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Modelling Floodplain Boundary Shear Distribution in Two-Stage Meandering Channels Using Machine Learning Techniques

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HIGHLIGHTS

- Machine learning models were developed to predict boundary shear distribution in two-stage meandering channels.
- Gaussian Process Regression achieved the highest prediction accuracy (R^2 = 0.984; RMSE = 2.0).
- The proposed approach improves reliability of floodplain shear stress estimation for complex channel geometries.

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ABSTRACT

The distribution of boundary shear stress plays a pivotal role in addressing various river engineering challenges, including flood control, sediment transport, and riverbank stabilisation. This study employs three machine learning (ML) techniques, *i.e.* Gaussian Process Regression (GPR), Extreme Learning Machine (ELM), and Relevance Vector Machine (RVM), to predict boundary shear distribution along the floodplains of a two-stage sinuous channel. Key geometric and hydraulic parameters such as the relative width $(\alpha = B/b)$, depth ratio $(\beta = (H-h)/H)$, sinuosity (s), slope of the channel bed (S_0), and sinuous relative belt width $(\omega = B_{MW}/B)$ of the two-stage meandering channels are used to create predictive models. A comprehensive comparative analysis was conducted using standard statistical performance metrics. Among the models, the GPR approach demonstrated superior predictive accuracy, achieving a coefficient of determination (R^2) of 0.984 and the lowest root mean squared error (RMSE) of 2.0. These findings highlight the potential of GPR as a robust tool for modelling shear stress distribution in complex channel geometries.

1. INTRODUCTION

Quantifying uncertainty in water resource engineering issues related to flood analysis may be difficult. Our fundamental knowledge of a river's flow characteristics falls short in many situations. River flow is a tremendously complicated natural phenomenon, and it is very difficult to describe the properties of river flow like discharge, velocity, and distribution of shear stress. The sharing of shear stress in compound channels is affected by various factors like secondary current structure and bed roughness (Ghosh & Roy, 1970; Kar, 1977; Knight & Patel, 1985; Knight et al., 1992). Numerous studies aimed to

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determine the sharing of shear force using direct and indirect methods (Ghosh & Roy, 1970; Hwang & Laursen, 1963; Patel, 1984; Patel, 1965; Preston, 1954). For the purpose of assessing shear stress along the straight compound channel's wetted perimeter, Knight (1981) presented an empirical method. Further, Knight and Hamed (1984) and Knight et al. (1992) amended the sharing of boundary shear forces for various meandering channels. The impacts of wall shear stress, shear force, and discharge features on the rectangular main channel of compound meandering channels have also been discussed by Patra and Kar (2000). Various empirical approaches to calculate shear stress distributions were also proposed by various researchers (Berlamont et al., 2003; Christensen & Fredsoe, 1998). Further, a reformed segregated channel method of the two-stage flow was created by Khatua and Patra (2007) for forecasting the sharing of shear force percentage throughout the floodplain boundaries. Khatua and Mohanty (2012) investigated meandering compound channels and developed a discharge estimation method based on channel division.

Along with experimental and numerical studies, machine learning (ML) algorithms are now being studied for flood modeling. Recently, ML methods such as relevance vector machines (RVM), support vector regression (SVR), Gaussian process regression (GPR), extreme learning machines (ELM), genetic algorithms (GA), model trees (MT), multivariate adaptive regression splines (MARS), and K-nearest neighbours (KNN) have been used successfully to address a variety of issues in hydraulic and hydrological engineering, as well as water resources (Deo & Sahin, 2015; Deo et al., 2016; Mehdizadeh et al., 2017; Milukow et al., 2018; Mohanta et al., 2018; Najafzadeh et al., 2018; Shende & Chau, 2018; Varvani & Khaleghi, 2018). Rasmussen et al. (1999; 2010) formulated a principled, practical, and probabilistic kernel-based algorithm of Gaussian process regression (GPR). GPR was used by Sun et al. (2014) to forecast probabilistic streamflow. GPR is also used in various engineering fields, such as evaluating pile capacity (Pal & Deswal, 2010), predicting seepage discharge for earth dams (Roushangar et al., 2016), predicting evaporative loss (Deo & Samui, 2017), and predicting water inflow for tunnel construction (Li et al., 2017). Similarly, the relevance vector machine (RVM) technique has drawn much attention for various hydraulic and hydrologic applications such as modelling the quality of groundwater (Khalil et al., 2005), sediment transport (Dogan et al., 2007); stream flow modelling (Ghosh & Mujumdar, 2008; Joshi et al., 2013); and evaporative losses in reservoirs (Samui & Dixon, 2012). Flake et al. (2010) developed a model for determining flow in canals using RVM for the basin of the Sevier River. Torres-Rua et al. (2012) studied the flow control scheme of canal irrigation to minimize the aggregate error using RVM, and Okkan and Inan (2014) studied the monthly precipitation of Kemer Dam in Turkey.

