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Monthly stream temperatures along the Danube River: Statistical analysis and predictive modelling with incremental climate change scenarios

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Abstract: The aim of the study is to analyse changes and predict the course of mean monthly water temperatures of the Danube River at various locations for the future. The first part of the study involves conducting a statistical analysis of the annual and monthly average air temperatures, water temperatures, and discharges along the Danube River. The study examines long-term trends, changes in the trends, and multiannual variability in the time series. The second part of the study focuses on simulating the average monthly water temperatures using Seasonal Autoregressive Integrated Moving Average (SARIMA) models and nonlinear regression models (NonL), based on two RCP based incremental mean monthly air temperature scenarios. To assess the impact of future climate on stream temperatures, the historical long-term average of the monthly water temperature (1990–2020) was compared with scenarios S1 (2041–2070) and S2 (2071–2100). The simulation results from the two stochastic models, the SARIMA and NonL, showed that in scenario S1, the Danube River's average monthly water temperature is projected to increase by 0.81/0.82°C (Passau), 0.55/0.71°C (Bratislava), and 0.68/0.56°C (Reni). In scenario S2, the models predict higher increases: 2.83/2.50°C (Passau), 2.06/2.46°C (Bratislava), and 2.52/1.90°C (Reni). Overall, the SARIMA model proved to be more stable and effective in simulating the increase in monthly water temperatures in the Danube River.

Keywords: SARIMA models; Nonlinear regression models; Water temperature changes; Climate change; Incremental scenarios.

1 INTRODUCTION

Physical, chemical, and biological processes in water bodies are driven, among other things, by the temperature of the water. In river systems, its significance extends beyond influencing water's physical, chemical and biological properties. It plays a direct role in shaping the ecosystems of streams and nearby land. The factors that determine the water temperature can be broadly grouped into four categories (Caissie, 2006):

Atmospheric conditions – including solar radiation, the air temperature, wind speed, precipitation, evaporation, and condensation.

Topographic conditions such as the altitude and latitude of a basin, main orientation of the slopes of the catchment, riparian vegetation along the rivers.

The hydrological regime of the flow – incorporating the amount, velocity and temporal distribution of flows, the stream depths, and the interactions with groundwater.

Anthropogenic activities in the basin – including the discharge of urban and industrial wastewaters, water withdrawals, impacts of reservoirs and diversion canals, and the removal of riparian vegetation (Heggenes et al., 2021).

Despite its crucial role, the temperature of the water has received less societal and scientific attention than other qualitative water properties, such as nutrients, various contaminants, and other water quality properties (Ficklin et al., 2023). As Garner et al. (2017) pointed out, most climate change related research has historically focused on rainfall and river flows. Recently rises in global air temperature and the corresponding increase in river temperatures have directed attention to the potential adverse consequences of warming water on the quality of water and diversity of connected ecosystems (Hannah and Garner, 2015; Stagl and Hattermann, 2015; Wanders et al., 2019). Consequently, a better understanding of the impacts of the changes in the drivers of river temperatures in space and over time has become imperative in research (Bisselink et al., 2018).

Significant gaps in our knowledge of the changes and dynamics in river temperatures in natural and anthropogenically dominated river system systems, especially those longer than 1000 km were detected. Only 37 percent of these systems are free-flowing over their whole course, and 23 percent flow uninterrupted to the ocean (Grill et al., 2019). Water temperature monitoring systems often have low spatial resolutions and series of short durations, which limit the potential for analysing changes, trends and spatiotemporal patterns (Dugdale et al., 2017; Okhravi et al., 2022; Vyshnevskyi and Shevchuk, 2021). This knowledge of the process limits our capacity to respond to

the resulting ecological challenges, to sustainably approach the protection and management of riverine ecosystems, and to pragmatically discuss controversial stakeholder interests (Ficklin et al., 2023).

The lack of local information has also fostered the development and use of models (both process based and stochastic) to generalize knowledge from existing data and generate river temperature estimates and predictions. Several significant review papers have relatively recently summarized the state-of-the-art concerning modelling river temperatures (Benyahya et al., 2007a; Caissie, 2006; Dugdale et al., 2017; Ouellet et al., 2020; Piotrowski et al., 2015; Sutadian et al., 2016; Webb et al., 2008).

Process-based models, which capitalize on knowledge of the physically-based mechanisms driving river temperatures (energy fluxes responsible for temperature changes), are data-intensive but enable estimations of the impact of projected changes, e.g., in land-use or the climate (e.g., Bahari and Hamid, 2019; Hebert et al., 2015; Leach and Moore, 2017; Li et al., 2022; Piotrowski and Napiorkowski, 2018; Tavares et al., 2020).

Their statistical counterparts can provide predictions at a much lower cost and are therefore advantageously used in more practically oriented studies and predictions for water management (Benyahya et al., 2007a; Dugdale et al., 2017; Jackson et al., 2018). Adequately chosen statistical temperature models can also supply reliable stream temperature forecasts and long-term predictions. They are often preferred in applications concerning large spatial scales where the data requirements of process-based models limit their usefulness.

These models explore the statistical dependence in the data and search for adequate structures to fit this observed behaviour between river temperatures and various related covariates. Parametric approaches, such as regressive, correlative or autoregressive models, have often been used (Ahmadi-Nedushan et al., 2007; Asarian et al., 2023; Benyahya et al., 2007b; Boudreault et al., 2019; Caissie et al., 1998; Kwak et al., 2016; O'Sullivan et al., 2020). Recently, non-parametric methods have also been gaining increased attention (e.g., artificial neural networks, random forecasts, nearest-neighbour approaches, etc. (Abdi et al., 2021; DeWeber and Wagner, 2014; Feigl et al., 2021; Graf et al., 2019; Liptay, 2022; Piotrowski et al., 2015; Rahmani et al., 2021; Sapin et al., 2017; Zhu et al., 2019, 2018)).

Because of the thermal inertia of rivers, water temperatures and air temperatures are better correlated on longer time scales (monthly, seasonal and annual) than in short-term steps (daily or weekly). In such a case, when using stochastic models, it is commonly attempted in the modelling of such periodic series to deseasonalize the series prior to applying the stationary models of the AutoRegressive Moving Average (ARMA) class. Benyahya et al. (2007a), Graf and Aghelpour (2021), and Jackson et al. (2018) have also noted that such filtering time series might not yield stationary residuals due to periodic autocorrelations. They suggested that it may be advantageous to model periodicity in autocorrelations, particularly with Periodic AutoRegressive (PAR) and Periodic AutoRegressive Moving Average (PARMA) models. Another option is using SARIMA models, an extension to Autoregressive Integrated Moving Average (ARIMA) models that explicitly support the direct modelling of the seasonal component of time series data and can incorporate exogenous variables. Contrary to ARIMA, it also uses past values and considers any seasonality pattern; therefore, it is more potent than ARIMA when forecasting complex data containing periodicity (Malki et al., 2022). Applications in meteorology and water sciences exist (Azad et al., 2022; Belotti et al., 2021; Chang et al., 2013; Chen et al., 2018; Oktaviani et al., 2021), but to our knowledge, modelling monthly river temperatures still need to be included. A series of model comparisons have been made to aid good stochastic and data based model selections for specific physiographic settings (Graf and Aghelpour, 2021; Yang and Peterson, 2017; Zhu et al., 2018).

The water temperature of Danube River was subject to a number of studies. The long-term water temperature trends of the Danube River were examined by Webb (1996). Data, including that of other European rivers, suggested warming up to ca. 1°C in the mean river temperatures during the 20th century. However, this trend was not continuous but was distorted by extreme hydrological events; moreover, it was not correlated with simple hydrometeorological factors and was influenced by various human activities. As part of the UNESCO International Hydrological Program (IHP), the water temperature of the Danube River was evaluated at stations along the river between 1956 and 1985 (Brilly, 2010; Stancikova, 2010). The water temperature from Ingolstadt (Germany) to Braila (Romania) increased from 1956–1985 by 0.5–4.0°C in general. However, episodes occurred with a decrease in temperature between particular water gauging stations, which resulted from mutual climatic relations affecting each other that changed along the river. The tributaries and various anthropogenic interventions also influenced the temperature.

Bonacci et al. (2022) showed that anthropogenic impacts may also affect changes in river temperatures of the Danube and its tributaries, in particular by causing them to increase. The construction of reservoirs influenced the rise in water temperatures downstream of the Botovo water measuring station on the Drava River (Croatia). The commissioning of a second reservoir in 1982 caused a significant rise in the water temperature at the station. Trends in water temperature increased during all months of the year, which were statistically significant, while the air temperature trends were statistically significant only during the warm parts of the year.

Caissie et al. (2014), Feigl et al. (2021), Jeong et al. (2013), and Letcher et al. (2016) have employed machine learning techniques such as artificial neural networks and random forests to analyse the water temperature regime of the Danube River and its tributaries in Austria, with a particular focus on predicting the water temperature of various streams. The research has provided insights into using machine learning methods for understanding and predicting water temperature dynamics in river systems, which can aid in developing effective management strategies for water resources.

Predictive studies indicated that an accelerated rise in stream and river temperatures could occur during the 21st century due to global warming. Dokulil (2018) analysed long-term water temperature data from the Danube River and selected tributaries collected by the Austrian Hydrographic Survey covering 1901–2015. Significant correlations between the air-to-water temperature were established at all stations. The temperature trends were extrapolated to 2050 using multiple regression analyses and scenarios of changes in future air temperatures and discharges. The results indicated a significant increase of about 1.4°C, which would be equivalent to 0.01°C per year. The impact of the North Atlantic Oscillation (NAO) on multiple-year water temperature oscillations in the Danube was investigated by Webb and Nobilis (2007). A significant increase in the annual mean values broadly followed an increase in the air temperature. As for the seasonal mean values, trends were also controlled by catchment characteristics and locations. Evidence was provided that the NAO influenced inter-annual variations in the water temperature, especially in the winter months. Bonacci et al. (2008) analysed the water temperature regime of the Danube

River and its tributaries in Croatia. Changes in the water temperature regime along the Sava, Mura, Drava, and Danube Rivers in Croatia over the past twenty to sixty years were investigated in their study. Particular emphasis was placed on investigating the alterations during the past thirty years that were probably caused by climate change, climate variability, or both. Their conclusions were supported in the broader region by Hrdinka et al. (2015), who studied the impacts of changes in the water temperature and flow on selected water quality parameters in the Czech Republic, including tributaries of the Danube. The impact of climate change was manifested by an increase in the stream temperature by 1.15°C over 28 years.

