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Using Machine Learning to Predict Suspended Sediment Transport under Climate Change

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Abstract
Sediment transport, an important element of the erosion–sedimentation cycle, can be very high during extreme flood events and can cause hydromorphological changes within river networks. Therefore, improved sediment transport predictions are needed to establish sediment management at the catchment scale. A machine learning model (i.e., XGBoost) and a sediment rating curve method were tested for predicting the suspended sediment load in the Sora River catchment in Slovenia. The evaluation of the models based on the historical data for 2016–2021 revealed that XGBoost outperformed the sediment rating curve model and resulted in a lower bias (i.e., approximately 15%). The XGBoost model was used to predict future suspended sediment load dynamics. Three representative concentration pathway (RCP) scenarios (RCP2.6, RCP4.5, and RCP8.5) and several climate change models were used. The rainfall–runoff model was set up, calibrated, validated and applied to simulate future daily discharge data, as this was the required input for the XGBoost and sediment rating curve models. The simulation results indicate that suspended sediment load is expected to increase in the future in the range 15–20% under both the RCP4.5 and RCP8.5 scenarios. Additionally, the number of days with a suspended sediment concentration (SSC) greater than 25 mg/l, which is often used an indicator of inadequate water quality, is expected to increase by 2–4%, whereas some models indicate an increase of up to 8%. Erosion and sediment management mitigation measures need to be applied in the future to ensure adequate water quality and good ecological status of the river.

Highlights
- • Sediment transport was modelled using the XGBoost algorithm and a sediment rating curve.
- • XGBoost outperformed the sediment rating curve model.
- • The impact of climate change on sediment transport was investigated.
- • The suspended sediment load is expected to increase in the future to 15–20%.
- • The number of days with suspended sediment concentrations greater than 25 mg/L will also increase.

Keywords Suspended sediment load · Future prediction · Climate change · Machine learning · Sediment rating curve · Rainfall–runoff model · Sediment management

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1 Introduction

The transport of suspended load and bedload in natural rivers is a crucial aspect of geomorphological processes on Earth (Lopez-Tarazon et al. 2009; Turowski et al. 2010; Barberena et al. 2023) and plays a central role in shaping riverine landscapes, aquatic ecosystems and even coastal areas. Suspended sediment transport is a complex phenomenon influenced by a variety of dynamic factors (Kisi et al. 2008; Bezak et al. 2017; Cendrero et al. 2022; Gardner et al. 2023), including precipitation patterns, land-use change, vegetation cover, and anthropogenic activities (Gholami et al. 2023). In the headwaters of alpine catchments, different torrential hazards, such as landslides or debris flows, occur during heavy rainfall events (Sodnik et al. 2023). This type of event generates much material that is a potential sediment supply source and can be transported during extreme events (Bezak et al. 2023). In alpine countries such as Slovenia, damage to infrastructure, such as roads, bridges, and culverts, and damage to residential, industrial, and agricultural buildings and other infrastructure resulting from erosion–sedimentation processes are common. Therefore, enhancing the knowledge of sediment transport to ensure adequate input data for sediment management (Khaleghi and Varvani 2018; Afan et al. 2024) and erosion mitigation in headwater parts of catchments is crucial.

Extreme torrential hazards such as flash floods or debris flows are expected to become more common due to changing climate patterns and extreme weather events (Nam et al. 2019; Jemec Auflič et al. 2021; Panagos et al. 2022). For example, climate scenarios predict an increase in the occurrence of heavy rainfall events (Burt et al. 2016; Panagos et al. 2022), which can trigger landslides, cause erosion processes and lead to intense sediment transport. The extent of damage to various infrastructure and buildings caused by torrential floods and similar hazards and the associated erosion processes are increasing worldwide and in Slovenia (Bezak et al. 2023; Sodnik et al. 2023). Torrential hazards are very problematic in the design of engineering structures for natural hazard mitigation (Sodnik et al. 2023). These climate-driven changes have the potential to exacerbate erosion, sedimentation, and geomorphic instability in many catchments worldwide. Thus, there is an urgent need to develop robust and adaptive predictive models capable of predicting suspended sediment transport under the influence of changing climate conditions for areas where sediment transport is important for water resource management (Brilly 2010; Wu and Chen 2012; Nones 2019; Afan et al. 2024).

