

## Development of a Water Solubility Dataset to Establish Best Practices for **Curating New Datasets for QSAR Modeling**

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## **Problem Definition and Goals**

Problem: There are numerous peer-reviewed publications and public websites that contain experimental data that could be used to improve existing QSAR/QSPR models. Commonly these data are not available in an ideal form: often limited to PDF supplementary info files for publications (with names or CASRNs and no electronic structure formant). However, when aggregation of these data has been attempted curation has been necessary.

Goals: Provide a de facto dataset for water solubility data that can be used to build multiple models and eventually a consensus model. Identify specific sets of chemicals that can improve existing models. Curate these data to ensure chemical identifiers represent the same chemical structure, physicochemical property data has consistent units, etc. Make these data available as downloadable data for use in QSAR/QSPR models and reuse in other databases.

## Simplified Workflow for Dataset Assembly

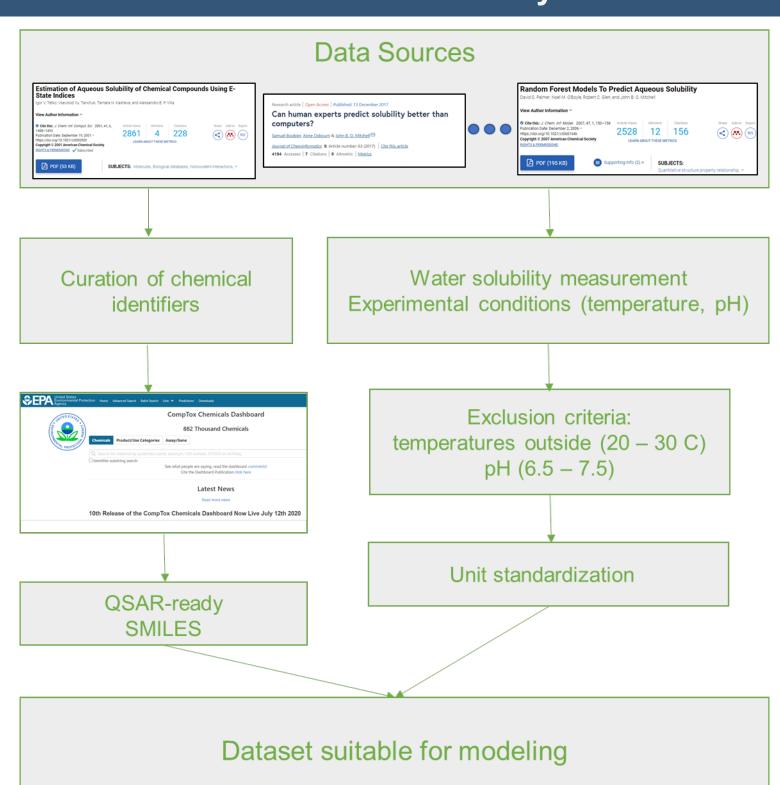


Figure 1: This diagram shows the simplified workflow used in the assembly of the water solubility dataset. Note that chemical structure is represented using QSAR-ready SMILES - a representation of the desalted, de-isotoped, stereo-neutral forms of chemical structures associated with particular chemical substances.

Article Identifier	Original No. of Chemicals	No. of QSAR-ready SMILES
https://doi.org/10.1021/ci700307p	287	286
https://doi.org/10.1002/minf.201000001	2810	2596
https://doi.org/10.1016/S0045-6535(02)00118-2	1719	1530
https://doi.org/10.1080/10807039.2015.1133242	1190	1155
https://doi.org/10.1186/s13321-017-0250-y	100	99
https://doi.org/10.6084/m9.figshare.1514952.v1	3315	1836
https://www.ebi.ac.uk/chembl/	326	323

Table 1: Current articles and databases assembled using the workflow shown in Figure 1. The number of QSAR-ready SMILES denotes the unique chemical structures available for modeling after curation and solubility measurement cleaning.

## Simplified Modeling Workflow Dataset suitable for modeling Remove insoluble compounds Generate PaDeL descriptors Take log<sub>10</sub> of solubility values For n > 1Remove descriptors with missing average solubility values values & those which are highlyif SD > 0.25, exclude chemicals correlated Split 75% of data into training set and 25% into test set Maintain endpoint distribution Random forest Weighted K-nearest neighbors Gradient boosting

Figure 2 (above): This diagram shows the simplified workflow used in the modeling of the water solubility dataset.

