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Estimation of water temperature changes in the Ipeľ River based on future scenarios

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Water is an irreplaceable resource for life and ecosystems, and among its key parameters is its temperature. The temperature of water and its fluctuations have a significant impact on aquatic ecosystems, highlighting the need for accurate prediction and monitoring. Therefore this study focuses on the analysis and simulation of monthly and daily water temperatures in the Ipeľ River Basin at two measuring stations. The first part of the study deals with the statistical analysis of daily water and air temperature values. The second part examines regression models for predicting daily and monthly water temperatures in the Ipeľ River Basin. The results of this analysis indicate that due to climate change, there is a gradual increase in temperatures in the Ipeľ River. This trend can have a negative impact on aquatic ecosystems and biodiversity, especially in extreme scenarios. Additionally, elevated water temperatures can affect water management and the utilization of the Ipeľ River, including the availability of drinking water and the quality of water sources. Overall, this study holds significant importance for the protection of aquatic ecosystems, and the insights gained can serve as a foundation for future strategies and measures to adapt to changing conditions and safeguard the valuable aquatic environment of the Ipeľ River Basin.

KEY WORDS: prediction of water temperature, change in water temperature, Ipeľ River, climatic scenarios

Introduction

Water temperature in rivers is not only a physical property, but also an important environmental factor and indicator of water quality and aquatic habitats (Grbić et al., 2013; Lešková and Skoda, 2003). Through the influence of water temperature on chemical processes, it indirectly affects key ecosystem processes (Hannah et al., 2008), such as primary production, decomposition and nutrient cycling in rivers (Friberg et al., 2009). These parameters and processes influence dissolved oxygen levels and, of course, have a major impact on water quality (Beaufort et al., 2016). In addition to ecological importance, water temperature in rivers also affects socio-economic concerns such as industry (cooling), drinking water production (Varga et al., 2023); (Varga and Velísková, 2021), sanitation, bacterial contamination, and fisheries (Hannah and Garner, 2015). Therefore, changes in the water temperature of a river can significantly alter the hydro-ecological and socio-economic conditions of the river and its catchment. Assessing changes in this variable and its drivers is essential to take action to manage impacts and enable preventative measures. Direct measurements of water temperature are often limited to gauge profiles, and the availability of longer series of measurements is limited to wake profiles. For optimised water management, it will be essential to derive how river water temperatures will evolve in the future, especially when considering global climate change processes. For example, predicting river temperatures a few days in advance can have a significant impact on possible countermeasures. Knowing the expected water temperature for the next few days is therefore an advantage. An important step in this context is the development of suitable model concepts for predicting river water temperature, describing thermal regimes and investigating the thermal evolution of the river. Among the variables that have the greatest influence on the temperature of the water in the river we can include meteorological conditions, especially air temperature, then wind speed, solar radiation and humidity. These determine the heat exchange and fluxes that take place at the surface of the river (Sleziak et al., 2023). In regression analysis of river water temperature, air temperature is often used as the only independent variable because it can be used as a proxy for net heat exchange fluxes affecting the water surface and also because air temperature is widely measured and more readily available than other parameters (Mohseni and Stefan, 1998), (Webb et al., 2008). Many water temperature prediction models have been successfully developed and applied in the past. Deterministic water temperature models simulate spatial and temporal changes in river water temperature based on the energy balance of heat fluxes and the mass balance of currents in the river. They require a large number of input variables and are often impractical and time consuming due to their complexity. On the other hand, because they are relatively simple and require less input data, statistical models are widely used. These include linear regression models (Morrill et al., 2005), nonlinear regression models (Bajtek et al., 2022; Mohseni and Stefan, 1998; van Vliet et al., 2023) and stochastic models (Ahmadi-Nedushan et al., 2007) for data over different time scales. Simultaneously, artificial neural network (ANN) models have recently been widely used to predict water temperature. DeWeber and Wagner, (2014) developed an ensemble ANN model for the prediction of daily mean water temperature with the use of air temperature and topography. With a particular focus on stream water temperature prediction, a recent study (Feigl et al., 2021) employed machine learning techniques to analyse the water temperature regime of the Danube River and its tributaries in Austria. In this study, the water temperature patterns of the Danube River and its tributaries were examined and predicted using advanced machine learning algorithms such as artificial neural networks and random forests. An important aspect is that it may be beneficial to consider the time lag of the influence of air temperature on practical temperature predictions (Benyahya et al., 2007), as stream water temperature does not respond instantaneously to changes in air temperature due to thermal inertia relative to hydrological regime fluxes (Isaak et al., 2017). This is broken down into two different parts: a long-term periodic part and a short-term variable part. In terms of land use change, many studies suggest that forest cover reduction (or vegetation shading reduction) (Pekárová et al., 2011) can have a significant impact on river water temperature change. Although the relationship between air temperature and water temperature is generally strong, the strength of these relationships varies regionally and temporally, and can change based on a number of external and internal aspects (Cisty and Soldanova, 2018; DeWeber and Wagner, 2014). For this reason, we set ourselves two objectives: the first one was to better analyse the variation of water temperature during the year, and the second one was to look for a suitable model to simulate the relationship between air temperature and water temperature. The catchment area of the Ipel River with its tributaries was chosen as the study area. The Cran R programming language (R Core Team, 2022) was chosen for the statistics and plotting of graphs because it provides a comprehensive set of analysis tools, as well as a great ability to visualise the results.

