Turbidity Permanence: Sensitivity-Driven Input Reduction in ANN Models for Stormwater TSS and DOC

S. B. M. Drummond [1,2] ; M. C. B. Braga [1] , S. Fuchs [2] , S. M. Braga [1]

Keywords – diffuse pollution, organic matter, particulate matter.

INTRODUCTION

ANNs (artificial neural networks) are effective tools for modeling diffuse pollution, capture nonlinear storm behavior, quantify concentrations across hydrological conditions and, provide process insight via sensitivity tools. Hydrological and water quality models are typically high-dimensional, strongly nonlinear, and often over parameterized relative to available data. Thus, parameters are weakly identifiable, and several distinct parameter sets can reproduce observations comparatively well. In this context, sensitivity analysis (SA) is a core element of good modeling practice, as it identifies influential inputs, guides calibration, and clarifies how parameter uncertainty propagates into predictive uncertainty (Sun et al., 2012; Gan et al., 2013; Song et al., 2015). Comparative studies consistently conclude that no single SA method is optimal in all settings and recommend combining complementary techniques (Sun et al., 2012; Vanrolleghen et al., 2015; Wang & Solomatine, 2019).

Total suspended solids (TSS) and turbidity are distinct water quality parameters; however, despite their nonlinearity, turbidity can be used as a proxy for suspended solids. Whereas total suspended solids represent the mass of particulate matter retained by a fine-pored filter during gravimetric analysis, turbidity is an optical property related to the degree to which particles scatter and absorb light and is determined by measuring the amount of light scattered at a 90º angle using a nephelometer (APHA, 2017). High frequency turbidity sensors outperform conventional sampling for capturing rapid storm event dynamics and pollutant loads (Braga, 2013); however, biofouling and entrained air bubbles may bias the results.

The TSS-turbidity relationship is well established in literature as nonlinear and dependent on the characteristics of suspended particle properties (Walling, 1977). Despite the absence of a universal relationship numerous studies report strong site-specific correlations and support the use of turbidity as a cost-effective surrogate for TSS in real-time monitoring, provided that local calibration curves are developed and maintained (Gippel, 1989, 1995; Lewis, 1996; Braga, 2013; Stutter et al., 2017).

As for dissolved organic carbon (DOC), rainfall events in rivers can sharply increase concentration, color, UV absorbance, and turbidity. After storms, DOC has been observed to rise by a factor of 3.5, whereas turbidity can increase up to 300-fold, which demonstrates that more turbid waters transport larger amounts of organic matter and oxygen-reactive particles (Volk, 2000). In highly turbid systems such as the Yellow River basin, DOC is positively correlated with chromophoric dissolved organic matter (CDOM), and turbidity strongly shapes CDOM composition (Zheng, 2023). In lake systems, fluorescent DOM components correlate with both COD and turbidity, indicating that a common humic-rich DOM pool controls these parameters (Tadeu, 2025).

1) Parana Federal University, School of Engineering – Polytechnic Center, Department of Hydraulics and Sanitation, Water Resources and Environmental Engineering Post-Graduate Program, Curitiba, Brazil

2) Karlsruher Institut für Technologie, Gotthard-Franz-Straße 3, Geb. 50.31, Karlsruhe, Germany

METODOLOGY

The sensitivity analysis aimed to identify and remove input variables that were unnecessary for optimal ANNs performance.

A weighted five-method sensitivity framework (Sobol, Morris, SHAP, OAT, Garson) was applied to the trained ANNs to rank hydrological driving factors, identifying the variables that most significantly influence the model performance of the model in predicting TSS and DOC concentrations during stormwater events.

Model performance was evaluated via a weighted composite score across seven metrics spanning efficiency, error magnitude, and bias. NSE and KGE received the highest weights (0.25 each) as primary efficiency criteria, with KGE's decomposition into correlation, variability, and bias addressing known NSE limitations (Gupta et al., 2009). RMSE (0.20) and MAE (0.15) quantified absolute error, differing in outlier sensitivity (Moriasi et al., 2007). |PBIAS| (0.10) captured systematic over- or under-prediction, while R^2 (0.03) and RSR (0.02) served as secondary, confirmatory indicators, given R^2's known insensitivity to additive and proportional differences. This structure follows the consensus that fit, error magnitude, and bias must be assessed jointly, as no single statistic suffices (Cinkus et al., 2023).

