BIOENG

Brazilian Journal of Biosystems Engineering (2022), 16 1094

REGULAR ARTICLE

Performance of sensors for quality analysis of irrigation water

Mádilo Lages Vieira Passos[1], Arthur Breno Rocha Mariano[2], Daniela Andreska da Silva[3], Alan Bernard Oliveira de Sousa[4]

[1]Doctoral candidate in the Postgraduate Program in Water Resources, School of Engineering, Federal University of Lavras - UFLA, Lavras, MG, Brazil.
[2]Graduating in Agronomy, Federal University of Ceará (UFC), Fortaleza, CE, Brazil.
[3]Master's student in the Postgraduate Program in Agricultural Engineering, Federal University of Ceará (UFC), Fortaleza, CE, Brazil.
[4]Department of Agricultural Engineering, Federal University of Ceará (UFC), Fortaleza, CE, Brazil.

Regular Section
Academic Editor: Fernando Ferrari Putti.

Statements and Declarations

Data availability
All data will be shared if requested.

Institutional Review Board Statement
Not aplicablle.

Conflicts of interest
The authors declare no conflict of interest.

Funding
The authors would like to thank the Coordination for the Improvement of Higher Education Personnel (CAPES) for the research grant of the first author, which enabled the development of the research.

Autor contribution
MLVP: Conceptualization, Experimental data collection, Data custody, Data analysis, Writing the manuscript; ABRM: Experimental data collection; DAdaS: Data analysis, Writing the manuscript, Manuscript Review; ABOdeS: Conceptualization, Data custody, Data analysis, Manuscript Review, Supervision.

Abstract

Monitoring the quality of irrigation water can help in the maintenance of filters and irrigation systems, avoiding clogs and uniformity problems. The objective of this work was, thus, to evaluate the performance of sensor modules for monitoring irrigation water quality variables. For that, three sensors were evaluated, and their performance was rated from the adjustment of calibration equations, obtained through linear regression analysis ($y_i = b_0 + b_1 x_i + \varepsilon_i$), using the ordinary least squares method (OLS) to estimate its parameters (β_0 and β_1). The first sensor evaluated was the Ph4502c for pH measurement. Direct methodology was used, using standard pH solutions (1.79; 4.5; 6.88; 12.13; and 13.99) and an electrode type BNC probe. The second evaluated sensor was turbidity model TSW30. To evaluate the total dissolved solids (TDS) sensor, the direct method was applied, using solutions with electrical conductivity of 0.50, 1.0, and 2.0 dS m^{-1}. To investigate the assumptions of independence, homoscedasticity, and normality of the residuals of the linear regression models, the Durbin-Watson, Breusch-Pagan, and Kolmogorov-Smirnov tests were respectively used. In the evaluation of the statistical performance, the indicators of the root-mean-square error, coefficient of determination, correlation coefficient, confidence index, and index of agreement were adopted. The ordinary least squares method did not produce the best unbiased linear estimators for the calibration equations of the pH, turbidity, and TDS sensors, due to the violation of the regression assumptions. The adjustments showed good accuracy for water quality assessment, according to high performance statistics and models classified as 'Excellent'.

Keywords

pH; turbidity; total dissolved solids.

Introduction

Water quality is directly related to its various components and concentrations in such a way that the classification of purity and potability is based on the amount of these elements (Brasil, 2014). In irrigated agriculture, the main parameters evaluated are the physical-chemical and biological variables. Thus, the main attributes analysed are pH, total dissolved solids (TDS), electrical conductivity, and ions (Almeida, 2010).

Water adequacy for irrigation purposes is still very subjective, however, it is important to evaluate and identify some parameters that may produce undesirable effects on the water, soil, and plant relationship (Sousa et al., 2001). Trentin and Souza (2006) emphasized the importance of analysing physicochemical characteristics, sanitary water quality, crop tolerance, soil characteristics, local climate, and irrigation management.

The methodologies for analysing water quality are diverse, either in the laboratory, using a previously collected sample, or using *in situ* devices for immediate data collection or monitoring (Leal Júnior et al., 2020). According to Pule et al. (2017), the adoption of sensors to the detriment of conventional collection methods has been highlighted in the most different means. In this respect, automatic data acquisition makes the course of the best management strategy.

Based on the above, the objective of this work was to evaluate the performance of sensor modules for monitoring irrigation water quality variables.

