# EFFECTS OF RIVER TEMPERATURE ESTIMATIONS ON 1D RESERVOIR TEMPERATURE MODELING

*Mayra Ishikawa [1]; Jucimara Andreza Rigotti [2]; Katharina Rosas [3]; Michael Mannich [4] & Tobias B. Bleninger [5]*

**Abstract:** Continuous water temperature data availability is often an issue with modeling of water bodies. In this study two methods, correlation and the *air2stream* model, are used to model the water temperature of the inflowing rivers and stream to the Passaúna Reservoir in Curitiba, Brazil. With the ability to regard different numbers of coefficients, *air2stream* was able to achieve marginally better results than the correlation method. However, both methods only portrait small differences. Applying the water temperature data to the GLM model to simulate reservoir's water temperature also provided very similar results at the surface and in the hypolimnion. Greater water temperature discrepancies were found in the midwater. Further calibration of both the *air2stream* model and of the GLM may lead to improved results in the future.
**Keywords** – *Air2stream*; lake modeling; thermal dynamic.

**Resumo:** A disponibilidade de dados contínuos sobre a temperatura da água é frequentemente um problema na modelagem de corpos d'água. Neste estudo, dois métodos, a correlação e o modelo *air2stream*, são usados para modelar a temperatura da água dos rios e córregos que deságuam no Reservatório Passaúna, em Curitiba, Brasil. Com a capacidade de considerar diferentes números de coeficientes, o modelo *air2stream* conseguiu resultados ligeiramente melhores do que o método de correlação. Contudo, ambos os métodos apresentaram apenas pequenas diferenças. Ao aplicar os dados de temperatura da água dos rios ao modelo GLM para simular as temperaturas do reservatório, também foram encontrados resultados muito semelhantes na superfície e no hipolímnio. Maiores diferenças na temperatura da água foram encontradas em profundidade intermediária. A calibração adicional do modelo *air2stream* e do GLM pode melhorar os resultados futuramente.
**Palavras-Chave** – *Air2stream*; modelagem de lagos; dinâmica térmica.

## INTRODUCTION

Temperature is the primary physical factor influencing the structure and distribution of species in freshwater ecosystems. Lake ecosystems are highly sensitive to temperature changes, since lake temperatures reflect a climate signal (Boehrer and Schultze 2008). Temperature influences fluid properties and impacts physical gas transfer processes. It also affects chemical reactions that coordinate nutrient availability and primary production (Dory *et al.* 2024). In this regard, water temperature in inflowing rivers is a key factor to simulate water quality on reservoir hydrodynamic

[1]) Federal Institute of Hydrology, Microbial Ecology, Koblenz, Germany, mayraishiakwa@gmail.com
[2]) Programa de Pós-graduação em Engenharia de Recursos Hídricos e Ambiental, Universidade Federal do Paraná, andrezarigotti@ufpr.br
[3]) Karlsruhe Institute of Technology, Karlsruhe, Germany, kirosas1708@gmail.com
[4]) Departamento de Engenharia Ambiental, Universidade Federal do Paraná, mannich@ufpr.br
[5]) Departamento de Engenharia Ambiental, Universidade Federal do Paraná, bleninger@ufpr.br

models (Feigl *et al.* 2021) besides the heat exchange with the atmosphere. According to Ishikawa *et al.* (2021), changing riparian vegetation coverage of river inflows of a subtropical reservoir to less shading conditions could increase stream water temperature near the reservoir inflow by +2.2 °C on average, with a maximum increase of daily mean temperature of +4.7 °C. The differences could impact the behaviour of the main inflow depth, and hence the delivery of nutrients.

Despite the relevance of inflow temperature on reservoir and lake modeling, there are few measurements of this input data (Almeida and Coelho 2023). Usually, estimations are made to obtain this parameter, for example, based on air temperature correlations because air temperature is easier to obtain (Toffolon and Piccolroaz 2015). Machine learning methods and multiple regression have also been applied (Almeida and Coelho 2023; Philippus *et al.* 2024). Toffolon e Piccolroaz (2015) developed the model *air2stream,* characterized by a single ordinary differential equation linearly dependent on air and water temperature, and discharge. This formulation enables the calibration of the model parameters by the Monte Carlo method (Toffolon and Piccolroaz 2015). Almeida and Coelho (2023) reported the validity of applying all the methods that were compared: random forest, artificial neural network, support vector regression, *air2stream*, and multiple regression, especially when there are limitations of predictor variables and observed water temperature values.

Different dimensionalities of hydrodynamic models can influence the sensibility of forcing datasets. In this study, the main goal is to assess the influence of different estimations of inflow water temperatures on lake temperature estimation by a one-dimension model, the General Lake Model (GLM), applied for the in Passaúna Reservoir, Curitiba, Brazil.

