) neural network, Support Vector Regression (SVR), Random Forest (RF), and Long Short-term Memory (LSTM) were investigated to predict the suspended sediment load. The proposed model attained a high correlation value between predicted and actual SSL (0.97), with a minimum RMSE (148.4 ton/day and a minimum MAE (33.43 ton/day).

and can thus be generalized for application in similar rivers around the world.

1. Introduction

Suspended sediment is sediment in a water body, like channels, rivers, and lakes that is transmitted through fluids and is fine as enough as the settling of the sediment particles can be out weighted by the rambunctious vortexes within a water body, resulting in making them suspended. Accumulation of sediments in rivers is a prevalent and expensive issue that has implications for environmental health, potable water resources, and farming activities. This occurs as a result of their negative impact on water quality, which causes pollution of water bodies, especially surface water. Moreover, suspended sediments can be interfered with the normal hydrological system of the rivers under particular circumstances. When the velocity and momentum of the river channel decreases,

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https://doi.org/10.1016/j.heliyon.2023.e18506
Received 5 May 2023; Received in revised form 2 July 2023; Accepted 19 July 2023
Available online 20 July 2023

suspended load of sediments could be accumulated at the bottom of river's channel, producing an elevated bottom of a river's channel, reduced river channel's cross-sectional area and choked hydrological system of the river. In addition, the territory of aqueous classes living in rivers is decreased [1–3].

For the reasons stated above, investigating and accurately predicting suspended load of sediments is critical to the long-range conservation and management of river quality, furthermore human impacts and essentials such as agriculture and drinkable water supplies, as well as problems associated with the designing, planning, and the managing of hydraulic structures such as dam-reservoir system, and thorough influence on the environment evaluations [4–6].

Various tough challenges are present in SSC prediction method. To begin with, SSC prediction varies from a single site to the next, hence it is necessary to be typified for each river employing data acquired at this unique location. Second, the data we utilized to train the model only has one variable: discharge data on a daily basis, which is employed for forecasting the daily suspended sediments. Third, the nature of daily sediment data is complicated, resulting in lower predicting accuracy. As a result, this work attempts to introduce a distinguished model that is able to discover complicated patterns in data, to overcome past issues [7,8].

Choi el. al. [9], used artificial neural network with wavelet algorithm to predict daily suspended sediment concentration in open channel flow.

Several research has looked at the SSL prediction method through utilizing different machine learning (ML) techniques. The primary sort of machine learning model examined is standalone machine learning model, which has been shown to be efficient for predicting SSL.

Choubin et al. [10], investigated the capabilities of several predictive models for SS prediction in Iran. The study found that the proposed model named CART outperformed other standalone ML models regarded to SSL prediction according to a three performance measures.

Within the drainage basin of Hyderabad in Iran (Talebi et al., 2017), [11], they studied the use of four predictive models including (CART, M5T, ANN and SRC) for SSL prediction. The CART and M5T algorithms beat other prediction methods, according to the findings. The traditional SRC approach was found to have excellent predictive accuracy daily sediment discharges of less than 100 tons per day, however the ML models were found to be more accurate in predicting large sediment discharge than the traditional SRC method.

The SSL prediction in India has been conducted by Agarwal et al. [12] employing three common methods named Adaptive Neuro Fuzzy Inference System (ANFIS) and Multi-Liner Regression, as well as the traditional SRC method. Three separate input scenarios were used to train the suggested methods. The results indicated that the ANFIS method outperformed MLR and SRC in predicting SSL.

Taşar et al. [13] used different machine learning models which are M5T, MLR, ANN and traditional SRC approach for suspended sediment (SS) prediction. The proposed methods were applied to simulate SS parameter in lowa located in United States. The comparison between the suggested predictive methods was carried out using several statistical indicators. The evaluation indicators displayed that ANN method is superior to other models in predicting suspended sediment. Hazarika et al. [14] investigated the capability of ANN and SVR models to predict daily SSL. The results indicated that SVR has better performance compared to ANN model.

Although solo ML algorithms are useful for predicting SSL, there are a few drawbacks to be aware of. In general, stand-alone machine method may not be as accurate or flexible as hybrid machine learning methods [15]. Hybrid methods are often more reliable than standalone ML methods because they take advantage of the advantages of their component algorithms [15]. Previous researches have shown that hybrid ML models outperform independent ML models when it comes to SSL prediction [16].

In comparison to hybrid ML models, independent ML models are less competent for pairing and processing the nonlinear situations, according to Qian et al. [17]. Hybrid models have also been applied to forecast several hydrological parameters such as streamflow parameter [18,19]. Overfitting, cognitive uncertainties, money absence, factors ambiguity, and limited minimization drawbacks, as well as the necessity to fulfill by information the presumptions, the ability to just begin offering linear answers, independence supposition among characteristics, and need of large data of samples for great results, are some of the other disadvantages, according to the application of standalone ML algorithm.

A review of previous literature on hybrid machine learning models able to accurately predict SSL was also conducted. Mohammadi et al. [20] used a hybrid MLP with particle swarm optimization (PSO) and D.E model for SSL prediction in a River located in Iran. MLP-PSODE was the name given to the resulting algorithm. The performance of this algorithm was assessed by comparing to that of additional hybrid algorithm. The results shown that the proposed model (i.e., MLPPSODE) is superior to MLPPSO and single models because it has more credible results in high value estimation [21–23].

Banadkooki et al. [24], used the ANN method combined optimizer algorithm named Ant Lion to investigate SSL prediction in the Goorganrood basin in Iran. Various input scenarios have been used to test a hybrid ML methods' capacity. The findings demonstrated that the ANNALLO method was more accurate for SSL prediction by comparing with another predictive methods.

In the Atrek River, Iran, Ehteram et al. [25] studied how to better predict suspended silt by using an ANFIS and a hybridized Multi-Layer Neural-Network (MLNN). Two algorithms including bat and weed algorithms have been used to hybridize two MFNN models. Also, the proposed algorithms have been used to hybridize two ANFIS models. Based on five performance factors, the study revealed that ANFIS-BA outperformed both other hybrid ML techniques in predicting SSL.

Three different methods were introduced by Adnan et al. [26] to estimate SSL parameter. The proposed methods are DENFIS, ANFIS and MARS methods. The DENFIS method was found to be more accurate for SSL prediction when comparing with the suggested methods using a set of conventional performance metrics.

Zounemat-Kermani et al. [27] studied the San Joaquin River in the USA to predict suspended sediment concentrations utilizing two ANN models, ANN-LM and ANN-PSO, which are hybridized with the Levenberg–Marquardt (L.M.) method and Practical Swarm

Optimization, respectively. In addition, a stand-alone ANFIS model was created. Based on the findings, ANN with PSO and stander alone ANFIS are better in predicting daily SSC data.

Extreme Learning Machine (ELM) and Support Vector Regression (SVR) with wavelet algorithm have been employed to predict SSL by Hazarika et al. [28]. In another study, Hazarika et al. [29] combined two different model with a wavelet algorithm. The proposed model was applied for SSL prediction. Hazarika and Gupta [30] used novel machine learning based non-liner random vector functional link method for river SSL prediction.