---

* Corresponding author
E-mail address: madilolages@hotmail.com (M. L.V. Passos).

https://doi.org/10.18011/bioeng.2022.v16.1094
Received: 04 February 2022 / Accepted: 10 June 2022 / Available online: 23 January 2022

Materials and methods

The experiment was carried out at the Hydraulics and Irrigation Laboratory of the Federal University of Ceará, Pici Campus, city of Fortaleza, state of Ceará, Brazil, under geographic coordinates 3° 45' latitude S, 38° 33' longitude W and mean altitude of 19 m.

Three sensors were evaluated in order to monitor irrigation water quality. To measure the pH, a sensor module Ph4502c, manufactured by Diymore, and an electrode type BNC probe were used. To quantify the turbidity, the sensor TZT teng Official Store, model TSW30, was adopted. In the quantification of total dissolved solids (TDS), a sensor model KS0429, from the manufacturer Keyestudio, was used to designate the quantity of milligrams of soluble solids in one litre of water.

For platform prototyping, Arduino Nano V3.0 hardware model and IDE (Integrated Development Environment) software were adopted. The construction of the multiparametric probe containing the components and the three water quality sensors cost about US$ 42.82. Figure 1 shows the probe prototyping scheme.

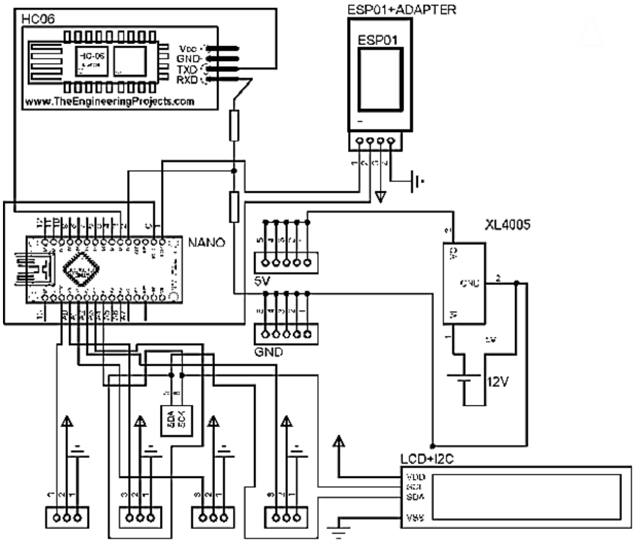

Figure 1. Schematic of multiparametric probe components.

In the calibration of the sensor module Ph4502c, the direct methodology was applied, using standard pH solutions, already known (pH=1.79; pH=4.5; pH=6.88; pH=12.13; and pH=13 .99), quantified by bench pH meter. For the turbidity sensor, the indirect method was applied, using a portable digital turbidimeter model Digimed DM-TU, previously calibrated in a Nephelometric Turbidity Unit (NTU) and with water solutions plus soil in different concentrations (1.3; 158.0; 255.4; 315.2; 427.4; 571.5; 632.8; and 713.0 NTU). To calibrate the total dissolved solids (TDS) sensor, the direct method was applied, using solutions with electrical conductivity of 0.50; 1.0; and 2.0 dS m^{-1}.

Most models applied to variables in the agricultural sciences are based on the structure response = structure + error (Mueller et al., 2001). In this sense, the calibration equations adopted the simple linear regression model, from which the coefficients were estimated by the ordinary least squares method (Equation 1). Adopting the method for estimating the regression parameters (b0 and b1), the modification is observed in Equation 2.

$$yi = \beta 0 + \beta 1xi + \varepsilon i \quad (1)$$

$$yi = b0 + b1xi + \varepsilon i \quad (2)$$

Where:
yi = predicted value for the i-th observation of the dependent variable y;
xi = value of the i-th observation of the independent variable x;
β0 = intercept parameter of the equation;
β1 = slope parameter of the equation; and
εi = random error in y for the i-th observation;

Regarding the independence of the regression residuals, the Durbin-Watson test was used to verify whether a sequential series of detail values is or is not serially correlated (Luo et al., 1999). To verify the problem of absence of homoscedasticity, the Breusch-Pagan test was adopted, which tests the null hypothesis of homoscedasticity against the alternative hypothesis of heteroscedasticity (Carvalho et al., 2017). For the normality assumption, the Kolmogorov-Smirnov test is the most used (Assis et al., 1996), so that the empirical probabilities of a variable are compared with the theoretical ones estimated by the distribution function that is being tested (Franscisco et al., 2016).

