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Evaluation of Machine Learning Techniques for Inflow Prediction in Lake Como, Italy

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Abstract

Accurate streamflow prediction is a fundamental task for integrated water resources management and flood risk mitigation. The purpose of this study is to forecast the water inflow to lake Como, (Italy) using different machine learning algorithms. The forecast is done for different days ranging from one day to three days. These models are evaluated by three statistical measures including Mean Absolute Error, Root Mean Squared Error, and the Nash-Sutcliffe Efficiency Coefficient. The experimental results show that Neural Network performs better for streamflow estimation with MAE and RMSE followed by Support Vector Regression and Random Forest.

Keywords: Inflow Prediction; Machine Learning; K-Nearest Neighbour; Random Forests; Support Vector Regression; Linear Regression; Artificial Neural Networks

1. Introduction

Controlling water level in a large lake is a critical environmental problem e.g. water overflow situations could result inconceivable disasters. A predictive system deployed to control water inflow can be useful to take actions and prevent natural disasters. The Accurate prediction of streamflow plays a significant role for effective water resources management during drought and flood events, municipal water supply and reservoir operations. The traditional approaches towards modeling the studies for predicting streamflow and rainfall are classified into two classes: physical methods and empirical methods [1], [2].

In the physical scheme, predictions are carried out by physically built models that are based on the equations of the system that forecast the stream flow/rainfall. The weather forecast systems that related (temperature change,

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rainfall forecasting and pressure change) use mathematical equations to model the forecast(conceptual rainfall-runoff model). The application of these models depends on the region of study and available data for that specific region. Physical models are more representative (providing comprehensive and direct information of the involved processes) for streamflow prediction. These models use parameters which are directly linked with watershed (an area of land where rainfall collects and drainoff into common points such as river and other water bodies) characteristics such as (vegetation, topography, soil and geology). However,the predictive capability of physical-based models demands comprehensive information which is sometimes difficult to obtain in a study area [3]. On the other hand, empirical methods are based on analysis of historical hydro-climatic data and their inter-relationship over diverse regions. Empirical techniques involve statistical models or classical machine learning models e.g. linear regression, support vector machine, fuzzy logic,the average nearest neighbor etc [4].

In this work, we evaluate different Machine learning models to predict streamflow in Lake Como which is situated in Lombardia, Italy. Lake Como is connected with the Olginate dam through Adda river [5]. For this reason, one way to control the water level of Lake Como is to act on the Olginate dam, which is situated on the south-side of the lake. In the Olginate dam there is a measuring station that monitors the level of water, which helps to make certain decisions regarding the water flow through the dam. The purpose of studying available data at the Olginate station is to define a dataset that takes into account exogenous features that contribute to the water inflow quantity to Lake Como. This work utilizes different machine learning techniques which get different input features that represent different information gathered at the Olginate dam. The prediction of inflow at Lake Como is predicted for upto three future days i.e. $d + 1$, $d + 2$, $d + 3$ considering the given current day, d. We adapt different notations to differentiate the multiple results. The multi-input-single-output (MISO) models are (where the algorithms takes multi-inputs to predict the inflow for 1-day, 2-day, and 3-day) represented as MISO1, MISO2, and MISO3 ahead for a given specific day, d. The input of the models are the features that are used to keep the record for hydrological data.

The Rest of the paper is organized as follows. We describe related work in section 2 whereas our dataset is discussed in section 3. The models used in this work are reported in section 4. The Results are discussed in Section 5 which is followed by section 6 that concludes our work.