In handling challenges like SSL prediction, hybrid ML models have restrictions that must be recognized. According to Qian et al. [17], hybrid Machine learning techniques require a lot of time to train, especially in handling complex circumstances. Hybrid Machine learning techniques require more input variables to be examined for the duration of training than single Machine learning methods do. It regularly restricts the creation and use of hybrid ML methods [17]. Moreover, using hybrid ML models has been observed to have drawbacks such as complicated design and an uncertain ideal number of clusters [15,31–34].

The convolutional NN is a form of machine learning method that hasn't gotten much attention in the area of SSL prediction (CNN). Based on past literature evaluations, this NN, which is a deep learning (DL) algorithm type, showed a lot of potentials in other disciplines. In Carlisle, United Kingdom (Kabir et al., 2020), Kabir et al. [35], built CNN for the prediction of the flood depths. In such Research, the hydraulic model's outputs were used to train CN–N method produced. The capacity of CN–N method has been compared with an SVR (i.e. support vector regression) model. Several accepted performance indicators demonstrated that suggested CNN model has been considerably better than SVR in forecasting the flood depths in this investigation.

To anticipate river flow in 4 rivers in UK, Huang et al. [36], used CNN that has been trained with the use of a strong loss function. The efficiency of CNN method that has been trained with robust loss function is examined by comparing against benchmark models based on a variety of methods, including auto-regression (AR), MLP, CN–N and other predictive models. The CN–N which has been trained with the use of robust loss function offers the greatest prediction results, according to the obtained results.

The performance of four distinct artificial intelligence methods has been investigated by Ref. [37] in predicting suspended sediment load in the longest waterways in the north of Iran (i.e., Jajrood River). The modelling was built utilizing the combinations of the present and antecedent river flow. The study explored that least square support vector machine (LS-SVM) outperformed other methods.

In 2021, Ehteram [38] introduced valuable study to predict SSL in the river using ANN. The study examined the performance of the proposed model based on two different scenarios. In the first scenario, three advanced optimization algorithms were employed to select the best input combinations. The second scenario introduced the multi-objective (MO) optimization algorithm which uses the same inputs from scenario 1. The study concluded that the high accuracy level was achieved by utilizing of a hybrid artificial neural network with whale algorithm.

Several soft computing methods combining with optimization algorithm have been proposed by Ref. [39]. The proposed methods were utilized to predict the SSL in Telar River, Iran. The lagged discharge, temperature, rainfall and SSL have been employed as inputs variables to the models. The results revealed that ANFIS-BWOA model is superior to other proposed models for SSL prediction.

In fact, there are a few numbers of research manuscripts that have been introduced to offer a prediction model for SSL in the same case study. In 2021, one research manuscript showed the procedure for the development of the LSTM model to predict the SSL. As shown in AlDahoul et al. [32], the duration of the data for the same case study was completely different than the one used in the current study. The current study developed the model using the data ranging between 2010 and 2020 while the previous study, AlDahoul et al. [32], used the data during the period between 1988 and 1998. In fact, substantiating the effectiveness of the model performance using different data duration is an essential step especially while studying the SSL. It should be noted here that there are different unmeasurable factors that affect the values of the SSL in the river which definitely changed in during these different durations, such as changing the land use along with river banks, urbanization along the river, and river morphology. Due to the fact that the Johor River basin has experienced significant urbanization, deforesting, and several residential developments, the SSL patterns in the river has been changed, and hence, there is a need to propose a new predictive method for SSL prediction in the river. On the other hand, in 2022, two research manuscripts have been proposed. The first one by Essam et al. [33], proposed different model architecture which includes not only the SSL but also the historical records of the river streamflow data to predict the future SSL. In fact, this model showed good performance to predict the SSL, however, similarly, this study used different data duration for different 11 stations at different rivers in Malaysia ranged between 1976 and 2000. Therefore, this study could be considered different than the current study for the same reason as mentioned earlier. In addition, the historical records of the river streamflow are not frequently available at the locations of SSL monitoring, and hence, it is necessary to examine the model performance that only dependent on the SSL data. Finally, AlDahoul et al. [34] offered completely different model for predicting the SSL as this research focused on predicting the category of the SSL rather than the exact value of the SSL utilizing different ranges of classifiers, five categories, and 10 categories. In this context, the models used in this research are completely different customization procedures as these models were developed to predict the category of the future SSL range rather than the value of the SSL.

The suspended sediment concentration was predicted using LSTM method in Vietnam [40]. They considered both monthly suspended sediment and runoff as input parameters for modelling. The evaluation indicators revealed the proposed model (i.e., LSTM) is superior to other prediction models.

In 2023, Jamei et al. [41], integrated LSTM with wavelet decomposition (WT) for suspended sediment prediction. The performance of the proposed model has been examined in two different case studies. In both cases, the LSTEM provided good prediction results compared to other models.

Conventional machine learning techniques, as noted in literature review, relied upon the feature extraction in order to manually choose characteristics prior to the simulation phase. The predictive accuracy would deteriorate if the variables were not carefully chosen. Furthermore, hyperparameter selection is crucial and has a major effect on predictive accuracy. Furthermore, traditional machine learning algorithms were found to decrease the efficiency of complicated data patterns. This type of intricate pattern was learned using more powerful automatic learning approaches like the DL models.

1.1. Novelty

Soft computing techniques, such as Artificial Intelligence models, have grown in popularity as a modelling tool for predicting suspended sediment load (SSL). Soft computing models have gradually superseded traditional models in the last three decades, demonstrating a stronger ability to recognize the nonlinearity dynamics contained in SSL patterns. Recent academic works dealing with the implementation of soft computing approaches attest to its popularity. However, linked mathematical techniques in machine learning, such as the Long-Short Term Method (LSTM), may have trouble detecting highly stochastic patterns and a large range of SSL properties contained in the data, necessitating the need to improve soft computing procedures.

The variation of the LSTM model is considered in this work with the goal of improving the prediction accuracy. It should be noted that the LSTM method is an excellent predictive tool due to its ability which has been demonstrated to have the strongest ability to detect nonlinear patterns in the input data among all soft computing methods. In the presented research, the back-propagation procedure has been modified to enhance the performance of proposed model. Because it includes the back-propagation process to enable a re-evaluation of the rule of the input and hidden layer used in the prediction algorithm, this novel procedure is anticipated to permit improvements in the traditional LSTM model. The LSTM approach will probably be able to detect nonlinearities and stochastic patterns at a number of local places in the predictor dataset with this enhancement. This is especially helpful when using extensive historical input data, like in our case study's predictive model.

1.2. Objectives

The presented research employed four different models as predictive models to predict suspended sediment load parameter. The proposed predictive models are Multi-Layer Perceptron (MLP) neural network, Support Vector Regression (SVR), Random Forest (RF) and Long Short-erm Memory (LSTM). The configuration of the suggested modelling was created by adopting historical data time series for sediment and discharge as input variables. An evaluation of the ability and provided evidence of the effectiveness of long-term memory (LSTM) for predicting suspended sediment load in the Johor River in Malaysia was performed. The proposed predictive models were examined by several statistical indicators.

