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Review of Statistical Water Temperature Models for a Peruvian Andean River

Efrain Noa-Yarasca[1], Diana Chaca Ayuque[2], Hugo A. Galvan Ccora[2], Ivan A. Ayala Bizarro[2] and Ada Arancibia[5]

1. School of Civil & Construction Engineering, Oregon State University, Corvallis, OR 97331, USA

2. Faculty of Civil Engineering, National University of Huancavelica, Huancavelica 09001, Peru

5. Faculty of Civil Engineering, National University of Engineering, Lima 15333, Peru

Abstract: The rapid increase in Water Temperature Rivers (WTR) observed globally in recent decades and projections for the coming decades under climate change scenarios make water temperature prediction essential to assess changes in aquatic biota. Statistical models for stream temperature prediction have been widely used because they are computationally simple, involve few parameters, and because of their relatively good accuracy. However, these models have not been evaluated in Peruvian Andean rivers. This work evaluates the main water temperature statistical models from the literature and fits them with data recorded in the Ichu River experimental watershed, Huancavelica-Peru. Three well-known models were reviewed: the Stefan & Preud'homme linear regression model and the Mohseni & Stefan 3- and 4-parameter logistic regression models. Ichu river water temperatures were simulated using the SWAT (Soil and Water Assessment Tool) hydrometeorological model, which defaults to the Stefan & Preud'homme model. Modifications and adjustment of coefficients of the evaluated models were configured in the SWAT code using the "Latin Hypercube Sampling" technique. The evaluated models showed poor performance in predicting the water temperature in the Ichu River with NSE (Nash-Sutcliffe Efficiency) values ranging from -2.6 to 0.49, while the modified models showed NSE values of 0.72 in all three cases. Findings suggest that the statistical models shown in the literature should be validated for Andean rivers.

Key words: Water temperature modeling, Ichu River, Peruvian Andes River, statistical modeling.

1. Introduction

The rapid increase in WTR (Water Temperature in Rivers) observed globally in recent decades and projections for the coming decades under climate change scenarios make water temperature prediction essential to assess changes in aquatic biota. Stream temperature as a key parameter of water quality is the main indicator and driver of the aquatic ecosystem and is strongly related to other water quality parameters, such as dissolved oxygen, salinity, pH, among others [1, 2]. Significant changes in stream temperature above natural ranges can cause death and/or migration of endemic species and the potential rise of exotic species that could lead to an ecological imbalance [3]. Increments in stream temperature of 1 to 2 ℃ combined with altered hydrologic regimes could be lethal for the physiological function of fish [4]. In addition, elevated stream temperatures can accelerate natural chemical reactions, release excess of nutrients, increase the solubility of heavy metals like cadmium and zinc, which are toxic for the aquatic ecosystem, reduce the dissolved oxygen levels, reduce the pH, increase the conductivity, among others [5]. Deployed water quality affects not only the aquatic ecosystem but also society in terms of health and economy. In health, individuals in contact with polluted water can get skin diseases. In economics, the treatment of poor-quality water demands a higher cost that is ultimately assumed by the community.

In the context of climate change, predictions estimate that stream temperature will continue to rise,

Corresponding author: Efrain Noa-Yarasca, Ph.D., research field: water resources, GIS, remote sensing, applied machine learning.

not only due to the increment of air temperature which has a direct effect on stream temperature, but also due to human activities such as the increase of effluents, implementation of barriers, changes in land use, and overexploitation of water resources [4, 6-9]. Global predictions of stream temperature rise indicate high increases in the US, Europe, East of China, and some regions of South America [9-11]. Global projections derived from global climate models of CMIP3 (Coupled Model Intercomparison Project Phase 3) and CMIP5 for RCPs (Representative Concentration Pathways) of 4.5 and 8.5 indicate increases in air temperature in +1.7 and +6.7 °C in South America [12]. These air temperature increases and consequently, stream temperature increase, could sharpen even more issues within the aquatic ecosystem. For instance, at the global level, the freshwater fish population has decreased on average by 76% in the last 50 years due to poor conditions. These include elevated stream temperatures, river barriers and overexploitation. In South America, this population reduction is even more worrying, with a reduction of 84% in the fish population during the same period [13].

The rise in stream temperature in recent decades has increased the interest of the scientific community in developing predictive models and mitigation measures. These models, mainly classified as mechanistic and statistics, vary from simple to complex, involving few to several variables, from fractions of hours to annual time step scale, and from local to regional space scale [7, 14]. Mechanistic models are numerical models based on physics that involve concepts of water and energy balance processes, while statistical models establish functional relationships between stream temperature and meteorological and physical variables of the watershed [15-17]. Statistical methods differ from mechanistic methods by their simplicity and fewer predictor variables. Within the statistical methods of daily scale, we have the linear model of Stefan [18], non-linear model of 3 and 4 parameters of Mohseni [19]. More complex statistical models involve autocorrelation components [20], multiple linear regression models, generalized additive models, and linear mixed models (Donato, 2002 [3, 21]. With fair accuracy, these models were primarily tested and calibrated on rivers in the United States. In contrast, stream temperature of the South American Andes' rivers has been studied to a much lesser extent than the rivers of other regions of the world. The Andes significantly interrupt atmospheric circulation, generating singular climate conditions along the eastern and western slopes and in adjacent valley areas [22]. In these peculiar conditions, it is necessary to review the stream temperature prediction equations presented in literature. In this work, the main statistical models for stream temperature prediction (the Stefan & Preud'homme linear model and the Mohseni & Stefan logistic models of 3 and 4 parameters) are evaluated and adjusted for the Ichu River, located in the Huancavelica region of the Peruvian Andes. This paper portrays an evaluation of the main statistical models for stream temperature prediction, applied to the IREW (Ichu River Experimental Watershed) located in the Peruvian Andes. After evaluating, this work also adjusted the coefficients of the Stefan & Preud'homme linear model and of the Mohseni & Stefan logistic models of 3 and 4 parameters with the daily stream temperature registered in the Ichu River.

