applied sciences

Article

Possibilities of River Water Temperature Reconstruction Using Statistical Models in the Context of Long-Term Thermal Regime Changes Assessment

Mariusz Sojka [1] and Mariusz Ptak [2,*]

[1] Department of Land Improvement, Environmental Development and Spatial Management, Poznań University of Life Sciences, Piątkowska 94E, 60-649 Poznań, Poland; mariusz.sojka@up.poznan.pl

[2] Department of Hydrology and Water Management, Adam Mickiewicz University, Krygowskiego 10, 61-680 Poznań, Poland

* Correspondence: marp114@wp.pl

Abstract: Water temperature in rivers is the key property determining the biotic and abiotic processes occurring in these ecosystems. In many regions of the world, the significant lack of measurement data is a serious problem. This paper presents reconstruction of water temperature for selected Polish rivers with monitoring discontinued in the period 2015–2020. Information regarding air temperature and water temperature in lakes provided the basis for the comparison of three models: multiple linear regression, random forest regression, and multilayer perceptron network. The results show that the best reconstruction results were obtained with a multilayer perceptron network model based on water temperatures in the lake and air temperatures from three meteorological stations. The average values of mean error, root mean square error and standard error were for the rivers in Poland: 1.52 °C, 5.03%, and 0.47 °C. The course of mean yearly water temperature in the years 1987–2020 showed a statistically significant increase from 0.18 to 0.49 °C per decade. The results show that the largest increases occurred in June, August, September, November, and December.

Keywords: artificial neural network; multiple linear regression; random forest regression; multilayer perceptron network; Mann–Kendall test; Sen test

check for updates

Citation: Sojka, M.; Ptak, M. Possibilities of River Water Temperature Reconstruction Using Statistical Models in the Context of Long-Term Thermal Regime Changes Assessment. *Appl. Sci.* **2022**, *12*, 7503. https://doi.org/10.3390/app12157503

Academic Editors: George Kontakiotis, Assimina Antonarakou and Maria V. Triantaphyllou

Received: 30 June 2022
Accepted: 24 July 2022
Published: 26 July 2022

1. Introduction

Continuous civilisational development directly contributes to the transformation of the natural environment, and its particular components respond to the process in different ways. The transformation is evident in reference to the hydrosphere due to the properties of water, with a high capacity for the accumulation and transfer of energy and matter. As a consequence, it is important in reference to water resources and water quality. One of the most elementary water properties is its temperature, which considerably determines the course of all processes that occur in water. Considering the currently observed [1,2] as well as forecasted climate changes [3,4], as well as the close relationship between air and water temperature [5,6], knowledge on these relationships is particularly important. Numerous studies point to an increase in the temperature of inland waters [7,8], which plays and will continue to play an important role in the transformation of their properties. The proper assessment of the distribution of its characteristics, and particularly the direction and rate of changes, is possible based on an appropriately organised monitoring system. This adopts various forms, both in reference to measurement methods and frequency [9–11]. In recent years, the role of remote sensing techniques has been increasing, offering, among others, possibilities of capturing thermal differentiation [12–14]. The role of traditional field measurements, however, is still of particular importance [15]—both in the context of their accuracy and providing the basis for the validation of satellite images. Considering the above, the lack or loss of data referring to water temperature in rivers and lakes can be of high importance for the management of these ecosystems—particularly in reference to biodiversity, oxygen conditions (and consequently for their self-cleaning capacity), and finally their quality. The loss of data can have different causes, both instrumental and administrative. Sensors collecting data in situ are susceptible to technical errors, resulting in failures to record observations and/or anomalies, and therefore in gaps in data [16]. In many parts of the globe, primarily due to the shortage of financial resources, the information collected on water temperature and the monitoring of other quality properties is limited [17,18]. Economic conditions have been the cause of changes in the observation network in Poland. In the case of rivers, records of water temperature were discontinued in some of the observation sites supervised by the Institute of Meteorology and Water Management—National Research Institute at the end of 2014. The decision was determined by limitations of sufficient financial resources for the functioning of the hydrological–meteorological measurement observation service in the scope of the institution's activity. As a consequence, many rivers have lost valuable data that had been recorded in detail for at least several decades. The situation is particularly unfavorable in the context of further transformations of these ecosystems.

Based on research conducted in Mackenzie and Yukon Basins, Yang and Peterson [19] determined that mean monthly water temperature shows an incoherence between sites located in the upper and lower courses of the rivers. This specifically results from the differences in the data collection systems. As emphasised by Arismendi et al. [20], the understanding of trends of changes in river temperature depending on the climate is limited by the data alone, and future improvements in forecasting changes will require the development of a network of monitoring sites offering better spatial and temporal representativeness. Due to the above, an increase in the density of the current observation sites should be expected instead of their complete liquidation. Based on such an assumption, with consideration of the maintenance of the current state of information, research has been undertaken towards the reconstruction of records lost to date. Such an approach aims at expanding knowledge and the proper interpretation of the course and distribution of one of the basic water properties, namely, temperature. The requirement of the availability of long-term data regarding inland water temperature is obvious due to the importance of this property for the entirety of processes and phenomena occurring in inland water. Therefore, studies have been undertaken with varied approaches, aimed at the reconstruction of water temperature. They are based on paleolimnological methods [21], apply mechanistic open source models [22], or use three estimators of mean annual water temperature depending on different measurement methodologies and periodicity [23]. Research conducted in the Anchor River watershed (Alaska) by Murphy et al. [24] shows that it is possible to reconstruct mean water temperatures in situ for small streams at the regional scale by means of the regression model in combination with Landsat or air temperature data.

The prediction of water temperature in rivers with the progressing application of advanced modelling techniques is currently a well-developed research trend referring to the thermal regime of rivers [25–27]. Against the background of the commonly used factor of air temperature, this paper applies data on water temperature in lakes in the vicinity of the analysed rivers as an additional predictor. It was assumed that the approach would improve the modelling accuracy.

The paper presents a reconstruction of water temperature for selected rivers in Poland in the period 2015–2020, based on air temperatures and water temperature in lakes. The detailed objectives are as follows: (1) determination of a set of input data optimal from the point of view of the reconstruction of river water temperature; (2) the selection of the optimal method for the reconstruction of water temperature in rivers among multiple linear regression (MLR), random forest regression (RF), and multilayer perceptrone network (MLP); (3) the identification of errors in the reconstruction of river water temperature; (4) the assessment of the effect of the results of data reconstruction on the estimation of long-term changes in the thermal regime of rivers.

2. Materials and Methods

2.1. Study Area

This paper employs data regarding water temperature in rivers and lakes, as well as air temperatures provided by the Institute of Meteorology and Water Management—National Research Institute. The provided data cover mean monthly water temperatures for 10 hydrological stations in rivers and 10 hydrological stations in lakes, and mean monthly air temperatures for 15 meteorological stations (Figure 1). The obtained data cover the period from 1987 to 2020. Complete data were obtained for five rivers. For the remaining five rivers in the period 2015–2020, the data are incomplete. The period of water temperature monitoring in rivers is presented in Table 1. The following method of coding the stations was adopted: hydrological stations on rivers were marked with capital letters from A to J; hydrological stations on lakes were marked with digits from 0 to 9, and meteorological stations were marked with lower case letters from the top (Figure 1; Table 1). Moreover, the table presents distances of hydrological stations on rivers (marked in capital letters) from meteorological stations (marked in small letters) and hydrological stations on lakes (marked by numbers).

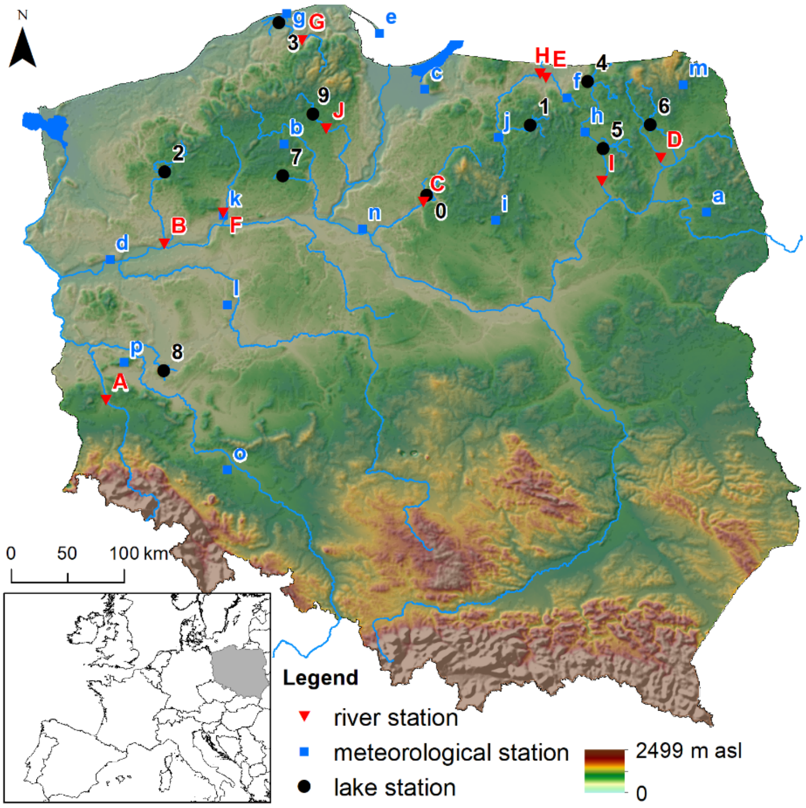

Figure 1. Locations of the analyzed river hydrological stations against the background of meteorological stations and lake stations [28] (descriptions of the stations are provided in Table 1). Developed in ArcGIS software [28].