Material and methods

River basin description and data

The Ipeľ River (Fig. 1, 2) (Ipoly in Hungarian, Ipell in German) is the third largest river in Slovakia and a part of it forms the border between Slovakia and Hungary. The Ipeľ rises in the Low Tatras and flows for 232.5 km through central Slovakia, 140 km of which forms the aforementioned border with Hungary. The river basin extends into Hungarian territory and covers an area of 5,151 km². The most important tributaries of the Ipeľ in Slovakia include the Krupinica, which rises in the Javorie Mountains at the western foot of Veľký Lysec (886.4 m above sea level), is 65.4 km long, has an average discharge of 2.2 m³ s^{-1} (near the village of Plášťovce) and a catchment area of 551 km².

The Štiavnica River, which flows through the Krupina Plateau, is about 54.6 km long and has a catchment area of 441 km². It is a highland-lowland river. The Krivánský Brook is sometimes called the Lučenský Brook. With a length of 48.2 km and a catchment area of 204.89 km², it is an important right tributary of the Ipeľ River. It is a third-order stream, with a fan-shaped course and a regulated channel, and rises in the Ostrôžky Mountains, on the north-eastern slope of Baranie Hill (726.8 m above sea level), at an altitude of about 670 m above sea level. The Tisovník River, which flows through the territory of

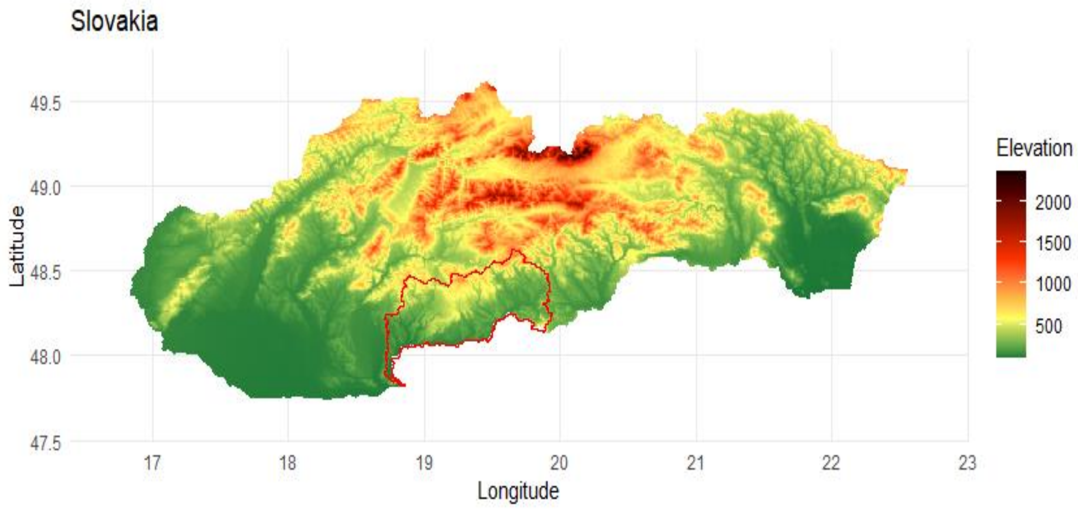

Fig. 1. Ipeľ River Basin, Slovakia map.

the Detva and Veľký Krtíš districts, is an important right tributary of the Ipeľ River with a length of 41 km and a catchment area of 441.1 km².