2. Related Work

Machine Learning Algorithms and particularly Artificial Neural Networks (ANNs) are successfully used in hydrological applications for modeling and estimating gaps and noise to time series datasets. The primary preference of using ANNs over conventional modeling tools is related to their flexible adaptation on both parametric as well as non-parametric data [6]. ANNs have been widely applied to various hydrological applications such as rainfall [7], ground water level anomalies [8] sediment transport [9] water quality [10] and Snow Water Equivalent [11]. Toth [12] examined a modular approach for real time streamflow prediction on the Sieve River basin, North-Central Italy. They used the clustering technique based on Self-Organising Maps (SOMs) in conjunction with different feedforward artificial neural networks that forecast flow for one to six hours ahead. The results show that SOM methods are helpful for a consistent identification of various future rainfall events. The study suggests that incorporating additional hydrological processes may increase rainfall-runoff modeling processes. Chen et al., [13] predicted rainfall in China to determine landslide susceptibility using various data mining algorithms such as Classification and Regression Tree models, the Logistic Model Tree and Random Forest. The results show that the RF model performs better over other algorithms by exhibiting a higher rate of $R^2 = 0.837$. However, they suggest precise examination of the model parameters and their contribution related factors (elevation and slope) changes dynamically. In Italy, Callegari et al. [14], predicted monthly river discharge using the Support Vector Regression (SVR) technique in 14 catchments in Northern Italy. Their result depicts that the SVR model is effective compared to other long term and linear models with $RMSE(Root\ Mean\ Square\ Error) = 22\%$ when forecasting at one month lead time scale. The study also highlighted the importance of the snow cover area for river flow predictions along with other metrological variables. Granata et al., [15] forecaste the spring discharge in Rasiglia Alzabove, (Umbria, Central Italy) using three machine learning algorithms (support vector machine, random forest, and MP5 regression tree). The results depict that the MP5 model provided reliable short streamflow prediction for one month ahead with $R^2 = 0.991$, $RAE(Relative\ Absolute\ Error) = 14.97\%$ and $MAE(Mean\ Absolute\ Error) = 0.0124$ followed by random forests and support vector machines. Lake Como is situated in the Italian Alps one of heavily man-overworked water management system irrigating the largest cultivated area (1,320 km^2) and providing the water supply to downstream masses of the city [16]. To our current knowledge, this is one of the few studies in Italy, especially related to Lake Como, that uses long historical (1946-2016) daily time series hydro-metrological data for stream flow predictions [17, 18]. Previous studies on lake Come estimated stream flow at seasonal and monthly scale. Giuliani et al. [19] estimated seasonal stream flow in Lake Como using the physical based E-HYPE hydrological model but no studies are found that have used machine learning algorithms to forecast the stream flow at a daily scale in this region. The present study attempts to to fill out that gaps.

3. Dataset preparation

In this paper, we use the hydro-climatic data for Lake Como that cover the period from January 01, 1946 to December 27, 2016. The lake mainly gets water from the Adda river as shown in Fig. 1. There are two stations which keep tracking the information for lake Como: Olginate and Sondrio stations. The Olginate station provides daily values for:

- *Water Level* of Lake Como;
- *Water Outflow* from Lake Como to the dam;
- *Water Inflow* to Lake Como from Adda river;

Another variable that we have considered is the precipitation for each day. However, it is important to identify whether this precipitation is due to rainfall or snow, as each precipitation contributes differently to the level of water. The precipitation parameter values are gathered at the Sondrio station. The data at Sondrio station are collected by ARPA[1], Lombardia [20] which is the only data collection center in the neighborhood of Lake Como with complete data for the period we are considering for our work. Thus, Sondrio station provides daily values for;

- *amount of precipitations*;
- *maximum of temperature*;
- *minimum of temperature*.

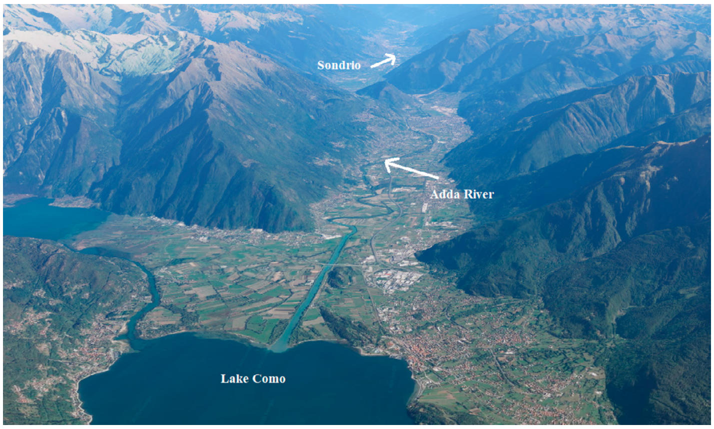


Fig. 1: 3D Map of Lake Como, his tributary the Adda River and the position of Sondrio.