Unlike air, water has an exceptionally high specific heat capacity; its temperature can be considered a stable indicator of long-term trends (Pekárová et al., 2022, 2008). In this respect, Romanova et al. (2019) called attention to the fact that, in general, there are some common long-time trends in climate change for the countries of the Danube River Basin. These changes include an increase in the average annual air temperature, resulting in a decrease in the percentage of snow in the total annual amount of precipitation. This trend was supported and quantified in a series of studies that utilized the high-resolution regional climate change ensemble that has been established for Europe within the World Climate Research Program Coordinated Regional Downscaling Experiment (EURO-CORDEX) initiative (Jacob et al., 2014, 2020). These studies have found numerous applications in the Danube basin in predicting changes in the hydrological regime (Stagl and Hattermann, 2015), riverine ecosystems (Stagl and Hattermann, 2016), management of protected areas (Stagl and Hattermann, 2015) and water resources (Probst and Mauser, 2023). Applications concerning the water temperature of the Danube and its tributaries are, to our best knowledge, still lacking.

In this paper, based on the outcomes of the previously cited research, our overall goal was to provide new and useful insights into the factors affecting the Danube River's water temperature regime and how it might change under different climate scenarios. The first part of the study involves a statistical analysis of the annual and monthly average air temperature, water temperature, and discharges in selected cross-sections along the Danube River. We examine changes in the long-term trends and multiannual variability in the annual time series. The second part of the study focuses on simulating the average monthly water temperatures using stochastic time series and nonlinear regression models based on incremental scenarios of changing air temperatures based on outcomes from the EURO-CORDEX simulations summarised in Probst and Mauser (2023). We have aimed to predict the water temperature and changes in it on a larger scale along the whole Danube River at various locations with two different statistical approaches. An innovative simulation of monthly water temperatures based on these scenarios of monthly air temperatures using Seasonal Autoregressive Integrated Moving Averages (SARIMA) models was conducted and compared with traditional nonlinear (NonL) multiple regression models.

2 DATA

The Danube River is a significant river in Europe; it ranks globally as the twenty-first largest in terms of its length. The river has a total length of 2857 km and a long-term daily mean discharge at the outlet of about 6500 $m^3 s^{-1}$, which is the second in Europe and twenty-first in the world. Its drainage area covers 817,000 km^2, ranking it as the twenty-fifth largest drainage area in the world (Figure 1).

The Danube River basin experiences varying climatic conditions, with the western part influenced by the Atlantic Ocean, the southern and south-western regions influenced by the Mediterranean climate, and the eastern part subject to colder continental conditions.

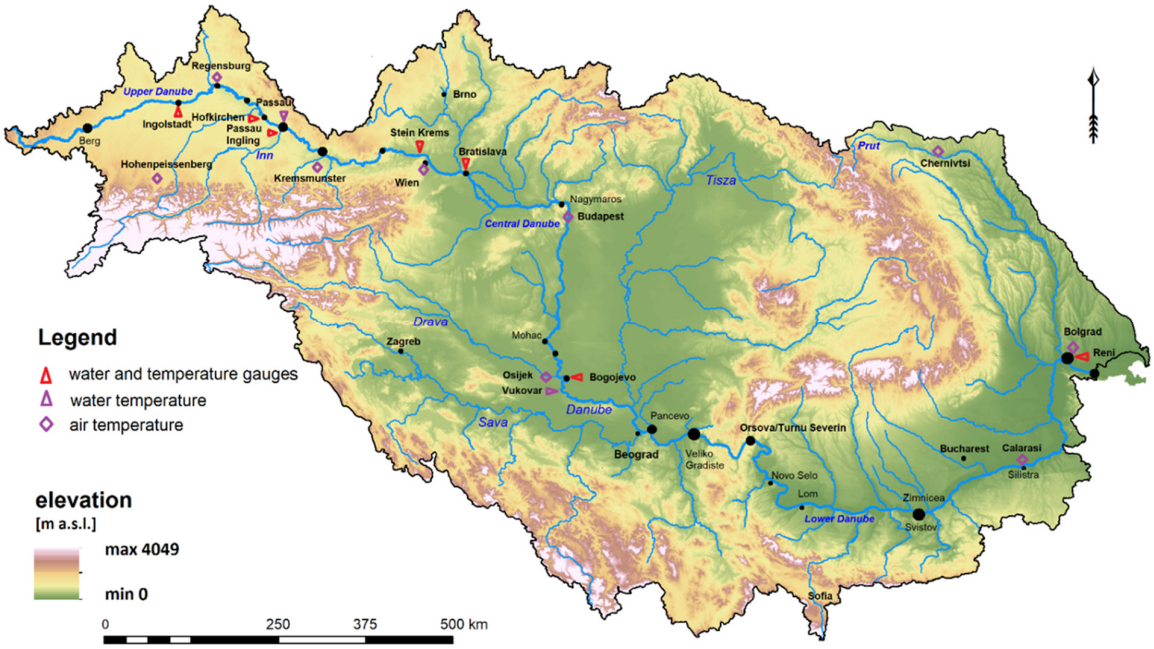


Fig. 1. The scheme of the Danube River basin. The black points indicate the location of the water gauge stations along the Danube River. The red triangles indicate the locations of the water and temperature stations used in this study. The purple triangles represent water temperature stations, and the purple rectangles denote air temperature stations.

Geographically and morphologically the Danube basin can be divided into three regions: the Upper, Central (or Middle), and Lower Danube (Figure 2). From its source in the Black Forest in Bavaria to its mouth at the Black Sea, the difference in altitude is 678 metres. The Upper Danube stretches from the Black Forest to the Devin Gate at Bratislava, the Central or Middle Danube, which includes the Pannonian plain, from the Devin Gate to the Iron Gate where it passes in the Southern Carpathians and the Balkan Mountains. The Lower Danube stretches from the Iron Gate to the Danube delta. A number of other large tributaries (e.g., the Inn, Morava, Drava, Tisza, Sava, Siret, Prut) flow into the Danube and contribute with their subbasins to the overall discharge. The Upper Danube is characterized by a steep gradient of 0.2–1.1‰, the Middle and Lower Danube by a low gradient of 0.01–0.03‰, except for the cataracts of Iron Gate of 0.3‰ (Figure 2).

In our analysis of long-term trends, we focused on the longest possible series of potential predictor variables for the stochastic prediction modelling. Long series of air temperatures, water temperatures, and flow data from the Upper, Middle, and Lower Danube were collected.

The earliest air temperature measurements in Central Europe date back to the late 18th century. The air temperature was recorded at three intervals each day, and the mean daily value was calculated. In this study, we collected and statistically analysed monthly data from nine meteorological stations in the Danube basin, i.e., Hohenpeissenberg, Regensburg, Kremsmuenster, Vienna-Hohe Warte, Budapest, Zagreb, Calarasi, Chernivtsi, and Bolgrad.

The first water temperature measurements in the Danube basin rivers started at the end of the 19th century. The temperatures were measured by a thermometer with a usual reading accuracy of 0.1°C. Measurements were performed once a day between 6.00 and 8.00 a.m., usually at a water gauge station (Stančíková, 2010). As part of the UNESCO International Hydrological Program (IHP), the water temperature of the Danube River was evaluated at stations along the river from 1956 to 1985. We extended these series to nine additional stations up until the year 2020: Ingolstadt (Germany), Deggendorf (Germany), Passau (Germany, at its confluence with the Inn River), Engelhartszell (Austria, below its confluence with the Inn River), Stein Krems (Austria), Bratislava (Slovakia), Vukovar (Croatia), Novo Selo (Bulgaria), and Reni (Ukraine). The measured data series were cleaned of erroneous measurements and missing data supplemented based on measurements from neighbouring stations (e.g., Bratislava (Slovakia) by Hainburg (Austria), and Vukovar (Croatia) by Bogojevo (Serbia)).

The water level observations on the Danube began in 1821 (Pekárová and Miklánek, 2019). We selected eight water gauge stations with long-term continuous observations: Ingolstadt (Germany), Hofkirchen (Germany), Achleiten (Austria), Stein Krems/Kienstock (Austria), Bratislava/Devín (Slovakia), Bogojevo (Serbia), Orsova/Turnu Severin (Romania), and Reni (Ukraine). (As a result of the construction of waterworks on the Danube (in Austria, Freudenau; Slovakia, Gabčíkovo; and Romania, Iron Gate), the observations of water levels from historical water gauge stations were relocated upstream from the Stein Krems water gauge to the Kienstock water gauge, from Bratislava to Devín, and from the Orsova gauge to the Turnu Severin gauge).

After 1980, resistance thermometers were installed at water gauge stations for continuous recording, thereby allowing for the hourly tracking of water temperatures. In Figure 3, an example of the hourly average water temperature course at the Danube - Bratislava water gauge in the year 2000 is shown. The Danube in Bratislava currently experiences a minimum water temperature at 6:00 a.m. and a maximum at 7:00 p.m. The average temperature difference in Danube between these two times was only 0.2°C, (in small mountain streams, the difference between water temperatures measured during the day can reach up to 5°C). This indicates that the water temperature readings at 7:00 a.m. represent temperatures close to the daily minimum water temperatures. The average annual water temperature in the Danube at the Bratislava station is only 0.1°C higher. Throughout this study, we use water temperature series measured daily at 7:00 a.m.