2. Materiales and Methods

2.1 Study Area

The IRW (Ichu River Watershed), located in the central highlands of Peru, is part of the Mantaro River watershed that contributes to the Amazon (Fig. 1). The IRW is characterized by its high mountains and narrow valleys typical of the South American Andes. The highest peaks have permanent glaciers throughout the year that maintain permanent flows in the various streams and tributary rivers of the Ichu River. The watershed drainage area at the Huancavelica station is 615.8 km^2.

The IREW shows varied land uses classified into ten types, of which the most representative are Andean grasslands and coastal and Andean agriculture. Land uses with smaller extensions are wetlands, high Andean areas with little or no vegetation, matorrals, ponds, glaciers, and urban areas [23, 24]. The IRW is mainly dominated by three types of soils: recent alluvial soils carried by rivers, deep old alluvial soils of low natural fertility, and residual soils formed by heterogeneous materials from the tertiary and quaternary (shales, siltstones, sandstones, and gravels) [25].

2.2 Data Collection and Processing

The Ichu River stream temperature was monitored in the section of the river 600 m upstream from the Huancavelica station, away from the influence of the two hot spring point sources located 350 and 365 m upstream from the Huancavelica station (Fig. 2). Temperatures were recorded three times a day (7-8 am, 12-1 pm and 5-6 pm) for a period of 16 months between 01/01/2000 and 04/30/2021. The three measurements were averaged and set as mean daily temperature. Daily temperatures show a mean of 11.27 ℃ (SD = 1.16 ℃) over a range of 7.40 to 14.35 ℃. Low temperatures were mainly observed in winter (June, July and August), while high temperatures were observed mainly in summer (November to March).

Daily records of precipitation and air temperature were available at six meteorological stations at IREW in the period from 01/01/2016 to 12/31/2021 (Fig. 1). This information was input into the SWAT (Soil & Water Assessment Tool) model for flow calibration purposes and subsequent water temperature simulation. Precipitation records show heavier rains in summer (December-April) and mild rains in winter (June-September). Regarding air temperature, high temperatures are shown between December and March and low temperatures between May and September.

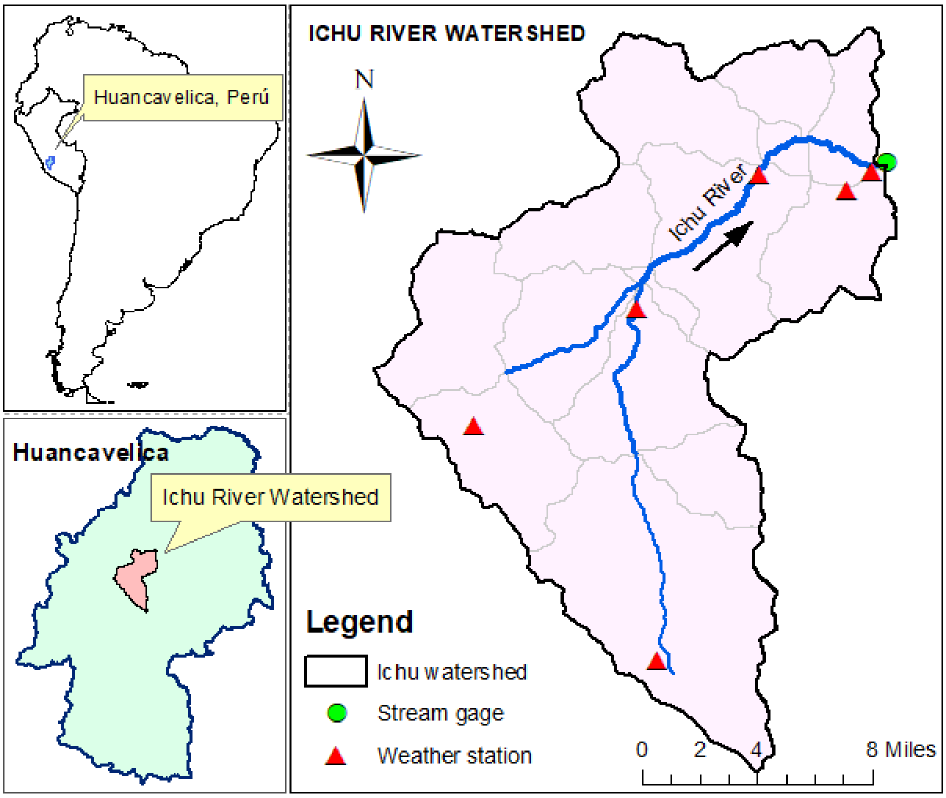

Fig. 1 Top left, location of Huancavelica department in Perú, Bottom left, location of IRW in the Huancavelica department; Right: streams, sub-basins, weather, and streamflow stations of the IRW.

This map is also available in an online version at https://noayarae.github.io/whis/projects/ichu_map.html.