Methods

In our research we worked with data that included water temperatures from two water gauging stations, namely Slovenské Ďarmoty and Kalinovo, and one climatic station, namely Bzovík, with which the air temperature was used (Fig. 2).

In the framework of data preparation, we chose the period from 2005 to 2020, when the measurements in these two stations were automated and the daily water temperature value was computed as the average value of daily measurements in an hourly step (Fig. 3). Then we divided the data into two sets in 80 to 20 ratio, where the first set (80%) was used to train the model and the second set (20%) was used to test the model.

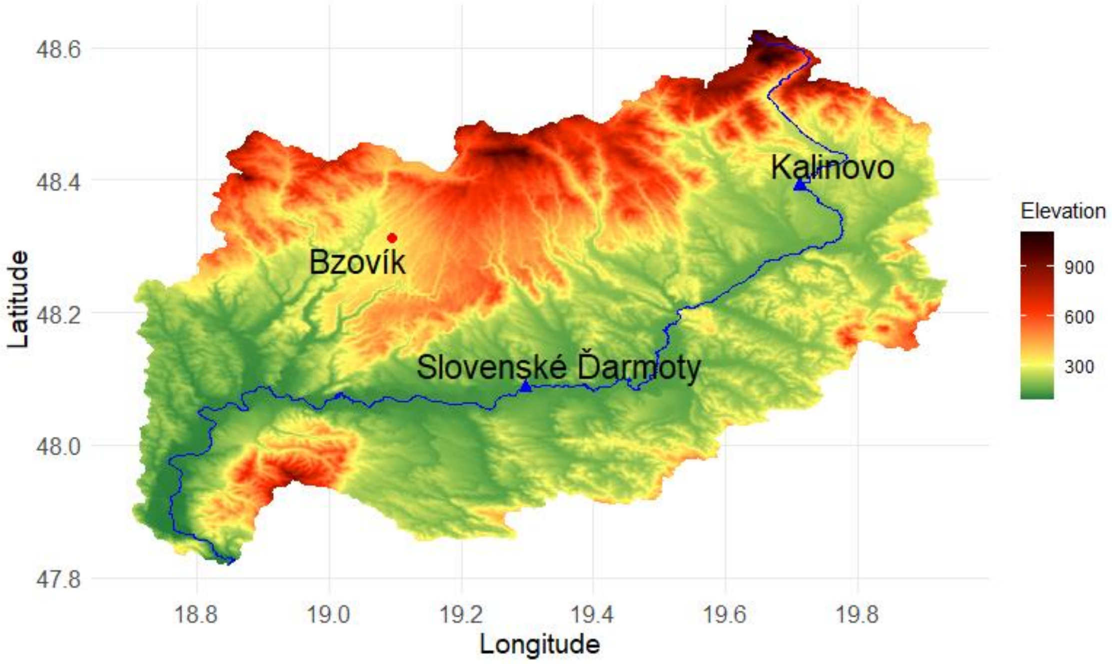

Fig. 2. Scheme of the Ipeľ River Basin, Gauging station Slovenské Ďarmoty, Kalinovo, and Bzovík climatic station.