All tests were verified from the analysis of residuals and were submitted to 5% of significance, which is the significance of the regression model given by Student's t-test of significance for the (a) linear and (b) angular coefficients. The significance of the adjustment equation was given by applying the Student's t-test of significance for the (b) angular and (a) linear coefficients. Hypothesis b, a, and null (Ho) do not differ statistically from zero, being rejected when the calculated t-value is greater than the tabulated critical value (t0), considering n-2 degrees of freedom and 5% significance.

To evaluate the statistical performance of the models, it was used: root-mean-square error (RMSE) indicators (Fares et al., 2011), correlation coefficient (r), coefficient of determination (R²), Willmott (1985) index of agreement (d), and the confidence index (c) (Camargo and Sentelhas, 1997). The RMSE indicators, r, d, and c were calculated according to Equations 3, 4, 5, and 6, respectively.

$$\text{REQM} = \left[\frac{\sum_{i=1}^{n} (\text{Pi-Oi})^2}{n}\right]^{\frac{1}{2}} \qquad (3)$$

$$r = \frac{\left[\sum_{i=1}^{n} \text{Pi}(\text{Oi-}\ \bar{\text{O}})\right]}{\left[\sum_{i=1}^{n} (\text{Oi-}\ \bar{\text{O}})^2 \sum_{i=1}^{n} (\text{Pi-}\ \bar{\text{P}})\right]^{\frac{1}{2}}} \qquad (4)$$

$$d = 1 - \frac{\sum_{i=1}^{n} (\text{Pi-Oi})^2}{\sum_{i=1}^{n} (|\text{Pi-}\ \bar{\text{O}}|+|\text{Oi-}\ \bar{\text{O}}|)^2} \qquad (5)$$

$$c = r*d \qquad (6)$$

Where:
Pi - values estimated by the models;
Hi - observed values; and
$\underline{O}$ - mean of observed values.

The accuracy of the fitted linear models was qualitatively classified according to the confidence index (Table 1), which ranges from 0 (no agreement) to 1 (perfect agreement between the data).

Table 1 - Performance classification according to the value of coefficient ‘c’.

Value of ‘c’	Performance
> 0.85	Excellent
0.76 a 0.85	Very good
0.66 a 0.75	Good
0.61 a 0.65	Median
0.51 a 0.60	Sufferable
0.41 a 0.50	Bad
≤ 0.40	Terrible

Source: Camargo and Sentelhas (1997).

Alluding to the agreement coefficient ‘d’, Walker et al. (2004) elucidates that values close to zero mean that there is no agreement between the data obtained, whilst close to 1 indicates a perfect agreement between them.

The analyses were performed using Microsoft® Excel 2019 spreadsheets and the R software, version 4.1.1, more specifically, the ‘lmtest’ and ‘MASS’ libraries, in order to perform the hypothesis tests.

Results and discussion

Analysing the calibration tests, through the linear regression curves of the models, as well as the pH, it is possible to see the behavior of the data tending to a decreasing linear adjustment (Figure 1a), evidencing a reduction of the voltage values as the solution pH increases. The turbidity also follows the same behavior, showing a reduction in tension values as it increases (Figure 1b). However, for TDS, the data tend to have an increasing linear fit, displaying a gain in tension as the total dissolved solids in the solution increase (Figure 1c).