2. Case study

Malaysia, which is located in Southeast Asia, is divided into two geographical regions, which are: Borneo Islands and Peninsular Malaysia, including the states of Sarawak and Sabah. Because Malaysia is surrounded by water, the air is often wet and cloudy. Due to its proximity to the equator, the country receives higher amounts of sunshine, as the Sun's rays almost totally strike the country over the year. Johor, the area of case study, is located in Peninsular Malaysia's southernmost region. Johor is formally divided into eight districts, with Johor Bahru serving as the state's capital and a heavily urbanized port of entry between Singapore and Malaysia, as well

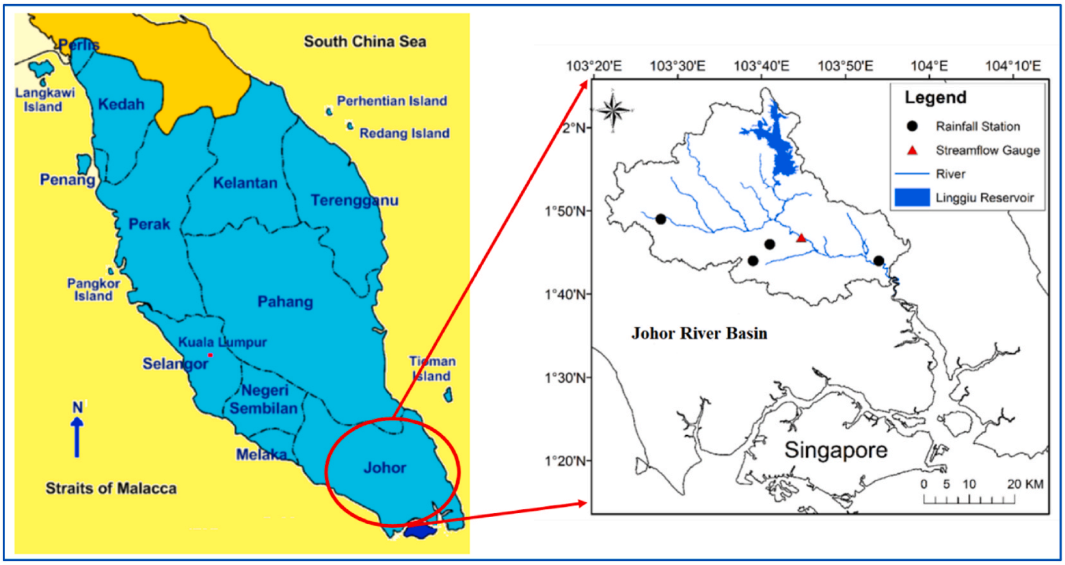

Fig. 1. Johor River case study in Malaysia.

as an international economic center. As a result of the fact that it is close Johor capital, the Kota Tinggi municipality, that covers 3644 km^2 and is located 42 km north-east city of Johor Bahru, has expanded quickly as a component of the Johor development corridor. The sea encompasses 65% of the border of Kota Tinggi, which is located in East Johor and comprises ten sub-districts [42,43].

As can be seen in Fig. 1, the Johor River basin serves as a case study for the research being conducted here. The total catchment area of Johor River basin is roughly 2286 km^2, with an overall length with approximately 122.7 km. Johor River's headwaters are on slope of eastern Kluang and Gunung Belumut, and it flows south before emptying into Johor Straits. Sayong River and the Linggiu River are two significant sources of the Johor River. From January 2005 through December 2006, the observed daily data of sediment and streamflow parameters were considered. The number of the hydrometric station for streamflow and sediment is (1737551). The data allocated is provided by Department of Irrigation and Drainage, Ministry of Environment and Water, Malaysia. In this investigation, these two parameters were used for modelling the prediction of sediment load parameter.

3. Data partitioning and training

The experimental approach and dataset splitting procedure are described in the current part of research. There are two significant data groups within this particular study: training and testing. The models' weights were adjusted using the training data groups, Understand the input's patterns and train them. Simultaneously, the validation set has been utilized in training step in order to avoid the issue of overfitting. A testing set, on the other hand, was used to assess the algorithms and compute performance measures. With the rule of 80/20, the data-set has been split in two, which are: training and testing. In this split, 80% of the data, which include the first nine months of our data-set, has been allocated in order to train the proposed models, whereas 20% was allocated to test the efficiency of models, containing the last 15 months.

There are 7 hyper-parameters that have been considered in this study to be optimized as followed:

- Number of Nodes and Hidden Layers.
  oNumber of Units in A Dense Layer.
- Dropout.
- Weight Initialization.
- Decay Rate.
- Activation Function.
- Learning Rate.

In order to optimize the values of these hyper-parameters within the LSTM model, these parameters are optimized through a self-tuned procedure optimization algorithm based on the Gradient Decent Optimization process.

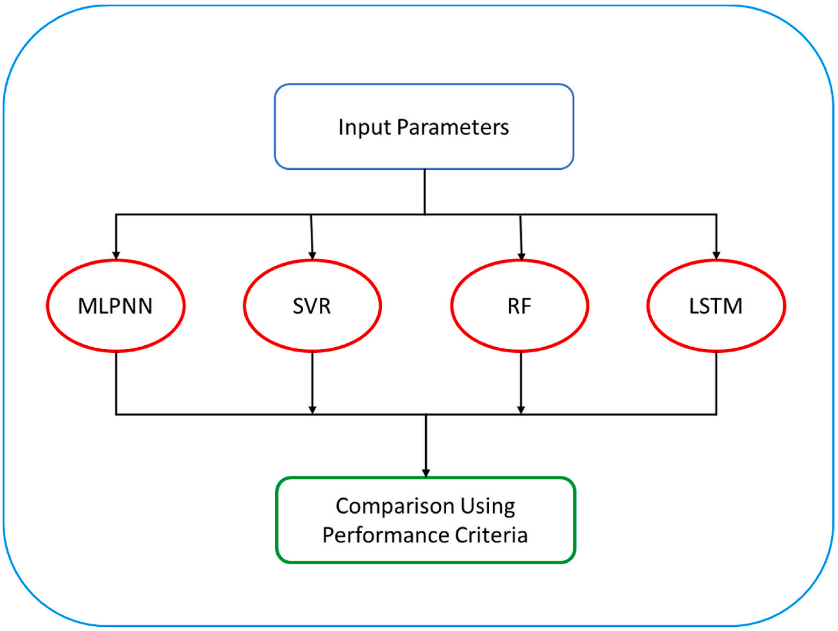

Fig. 2. Flowchart for the methodology.