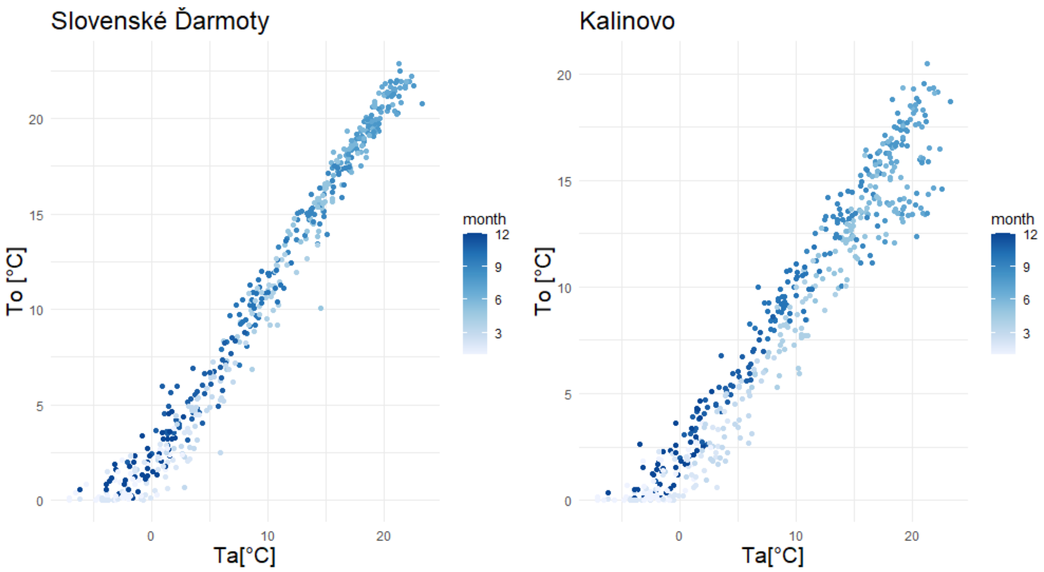

Fig. 3. Water temperature To and air temperature Ta dependence for "Slovenské Ďarmoty and Kalinovo" gauging station.

To build the model, we used non-linear multiple regression models, which are statistical models that are used to analyse the relationship between two or more independent variables and the dependent variable. Multiple regression models can be used to test hypotheses, make predictions and identify significant predictors of the outcome variable. The model used here is a version of the model (a four parameter non-linear function of air temperature) that was originally proposed by Mohseni et al., (1998) for the estimation of weekly stream temperatures over an annual cycle. According to this method, a continuous function of the form S curve' can describe the relationship between water and air, and its parameters have physical meaning:

$$To=\mu+((\alpha-\mu))/(1+e^{\wedge}(\gamma(\beta-Ta))), \quad (1)$$

where
To – daily water temperature [°C],
Ta – daily air temperature [°C],
μ – lower asymptote of the dependent variable,
α – upper asymptote of the dependent variable,
β – inflection point of the dependent variable growth,
γ – slope of the curve at the inflection point.

We usually estimate the model using least squares regression, which minimizes the sum of squared differences between the observed and predicted values of the dependent variables.
We built the model for both stations based on a full year of data (Fig. 4a, b). The second alternative we tested was to further split the training data based on months and then create a model for each month separately (see Fig. 4c, d). To evaluate the models, we used statistical metrics that are often used to evaluate the performance of regression models, including those used in hydrologic prediction, specifically MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and R-squared. The resulting values can be seen in Table 1.
In the next step, we focused on predicting daily water temperature values in the Ipeľ River using four climate scenarios for future periods: RCP2.6 (2031–2060), RCP2.6 (2071–2100), RCP8.5 (2031–2060) and RCP8.5 (2071–2100). We calibrated non-L multiple regression models for two stations (see Table 1): Kalinovo and Slovenské Ďarmoty. We used air temperature scenarios S1 to S4 according to Table 2. During the calibrations, we used the monthly water temperature and air temperature series in the base period from 2005 to 2020.