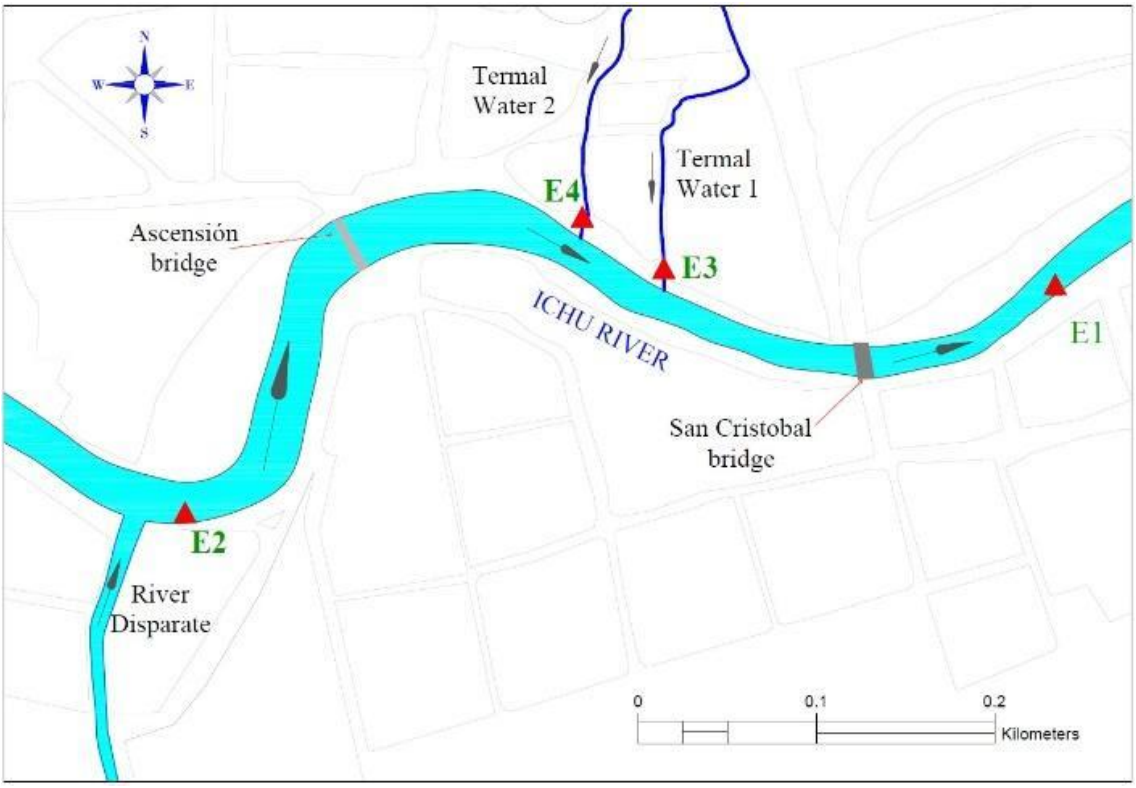

Fig. 2 Water temperature monitoring sites in the Ichu River (E1 and E2) and at the mouth of two thermal water tributaries (E3 and E4).

The topographic data were obtained from the DEM (Digital Elevation Model) which was retrieved from the NASA (National Aeronautics and Space Administration) Earth data repository [26] in raster format of 12.5 × 12.5 m cell size. The land use data corresponded to the Landsat 4 and Landsat 7 satellite measurements from 2010, obtained from the United Nations Land Cover Map (Globe land 30-NGCC) database (United Nations, 2021) in raster format of 30 × 30 m cell size. Soil information was obtained from the "Food and Agriculture Organization of the United Nations" database [27] in raster format of 500 × 500 m cell size.

The Ichu River flow is measured at the Huancavelica station (Fig. 1) (Lat.: -12.7893°, Long.: -74.9791°). Daily flow data were available for the period from 01/01/2016 to 12/31/2021, of which the first two years were used for warming up the SWAT model and the following years for model calibration and validation. The flow average in this period was 3.26 m^3/s (SD = 15.69 m^3/s). High flows were registered from December to February and low flows from June to September.

2.3 Flow and Stream Temperature Modeling

2.3.1 Flow Modeling

Flow and water temperature modeling were conducted using the SWAT 2012 [28, 29]. For this purpose, the IRW was divided into fourteen sub-basins, with areas ranging from 5.38 km^2 to 136.20 km^2. After setting the DEM into the SWAT model, the topographic slope was calculated and classified into four ranges (0-5%, 5%-15%, 15%-30%, and > 30%). After entering the land use and soil data into the SWAT model, the IRW was divided into 58 HRUs (Hydrologic Response Units), which are the basic SWAT analysis units. HRUs are portions of areas that have a unique combination of topographic slope, land use, and soil type. To avoid forming very small HRUs, HRUs with area portions less than 10% of the sub-basin were aggregated to neighboring HRUs [28]. Other considerations in the SWAT model were curve number method for runoff