We obtained complete monthly data series from 1980 to 2020 for 6 profiles on the Danube (as shown in Table 1). In the second part of the study, three stations, from these data series were selected. Since the longitudinal change of the water temperature

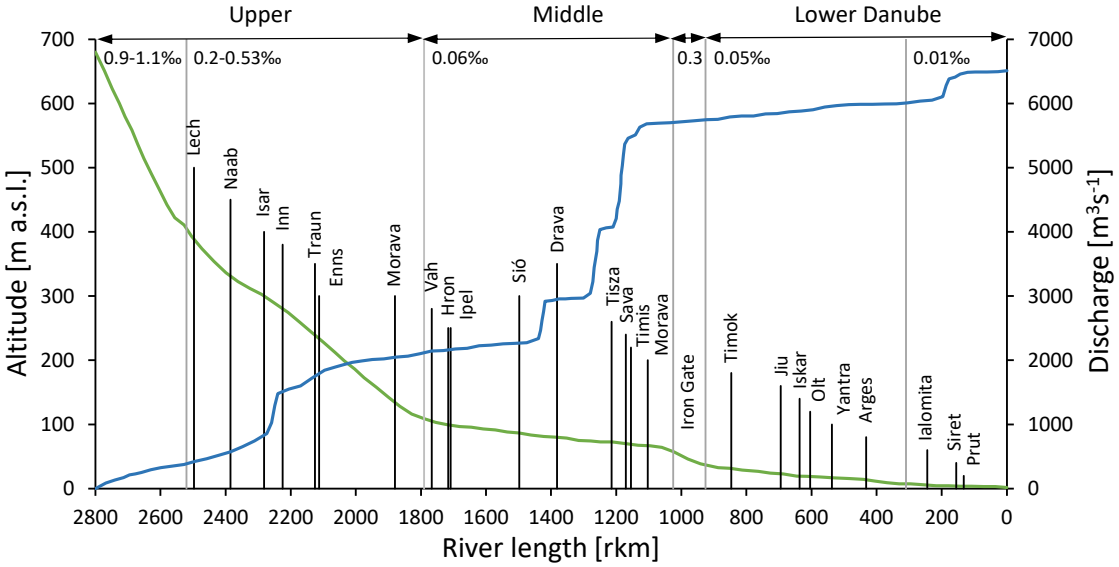


Fig. 2. The main tributaries, longitudinal profile of the Danube and the mean discharge, and the gradient of the three main section of the Danube River (based on data from Schiemer et al. (2004) and Waterway transport on Europe's lifeline (2002)).

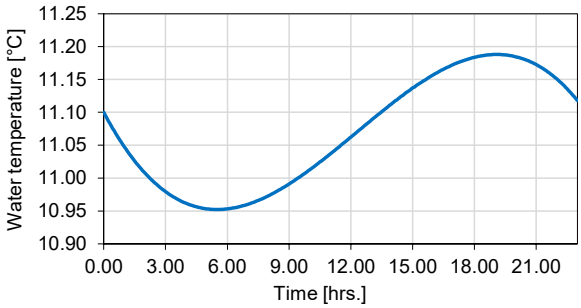


Fig. 3. The average hourly water temperature course at the Bratislava station in the year 2000.

is monotonously slowly rising along the whole river (except the jump in the Austrian reach caused by the tributaries from the Alps), these stations were considered as representative for the whole three characteristic reaches of the Danube in the modelling of the monthly water temperature changes based on the incremental scenarios of changes in the air temperature (Passau for the Upper Danube, Bratislava for the Middle Danube, and Reni for the Lower Danube).

Probst and Mauser (2023) published, based on selected high-resolution GCM-RCM ensembles and high-resolution regional climate change projections for Europe from the EURO-CORDEX initiative and two emission scenarios RCP2.6 and RCP8.5 for both the near future (2031–2060) and the and the far future (2071–2100), seasonal climate change scenarios for the three regions of the Danube River. Based on their results for the whole Danube Basin it can be realistically presumed that the increase of air temperature will experience an annual cycle with more pronounced increase during the winter months. To construct physically plausible incremental scenarios of the future projections of air temperature in the Danube River their temporal and spatial differentiation was adopted in the construction of the scenarios of the development of the air temperature in the Danube basin in the future. The measured series of monthly air temperatures from 1990 to 2019 were scaled for the Upper, Middle, and Lower Danube based on the EURO-CORDEX Climate Scenarios processed by Probst and Mauser. Two scenarios were developed for three stations representative for the three sections of the Danube (Figure 2):

- The first (S1) is considered to be a moderate scenario. It utilizes the RCP2.6 projections for the near future (2031–2060) by additively modifying the monthly mean air temperature (see Table 2).
- The second (S2) is an extreme scenario, which utilizes the RCP8.5 projections for the far future (2071–2100) by additively modifying the monthly mean air temperature (see Table 2).

Table 1. The series of annual data used, *To,y* - water temperature; *Ta,y* - air temperature; *Q,y* - discharge.

To,y Danube River	Period	*Ta,y*	Period	*Q,y*	Period
Ingolstadt (GE)	1956–2020	Regensburg (GE)	1773–2015	Ingolstadt (GE)	1924–2020
Passau (GE)	**1956–2020**	**Regensburg (GE)**	**1773–2015**	**Hofkirchen (GE)**	**1901–2020**
Stein Krems (AT)	1901–2020	Kremsmuenster (AT)	1871–2020	Stein Krems/Kienstock (AT)	1829–2020
Bratislava (SK)	**1926–2020**	**Vienna – Hohe Warte (AT)**	**1775–2020**	**Bratislava/Devín (SK)**	**1876–2020**
Vukovar (HR)	1953–2020	Zagreb (HR)	1900–2020	Bogojevo (SR)	1931–2020
Reni (UKR)	**1945-2020**	**Bolgrad (UKR)**	**1881–2020**	**Reni (UKR)**	**1921–2020**

(GE) – Germany; (AT) – Austria; (SK) – Slovakia; (HR) – Croatia; (SR) – Serbia; (UKR) – Ukraine

Table 2. Seasonal scenarios S1 and S2 of the air temperature for future periods.

	S1, RCP2.6 2031–2060				S2, RCP8.5 2071–2100			
Station	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter
Regensburg	1.2	1.2	1.3	1.5	3.8	4.3	4.1	4.6
Vienna	1.2	1.1	1.1	1.4	3.9	4.4	3.8	4.7
Bolgrad	1.4	1.1	1.0	1.6	4.8	4.3	4.8	3.9
Average	1.27	1.13	1.13	1.50	4.17	4.33	4.23	4.40

3 METHODS

The first part of the study involves established basic statistical analysis of the annual and monthly average air temperature, water temperature, and discharges in selected cross-sections along the Danube River. Standard statistical exploratory methods are applied to examine the changes in the long-term means and variability in the time series. Additionally, the P90, P50, and P10 values, which represent the upper, median, and lower deciles are also calculated.

Basic methods of time series analysis are used to can detect and quantify trends and fluctuations in records. Fluctuations in the time series are visualized by (5-year) moving averages and general tendencies estimated by linear trend analysis. The break points indicating a change in the long-term trends are identified using the Rescaled Adjusted Partial Sums (RAPS) method described in Garbrecht and Fernandez (1994), Bonacci and Oskoruš (2010) or Bonacci et al. (2020).

The values of RAPS in the times series $Y = (Y_t, t = 1, 2, \ldots, n)$ are defined as:

$$RAPS_k = \sum_{t=1}^{k} \frac{Y_t - \bar{Y}}{S_Y} \quad (1)$$

where:
$\bar{Y}$ – the sample mean;
S_Y – the standard deviation;
n – the number of values in the time series;
k – the counter limit of the serial summation ($k = 1,2 \ldots, n$).

The plot of the RAPS in time is the visualization of the trends and fluctuations of Y_t. The visualization approach based on RAPS overcomes small systematic changes in records and the variability of data values. The RAPS visualization highlights trends, shifts, data clustering, irregular fluctuations, and periodicities in the record.

It has to be noted that despite being objective, the RAPS method is not without shortcomings (Bonacci et al., 2020; Garbrecht and Fernandez, 1994). Applications in hydrology were reviewed in Đurin et al. (2022).

The effect of an increase in air temperature on the water temperature plays an important role in relation to the development and implementation of effective measures for the protection of water resources and for ensuring a sufficient amount of quality water. Extreme increases in the air temperature are generally reflected in an increased water temperature in the streams. This expected increase can be evaluated using models that predict the time series, in this case, the water temperature, based on the air temperature. For this purpose, Seasonal Autoregressive Integrated Moving Average models and nonlinear multiple regression models in monthly time step with additional regression components (regressors) have been used in the paper.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a time series forecasting model, which incorporates both autoregressive (AR) and moving average (MA) components, as well as differencing and seasonal components. The model is designed to capture and account for patterns and trends within the time series data, including seasonality. The seasonal component is particularly important in the SARIMA model, as it allows for the modelling of data with seasonal fluctuations or cycles. The model involves fitting a regression equation to the data, where the dependent variable is the time series data, and the independent variables are lags of the series and lagged errors. The model is typically estimated using a maximum likelihood estimation, and the accuracy of the model can be evaluated using various statistical measures such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Pekárová, 2009).

The general form of the SARIMA (p, d, q) x $(P, D, Q)_L$ model takes the following form:

$$\varphi(B)\,\varphi(B^L)\,\nabla^d\,\nabla^D{}_L\,Y_t = \Theta(B)\Theta(B^L)E_t, \tag{2}$$

where:
E_t – independent and normally distributed random variable with zero mean value $\mu = 0$ and variance $\sigma_E{}^2$;
p – trend in autoregressive order;
d – trend in difference order;
q – trend in moving average order.
P – seasonal autoregressive order;
D – seasonal difference order;
Q – seasonal moving average order;
L – the number of time steps for a single seasonal period (an L of 12 for monthly data suggests a yearly seasonal cycle);
B – reversion shift operator defined as $BY_t = Y_{t-1}$;
∇^l – the backwards difference operator;
φ – the regular auto-regressive (AR) operator of the order p;
Θ – the regular moving average (SMA) operator of the order q;
$\nabla^D{}_L$ – the seasonal backwards difference operator;
φ – the regular seasonal auto-regressive (SAR) operator of the order P;
Θ – the regular seasonal moving average (SMA) operator of the order Q.

To identify this model, it is necessary to analyse the particular components of the time series in the following sequence:

- identification of a trend (differentiating of order d) and seasonality (seasonal differentiating of order D);
- selection of a model type (AR, MA, ARMA) and determination of the model's order;
- estimation of the model parameters;
- verification of the model.