## METHODS

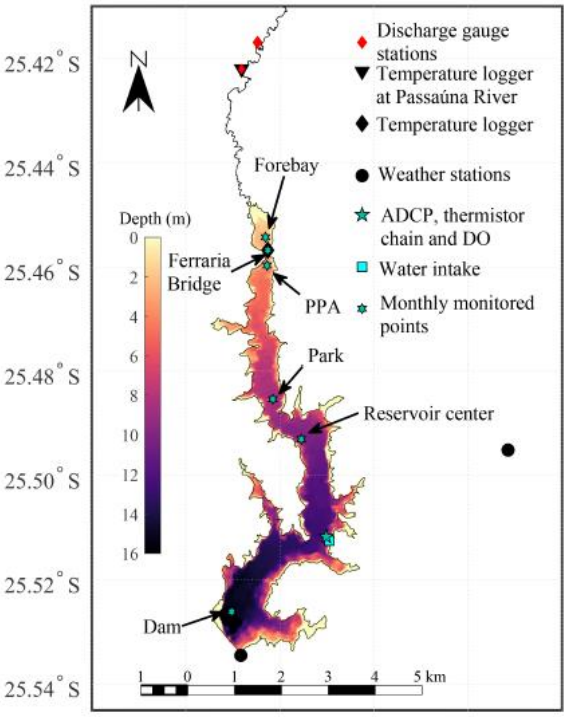
### *Study area*

Passaúna Reservoir is a water supply reservoir that has been studied in terms of reservoir water quality monitoring and modeling (Ishikawa *et al.* 2021; Ishikawa *et al.* 2022). Passaúna Reservoir is located in the Metropolitan Region of Curitiba, covering an area of around 8.5 km² (Marcon, 2019). The Passáuna River, Ferraria River and other small streams feed into the reservoir (Figure 1). The reservoir has an average depth of 8.3 m and a maximum depth of 17.5 m.

### *General Lake Model (GLM)*

To simulate water temperature in the Passaúna Reservoir and to test different estimations of river temperatures, the General Lake Model (GLM) version 3.05 was applied. GLM is a one-dimensional model with a broad application in the context of GLEON (Global Lake Ecological Observatory Network). GLM simulates lake, reservoirs and wetlands water balance and thermal stratification dynamics (Hipsey *et al.* 2019). One of the advantages of using GLM is the ease of simulation, allowing for the rapid simulation of long periods, as well as the possibility of coupling with an ecological library (Aquatic ecodynamics (AED)) that includes biogeochemical variables and ecology (Hipsey *et al.* 2019). The basic input data for the model are river flows, temperature, and salinity. Morphometry, bathymetry, meteorological data, and operational data are used in the case of reservoir modeling. The model was calibrated with data from 2018 to 2019 and the temperature data for the inflows derived from the correlation method. The model showed a RMSE of 0.98 °C. In this study, no calibrated parameter was changed.

Figure 1 – Passaúna Reservoir localization and bathymetry (Ishikawa et al. 2022).



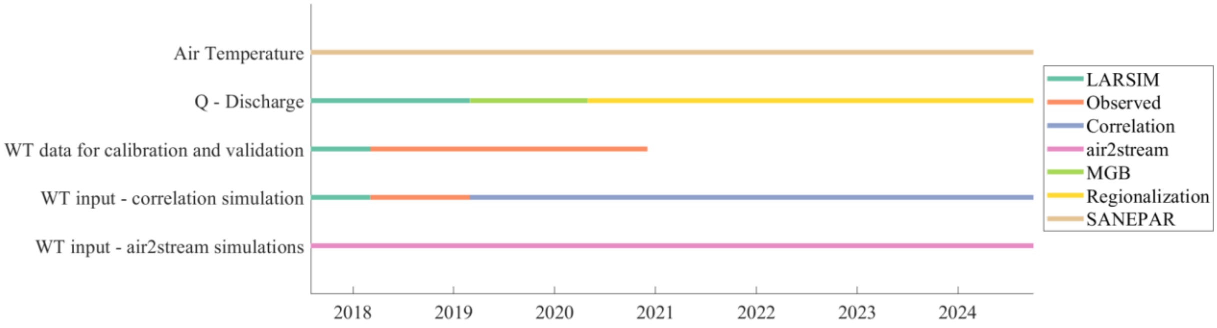

*Hydrological models and input datasets*

To implement GLM, three inflow datasets for river discharges were used, because they encompass different time periods: LARSIM-WT (Large Area Runoff SIMulation Model - Water Temperature - Haag and Luce 2008), MGB (Large-Scale Distributed Hydrological Model - Collischonn and Tucci 2001; Fan and Collischonn 2014) and regionalization (Figure 2).

