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Models for Predicting River Suspended Sediment Load Using Machine Learning: A Survey

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Abstract. Suspended sediment load (SSL) prediction study is critical to water resource management. This paper presents studies related to the prediction of SSL using machine learning (ML) algorithms over the last 13 years. This research gives a survey of current studies that are used machine learning techniques to predict sediment load on several rivers in different reign. Also, it aims to find a performance model to predict the SSL. This is done by making comparisons between several studies that used machine learning techniques to predict sediment load on several rivers using different time scales. Several metrics were used to determine the best prediction model. Most of the metrics used are: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-Squared (R2) and Nash-Sutcliffe Efficiency Coefficient (NSE). The results of comparisons using different ML algorithms to predict the SSL have shown that the Multilayer perceptron (MLP) algorithm is the best compared to other algorithms.

Keywords. Prediction, Suspended Sediment Load, Machine Learning, Artificial Intelligence.

1. Introduction

Suspended sediments are generally sediments within water bodies such as rivers. These sediments are transported by the liquid and are fine enough that the turbulent eddies can outpace the sedimentation of sediment particles within the water body, leading them to be suspended. Estimating SSL is critical for both short- and long-term water resource management [1],[2]. Sediment deposition in rivers is a well-known and costly problem that has an impact on environmental health, agricultural activities, and potable water sources. This is due to its negative effects on water quality, which causes pollution of bodies of water, particularly rivers. Suspended sediments can also disrupt a river's normal hydrological system under certain conditions [3],[4]. When the velocity and momentum of the river channel decrease, suspended sediments may begin to accumulate at the river channel's bottom, causing the river channel's bottom to rise, reducing the cross-sectional area of the river channel and choking the river's hydrological system, as a result, the habitat of aquatic creatures living in rivers is reduced [5],[6],[7]. Because of the aforementioned reasons, investigating and accurately predicting SSL is critical for the long-term preservation and conservation of river health. Predicting SSL in river flow is a major issue in watershed management and the design of river structures. Rivers with high suspended sediment loads have been shown to have negative effects on irrigation activities, dam or reservoir operations, river water quality, and drinking water supplies [8],[9],[10]. The study of suspended sediment load SSL prediction is critical for the goal of monitoring and damage mitigation [11],[12].

Several studies have been conducted to solve many complex problems of SSL prediction using various ML techniques [13], [14]. This paper presents a survey of ML techniques for predicting SSL over the last 13 years. It is organized as follows: Section 2 reviews the datasets of rivers, assessment metrics, and methods for predicting SSL. The results and discussion are presented in Section 3. Finally, Section 4 presents the conclusions and a vision of the work for the future.

2. Materials and methods

This section provides an overview of the data sets used in literature reviews for the last 13 years as well as evaluation metrics and a summary of ML techniques used to predict SSL.

2.1 Datasets

The suspended sediment data that used ML techniques to predict SSL over 13-year past are from different rivers of several regions such as Turkey, USA, Algeria, India, Iraq, London, China, Pakistan and Malaysia. Table 1 presents the details of datasets

2.2 Evaluation Metrics

There are several evaluation metrics used by researchers to evaluate the ML models used, such as Coefficient of determination (R2)[15], Mean Absolute Error (MAE)[16], Root Mean Squared Error (RMSE)[17], Nash-Sutcliffe Efficiency Coefficient (NSE)[18], Sum of squares error (RS)[19], Relative error (RE)[20], Ranking mean (RM)[21], percent bias (PBIAS), standard deviation ratio(RSR)[22], Willmott's Index (WI)[23], coefficient of efficiency(CE)[24],efficiency factor (EF)[25], Model efficiency (E)[26]. The R2, MAE, RMSE, NSE scales are the most of scales used in the comparisons, so they will be presented. The model is better if the RMSE and MAE values are close to 0, so the NSE and R2 values are close to 1.