The NonL nonlinear multiple regression models are statistical models used to analyse the relationship between two or more independent variables and a dependent variable. Multiple regression models can be used to test hypotheses, make predictions, and identify significant predictors of the outcome variable. They are a valuable tool for understanding the complex relationships between multiple variables and can provide insights into the factors that drive particular outcomes. However, they require careful analysis and interpretation to ensure the results are valid and reliable.

The model version (a four-parameter, nonlinear function of air temperatures) used here was proposed originally to estimate weekly stream temperatures needed for the evaluation of a fish habitat throughout an annual cycle by Mohseni et al. (1998). According to this method, the relationship between water and air temperatures can be described by a continuous S-shaped function. Its parameters have a physical meaning:

$$T_o = \mu + \frac{(\alpha - \mu)}{1 + e^{\gamma(\beta - T_a)}}, \tag{3}$$

where:
To – represents the average monthly water temperatures;
Ta – represents the average monthly air temperatures;
μ – the lower asymptote of the dependent variable;
α – the upper asymptote of the dependent variable;
β – the inflection point of the growth of the dependent variable;
γ – the slope of the curve at the inflection point.

The model is typically estimated using least squares regression, which minimizes the sum of the squared differences between the observed and predicted values of the dependent variable.

The quality of the predictions by the stochastic models is estimated using the following criteria:

Absolute errors:

– Mean error

$$ME = \frac{1}{N}\sum(y_t - \hat{y}_t) \tag{4}$$

– Mean squared error

$$MSE = \frac{1}{N}\sum(y_t - \hat{y}_t)^2 \tag{5}$$

– Root mean squared error

$$RMSE = \sqrt{MSE} \tag{6}$$

– Mean absolute error

$$MAE = \frac{1}{N}\sum|y_t - \hat{y}_t|\,| \tag{7}$$

Relative errors:

– Mean absolute percentage error

$$MAPE = \frac{1}{N}\sum\left|{}^{(y_t - \hat{y}_t)}/_{y_t}\right|.100\% \tag{8}$$

– Mean percentage error

$$MPE = \frac{1}{N}\sum\frac{(y_t - \hat{y}_t)}{y_t}.100\% \tag{9}$$

4 RESULTS

The first part of the study involves basic statistical analysis of the annual and monthly average air temperature, water temperature, and discharges in selected cross-sections along the Danube River. The results of each analysis target the three characteristic sections of the Danube River (Upper, Middle, or Central and Lower), respectively. In each river section the hydrological regime is described through at least one representative station. The selection of these representative stations is not fully consistent in each step of the analysis, since the specific data requirements of the particular analyses were not met by all stations. For instance, the station in Vienna Hohe, which is just 60 km from Bratislava, is also used to describe the Middle Reach starting in Bratislava in some cases.

Figure 4 presents the comparative analysis of the development of trends in the annual data series of the Upper Danube. Figure 4a presents the average annual air temperature Ta,y from the Vienna-Hohe Warte station (HISTALP, n.d.) and illustrates the deviations of the average annual temperatures from the 5-year moving averages. In Figure 2b, the course of the annual average water temperature To,y from the Danube at the Stein Krems station is presented. Figure 2c presents the trends of the average annual flows Q,y on the Upper Danube above Vienna at the Stein Krems water gauge station. The course of the time series illustrates our hypothesis, that the main driver of the increase of water temperature is the increase in the air temperature, whereas since the annual discharge series do not exhibit a trend, these would not have to be considered in the stochastic modelling as regressors.

Therefore in the first step, we examined the long-term trends of the air temperature (*Ta,y*) and water temperature (*To,y*), as well as discharges (*Q,y*), using the longest series of the available average annual data measured in the Danube River basin. Next, we tried to locate the break point in the series along the Danube River by the RAPS analysis in order to select a baseline period used in the model parametrisations and the construction of the incremental climate change scenarios. This exploratory part of the results will be followed by the modelling exercise which targets the possible change in water temperature in the future.

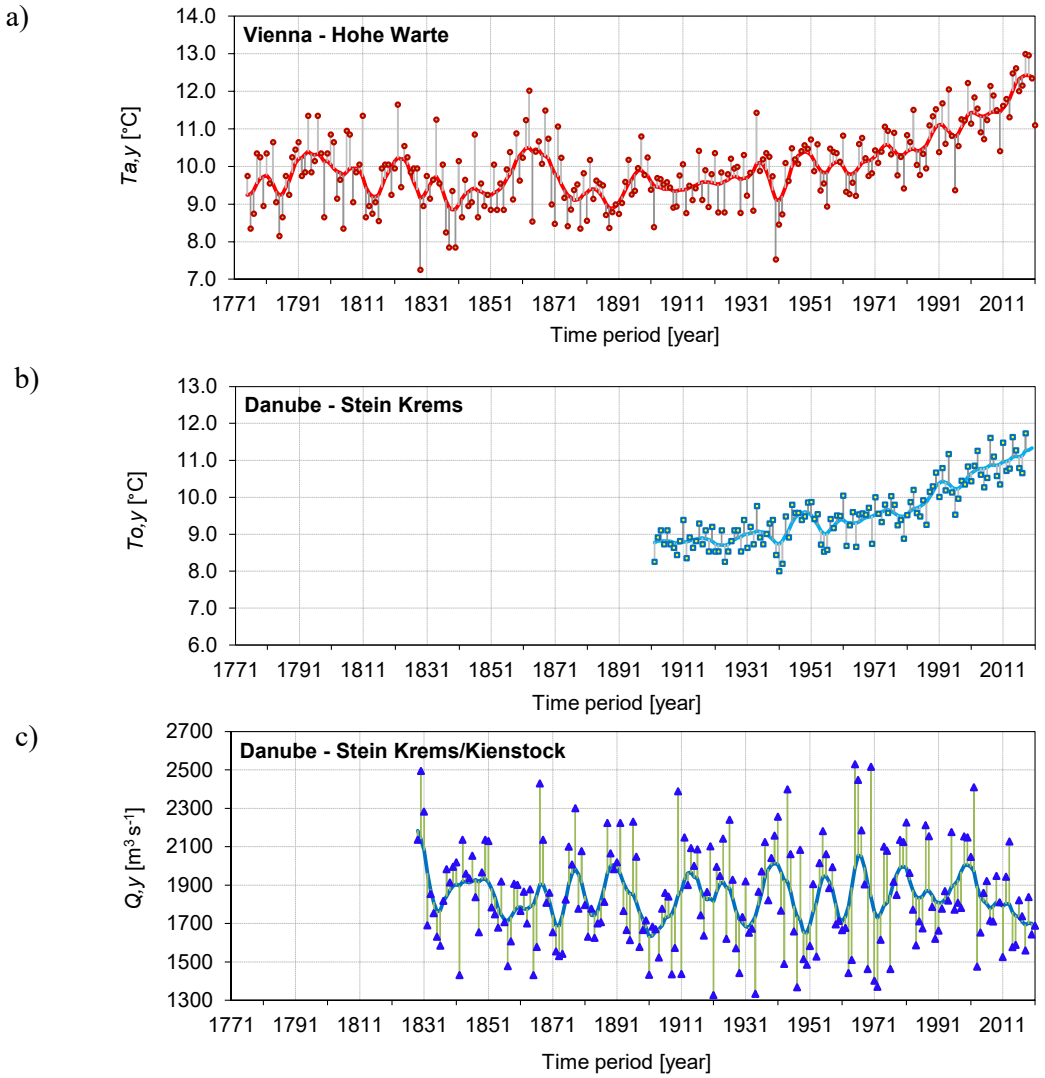


Fig. 4. Comparative analysis of the development of trends in the annual data series of the Upper Danube. 4a) Average annual air temperatures for the station Vienna-Hohe Warte (Austria) for the period of 1776–2020, using homogenized data from the database (HISTALP, n.d.). 4b) Average annual water temperatures from the station Danube - Stein Krems (Austria, Dokulil (2018)). 4c) Course of average annual Danube River discharge from the Stein Krems/Kienstock stations (Austria) for the period of 1829–2020.

4.1 Statistical analysis of input data

4.1.1 Analysis of the air temperature along the Danube River

The air temperature series in the north western part of the Danube Basin are some of the oldest in the world. Homogenized air temperature series from the Hohenpeissenberg, Regensburg, Vienna-Hohe Warte, and Budapest stations have been evaluated back to 1780. In the eastern south part of the Danube Basin, air temperature series have been available since 1871 or 1881. We aim to demonstrate that similar long-term changes occurred in the air temperature in the Danube Basin through nine examples of 30-year moving averages with a 15-year shift.

It can be observed in Figure 5 that from 1781 to 1871, air temperatures in the Danube basin declined, then slightly rose until 1980, after which a significant increase in air temperature was observed in all the stations within the basin. It is interesting to note that the air temperature trends are consistent across all the stations analyzed, whether they are located in the Alpine region (Hohenpeissenberg) or in the coastal area (Bolgrad). Overall, the 30-year period from 1991 to 2020 was 1.2°C warmer than the 30-year period from 1961 to 1990.

To compare the growth in temperature in the cold and warm halves of the year, we created an air temperature series for the winter-spring (November to April) and summer-autumn (May to October) seasons at all the stations. The moving averages of the seasonal series from three stations are displayed on the left side of Figure 6. The increase in the air temperature during the cold half of the year is higher compared to the warm half of the year. This difference is even more pronounced on a monthly basis, with a greater variability in temperature in the winter months compared to the summer months. The P90, P50, and P10 values, which represent the upper, median, and lower deciles of monthly air temperatures, were calculated and are shown on the right side of Figure 6.

Based on the statistical analyses provided, it can be presumed that the air temperature will experience a more pronounced increase during the winter months, which was reflected in the incremental scenario development of the air temperature in the Danube basin presented in the Data section of the paper.