Recent advances in machine learning (ML) algorithms combined with the availability of high-resolution spatial and temporal datasets provide an unprecedented opportunity to improve our ability to model and predict the dynamics of sediment transport (Khaleghi and Varvani 2018; Varvani and Khaleghi 2019; Sharghi et al. 2019; Grangeon et al. 2023; Hosseiny et al. 2023; Piraei et al. 2023; Sahoo et al. 2023; Shakya et al. 2023; Afan et al. 2024; Baharvand and Ahmari 2024; Efthimiou 2024). Unlike traditional analysis methods, which often rely on simplifying assumptions and linear or logarithmic relationships (Harrington and Harrington 2013; Isik 2013; Bezak et al. 2017; Khaleghi and Varvani 2018), machine learning methods are capable of capturing complex, nonlinear interactions within the data (Kisi et al. 2008; Rajaee et al. 2009). This allows researchers, water managers and engineers to uncover hidden patterns and make accurate predictions even in the face of complex erosion and sedimentation processes (Betrie et al. 2011; Varvani and Khaleghi 2019).

Therefore, the main objective of this study is to expand our knowledge of suspended sediment transport in a typical alpine catchment over the coming decades. The specific objectives of the study are as follows: (i) to evaluate the performance of the sediment rating curve model compared with a machine learning algorithm (i.e., XGBoost) based on historical data; and (ii) to evaluate potential future changes in hydrological processes and suspended sediment transport rates using the combined rainfall–runoff and machine learning model up to the year 2100 based on the three representative concentration pathways (RCPs) (i.e., RCP2.6, RCP4.5, and RCP8.5). Hence, the main novelty of this study is that the impact of climate change on sediment transport is evaluated using a combination of rainfall-runoff modelling and machine learning technique. Although several studies have used machine learning techniques, only a limited number of studies have focused on future predictions under multiple RCP scenarios. Additionally, to the best of the authors' knowledge, XGBoost has not yet been used to simulate future suspended sediment load.

2 Materials and Methods

2.1 Case Study and Historical Data

The Sora River catchment up to the Suha gauging station (Fig. 1), which is operated by the Slovenian Environment Agency, was used in this study to assess the impact of climate change on suspended sediment transport rates under three RCP scenarios. The Sora River exhibits a typical rain–snow–water regime, with a pronounced first runoff peak in late fall (October–December) and a second runoff peak in spring (March–April). The fall discharge peak is the result of prolonged fall precipitation, when most of the rain falls in the Alpine–Dinaric mountains (Frantar and Hrvatin 2005), whereas the second discharge peak is the result of snowmelt in the mountains and spring precipitation. The summer low-flow periods are often very pronounced, whereas the winter low-flow periods are less pronounced, as it rains more frequently in the mountainous regions of western Slovenia, even in the winter months. Due to the increase in air temperature, winter snow precipitation is decreasing (Mikoš et al. 2022). The Sora River is a typical torrential stream, and flooding is frequent in this catchment (Rusjan et al. 2009; Bezak et al. 2023). The geological features of the study area are heterogeneous, with limestone predominating and some karst features (Zanon et al. 2010). These geological characteristics were found to have important impacts on the generation of flood events (Zanon et al. 2010). Parts of the catchment are also composed of highly erodible rocks (Ribičič et al. 2003), which, in combination with the high rainfall erosivity in this area (Panagos et al. 2022), present important sources of fluvial sediments. This leads to relatively intense sediment transport dynamics and high sediment transport rates. Moreover, parts of the catchment also have a relatively high possibility of landslide occurrence (Ribičič et al. 2003; Auflič et al. 2021).

The period from 2016 to 2021 was used for the calibration and validation of the hydrological model (Sect. 2.3), the sediment rating curve and the machine learning model (Sect. 2.3 and 2.4), as measurements of suspended sediment concentrations are available for this period. All the data were available at daily time steps (Table S1). The measurements of the suspended sediment concentrations were performed with the Hach Solitax_sc sensor, and the suspended sediment concentrations were derived based on the relationship between