4. Methodology

Forecasting was done using four methods: Multilayer Perceptron Neural Network (MLPNN), Random Forest (RF), Support Vector Regression (SVR), and the Long Short-Term Memory (LSTM). In the literature review, a variety of approaches were employed to forecast SSL. The approaches have been classified into two categories: traditional machine learning and deep learning [44,45]. In the present work, we used a variety of ML approaches as a baseline to compare to our suggested LSTM. To ensure a fair comparison, the models were chosen based on their diverse model architectures and learning techniques. The value of k is set to 10, which is generated by experiment to produce an estimate of modeling ability often with little bias and little variability. Fig. 2 presents the flowchart for the methodology used in this research.

4.1. Multi-layer neural network

The suggested technique consists of a multilayer network with non-linear activation functions. To identify the best parameters for that network, iterative tuning (1000 iterations) is used. To discover the optimal hyperparameters, several were examined. These are the hyperparameters:

1. Activation function: tanh and logistic
2. Solver: adam and lbfgs
3. Learning rate: adaptive and constant

The number of hidden layers, the number of nodes in each hidden layer, and the activation function type that makes up a neural network's architecture are selective parameters [46,47]. Various MLP NN topologies were investigated in the present work using different number of hidden layer and several and nodes inside layers. The following was the final optimal architecture that had delivered optimum statistics in terms of R^2, MAE, and the RMSE:

1. The numbers of input nodes match historical sediment and discharge measurements.
2. Two hidden layers with 25 nodes for each layer
3. The output layer comprises a single node for sediment prediction.

4.2. Support vector regression

The SVM is a binary supervised learning approach depend on a structural reduction and statistical learning method, which was established first by Vapnik (1995) [48] and Vapnik et al. (1997). A SVM model's purpose is to reduce model complexity and mistakes. To discover an ideal separation hyper-plane derived from a training set, SVM translates input vector into a greater feature set. In practice, the SVM can transform a variable's nonlinear nature into a linear one. By constructing a hyperplane, this technique generates simple and processable classes. A kernel function is the name given to this mathematical relationship. In the initial space of n co-ordinates, an ideal separation hyper-plane is projected.

A linear, polynomial, RBF, or sigmoidal kernel function can be used. The normalized polynomial kernel (NPK) and RBF are the two commonly frequent kernel functions, albeit RBF is more commonly utilized due to its simplicity, which allows for effective generalization, high resistance to the noise environment, and online learning capacity. The following are the definitions for the NPK and RBF kernel functions, respectively.

$$K(x_i, x_j) = (x_i x_j + C)^d \tag{1}$$

$$K(x_i, x_j) = exp\ (-\gamma x_j + x_j)^2 \tag{2}$$

where γ regulates the SVM model's degree of nonlinearity, d is the kernel function's polynomial degree, and the free parameters represent by C symbol that balances the effect of higher against lower order elements in the polynomial. Under-fitting and over-fitting of the training data are caused by small and large values of respectively [49,50]. offered thorough explanations of the RF model's variables.

4.3. Random forest (RF)

The RF, which was first developed by Ref. [51], using a nonparametric ensemble learning method, is a hybrid and flexible approach among a decision tree of this kind and the regression. The Random Forest is made up of several trees, each of that is constructed using bootstrap samples [52]. The random forest model is made up of two basic processes: Breiman's bagging idea and Ho's [53] random selections [54]. The RF approach looked at how much estimate error increases when the output of data for some variables is modified whereas keeping everything else the same [55]. More detailed about the mechanism of the RF could be found in Refs. [51,55].

The samples that are not included in the bootstrap procedure are namely of the bag (OOB). The RF model was validated by measuring its accuracy in making predictions using OOB samples from the training set (i.e., prediction performance was evaluated by assessing prediction on observation that was not included in the construction of the next base learner) [56].

4.4. Long Short-Term Memory (LSTM)

Long-range sequence modeling is performed using LSTM, which is a sort of Recurrent Neural Network (RNN) [57,58]. Fig. 3 shows a memory cell that works as a state accumulator and is supported by control gates in an LSTM. This construction has the advantage of reducing the time it takes for the gradient to disappear. Temporal correlations were captured by an LSTM network [59–61].

In this study, LSTM has been utilized in conjunction with streamflow and sediment data. To fit the data, the LSTM variables have been repeatedly modified. Number of hidden layers, neurons number in the input and hidden layer and activation function have all been investigated and evaluated in order to determine the ideal topology which provides the best performance indicators. The suggested LSTM model's optimal topologies comprise of the 64-nodes and ReLU activation function.

Different hyperparameters have been studied and assessed, comprising learning rate, ratio of dropout, loss function, size of batch, optimizer, and total of epochs, in order to find the best performance measures. Loss functions for MAE and MSE were analyzed. The Adam optimizer was shown to be more effective in minimizing the MAE loss function.

In summarize, the methods outlined before were used for sediment forecasting, with standard machine learning approaches serving as benchmark dataset and LSTM serving as the suggested model. Different elements, like the history of inflow and sediment, influence sediment behavior.

4.5. Performance evaluation

The regression line (R^2), root mean square error (RMSE), relative square error (RSE), mean absolute error (MSE), and relative absolute error (RAE) have been used as performance indicators the current research. The model's prediction performance improves as R2 increases. R2, on the other hand, is insufficient to determine whether or not the factor prediction is skewed. Other metrics of the errors, like RSE, RAE, RMSE and MAE, were utilized to identify error or difference between actual and anticipated outcomes in order to further evaluate whether a model of regression gives good fit to the data. The model's higher Performance in forecasting is expressed by lower RSE, MAE, RAE, and RMSE values.

The disadvantage of RMSE its higher sensitivity compared with the MAE to large outliers and errors. The RMSE fault of forecast sensitivity to scale and mean, on the other hand, was discovered to be solved by RSE. In addition, we calculated frequency of the absolute errors in 4 scenarios and utilized absolute error (AE) distribution plots for the evaluation of models of prediction. Using this collection of past measures, we can conduct comprehensive evaluations of suggested and base-line models, addressing all individual metric shortcomings. The evaluation indexes are computed as the following equations [45,46,62,63]:

$$R^2 = \frac{\sum_{i=1}^{n} (S_a - S)(S_p - S)}{\sqrt{\sum_{i=1}^{n} (S_a - S)^2 \sum_{i=1}^{n} (S_p - S)^2}} \tag{3}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |S_p - S| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (S_a - S)^2}{n}} \tag{5}$$

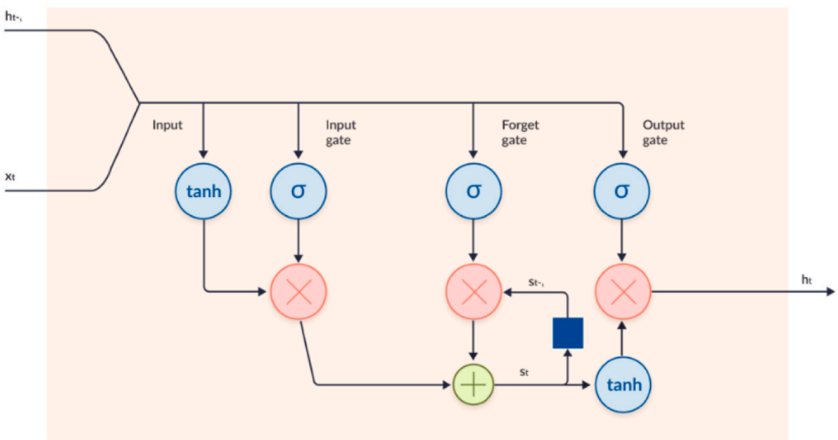

Fig. 3. Short-long term memory network.

$$RAE = \frac{\sum_{i=1}^{n} |S_p - S|}{\sum_{i=1}^{n} |S_p - S|} \quad (6)$$

$$RSE = \frac{\sum_{i=1}^{n} (S_p - S)^2}{\sum_{i=1}^{n} (S_p - S)^2} \quad (7)$$

Where, S_p is the value of the predicted sediment, S_a is the actual value and S is the average value of the sediment.