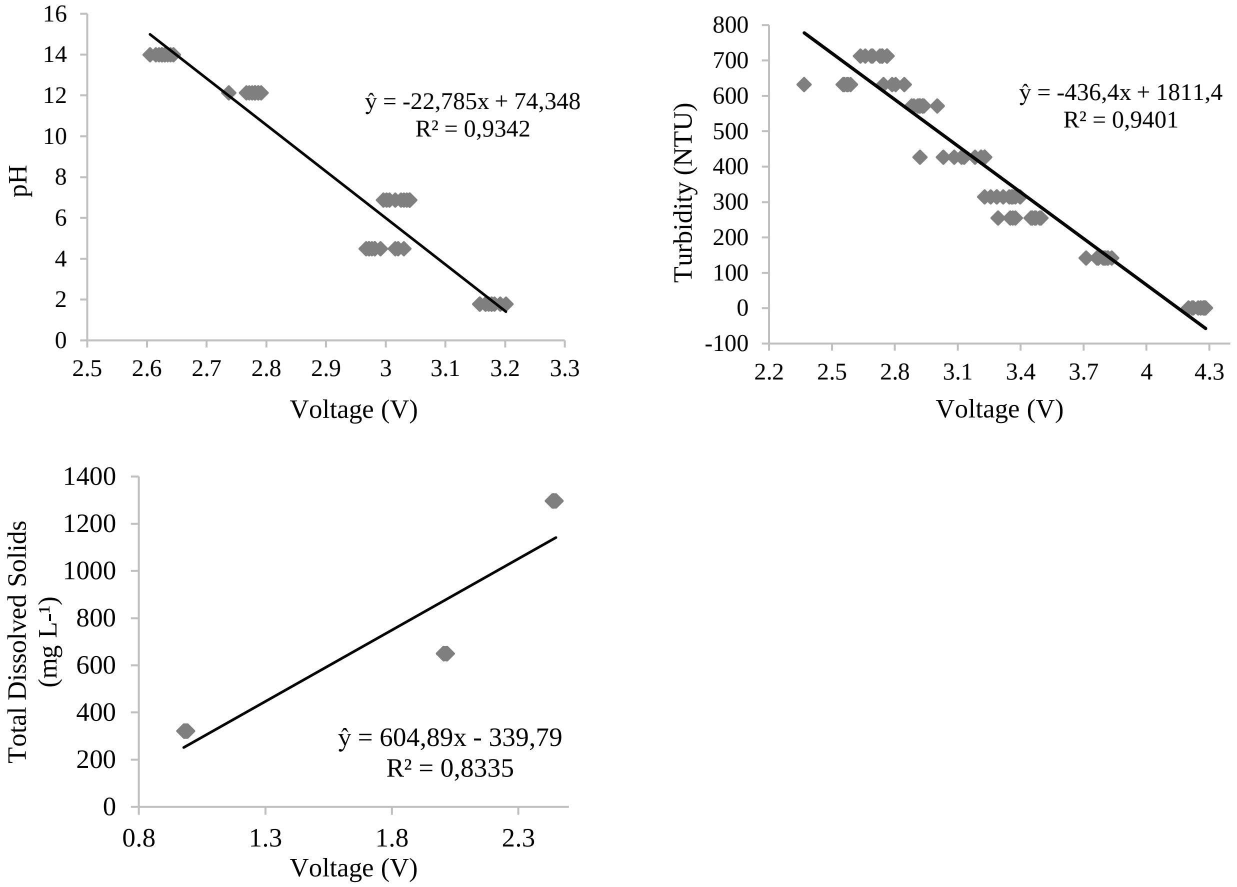

Figure 1. Model regression curves (ŷ) of the relationship between pH, total dissolved solids, and Turbidity values with voltage (x, volts).

The coefficients of determination (R2) showed values of 0.9342, 0.9401, and 0.8335 in the regression curves for pH, turbidity, and TDS, respectively. These values are close to 1, thus showing a good correlation between the results obtained by the standard method and those measured by the sensors.

Table 2 presents the results obtained in the t-test for the (a) linear and (b) angular coefficients of the regressions for all investigated sensors, making it possible to verify that all the estimated coefficients showed statistical significance.

Table 2 - Significance t-test statistics for coefficients ‘b’ and ‘a’.

Sensor	Student's t-test statistics	
	a	b
pH	29.1250*	-26.1044*
TDS	-3.4783*	11.8405*
Turbidity	43.7981*	-34.9831*

* Significant at 5% significance.

.

The evaluation of the calibration models by the Durbin-Watson, Breusch-Pagan, and Kolmogorov-Smirnov tests, in the verification of the premises of independence, homogeneity of variance, and normality of the residues, for the pH, turbidity, and TDS sensors, are shown in the Table 3.

Table 3 - Statistics of Durbin-Watson, Breusch-Pagan, and Kolmogorov-Smirnov tests, as well as sample size (n) of simple linear calibration equations.

Sensor	Durbin-Watson	Breusch-Pagan	Kolmogorov-Smirnov	n
pH	0.3755^{NS}	1.1921*	0.1290*	50
Turbidity	0.3932^{NS}	12.3608^{NS}	0.09123*	80
TDS	0.2936^{NS}	11.1543^{NS}	0.3111^{NS}	30

*: significant at the 5% level, according to Student's t-test. NS: not significant.