For our work, we consider the above mentioned information from both stations. From these values the dataset is built with 3-day temporal windows for a specific day. Furthermore, we split the data into train and test set where

[1] Agenzia Regionale per la Protezione dell'Ambiente

the train set contains the data from 01-01-1946 to 30-09-2003 while the test set contains the data from 1-10-2003 to 27-12-2016 making the training/test split with approximately a 80/20 ratio.

Table 1 summarises the features and their notations we use in this paper. As described in the previous paragraph, some of the values of the features are gathered from the Olginate station while some others are collected at Sondrio station. The inflow (IN), outflow (OUT), and water level (WL) for a specific day are collected at Oliginate station. Similarly, minimum temperature (Tmin_S), maximum temperature (Tmax_S), snow status (Snow_S), and precipitation (Prec_S) values are collected at the Sondrio station. Furthermore, we define some more features using these basic features. We also use 1-day earlier values of these features represented by the suffix; 1d e.g. one day earlier inflow is represented as IN_1d, one-day precipitation value is represented as Prec_S_1d. Likewise, we also use the values of these features for the inflow prediction of two-days before head e.g. IN_2d represent the inflow value of the two days earlier given the current day d. Moreover, we also use Mean (MEAN_IN_7d) and standard deviation (SD_IN_7d) of inflow (IN) for the last one week. As we also mentioned we are using different MISO models in our work, therefore, we use different features for each model which are briefly described in section 4. In this table, it can be noticed that models of MISO2 use the output of MISO1 $IN\hat{\_}p1d$ models. Similarly, the MISO3 models use the output of MISO1 $IN\hat{\_}p1d$ and MISO2 $IN\hat{\_}p2d$.

Table 1: Summary table of all the features considered in the analysis.

Feature Name	Description
IN	Inflow in this day at the Olginate station
OUT	Outflow in this day at the Olginate station
WL	Water level in this day at the Olginate station
IN_1d	Inflow in one day before
OUT_1d	Outflow in one day before
WL_1d	Water level in one day before measured in millimetre
IN_2d	Inflow in two days before
OUT_2d	Outflow in two days before
WL_2d	Water level in two days before measured in millimetre
MEAN_IN_7d	Mean inflow in 7 days
SD_IN_7d	Inflow standard deviation in 7 days
Tmin_S	Minimum temperature collected at Sondrio station
Tmax_S	Maximum temperature collected at Sondrio station
Snow_S	Flag for snowing precipitation in Sondrio station
Prec_S_2d	Precipitation millimeters detected in Sondrio station 2-days before
Prec_S_1d	Precipitation millimeters detected in Sondrio station 1-day before
Prec_S	Precipitation millimeters detected in Sondrio station

4. Models description

The purpose of this research is to predict the future inflow of Lake Como given that we have the actual inflow for a specific day. We use different algorithms that render the features described in the above section to predict future inflow values. To differentiate prediction for different days, we use notation Multi-Input-Single-Output (MISO) where the algorithms take multi-inputs to predict the inflow for 1-day, 2-days, and 3-days ahead for a given specific day and are referred as MISO1, MISO2, and MISO3 as indicated in Table 2. The output of the MISOś models are represented by IN_p1d,IN_p2d and IN_p3d in the same way the MISO models are predicting the water Inflow value for Lake Como. Furthermore, we use the output of MISO1, which is the inflow prediction for 1-day ahead, as an auxiliary input for MISO2. Similarly, MISO3 uses the output of MISO1 and MISO2 along with other features as shown in Fig. 2.

4.1. Training Algorithms

Machine learning is a field of artificial intelligence that studies an effective way to construct computer programs that automatically improve their performance with experience [21]. Due to the effectiveness of the existing machine learning techniques and the increasing amount of available data, the demand to implement machine learning techniques