5. Results and discussion

As mentioned before, the study aimed to predict sedimentation load for 1 day ahead employing ML methods, which include Multilayer Perceptron Neural Network (MLPNN), SVR, RF, and LSTM. The efficiency of the proposed predictive models is evaluated by adopting several performance indicators. The hyper - parameters of the methods were tweaked to get the best results possible. The goal of exhibiting those 4 situations is to investigate the data disparity and reveal implied patterns that the approach must be able to recognize.

The optimal combination of input parameters was determined utilizing trial-and-error methods employing default operators and the RMSE of the projected suspended sediment load (Table 1). Only the most significant factor (Q) is examined for predicting in combination 1 and 2, and then Q and next most significant factor (SSL) have been included in combination 3 and 4. This pattern maintained till all factors were taken into account in modeling process. The optimum input combination, according to results, has been found in combination 4, which all factors were evaluated as inputs. As a result, for further modeling and analysis, combination 4 has been utilized. Despite the fact that flow was the most essential parameter, combination 3 had relatively largest RMSE due to a hysteresis effect with both streamflow and sediment load. In addition, the fact that the Suspended Sediment Load (SSL) for a given flow was greater for the critical elevation of the hydrograph than for the tip of the slump.

The comparison between the capacity of the proposed models was carried out as shown in Table 2. The LSTM model has the best prediction result in point of view most of the statistical indicators. The RF method is the second best predictive method according to the evaluation indicators. The study showed that the SVR model provided better predictions with RBF kernel compared to the NPK kernel. These results are consistent with past studies presented by Dibike et al. (2001), Lin et al. (2006) and Kakaei Lafdani et al. (2013). The predictions obtained by SVR and MLPNN model underestimated the sediment load, whereas the others predictive models overestimated SSL.

The ability of the suggested methods is was further evaluated using percentage bias (PBIAS) [64]. classified the predictive model to four classes based on the PBIAS value. The capacity of the model is classified as a very good when the PBIAS $< \pm$ (10), good $\pm$ 10 $\leq$ PBIAS $< \pm$ 1–5, satisfactory $\pm$ 15 $\leq$ PBIAS $< \pm$ 25, unsatisfactory PBIAS $\geq \pm$ 25. Table 3 presented the PBIAS values for all models during testing period. It could be noted that the ability of MLP and SVR are satisfactory. The results indicated that the RF model has a good result as PBIAS was less than $\pm$15. Whereas the reliable prediction accuracy was achieved by LSTM model. According to the PBIAS value, LSTM has very good performance in SSL parameter prediction.

The pattern of the actual and predicted SSL data using four machine leaning models is presented in Figs. 4 and 5. It could be observed from this figure that the LSTM model predictions were closer to the corresponding actual SSL values compared to other predictive models. The MLPNN model had the worst predictions among all the models, which confirms the results in Table 2.

Fig. 6 illustrated the scatter plots of the MLP, SVR, RF and LSTM method over testing period. The regression values between predicted and actual data were different between the proposed methods. The results revealed that the SVR is relatively better than RF method in achieving an acceptable regression magnitude. In general, the scatter plots appeared that the performance of LSTM method is more reliable for SSL prediction compared to other predictive models.

Further analysis was carried out to assess the performance of predictive models using the relative error index. This indicator shows the error for each record separately which can be a more accurate indicator than others. Figs. 7 and 8 illustrated the percentage error relative between predicted and actual SSL data. It should be noted that a large error was obtained using the MLP method. In more details, it could be observed that the maximum positive relative error has been experienced while applying the MLP and SVR models

Table 1
The optimal input combination for each proposed prediction method. "Note: RMSE: Root Mean Square Error."

Model	MLP	SVR	RF	LSTM
Input Combination 1: (Q)				
RMSE	169.3	168.7	166.4	165.7
Input Combination 2: (Q, Q_{t-1})				
RMSE	165.5	163.8	160.3	156.8
Input Combination 3: Q, SSL_{t-1}				
RMSE	161.2	159.3	157.8	152.4
Input Combination 4: Q_{t-1}, SSL_{t-1}				
RMSE	158.6	156.1	153.7	150.3
Input Combination 5: Q, Q_{t-1}, SSL_{t-1}				
RMSE	155.8	155.7	151.2	148.4

Table 2
Performance indicators for the proposed predictive models under testing period. "Note, RMSE: Root Mean Square Error, MAE: Mean Absolut Error, MBE: Mean Bias Error, NSE Nash-Sutcliffe Efficiency, SI: Scatter Index and d: Willmott Index of Agreement."

Model	RMSE	MAE	MBE	NSE	SI	BIAS	d
LSTM	148.4	33.43	−0.03	0.95	0.40	30.58	0.97
RF	151.2	85.48	0.14	0.83	0.76	41.13	0.91
SVR	155.7	104.30	−0.02	0.77	0.89	66.26	0.89
MLP	155.8	125.90	0.32	0.74	0.97	−25.84	0.88

Table 3
PBIAS indicator values for all predictive models. "Note, PBIAS: Percent bias."

Model	MLP	SVR	RF	LSTM
PBIAS	−21.6	18.8	13.2	−8.6

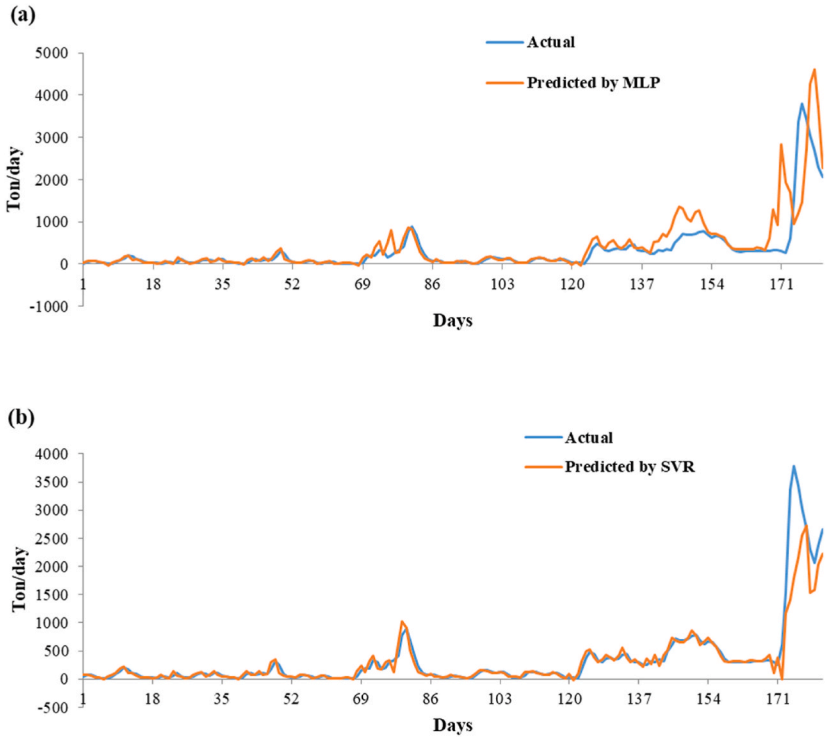

Fig. 4. The pattern of the actual data versus predicted pattern (a) using MLP and (b) using SVR.