Researchers in a variety of engineering fields have recently shown a strong interest in the ELM, particularly in hydrology and hydraulic applications such as the prediction of sediment flow in open channels (Ebtehaj et al., 2016), streamflow forecasting (Deo & Sahin, 2016), organisation of water network (Sattar et al., 2017), discharge estimation capacity of side weir (Azimi et al., 2017; Shabanlou, 2018), calculation of coefficient of discharge in triangular labyrinth weir (Karami et al., 2018); dew point temperature estimation by (Deka et al., 2018), and velocity distribution of a narrow sewer channel (Bonakdari et al., 2018).

The transfer of percentage of shear force at the boundary on the floodplain ($\%S_{fp}$) in meandering compound channels was the subject of a comparative research by Mohanta and Patra (2019). They provided quantitative methods for predicting $\%S_{fp}$ using group method of data handling (GMDH), MARS, support vector regression (SVR), and k-nearest neighbour (KNN) and show the compatibility of these approaches in natural applications. Further, Mohanta et al. (2019; 2020) created the enhanced channel division method, that divides a meandering compound channel portion into two distinct zones at an confluence line with zero shear stress at the interaction of the main channel and the floodplain (ECDM). Mohanta et al. (2021) expanded the study to meandering compound channels with differential roughness. By taking into account numerous geometric and hydraulic characteristics from experimental research, an expression for $\%S_{fp}$ was created using the Gene-expression Programming (GEP) approach. The GEP technique was used by Mohanta and Patra (2019) to forecast discharge in a meandering compound channel. Mohanta et al. (2022) developed unique methods for determining the proportion of discharge in the main channel of two-stage sinuous channels with changing roughness using the GMDH-Neural Network and GEP. In this paper, three machine learning models, namely, Gaussian process regression (GPR), relevance vector machine (RVM), and extreme learning machine (ELM), are used for the forecasting of two-stage meandering channels by taking the relative width $(\alpha = B/b)$, depth ratio $(\beta = (H-h)/H)$, sinuosity (s), slope of channel bed (S_0), and sinuous relative belt width $(\omega = B_{MW}/B)$ of the two-stage sinuous channels as input data.

2. STUDY AREA AND DATA COLLECTION

Quantifying uncertainty in water resource engineering issues related to flood analysis may be difficult. Our fundamental knowledge of a river's flow characteristics falls short in many situations. River flow is a tremendously complicated natural phenomenon, and it is very difficult to describe the properties of river flow like discharge, velocity, and distribution of shear stress. The sharing of shear stress in compound channels is affected by various factors like secondary current structure and bed roughness (Ghosh & Roy, 1970; Kar, 1977; Knight & Patel, 1985; Knight et al., 1992). Numerous studies aimed to determine the sharing of shear force using direct and indirect methods (Ghosh & Roy, 1970; Hwang & Laursen, 1963; Patel, 1984; Patel, 1965; Preston, 1954). For the purpose of assessing shear stress along the straight compound channel's wetted perimeter, Knight (1981) presented an empirical method. Further, Knight and Hamed (1984) and Knight et al. (1992) amended the sharing of boundary shear forces for various meandering channels. The impacts of wall shear stress, shear force, and discharge features on the rectangular main channel of compound meandering channels have also been discussed by Patra and Kar (2000). Various empirical approaches to calculate shear stress distributions were also proposed by various researchers (Berlamont et al., 2003; Christensen & Fredsoe, 1998). Further, a reformed segregated channel method of the two-stage flow was created by Khatua and Patra (2007) for forecasting the sharing of shear force percentage throughout the floodplain boundaries. Khatua and Mohanty (2012) investigated meandering compound channels and developed a discharge estimation method based on channel division.