1-Coefficient of determination (R2): It is a gauge of how well an estimated model's estimated values match up with actual data.[27],[28]:

$$R2= \frac{[\sum_{I=1}^{n}(Mi-\bar{M})(Pi-\bar{P})]^2}{\sum_{i=1}^{n}(Mi-\overline{M})^2 \sum_{i=1}^{n}(Pi-\overline{P})^2} \qquad (1)$$

2-Mean Absolute Error (MAE): The average sum of all absolute errors is referred to as MAE [29],[30]:

$$MAE= \frac{1}{N}\sum_{I=1}^{n}|(Mi-Pi)| \qquad (2)$$

3-Root Mean Squared Error (RMSE): It is a measure of the Evaluated deviation's Standard Deviation (SD), which is calculated using [31],[32]:

$$RMSE= \sqrt{\frac{1}{N}\sum_{I=1}^{n}(Mi-Pi)^2} \qquad (3)$$

4-Nash-Sutcliffe Efficiency Coefficient (NSE): is a metric for determining the proportional size of fluctuations in projected data in relation to observed data [33],[34]:

$$NSE= 1-\frac{\sum_{i=1}^{n}(Mi-Pi)^2}{\sum_{i=1}^{n}(Mi-\overline{M})} \qquad (4)$$

where n denotes the total number of observed or predicted values, Pi and Mi and denote observed and predicted values, $\overline{P}$ *and* $\overline{M}$ *and denote the average of observed and predicted values, respectively.*

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2.3 Suspended Sediment Load Prediction Techniques

Machine learning techniques have been widely used to predict SSL. Table I describes a survey of SSL prediction in the last 13 years using these algorithms and evaluating their performance on different types of data.

Table 1-A survey of SSL using different ML algorithm

Author	Details of Datasets					ML algorithms for SSL prediction			
	Year	Datasets	Period of data	Time scale	Data availability	Algorithms	performance	Evolution measures	Results
"Asli Ulke, Gokmen Tayfur, Sevinc Ozkul"[35]	2009	Gediz River inTurkey	13/3/1979-2/4/1985	Semi monthly	The State Meteorological Service of Turkey.	-Artificial neural networks (ANN) -Neurofuzzy inference system (ANFIS) -Sediment rating curve (SRC) -Multiple linear regressions (MLR) -Multiple non-linear regression (MNLR)	ANN_CG slightly better results than ANN_LM and ANFIS and it outperformed SRC, MLR, NLMR.	-R2 -RMSE -MAE	Dataset1 R2= 0.919 RMSE= 1.799 MAE= 696 Dataset2 R2= 0.89 RMSE= 4.384 MAE= 1.332
"A.M. Melesse, S. Ahmad, M.E. McClain,X. Wang, Y.H. Lim "[36]	2011	Mississi-ppi, Missouri and Rio Grande in USA	1/1/1974-1/10/1975 and 1/1/1980 - 1/10/1981	Daily and weekly	US Geological Survey and National Climatic Data Center	-ANN -Multilayer perceptron (MLP) -ANN with an error back propagation algorithm, - MLR -MNLR -Autoregressive Integrated moving average (ARIMA)	ANN predictions for most simulations were superior	-R2 -E	for Missouri (R2 = 0.97) and Mississippi (R2 = 0.96) better than those of Rio Grande (R2 = 0.65). E= 0.90
"Z A Boukhrissa, K Khanchoul, Y Le Bissonnais, M Tourki " [37]	2013	Gauging station of Ain Assel,inAlgeria	1975–1999	Daily	National Agency of Hydraulic Resources in Algeria	-SRC -ANN based on the cascade-forward and feed-forward back-propagation	ANN models have the highest efficiency	-RMSE -EF -R	RMSE= 2.00 EF= 0.20 R= 0.59
"Shima Sajadi.J, Ramu" [38]	2016	Lokapavani river basin in India	2006-2007	Daily	Obtained from a river gauge station	-MLP -SRC	MLP network was accurated comparison with SRC model.	-R2 -RMSE -Bias	R2 = 0.88 RMSE= 0.18 Bias=0.002
"Housseyn BOUZERIA, Abderrahmae N. GHENIM, Kamel KHANCHOL" [39]	2016	Gauging station of Bouchegouf northeast Algeria	1970 - 2000	Annual and Monthly	National Agency of Hydraulic Resources (ANRH) in Algeria.	-MLP	satisfactory results	-RMSE -MAE -CE -R2	RMSE= 0.0131 MAE= 0.00711802 CE=0.98, R2=0.99
"Shreya Nivesh, Pravendra Kumar" [40]	2017	Vamsadhara river India	1972-2010	Monthly	India Meteorological Department and Central Water Commission	- MLR - ANNs	ANN can predict sediment load more efficiently than MLR	-RMSE -R -CE	RMSE = 110.15 R = 0.97 CE = 94.22
"Mahmoud Saleh AlKhafaji, MustafaAl-Mukhtar, AhmedSaud Mohena " [41]	2017	Al-Adhiam watershed-Iraq	1983-1984	Daily	http://globelweather.tamu.edu/	- ANN	satisfactory agreement best performance	-R2 - NS -RSR	R2= 0.99, NS = 0.8 RSR= 0.2
"Shreya Nivesh, Pravendra Kumar" [42]	2018	Vamsadhara River India Mahanadi and Godavari River basins	1/6/ 1997-31/1/ 2000	Daily	India Meteorological Department and Central Water Commission	-ANFIS -MLR -SRC	a greater accuracy with ANFIS	-RMSE -R2 -CE	RMSE = 44.02 R2 = 0.99 CE = 99.06
"Issam Mohamed, Imtiaz Shah " [43]	2018	Thames River at Byron Station, London Ontario	1993 – 2016	Daily	water quality monitoring site at Byron	-SRC -Simple linear regression (SLR) -MLR - ANFIS - ANN	ANN models are more accurate than other modeling	-MAE -RMSE -NSE	MAE=2.823 RMSE= 3.720 NSE=0.860
"Mahmoudreza Tabatabaei, Amin Salehpour Jam, Seyed Ahmad	2019	Ghorichay River,Iran	1966-2012	Monthly	Sediment runnoff in the Ramian hydrometric station	-SRC through Non-dominated Sorting Genetic Algorithm NSGA-II	NSGA-II algorithm was superior	-RMSE -MAE -NSE -R2	RMSE= 669.13 MAE= 209.39 NSE= 0.83 R2= 0.84