It was found that the premise of absence of residual autocorrelation for the calibration equations of the investigated sensors was not met, according to the Durbin-Watson test. However, the presence of correlation between the errors was already expected, which was justified by the way in which the calibration data was collected, since, in the same sample (solutions) the sensors performed ten readings, configuring a procedure with repeated measurements in time, which, consequently, provides correlated information. According to Kutner et al. (2004), when there is dependence between the error terms, this leads to unbiased estimation coefficients. Nevertheless, confidence intervals and significance tests are not completely reliable, since the error variance is incorrect.

Regarding heterogeneity, variance of error terms was observed for the turbidity and TDS adjustments, and not normality for the latter. According to Figueiredo Filho et al. (2011), one of the causes of heteroscedasticity is when there are measurement errors in the independent variables. The Gauss-Markov theorem reports that, under the veracity of the assumptions, the estimators obtained by the ordinary least squares method will be the best linear unbiased prediction (BLUP) (Figueiredo Filho et al., 2011). Thus, it is possible to infer that, for the calibration equations of the pH, turbidity, and TDS sensors, the ordinary least squares method did not produce the best linear unbiased prediction, since at least one premise was not met.

It is important to highlight that, among the evaluated meters, only the sensor module Ph4502c that has automatic compensation for the ambient temperature did not provide the relaxation of the premises of heterogeneity of variance and normality of the residuals. According to Pratami et al. (2020), generally, the temperature of the sample interferes with the pH reading, with an increase in pH as the temperature rises.

For the turbidity measurements, part of the temporal dispersion of the readings is due to the soil + water solutions used for sensor calibration, as the turbidity is reduced while the suspended material is deposited at the base of the container. Regarding TDS, Rietmanm et al. (1985) elucidates that the speed of ion movement is greater when the water is hotter, thus increasing the apparent conductivity.

It was observed that, in the calibration of the sensors (Table 4), the root-mean-square error (RMSE) values for all sensors indicate very poor accuracy (RMSE ≥ 0.1), according to the classification by Fares et al. (2011), displaying poor sensor accuracy in data acquisition. However, the confidence indexes (c) for both sensors were considered optimal, showing values above 0.85, according to the classification by Camargo and Sentelhas (1997), revealing high sensor reliability.

Table 4 - Performance statistics of the proposed linear models.

Sensor	RMSE	R²	d	r	c	Performance
pH	1,1750	0,9342	0,9827	0,9827	0,9500	Excellent
TDS	165,1435	0,8335	0,9538	0,9538	0,8700	Excellent
Turbidity	56,9850	0,9401	0,9843	0,9843	0,9500	Excellent

RMSE: root-mean-square error; c: confidence index; d: index of agreement.

Likewise, the indexes of agreement (d) showed values close to 1.0, evidencing perfect agreement between the values. It is worth recalling that, according to Walker *et al.* (2004), values close to 1 mean that there is perfect agreement, while close to zero indicated no agreement between the obtained data.

It was found that the calibration equations for the hydrogenic potential and turbidity showed similar performance, according to the coefficient of determination (R^2) of 0.9342 and 0.9401, respectively. Concerning the confidence index 'c', in general, the adjustments offered similar performance, classified as 'Excellent'.

Conclusions

For the calibration equations of the pH, turbidity, and total dissolved solids (TDS) sensors, the estimation by the ordinary least squares (OLS) method did not produce the best linear unbiased prediction (BLUP).

There was statistical significance of the regression coefficients for all investigated sensors.

Overall, the sensors showed good accuracy for water quality assessment, according to high performance statistics and adjustments classified as 'Excellent'.

References

Almeida, O. A. de. (2010). Qualidade da água de irrigação. Embrapa Mandioca e Fruticultura, Cruz das Almas. 234p.

Assis, F. N., Arruda, H. V. de, Pereira, A. R. (1996). Aplicações de estatística à climatologia: teoria e prática. Pelotas: UFPel, 1996. 161p.

Brasil. (2014). Ministério da Saúde. Fundação Nacional de Saúde. Manual de controle da qualidade da água para técnicos que trabalham em ETAs.

Camargo, A. P., Sentelhas P. C. (1997). Avaliação do desempenho de diferentes métodos de estimativas da evapotranspiração potencial no Estado de São Paulo, Brasil. *Revista Brasileira de Agrometeorologia*, Santa Maria, 5(1), 89-97.