2.2. Development of Models Multiple Linear Regression, Multilayer Perceptrone Network, and Random Forest Regression for the Reconstruction of Water Temperature in Rivers

Due to the limitation of observations of water temperature in rivers, the analysis of trends first requires the reconstruction of the missing data. This paper implements such an approach based on mean monthly air and water temperatures in lakes. Although the relationship of water temperatures in rivers with water temperatures in lakes and air temperatures is obvious, the following research questions appeared: (1) What is the necessary set of data for the reconstruction of water temperature in rivers? (2) What statistical method will allow obtaining the best results? (3) How will the reconstructed data affect the directions and values of trends?

Table 1. River water temperature data—Institute of Meteorology and Water Management—National Research Institute. The locations of the stations are shown in Figure 1.

River–Station (Code)	River Monitoring Period	Lake (Code)	Meteorological Station (Code)
Bóbr–Żagań (A)	1987–2014	Sławskie (57.4 km) (8)	Zielona Góra (37.6 km) (p) Wrocław (124.3 km) (o) Gorzów Wielkopolski (125.0 km) (d)
Drawa–Drawiny (B)	1987–2014	Lubie (63.8 km) (2)	Gorzów Wielkopolski (49.9 km) (d) Piła (58.4 km) (k) Poznań (78.0 km) (l)
Drwęca–Brodnica (C)	1987–2020	Bachotek (7.2 km) (0)	Toruń (58.8 km) (n) Mława (66.3 km) (i) Olsztyn (88.5 km) (j)
Ełk–Przechody (D)	1987–2014	Selmęt Wielki (30.7 km) (6)	Białystok (62.9 km) (a) Suwałki (68.4 km) (m) Mikołajki (70.9 km) (h)
Guber–Prosna (E)	1987–2016	Mamry (37.1 km) (4)	Kętrzyn (26.0 km) (f) Mikołajki (59.4 km) (h) Olsztyn (67.7 km) (j)
Gwda–Piła (F)	1987–2014	Sępoleńskie (62.4 km) (7)	Piła (2.4 km) (k) Poznań (82.0 km) (l) Chojnice (82.0 km) (b)
Łeba–Lębork 2 (G)	1987–2020	Łebsko (25.8 km) (3)	Łeba (27.3 km) (g) Hel (69.1 km) (e) Chojnice (93.0 km) (b)
Łyna–Sępopol (H)	1987–2020	Dadaj (46.8 km) (1)	Kętrzyn (32.3 km) (f) Mikołajki (65.4 km) (h) Olsztyn (67.3 km) (j)
Pisa–Ptaki (I)	1987–2020	Roś (28.7 km) (5)	Mikołajki (46.1 km) (h) Kętrzyn (80.1 km) (f) Białystok (96.8 km) (a)
Wda–Czarna Woda (J)	1987–2020	Wdzydze (17.4 km) (9)	Chojnice (39.5 km) (b) Elbląg (94.7 km) (c) Toruń (94.9 km) (n)

The answer to the first question was based on the assumption that the reconstruction of mean monthly water temperatures in rivers would employ mean monthly air temperatures from a maximum of three meteorological stations located in different directions from the point of measurement of river water temperature and lake water temperature from the closest hydrological station. In order to answer the second research question, it was assumed that the reconstruction of mean monthly water temperatures in lakes would employ three statistical methods with different degrees of advancement, namely, multiple linear regression, multilayer perceptrone network, and random forest regression. Answering the third question involved the comparison of the directions and values of trends in the mean monthly and annual water temperatures in rivers obtained for use as measurement data with those obtained for use as sets with reconstructed data. The research material covers data for five rivers for which complete data were obtained in the period from 1987 to 2020. The data series was divided into two parts: the first one from 1987 to 2014, and the second one from 2015 to 2020. The first series (from 1987 to 2014) was used for the development and testing of the models of multiple linear regression, multilayer perceptrone network, and random forest regression. The second series (from 2015 to 2020) comprised independent material, used for the final verification of the aforementioned research questions (Figure 2).

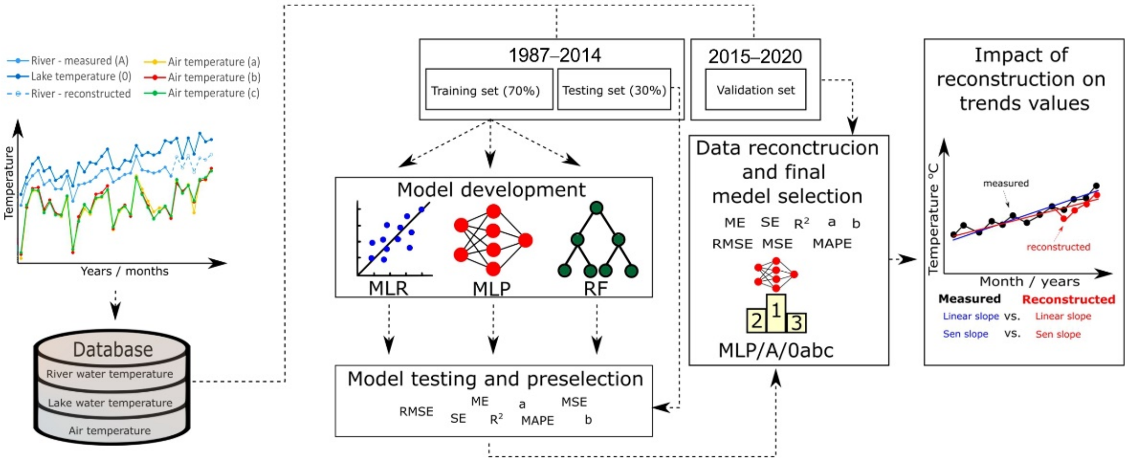

Figure 2. Diagram of data reconstruction and uncertainty of climate change estimation.

The development of multiple regression models involved the search for an optimal set of independent data. The analysis considered all possible combinations of independent variables (water temperature in the lake and air temperature from three meteorological stations). A total of 15 multiple linear regression models was obtained for each river. The multiple linear regression models were developed based on data from the period 1987–2014. The development of multiple linear regression models employed 70% of the first data series (training sample), and the remaining 30% of data (test sample) were used for testing the models. The multiple linear regression models were developed in the programme Statistica version 13.1 [29].

An analogical procedure was applied for the multilayer perceptrone network. Multilayer perceptrone network learning was based on data from the period 1987–2014. Data from the period were divided into two analogical parts; 70% of the data were used at the stage of network learning, and 30% of data at the stage of testing and verification. Finding an optimal multilayer perceptrone network diagram involved using the automatic network search diagram. Designing the network architecture included determining the number of input and output variables (i.e., neurons in input and output layers), and determining the number of hidden layers and neurons in each hidden layer. A three-layer multilayer perceptrone network model was tested, with a hidden second layer with 3 to 20 hidden neurons. The input (independent) variables were mean monthly air temperatures (from a maximum of three meteorological stations) and mean monthly lake water temperatures (from the nearest lake). Moreover, the development of a multilayer perceptrone network employed additional qualitative data, i.e., month index (M), and the output variable was mean monthly river water temperature. The functions of activation while learning for hidden neurons and output neurons were linear, logistic, tanh, exponential, and sinus. An automatic way of designing the network was applied, testing 100 different network architectures, and eventually keeping the 5 best ones. Finally, out of the five best networks, one referential network was selected based on statistical parameters describing errors obtained at the stage of model testing. The multilayer perceptrone network models were developed in the programme Statistica version 13.1 [29].

An analogical procedure was adopted for the reconstruction of water temperature in rivers by means of the random forest regression method. In this case, a single random forest regression model was built, using a full set of predictors, including water temperature from one hydrological station on a lake and air temperature from the three nearest meteorological stations. Moreover, the month index (M) was used as the auxiliary variable to maximize prediction performance. The calculations related to the random forest regression were performed using the ranger [30,31] package within statistical software R 4.1.2 [32]. The multiple linear regression, multilayer perceptrone network and random forest regression models were tested on 30% of the data not used at the stage of model development. The statistics described in Section 2.3 were calculated for all models. This analysis was performed to show whether the obtained values of goodness-of-fit measures are significantly different from those obtained at the model development stage. Finally, as a result of the adopted procedure, 15 multiple linear regression and multilayer perceptrone network models and one random forest regression model were obtained. The following method of coding the models was adopted: multiple linear regression/A/8dop, wherein the first part of the name signifies the type of model (multiple linear regression) the second part signifies the name of the hydrological station on a river (River–Station—code—Table 1), and the third part shows the range of used independent data (lake and meteorological station code—Table 1). In the presented example, multiple linear regression/A/8dop means a multiple regression model used for data reconstruction on the Bóbr River (No. A), developed based on independent data obtained from one hydrological station on Lake Sławskie (No. 8) and three meteorological stations Gorzów Wielkopolski (No. d), Wrocław (No. o), and Zielona Góra (No. p). Each of the developed and tested models was used for the reconstruction of water temperature in rivers in the period from 2015 to 2020.