LARSIM-WT is a process-based water balance model, it includes an optional water temperature module. The discharge from August 2018 to February 2019 was estimated with LARSIM, and for the same period water temperatures were also estimated by the model, both in a daily resolution. However, from March 2018 to November 2020 water temperature was measured at Passaúna River, around 3 km upstream from the Passaúna Reservoir. Measurements were performed by a miniDOT (Precision Measurement Engineering Inc.), the sensor had an accuracy of ±0.1°C and resolution of 0.01°C. Temperatures were recorded every 15 min and later daily averaged. The MuDaK-WRM project was conducted from August 2018 to February 2019. For this reason, we have results during this period from LARSIM.

MGB is a hydrological model developed in the Hydraulic Research Institute of Federal University of Rio Grande do Sul (IPH-UFRGS). MGB is a distributed model with basin discretization in irregular units, these smaller basins are divided into similar areas called Hydrological Response Units (Fan and Collischonn 2014). The MGB was implemented and calibrated to Passaúna catchment by Muhlenhoff (2023). In this study a period from March 2019 to April 2020 was used. Regionalization was applied from May 2020 to September 2024. There was a river station with discharge measurement (station code 65021800) in the Passauna river. The station has a level-discharge relation for a correspondent hydrographic area of 92 km². The regionalization is based on the catchment area relation of Passaúna river (103 km²), Ferraria river (10 km²) and the other rivers, called streams, whose sum of their contribution area is about 36 km².

Figure 2 – Overview of the different data sources available over time.

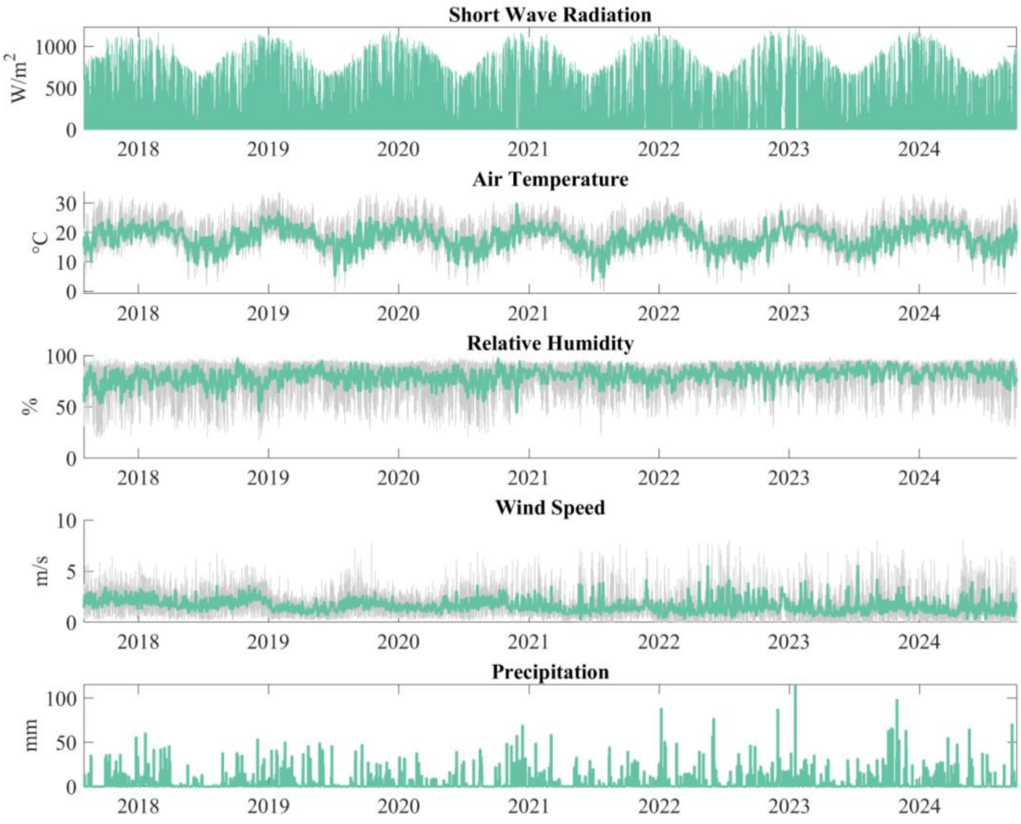



*Boundary conditions*

The meteorological data was taken from the weather station sensors provided by SANEPAR between August 2017 until September 2023 (Figure 3). SANEPAR is the state-owned public utility company of Paraná. The data was recorded by the sensor installed near the Passaúna reservoir and delivered in a one-minute temporal resolution.