RESULTS

The TSS–turbidity relationship is well established in the literature as nonlinear and dependent on the characteristics of the suspended particles (Walling, 1977), yet turbidity consistently outperformed variables with ostensibly more direct hydrological meaning.

This outcome can be explained by what turbidity represents during storm events: not a single pollutant fraction, but the aggregate optical response to suspended mineral particles, organic debris, and colloidal matter mobilized simultaneously under high-flow conditions, the same material that constitutes TSS and drives DOC dynamics. Storm-driven co-mobilization of these fractions has been documented across river and lake systems, with turbidity increases reaching up to 300-fold and DOC rising by a factor of 3.5 (Volk et al., 2000). The continuous turbidity signal delivered by in situ sensors therefore carries more predictive information per variable than any discrete hydrological measure offered to the model, since rainfall events simultaneously increase DOC concentration, color, UV absorbance, and turbidity.

For DOC and TSS, turbidity was the sole input retained with no exception, a result that warrants interpretation rather than mere reporting. The relationship between TSS and turbidity was well established as nonlinear by literature and dependent on the characteristics of the suspended particles (Walling, 1977), yet turbidity consistently surpassed variables with ostensibly more direct hydrological meaning. This can likely be explained by what turbidity indicates during storm events: not a single pollutant fraction, but the aggregate optical response to suspended mineral particles, organic debris, and colloidal matter mobilized simultaneously under high-flow conditions. The turbidity signal delivered continuously by *in situ* sensors, carries more predictive information per variable than any discrete hydrological measure the model was offered.

CONCLUSIONS

The application of five independent sensitivity methods demonstrated that the adopted multi-method approach was both methodologically sound and practically significant. The five techniques differ in their underlying logic, variance decomposition, derivative estimation, game-theoretic attribution, weight-based inference, and their convergence on a single retained variable, turbidity, for

both TSS and DOC prediction in ANNs constitutes stronger evidence of genuine input dominance than any single method could provide in isolation.

The site specificity of TSS–turbidity and DOC–turbidity relationships, extensively reported across catchments of differing scale, geology, and land use, defines the operational boundary of this approach rather than undermining it. The ANNs learn the local, non-linear mapping between optical signal and pollutant concentration that neither universal empirical equations nor gravimetric sampling can provide continuously. What the sensitivity framework contributes is a reproducible, quantitative basis for determining which inputs this mapping genuinely requires — and across all five methods, the answer was consistently turbidity.

For operational monitoring, this finding has direct implications: it supports turbidity-based sensor networks as a parsimonious and physically justified basis for real-time TSS and DOC estimation. The results presented here provide an independent, model-based line of evidence reinforcing the broader literature consensus that turbidity is not merely a convenient proxy, but a robust and informative predictor in ANN-based stormwater quality models.

REFERENCES

APHA – AMERICAN PUBLIC HEALTH ASSOCIATION (2017). *Standard Methods for the Examination of Water and Wastewater*. 23rd ed. Washington, DC: APHA.

BRAGA, S. M. (2013). *A new approach to integrating water quantity and quality for the assessment of diffuse pollution* (Uma nova abordagem para integração entre quantidade e qualidade da água para a avaliação da poluição difusa – In Portuguese). PhD Thesis – Universidade Federal do Paraná, Curitiba, 195 p. Disponível em: https://acervodigital.ufpr.br/handle/1884/36071. Acesso em: 15 jul. 2025.

CINKUS, G.; MAZZILLI, N.; JOURDE, H.; WUNSCH, A.; LIESCH, T.; RAVBAR, N.; CHEN, Z.; GOLDSCHEIDER, N. (2023). *When best is the enemy of good – critical evaluation of performance criteria in hydrological models*. Hydrology and Earth System Sciences, v. 27, p. 2397-2423. DOI: 10.5194/hess-27-2397-2023.

GAN, Y.; DUAN, Q.; GONG, W. et al. (2013). *A comprehensive evaluation of various sensitivity analysis methods: a case study with a hydrological model*. Environmental Modelling & Software, v. 51, p. 269-285. DOI: 10.1016/j.envsoft.2013.09.031.

GIPPEL, C. J. (1989). *The use of turbidimeters in suspended sediment research*. Hydrobiologia, v. 176-177, p. 465-480. DOI: 10.1007/BF00026582.