Table 2 (below): Modeling approaches with performance values for cross-validated training and both internal and external test datasets<sup>1</sup>.

	Training Dataset (5-fold CV)  Dataset Size: 3153		Test Dataset  Dataset Size: 1049		External Test Dataset  Dataset Size: 4224	
Model Name	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>
Weighted K-Nearest Neighbors	0.95	0.82	0.98	0.81	0.76	0.89
Gradient Boosting	0.84	0.86	0.90	0.84	0.68	0.91
Random Forest	0.89	0.85	0.92	0.84	0.69	0.91

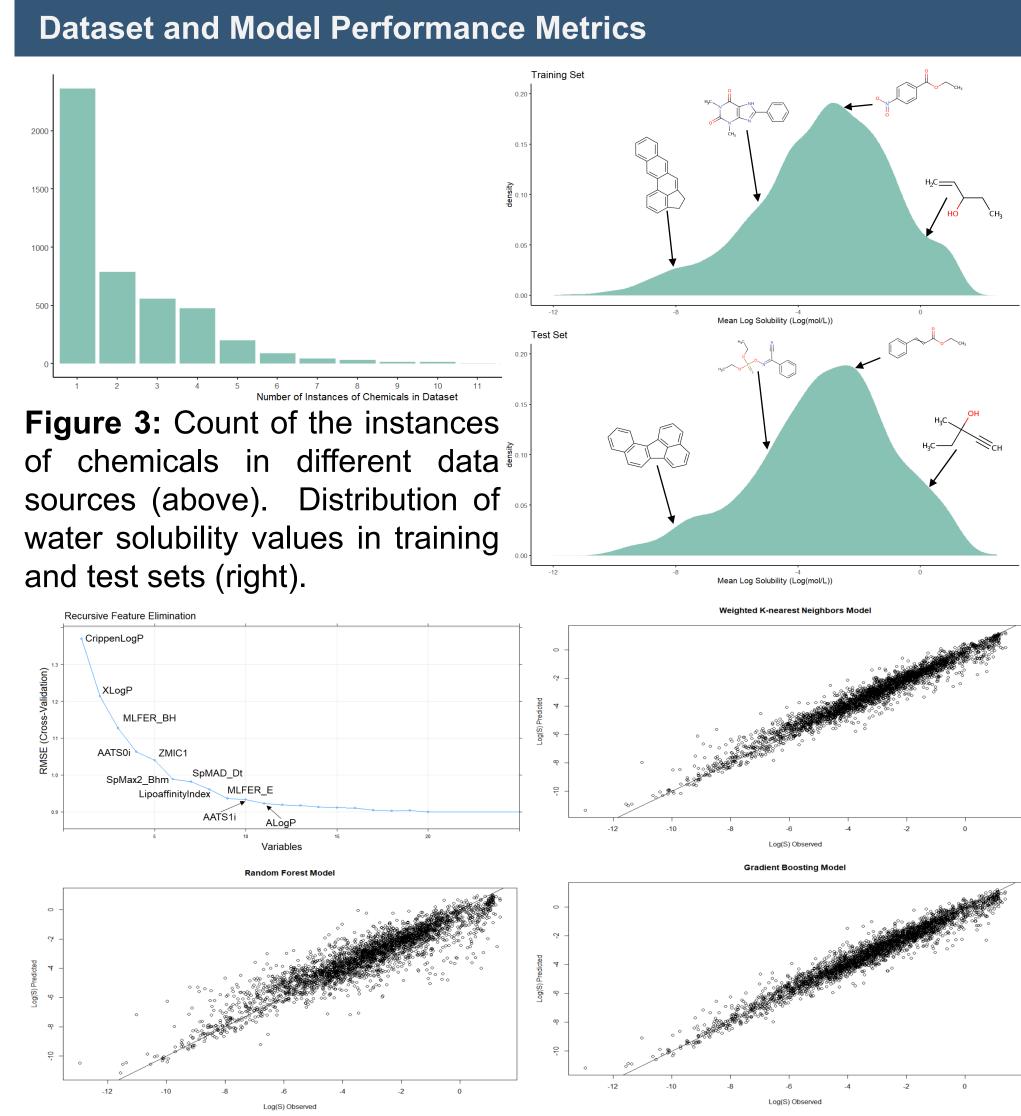


Figure 4: Selection of PaDeL descriptors via recursive feature elimination for K-NN model (top left). Correlation of predicted and