The inflows primarily consist of tributaries entering the reservoir as mentioned before (Passaúna river, Ferraria river and small streams), and are captured into one file. The discharge was determined using outputs of the hydrological models (LARSIM and MGB) or regionalization for each tributary. The outflow, which includes discharge from the bottom outlet and water withdrawal through the intake structure, was measured and provided by SANEPAR. In GLM, each inflow and outflow has its own input file.

Figure 3 – Meteorological input data. For Air Temperature, Wind Speed and Relative Humidity the grey lines are in hourly resolution and the green lines in daily averages. Short Wave Radiation is in hourly resolution.



*Water temperature estimations of inflows*

For river water temperature estimations, two methods were applied: water temperature estimation based on air temperature correlation (Colombo 2019), and water temperature estimation based on the *air2stream* model (Toffolon and Piccolroaz 2015). River temperature estimation based on air temperature data is an usual approach when there are no river temperature measures. Colombo (2019) correlated air temperature data with water temperature based on equations described in the literature. In this study, the equation A7N was chosen because of the good fit (0.967 Nash-Sutcliff coefficient), according to Colombo (2019).

*Air2stream* is a hybrid model developed to predict river water temperature based on air temperature and stream discharge (Toffolon and Piccolroaz 2015). The model combines a physically based structure with stochastic parameter calibration, making it effective for simulating daily stream temperatures. The model has different versions depending on the simplifications of the main equation, varying from 3 to 8 coefficients. The simpler versions with 3, 4 and 5 coefficients disregard the influence of discharge and can provide satisfactory results, especially for rivers that are not significantly affected by external factors, such as hydropower and industrial inputs, which is the case of Passaúna River.

## RESULTS AND DISCUSSION

*Estimations of river water temperature based on air temperature*

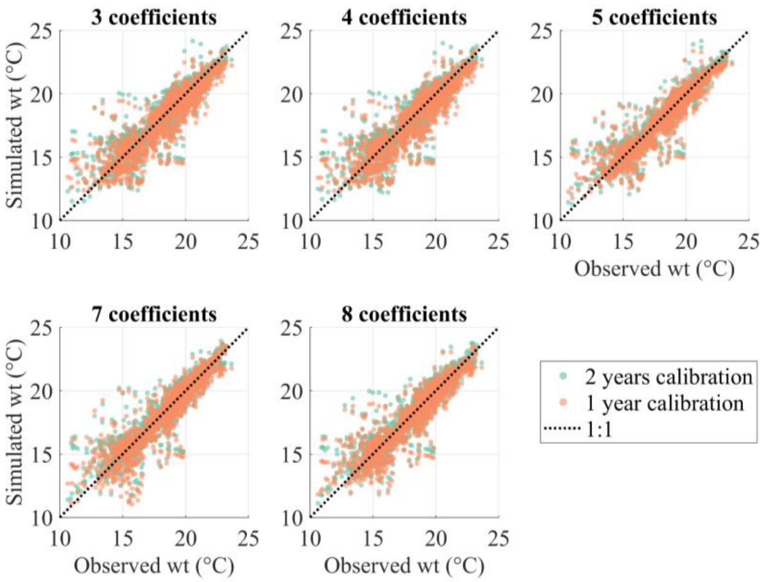
*Air2stream* results depend on the quality of the calibration of their coefficients, for this reason we decided to run *air2stream* with two time periods of calibration, with the aim to compare its results. The periods were 1 year (from August 2017 to July 2018) and 2 years (August 2017 to July 2019). The model was also run with the different number of coefficients, the results selected to be used as input data for GLM were the ones with the smallest root mean squared error (RMSE) from each period of calibration. Results did not present large discrepancies, the *air2stream* version with 5 coefficients showed the best performance for both periods of calibration (Figure 4). The RMSE for all simulations are shown in Table 1. The equation with 5 parameters disregards the influence of discharge, but it can compensate for the lag between air and water temperature.

Although the RMSE increased for a longer period of calibration, it is important to keep in mind that the observed data used for comparison was the same. Therefore, the validation period was smaller for the case with 2 years of calibration. In addition, the larger errors are towards the end of the observations, most likely due to the drought that occurred in 2020. The RMSE between observation and each estimation for an equal period of time (August 2019 to December 2020) were of 2.07, 1.54 and 1.51 °C, respectively for correlation, *air2stream* 1 and 2 years of calibration.