2.3. Procedure for Testing and Validation of Multiple Linear Regression, Multilayer Perceptrone Network and Random Forest Regression Models

The verification of the multiple linear regression, multilayer perceptrone network, and random forest regression models employed monthly data from the period from 2015 to 2020. Model validation involved the calculation of the values of the standard error (SE), maximum error (ME), root mean square error (RMSE), coefficient of determination (R^2), Nash–Sutcliffe model efficiency coefficient (NSE) [33], and mean absolute percentage error (MAPE) [34]. The mathematical expressions of these statistics can be written as follows.

Standard error (SE):

$$SE = \sqrt{\frac{1}{n-2}\left\{\sum_{i=1}^{n}\left(M_i-\overline{M}\right)^2 - \frac{\left[\sum_{i=1}^{n}\left(P_i-\overline{P}\right)\left(M_i-\overline{M}\right)\right]^2}{\sum_{i=1}^{n}\left(P_i-\overline{P}\right)^2}\right\}} \tag{1}$$

Maximum error (ME):

$$ME = max|P_i - M_i|_{i=1}^{n} \tag{2}$$

Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(P_i-M_i\right)^2}{n}}\frac{100}{\overline{M}} \tag{3}$$

Mean absolute percentage error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{M_i-P_i}{M_i}\right| \tag{4}$$

Coefficient of determination (R^2):

$$R^2 = \frac{\sum_{i=1}^{n}\left(M_i-\overline{M}\right)^2}{\sum_{i=1}^{n}\left(P_i-\overline{M}\right)^2} \tag{5}$$

Nash–Sutcliffe model efficiency coefficient (NSE):

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(P_i-M_i\right)^2}{\sum_{i=1}^{n}\left(M_i-\overline{M}\right)^2} \tag{6}$$

The above statistical metrics are often used when validating models [27,35,36].

Moreover, for the purpose of the estimation of errors related to the reconstruction, the application of a linear regression equation was proposed in the form of P = aM + b, describing the dependency between measured (M) and forecasted water temperatures (P). The values of the equation coefficients can be calculated from the following formulas:

$$a = \frac{n\sum_{i=1}^{n} M_i P_i - \sum_{i=1}^{n} M_i \sum_{i=1}^{n} P_i}{n\left(\sum_{i=1}^{n} M_i^2\right) - \left(\sum_{i=1}^{n} M_i\right)^2} \tag{7}$$

$$b = \frac{\sum_{i=1}^{n} P_i \sum_{i=1}^{n} M_i^2 - \sum_{i=1}^{n} M_i \sum_{i=1}^{n} M_i P_i}{n\left(\sum_{i=1}^{n} M_i^2\right) - \left(\sum_{i=1}^{n} M_i\right)^2} \tag{8}$$

The analysis of the location of the regression line P = aM + b in reference to the regression line in the form of P = M (full compatibility of results P and M) permits drawing detailed conclusions regarding the prediction (reconstruction) results. Solving the system of equations (Equation (9)) allows for the determination of the values of M_0 and P_0 (i.e., point of line intersection).

$$\begin{cases} P = aM + b \\ P = M \end{cases} \tag{9}$$

From the point of view of the assessment of prediction results themselves, it is possible to underestimate or overestimate the values throughout the variation range, or to under- or overestimate the values in certain intervals (Table 2).

Table 2. Assessment of model prediction quality.

Cases	Slope	Intercept	M-Value	Underestimate	Overestimate
Case 1	a < 1	b < 0	$M_0 < M_{min}$	$<M_{min}, M_{max}>$	
Case 2	a < 1	b > 0	$M_{min} < M_0 < M_{max}$	$(M_0, M_{max}>$	$<M_{min}, M_0)$
Case 3	a > 1	b > 0	$M_0 > M_{max}$		$<M_{min}, M_{max}>$
Case 4	a > 1	b < 0	$M_{min} < M_0 < M_{max}$	$<M_{min}, M_0)$	$(M_0, M_{max}>$

M_0—point of line intersection; M_{min}—minimum measured value; M_{max}—maximum measured value.

At the final stage of model validation, directions and trendline slope values for the courses of river water temperatures in the period from 1987 to 2020 were also obtained, based on original measurement data and based on data with partial reconstruction performed for the years 2015–2020. A Mann–Kendall test [37] was used to determine the direction of changes in river water temperatures. The extent of river water temperature changes was determined using a non-parametric Sen test [38]. In order to remove the autocorrelation from the data series, a trend-free prewhitening procedure was used [39]. The adopted procedure is the most frequently used when analysing hydrological data [40,41]. This is because the method based on the Mann–Kendall and Sen test is less sensitive to extreme values compared to the linear regression method and Student's *t*-test. A modified Mann–Kendall and Spearman's Rho Trend Tests package developed by Patakamuri and O'Brien [42] was used to analyse the direction and extent of river water temperature changes.

3. Results

Mean annual water temperatures in the five rivers for which complete data were available (1987–2020) ranged from 8.0 (Łeba) to 9.7 °C (Drwęca). The mean monthly water temperatures in the rivers were at a level from 2.9 to 13.9 °C and from 1.1 to 19.3 °C. The Łeba River is subjected to the evident influence of air masses from over the Baltic Sea, and water temperatures in the Drwęca River are primarily shaped as a result of the impact of continental air masses from the east. The courses of mean monthly and annual water temperatures in rivers are presented in Figure 3. The highest mean monthly temperatures occur in July, and the lowest in January. The greatest increase in water temperature in rivers occurs in the period from March to May, and the greatest decrease in temperatures occurs in the period from September to November.

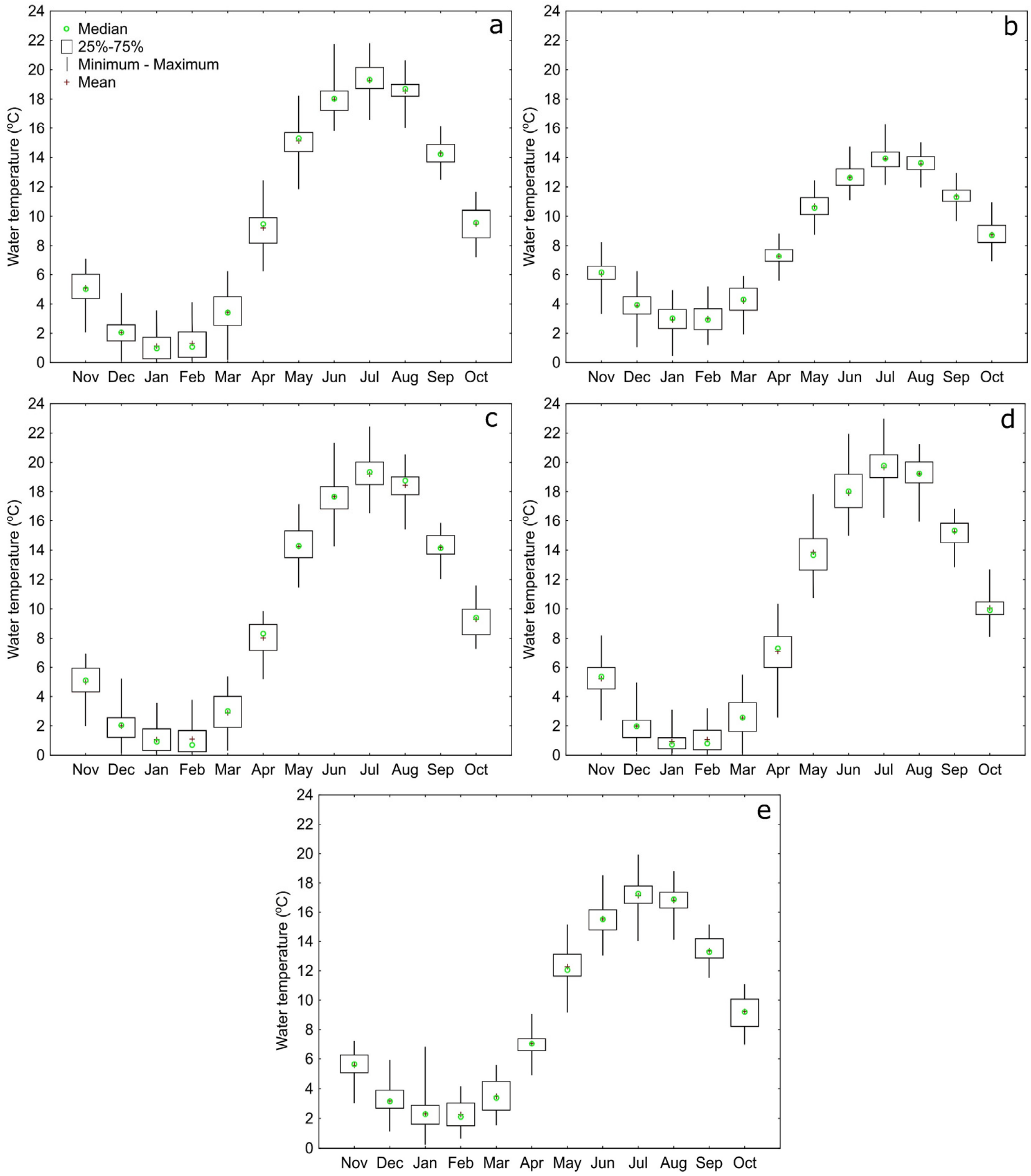

Figure 3. Changes in mean monthly temperatures in the years 1987–2020 in rivers: Drwęca (**a**); Łeba (**b**); Łyna (**c**); Pisa (**d**) and Wda (**e**).