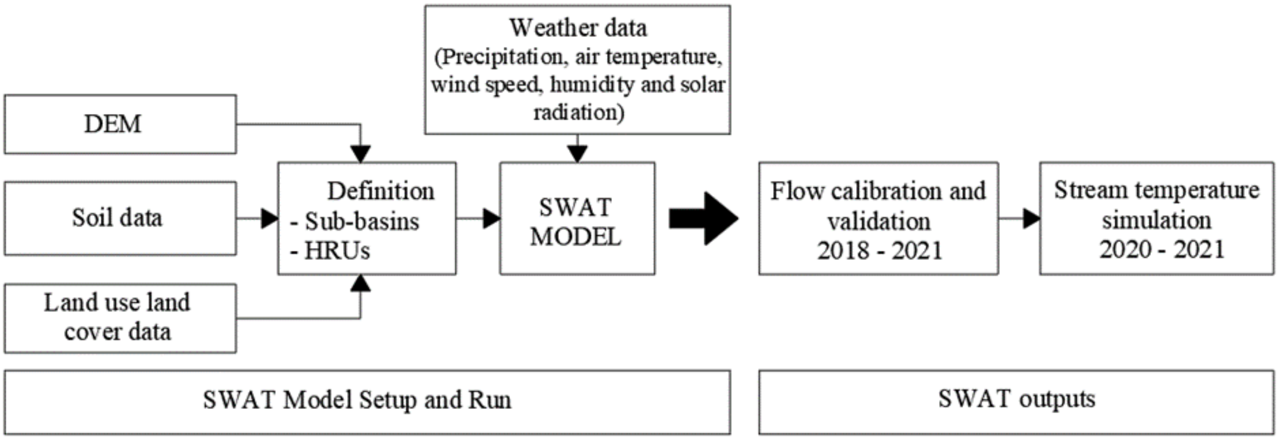

Fig. 3 Flowchart of Ichu River stream temperature simulation using the SWAT model.

estimation, variable storage method for flow runoff, no agricultural drainage, no reservoirs, no ponds, no wetlands, and no farming operations. Then, the streamflow was simulated on a daily time step from 01/01/2016 to 12/31/2021. The model calibration and validation were conducted at the Huancavelica station.

2.3.2 Stream Temperature Modeling

The Ichu River stream temperature was simulated using the SWAT water temperature sub-model, which by default uses the linear model of Stefan & Preud'homme [18, 29] with the air temperature as the only predictor. The evaluation period was from 01/01/2000 to 04/30/202. Fig. 3 shows the flow chart of streamflow and water temperature simulation using the SWAT model.

2.4 Stream Temperature Models

Statistical water temperature models evaluated in this work were the linear model of Stefan & Preud'homme [18] and the logistic (no-linear) model of three and four parameters (3P, 4P) of Mohseni & Stefan [19] that consider the air temperature as the only predictor. The Stefan & Preud'homme [18] model for daily temperatures is given by Eq. (1).

$$T_{\mathrm{w}} = a + b \ T_{\mathrm{air}} \tag{1}$$

where T_{air} and T_{w} are the air and water temperature in ℃, respectively, and a = 5.0 and b = 0.75. This equation was calibrated and used in several rivers of the Mississippi River Basin with satisfactory results in moderate ranges of air temperature. However, in very cold and very hot regions, the air temperature-water temperature relationship does not follow a linear relationship but takes the form of S [19]. Stream temperature non-linear models [19, 20, 30] are given by:

$$T_w = \frac{\alpha}{1 + e^{\ \gamma(\beta - T_{air})}} \tag{2}$$

$$T_w = \mu + \frac{\alpha - \mu}{1 + e^{\ \gamma(\beta - T_{air})}} \tag{3}$$

where α is the coefficient that determines the upper limit of stream temperature, β is the coefficient that determines the inflection limit of the logistic function, γ is the coefficient that represents the steepness of the slope of the function, and μ is the coefficient representing the lower limit of the water temperature.

3. Results and Discussion

3.1 Flow Calibration

The daily streamflow calibration was conducted using the SUFI-2 algorithm within the SWAT-CUP software [31]. The NSE (Nash Sutcliffe Efficiency) value for the calibrated flow model was 0.61; and the PBIAS (Percentage of Bias) was 7.4%. The NSE value is consistent with calibrations conducted in other watersheds [28, 32], in which the NSE value for flow calibration was in the range of 0.58 and 0.98 and the PBIAS was less than 10%. The calibrated parameters and the observed and calibrated flow at the Huancavelica station are shown in Table S1 and Figure S1 of the supplementary material accompanying the article.

3.2 Stream Temperature Simulation

Simulation of the Ichu River stream temperature using the Stefan & Preud'homme linear model in the SWAT showed values above the observed stream temperatures. While the average of the observed temperatures was 11.27 ℃, the average of the simulated temperatures was 13.46 ℃. Simulated water temperatures show an NSE value of -2.67, Pearson's coefficient of 0.85, RMSE (Root Mean Square Error) of 2.24, and PBIAS of 18.9%. Despite the high Pearson coefficient indicating that the model is relevant in representing the behavior of the observed water temperature, the model is not capable of representing the mean of the observed water temperature (Fig. 4). Simulated stream temperatures using the Mohseni & Stefan nonlinear model of 3P and 4P showed NSE values of 0.33 and 0.49, respectively. Although this model improved the stream temperature predictions, the NSE values are still relatively low.

3.3 Linear Model for the Ichu River

The SWAT water temperature sub-model code version rev.681 [33] was modified by replacing the two fixed coefficients of the Stefan & Preud'homme equation [18] with two variables. Following the Latin Hypercube Sampling criterion [34], 500 samples of pairs of the Stefan & Preud'homme equation's coefficients (a and b, Eq. (4)) have been generated, in the neighborhood of the default values to perform 500 simulations. These coefficients converged in a = 4.18 and b = 0.63. Details of the convergence are available as Supplementary Material accompanying the article. With these coefficients, the values of NSE, Pearson's coefficient, RMSE and PBIAS obtained were 0.72, 0.85, 0.62 and 0.1%, respectively, which are considerably higher than the corresponding values obtained using the default Stefan & Preud'homme equation. Fig. 5 shows the Ichu River stream temperature simulated with the modified Stefan & Preud'homme equation.