while the maximum negative relative error has been observed while using the MLP. In other word, the SVR method provided over-predictions most of the time during testing period. The minimum percentage error was achieved by LSTM model as show in Fig. 8b. This indicator confirmed that the LSTM has the ability to provide accurate prediction results compared to other proposed models.

Furthermore, it could be noted that although the LSTM, in general, outperformed the other models in providing better prediction accuracy, it provides a significant enhancement for the prediction accuracy for SSL accuracy compared to the other models in the most recent duration between Day 171 and 181. In fact, this duration represents the most recent data records for SSL in the year 2020 that experienced significant changes in the SSL patterns. Although during this special duration, the LSTM showed relatively low performance for the prediction accuracy reached almost 35%, the LSTM could successfully achieve reasonably good accuracy compared to the other models. With careful investigation of Fig. 7 (b), Fig. 8 (a) compared to Fig. 8 (b), it could be noticed that the achieved relative error using LSTM as shown in Fig. 8 (b) at the tail starting from Day 171 until the last Day on 181 is lower than those achieved prediction errors using MLP, SVR and RF models. Although LSTM, which has already been established by other researchers, was offered in the current study as a feasible model for predicting the SSL The current study demonstrated a distinct method for developing the model. When compared to the LSTM version utilized in the prior study, the one used in this one is more sophisticated. For instance, the LSTM's parameters were repeatedly modified for fitting the data. In order to identify the ideal topology that yields the best

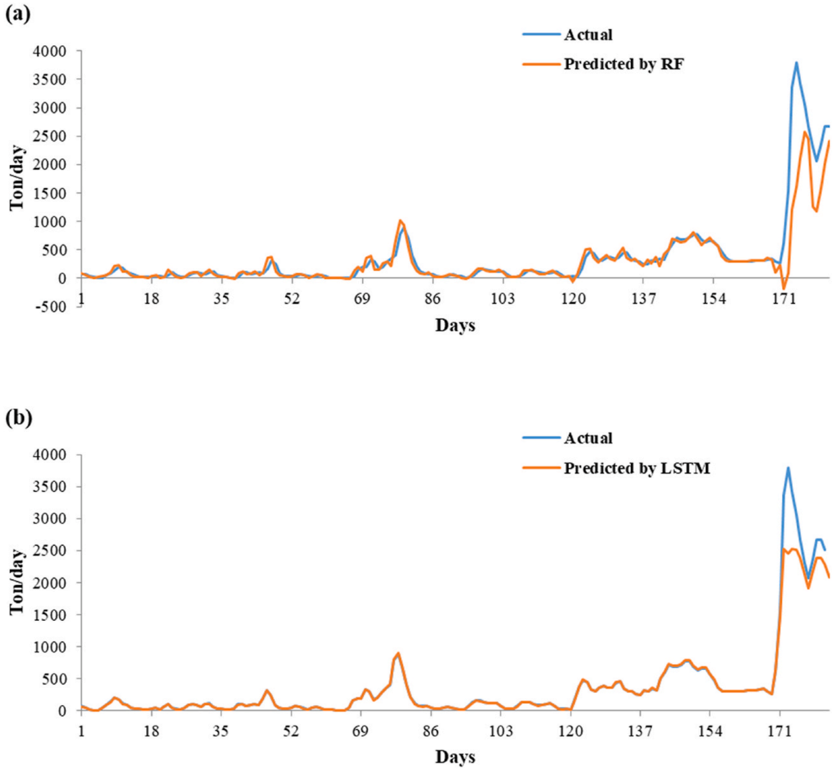

Fig. 5. The pattern of the actual data versus predicted pattern (a) using RF and (b) using LSTM.

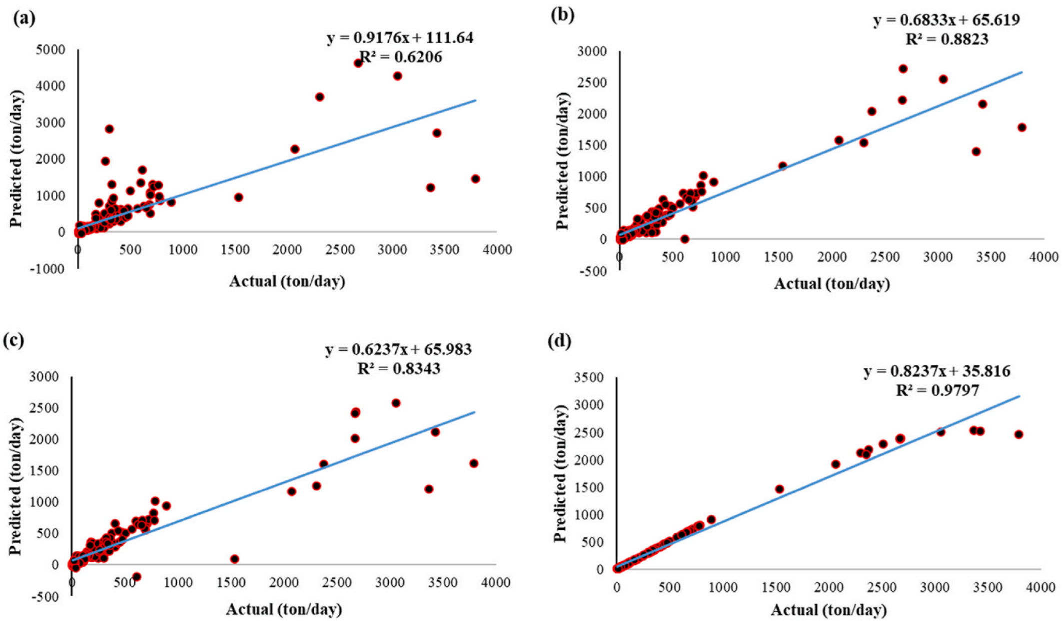

Fig. 6. Scatter plots for all predictive models (a) using MLP, (b) using SVR, (c) using RF and (d) using LSTM model.