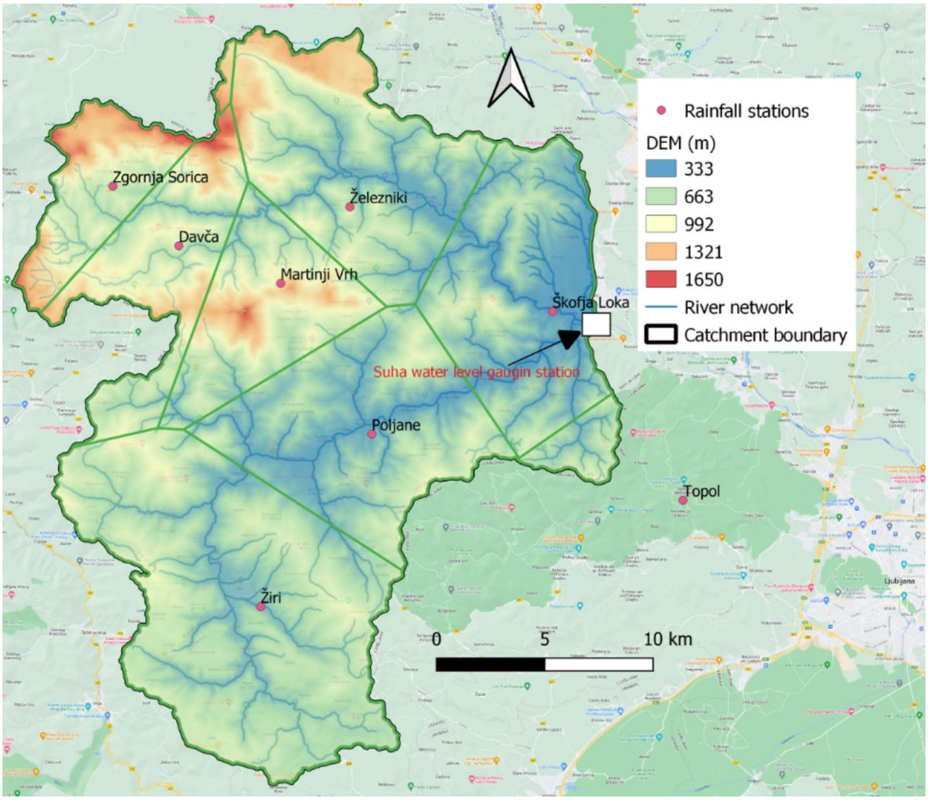

Fig. 1 Map of the study area with the locations of the precipitation (red circle) and discharge (white box) gauging stations and the digital elevation model (DEM) as a background

turbidity and the suspended sediment concentration, which was derived based on manual regular suspended sediment sampling (Ulaga 2020). The catchment and part of the data are also included in the EUSEDcollab dataset (Matthews et al. 2023). To derive the catchment-averaged precipitation, the Thiessen polygon method was used based on the eight precipitation stations shown in Fig. 1. The Topol station was used for the air temperature data, as it was the only station for which air temperature data were available (Fig. 1). The 2016–2020 data period was used to calibrate the sediment rating curve and machine learning models, and the year 2021 was used to test (i.e., validate) the performance of these two methods (Figure S1). We used the coefficient of determination (R2), percentage bias (PB), Nash–Sutchliffe efficiency (NSE) and root mean square error (RMSE) criteria to evaluate the performance of the tested models (Zambrano 2017).

2.2 Climate Change Data

To assess the impact of climate change on suspended sediment concentration, we used the downscaled and bias-corrected data produced by the Slovenian Environment Agency (ARSO) (Bertalanič et al. 2018) (Figure S1). This study analysed the bias-corrected ensemble of regional climate model projections from the EURO-CORDEX database (Sezen et al.

2020). ARSO used bias correction with nonparametric quantile mapping using empirical quantiles (Gudmundsson et al. 2012) with a 61-day moving window for each grid cell. A more detailed description of the bias-correction procedure can be found in Sezen et al. (2020). The spatial resolution of the data is 1 km (Jemec Auflič et al. 2021). These data have already been used in several studies on climate change with a focus on Slovenia, e.g., investigations of low and high water discharges in karst areas in Slovenia (Sapač et al. 2019) and studies of rain-on-snow floods in Slovenia (Sezen et al. 2020). For this study, we used six different combinations of global climate models (GCMs) and regional climate models (RCMs), namely, GCM/RCM models, as shown in Table S2. Three different representative concentration pathway (RCP) scenarios were used. The daily precipitation and mean daily air temperature data were available for all 14 models listed in Table S2. A data period from 1981 to 2100 was examined. The period from 1981 to 2020 was used as the past (i.e., reference) period, and the periods from 2021 to 2060 and 2061–2100 were used as future periods (i.e., near- and far-future, respectively).