At the first stage of analysis, the models of multiple linear regression, multilayer perceptrone network, and random forest regression were developed based on data from the period 1987–2014. This period was adopted after conducting water temperature measurements in rivers at the Institute of Meteorology and Water Management—National Research Institute. In the process of the development of multilayer perceptrone network models, the data series is by default divided into two parts, one constituting 70%, and the other 30%. The first series was used at the stage of learning in the multilayer perceptrone network. The second series was used for the testing (15% of sample) and validation of the multilayer perceptrone network (15% of sample). In order to ensure the comparability of results between the multilayer perceptrone network, multiple linear regression, and random forest regression methods, in each case during model development (learning), the same random learning sample was used, resulting from the application of artificial neural networks. Model validation was eventually performed based on an independent set from the period 2015–2020 not used at any of the previous stages of learning, testing, or validation. The comparison of measured values (mean monthly water temperatures) with temperatures obtained from the models covered the calculation of the values of the standard error, maximum error, root mean square error, coefficient of determination (R^2), Nash–Sutcliffe model efficiency coefficient, and mean absolute percentage error. The results obtained at the model validation stage have been aggregated to show the effect of the selection of data for reconstruction and the applied statistical method on the obtained results (Figure 4).

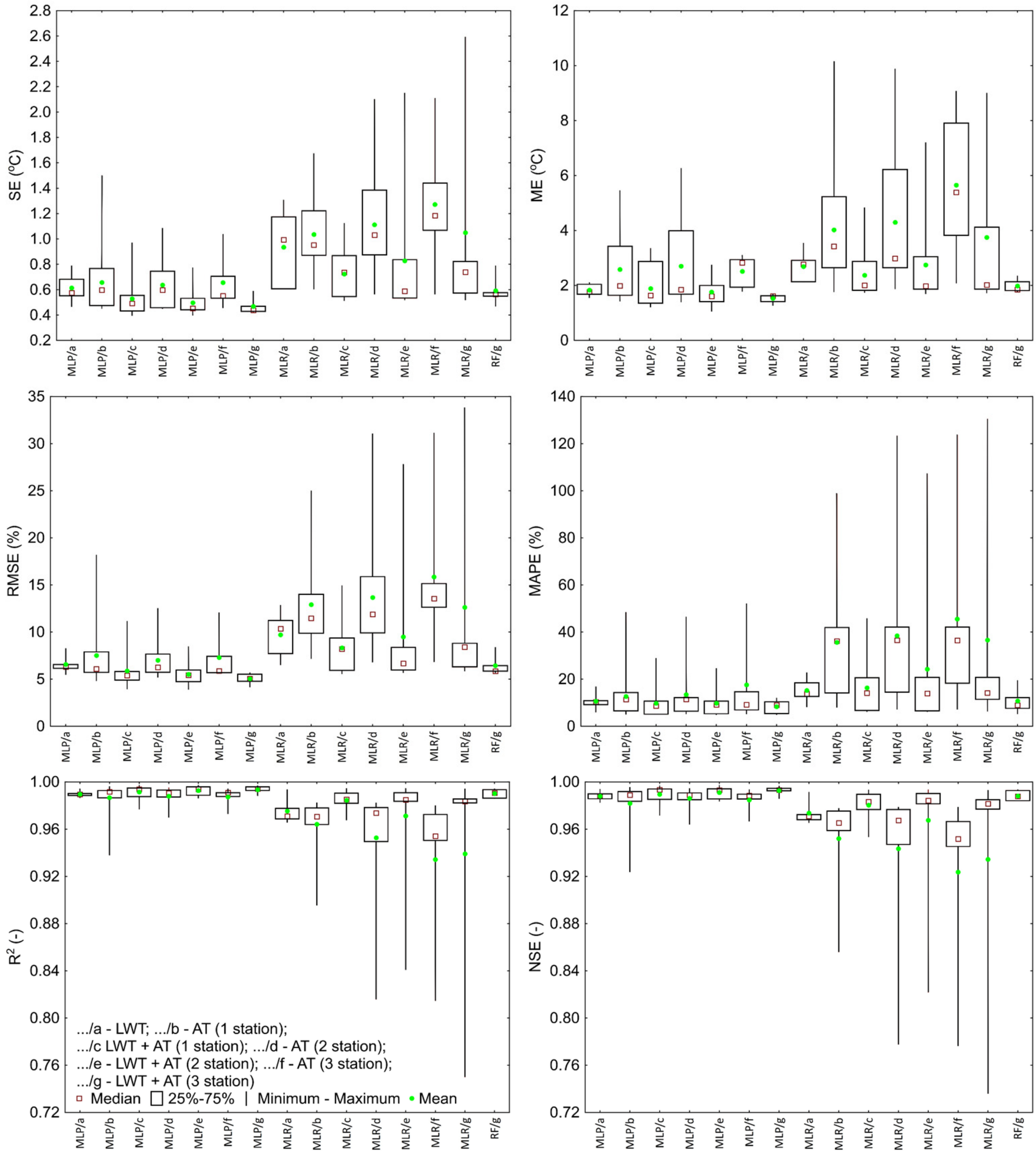

Figure 4. The results of the validation of the reconstruction of water temperatures in rivers are based on a variable range of output data and the statistical methods multilayer perceptrone network, multiple linear regression, and random forest regression.

The performed calculations show that the best results in terms of all parameters were obtained for multilayer perceptrone network models. The comparison of corresponding groups of models by means of a non-parametric U Mann–Whitney test, grouped based on a range of input data used for the reconstruction of water temperatures in rivers based on values of standard error, maximum error, root mean square error, Nash–Sutcliffe model efficiency coefficient, and mean absolute percentage error, suggests that in all cases, the values were lower for multilayer perceptrone network models than for multiple linear regression models (differences significant at a level of 0.05). The values of the coefficient of determination (R^2) and Nash–Sutcliffe model efficiency coefficient statistics were higher for multilayer perceptrone network models than for multiple linear regression models (differences significant at a level of 0.05). The comparison of groups of multilayer perceptrone network/g and random forest regression/g models (reconstruction based on water temperatures in the lake and air temperatures from three meteorological stations) shows that maximum error and root mean square error values averaged 1.52 °C and 5.03%, and 1.97 °C and 6.43%, respectively. Differences between maximum error and root mean square error values were significant at a level of 0.05. The standard error values averaged 0.47 °C for the multilayer perceptrone network/g model, and 0.59 °C for the random forest regression/g model, and differed at a significance level of 0.10. The remaining values of the Nash–Sutcliffe model efficiency coefficient and the mean absolute percentage error, and the coefficient of determination and Nash–Sutcliffe model efficiency coefficient, were respectively lower and higher for multilayer perceptrone network/g models, although the differences were not as statistically significant. The obtained results point to the advantage of the multilayer perceptrone network method over the multiple linear regression method. Differences between the multilayer perceptrone network/g and random forest regression/g models are smaller, with a slight advantage of the multilayer perceptrone network model.