4.1.2 Statistical analysis of discharges in selected stations along the Danube River

Flow rates in rivers provide a reliable indication of climate changes within the watershed above a water gauge. They are affected by both temperature fluctuations across the basin and variations in the precipitation within the basin. As mentioned previously, the earliest recorded observations of the water levels on the Danube River can be traced back to 1821. The study utilizes the longest data series available, which was derived from the Stein Krems/Kienstock station on the Danube (1829–2020 as shown in Figure 4c), followed by data from Orsova and Reni (1840–2020) (Romanova et al., 2019). Despite the overall increase in air temperatures since 1870, the flow rates of the Danube exhibit cyclic fluctuations of approximately 28–30 years (Figure 7) along the entire length of the river. Notable periods of severe drought occurred following the years 1860, 1945, 1990, and 2018.

Unlike the air temperature, the flow of the Danube until 2020 does not show a constant increasing or decreasing trend. In our previous works (Pekárová et al., 2022), scenarios for the development of the Danube flows were created by performing a stochastic flow forecast based on autocorrelation and a spectral analysis of the annual flow series from six stations on the Danube. The stochastic models suggest that the next few years on the Danube should have above-average water levels, with dry years expected around 2050. However, it is important to note that there has been a significant decrease in lowland areas in the Danube sub-basins over the last 20 years, despite a slight increase in precipitation totals in the Danube sub-basins (e.g., the Ipeľ River, see Pekárová et al. (2022); Keszeliová, (2022); Bačová Mitková et al. (2023)). This decrease is due to a sharp increase in air temperature, which results in increased evapotranspiration in the Danube basin and, subsequently, a decrease in flows in the Danube. Because of these results, the discharge was excluded from the regressors for the water temperature modelling along the whole Danube River.

4.1.3 Analysis of changes in the water temperature at the stations along the Danube River

The trends in the annual water temperature of the Danube River at various stations along the river for the period of 1956–1985 were evaluated by Stančíková (2010). As mentioned earlier, we utilized the data from Stančíková's work in this study, and the data series were extended to the year 2020 for eight stations representing the characteristic river reaches (Figure 8). The Engelhartszell station, located downstream of the Danube River and the Inn River confluence, exhibited the lowest average annual water temperature among the stations evaluated (Table 3).

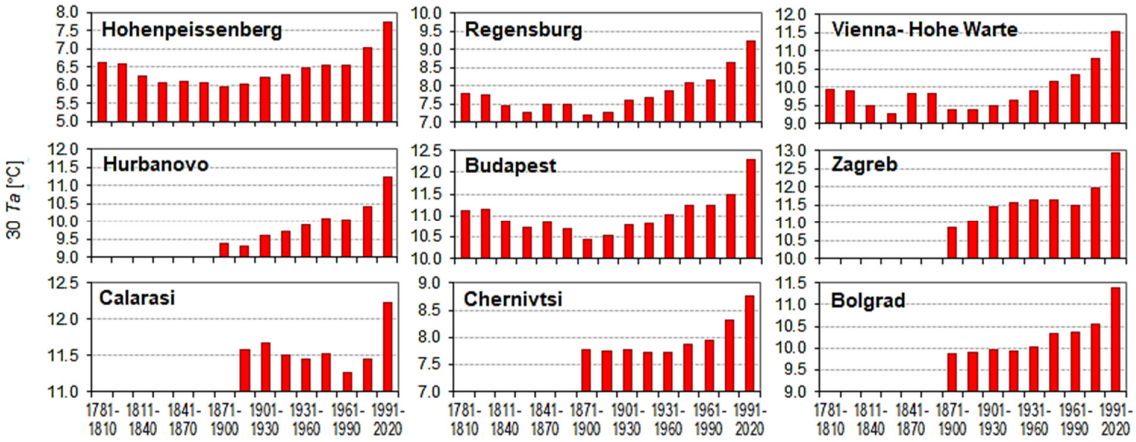


Fig. 5. Course of the 30 yearly averages of the air temperature with a 15-year shift in the Danube basin station in representative statins for the three characteristic reaches of the Danube River.

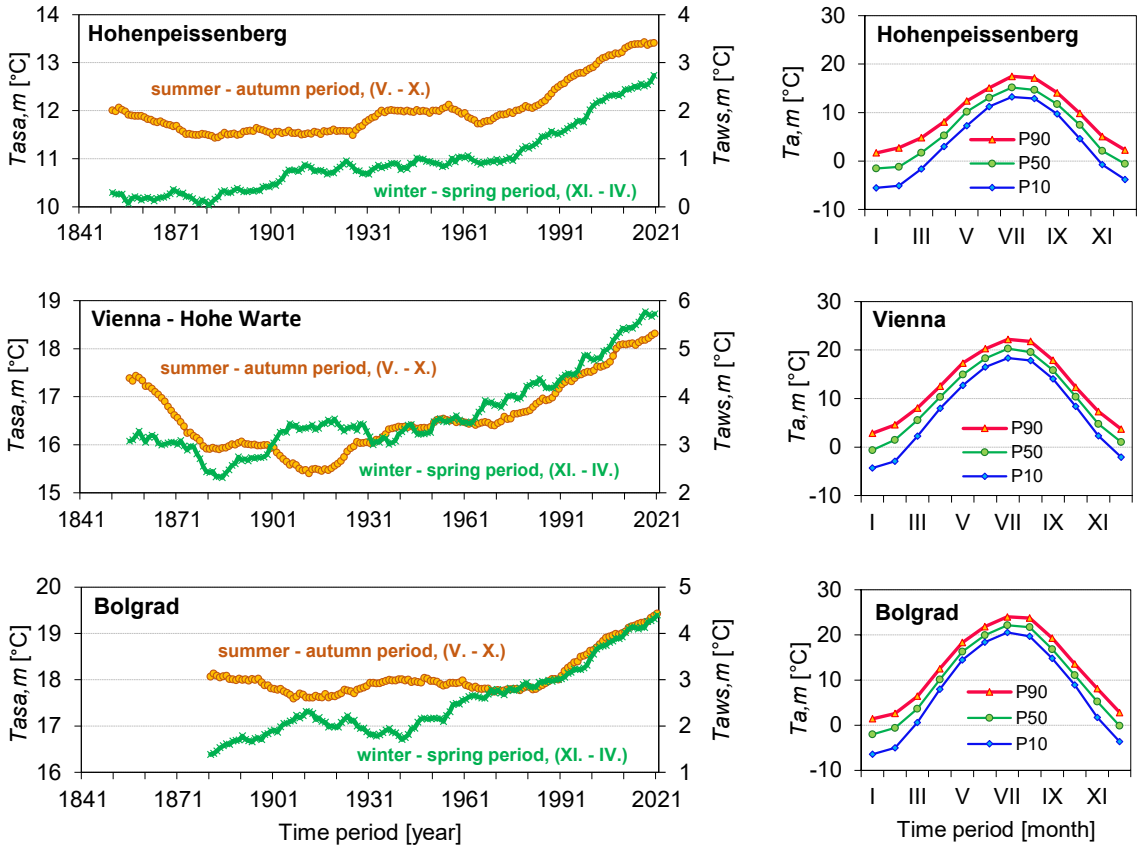


Fig. 6. The graph on the left shows the course of the seasonal moving average air temperature fluctuations from three climatological stations in the Danube River basin which represent the three characteristic river reaches. On the right is the course of the monthly values of P90, P50, and P10, which represent the upper and lower deciles of the monthly air temperatures from the same three representative stations.

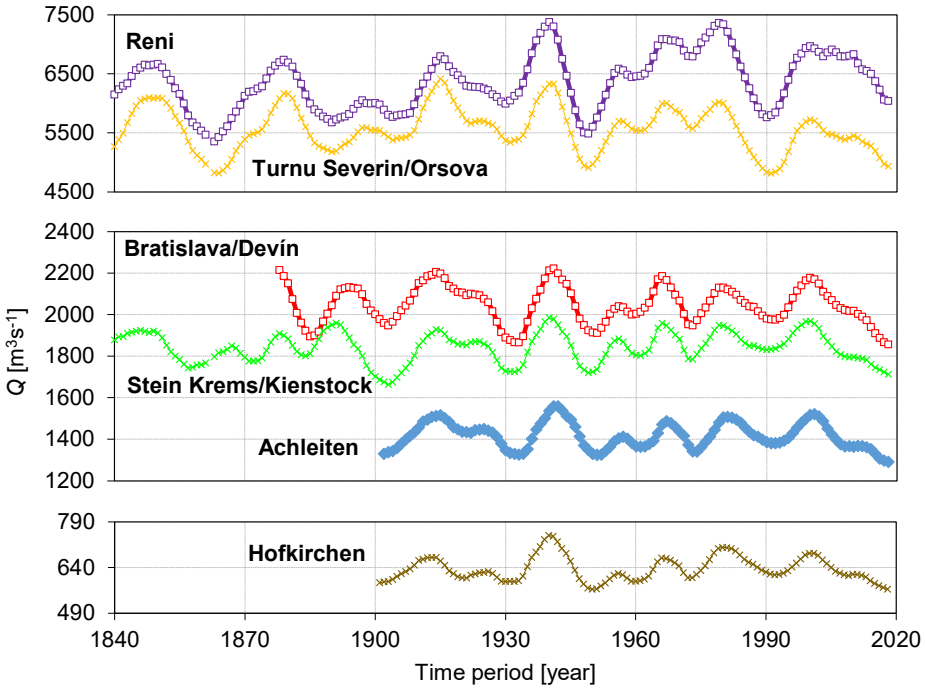


Fig. 7. Course of the two 5-year moving averages of the average annual discharges along the Danube River in gauging stations representing the Lower, Middle and Upper Danube.

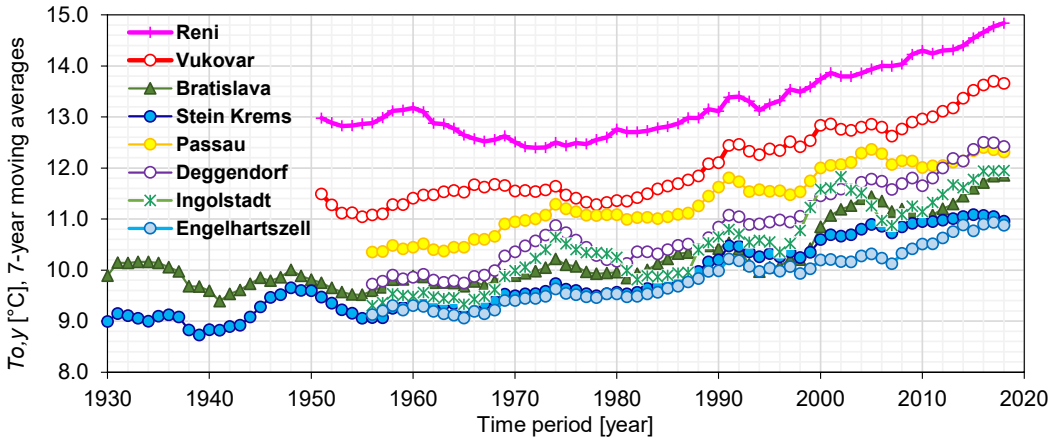


Fig. 8. Long-term trends and variability of the 7-year moving averages of the annual water temperature along the Danube River.