2.3 Hydrological Model and Sediment Rating Curve

Because the climate projections (Sect. 2.2) include only precipitation and air temperature and discharge data are also needed to predict the suspended sediment load, we also set up a rainfall–runoff model with a daily time step (Figure S1). For this purpose, the GR6J CemaNeige model was used (Coron et al. 2017, 2018). The GR6J model (Pushpalatha et al. 2011) is an enhanced (improving low-flow simulations) version of the GR4J (Génie Rural à 4 paramètres Journalier) model (Perrin et al. 2003) that was developed with the aim of robustly modelling rainfall–runoff processes using a relatively small number of parameters (i.e., GR4J uses 4 parameters and GR6J uses six parameters). The model structure can be found in Perrin et al. (2003) or Pushpalatha et al. (2011). The input data used in the GR4J model are precipitation (P) and potential evapotranspiration (E). E is a function of air temperature (T) and was calculated in this study using the Oudin equation (Oudin et al. 2005). Additionally, we used the CemaNeige snow module (Valery et al. 2014a, b) to correctly capture snow accumulation and melting within the catchment. The CemaNeige model is a semidistributed snow calculation routine that implements a snow melt factor and a cold content factor (Valery et al. 2014a, b). The required inputs are P and T. The catchment is divided into five equal elevation zones. The CemaNeige model uses two additional parameters (Valery et al. 2014a, b). The CemaNeige model additionally requires a catchment hypsometric curve to derive the elevation zones. In this study, a digital elevation model (DEM) with 20 m spatial resolution was used. The percentage of snowmelt (relative to total annual precipitation) was calculated using an empirical equation derived by Alexopoulos et al. (2023). In total, the CemaNeige GR6J model used eight model parameters to predict the future daily discharge values for the multiple climate change scenarios and models shown in Table S2. The CemaNeige GR6J model was calibrated with data from 2017 to 2021, and 2016 was used for model warm-up. CemaNeige GR6J model calibration was performed using the methodology proposed by Michel (1991), which is implemented in the R software package airGR (Coron et al. 2017). We chose the Nash–Sutcliffe (NS) coefficient (Nash and Sutcliffe 1970) as the efficiency criterion for model calibration. The calibrated model was used to predict the daily discharge based on P and T for the selected GCM/RCM models (Table S2; Figure S1).

The following equation was used for the sediment rating curve model:

$$SSC = a{*}Q^2 + b * Q + c \tag{1}$$

where the suspended sediment concentration (SSC) is the daily suspended sediment concentration in mg/l, Q is the discharge and a, b, and c are parameters that were estimated from the measured data for the period 2016–2020. The nonlinear least squares method was used to estimate the a, b, and c coefficients. The 2021 period was used to evaluate the performance of the sediment rating curve model (Figure S1). The workflow for evaluating the climate change prediction for the suspended sediment load is shown in Figure S1.

2.4 XGBoost Model

In addition to the sediment rating curve mode, we also applied the XGBoost (eXtreme Gradient Boosting) algorithm (Chen and Guestrin 2016) to predict future suspended sediment rates (Figure S1). This model was selected because it has not yet been tested for the prediction of the future suspended sediment load in alpine catchments. The model has several positive characteristics such as high performance, handling missing data, scalability, regularization, etc. XGBoost is an ensemble learning method, i.e., it combines the predictions of several weaker models (usually decision trees) to create a stronger, more accurate model. It uses a gradient boosting framework, which is an iterative approach to gradually improve the predictive power of the model. Python 3.10 was used for modelling. The modelling structure of XGBoost consists of five key components (Chen and Guestrin 2016) and is described in detail in the Supplement. The goal of XGBoost is to find the optimal set of model parameters (tree structures and leaf values) that minimize this objective function:

$$obj = \sum\nolimits_{i=1}^{n} loss(x_i, \bar{x}_i) + \sum\nolimits_{k=1}^{K} \phi\ (f_k) \tag{2}$$

where n is the number of samples, x_i is the i-th real sample, $\bar{x}_i$ is the i-th output, K is the number of trees, f_k is the mapping from the sample to the leaf in the k-th tree, *loss*(.) quantifies the model's prediction error (the mean squared error is used in this study), and ϕ (.) is a penalty term that discourages complex models (L1 is used in this study). This involves an iterative process where each new tree is added to the model to reduce the error caused by the previous trees. It uses gradient descent to find the optimal model parameters. The gradients of the objective function with respect to the model parameters are computed and used to update the model parameters in the direction of steepest descent.

The main training steps of the XGBoost model are described in the Supplement. The family of parameters for subsampling the columns was 0.9, the learning rate was 0.1, the maximum depth of the tree was 4, the L1 regularization was 5, and the number of trees was 600. In our study, the following parameters were used to set up, calibrate and evaluate the XGBoost model: input: Q, P and T; output: SSC; objective error function: mean square error (MSE).