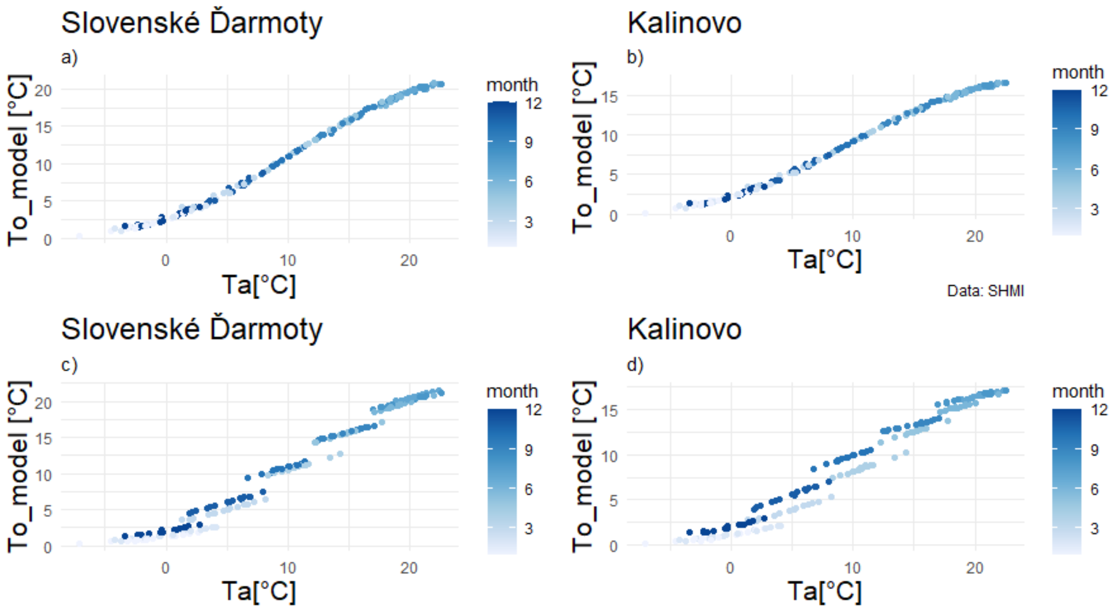

Fig. 4. Dependence of modelled water temperature To model and air temperature Ta for Slovenské Ďarmoty and Kalinovo water gauging stations. a, b) model for the whole year and c, d) models by months.

Table 1. Model parameters summarised

Station/model	MAE	MSE	RMSE	R-squared
Slovenské Ďarmoty (model for the whole year)	1.748	5.025	2.242	0.913
Slovenské Ďarmoty (models by months)	1.276	2.648	1.627	0.957
Kalinovo (model for the whole year)	1.737	4.697	2.167	0.862
Kalinovo (models by months)	1.526	3.631	1.906	0.897

Results and discussion

This study aimed to predict water temperature and its changes in two gauge profiles of the Ipeľ River using statistical approaches. Two different modelling methods were used, one using annual data and the other using monthly data. Non-linear multiple regression models were tested. The models were then used to predict water temperature on the basis of air temperature change scenarios derived from EURO-CORDEX simulations by Probst and Mauser, (2023). The results (Fig. 5, 6, 7) showed that the mean monthly water temperature in the Ipeľ River is predicted to increase under scenarios S1 to S4. The model working with annual data predicted the greatest increase of the water temperature at the station Slovenské Ďarmoty in the month of April, with a maximum increase of 4.01°C in the scenario S4. Conversely, models using monthly data predicted the largest increase at Slovenské Ďarmoty in the month of June, with a maximum increase of 2.1°C for scenario S4.

Table 2. **Seasonal scenarios S1 to S4 of the air temperature for future periods**

	Temperature [°C]			
Emission Scenario	Spring	Summer	Autumn	Winter
S1, RCP2.6 (2031–2060)	1.2	1.1	1.1	1.4
S2 RCP2.6 (2071–2100)	1.4	1.0	0.9	1.4
S3, RCP8.5 (2031–2060)	2.2	2.1	2.0	2.5
S4, RCP8.5 (2071–2100)	3.9	4.4	3.8	4.7

