



The Critical Role of Quantitative Structure Activity Relationship in Predicting the Removal of Organic Micropollutants

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Organic micropollutants (OMPs), a group of natural and synthetic organic materials, enter the environment from various domestic, industrial, and agricultural sources and are one of the most pressing environmental challenges¹. These persistent compounds originate from various pharmaceuticals, personal care products, pesticides, microplastics, and industrial waste². They frequently bypass conventional treatment processes, posing a serious threat to aquatic ecosystems and human health³. Although advanced technologies are being developed to remove these compounds, the research community faces a fundamental bottleneck (the cost, time, and enormous resources required for experimental testing) in determining the optimal conditions for new and emerging compounds⁴.

To overcome these problems, computational prediction methods are not only useful but also essential. Among these, chemometric modeling methods based on quantitative structure–activity relationships (QSAR) offer a powerful and attractive solution to these problems⁵. QSAR is a powerful method that establishes relationships

between molecular descriptors, including the structural, topological, physical, geometric, and electronic properties of a contaminant with physical, chemical, or biological activity. This transforms the process for determining the activity of a new compound from a random, trial-and-error approach to a rational, targeted, and efficient one. Consequently, QSAR serves as a standard and prerequisite tool for decreasing the time, cost, and number of animal testing, thus facilitating green chemical design across various scientific and industrial fields⁶.

In this approach, molecular descriptors are first calculated, and then statistical techniques such as multiple linear regression (MLR), artificial neural network (ANN), and mathematical relationships are used to establish the relationship between the experimental values of degradation (dependent data) and the molecular descriptors (independent data). This relationship is expressed as a mathematical equation based on the most significant descriptors⁷. The descriptor most closely related to OMP degradation is considered the most appropriate model for OMP degradation⁸.

The validity of the generated model was tested using the testing set molecules, along with a scatter plot and residual error plot. Once validated, the degradation efficiency of a new OMP can be predicted by inputting its molecular descriptors into the selected model. Furthermore, these models can predict how changes in specific molecular descriptors affect degradation efficiency within a given treatment process⁹.

The use of QSAR in research offers the following benefits

1-Screening: Researchers can virtually screen vast chemical libraries to prioritize compounds that are most likely to pose a risk. This allows them to focus their experimental efforts where they are most needed¹⁰.

2-Mechanism prediction: These models do more than predict the outcomes of the degradation process; they help understand why and how a compound is eliminated or degraded. By identifying key molecular descriptors, QSAR reveals the underlying mechanisms governing these processes¹¹.

3-Green design: QSAR can guide the green design for the removal of future compounds and determine how new compounds should be removed before entering the environment with at least chemicals¹⁰.

However, for QSAR to reach its full potential, the scientific community must produce high-quality, standardized experimental data for model training and validation. This requires interdisciplinary collaboration among chemists, environmental engineers, and scientific computing experts in artificial intelligence. By using QSAR, we can shift from a reactive to a proactive stance and manage the vast universe of OMPs not only by testing a compound at a great time and expense but also through the powerful lens of predictive science⁶.

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References

1. Wołowicz A, Munir HM. Emerging organic micropollutants as serious environmental problem: a comprehensive review. *Sci Total Environ.* 2025; 958: 177948.
2. Kalita AJ, Sarma J, Hazarika A, et al. Organic Micropollutants in Environment: Origin and Occurrence. In *Organic Micropollutants in Aquatic and Terrestrial Environments 2024*. Cham: Springer Nature Switzerland. 2024. p. 3-23.
3. Figuière R, Ahrens L, Golovko O, et al. Risk to aquatic organisms posed by organic micropollutants. *Sveriges Lantbruksuniversitet*; 2021.
4. Huang Y, Li T, Zheng S, et al. QSAR modeling for the ozonation of diverse organic compounds in water. *Sci Total Environ.* 2020; 715: 136816.
5. Ammi Y, Khaouane L, Hanini S. A comparison of “neural networks and multiple linear regressions” models to describe the rejection of micropollutants by membranes. *Kemija u industriji: Časopis kemičara i kemijskih inženjera Hrvatske.* 2020; 69(3-4): 111-27.
6. Glienke J, Stelter M, Braeutigam P. Influence of chemical structure of organic micropollutants on the degradability with ozonation. *Water Res.* 2022; 222: 118866.
7. Li Y, Mahy J, Lambert S. Finishing treatment processes for micropollutant degradation at the outlet of WWTP: Bibliometric analysis and QSPR/QSAR modeling. *ChemRxiv.* 2024.
8. Glienke J, Schillberg W, Stelter M, et al. Prediction of degradability of micropollutants by sonolysis in water with QSPR—a case study on phenol derivatives. *Ultrason Sonochem.* 2022; 82: 105867.
9. Salmani MH, Garzegar S, Ehrampoush MH, et al. Predicting anionic surfactant toxicity to *Daphnia magna* in aquatic environment: a green approach for evaluation of EC50 values. *Environ Sci Pollut Res Int.* 2021; 28(36): 50731-46.
10. Ishfaq M, Shah SWA. An overview of computational tools and approaches for green molecular design to minimize toxicological risk

in chemical compounds. *Computational Methods in Medicinal Chemistry, Pharmacology, and Toxicology*. 2025; 1: 223-38.
11. Wang L, Lei Z, Yun S, et al. Quantitative

structure-biotransformation relationships of organic micropollutants in aerobic and anaerobic wastewater treatments. *Sci Total Environ*. 2024; 912: 169170.