3 Results and Discussion

3.1 Comparison of the Sediment Rating Curve and XGBoost Model

In the first step of the study (Figure S1), the sediment rating curve (a = 0.01, b = −0.022, c = 11.68) and XGBoost models were set up and calibrated based on the historical data from 2016 to 2020 and evaluated for 2021. The evaluation of both models is shown in Table 1 and Figure S2. Moriasi et al. (2015) presented guidelines for the assessment of sediment, runoff and nutrient models in catchments on temporal scales (annual, monthly, and daily). Unfortunately, no recommendation is given for the daily time scale for sediment transport. If the criteria for monthly time steps are used, the performance of the XGBoost model (Table 1) can be considered satisfactory in the cases of NSE and PBIAS and good in the case of R^2. However, the evaluation of the sediment rating curve model can be considered unsatisfactory based on NSE and PBIAS and satisfactory according to R^2. Notably, the criteria for the daily time step are generally lower than those for the monthly time step (Moriasi et al. 2015). Some studies have reported better performance in the prediction of the suspended sediment load (Gholami et al. 2023; Afan et al. 2024). However, it should be noted that the performance of the model strongly depends on the input data and catchment characteristics (Bezak et al. 2017). There are several reasons for the slightly lower performance of the selected models (Efthimiou 2024): (i) sediment transport processes can vary over time due to seasonal changes (e.g., influence of vegetation) or extreme weather events (e.g., local flash floods in sub-catchments) with intensive sediment transport on a subdaily time step, ii) there is potential for human activities (e.g., water works in the riverbed) during low-flow conditions, iii) there is potential uncertainty in the relationship between turbidity and suspended sediment concentration (Jastram et al. 2010), and iv) specific impacts such as the first flush (Russo et al. 2023) are relatively difficult to include in the model. Notably, the Sora River is a typical torrential river, and many factors significantly affect erosion processes, landslide occurrence, sediment connectivity and deposition and sediment transport within the river network (Nourani et al. 2012; Bezak et al. 2017). Therefore, due to complex interplay between the rainfall runoff and sediment transport processes, there is relatively weak relationship between discharge and the suspended sediment concentration ($R^2 = 0.44$) and between precipitation and the suspended sediment concentration ($R^2 = 0.47$) for the historical data (i.e., 2016–2021) (Figure S3). Specifically, a suspended sediment concentration of 100 mg/L can be associated with a discharge of almost 150 m^3/s or with low-flow conditions. Therefore, we argue that the XGBoost model can satisfactorily describe the dynamics of the suspended sediment load in the Sora River catchment and that it can be used to predict suspended sediment concentrations under climate change scenarios (Figure S1).

Table 1 Evaluation of the performance of the sediment rating curve and XGBoost models for predicting suspended sediment concentrations in 2021

Metrics	Sediment rating curve	XGBoost model
R^2	0.54	0.71
PBIAS [%]	27.7	−15.2
NSE	0.42	0.58
RMSE [mg/l]	19.3	16.4

3.2 Hydrological Modelling

To estimate future suspended sediment concentrations, we also need simulated discharge data (Figure S1). Therefore, the methodology described in Sect. 2.3 was applied to simulate the daily discharge data for the period of 1981–2100 based on P and T (Figure S1) from the selected RCP scenarios (Table S2). Figure S4 shows the performance of the rainfall–runoff model for 2017–2021. The NSE, R^2, PBIAS, and RMSE values calculated between the simulated and observed data were 0.87, 0.93, 1.4% and 1.3 mm, respectively. According to the performance evaluation indicators for daily flow values proposed by Moriasi et al. (2015), this can be considered very good model performance. As shown in Figure S4, the performance of the CemaNeige GR6J model is somewhat worse during low-flow periods. However, from the suspended sediment transport point of view, this does not have a significant effect on the suspended sediment concentration, as most of the sediment transport takes place during high-flow periods. Therefore, the calibrated CemaNeige GR6J model was used to simulate the daily discharge values for 1981–2100 (Figure S5). The simulation results differ relatively strongly depending on the model selected (Figure S5 and Table S2). This is related to the input data for the rainfall–runoff model (Figure S6 and Figure S7). The discharge is expected to increase in both the near-future and far-future periods. The relative changes compared with the historical period are approximately 4–6% for both RCP4.5 and RCP8.5 (Figure S8). Similar increases were also detected for the 75% percentile discharge values, whereas a decrease in the range up to −5% was detected for the 25% percentile discharge values, which could be related to more severe low-flow conditions in the future (Sapač et al. 2019).