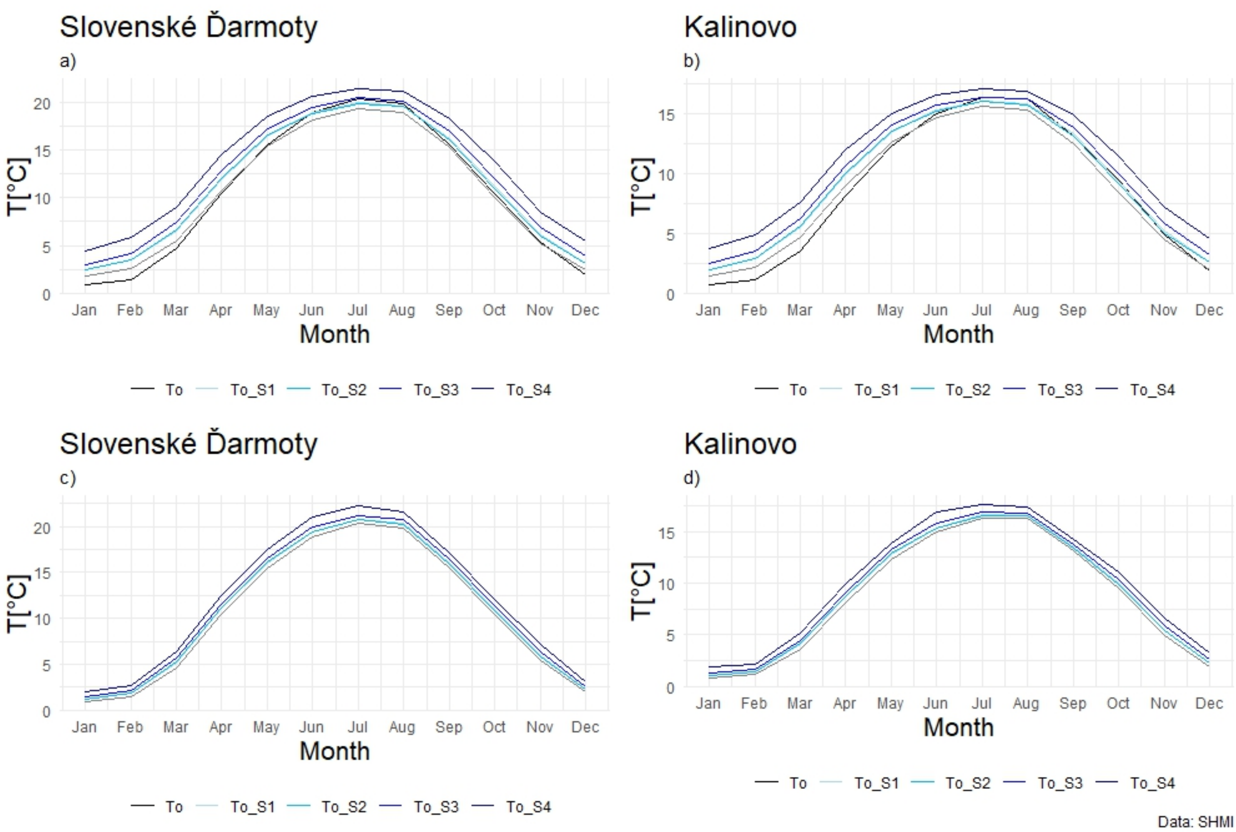

Fig. 5. Comparison of predicted monthly To according to scenarios S1 to S4 for stations Slovenské Ďarmoty and Kalinovo; a, b) model for the whole year and c, d) models by months.

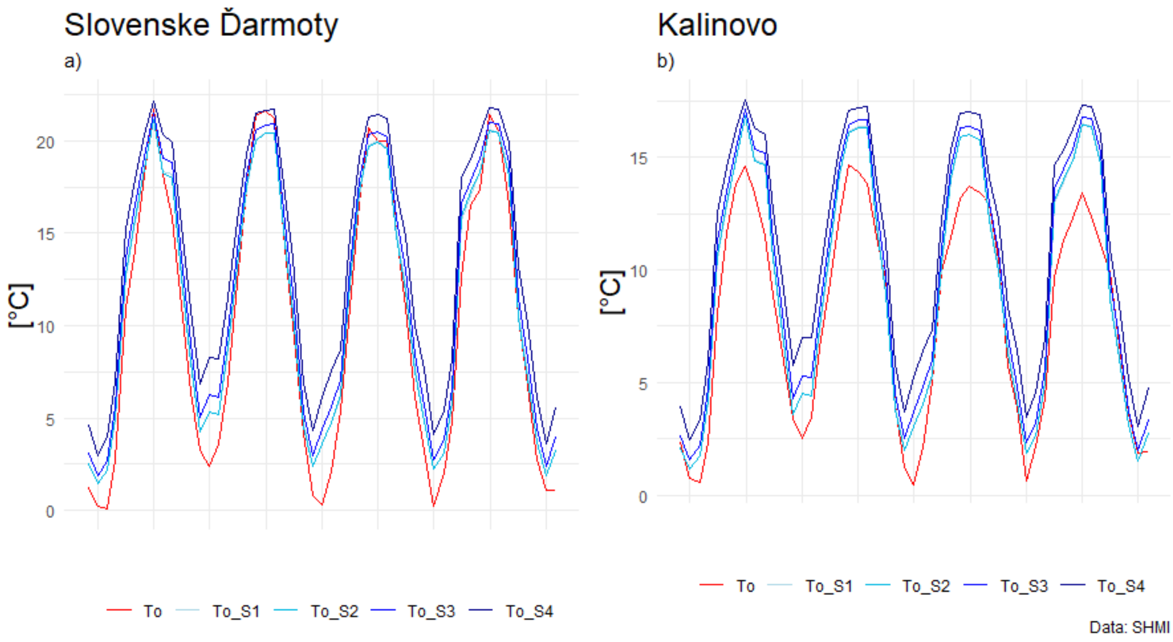

Fig. 6. Comparison between measured and modelled monthly water temperature values in the Ipeľ River at Slovenské Ďarmoty and Kalinovo stations using model under scenarios S1 to S4. (model for the whole year).