Hosseini ” [44]									
“Sarita Gajbhiye Meshram” [45]	2019	a hydrological catchment in India	2000-2009	Monthly	CentralWater Commission (CWC) Bhopal, India	-ANN -Feed Forward Neuron Network Particle Swarm Optimization Gravitational Search Algorithm (FNN-PSOGSA) -ANFIS - FNN -FNN-PSO	FNN-PSOGSA model outperformed all comparison models.	-MAE -NSE -WI	MAE= 22.093.3 NSE= 0.612 WI= 0.832
“Rana Muhammad Adnanm, Zhongmin Liang, Ahmed El-Shafie , Mohammad Zounemat-Kermani, Ozgur Kisi” [46]	2019	China-Guangyuan and Beibei	01/04/2007 - 12/31/2015	Daily	Hydrological Yearbooks of the People’s Republic of China.	-Dynamic evolving neural fuzzy inference system (DENFIS) -ANFIS-FCM -Multivariate adaptive regression splines MARS	DENFIS best performance	-RMSE -MAE -NSE	RMSE=134 MAE=32.2 NSE= 0.861
“Mohammad Ehteram, Samira Ghotbi , Ozgur Kisi, Ali Najah Ahmed, Gasim Hayder , Chow Ming Fai, Mathivanan Krishnan, Haitham Abdulmohsin Afan and Ahmed EL-Shafie” [47]	2019	Atrek basin in Iran	1997–2011 2012–2017	Monthly	water resource management authorities in Iran.	-ANFIS -Multilayer feed-forward neural network (MFNN) - ANFIS -bat algorithm (BA) - ANFIS -Weed algorithm (WA)	the ANFIS–BA had more reliable performance compared to other models high potential	-RMSE -NSE -RSR -PBIAS	RMSE and RSR varied from 1.5 to 2.5 ton/d and from 5% to 25%, NSE was between very good and good performance (0.75 to 0.85 and 0.85 to1
“Marzieh Fadaee,, Amin Mahdavi-Meymand , Mohammad Zounemat-Kermani” [48]	2020	Eagle Creek Watershed	01 /1/ 2015 - 31 /12/2018	Daily	U.S. Geological Survey (USGS) Web server. website for the Eagle Creek	-ANFIS-FCM -Butterfly Optimization Algorithm (ANFIS-BOA) -ANFIS-GA -ANN-ML - ANN-BOA -ANN -GA -MLR	ANFIS-BOA model was more accurate compared to other models	-R2 -RMSE -MAE - NSE	R2= 0.93 RMSE= 15.93 MAE= 8.23 NSE=0.92
“Fatih ÜNEŞ , A. Burhan KARAEMİNO ĞULLARI, Bestami TAŞAR” [49]	2020	Omaha Station in Nebraska Data Missouri River	2011-2017	Daily	USGS (US Geological Survey).	-Support Vector Machines (SVM) -Generalized Regression Neural Network (GRNN)	SVM method better than GRNN method	-R -MAE -RMSE	R=0.90 MAE=24.38 RMSE= 55.61
“Fatemeh Barzegari Banadkooki,Mohammad Ehteram,Ali Najah Ahmed, Fang Yenn Teo,Mahboube Ebrahimi, Chow Ming Fai,Yuk Feng Huang, Ahmed El-Shafie” [50]	2020	Goorganrood basin in Iran	600 daily data	Daily	meteorological input data	- ANN-ant lion optimization (ANN-ALO) - ANN-BA -ANN- PSO	ANN-ALO model was the optimum model than others	-RMSE -MAE -NSE	RMSE= 1.10 MAE= 1.06 NSE= 0.90
“Waqas Ul Hussan, Muhammad Khurram Shahzad, Frank Seidel, Franz Nestmann” [51]	2020	Gilgit River Pakistan	1981-2010	Daily	The Water and Development Authority (WAPDA)	-ANN -ANFIS- grid partition GP -ANFIS- subtractive clustering SC -ANFIS-FCM - multiple adaptive regression splines (MARS) - SRC	the ANN model performed better than all other models	-R2 -RMSE -NSE	R2= 0.82 RMSE= 0.43 NSE= 0.81
“Dieu Tien Bui, Khabat Khosravi, James R. Cooper, Mahshid Karimi, Ozgur Kisi, Binh	2020	Haraz River in Iran	1972 - 2010	Monthly	Kareh-Sang Hydrometric Station, Mazandaran regional water authority	-random subspace (RS) -random forest (RF) -SVM- radial basis function kernel (SVM –RBF) - normalized polynomial kernel (SVM – NPK)	The RS model had the best predictive power a superior predictive accuracy	-RMSE -MAE -PBIAS -RSR -R2 -NSE	RMSE=989.6 MAE=10.5 PBIAS=-5.9 RSR =0.33 R2= 0.90 NSE=0.83