Table 1 – Errors between estimated and simulated water temperature by *air*2stream

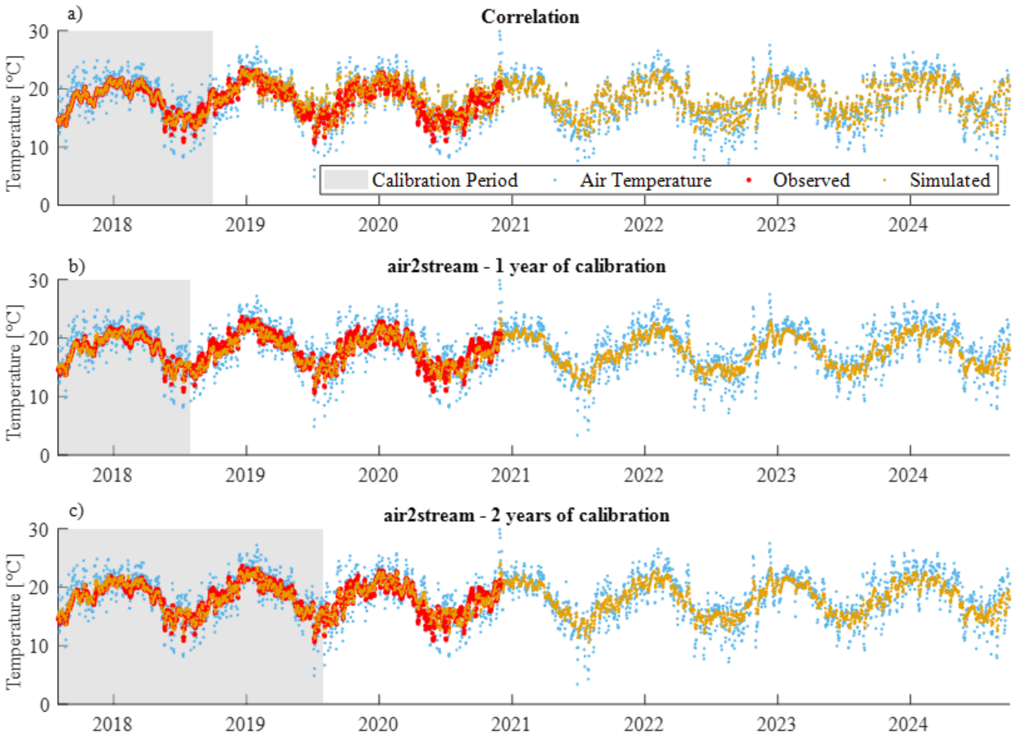
| | **n° of coeff.** | **3** | **4** | **5** | **7** | **8** |
|---|---|---|---|---|---|---|
| 1 year calibration | calibration | 0.66 °C | 0.66 °C | 0.53 °C | 0.64 °C | 0.62 °C |
| | validation | 1.46 °C | 1.46 °C | 1.26 °C | 1.34 °C | 1.3 °C |
| 2 years calibration | calibration | 0.77 °C | 0.77 °C | 0.59 °C | 0.68 °C | 0.67 °C |
| | validation | 1.72 °C | 1.73 °C | 1.51 °C | 1.59 °C | 1.57 °C |

Figure 4 – Scatter plots of simulated vs observed water temperature. Simulations are results from *air2stream* with 1 and 2 years of calibration. Each panel shows results using the main equation with different numbers of coefficients.




A comparison between air temperature, observed water temperature and simulated water temperature by correlation and the *air2stream* model showed a better estimation of *air2stream* (Figure 5).