3.3 Sediment Transport Predictions Using Machine Learning

The simulated discharge values presented in the previous chapter were used as the input data to simulate the SSC values. To synthesize a large amount of data, we calculated statistical values for each of the models for the individual time periods considered. For the RCP4.5 and RCP8.5 scenarios, we provide the medians of these values, whereas for the RCP2.6 scenario, we present the results of each model (Fig. 2), as the difference in the results is quite large. To compare the results of the different scenarios, we also present them as percentage increases or decreases compared with the 1981–2020 reference period. As shown in Fig. 2 (left), in both future periods (with suffixes 1 and 2 on the x-axis) and according to RCP4.5, RCP8.5 and the second model of RCP2.6, SSC values are generally expected to increase. Similarly, but to an even greater extent, an increase in the suspended solids load (SSL) is predicted because the sediment load is a product of the sediment concentration and discharge data (Fig. 2).

The average values of SSC in the near-future and far-future periods will increase by 7% and 12% according to RCP4.5, respectively, and by 12% and 18% according to RCP8.5, respectively. As mentioned, the two RCP2.6 models are not consistent in terms of the predictions; the first model shows a decrease in SSC of 4.1% from 2021 to 2060 and an increase of 4% from 2061 to 2100. The second RCP2.6 model shows increases of approximately 23% in both future periods. The RCP2.6_2 model, however, shows an even twofold relative increase in average SSL values compared with those of SSC (Fig. 2). Interestingly, less optimistic scenarios, i.e., RCP4.5 and RCP8.5, suggest that the average values of SSL will

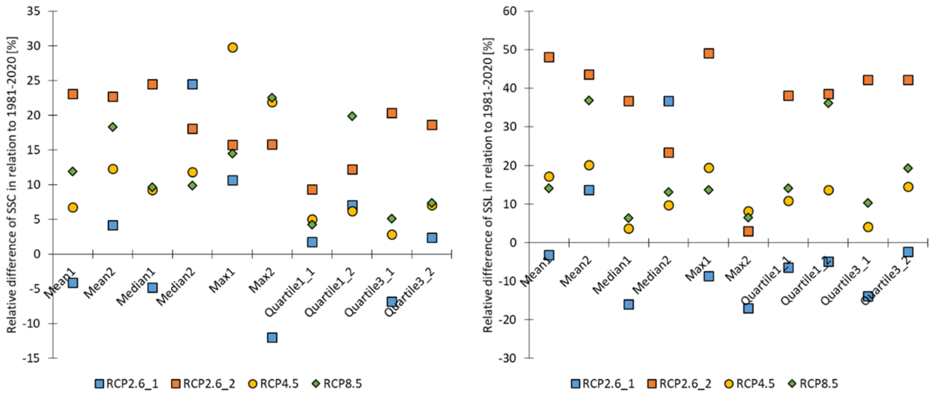

Fig. 2 Expected future relative changes in the statistical values (i.e., mean, median, and 1st and 3rd quartiles) of suspended sediment concentrations (SSC) and suspended sediment load (SSL) with respect to the reference period from 1981–2020. For the RCP4.5 and RCP8.5 models, the median values are shown, whereas for RCP2.6, the results of both models are presented. Suffixes 1 and 2 on the x-axis refer to the near-future (2021–2060) (1) and far-future (2061–2100) (2) periods, respectively

be higher, at 14–37%, with a greater increase in the far-future period. General increases in the SSC and SSL values in the future are also confirmed by analysis of the data distribution and spread. All three quartile values (1st quartile, median, and 3rd quartile) will be higher in both future periods than in 1981–2020 for all scenarios; again, the exception is model RCP2.6_1, which shows slight decreases. Higher quartile values indicate general increases in sediment concentrations and load compared with those in the reference period. Moreover, detailed insight into SSL values based on time exceedance (Fig. 3) reveals that sediment transport will increase mainly due to extreme events. More specifically, in the time exceedance range of 0–25% (25% in Fig. 3), average increases of 21% and 36% can be expected in the 2021–2060 and 2061–2100 periods, respectively, regardless of the model and climate scenario. In other words, at 25% of the most extreme discharge values, for $160*10^3$ t and $250*10^3$ t, more sediment load is expected to be transported during the near-future and far-future periods, respectively. Additionally, other changes have indicated possible alterations in water quality parameters in the future (van Vliet et al. 2023).