Thai Pham, Zongjie Lyu” [52]									
“Banu YILMAZ, Egemen ARAS, Murat KANKAL, Sinan NACAR4” [53]	2020	Çoruh River in Turkey	20/6/1967 16/7/2002	Annual	Karşıköy Gauging Station and the flow observation annual	-multiple regression - multivariate adaptive regression splines -ANN -ANN-BP - ANN teaching-learning-based optimization algorithm -ANN-artificial bee colony	ANN-BP Better than others	-RMSE	RMSE values of ANN-BP were lower 2.8% from ANN-ABC model and %4.4 from ANN-TLBO model.
“Zaki Abda, Bilel Zerouali, Muwaffaq Alqurashi,. Mohamed Chettih, Celso Augusto Guimarães Santos, and Enas E. Hussein” [54]	2021	Chemourah and Gueiss rivers	Gueiss River 17 /9/ 1971 - 11/1/ 1996 Chemorah 17 /8/ 1985 - 11 /6/1997	Monthly	Directorate General for Scientific Research and Technological Development and ANRH of Algeria	-ANN-PSO -ANFIS-PSO -random forest (RF) - long short-term memory (LSTM)	ANN-PSO, models have given a better accuracy of simulations	-RMSE - U2 -E -R	Chemourah ANN- PSO RMSE= 67.2990 U2= 0.3274 E= 0.6346 R= 0.8003 Garaet el tarf ANN- PSO RMSE= 55.8737 U2= 0.2904 E= 0.6971 R= 0.8392
“Fatih Üneş, Bestami Taşar, Mustafa Demirci, Martina Zelenakova, Yunus Ziya Kaya, Hakan Varçin” [55]	2021	Augusta station by the US	2007-2009	Daily	Augusta Station at the Skunk River in the USA. obtained from the USGS	- MLR -SRC - neuro-fuzzy (NF) -poly kernel learning algorithms (SVM- PK) -Library SVM (LibSVM) -Radial basis function kernel (SVM-RBF)	NF and LibSVM obtained the best result	-MAE -RMSE -R	RMSE =125.74 MAE=64.53 R=0.89
“Maryam Asadi, Ali Fathzadeh, Ruth Kerry, Zohre Ebrahimi-Khusfi, Ruhollah Taghizadeh-Mehrjardi ” [56]	2021	several river basins in Lorestan and Gilan, Iran	1983–2014	annual	The data are not publicly available due to privacy restrictions	-MLR - ANN - K-nearest neighbor (KNN) - SVM - Gaussian-Processes (GP) - Evolutionary support vector machines (ESVM)	ESVM for obtained the better result	-R -RMSEs	GP RMSE= 0.19 ESVM RMSE= 0.17 R= 0.99
“Nouar AlDahoul, Yusuf Essam, Pavitra Kumar, Ali Najah Ahmed, Mohsen Sherif, Ahmed Sefelnasr Ahmed Elshafie” [57]	2021	Malaysia’s Johor River	1988–1998.	Daily, Weekly, 10-days, and Monthly	Department of Environment Malaysia (DOE).	-LSTM - ElasticNet Linear Regression (ElasticNetLR) -MLP - Extreme Gradient Boosting (EGB)	LSTM outperformed other models	-R2 -RAE -RSE -RMSE -MAE.	Monthly RAE=0.075 RSE=0.05 RMSE= 3.236 MAE= 2.447
“Yusuf Essam, Yuk Feng Huang, Ahmed H. Birima, Ali Najah Ahmed Ahmed El-Shafie” [58]	2022	Peninsular Malaysia	Several period about: 1976 -2010	Daily	Malaysian Department of Irrigation and Drainage	-SVM -ANN -LSTM	ANN is the best predictive model	-RM	RM= 2.64
“Pankaj Chauhan, Muhammed Ernur Akıner, Kalachand Sain, Amit Kumar” [59]	2022	Pindari-Kafni glacier valley in Central Himalayan	2017–2019	Daily	The Dwali station meteorological	-MLR -ANN (MLP, RBF)	ANN model outperforms the MLR model	-RSS -RE -MSE -R2	MLP Pindari RSS= 5.776 RE=0.111 R2= 0.914 MSE=0.056