GIPPEL, C. J. (1995). *Potential of turbidity monitoring for measuring the transport of suspended solids in streams*. Hydrological Processes, v. 9, n. 1, p. 83-97. DOI: 10.1002/hyp.3360090108.

GUPTA, H. V.; KLING, H.; YILMAZ, K. K.; MARTINEZ, G. F. (2009*). Decomposition of the mean squared error and NSE performance criteria*: Implications for improving hydrological modelling. Journal of Hydrology, v. 377, n. 1-2, p. 80-91. DOI: 10.1016/j.jhydrol.2009.08.003.

LEWIS, J. (1996). *Turbidity-controlled suspended sediment sampling for runoff-event load estimation*. Water Resources Research, v. 32, n. 7, p. 2299-2310. DOI: 10.1029/96WR00991.

MORIASI, D. N.; ARNOLD, J. G.; VAN LIEW, M. W.; BINGNER, R. L.; HARMEL, R. D.; VEITH, T. L. (2007). *Model evaluation guidelines for systematic quantification of accuracy in watershed simulations*. Transactions of the ASABE, v. 50, n. 3, p. 885-900. DOI: 10.13031/2013.23153.

SONG, X.; ZHANG, J.; ZHAN, C.; XUAN, Y.; YE, M.; XU, C.-Y. (2015). *Global sensitivity analysis in hydrological modeling: concepts, methods and applications.* Journal of Hydrology, v. 523, p. 739-757. DOI: 10.1016/j.jhydrol.2015.02.013.

STUTTER, M.; DAWSON, J.; GLENDELL, M.; NAPIER, F.; POTTS, J.; SAMPLE, J.; VINTEN, A.; WATSON, H. (2017). *Evaluating the use of in-situ turbidity measurements to quantify fluvial sediment and phosphorus concentrations and fluxes in agricultural streams.* Science of the Total Environment, v. 607-608, p. 391-402. DOI: 10.1016/j.scitotenv.2017.07.013.

SUN, X.; NEWHAM, L.; CROKE, B.; NORTON, J. (2012). *Three complementary methods for sensitivity analysis of a water quality model.* Environmental Modelling & Software, v. 37, p. 19-29. DOI: 10.1016/j.envsoft.2012.04.010.

TADEU, C. M. O.; PUJONI, D.; AMADO, A.; BRIGHENTI, L. S.; DE AZEVEDO BARROS, C. F.; OPORTO, L. T.; REIS PELEGRINE, D. D.; PEREIRA, G.; DA SILVA CARDOZO, F.; PACHECO, S. P.; VALLE, B. L. D.; FONSECA, L. M.; SALGUEIRO, T. M.; BEZERRA-NETO, J. F. (2025). *Linking Land Use, Seasonal Variation and Water Quality Through Dissolved Organic Matter Optical Properties in the Doce River Basin*. Ecohydrology, v. 18. DOI: 10.1002/eco.70130.

VANROLLEGHEM, P.; MANNINA, G.; COSENZA, A.; NEUMANN, M. (2015). *Global sensitivity analysis for urban water quality modelling: terminology, convergence and comparison of different methods*. Journal of Hydrology, v. 522, p. 339-352. DOI: 10.1016/j.jhydrol.2014.12.056.

VOLK, C.; BELL, K.; IBRAHIM, E.; VERGES, D.; AMY, G.; LE CHEVALLIER, M. (2000). *Impact of enhanced and optimized coagulation on removal of organic matter and its biodegradable fraction in drinking water.* Water Research, v. 34, n. 12, p. 3247-3257. DOI: 10.1016/S0043-1354(00)00033-6.

WALLING, D. E. (1977). *Limitations of the rating curve technique for the estimation of sediment yields, with specific reference to British rivers.* Journal of Hydrology, v. 33, n. 3-4, p. 233-248. DOI: 10.1016/0022-1694(77)90108-9.

WANG, A.; SOLOMATINE, D. P. (2019). *Practical experience of sensitivity analysis: comparing six methods, on three hydrological models, with three performance criteria.* Water, v. 11, n. 5, p. 1062. DOI: 10.3390/w11051062.

ZHENG, K.-H.; SHAO, T.; NING, J.; ZHUANG, D.; LIANG, X.; DING, X. (2023). *Water quality, basin characteristics, and discharge greatly affect CDOM in highly turbid rivers in the Yellow River Basin, China.* Journal of Cleaner Production. DOI: 10.1016/j.jclepro.2023.136995.

Aknowlegments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.