Table 2: Table Shows the input features Use for Training of the Models

Model	Input Parameters	Model's output	Model's target feature
MISO1	IN, OUT, WL, IN_1d, OUT_1d, WL_1d, IN_2d, OUT_2d, WL_2d, MEAN_IN_7d, SD_IN_7d, Tmin_S, Tmax_S, Snow_S, Prec_S, Prec_S_1d, Prec_S_2d	$IN\_\hat{p}1d$	IN 1 day ahead
MISO2	IN, OUT, WL, IN_1d, OUT_1d, WL_1d, MEAN_IN_7d, SD_IN_7d, Tmin_S, Tmax_S, Snow_S, Prec_S, Prec_S_1d, $IN\_\hat{p}1d$	$IN\_\hat{p}2d$	IN 2 days ahead
MISO3	IN, OUT, WL, MEAN_IN_7d, SD_IN_7d, Tmax_S, Snow_S, Prec_S, $IN\_\hat{p}1d$, $IN\_\hat{p}2d$	$IN\_\hat{p}3d$	IN 3 days ahead

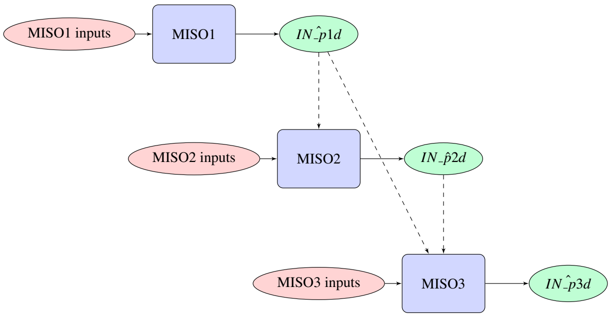


Fig. 2: Table of the models chain. Red ellipses refer to the input taken from Table 1, blue rectangles refer to MISO models, green ellipses refer to MISO models' outputs. Lines that enter in rectangles indicate models inputs, while the lines that come out indicate model outputs.

in different fields is also increased. Machine learning algorithms are mainly divided into supervised, unsupervised, and reinforcement learning. Supervised learning algorithms are trained with the examples given along with the output desired. In contrast to supervised learning algorithms, unsupervised algorithms are trained with examples that do not include the corresponding desired output for the given examples. In reinforcement learning, algorithms are trained in a way that algorithms learn the suitable action, for which they get a reward, in the given environment.

In this paper, we implement different supervised machine learning algorithms, which are briefly described below, for our prediction task. The task described in this article is a regression problem i.e. for the given data, the output desired is continuous. For this reason, we use supervised regression algorithms in this paper.

Linear Regression (LR) is a linear approach for modelling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables) [22]. In other words, linear regression defines a linear function between the input variables and the output variable. This linear function draws a straight line for the relationship of the input variables and an output variable. The linear function is fitted using some optimisation criteria.

Random Forests (RF) method [23] is an ensemble learning method [24] that constructs several regression decision trees the training time and defines a regression variable that is a linear combination of the variables of the individual trees. For constructing each tree of the random forest, a randomly chosen subset of the data attributes is used. Furthermore, during the construction of decision trees, the random forest performs random sampling of training data. This involves the training of each single decision tree on different sampling training data. Apart from using a random sampling of training data, the random forest considers the subset of all features for splitting each node in each decision tree.

Support Vector Regression (SVR) is a variant of the support vector machine (SVM) algorithm. The SVM is a supervised algorithm that distinguishes the data belonging to different classes using the hyperplane line. This hyperplane is a maximal separable line between different class data [25]. If the data are non-linearly separable then SVM uses non-linear functions called *kernels*, in order to automatically translate the instances of the training data in a multi-dimensional space where linear classification techniques can be directly applied. The Support vector regression (SVR) is a type of SVM applied on a real number which becomes very difficult to predict the information at hand that has infinite possibilities. In the case of regression, a margin of tolerance or maximum error (ϵ) is set to accommodate the accuracy desired. However, the main idea is always the same: to minimize the error, the hyperplane which maximizes the margin must be computed, keeping in mind that part of the error is tolerated [26].

The Artificial Neural Networks (ANNs) algorithm is inspired by the working mechanism of a human brain. The human brain consists of billions of neurons that communicate with each other to perform any task. These communications are performed in the form of electric pulses called spikes [27]. The artificial neural network consists of an input layers, an arbitrary hidden layer, and an output layer. The neural network approach is a well-studied method that can be very effective in complex contexts [28]. Neural networks are suitable when the model of the target variable can be (highly) non-linear and complex, the training data may have hidden (unseen) relationships that are inferred by network training, and the amount of training data can be very large and noisy [29].