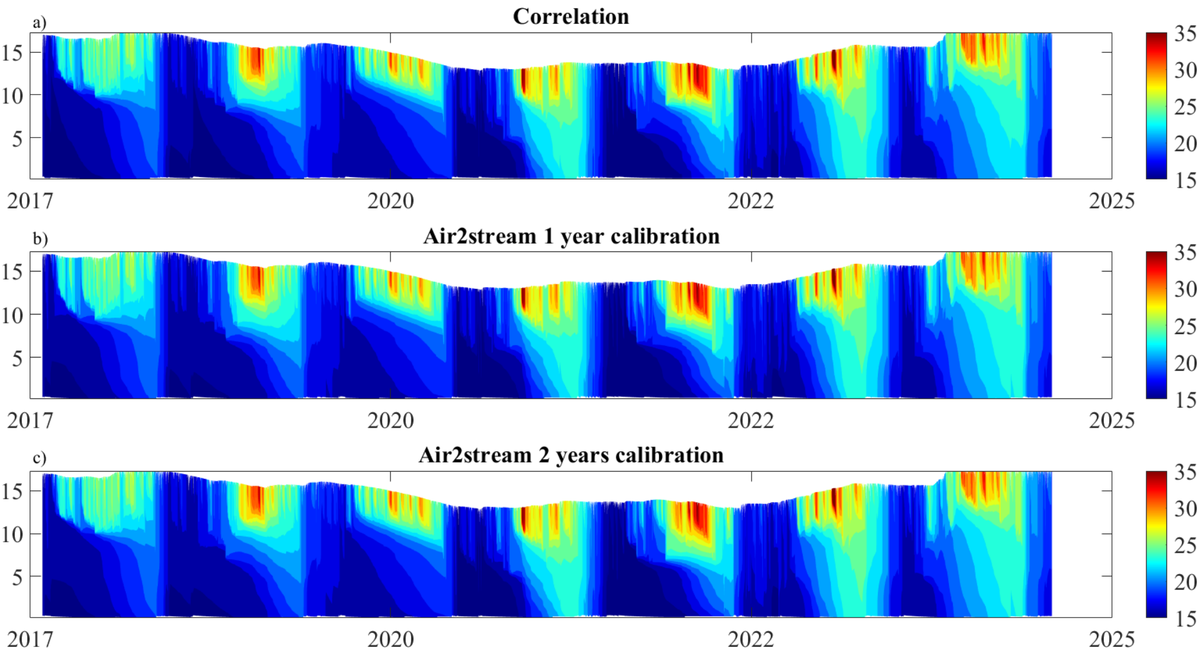
Figure 5 – Each panel shows in light blue the air temperature, in red the observed temperature and in dark yellow the simulated temperatures by: a) correlation between air temperature and water temperature; b) *air2stream* model with 1 year of calibration period; and, c) *air2stream* model with 2 years of calibration period



*Reservoir water temperatures modelled with GLM*

The GLM model was run for both methods of river temperature estimation, air temperature correlation and *air2stream* (5 coefficients). The results showed that temperature differences increased with depth, while surface level temperatures exhibited only minimal variation (Figure 6). The maximal difference at surface level lies by 1.6 °C. Punctual higher temperatures were identified on the surface that could be related to the interpolation in the radiation input data. However, this result does not interfere in the comparison of the methods to river temperatures estimations, but highlights the need to also improve also this gap fill methodology.

Figure 6 – General lake model simulation results using river temperatures obtained by: a) air temperature correlation (Colombo 2019); b) *air2stream* with 1 year of calibration and c) *air2stream* with 2 years of calibration.




Depending on the depth, the differences are more observable (Figure 7). Figure 8 exhibits the difference plot for the depth 0 to 14 m. In the midwater depth at 4 and 8 m depth the greatest differences are recorded. The highest differences recorded are around 5 °C, but only in isolated instances. Overall, it can be seen that the surface temperature differentiates only under 0.5 °C to each other when used in the GLM model.

Figure 7 – Contour plot of the differences between water temperatures (in °C) from correlation and air2stream 2 years.