3. *Results and Discussion*

Table 2 presents the prediction accuracy results of best ML algorithms for each study using different datasets with descriptions of the R-Squared, RMSE, MAE, NSE and other performance measures. Also, figure 1 shows the best results of RMSE for ML algorithms. According to the interpretation in table 2 and figure 1 , the performance of MLP technique outperforms all other techniques despite the variety of data sets used. Whereas, MLP produces lower MAE and RMSE and higher value of R2 and NSE. It is also evident from the table III that the ANN algorithms are frequently used in prediction operations and give good performance

Table 2-SSL prediction performance measures for the best Algorithm study using different datasets

No.	Best ML techniques	R^2	RMSE	MAE	NSE	Other measures
[35]	ANN_CG	0.919	1.799	696	—	—
[36]	ANN	0.97	668	—	—	E= 0.90
[37]	ANN	0.59	2.00	—	—	EF = 0.20
[38]	MLP	0.88	0.18	—	—	Bias= 0.002
[39]	**MLP**	**0.99**	**0.0131**	**0.00711**	**0.99**	**CE = 0.98**
[40]	ANN	0.97	110.15	—	—	CE = 94.22
[41]	ANN	0.99	—	—	—	RSR = 0.2 NS = 0.8
[42]	ANFIS	0.99	44.02	—	—	CE =99.06
[43]	ANN	—	3.720	3.720	0.860	—
[44]	NSGA-II	0.84	669.13	209.39	0.83	—
[45]	FNN-PSOGSA	—	—	22.093.3	0.612	WI=0.832
[46]	DENFIS	—	134	32.2	0.861	—
[47]	ANFIS–BA	—	1.5	—	0.75	RSR=0 .5
[48]	ANFIS-BOA	0.93	15.93	8.23	0.92	—
[49]	SVM	0.90	55.61	24.38	—	—
[50]	ANN-ALO	—	1.10	1.06	0.90	—
[51]	ANN	0.82	0.43	0.81	–	–
[52]	RS	0.90	989.6	10.5	0.88	PBIAS= -5.90 RSR= 0.33
[53]	ANN-BP	–	–	–	–	RMSE value of ANN-BP was lower 2.8% from ANN-ABC model
[54]	ANN- PSO	0.8392	55.8737	–	–	U2= 0.2904 E= 0.6971
[55]	LibSVM	0.89	125.74	64.53	–	–
[56]	ESVM	0.99	0.17	–	–	–
[57]	LSTM	–	3.236	2.447	–	RA= 0.075 RSE= 0.05
[58]	ANN	–	–	–	–	RM= 2.64
[59]	ANN	0.914	0.051	–	–	RS= 5.776 RE= 0.111