5. Results and Discussion

We consider the below measurement to evaluate the performance of our models;

- The Mean Absolute Error: $MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right|$
- The Root Mean Squared Error: $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$
- The Nash-Sutcliffe Model Efficiency Coefficient [30]: $NSE = 1 - \left(\sum_{i=1}^{n}(\hat{y}_i - y_i)^2\right) / \left(\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2\right)$

The first two indexes give an amount of error and therefore the least value is considered the best performance. Whereas the third provides an estimation of precision, with a value clipped between zero and one, hence the greater value is measured as the best performance. We use the R programming language for our experiments[2]. The results comparisons of different temporal widows (1d, 2d, 3d) with different algorithms are reported in Table 3. We can observe that considering the MAE and RMSE scores we conclude that RF and SVR are the right models for MISO1. Besides, the SVR and ANN produce the best scores for MISO1 considering the NSE score. We also notice that SVR results in best MAE score for MISO2 whereas ANN is the best model for MISO2 and MISO3 considering RMSE and NSE scores.

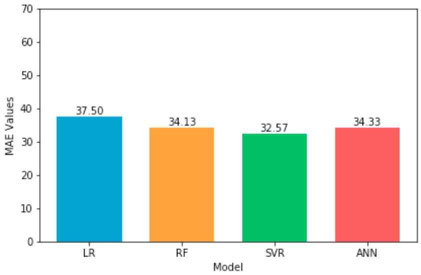
To get a more precise idea, we also present the bar graphs of the outputs of different algorithms which are given in Fig. 3, 4 and Fig. 5. Considering the MAE evaluation, we can notice that SVR outperforms compared to all algorithms for MISO1, MISO2, and MISO3. The SVR results MAE-score values are 32.57, 36.44, 39.83 for MISO1, MISO2, MISO3 respectively These three values determine the average MAE-score to 36.28. The SVR produces less error (MAE) for MISO1, MISO2, and MISO3. However, we see the trend in increase of error as we move from MISO1 to MISO3. The RF performs second best after SVR. Neverthless, we see that for MISO1 RF the results MAE score of 34.13 and can be considered far from the best MAE score i.e. 32.57 which is produced by SVR. However, for MISO2 and MISO3 we notice this gap is less from the best MAE score that is produced by SVR. The ANN produces comparable results with the RF whereas the LR model produces poor MAE scores. The reason could be related to the fact that LR uses the simple linear function for the prediction. Furthermore, taking into account the RMSE-score, we find that RF performs best for the MISO1 but fails to achieve the best RMSE-score for MISO2 and MISO3. We also see that ANN outperform for MISO2 and MISO3 The SVR which produces best MAE-scores for MISO1, MISO2, and MISO3 also showed increase in error considering RMSE measurements. Likewise, in MAE, the LR again results is worst RMSE-score for MISO1, MISO2, and MISO3. We again notice a direction of continuous increase in RMSE moving MISO1 to MISO3. Furthermore, we can observe that ANN surpasses the NSE score for MISO1, MISO2, and MISO3 compared to all algorithms determining an average NSE-score of 0.71. Moreover, the RF and SVR algorithms also produce the best results for MISO1 and MISO2. We can observe that the models that use non-linear functions to learn the pattern of the data are able to produce the best results compared to the LR algorithm which uses a linear function. We also observe that moving the predictions from MISO1 to MISO3, all techniques share a consistent

[2] The following main R packages were used in this study for analysis and plotting: randomForest, dplyr, devtools nnet, neuralnet, e1071, lubridate and ggplot2.

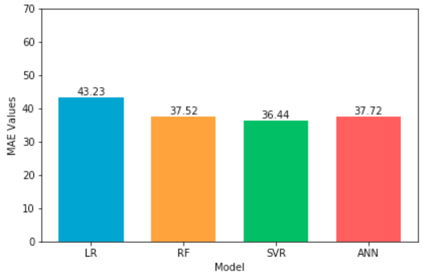
decrease in performances. This is expected, considering that the error introduced in earlier results accumulate through models. In other words, MISO2 incorporates the prediction (output) of MISO1 as one input features for its training. Similarly, MISO3 considers the output prediction of MISO1 and MISO2 for its output prediction.