3.4 Nonlinear Model for the Ichu River

The two nonlinear models of Mohseni & Stefan (3P & 4P) [19] were also implemented in the water temperature sub-model of the SWAT code version rev.681. Using the Latin Hypercube Sampling criterion [31], 500 samples of three variables (α, β and γ) and four variables (α, β, γ and μ) were generated for the 3P and 4P models, respectively (Eqs. (2) and (3)). In the 3P model, the α, β and γ coefficients converged to 28.93, 16.05 and 0.093, respectively. With these coefficients, the values of NSE, Pearson's coefficient, RMSE and PBIAS obtained were 0.715, 0.85, 0.62 and 0.2%, respectively.

Similarly, in the 4P model, the coefficients α, β, γ and μ converged to 30.04, 17.08, 0.097 and 0.669, respectively. With these coefficients, the NSE, Pearson's coefficient, RMSE and PBIAS were 0.714, 0.85, 0.62 and 0.34%, respectively. Details of the 3P and 4P model parameters' convergences and simulated stream temperatures are available as Supplementary Material accompanying the article.

3.5 Performance of Statistical Models

The performance of the three statistical models evaluated, as well as the fitted models (modified models) together with the observed water temperature, is shown in Fig. 6. The observed water temperature shows the effect of seasonal hysteresis between air and water temperatures. This could be due to the influx of uncontrolled flows, such as hot springs and spring thaws, which make the river temperature cooler during this period than a similar air temperature during the fall [35].

Regarding the evaluated models, the default Stefan & Preud'homme model shows an overestimation of the water temperature of the Ichu River even above the hysteresis. Although this model manages to maintain a

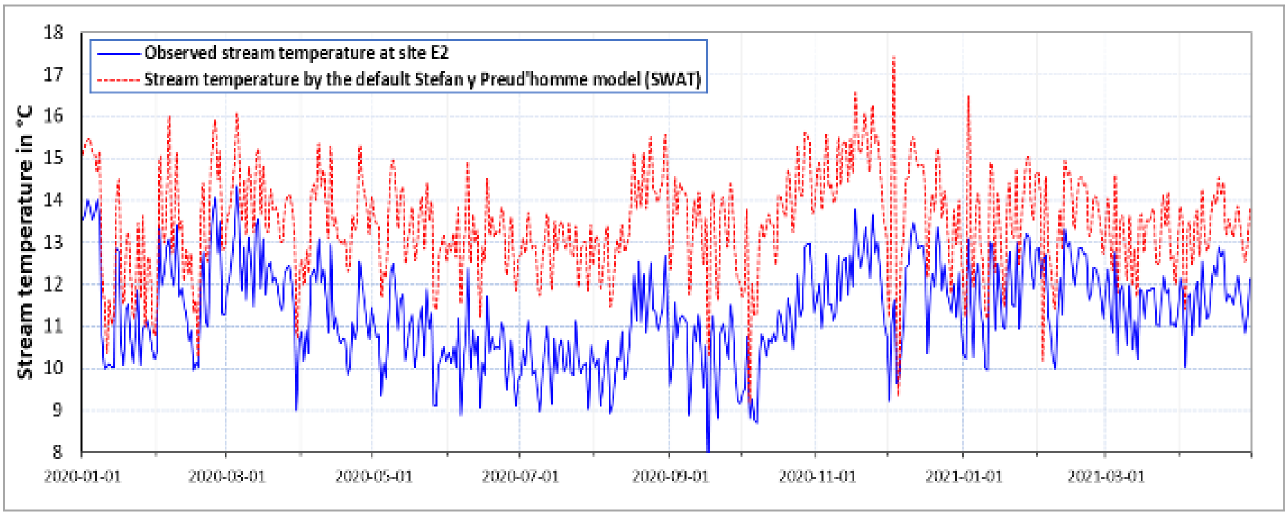

Fig. 4 Performance of the default Stefan & Preud'homme linear model in the Ichu River stream temperature simulation.