Table 3. Long-term average annual Danube water temperature in two periods; diff - the difference in the average water temperatures between the two mentioned periods.

Year/ Station	Ingolstadt	Deggendorf	Passau	Engelhartszell	Stein Krems	Bratislava	Vukovar	Novo Selo	Reni	Average
1961–1990	10.00	10.29	10.94	9.47	9.60	10.02	11.57	12.23	12.71	10.76
1991–2020	11.26	11.64	12.01	10.37	10.71	11.01	12.90	13.30	13.98	11.91
dif	1.26	1.36	1.07	0.90	1.11	0.99	1.33	1.08	1.26	1.15

This can be attributed to the Inn River, which flows through a chilly high-mountain Alpine region. Conversely, the Reni station (Ukraine) recorded the highest temperature on the Danube. Notably, over the past three decades, the long-term water temperature of the Danube has risen by 1.15°C, trailing only 0.05°C behind the increase in air temperature.

The minimum, average, and maximum water temperatures for two periods (1961–1990 and 1991–2020) at the stations along the Danube are depicted in Figures 9a, b.

A breakpoint of the change in the long-term trends of the Danube's water temperature at the Stein Krems and Bratislava stations was identified using the Rescaled Adjusted Partial Sums (RAPS) method (Bonacci and Oskoruš, 2010; Bonacci et al., 2022). This method determined the year 1988 as the year when the trend changed. Figure 10 illustrates this on two subseries of the mean annual water temperatures of the Danube at the Bratislava and Stein Krems stations: (1) 1930–1987 and (2) 1988–2020. In both stations, the first sub-period (1930–1987) exhibits a statistically insignificant upward trend. However, in a recent sub-period (1988–2020), statistically significant increases in the water temperatures are observed. Because of this finding, the baseline period for the stochastic modelling was located into the period after 1988.

4.2 Predictive modelling of the stream temperature in the Danube River

In the second part of the study, we focused on predicting monthly water temperature values in the Danube River using two models for two future periods: 2031–2060 and 2071–2100. We calibrated SARIMA and NonL multiple regression models for three stations (see Table 1): Passau (Germany), Bratislava (Slovakia), and Reni (Ukraine) representing the Upper, Middle and Lower Danube, respectively. We used the air temperature scenarios S1 and S2 according to Table 2. During the calibrations, we utilized the monthly water temperature and air temperature series in the baseline period from 1990 to 2019.

4.2.1 Selection of the SARIMA model

The process of model selection is presented for the water temperature data from Danube – Passau gauging station. The measured monthly water temperature *To* (Passau) and monthly air temperature *Ta* (Regensburg station) from 1990 to 2018 were used to model the calibration. Neither the order nor nonseasonal order differencing was used because of the modelling without a trend ($d = 0$, $D = 0$).

Five seasonal autoregressive models were selected (with the monthly air temperatures *Ta* and Ta^3 as regressors):

(A) SARIMA (1, 0, 1) x $(1, 0, 1)_{12}$ + 2 regressors;
(B) SARIMA (1, 0, 0) x $(0, 0, 1)_{12}$ with constant + 2 regressors;
(C) SARIMA (1, 0, 0) x $(1, 0, 1)_{12}$ with constant + 2 regressors;
(D) SARIMA (1, 0, 1) x $(1, 0, 1)_{12}$ with constant + 2 regressors;
(E) SARIMA (1, 0, 0) x $(1, 0, 1)_{12}$ + 2 regressors.

The differences between the measured data y_t and those predicted at time t ($\hat{y}_t$), i.e., residuals $y_t - \hat{y}_t = e_t$, $t = 1, 2, ..., N$, were used to evaluate the model fit using the formulae (4) to (9). The comparison of the predicted results for the five models selected is presented in Table 4.

The procedure for testing the autoregressive models resulted in the selection of model (C) as the best simulation model for Passau. The regressor was the average monthly air temperature at the Regensburg meteorological station for the same time period.

The resulting parameters of the model simulation (C) SARIMA (1, 0, 0) x $(0, 1, 1)_{12}$ + two regressors are given in Table 5. The marginal significance levels of each model parameter (p-value) were less than 0.05, so any parameter of the model does not have to be excluded. The models were verified in such a way that the period of calibrating the parameters was reduced by one year, and the last year 2019 (12 values), was used for verifying the model.

4.2.2 Nonlinear (NonL) regression model selection

To avoid the problem of hysteresis (the water temperature lagging behind the air temperature), we derived equations separately for each month. For some months, it was sufficient to derive 3-parameter relationships. The results of the calibration of the model for the SARIMA (R^2 = 0.9837) and NonL (R^2 = 0.9863) models can be compared in Figure 11a for Passau, Figure 11b for Bratislava, and Figure 11c for the Reni stations.

The STATGRAPHICS software package was used when modelling with SARIMA models, and the R system was used for the nonlinear regression.

4.2.3 Results of simulating the monthly water temperature with the air temperature scenario at Passau, Bratislava and Reni

The objective of the simulation was to predict the impact of an increase in the average monthly air temperature on the average monthly water temperature. To accomplish this, the incremental scenarios S1 and S2 of the average monthly air temperatures were constructed using a measured series of the monthly air temperatures from the period 1990–2019.

Figure 12 shows the observed and modelled monthly water temperatures for the Danube Passau station by the SARIMA model (C), as well as the observed and simulated monthly water

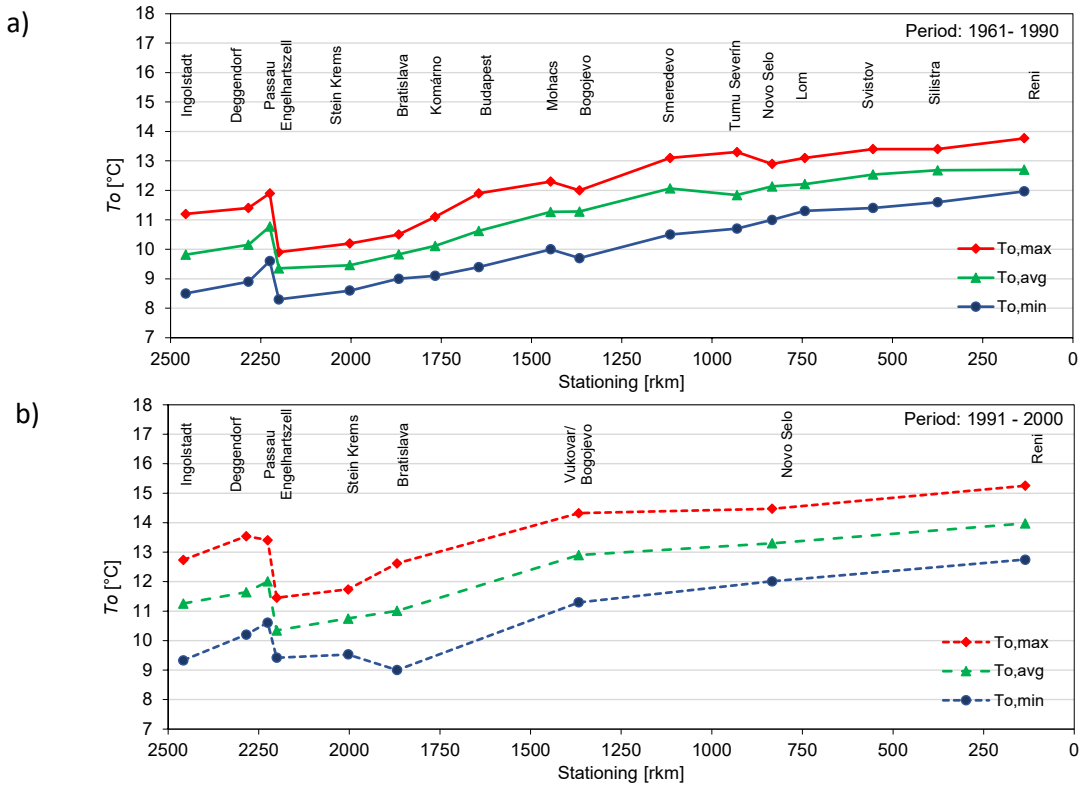


Fig. 9 a, b) Minimum, average and maximum yearly water temperature along the Danube River, two periods: 1961–1990 and 1991–2020.

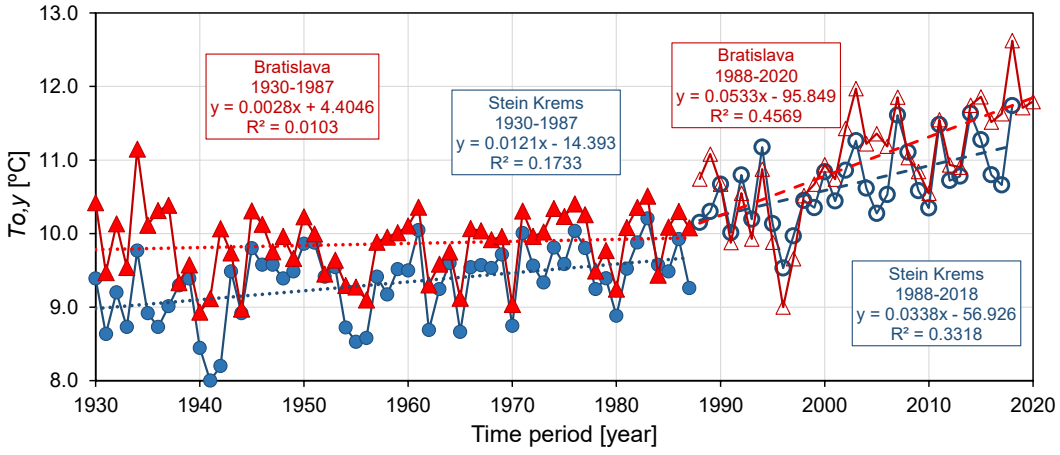


Fig. 10. Mean annual water temperature of the Danube at the Bratislava and Stein Krems stations in the two sub-periods: (1) 1930–1987; (2) 1988–2020.