Table 3: Results Comparison for Different Models

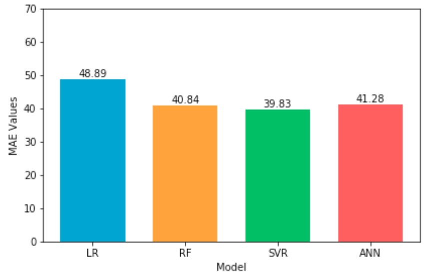
	MAE			RMSE			NSE		
Algorithms	MISO1	MISO2	MISO3	MISO1	MISO2	MISO3	MISO1	MISO2	MISO3
LR	37.50	43.23	48.89	64.77	70.83	76.64	0.70	0.64	0.58
RF	34.13	37.52	40.84	**58.98**	64.81	69.53	**0.75**	0.70	0.65
SVR	**32.57**	**36.44**	**39.83**	59.11	65.43	71.11	**0.75**	0.69	0.64
ANN	34.33	37.72	41.28	59.26	**62.23**	**68.55**	**0.75**	**0.72**	**0.66**



(a) MISO1.

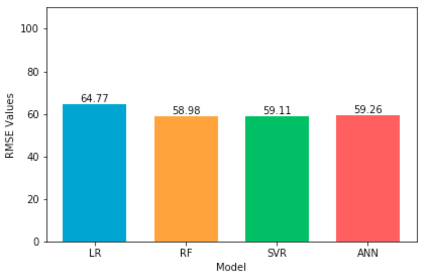


(b) MISO2.

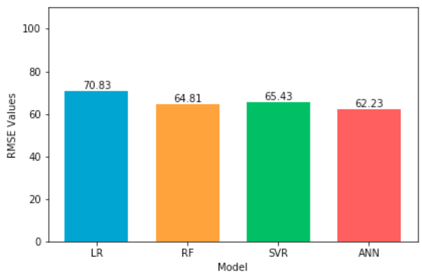


(c) MISO3.

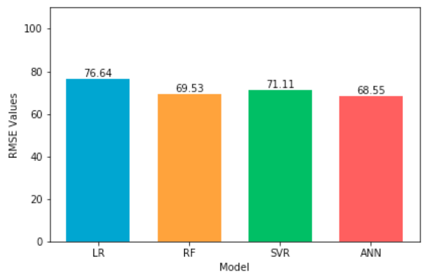
Fig. 3: Bar Chart Comparison using MAE



(a) MISO1.

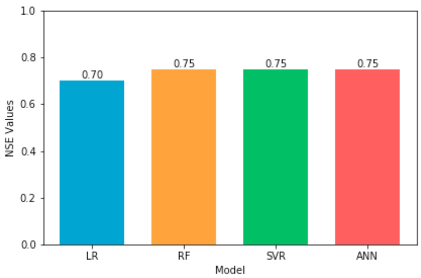


(b) MISO2.

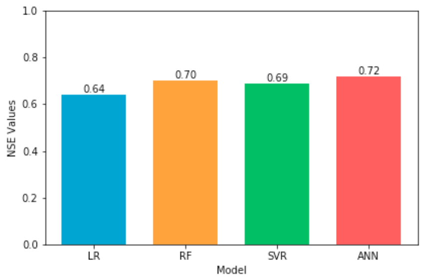


(c) MISO3.

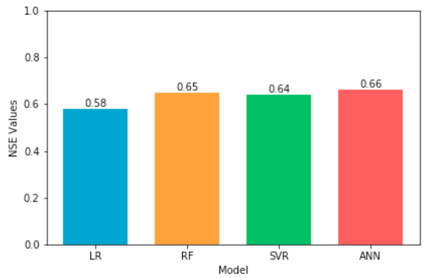
Fig. 4: Bar Chart Comparison using RMSE



(a) MISO1.