The analysis of the scope of data permitting the most credible prediction of water temperatures in rivers was performed by means of the multilayer perceptrone network method. The obtained results show that the best results are generated by models from the multilayer perceptrone network/g group, where the reconstruction is based on lake water temperatures and air temperatures from three meteorological stations. Mean values of root mean square error provide the basis for systematising multilayer perceptrone network models in the following order: g < e < c < a < b < f < b. Similar results were obtained based on the remaining statistical measures describing the range of prediction errors. Values of statistics describing the quality of the models' coefficient of determination and Nash–Sutcliffe model efficiency coefficient were at a high level in all cases, and ranged from 0.9865 to 0.9935, and from 0.9820 to 0.9925. The analysis of differences in values of standard error, maximum error, root mean square error, Nash–Sutcliffe model efficiency coefficient, and mean absolute percentage error between particular groups of multilayer perceptrone network models points to the advantage of models employing a mixed set of input data, i.e., lake water temperature and air temperature. The worst results of the estimation have been provided by models based only on a set of data regarding air temperatures. It should be emphasised that the values of the analysed statistics describing prediction quality adopt approximate values for model groups multilayer perceptrone network/c (prediction based on lake water temperature and air temperature from one meteorological station), multilayer perceptrone network/e (prediction based on lake water temperature and air temperature from two meteorological stations), and multilayer perceptrone network/g (prediction based on lake water temperature and air temperature from three meteorological stations), significantly differing at a level of 0.05 (according to the U Mann–Whitney test). It should be emphasised, however, that the lowest values of standard error, maximum error, root mean square error, Nash–Sutcliffe model efficiency coefficient, and mean absolute percentage error statistics, and the highest coefficient of determination and Nash–Sutcliffe model efficiency coefficient values, have been shown by the multilayer perceptrone network/g model. The location of the regression line P = aM + b in reference to the regression line in the form of P = M (full compatibility of results of P with M) allows for the designation of the Mo and Po values, and drawing detailed conclusions regarding the results of the prediction (reconstruction) (Table 3). The results show that in a broader range of variability of water temperatures, multilayer perceptrone network models underestimate values. This is particularly evident in the case of the Łeba and Łyna Rivers. Generally, in almost any model, underestimations primarily concern predictions of higher temperatures. The only exception pertains to the Pisa River, where the highest values are slightly overestimated.

Table 3. The quality of the prediction of river water temperatures was based on the multilayer perceptrone network/g model based on lake water temperature and air temperature from three meteorological stations.

River	Temperature			a	b	Mo/Po	Underestimate	Overestimate
	Min	Max	Mean					
Drwęca	0.1	21.8	9.8	0.9839	0.1491	8.8	(8.8–21.9)	(0.1–8.8)
Łeba	0.5	16.3	8.2	0.9753	0.0174	0.7	(0.7–16.3)	(0.5–0.7)
Łyna	0.1	22.4	9.4	0.9918	0.0237	2.9	(2.9–22.4)	(0.1–2.9)
Pisa	0.1	23.0	9.6	1.0184	−0.3877	21.1	(0.1–21.1)	(21.1–23.0)
Wda	0.2	19.9	9.0	0.9702	0.1871	6.3	(6.3–19.9)	(0.2–6.3)

The last stage involved the validation of all multilayer perceptrone network models based on the slope values of trendlines (Sen slope, Linear slope) obtained for the original measurement data from the period 1987–2020, and data in which the period 2015–2020 was supplemented based on results from the models (Figure 5). A tendency has been generally observed in which the slope values of linear regression lines and Sen slope values are lower for the data series supplemented with results of the multilayer perceptrone network/g model. For the Łeba River, such a situation occurs in each month. In the remaining cases, a similar trend has been generally observed, although in individual months the opposite situation regarding the slope value of trendlines can be seen—they are higher for data supplemented with the multilayer perceptrone network/g model. In November and December, the Sen slope and linear slope values are higher for data reconstructed by means of the multilayer perceptrone network/g model for the Drwęca, Łyna, and Wda Rivers. In June, in almost every case, the slope values of trendlines are higher in the original measurement data. The results show that even the best model can generate uncertainties related to data reconstruction. Therefore, the measurement of river water temperatures should be restarted as soon as possible.

Trendline slope values in reference to the values of mean annual water temperatures in rivers are presented in Figure 6. The reconstructed curves have a course compatible with that towards curves based on in situ measurements. It is worth emphasising that the deviations do not exceed 0.5 °C (at a minimum measurement accuracy of 0.1 °C).

Eventually, based on knowledge pertaining to the selection of the statistical model and the selection of a data set for the supplementation of missing water temperatures, reconstruction was performed. The results for all the analysed rivers are presented in Table 4.

The obtained results show that the greatest increase in water temperatures occurred in June, August, September, November, and December. The changes can be observed in 8 to 10 rivers, and are statistically significant at a level of 0.05. The smallest changes occurred in January, February, and March (not statistically significant). Considering the values of changes in the mean annual river temperatures, in each river, water temperature increased from 0.18 to 0.49 °C per decade. In each case the changes are statistically significant at a level of 0.05. Among the analysed rivers, the greatest water temperature increase can be seen to occur in the Wda River, and the lowest in the Bóbr River.

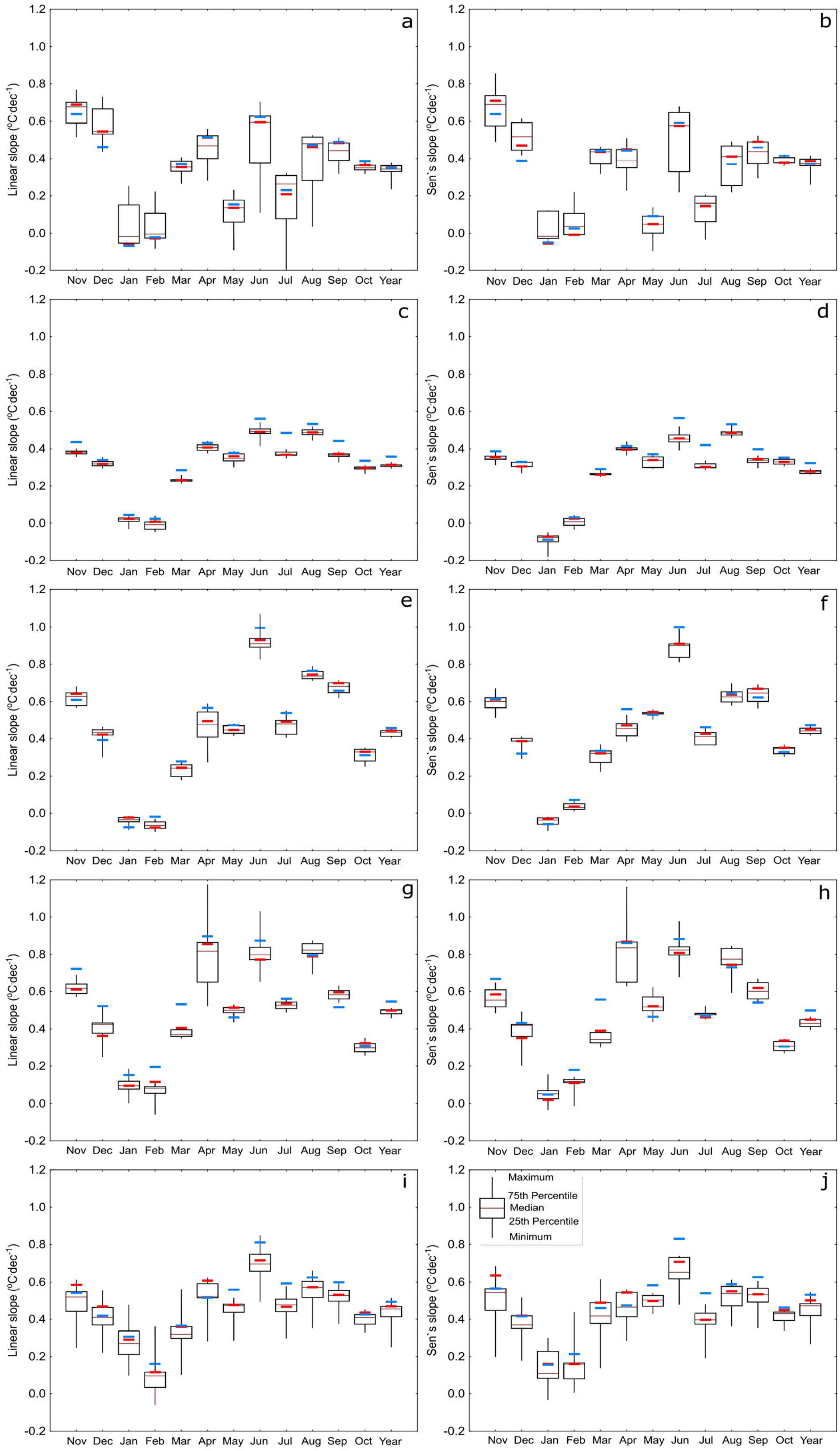

Figure 5. Linear slope (**a**,**c**,**e**,**g**,**i**) and Sen slope (**b**,**d**,**f**,**h**,**j**) values based on data reconstructed by means of multilayer perceptrone network models in the context of values obtained based on measurement data (blue line) and values obtained from the best multilayer perceptrone network/g model (red line) for rivers: Drwęca (**a**,**b**), Łeba (**c**,**d**), Łyna (**e**,**f**), Pisa (**g**,**h**) and Wda (**i**,**j**).