Table 4. Estimation period, comparison of predictions for the five SARIMA models for Passau.

Model	RMSE	MAE	MAPE	ME	MPE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.83057	0.63628	7.47805	–0.015388	–1.0890	OK	OK	***	OK	OK
(B)	1.03956	0.83419	11.7854	0.000900	–2.7914	OK	OK	***	OK	OK
(C)	**0.80721**	**0.62259**	**7.38416**	**0.014880**	**–0.8170**	**OK**	*	**	**OK**	**OK**
(D)	0.79979	0.61927	7.52884	0.014041	–1.2258	OK	OK	**	OK	OK
(E)	0.83904	0.63993	7.58659	–0.017822	–1.1625	OK	*	***	OK	OK

Note: RMSE = Root Mean Squared Error; RUNS = Test for excessive runs up and down; RUNM = Test for excessive runs above and below the median; AUTO = Ljung-Box test for excessive autocorrelation; MEAN = Test for the difference in mean 1st half to 2nd half; VAR = Test for difference in variance 1st half to 2nd half; OK = not significant (p >= 0.05); * = marginally significant (0.01 < p <= 0.05)

Table 5. Summary parameters of the model (C) SARIMA (1, 0, 0) x (1, 0, 1)$_{12}$ with the constant + 2 regressors *Ta,m* and *Ta,m*^{3} (monthly air temperature at Regensburg).

Parameter	Estimate	Std. Error	*t*	*p*-value
AR(1)	0.41117	0.0481795	8.53413	0.000000
SAR(1)	1.00881	0.00649014	155.437	0.000000
SMA(1)	0.761826	0.032753	23.2597	0.000000
Ta,m	0.470138	0.0276142	17.0252	0.000000
Ta,m^3	0.000357106	0.0000488381	7.31203	0.000000
Mean	6.52744	0.725247	9.0003	0.000000
Constant	–0.0338568			

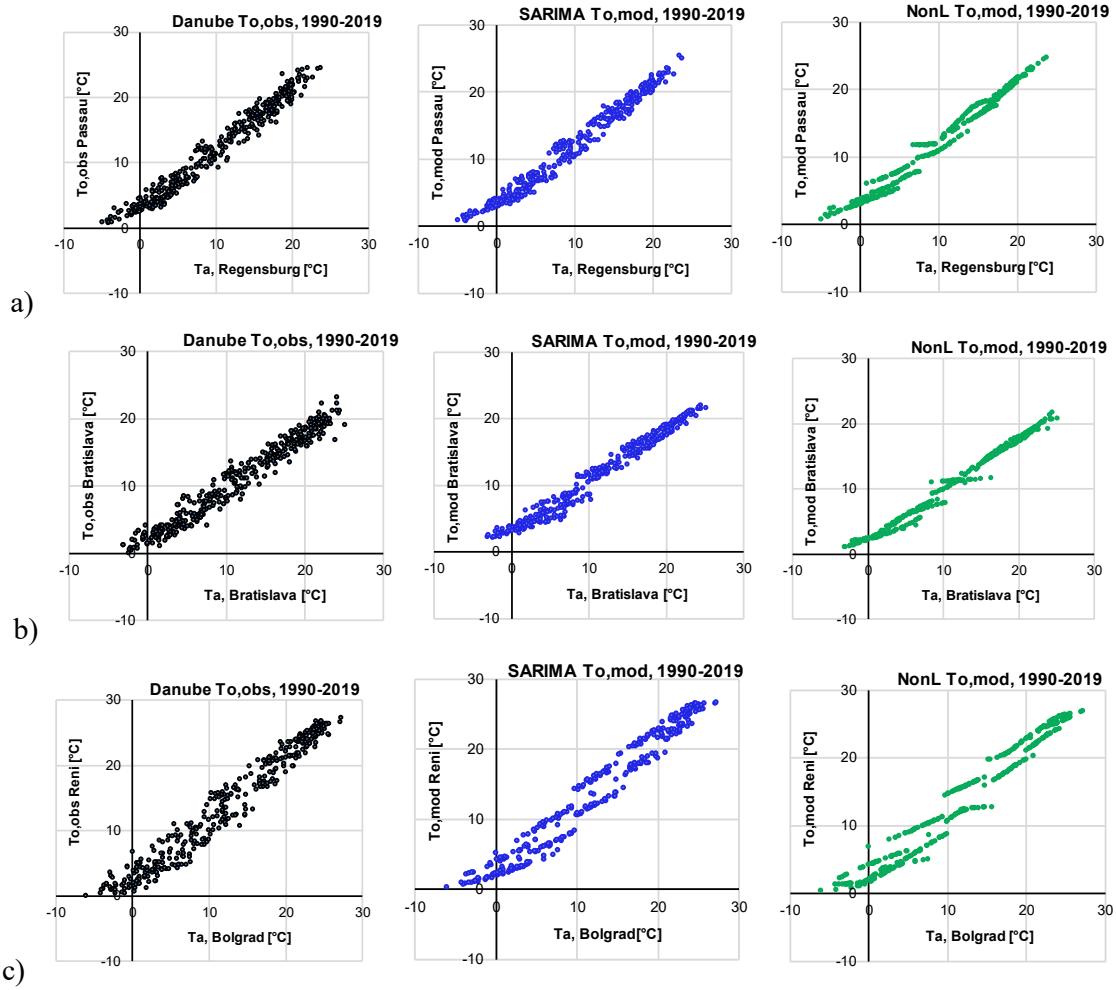


Fig. 11. Comparison of the monthly water temperatures measured at the Danube stations: **a)** Passau, **b)** Bratislava, and **c)** Reni (left graphs), monthly water temperatures modelled using the SARIMA model (E) (middle graphs) and NonL model (right graphs), period 1990–2019.

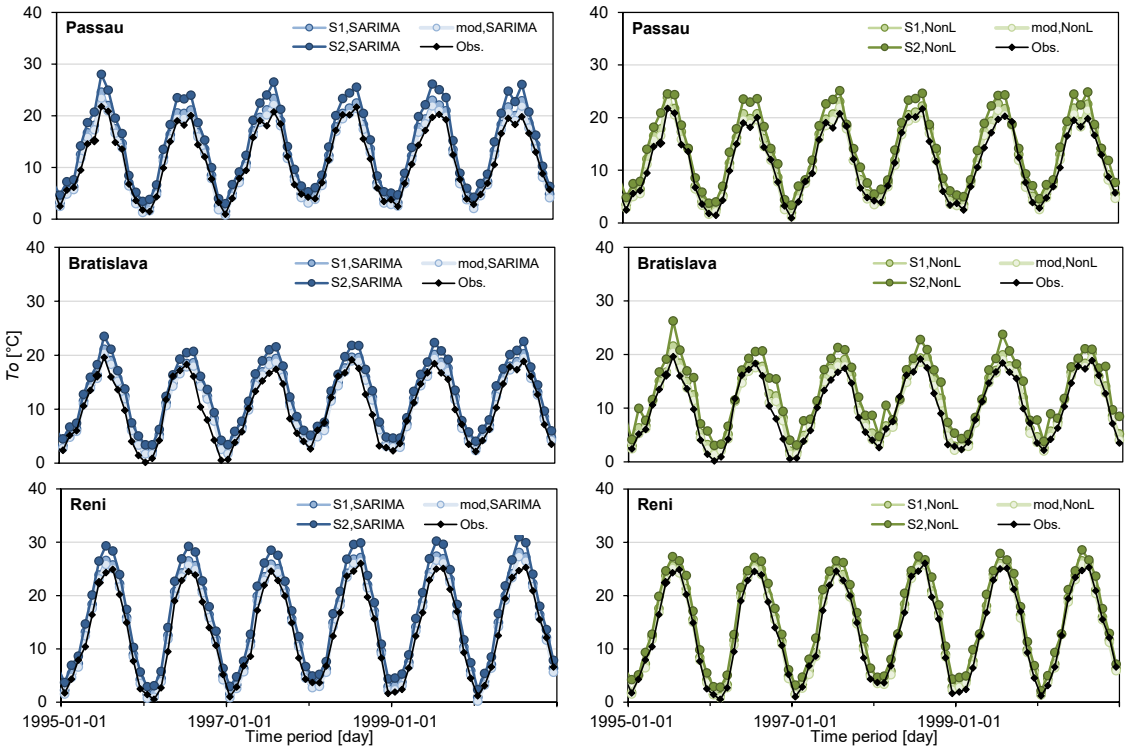


Fig. 12. Comparison between measured and modelled monthly water temperature values in the Danube River at Passau, Bratislava and Reni stations using the SARIMA model (left) and the NonL (right) model under scenarios S1 and S2. (Note: The time period presented is 1995–2000 from the period of observation 1990–2019, the scenario period S1 is 2031–2070, and scenario period S2 is 2071–2100).

temperatures for the second scenario S2. Figure12 presents the same comparison using the NonL model. The results for the Bratislava and Reni stations had a similar course as at the Passau station, which is why only the inputs for this station are presented here.

5 DISCUSSION

Both models provide very good results for the mean values. However, the regression model has failed, overestimated, or underestimated the extreme monthly water temperatures of the scenario in some months (Table 6). The SARIMA model is very stable. It has proven to be a suitable tool for simulating the growth of monthly water temperatures under the effect of the growth in air temperatures.

According to the simulation results obtained from the SARIMA/NonL models, scenario S1 predicts that the average monthly water temperature of the Danube River will increase by 0.81/0.82°C at the Passau station, 0.55/0.71°C at Bratislava, and 0.68/0.56°C at the Reni station. Similarly, under scenario S2, if there is an increase in the mean monthly air temperature, the average monthly water temperature at the Passau station is projected to rise by 2.83/2.50°C, at Bratislava by 2.06/2.46°C, and at the Reni station by 2.52/1.90°C, as indicated by the SARIMA/NonL model simulations.