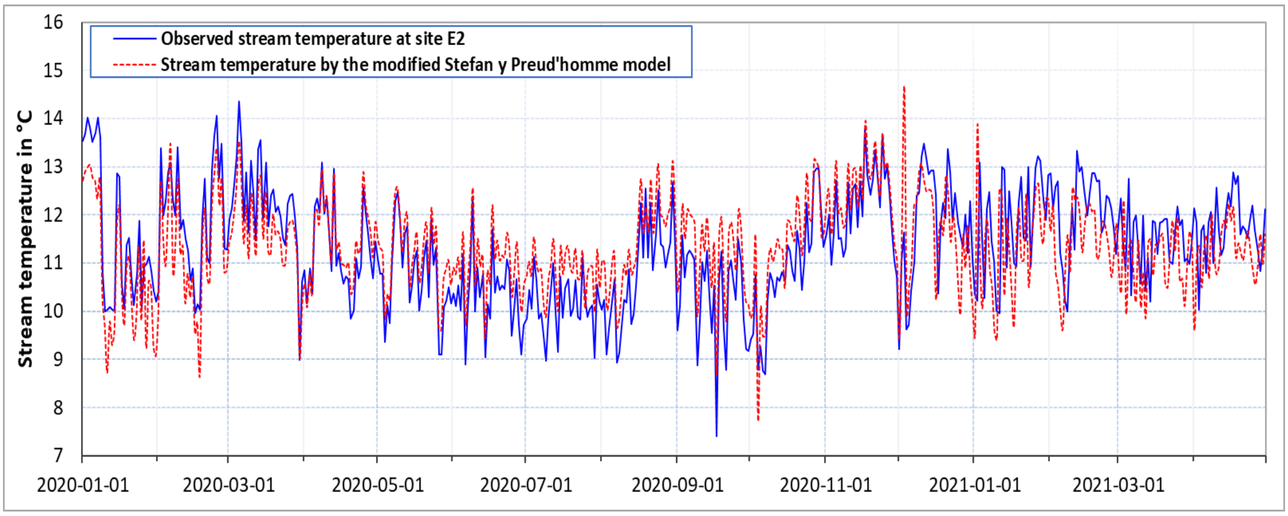

Fig. 5 Performance of the modified Stefan & Preud'homme linear model in the Ichu River stream temperature simulation.

Table 1 Evaluation and calibration statistics for the original and modified statistical water temperature models for the Ichu River.

Performance parameters	Stefan & Preud'homme	Mohseni & Stefan 3P	4P	Stefan & Preud'homme	Mohseni & Stefan 3P	4P
	Default models			Modified models		
NSE	-2.67	0.33	0.49	0.72	0.72	0.72
R	0.85	0.85	0.85	0.85	0.85	0.85
RMSE	2.24	0.96	0.84	0.63	0.62	0.62
PBIAS	18.90	-3.64	0.47	0.14	0.23	0.34

similar slope to the observed data, it does not manage to preserve the mean. On the other hand, the Mohseni & Stefan default nonlinear models show better performance than the linear model, with PBIAS coefficients in accepted good fit ranges (PBIAS < 10%) in Table 1. However, these nonlinear models show a different trend to the observed data, with significantly different slopes (p = 0.49). These models achieved relatively good prediction over a small range of the air temperature (11-13 ℃); however, for high air temperature records, predictions are overestimated, while for low air temperatures, they are underestimated (Fig. 6).

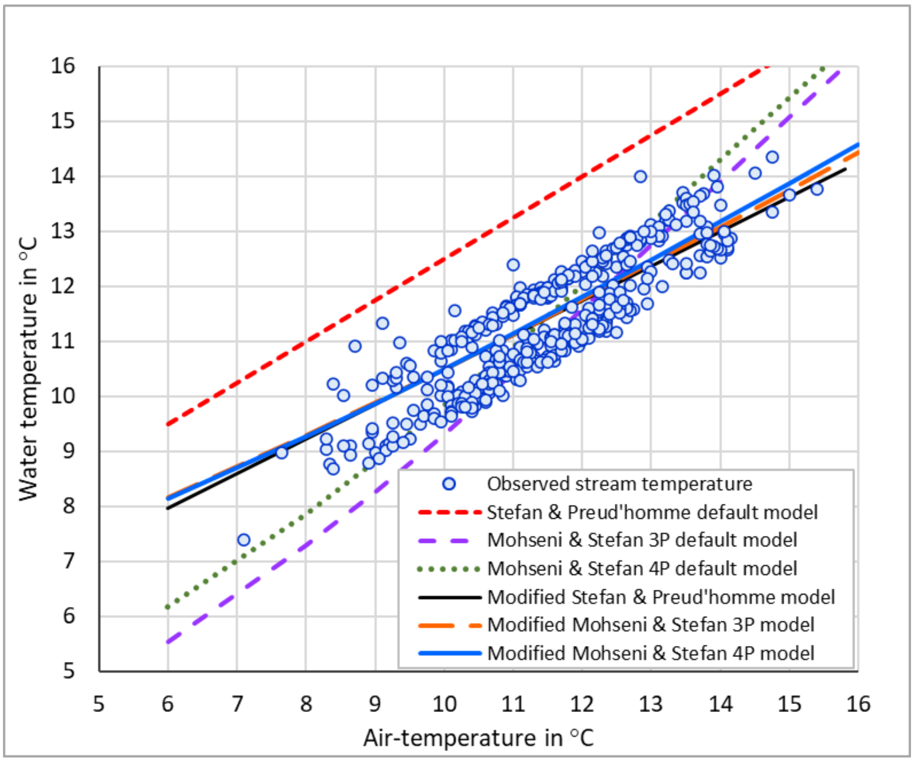

Fig. 6 Prediction of the water temperature for the Ichu River using the default and modified model of Stefan & Preud'homme and the Mohseni& Stefan model of 3P and 4P.

The modified statistical models with fitted coefficients for the Ichu River generally performed better than their corresponding ones. The performance coefficients among the modified statistical models were quite similar as shown in Table 1.

4. Conclusions

This article portrays an assessment of the main statistical water temperature models applied to the IRW in the Peruvian Andes. The linear model of Stefan & Preud'homme, used by default in the SWAT, and the non-linear models of Mohseni & Stefan with 3 and 4 parameters were reviewed. Modifications of these statistical models for the Ichu River were configured in the SWAT code and the corresponding coefficients were identified using the Latin Hypercube Sampling technique.

Findings showed that the default linear model of Stefan & Preud'homme overestimates the water temperature in this part of the Peruvian Andes, despite showing a good representation of variability. Therefore, this work suggests fitting new linear model parameters for the Ichu River. The fitted linear model for the Ichu River (modified model) showed a relevant representation of both the mean and the variability of the observed water temperature. The non-linear models of Mohseni & Stefan of 3P and 4P fitted to the Ichu River also showed a relevant representation of the mean and variability of the water temperature. Overall, the modified statistical models for the Ichu River outperformed the default models. However, the modified model of Stefan & Preud'homme could be recommended as it is simple with fewer parameters.