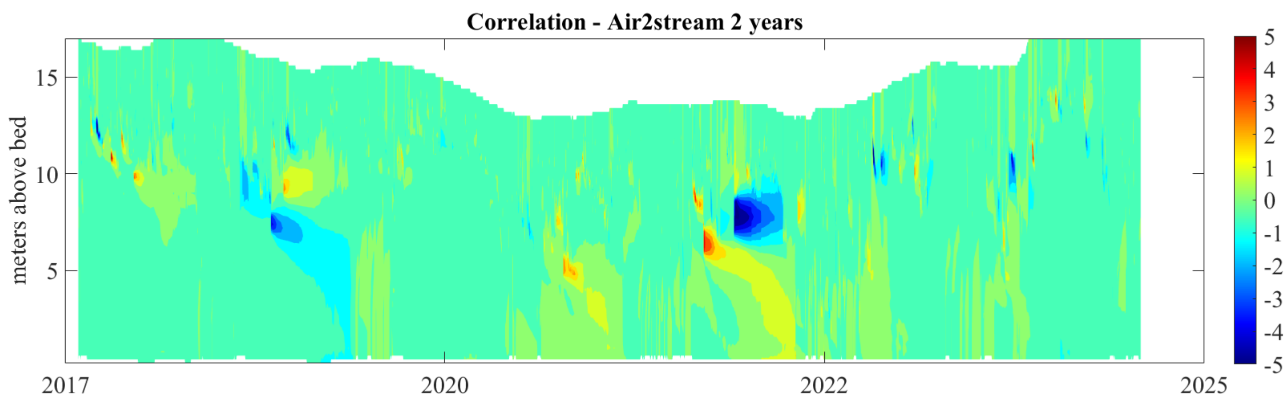
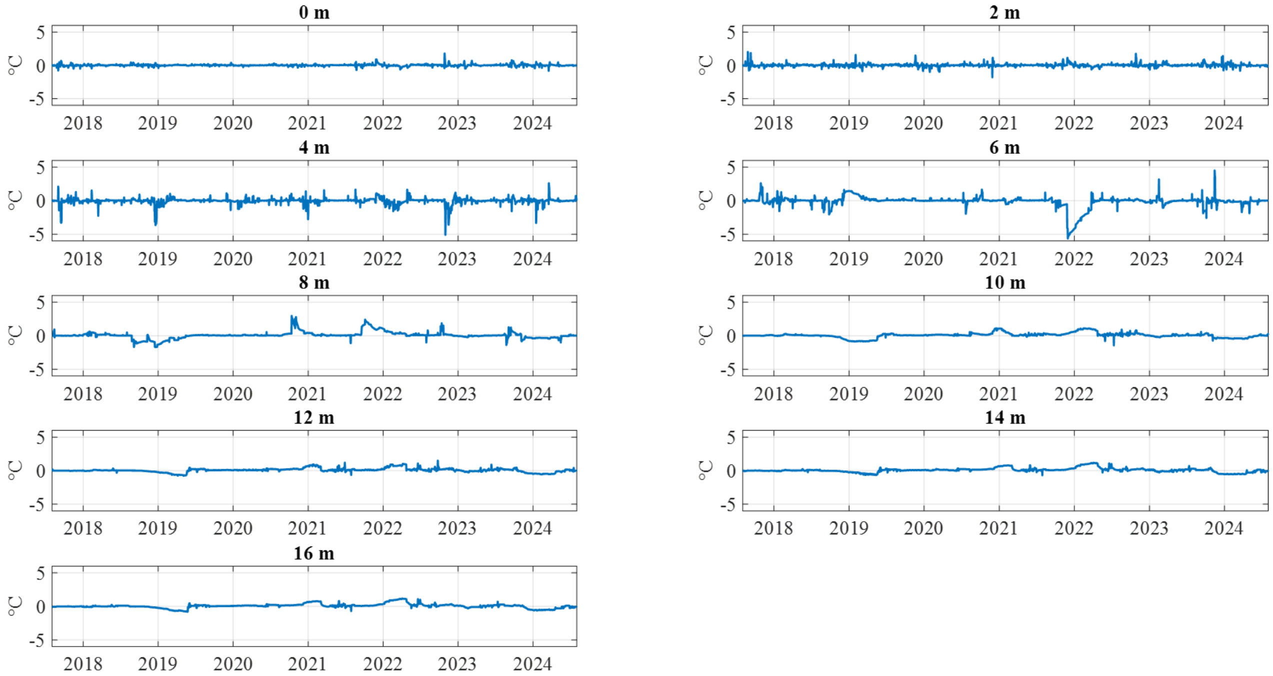


Figure 8 – Differences between correlation and air2stream temperatures in each depth.




## CONCLUSION

Since water temperature plays an integral role in water body modeling, high quality data for inputs is important. The two methods, correlation and *air2stream*, showed in this study their suitability to fill in incomplete or missing data. This plays an important role, since monitored data is not always available. Since the *air2stream* model can be calibrated using different numbers of coefficients it was found that using five coefficients resulted in the best results for Passaúna River. This can be traced back to the better adaptation to the gaps in the air and water temperature data. Also, calibrating the data with longer (2 years) and shorter periods (1 year) proved to lead to different results with the two-year calibration yielding better results.

Directly comparing the two methods to the measured data, showed only minor discrepancies, with *air2stream* performing marginally better than the correlation approach. Applied to the Passaúna reservoir with the GLM model, only small variations were displayed as well. The surface temperature and bottom layers appeared nearly identical, whereas the mid-depth more pronounced discrepancies were found. The surface is primarily influenced by the meteorological conditions such as air temperature and radiation. In contrast, the mid-depth region, where the inflow is introduced and temperatures are similar, experiences greater impact from the input.

Air2stream, with its basis on air temperature and stream discharge also provides the option to model future climate conditions, enabling the options to model different scenarios with greater certainty than other regressive models. In the case of the Passaúna river, by disregarding the influence of the discharge, better results can be achieved for rivers, since they are not significantly affected by external factors, as seen here.

Since GLM is only a 1D- model, performances of these methods can differ with dimensionality (2D and 3D). 1D- models often struggle to accurately simulate thermal stratification patterns and thermocline depth. Water temperature is closely reflected in these dynamics, leading to the question whether such patterns are even more affected by the limitations of 1D modeling.