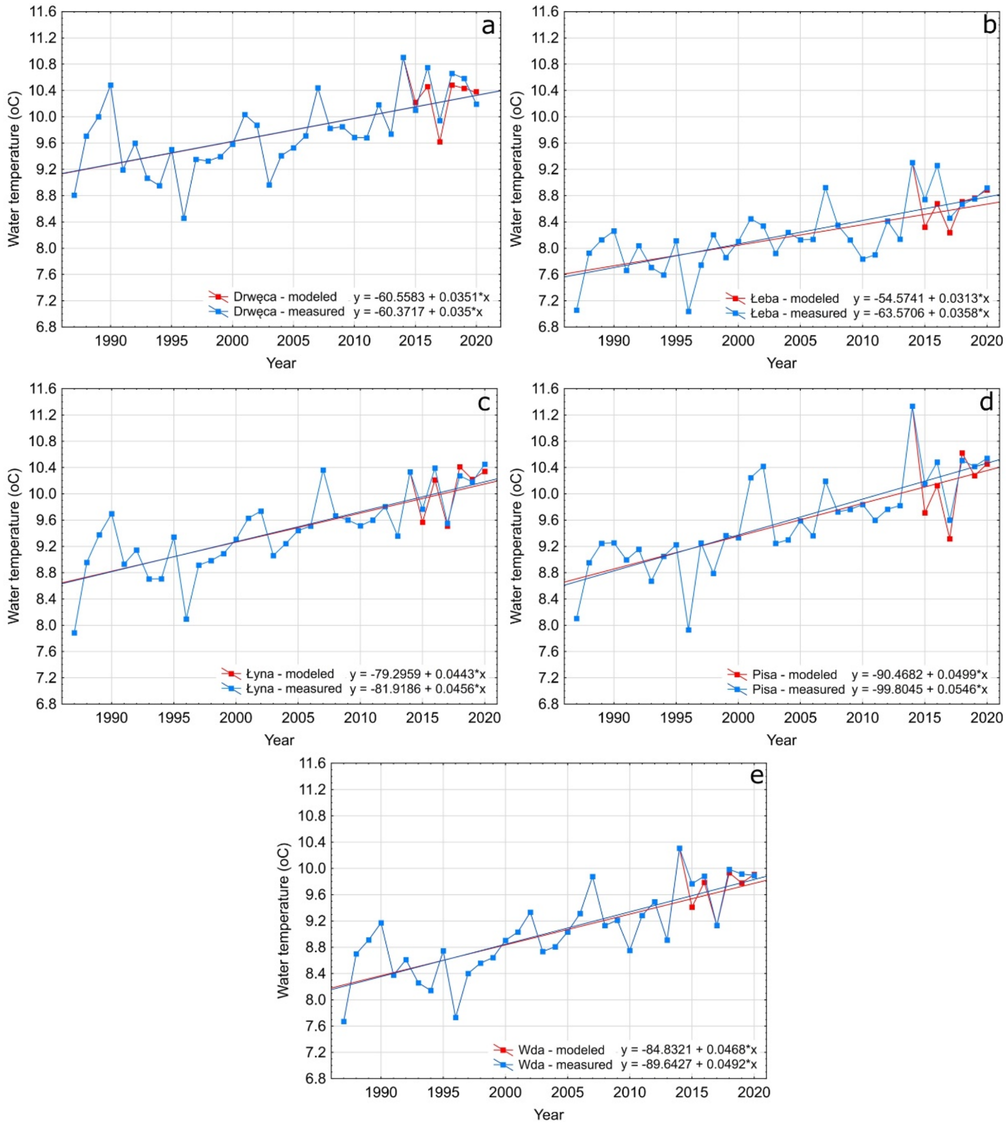

Figure 6. Trendline slope value in the years 1987–2020 for the original measurement data (blue line) and reconstructed data (red line) for rivers: Drwęca (**a**), Łeba (**b**), Łyna (**c**), Pisa (**d**) and Wda (**e**).

Table 4. Trendline slope values (Sen slope) in °C per decade in river waters in Poland.

Period	Bóbr *	Drawa *	Ełk *	Guber *	River	Drwęca	Łeba	Łyna	Pisa	Wda
					Gwda *					
Nov	**0.68**	**0.65**	**0.65**	**0.65**	**0.55**	**0.73**	**0.44**	**0.66**	**0.77**	**0.64**
Dec	**0.50**	**0.35**	**0.40**	0.36	**0.43**	**0.47**	**0.37**	**0.43**	**0.52**	**0.48**
Jan	−0.13	0.12	−0.18	−0.18	−0.18	−0.08	−0.18	−0.20	0.03	0.11
Feb	−0.17	−0.10	−0.03	−0.04	−0.16	0.00	−0.04	0.07	0.15	0.18
Mar	−0.12	0.02	0.06	0.12	0.24	0.30	0.19	0.26	0.47	0.41
Apr	**0.39**	0.32	0.40	0.35	**0.45**	0.41	**0.39**	0.45	**0.79**	**0.42**
May	0.17	0.15	0.30	0.32	0.12	0.06	**0.30**	0.46	0.35	**0.55**
Jun	**0.44**	**0.49**	**0.65**	0.57	**0.60**	**0.53**	**0.52**	**0.84**	**0.80**	**0.72**
Jul	0.27	0.22	0.27	0.22	**0.44**	0.14	**0.48**	**0.43**	0.44	**0.49**
Aug	0.18	**0.50**	**0.53**	0.28	**0.50**	**0.37**	**0.48**	**0.63**	**0.69**	**0.53**
Sep	**0.24**	**0.40**	**0.61**	**0.40**	**0.51**	**0.53**	**0.40**	**0.61**	**0.48**	**0.60**
Oct	0.24	**0.45**	0.40	0.37	0.36	**0.45**	**0.34**	0.41	**0.34**	**0.48**
Year	**0.18**	**0.33**	**0.30**	**0.25**	**0.29**	**0.34**	**0.28**	**0.44**	**0.47**	**0.49**

Bold—values statistically significant at a level of 0.05 based on Mann–Kendall test; *—reconstructed data.

4. Discussion

Water temperature in rivers is an important property determining its quality, yet data regarding it in many river systems are scarce or non-existent [43]. According to Rosencranz et al. [44], in regions poor in data, modelling water temperature in rivers is necessary to predict potential stress-inducing factors for endangered species. Further, the same authors predicted water temperature (for three rivers in Canada) based on air temperature from nearby meteorological stations, and revealed that the best model proved to be linear regression using a 5-day delay in air temperature. Chen et al. [45] used modified sinusoidal functions and sinusoidal wave functions (MSSWF) for the estimation of hourly water temperatures in rivers. It was, among other things, determined that the distance of the river monitoring site from the meteorological station has little effect on the efficiency of particular models (in the case of a distance smaller than 300 km). In the case of the analysed rivers, it was also determined that the distance of the site of air temperature measurement from the hydrological station (at maximum not reaching 130 km) has no effect on the accuracy of the models. Possibilities not achievable in hydrology to date are offered by the implementation of an approach based on the assumptions of artificial intelligence. Machine learning is increasingly frequently applied due to its ability to model complex and non-linear dependencies between river water temperature and its predictors [46]. Machine learning models offer an empirical approach to predicting water temperature with a high level of accuracy [47], and the advantages of models of artificial neural networks in modelling water temperature involve their simplicity of use, good ability to generalise, and flexibility [48]. Due to all the above, it is possible to obtain results at a good adjustment level, as confirmed by the results obtained in the paper referring to the reconstruction of the discontinued in situ measurements. According to current studies, the scope and availability of input data and the adopted modelling methodology have a different character. The use of classic models of machine learning for forecasting monthly water temperatures (USA) showed that such an approach can be applied for the spatial and temporal modelling of the majority of locations, with an accuracy of <1 °C [49]. Water temperature modelling by means of neural networks and multiple linear regression in the case of the Catamaran Brook (Canada) showed that neural networks offered better results in terms of adjustment, but an inconsiderable difference in results suggests that both approaches are equally good [50]. The development of a model composed of artificial neural networks (ANN) for predicting mean daily water temperature in individual sections of streams showed that the most important predictors were mean daily air temperature, prior 7-day mean air temperature, and network catchment area [51]. The analysis of the dependency between mean daily air temperature and water temperature in the Drava River (Croatia) by means of linear regression, stochastic modelling, non-linear regression, and multilayer perceptron showed that the latter are considerably better models in the estimation and prediction of mean daily river temperature [48]. The findings are in accordance with results presented in the present paper, where the multilayer perceptrone network also obtained the best results against the background of other proposed methodical solutions. Along with this variable that is commonly used in this type of research on air temperature [27,52], this paper employed additional information regarding water temperature in lakes (unlike in the case of some rivers—subject to continuous monitoring). The combination of both input attributes permitted obtaining even better results in the reconstruction of the missing water temperature records.