Although linear and non-linear statistical models for water temperature have been well studied in various rivers around the world, they have not been verified in rivers of the South American Andes. In this line, this study contributes to the understanding of the relationship between air and water temperature of the Ichu River in the Peruvian Andes. However, findings of this study are limited to the ranges used here, as well as the Ichu Rive characteristics. Future research should continue exploring larger temperature ranges to develop a broad and general understanding of the air-water temperature relationship in the Peruvian Andes. Within this region, it is also suggested to evaluate other water temperature models using more predictors to improve accuracy. Finally, it is also recommended to continue and expand water temperature monitoring in several rivers in the South American Andes, which are vulnerable to climate change.

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Supplementary Material

Additional tables, figures and data employed in this study are available as supplementary material on: Noa-Yarasca, Efrain, & Ayala Bizarro, Ivan. (2022). Tables, Figures, and data on Review of statistical water temperature models for a Peruvian Andean River. https://doi.org/10.5281/zenodo.7069415.

References

[1] Manasrah, R., Raheed, M., and Badran, M. I. 2006. "Relationships between Water Temperature, Nutrients and Dissolved Oxygen in the Northern Gulf of Aqaba, Red Sea." *Oceanologia* 48 (2): 237-53.

[2] Webb, B. W., and Walsh, A. J. 2004. "Changing UK River Temperatures and Their Impact on Fish Populations." *Hydrology: Science and Practice for the 21st Century* 2: 177-91. http://hdl.handle.net/10036/41373.

[3] Wehrly, K. E., Brenden, T. O., and Wang, L. 2009. "A Comparison of Statistical Approaches for Predicting Stream Temperatures across Heterogeneous Landscapes." *J Am Water Resour Assoc*. 45 (4): 986-97. doi: 10.1111/j.1752-1688.2009.00341.x.

[4] Ficke, A. D., Myrick, C. A., and Hanse, L. J. 2005. "Potential Impacts of Global Climate Change on Freshwater Fisheries." *Rev Fish Biol Fisheries* 17: 581-613. doi: 10.1007/978-4-431-53985-8_3.

[5] Fondriest Environmental Inc. 2014. "'Water Temperature.' Fundamentals of Environmental Measurements." https://www.fondriest.com/environmental-measurements/parameters/water-quality/water-temperature/.

[6] Hari, R. E., Livingstone, D. M., Siber, R., Burkhardt-Holm, P., and Güttinger, H. 2006. "Consequences of Climatic Change for Water Temperature and Brown Trout Populations in Alpine Rivers and Streams." *Glob Chang Biol*. 12 (1): 10-26. doi: 10.1111/j.1365-2486.2005.001051.x.

[7] Isaak, D. J., Wollrab, S., Horan, D., and Chandler, G. 2012. "Climate Change Effects on Stream and River Temperatures across the Northwest U.S. from 1980-2009 and Implications for Salmonid Fishes." *Clim Change* 113 (2): 499-524. doi: 10.1007/s10584-011-0326-z.

[8] Samuels, R., Hochman, A., Baharad, A., Givati, A., Levi, Y., Yosef, Y., Saaroni, H., Ziv, B., Harpaz, T., and Alpert, P. 2018. "Evaluation and Projection of Extreme Precipitation Indices in the Eastern Mediterranean Based on CMIP5 Multi-model Ensemble." *International Journal of Climatology* 38 (5): 2280-97. doi: 10.1002/joc.5334.

[9] Van Vliet, M. T. H., Ludwig, F., Zwolsman, J. J. G., Weedon, G. P., and Kabat, P. 2011. "Global River Temperatures and Sensitivity to Atmospheric Warming and Changes in River Flow." *Water Resour. Res*. 47 (2): 19. doi: 10.1029/2010WR009198.

[10] Kaushal, S. S., Likens, G. E., Jaworski, N. A., Pace, M. L., Sides, A. M., Seekell, D., Belt, K. T., Secor, D. H., and Wingate, R. L. 2010. "Rising Stream and River Temperatures in the United States." *Front Ecol. Environ*. 8 (9): 461-6. doi: 10.1890/090037.

[11] Van Vliet, M. T. H., Franssen, W. H. P., Yearsley, J. R., Ludwig, F., Haddeland, I., Lettenmaier, D. P., and Wimek, P. K. 2013. "Global River Discharge and Water Temperature under Climate Change." *Global Environmental Change* 23 (2): 450-64. doi: 10.1016/j.gloenvcha.2012.11.002.

[12] Magrin, G. O., Magrin, G. O., Marengo, J. A., Boulanger, J.-P., Buckeridge, M. S., Castellanos, E., Poveda, G., Scarano, F. R., and Vicuna, S. 2014. "Central and South America." In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Barros, Field, D. J. Dokken, M. D. Mastrandrea, K. J. Mach, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White. Cambridge and New York: Cambridge University Press. doi: 10.1177/136346157100800221.

[13] Deinet, S., Scott-Gatty, K., Rotton, H., Twardek, W. M., Marconi, V., McRae, L., et al. 2020. "The Living Planet Index for Migratory Freshwater Fish—Technical Report."

In *Science Into Policy*. Groningen: World Fish Migration Foundation, pp. 131-49.