The suspended sediment concentration can also be an important indicator of water quality and ecological status of surface waters. According to Alabaster (1982), for inland fisheries, there is no evidence that concentrations of suspended solids up to 25 mg/L have any harmful effect on fish. This concentration is also considered in Slovenian national legislation (Decree on the quality required of surface waters supporting freshwater fish life (Uradni list RS, št. 46/02, 41/04 – ZVO-1 in 44/22 – ZVO-2). The results of the frequency of exceeding this threshold concentration are shown in Fig. 4. More specifically, the relative change in the frequency of exceeding this threshold is estimated. In the reference period, this concentration would be exceeded 16% of the time based on the 14 models used. For the near-future period (2021–2060), only three models, one for each RCP scenario (1, 3, and 13), show relative decreases in frequency, namely, decreases of 2, 1, and 1%, respectively (Fig. 4). Conversely, the other 11 models show increases in frequency of 1–5% (Fig. 4). For the far future period (2061–2100), the models are more consistent, suggesting increases in frequency (3 ± 2%). Although the suggested increases in the frequency of high suspended concentration events

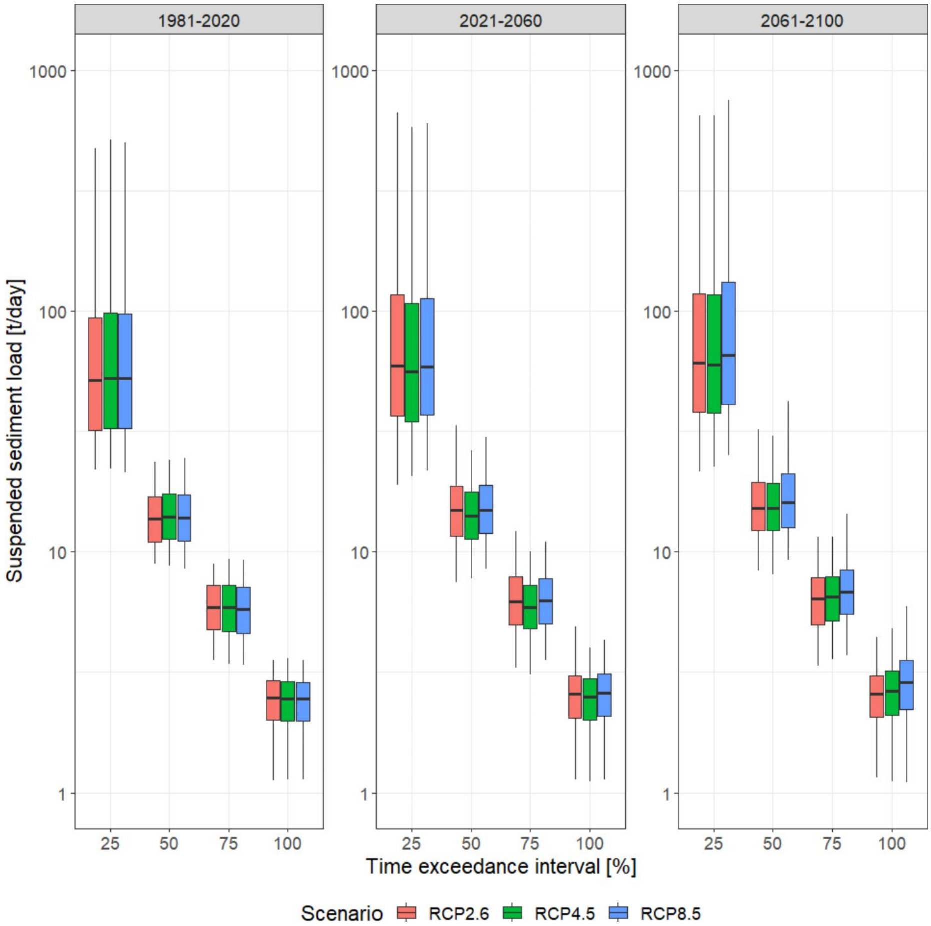

Fig. 3 Boxplots of the suspended sediment load (SSL) in tons per day according to the scenarios RCP2.6, RCP4.5, and RCP8.5 and for three time periods from 1981–2100. Time exceedance is shown in three intervals, namely, 0–25 (25%), 25–50 (50%), 50–75 (75%), and 75–100 (100%). The outliers are not shown in the plot for the sake of better data visibility

are relatively small, even a small increase in suspended sediment transport dynamics for short time periods may cause deterioration of numerous water quality parameters and present considerable stress to aquatic organisms. Periodic increases in water turbidity reduce the penetration of sunlight, affecting photosynthesis; consequently, reduced light availability can disrupt whole-stream productivity (Parkhill and Gulliver 2002). Changes in the amount of suspended sediment load and nutrient flushing into water bodies can considerably affect the water bodies (Fong et al. 2020; Lebar et al. 2023). Moreover, possible intensified mobilization of toxic particles adsorbed to sediments can lead to the spread of toxic matter (Bednářová et al. 2015; van Vliet et al. 2023) and the reactivation of past environmental burdens (Ponting et al. 2021). Therefore, a possible increase of suspended sediment transport can have several negative impacts on the river ecosystem functioning.