The final effect of the reconstruction of the thermal conditions of rivers is the maintaining of continuity in information regarding them, permitting among others the analysis of their long-term (1987–2020) changes. It was determined that in all cases, a statistically significant increase in water temperature occurred, averaging 0.33 °C per decade. The results are in accordance with the broad trend of hydrological research analysing the scale and rate of changes in water temperature in rivers. In the case of rivers in the Loire River catchment, the highest increases were recorded in spring and summer, reaching +0.38 °C and +0.44 °C per decade, respectively [53]. The analysis of the temperature trend for the

Salaca River (Latvia) showed its increase in the autumn and winter months and in early spring, from November to April and September, and a decrease in June [54]. The analysis of four sites on the Danube River revealed statistically significant warming trends for all of them in reference to the annual and seasonal minimum and maximum water temperatures [7]. The strongest warming was recorded at the measurement station Bogojevo for the seasonal maximum Tw, with an average of +0.05 °C annually. An evident increase in water temperature is a result coherent with findings for other rivers in the discussed region [55,56]. It is characteristic that in the case of winter and early spring months (Jan–Mar), trends of changes in water temperature are not statistically significant. This is related to the ice phenomena occurring during the period, which effectively determine the aforementioned situation due to water cooling and its isolation from external conditions [57,58]. This results in the lack of evident responses in the river ecosystems to changes in climate elements.

The development of the modelling concept for the purpose of predicting water temperature in rivers is and will remain necessary for the effective integrated management of water resources, and the development of strategies for adaptation to future global changes [59]. Detailed forecasts at different spatial and temporal scales can be a source of information for decisions regarding water management that consider the effects of the changing climate and extreme phenomena. The common prediction of temperature in sections of streams not subject to monitoring can specifically allow decision-makers to respond to changes caused by unpredicted disturbances [49]. Such assumptions are important in the case of many regions in Poland (also covering catchments where river temperature monitoring has been discontinued), where substantial water deficits are recorded. A smaller amount of water resources increases the risk of their faster degradation [40], and precise data regarding water temperature, determining, among other things, dissolved oxygen concentration [60], provide the basis for undertaking appropriate reclamation activities.

5. Conclusions

Water temperature in rivers is an elementary characteristic that determines the course of many processes of both biotic and abiotic nature. Hence, information on it is crucial for understanding the overall functioning of these ecosystems. In this context, data shortages are a problem, one of the reasons for which may be the cessation of previous monitoring. New opportunities for water temperature reconstruction are provided by methods based on artificial intelligence and the approach realised in this article. It was established that the best statistical method allowing for the reconstruction of mean monthly water temperatures in rivers is the method using artificial neural networks—multilayer perceptrone network (mean error, root mean square error and standard error of 1.52 °C, 5.03% and 0.47 °C, respectively). As a result of the reconstruction, the course of mean yearly water temperature in the years 1987–2020 showed a statistically significant increase from 0.18 to 0.49 °C per decade, averaging 0.33 °C per decade. Further research into water temperature reconstruction based on artificial intelligence solutions should focus on using a broader set of input predictors. Irrespective of the modelling results, where it is possible for formal and organisational reasons, it is recommended to resume in situ measurements of water temperature in rivers as key data necessary for the assessment of the effect of climate change on water ecosystems and those dependent on waters.

Author Contributions: Conceptualisation, M.S.; methodology, M.S.; software, M.S.; validation, M.S. and M.P.; formal analysis, M.S.; investigation, M.P.; resources, M.P.; data curation, M.P.; writing—original draft preparation, M.S. and M.P.; writing—review and editing, M.P.; visualisation, M.S.; supervision, M.P. and M.S.; project administration, M.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Papić, D.; Bačević, N.R.; Valjarević, A.; Milentijević, N.; Gavrilov, M.B.; Živković, M.; Marković, S.B. Assessment of air temperature trend in South and Southeast Bosnia and Herzegovina from 1961 to 2017. *Idojaras* **2020**, *124*, 381–399. [CrossRef]
2. Kejna, M.; Rudzki, M. Spatial diversity of air temperature changes in Poland in 1961–2018. *Theor. Appl. Climatol.* **2021**, *143*, 1361–1379. [CrossRef]
3. Snizhko, S.; Shevchenko, O.; Buznytskyi, B.; Krukivska, A.; Matviienko, M. The projections of air temperature in the Northern region of Ukraine following the intermediate scenario (RCP 4.5) and the high-end scenario (RCP 8.5). In Proceedings of the 14th International Scientific Conference on Monitoring of Geological Processes and Ecological Condition of the Environment, Kiev, Ukraine, 10–13 November 2020.
4. Tomczyk, A.M.; Piniewski, M.; Eini, M.R.; Bednorz, E. Projections of changes in maximum air temperature and hot days in Poland 2022. *Int. J. Climatol.* **2022**. [CrossRef]
5. Arora, R.; Tockner, K.; Venohr, M. Changing river temperatures in northern Germany: Trends and drivers of change. *Hydrol. Processes* **2016**, *30*, 3084–3096. [CrossRef]
6. Choiński, A.; Ptak, M.; Strzelczak, A. Changeability of accumulated heat content in alpine-type lakes. *Pol. J. Environ. Stud.* **2015**, *24*, 2363–2369. [CrossRef]
7. Basarin, B.; Lukić, T.; Pavić, D.; Wilby, R.L. Trends and multi-annual variability of water temperatures in the river Danube, Serbia. *Hydrol. Processes* **2016**, *30*, 3315–3329. [CrossRef]
8. Liu, S.; Xie, Z.; Liu, B.; Wang, Y.; Gao, J.; Zeng, Y.; Xie, J.; Xie, Z.; Jia, B.; Qin, P.; et al. Global river water warming due to climate change and anthropogenic heat emission. *Glob. Planet. Change* **2020**, *193*, 103289. [CrossRef]
9. Jurgelenaite, A.; Kriaučiuniene, J.; Šarauskiene, D. Spatial and temporal variation in the water temperature of Lithuanian rivers. *Baltica* **2012**, *25*, 65–76. [CrossRef]
10. Frechette, D.M.; Dugdale, S.J.; Dodson, J.J.; Bergeron, N.E. Understanding summertime thermal refuge use by adult Atlantic salmon using remote sensing, river temperature monitoring, and acoustic telemetry. *Can. J. Fish. Aquat. Sci.* **2018**, *75*, 1999–2010. [CrossRef]
11. Łaszewski, M.A. The effect of environmental drivers on summer spatial variability of water temperature in Polish lowland watercourses. *Environ. Earth Sci.* **2020**, *79*, 244. [CrossRef]
12. Ling, F.; Foody, G.M.; Du, H.; Ban, X.; Li, X.; Zhang, Y.; Du, Y. Monitoring Thermal Pollution in Rivers Downstream of Dams with Landsat ETM+ Thermal Infrared Images. *Remote Sens.* **2017**, *9*, 1175. [CrossRef]
13. Martí-Cardona, B.; Prats, J.; Niclòs, R. Enhancing the retrieval of stream surface temperature from Landsat data. *Remote Sens. Environ.* **2019**, *224*, 182–191. [CrossRef]
14. Al-Murib, M.D.; Wells, S.A.; Talke, S.A. Integrating Landsat TM/ETM+ and Numerical Modeling to Estimate Water Temperature in the Tigris River under Future Climate and Management Scenarios. *Water* **2019**, *11*, 892. [CrossRef]
15. Nowak, B.; Grześkowiak, A. Czy rejestracja elektroniczna może zastąpić obserwatorów w pomiarach na jeziorach? *Hydrol. W Ochr. I Kształtowaniu Sr.* **2010**, *2*, 361–369.
16. Kermorvant, C.; Liquet, B.; Litt, G.; Jones, J.B.; Mengersen, K.; Peterson, E.E.; Hyndman, R.J.; Leigh, C. Reconstructing Missing and Anomalous Data Collected from High-Frequency In-Situ Sensors in Fresh Waters. *Int. J. Environ. Res. Public Health* **2021**, *18*, 12803. [CrossRef] [PubMed]
17. Tabari, H.; Talaee, P.H. Reconstruction of river water quality missing data using artificial neural networks. *Water Qual. Res. J. Can.* **2015**, *50*, 326–335. [CrossRef]
18. Jackson, F.L.; Fryer, R.J.; Hannah, D.M.; Malcolm, I.A. Can spatial statistical river temperature models be transferred between catchments? *Hydrol. Earth Syst. Sci.* **2017**, *21*, 4727–4745. [CrossRef]
19. Yang, D.; Peterson, A. River water temperature in relation to local air temperature in the Mackenzie and Yukon basins. *Arctic* **2017**, *70*, 47–58. [CrossRef]
20. Arismendi, I.; Johnson, S.L.; Dunham, J.B.; Haggerty, R.; Hockman-Wert, D. The paradox of cooling streams in a warming world: Regional climate trends do not parallel variable local trends in stream temperature in the Pacific continental United States. *Geophys. Res. Lett.* **2012**, *39*, L10401. [CrossRef]
21. Luoto, T.P.; Nevalainen, L. Long-term water temperature reconstructions from mountain lakes with different catchment and morphometric features. *Sci. Rep.* **2013**, *3*, 2488. [CrossRef]
22. Piccolroaz, S.; Woolway, R.I.; Merchant, C.J. Global reconstruction of twentieth century lake surface water temperature reveals different warming trends depending on the climatic zone. *Clim. Change* **2020**, *160*, 427–442. [CrossRef]
23. Prats, J.; Val, R.; Armengol, J.; Dolz, J. A methodological approach to the reconstruction of the 1949–2000 water temperature series in the Ebro River at Escatrón. *Limnetica* **2007**, *26*, 293–306. [CrossRef]
24. Murphy, R.D., Jr.; Hagan, J.A.; Harris, B.P.; Sethi, S.A.; Smeltz, T.S.; Restrepo, F. Can landsat thermal imagery and environmental data accurately estimate water temperatures in small streams? *J. Fish Wildl. Manag.* **2021**, *12*, 12–26. [CrossRef]