evaluation metrics, various factors have been looked into and analyzed, including number of hidden layers, the amount of neurons in the input and hidden layer, the number of fully connected layers, the types of activation function, and the number of dropout layers. To achieve the best results, for instance, the methods' hyper-parameters were adjusted. Investigating data variety, identifying underlying patterns that the approach should be able to recognize, and optimizing model topologies to achieve model generalization are the goals

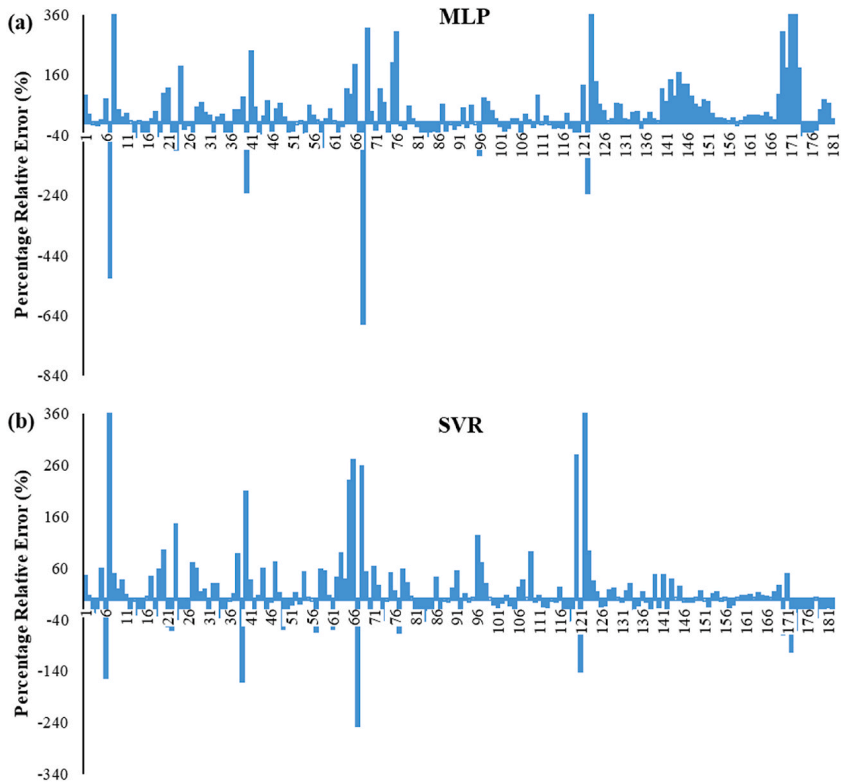

Fig. 7. Percentage relative error between predicted and actual SSL during testing period (a) using MLP and (b) using SVR.

of showcasing these model procedures.

Fig. 9 displays the box plot of the distribution of the predicted suspended sediment load values for all proposed models compared to the actual data during testing period. The whisker-based metrics show the quartiles for both the predicted and observed SSL attributes as well as their extreme values. It should be noted that the boxplot's lower end displays the lower quartile, I_{25}, which reflects values at the 25th percentile, whereas the boxplot's upper end, I_{75}, displays data at the 75th percentile. The 2nd quartile is the median of the suspended sediment load amount shown by I_{50} (i.e., the 50%). It can be seen that the proposed prediction models presented different suspended sediment load distribution when compared among themselves. By comparing with the actual data, the results indicated that the LSTM is more closely related actual data. The box plot indicator confirmed that LSTM model is superior to other proposed models for predicting suspended sediment load data.

The performance of the proposed models was also evaluated using histogram (see Fig. 10). Histogram graphs displaying the projected value distribution. Clear forecasts that are close to either 0 or 1 are the desired outcome. Nearly all SSL values were expected to be in the range of 0 or 1, which was a very unambiguous prediction from the LSTM model. Additionally, other models generated more SSL data with values close to 0 or 1. When utilizing LSTM, the majority of the intervals on histogram plots are tiny, indicating a high degree of certainty in the majority of the predictions.

The performance of the proposed models was further analyzed with a Taylor diagram. This diagram displays the patterns of the prediction's models and their position relative to the actual pattern. Fig. 11 shows the pattern of the MLP, RF, SVR and LSTM models relative to the observed data. It should be noted that LSTM performance is better than other proposed models because it is closer to the observed data and reference line.

Despite that MLPNN, RF and SVR successfully predicted SSL values in past studies, in the current research, the LSTM model made more accurate predictions than other predictive models. Generally speaking, our findings show that LSTM model has the potential to provide strong sediment load predictions based on daily river flow records in watersheds like the one under study where data are scarce. This form of data-driven method can be used to supplement presenting process-based methods in well-measured watersheds by recognizing patterns in data collected which can disclose important details regarding behavior, provide completely undiscovered environmental linkages, or reduce model uncertainty.

6. Conclusion

Daily suspended sediment load prediction (SSL) is a vital need for managing decision tasks involved in water resources that are implemented in basic hydrological procedures. In fact, numerous predictive methods utilized for SSL prediction, but in the present research, the modern machine learning model was employed to enhance the prediction accuracy. To assess the capacity model, the

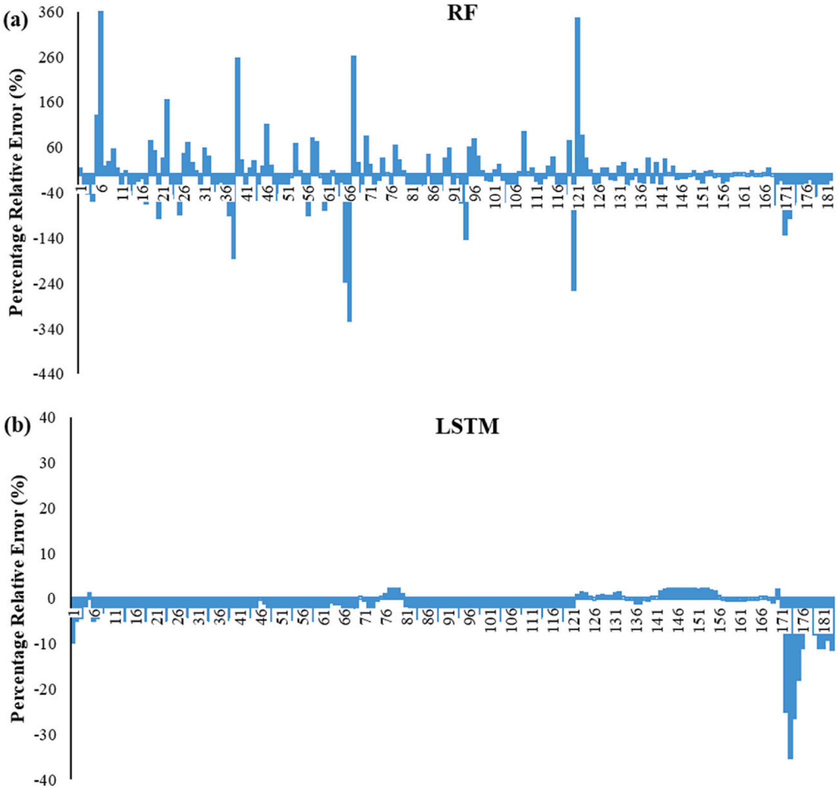

Fig. 8. Percentage relative error between predicted and actual SSL during testing period (a) using RF and (b) using LSTM.