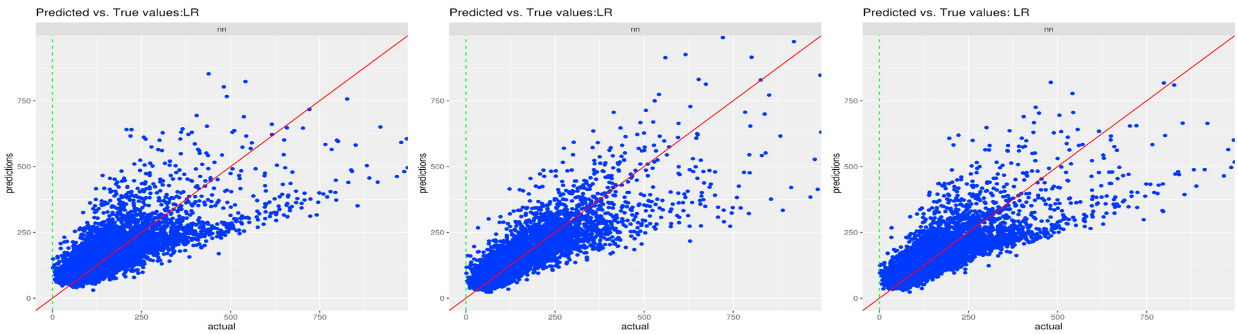
(b) MISO2.



(c) MISO3.

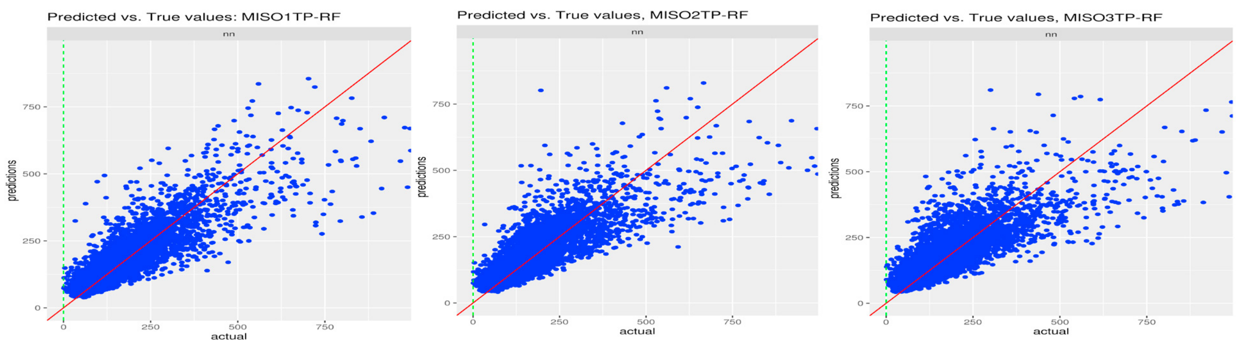
Fig. 5: Bar chart Comparison using NSE.

We further analyse the models performance using scatter plots where predicted values are plotted on y-axis against actual/real values that are plotted on x-axis. The predictions of the LR model are shown in Fig. 6 where blue dots show the examples/instances predicted and the objective is to find the predictions close to the diagonal red line. However, analysing the LR results for MISO1 and MISO3, we see that predictions are not close to the diagonal red line. Such poor results can be seen by analyzing the MAE/RMSE/NSE values of LR for MISO2 and MISO3. The scatter plot for RF is shown in Fig. 7 where we can notice the best result for MISO1. The scatter plots of SVR are shown in Fig. 8. We see that SVR is able to produce results that are more skewed towards diagonal results. Furthermore, we notice sparse predictions for MISO1 by ANN as shown in Fig. 9. However, we observe better predictions for MISO2 and MISO3.