25. Zhu, S.; Heddam, S.; Wu, S.; Dai, J.; Jia, B. Extreme learning machine-based prediction of daily water temperature for rivers. *Environ. Earth Sci.* **2019**, *78*, 202. [CrossRef]
26. Zhu, S.; Hadzima-Nyarko, M.; Bonacci, O. Application of machine learning models in hydrology: Case study of river temperature forecasting in the Drava River using coupled wavelet analysis and adaptive neuro-fuzzy inference systems model. *Basics Comput. Geophys.* **2020**, 399–411.
27. Heddam, S.; Ptak, M.; Sojka, M.; Kim, S.; Malik, A.; Kisi, O.; Zounemat-Kermani, M. Least square support vector machine-based variational mode decomposition: A new hybrid model for daily river water temperature modeling. *Environ. Sci. Pollut. Res.* **2022**, 1–28. [CrossRef]
28. ESRI. *ArcGIS Desktop: Release 10.7.1.*; Environmental Systems Research Institute: Redlands, CA, USA, 2019.
29. TIBCO Software Inc. *Statistica (Data Analysis Software System)*; Version 13; Stanford Research Park: Palo Alto, CA, USA, 2017.
30. Wright, M.N.; Ziegler, A. Ranger: A fast implementation of random forests for high dimensional data in C++ and R. *arXiv* **2015**, arXiv:1508.04409. [CrossRef]
31. Wright, M.N.; Wager, S.; Probst, P. *A Fast Implementation of Random Forests*; R Package Version 0.13.1; R Foundation for Statistical Computing: Vienna, Austria, 2021; pp. 1–25. Available online: https://cran.r-project.org/web/packages/ranger/index.html (accessed on 15 March 2022).
32. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021. Available online: https://www.R-project.org/ (accessed on 15 March 2022).
33. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290. [CrossRef]
34. Makridakis, S.; Andersen, A.; Carbone, R.; Fildes, R.; Hibon, M.; Lewandowski, R.; Newton, J.; Parzen, E.; Winkler, R. The accuracy of extrapolation (time series) methods: Results of a forecasting competition. *J. Forecast.* **1982**, *1*, 111–153. [CrossRef]
35. Qian, X.; Lee, S.; Soto, A.M.; Chen, G. Regression model to predict the higher heating value of poultry waste from proximate analysis. *Resources* **2018**, *7*, 39. [CrossRef]
36. Zhu, S.; Luo, Y.; Ptak, M.; Sojka, M.; Ji, Q.; Choiński, A.; Kuang, M. A hybrid model for the forecasting of sea surface water temperature using the information of air temperature: A case study of the Baltic Sea. *All Earth* **2022**, *34*, 27–38. [CrossRef]
37. Kendall, M.G.; Stuart, A. *The Advanced Theory of Statistics*, 3rd ed.; Charles Griffin Ltd.: London, UK, 1968.
38. Gilbert, R.O. *Statistical Methods for Environmental Pollution Monitoring*; Van Nostrand Reinhold Co.: New York, NY, USA, 1987; p. 320.
39. Yue, S.; Pilon, P.; Phinney, B.; Cavadias, G. The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrol. Processes* **2002**, *16*, 1807–1829. [CrossRef]
40. Sojka, M. Directions and Extent of Flows Changes in Warta River Basin (Poland) in the Context of the Efficiency of Run-of-River Hydropower Plants and the Perspectives for Their Future Development. *Energies* **2022**, *15*, 439. [CrossRef]
41. Ptak, M.; Sojka, M.; Graf, R.; Choiński, A.; Zhu, S.; Nowak, B. Warming Vistula River—the effects of climate and local conditions on water temperature in one of the largest rivers in Europe. *J. Hydrol. Hydromech.* **2022**, *70*, 1–11. [CrossRef]
42. Patakamuri, S.K.; O'Brien, N.M. *Modified Versions of Mann Kendall and Spearman's Rho Trend Tests 2019*; The R Project for Statistical Computing: Vienna, Austria, 2019; p. 19.
43. Segura, C.; Caldwell, P.; Sun, G.; Mcnulty, S.; Zhang, Y. A model to predict stream water temperature across the conterminous USA. *Hydrol. Processes* **2015**, *29*, 2178–2195. [CrossRef]
44. Rosencranz, J.; Cuddington, K.; Brook, M.; Koops, M.A.; Drake, D.A. Data-limited models to predict river temperatures for aquatic species at risk. *Can. J. Fish. Aquat. Sci.* **2021**, *78*, 1268–1277. [CrossRef]
45. Chen, G.; Fang, X.; Fan, H. Estimating hourly water temperatures in rivers using modified sine and sinusoidal wave functions. *J. Hydrol. Eng.* **2016**, *21*, 05016023. [CrossRef]
46. Rajesh, M.; Rehana, S. Prediction of river water temperature using machine learning algorithms: A tropical river system of India. *J. Hydroinf.* **2021**, *23*, 605–626. [CrossRef]
47. Qiu, R.; Wang, Y.; Rhoads, B.; Wang, D.; Qiu, W.; Tao, Y.; Wu, J. River water temperature forecasting using a deep learning method. *J. Hydrol.* **2021**, *595*, 126016. [CrossRef]
48. Rabi, A.; Hadzima-Nyarko, M.; Šperac, M. Modelling river temperature from air temperature: Case of the River Drava (Croatia). *Hydrol. Sci. J.* **2015**, *60*, 1490–1507. [CrossRef]
49. Weierbach, H.; Lima, A.R.; Willard, J.D.; Hendrix, V.C.; Christianson, D.S.; Lubich, M.; Varadharajan, C. Stream Temperature Predictions for River Basin Management in the Pacific Northwest and Mid-Atlantic Regions Using Machine Learning. *Water* **2022**, *14*, 1032. [CrossRef]
50. Bélanger, M.; El-Jabi, N.; Caissie, D.; Ashkar, F.; Ribi, J.-M. Water temperature prediction using neural networks and multiple linear regression. *Rev. Sci. L'eau* **2005**, *18*, 403–421.
51. DeWeber, J.T.; Wagner, T. A regional neural network ensemble for predicting mean daily river water temperature. *J. Hydrol.* **2014**, *517*, 187–200. [CrossRef]
52. Zhu, S.; Nyarko, E.K.; Hadzima-Nyarko, M. Modelling daily water temperature from air temperature for the Missouri River. *PeerJ* **2018**, *6*, e4894. [CrossRef]

53. Seyedhashemi, H.; Vidal, J.-P.; Diamond, J.S.; Thiéry, D.; Monteil, C.; Hendrickx, F.; Maire, A.; Moatar, F. Regional, multi-decadal analysis on the Loire River basin reveals that stream temperature increases faster than air temperature. *Hydrol. Earth Syst. Sci.* **2022**, *26*, 2583–2603. [CrossRef]
54. Birzaks, J. Climate Change Impact on Salmon (*Salmo salar*) and Sea Trout (*Salmo trutta*) in the Salaca River, Latvia. *Zool. Ecol.* **2020**, *30*, 1. [CrossRef]
55. Kędra, M. Regional Response to Global Warming: Water Temperature Trends in Semi-Natural Mountain River Systems. *Water* **2020**, *12*, 283. [CrossRef]
56. Ptak, M.; Sojka, M.; Kałuża, T.; Choiński, A.; Nowak, B. Long-term water temperature trends of the Warta River in the years 1960–2009. *Ecohydrol. Hydrobiol.* **2019**, *19*, 441–451. [CrossRef]
57. Ptak, M.; Sojka, M. The disappearance of ice cover on temperate lakes (Central Europe) as a result of global warming. *Geogr. J.* **2021**, *187*, 200–213. [CrossRef]
58. Choiński, A.; Ptak, M.; Strzelczak, A. Areal variation in ice cover thickness on lake Morskie Oko (Tatra Mountains). *Carpathian J. Earth Environ. Sci.* **2013**, *8*, 97–102.
59. Feigl, M.; Lebiedzinski, K.; Herrnegger, M.; Schulz, K. Machine-learning methods for stream water temperature prediction. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 2951–2977. [CrossRef]
60. Ptak, M.; Nowak, B. Variability of oxygen-thermal conditions in selected lakes in Poland. *Ecol. Chem. Eng. S.* **2016**, *23*, 639–650. [CrossRef]