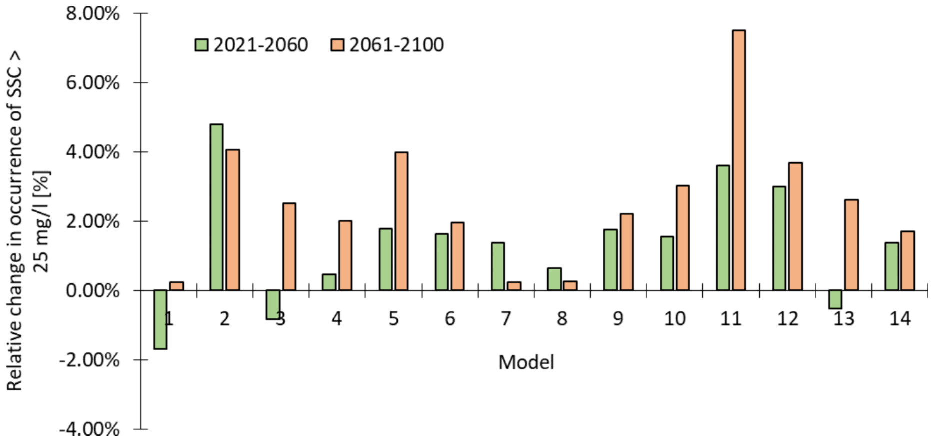

Fig. 4 Predicted future relative changes in the frequency of occurrence of suspended sediment concentrations (SSC) greater than 25 mg/L with respect to the reference period of 1981–2020 for the 14 GCM/RCM models used in this study (Table S2)

3.4 Study Limitations

This study has several limitations that should be clearly noted. First, the measured suspended sediment concentration is only relatively weakly correlated with the discharge and precipitation data, as the Sora River catchment has typical characteristics of torrents, and many factors influence these relationships. Therefore, the performance of the XGBoost model (and the rating curve) is limited by this weaker dependency. Furthermore, in the future, other machine learning models (e.g., random forest, LightGBM) could be tested to improve our understanding of the role of factors which control the suspended sediment concentrations and further, to predict the future suspended sediment loads under different climate change scenarios. Second, climate change predictions also contain certain degrees of uncertainty, which are transferred from the precipitation and air temperature data to the runoff simulations. Third, sediment transport processes are significantly influenced by the intensity of precipitation events. For example, extreme flood events such as those in August 2023 in Slovenia (Bezak et al. 2023) can lead to very high sediment transport rates, and during these types of events, the amount of transported material can be considerably greater than the average annual rates.

4 Conclusions

Based on the results presented, the following conclusions can be drawn:

- The relationship between discharge and the suspended sediment concentration is relatively weak (i.e., $R^2 = 0.44$), indicating the complexity of erosion–sedimentation processes in torrent catchments.
- The XGBoost model outperformed the sediment rating curve model, and the XGBoost model performance can be classified as satisfactory, with a slight underestimation (i.e.,

percent bias of approximately −15%).
- The CemaNeige GR6J rainfall–runoff model can predict daily runoff values relatively well (i.e., a percent bias of approximately 1.5%), although there are slight discrepancies between the measured and simulated data during low flows.
- SSC and SSL are expected to increase in the future for both the RCP4.5 and RCP8.5 periods, and the increases for some climate models are as high as 20%. The increase in the SSL is even greater than the increase in the SSC (i.e., up to 40%).
- Our results show that water quality related to the suspended sediment concentration is expected to worsen in the future, as the number of days with potentially problematic SSC concentrations for water organisms (e.g., exceeding 25 mg/l) is expected to increase in the future, where this increase will be in the range of up to 8%.
- These increases can be attributed mainly to changes in the frequency of high-flow events. Moreover, 25% of the most extreme discharge values caused sediment transport of approximately $200*10^3$ t. Therefore, more suspended sediment is expected to be transported under considered climate change scenarios.

The results of our research contribute to an improved understanding of the complex hydro-climatic drivers that impact suspended sediment transport and will undoubtedly influence ecological status of surface waters and water quality in light of future climate change. The results indicate that erosion and sediment management and mitigation measures need to be applied in the future to ensure adequate water quality. Multiple green, hybrid and grey (Anderson et al. 2022; Nakamura 2022) soil erosion mitigation measures could be applied to most critical areas within the catchment to decrease soil erosion.

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Data Availability Data can be obtained upon request from the first author.

Declarations

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