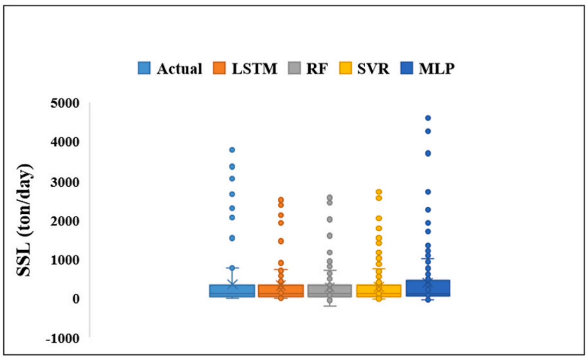

Fig. 9. Boxplots of the actual and predicted SSL values using all proposed models.

suggested model was used to predict the daily suspended sediment load for Johor River, located in Malaysia. The predicting methods were structured by using different scenarios to detection the reliable input patterns. Moreover, four different input combinations were examined with considering river flow and suspended sediment parameters as input parameters. Several statistical indicators have been used to evaluate the capacity of the predictive models. Four different machine learning methods (i.e., MLP, SVR, RF and LSTM) have been employed for sediment load prediction.

Generally, the LSTM method outperformed other predictive models for all modelling scenarios. The current research reveals that the accurate prediction results were obtained by LSTM that used two different input parameters. Clearly, the current research work supported the preferable utilize of LSTM model with considering suspended sediment load and river flow as input pattern. The research concluded that the LSTM could be candidate tool for SSL prediction in another case studies. In addition, the performance of LSTM superior to SVR, MLP and RF predictive models.

Although the LSTM model performed well in this research, there are several potential limitations that could be addressed in future studies. LSTM suffers from detecting the relevant input parameters with the expected output. Integration of the optimizer model with LSTM can improve prediction results. Since climatic and other environmental variables such as precipitation have an impact on the SSL

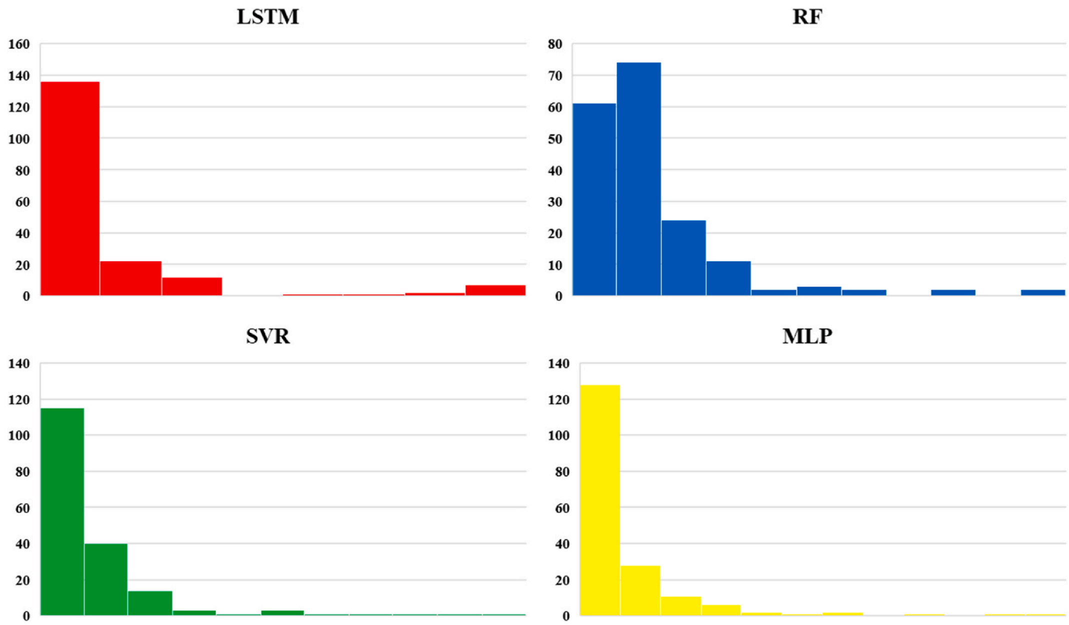

Fig. 10. Histogram plots for all proposed models.

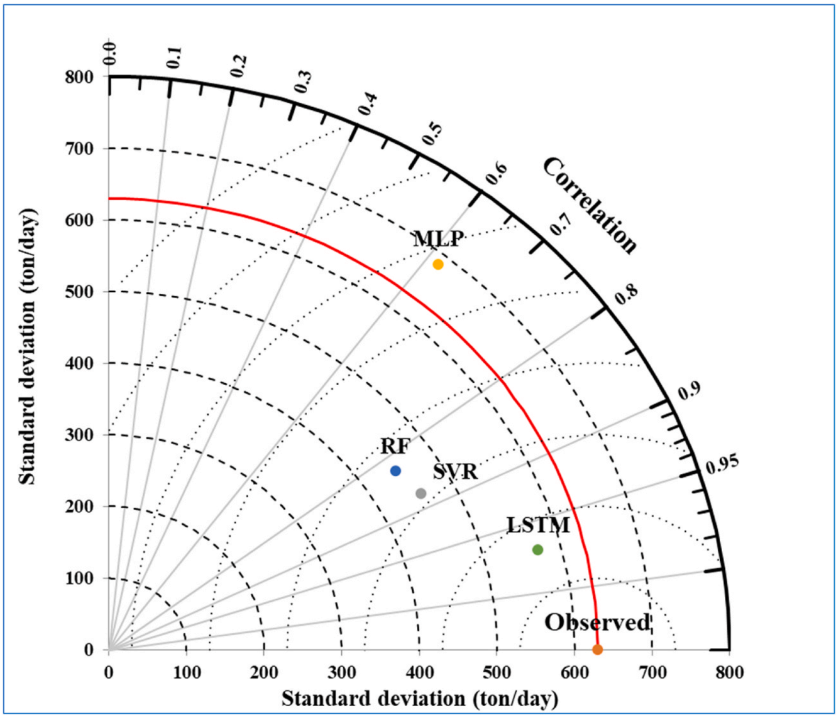

Fig. 11. Taylor diagram for the best prediction results utilizing MLP, SVR, RF and LSTM models.

pattern, it is expected that these variables will be used with SSL data. Therefore, more studies are required to properly include their inputs into the LSTM model in order to increase prediction accuracy. In fact, this stage is crucial for both recognizing the factor that has the greatest impact on the model's output accuracy and to design a practical intelligence machine model.

Author contribution statement

Mohammed Falah Allawi: Wrote the paper; Analyzed and interpreted the data.
Sadeq Oleiwi Sulaiman and Khamis Naba Sayl: Analyzed and interpreted the data.
Mohsen Sherif and Ahmed El-Shafie: Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare no conflicts of interest.

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