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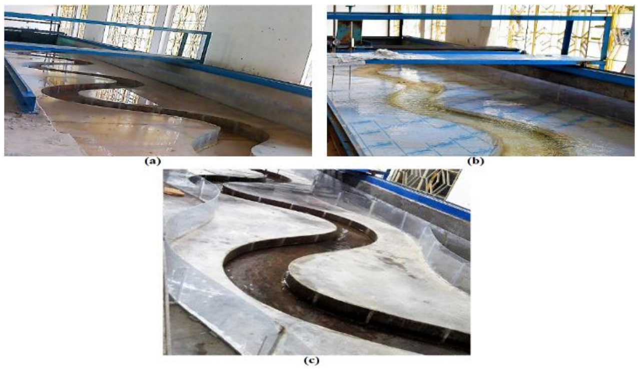

Figure 1. Visual representation of experimental channel setup (a) NITR Type-I; (b) NITR Type-II; (c) NITR Type-III.

Table 1. Geometric constraints of the three sinuous two-stage channels.

Sl. No	Constraints	NITR Type I*	NITR Type II**	NITR Type III***
(1)	(2)	(3)	(4)	(5)
1	Nature of Channel Bed surface	Smooth	Smooth	Smooth
2	Slope of the Channel Bed (S_o)	0.001	0.001	0.001
3	Main channel arc angle (ϕ_m)	60^o	30^o	60^o
4	Floodplain arc angle (ϕ_f)	0	0	30^o
5	Sinuosity of the main channel (s_{mc})	1.37	1.06	1.37
6	Sinuosity of the floodplain (s_{fp})	1	1	1.06
7	Wavelength of the channel (λ)	2.23m	2.23m	2.23m
8	Width of the main Channel (b)	0.28m	0.28m	0.28m
9	Total width of the channel (B)	1.67m	1.67m	1.35m
10	Bankfull Depth of main channel (h)	0.12m	0.12m	0.12m
11	Width of outer Floodplain (b_o)	0.25m	0.52m	0.25m
12	Width of inner floodplain (b_i)	1.14m	0.87m	0.82m
13	Meander Belt Width (B_{MW})	1.17m	0.61m	1.17m

*Sinuous two-stage channel of 60^o sinuosity with straight floodplain wall; **Sinuous two-stage channel of 30^o sinuosity with straight floodplain wall; *** Sinuous two-stage channel of 60^o and 30^o sinuosity of main channel and floodplain wall.

At the fifth bend-apex of the two-stage meandering channels, the boundary shear stress is measured (which is about 6 meters from the inlet) by using Preston tubes. The floodplain section's shear force percentages of various portions in meandering compound channels are calculated by dividing the shear force of individual boundary segments with the over-all boundary shear force.

In addition to the current work, the authors have also used data from previous studies to calibrate models for forecasting the sharing of shear force percentage in floodplains. Studies used in the present research are Kar (1977), Das (1984), Willetts and Hardwick (1993), Patra and Kar (2000), Khatua (2007), Mohanty (2013), and Pradhan and Khatua (2017), and the details of experimental configurations can be found in the author's previous research articles (Mohanta et al., 2021; Mohanta et al., 2022).

3. METHODOLOGY

The sole objective of the paper is to examine the practicability of the machine learning (ML) methods, namely GPR, ELM, and RVM, for predicting the $\%S_{fp}$ at floodplain of compound meandering channels. The randomly sampled training subset (70%) and the rest (30%) are utilized to build the GPR, ELM, and RVM, models.

The Gaussian Process consists of Gaussian distributions of random variables, which makes it especially well-suited for modeling complex data sets. GPR has the advantage of being able to combine several ML techniques, including hyper-parameter estimation and model preparation, into one unified process. This results in more accurate and less biased results (Rasmussen & Williams, 2006). The Relevance Vector Machine (RVM) is an example of a sparse kernel function that often reflects Bayesian management of a generalised linear model with a similar functional shape to the support vector machine (SVM). The RVM, a Bayesian method for classification and regression models, was first described by Tipping (2001). The ELM model is a feed-forward type neural network that forecasts results by using input weights and hidden layer biases. The hidden neuron layer and the output layer are connected via the output weights. The concealed layer bias is acquired from separate conclusions and short time periods are allotted for the training (Acharya et al., 2014; Deo & Sahin, 2015).