The predicted monthly temperature increases vary across different months. Based on the SARIMA model and the S2 scenario, the lowest expected increase in water temperature could occur during the winter months, specifically from November to March, at all the stations. Conversely, the highest increase in the water temperature is projected during the summer months, from May to September, at all the stations, as shown in Figure 13. On the other hand, the NonL model and the S2 scenario predict a variable monthly increase in water temperature in the Danube River at the Passau, Bratislava, and Reni stations, depending on the month, as illustrated in Figure 13.

The proposed study provides a current comprehensive overview of the long-term evolution of water temperature in the Danube River along its length. It highlights the long-term trends in air temperature within the Danube River basin at stations with the longest observational records. Based on scenarios of air temperature development, the study presents potential scenarios for the evolution of Danube water temperature in the Upper, Central, and Lower Danube reaches up to the year 2100.

Comparable results were published by Tang and Gracia (2023) in the Mississippi River Basin (MRB). The authors employed the Variable Infiltration Capacity hydrological model and the Weather Research & Forecasting Model. Further sensitivity analysis suggests that the average water temperatures may rise by 1.3, 1.5, and 1.8°C in the northern, central, and southern MRB regions, respectively, in response to a hypothetical uniform increase in air temperature of 3.0°C. If air temperatures uniformly increase by 6.0°C in this scenario, then water temperatures are projected to increase by 3.3, 3.5, and 4.0°C.

In the watershed of the Polish Warta River, earlier research on its thermal conditions revealed an increase in annual water temperatures from 1960 to 2009, ranging from 0.096 to 0.281°C per decade, as reported by Gizinska and Sojka (2023). In their study, changes in mean annual water temperatures in the Warta River for the period 1984–2020, especially at specific hydrological stations, varied from 0.16 to 0.54°C per decade. The study highlighted that the magnitude of air temperature changes was significantly higher than that of water temperature changes in rivers.

Table 6. Comparison of the predicted long-term monthly increase in water temperatures in the Danube River at the Passau, Bratislava, and Reni stations according to the SARIMA as well as the NonL models under scenarios S1 and S2.

Stations	Scenario	Type of model	1	2	3	4	5	6	7	8	9	10	11	12
Passau	S1	SARIMA	0.7	0.7	0.6	0.7	0.9	1.0	1.1	1.1	0.9	0.8	0.6	0.7
		NonL	0.7	0.7	0.6	0.8	0.8	1.2	1.1	1.1	0.9	0.5	0.8	0.8
	S2	SARIMA	2.2	2.3	2.0	2.4	2.9	3.9	4.2	4.1	3.1	2.5	2.1	2.2
		NonL	2.0	2.2	1.3	2.5	2.4	4.0	2.9	3.4	1.6	1.7	3.2	2.7
Bratislava	S1	SARIMA	0.5	0.5	0.5	0.5	0.6	0.6	0.7	0.7	0.6	0.5	0.4	0.5
		NonL	0.5	0.7	0.5	0.1	0.8	0.7	0.9	0.8	0.9	0.9	0.6	1.0
	S2	SARIMA	1.7	1.8	1.6	1.8	2.1	2.8	3.0	3.0	2.1	1.7	1.5	1.7
		NonL	1.6	3.0	1.3	0.3	2.2	1.8	4.9	2.2	2.3	3.8	2.0	4.0
Reni	S1	SARIMA	0.7	0.7	0.7	0.7	0.8	0.7	0.8	0.8	0.6	0.5	0.5	0.7
		NonL	0.4	0.5	0.7	0.4	0.7	0.7	0.5	0.5	0.8	0.5	0.5	0.4
	S2	SARIMA	2.2	2.2	2.1	2.3	2.6	3.3	3.5	3.5	2.4	2.1	1.9	2.2
		NonL	1.8	1.5	2.8	0.8	2.6	1.8	2.3	1.2	2.6	2.1	1.9	1.6

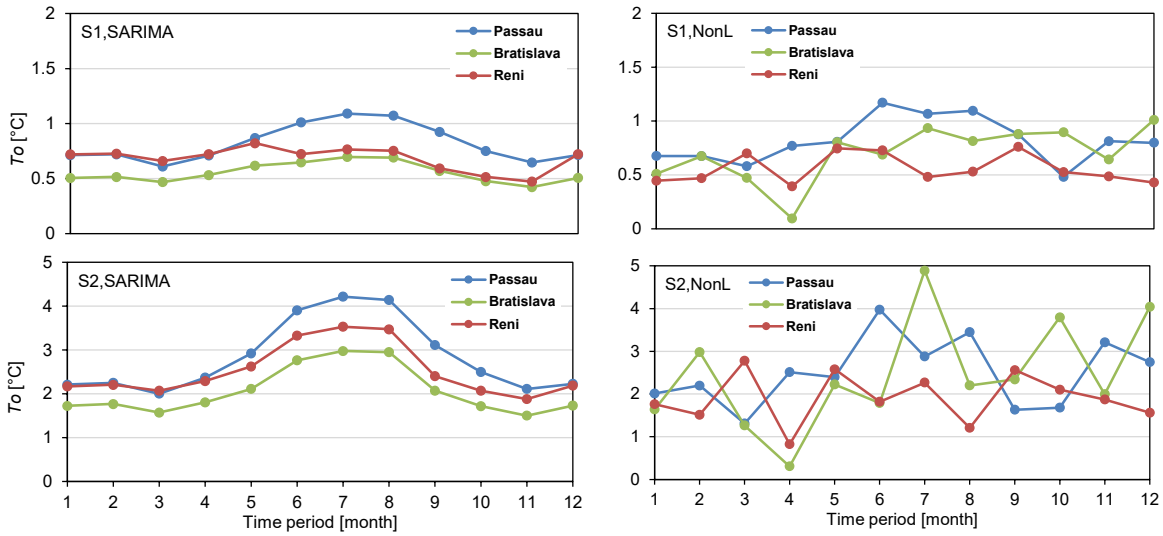


Fig. 13. Comparison of the predicted long-term monthly increase in water temperatures in the Danube River at the Passau, Bratislava, and Reni stations according to the SARIMA (left) as well as the NonL (right) models under scenarios S1 and S2.

In the Danube Delta region, Vyshnevskyi and Shevchuk (2023) calculated an identical development of water temperature at the Izmail station up to the year 2021 as we calculated in this study at the Reni station. On the other hand, our predictions for the development of water temperature in the Danube differ from the results of Dokulil (2018) at stations in the Austrian Danube covering the period 1901–2015. According to Dokulil, the average air temperature and water temperature have increased by 0.7 and 1.2°C, respectively, and are likely to further increase until 2050 by 0.7°C for air temperature and 1.3°C for water temperature. Dokulil based his predictions on long-term water temperature trends rather than climatic scenarios. If we had used this approach, we would probably have obtained similar results.

6 CONCLUSION

This study employed statistical approaches to predict the water temperature and its variations at cross-sections of various locations along the Danube River. We analysed the air temperature, water temperature, and discharge data and employed stochastic time series and nonlinear regression models. The study aimed to understand the factors influencing the water temperature and its potential changes under different climate scenarios.

The air temperature series in the western north part of the Danube Basin are some of the longest maintained series in the world. Homogenized air temperature series from multiple stations have been evaluated since 1780. From 1781 to 1871, air temperatures in the Danube Basin declined and then slightly rose until 1980. Subsequently, a significant increase in the air temperature was observed across all the selected stations in the basin. Comparing the 30-year periods from 1991 to 2020 and from 1961 to 1990, the former was 1.2°C warmer. Regarding the flow of the Danube, no consistent increasing or decreasing trend was observed until 2020. However, there has been a significant decrease in the lowland rivers within the Danube sub-basins over the past two decades, despite a slight increase in precipitation totals in the Danube sub-basins. This decrease is attributed to a sharp rise in the air temperature, leading to increased evapotranspiration within the Danube basin and subsequently resulting in decreased flows in the Danube.

This study presents the process of model selection for predicting the monthly water temperature in the Danube River at the Passau, Bratislava and Reni stations, using the monthly air temperature from the Regensburg, Vienna-Hohe Warte, and Bolgrad stations as a regressor. Several seasonal autoregressive (SARIMA) models and nonlinear (NonL) multiple regression models were tested. The SARIMA (1, 0, 0) x (1, 0, 1)$_{12}$ with constant + 2 regressors Ta,m and Ta,m^3 was selected. Modelling the average monthly water temperature was carried out based on

a scenario of the changing air temperature derived from the EURO-CORDEX simulations. According to the SARIMA/NonL models, an increase in the average monthly water temperature of the Danube River is predicted under the S1 and S2 scenarios. At the Passau station, the expected increase under the S2 scenario is 2.83/2.5°C; at Bratislava, it is 2.06/2.46°C; and at the Reni station, it is projected to be 2.55/1.9°C. Similarly, under the S1 scenario, there is also an increase in the average monthly water temperature, but to a lesser extent.

The results obtained from the SARIMA/NonL models also indicated that the increase in water temperature is not the same for each month. The predicted monthly temperature increases vary across the months. According to the SARIMA model and S2 scenario, the absolute lowest increase may occur during the winter, while the highest increase is projected for the summer at all the stations. The NonL model and S2 scenario show variable monthly increases in the water temperature at the Passau, Bratislava, and Reni stations. Overall, the SARIMA model has demonstrated stability and effectiveness in modelling the monthly water temperature fluctuations in the Danube River. It appears to be a suitable tool for predicting the growth of monthly water temperatures in response to increasing air temperatures.

The water temperature plays a key role from environmental, biochemical as well as chemical perspectives. An increase in water temperature, e.g., during extreme and long-lasting heat waves and drought, can cause undesirable chemical and biochemical reactions. The adverse reactions can directly or indirectly impact the quality as well as the status of the surface water and possibly the groundwater as well. Due to its high correlation with the air temperature, the water temperature belongs among the parameters for which direct measures for reduction are not typically proposed.

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