[14] Isaak, D. J., Luce, C. H., Horan, D. L., Chandler, G. L., Wollrab, S. P., and Nagel, D. E. 2018. "Global Warming of Salmon and Trout Rivers in the Northwestern U.S.: Road to Ruin or Path through Purgatory?" *Trans Am Fish Soc*. 147 (3): 566-87. doi: 10.1002/tafs.10059.

[15] Boyd, J. W. 2006. "Practical Measurement of Ecosystem Services: Can We Standardize the Way We Count Nature's Benefits?" https://yosemite.epa.gov/ee/epa/eerm.nsf/vwAN/EE-0507-01.pdf/$file/EE-0507-01.pdf.

[16] Noa-Yarasca, E., Babbar-Sebens, M., and Jordan, C. 2021. "A Machine Learning Model of Riparian Vegetation Attenuated Stream Temperatures." In *An Abstract of the Dissertation*.

[17] Noa-Yarasca, E., Babbar-Sebens, M., and Jordan, C. 2021. "An Improved Model of Shade-affected Stream Temperature in Soil & Water Assessment Tool." *Hydrol. Earth Syst. Sci. Discuss. [preprint]*, https://doi.org/10.5194/hess-2022-116, in review, 2022.

[18] Stefan, H. G., and Preud'homme, E. B. 1993. "Stream Temperature Estimation from Air Temperature." *JAWRA Journal of the American Water Resources Association* 29 (1): 27-45. doi: 10.1111/j.1752-1688.1993.tb01502.x.

[19] Mohseni, O., and Stefan, H. G. 1999. "Stream Temperature/Air Temperature Relationship: A Physical Interpretation." *J. Hydrol. (Amst)* 218 (3-4): 128-41. doi: 10.1016/S0022-1694(99)00034-7.

[20] Benyahya, L., Caissie, D., St-Hilaire, A., Ouarda, T. B. M. J., and Bobée, B. 2007. "A Review of Statistical Water Temperature Models." *Canadian Water Resources Journal* 32 (3): 179-92. doi: 10.4296/cwrj3203179.

[21] Donato, M. M. 2002. "A Statistical Model for Estimating Stream Temperatures in the Salmon and Clearwater River Basins, Central Idaho YR-2002." *Water-Resources Investigations Report*, p. 46 p., 2002, [Online]. Available: http://pubs.er.usgs.gov/thumbnails/usgs_thumb.jpg%5Cn http://pubs.water.usgs.gov/wri024195/

[22] Garreaud, R. D. 2009. "The Andes Climate and Weather." *Advances in Geosciences* 22: 3-11. doi: 10.5194/adgeo-22-3-2009.

[23] Ayala, I. 2020. *Estudio Hidrologico de la Sub cuenca del rio Ichu*. Huancavelica. (in Spanish)

[24] Ayala, I., Zubiaur, M., and Zúñiga, J. 2018. "Prediction of Drought with Artificial Neural Networks and Genetic Algorithms Using Precipitation by Remote Perception." *Journal of Environmental Science and Engineering B* 7 (7): 253-65. doi: 10.17265/2162-5263/2018.07.002.

[25] Caso, E. 2012. *Estudio de suelos y capacidad de uso mayor de tierras—Huancavelica.* Huancavelica. (in Spanish)

[26] NASA. 2021. "Earthdata Open Access for Open Science." https://www.earthdata.nasa.gov/esds.

[27] Fischer, G., Nachtergaele, F., Prieler, S., Velthuizen, V. H. T., Verelst, L. and Wiberg, D. 2008. "Global Agro-ecological Zones Assessment for Agriculture (GAEZ 2008)." Laxenburg, Austria & Rome, Italy., 2008. [Online]. Available: https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/

[28] Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., van Griensven, A., Van Liew, M. W., Kannan, N., and Jha, M. K. 2012. "SWAT: Model Use, Calibration, and Validation." *American Society of Agricultural and Biological Engineers* 55 (4): 1491-508.

[29] Neitsch, S. L., Arnold, J. G., Kiniry, J. R., and Williams, J. R. 2011. "Soil and Water Assessment Tool Theoretical Documentation." Texas Water Resources Institute Technical Report No. 406. Agricultural Research Service (USDA) & Texas Agricultural Experiment Station, Texas A&M University, Temple.

[30] Mohseni, O., Stefan, H., and Erickson, T. 1998. "A Nonlinear Regression Model for Weekly Stream Temperatures." *Water Resour Res*, vol. 34, no. 10, pp. 2685–2692, Oct. 1998.

[31] Abbaspour, K. C. 2015. "SWAT-CUP: SWAT Calibration and Uncertainty Programs—A User Manual." doi: 10.1007/s00402-009-1032-4.

[32] Moriasi, D. N., Arnold, J. G., van Liew, M. W., Binger, R. L., Harmel, R. D., and Veith, T. L. 2007. "Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations." *American Society of Agricultural and Biological Engineers* 50 (3): 885-900. doi: 10.13031/2013.23153.

[33] TAMU. 2021. "SWAT: Soil & Water Assessment Tool." Texas A&M University. Accessed Oct. 27, 2021. https://swat.tamu.edu/.

[34] Iman, R. L. 2008. "Latin Hypercube Sampling." In *Encyclopedia of Quantitative Risk Analysis and Assessment*. doi: 10.1002/9780470061596.risk0299.

[35] Fellman, J. B., Nagorski, S., Pyare, S., Vermilyea, A. W., Scott, D., and Hood, E. 2014. "Stream Temperature Response to Variable Glacier Coverage in Coastal Watersheds of Southeast Alaska." *Hydrol Process* 28 (4): 2062-73. doi: 10.1002/hyp.9742.