With better calibration of the air2stream and GLM models, results can further be improved. As a next step, the comparison of the total energy input from the inflows and heat fluxes can be considered, to investigate the overall energy input from the river, changes in the temperature profile, and stability.

## REFERENCES


ALMEIDA, M. C.; COELHO, P. S. (2023). "*Modeling river water temperature with limiting forcing data: Air2stream v1.0.0, machine learning and multiple regression*". Geosci. Model Dev., 16, 4083–4112.

BOEHRER, B.; SCHULTZE, M. (2008). "*Stratification of lakes*", Rev. Geophys., 46, RG2005.

COLLISCHONN, W.; TUCCI, C. E. M. (2001). "*Simulação hidrológica de grandes bacias*". Revista Brasileira de Recursos Hídricos, v. 6, n. 2.

COLOMBO, G. T. (2019). "*Dinâmica Térmica Em Rios E Relações Com Variáveis Meteorológicas*". (Dissertação Mestrado) Programa de Pós-Graduação em Engenharia Ambiental da Universidade Federal do Paraná. Curitiba, 145 pp.

DORY, F.; NAVA, V.; SPREAFICO, M.; ORLANDI, V.; SOLER, V.; LEONI, B. (2024). "*Interaction between temperature and nutrients: How does the phytoplankton community cope with climate change?*". Science of the Total Environment, v. 906, 167566.

FEIGL, M.; LEBIEDZINSKI, K.; MATHEW HERRNEGGER, M.; SCHULZ, K. (2021). "*Machine-learning methods for stream water temperature prediction*". Hydrol. Earth Syst. Sci., 25, 2951–2977.

FAN, F. M.; COLLISCHONN, W. (2014). "*Integração do Modelo MGB-IPH com Sistema de Informação Geográfica*". Revista Brasileira de Recursos Hídricos, v. 19, p. 243-254.

HAAG, I.; LUCE, A. (2008), "*The integrated water balance and water temperature model LARSIM-WT*". Hydrol. Process., 22: 1046-1056. https://doi.org/10.1002/hyp.6983

HIPSEY, M. R.; BRUCE, L. C.; BOON, C.; BUSCH, B.; CAREY, C. C.; HAMILTON, D. P.; HANSON, P. C.; READ, J. S.; DE SOUSA, E.; WEBER, M.; AND WINSLOW, L. A. (2019). "*A General Lake Model (GLM 3.0) for linking with high-frequency sensor data from the Global Lake Ecological Observatory Network (GLEON)*", Geosci. Model Dev., 12, 473–523.

ISHIKAWA, M.; HAAG, I.; KRUMM, J.; TELTSCHER, K.; LORKE, A. (2021). "*The effect of stream shading on the inflow characteristics in a downstream reservoir*". River Res Applic. 37:943–954.

ISHIKAWA, M.; GONZALEZ, W.; GOLYJESWSKI, O.; SALES, G.; RIGOTTI, J. A.; BLENINGER, T.; MANNICH, M.; LORKE, A. (2022). "*Effects of dimensionality on the performance of hydrodynamic models for stratified lakes and reservoirs*". Geoscientific Model Development, v. 15, p. 2197-2220.

MUHLENHOFF, A. P. (2023). "*Calibração De Modelo Hidrológico Usando Informação "A Priori" Utilizando Técnica De Otimização Estocástica*". (Tese Doutorado). Programa de Pós-Graduação em Engenharia de Recursos Hídricos e Ambiental da Universidade Federal do Paraná. Curitiba, 158 pp.

MARCON, L. (2019). "*Investigation of the spatial and the temporal dynamics of ebullition from water bodies*". Curitiba: Universidade Federal do Paraná (UFPR), Relatório de Qualificação de Tese (Doutorado). 71 p.

PHILIPPUS, D.; SYTSMA, A.; RUST, A.; HOGUE, T. S. (2024). "*A machine learning model for estimating the temperature of small rivers using satellite-based spatial data*". Remote Sensing of Environment, 311, 114271.

TOFFOLON, M.; PICCOLROAZ, S. (2015). "*A hybrid model for river water temperature as a function of air temperature and discharge*". Environ. Res. Lett. 10 114011, 2015.

## ACKNOWLEDGMENTS

The authors acknowledge provision of data from SANEPAR (Paraná State Water and Sanitation Company, Brazil). Tobias Bleninger acknowledges the productivity stipend from the National Council for Scientific and Technological Development – CNPq, grant no. 313491/2023-2, call no. 09/2023. Michael Mannich acknowledges productivity stipend from the National Council for Scientific and Technological Development—CNPq, grant no. 308744/2021-7, call 04/2021.