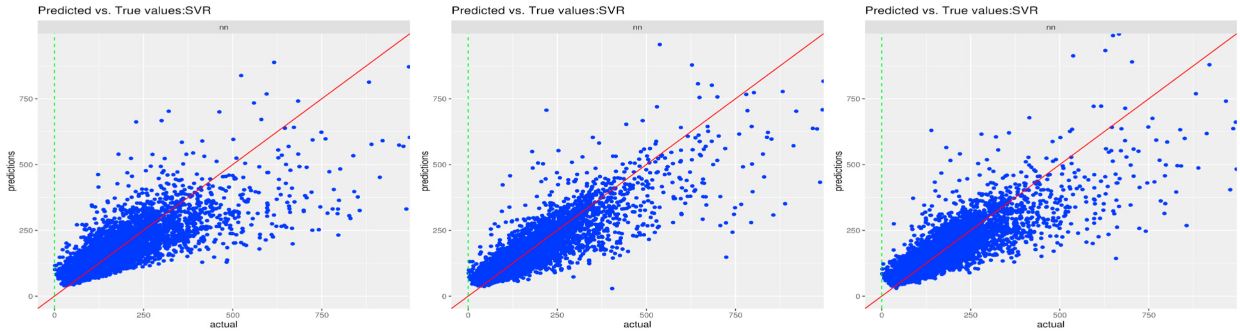
(a) MISO1. (b) MISO2. (c) MISO3.

Fig. 6: Scatter plots on test set using LR. In x-axis actual values, in y-axis predicted values. In red the line of perfect agreement.



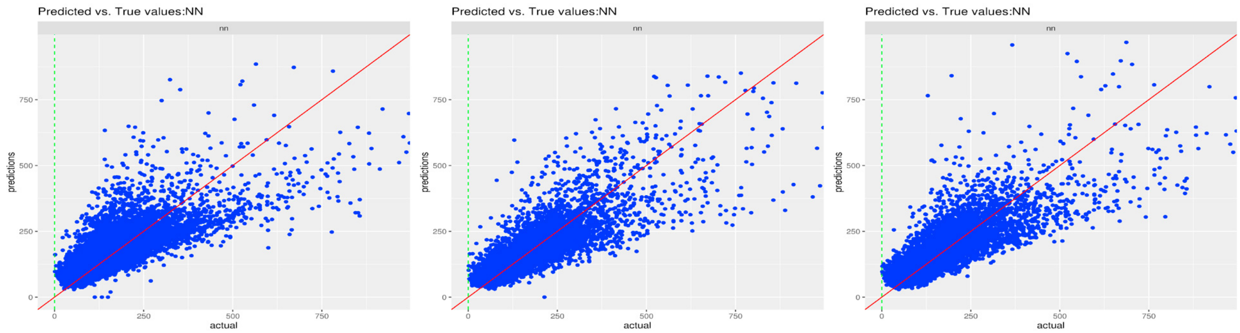
(a) MISO1. (b) MISO2. (c) MISO3.

Fig. 7: Scatter plots on test set using RF. In x-axis actual values, in y-axis predicted values. In red the line of perfect agreement.



(a) MISO1. (b) MISO2. (c) MISO3.

Fig. 8: Scatter plots on test set using SVR. In x-axis actual values, in y-axis predicted values. In red the line of perfect agreement.



(a) MISO1. (b) MISO2. (c) MISO3.

Fig. 9: Scatter plots on test set using ANN. In x-axis actual values, in y-axis predicted values. In red the line of perfect agreement.

6. Conclusions

The reliable estimation of hydrological parameters is essential for managing and preventing natural hazard events. The streamflow forecasting pays a vital role in controlling flood magnitude, crests duration that could save countless lives. The data driven models provide insights for decision making regardless of the application. The hydrological data show a non-linear data pattern. In this study, various machine learning models are examined for effective streamflow forecasting in Lake Como in Italy. We considered different statistical measurements to evaluate the performance of the models. We find that ANN shows prominent results compared to the other models and we think that this is due to the ability of ANN to learn the non-linear pattern of the data. Furthermore, we find that LR which uses a linear function for the prediction showed poor performance. This work requires further investigation using statistical and the cross validation analyses. However, applying a simple cross validation technique on time series data can be problematic since the temporal coherent property is lost when the cross validation method is performed. For future work, we will utilize the cross validation method on our work using the Day Forward Chaining method which is also referred as rolling-origin evaluation [31] as well as rolling-origin-recalibration evaluation [32]. In a Day Forward Chaining technique, the test set always contains the values/data from future dates in a chronicle way whereas we assign the values/data of the past dates to the train set in a chronicle way. We will further extend our work using deep learning models that have shown prominent results in many other fields [33]. In future work we will also consider other meteorological variables such as (snow depth, snow cover, wind speed and solar radiation) which are also important parameters that influence the total stream flow in Lake Como.

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