The model design for $\%S_{fp}$ prediction using the ELM framework is built using three-layer networks. The predictor variables are the five input neuron numbers, which are used. The predictor variables are the five numbers of input neurons i.e., $x = [\alpha, \omega, s, S_o, \beta]$. The output layer in the ELM architecture has one neuron demonstrating the predicted distribution of shear force $\%S_{fp}$. In the hidden levels, up to 20 neurons are randomly tested. The ideal number of nodes for the ELM design is finally chosen to be 10. The ELM model developed with the help of radial bias function (RBF) as the activation function. Finally, a 6-10-1 neural network framework of ELM is obtained.

Model Performance Valuation

It's important to compare the observed values of the shear force percentages (S_{oi}) to the anticipated values (S_{pi}) after constructing a model in order to assess its performance. Typical arithmetical inaccuracy measurements, such as the coefficient of determination (R^2), mean percentage error (ME), root-mean-square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), scatter index (SI), and coefficient of efficiency (E), can be used to conclude the concert of the GPR, ELM, and RVM models. We may assess the model's suitability for the dataset by taking into account the values of R2, RMSE, MAE, MAPE, E, and SI those are described in previous research papers of author (Mohanta et al., 2021; Mohanta et al., 2022).

The correlation between the experimental values and the model's anticipated values is best when the R2 value is close to 1. RMSE value illustrates gap between anticipated value and experiential value, whereas MAE quantifies how well anticipated and experiential values match each other. A lower anticipated value of MAE and RMSE indicates a stronger forecast model.

The experimental measurements are subjected to a quantitative uncertainty analysis for forecasting $\%S_{fp}$. The distinct estimate error is generally defined as $E_i = S_{ai} - S_{ei}$. Mean $(\overline{E_i})$ and standard deviation (SD) are calculated using errors of the complete test data, using the relations $\overline{E_i} = \frac{1}{n}\sum_{i=1}^{n} E_i$ and $SD = \sqrt{\sum_{i=1}^{n}\left(E_i - \overline{E_i}\right)^2 / n-1}$, respectively (Mohanta & Patra, 2019; Mohanta et al., 2022).

A negative and positive mean error value demonstrates the under and over estimation of the observed values by the predictive models, respectively. Wilson score method is used to define confidence band using E_i and SD values around the error of the forecast values without consistent correction. The calculation of 95% confidence band can be done as $\pm 1.96SD$ (Mohanta & Patra, 2019).

4. RESULTS AND DISCUSSION

The models are developed to forecast the $\%S_{fp}$ at individual segments, and the performance of individual datasets was determined. Figure 2 illustrates the performance of individual datasets of $\%S_{fp}$ for three different methods. All ML methods used in this paper illustrate encouraging results for predicting $\%S_{fp}$.

Training and testing dataset performance often abides by the 45% limit, indicating acceptable fit. Compared to RVM (0.94) and ELM (0.91), the GPR model achieved the maximal determination coefficient $(R^2 = 0.98)$ in the test phase.

Table 2 is shown the values of the R^2, ME, RMSE, MAE, MAPE, E and SI acquired during the training and testing period by the three refined ML methods used in this paper for a better consideration of model performance. Referring to Table 2, in comparison to the RVM and ELM methods, the GPR method is given a minimal RMSE value for the training and testing datasets of 1.52 and 2.49, respectively. Similar findings are drawn for the error analysis of MAPE and MAE for the calculation of %Sfp for these predictive ML methods.

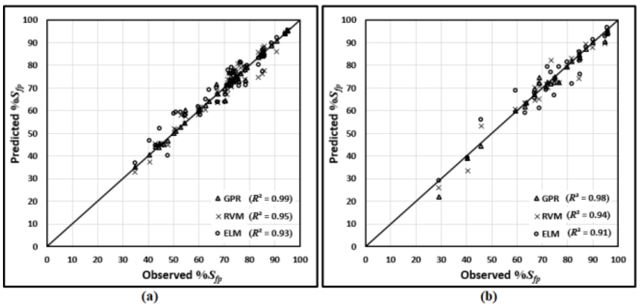

Figure 2. The scatter plots showing determination coefficient between the observed and predicted $\%S_{fp}$ of GPR, RVM and ELM model for (a) training; (b) testing dataset.

Table 2. Performance Metrics for GPR, RVM, and ELM Model by Various Statistical Measures.