Carvalho, F. P., Maia, V. M., Louzada, L. C., Gonçalves, M. A. (2017). Desempenho setorial de empresas brasileiras: um estudo sob a ótica do ROE, Q de Tobin e Market to Book. *Revista de Gestão, Finanças e Contabilidade*, 7(1), 149-163. http://dx.doi.org/10.18028/2238-5320/rgfc.v7n1p149-163

Durbin, J., Watson, G. S. (1951). Testing for serial correlation in least squares regression ii. *Biometrika*, 38(1-2), 159-178. https://doi.org/10.1093/biomet/58.1.1

Francisco, P. R. M., Mello, V. D. S., Bandeira, M. M., De Macedo, F. L., Santos, D. (2016). Geoespacialização de cenários pluviométricos através de krigagem utilizando distribuição gama incompleta e teste Kolmogorov-Smirnov. Congresso Técnico Científico da Engenharia e da Agronomia CONTECC 2016. Paraná, 5 p.

Figueiredo Filho, D., Nunes, F., Rocha, E. C., Santos, M. L., Batista, M., Silva Júnior, J. A. (2011). O que fazer e o que não fazer com a regressão: pressupostos e aplicações do modelo linear de Mínimos Quadrados Ordinários (MQO). *Revista Política Hoje*, 20(1), 44 – 99.

Kutner, M. H.; Nachtsheim, C. J.; Neter, J.; Li, W. (2004). Applied linear statistical models. 5. ed. New York: McGraw-Hill, 1396p.

Leal Junior, W. B., Araujo, H. X., Tavares, F. M. (2020). Monitoramento da qualidade da água utilizando plataforma de internet das coisas. *Humanidades & Inovação*, 7(9), 46-53.

Luo, R., Misra, M., Himmelblau, D. M. (1999). Sensor fault detection via multiscale analysis and dynamic PCA. *Industrial & Engineering Chemistry Research*, 38(4), 1489-1495. https://doi.org/10.1021/ie980557b

Mueller, T. G., Pierce, F. J., Schabenberger, O., Warncke, D. D. (2001). Map quality for site-specific fertility management. *Soil Science Society of America Journal*, Madison, 65(5), 1547-1558. https://doi.org/10.2136/sssaj2001.6551547x

Pratami, L. W. D., Ariswati, H. G., Titisari, D. (2020). Effect of Temperature on pH Meter Based on Arduino Uno With Internal Calibration. *Journal of Electronics, Electromedical*, and Medical Informatics, 2(1), 23-27. https://doi.org/10.35882/jeeemi.v2i1.5

Pule, M., Yahya, A., Chuma, J. (2017). Wireless sensor networks: A survey on monitoring water quality. *Journal of Applied Research and Technology*, 15(6), 562–570. https://doi.org/10.1016/j.jart.2017.07.004

Rietmanm, A., Kaplan, M. L., Cava, R. J. (1985). Lithium ion-poly (ethylene oxide) complexes. I. Effect of anion on conductivity. *Solid State Ionics*, 17(1), 67-73. https://doi.org/10.1016/0167-2738(85)90124-9

Sousa, J. T. D., Leite, V. D., & Luna, J. G. D. (2001). Desempenho da cultura do arroz irrigado com esgotos sanitários previamente tratados. *Revista Brasileira de Engenharia Ambiental*, 5(1), 107-110.

Trentin, C. V., Souza, J. L. M. (2006). Possibilidade de utilização da irrigação com água residuária em torno das principais estações de tratamento de efluentes da Região Metropolitana de Curitiba, Estado do Paraná, Brasil. *Acta Sci. Agron*, 28(2), 291-298. https://doi.org/10.4025/actasciagron.v28i2.1132

Walker J. P., Willgoose G. R., Kalma J. D. (2004) In situ measurement of soil moisture: a comparison of techniques. *Journal of Hydrology*, 293(1-4), 85-99. https://doi.org/10.1016/j.jhydrol.2004.01.008

Willmott, C. J., Ackleson, S. G., Davis, J. J. Feddema, K.; Klink, D. R. (1985). Statistics for the evaluation and comparison of models. Journal of Geophysical Research, Ottawa, 90(5), 8995-9005. https://doi.org/10.1029/JC090iC05p08995