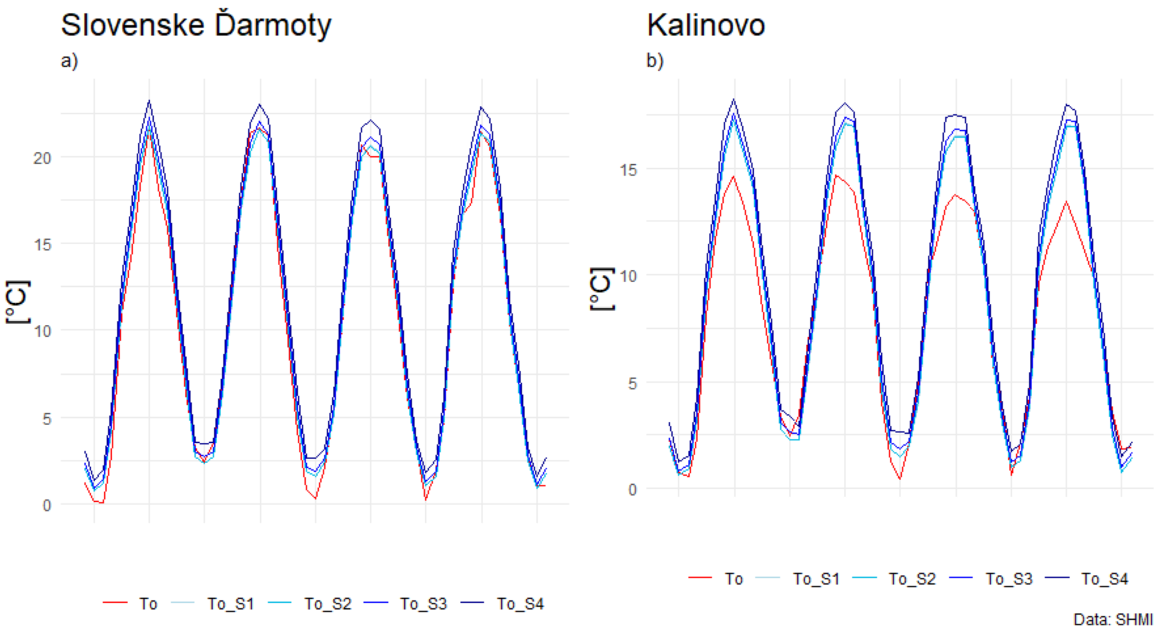

Fig. 7. Comparison between measured and modelled monthly water temperature values in the Ipeľ River at Slovenské Ďarmoty and Kalinovo stations using model under scenarios S1 to S4 (models by months).

Conclusion

To predict water temperature and its changes in two gauge profiles of the Ipeľ River, statistical approaches were used. Two types of non-linear multiple regression models were used to predict the monthly water temperature in the Ipeľ River at the Slovenské Ďarmoty and Kalinovo stations using the air temperature from the Bzovík station, where in the first case the model worked with annual data and in the second case with monthly step data. The air temperature was used to model the monthly mean water temperature. In the second phase, in order to predict the impact on water temperature, a climate change scenario derived from EURO-CORDEX simulations was used. According to the models, monthly mean water temperature in Ipeľ will increase under scenarios S1 to S4. For the model working with the whole annual data series, the largest increase in water temperature at the station Slovenské Ďarmoty is 4.01°C in the month of April for S4. Conversely, models working with monthly data predict the largest increase in S4 at the Slovenské Ďarmoty station in the month of June at 2.1°C. According to the models for the whole year, the absolute smallest increase may occur in summer, while the largest increase is expected in the months of February, March and April at both stations. For both stations, the monthly models show smaller monthly increases in water temperature. Overall, in modelling the monthly water temperature variations in the Ipeľ River, the month-by-month model has shown greater stability and efficiency. It appears to be a useful tool for prediction of water temperatures in rivers without measurements, but for modelling future development it has some limitations which make this model less useful.

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