Index	Training			Testing		
	GPR	RVM	ELM	GPR	RVM	ELM
(1)	(2)	(3)	(4)	(5)	(6)	(7)
R2	0.99	0.95	0.93	0.98	0.94	0.91
ME (%)	0.03	-0.15	1.83	-1.34	-1.04	0.19
MAE	0.75	2.35	2.99	1.66	2.87	3.61
RMSE	1.52	3.09	3.88	2.49	3.93	4.89
MAPE (%)	1.14	3.44	4.81	2.88	4.51	5.30
E	0.99	0.95	0.93	0.98	0.94	0.91
SI	0.02	0.04	0.05	0.03	0.05	0.07

In terms of error analysis, the GPR model outperformed the other models in the testing period, which suggests that the GPR model is more accurate in predicting the shear force percentage terms. MAPE provides certainty in percentage. The MAPE values indicated the best compatibility of the GPR model for predicting %Sfp with the least error amount when compared with the other two methods. The MAPE values are less than 6% for all models, which means that all models provide accurate predictions. GPR shows the MAPE value for testing data to be less than 4%. As a result, GPR can predict the percentage of shear force with greater accuracy.

A more in-depth look at the models' performances was carried out by testing the predicted $\%S_{fp}$ results of the RVM, GPR, and ELM models. The results are shown in Fig. 3 below, and they represent the predicted results of the $\%S_{fp}$ for each model. Graphical analysis directs inter-model performance throughout the training and testing period, showing the ELM approach as showing the greater deviance from the experimental data.

GPR, RVM, and ELM models for forecasting $\%S_{fp}$ in two-stage meandering channels are presented with their level of uncertainty. Table 3 displays the results of the uncertainty analysis together with the mean errors of the prediction value, the size of the uncertainty band, and the error within the 95% confidence interval. The mean estimate error of -0.9 and the minimal width of the uncertainty band ($\pm$ 6.67) for the GPR model indicate that the model is more appropriate for predicting $\%S_{fp}$ when compared to the other two ML models (RVM and ELM).

Table 3. Measure of uncertainty for forecasting $\%S_{fp}$ by different ML methods.

Methods	Mean Estimate Error	Width of Uncertainty Band	95% Prediction Error Interval
(1)	(2)	(3)	(4)
GPR	-0.21	3.65	-3.86 to 3.44
RVM	-0.32	6.58	-6.90 to 6.26
ELM	0.59	8.19	-7.60 to 8.77

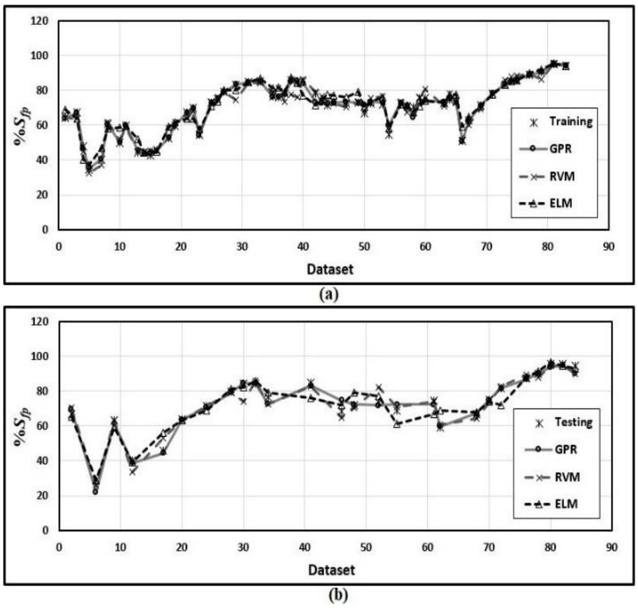

Figure 3. Performance Matrices for the Prediction of the Shear Force Percentage during (a) the Training Period; (b) the Testing Period.

5. CONCLUSIONS

The aim of the study is to explore the capability of three different machine learning models (GPR, ELM, and RVM) to predict the sharing of shear force percentage in compound meandering channels. All three models performed very well, but the GPR approach showed slightly better outcomes than the ELM and RVM approaches. This is evident from the higher correlation coefficient, smaller error statistics, and narrower width of the uncertainty band. This means that the GPR model was more accurate in its predictions $\%S_{fp}$. The ML models used in this study could help predict the amount of shear force sharing at the floodplain of two-stage meandering channels.

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Author Contributions: AM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software. CD: Validation, Visualization, Writing – original draft. MM: Supervision, Project administration, Resources, Validation, Writing – review & editing.

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