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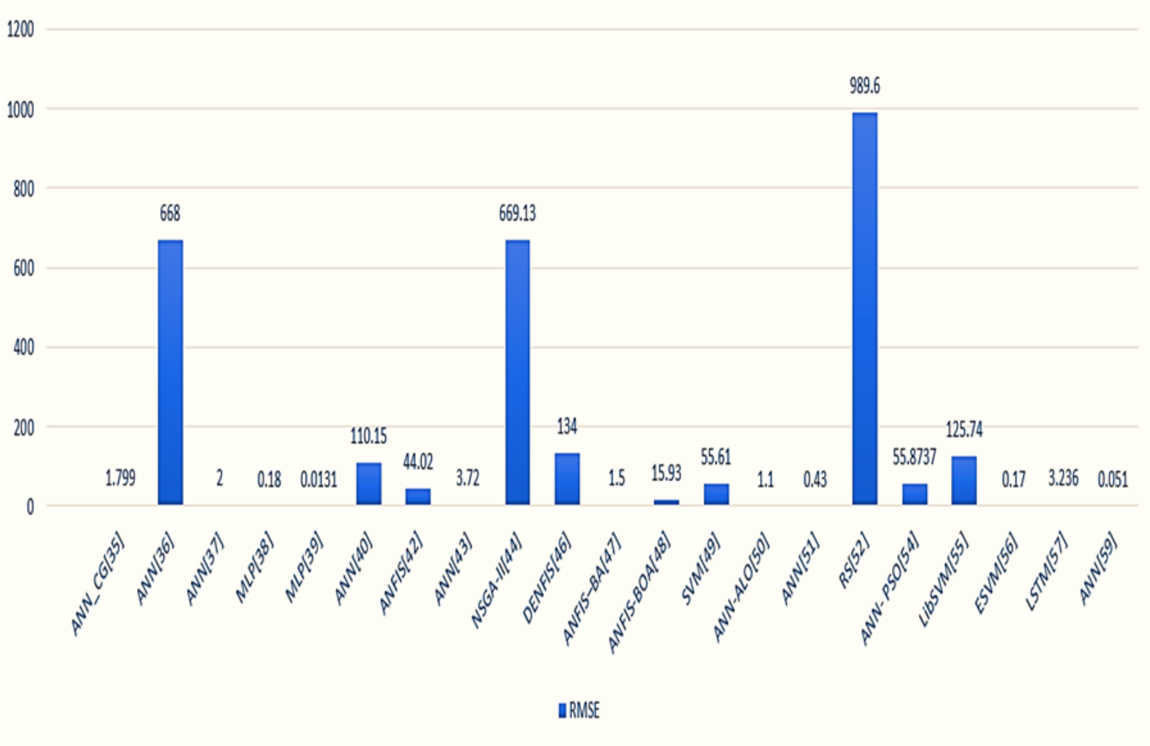

Figure 1-The best RMSE of ML algorithms using different datasets.

4. *Conclusion*

Several ML algorithms have been studied and compared. These algorithms were used to predict the SSL of different rivers data covering several places such as Turkey, USA, Malaysian, Algeria, Iran, China, India, Iraq and London. Based on the comparison of multiple ML methods, it was found that MLP algorithm outperforms all other metrics, which produces lower values of RMSE and MAE and higher value for R-Squared and NSE. We also find, in general, that ANN algorithms have been widely used for SSL prediction and give good results. It also shows that deep learning algorithms are rarely used for SSL prediction so this would be a good entry point to work with.

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