Cite this article
Nash S (2024)
Editorial: Navigating uncharted waters: the risks of machine learning in the hands of non-experts.
Proceedings of the Institution of Civil Engineers – Water Management **177(6)**: 359–360,
https://doi.org/10.1680/jwama.2024.177.6.359

Editorial

Water Management

Editorial: Navigating uncharted waters: the risks of machine learning in the hands of non-experts

Stephen Nash PhD
Ollscoil na Gaillimhe – University of Galway, Galway, Ireland

Machine learning (ML) is everywhere. We encounter it daily, from viewing personalised feeds on our smart phones, to checking traffic predictions with apps like Google Maps and using our email accounts. It is no surprise then that it has become so pervasive in scientific literature. The 2024 AI Index Report reveals there were more than 77,000 ML publications in 2022 (one every 7 minutes), representing a 10-fold increase from 2012 (Maslej *et al*., 2024).

The water sector is no different. Recent issues of this journal contain very interesting applications of ML to the study of stage-discharge relationships (Gao *et al*., 2024), forecasting of river discharge (Kabootarkhani *et al*., 2024), prediction of scour depth around bridge piers (Deng *et al*., 2024) and identification of dams from remote sensing images (Hou *et al*., 2024). Indeed, using Google Scholar search results as a crude metric, entering the keywords “machine learning” and “hydrology” as an example, returns 22,100 results for 2022 versus 3,700 for 2012.

ML lends itself to the analysis of large datasets. It therefore has many potential applications in the water management sector where the number and size of datasets from sensors, satellites and numerical models has increased exponentially in recent years. In particular, it offers potential advantages over traditional mechanistic and statistical models such as faster and smarter analysis of observational data and recognition of recurring patterns/behaviours, shorter run-times and better scalability with high performance computing resources and cloud computing, improved ability to capture the non-linear behaviours of natural environmental processes (Durap *et al*., 2023) and the potential for reducing human-induced biases such as those introduced to numerical models through process simplification and parameterisation (Jacox *et al*., 2020).

While these potential benefits have no doubt contributed to the exponential increase in ML investigations over the last decade, so too has the ever-growing number of ML algorithms and their increasingly easier accessibility. The rise in investigative ML studies in the water sector is certainly helpful as they provide learnings on the benefits of ML to the sector and the challenges in developing suitable real-world ML applications. Easier access, however, has also led to increased ML use by non-experts and thus a higher risk of inaccurate models due to poor model design and/or misinterpretation of model outputs. Since ML models have not yet been widely deployed in real-world settings in the water sector, the current risk to the public is low and primarily limited to misinformation but a 2022 incident in Toronto, Canada, demonstrates the potential dangers of inaccurate ML models (Cohen, 2022). In this instance, a ML-based predictive water quality assessment tool deployed by Toronto’s public health department to replace its traditional method of laboratory testing was found to have misclassified bathing waters as safe when levels of E.Coli were actually excessively high. Its use resulted in 30 instances of public bathers being exposed to dangerous bacteria levels over the summer period.

A number of recent studies have warned of some risks of ML to the water sector (Water Source, 2024), as well as highlighting some common pitfalls and challenges of ML model development and offering recommendations for responsible model development and deployment (Liu *et al*. (2024); Grey *et al*. (2024); Richards *et al*. (2023)). Model training requires continuous datasets covering large spatial extents, long time periods and a diverse set of conditions. These can be difficult to obtain and can lead to poor model performance if not of sufficient quality. Datasets require careful pre-processing; gaps and noise/outliers must be removed as they can cause model errors. Choice of model is key and, like traditional mechanistic modelling, simpler is usually better as it means models are easier to interpret, faster to train and can provide solid baseline results before moving onto more complex algorithms. Some researchers make the mistake of starting off with an overly complex model where model behaviour and results are then difficult to interpret. Insufficient, or poorly designed, model validation can also result in over-fitting or under-fitting meaning models will subsequently perform poorly on new data.

Going forward, it is important that the water engineering community question the advantages and disadvantages of employing ML models, make themselves aware of their limitations and use best practice in model development and validation. Possibly of greatest importance is that developers first have a clear understanding of the problem they are trying to solve - maybe an ML model is not the best solution. A key weakness of ML models is that they are not based on the laws of physics, although recent research has seen the development of physics-constrained models (e.g. Wu, 2021). While it is unlikely that ML models will replace traditional process-based models, they can certainly compliment them by helping with parameterisation, data assimilation and calibration. When used correctly, they are another valuable tool that can help us to achieve sustainable developments goals in the water sector. ML models currently sit at a developmental stage similar to that of numerical models in the 1950s and 60s. In order for them to become as widely accepted and trusted as numerical models it is crucial that they are developed in a similarly robust and rigorous manner.

REFERENCES

Cohen B (2022) Safe for swimming? Toronto's new tool for measuring water quality at its beaches is misleading, say advocates, Toronto Star, Toronto, CA. See https://www.thestar.com/news/gta/safe-for-swimming-toronto-s-new-tool-for-measuring-water-quality-at-its-beaches-is/article_f6a6ef1d-6125-5699-809b-89a42b9e6dce.html (accessed: 16/10/2024).

Deng Y, Liu Y, Zhang D and Cao Z (2024) Machine learning-based prediction of scour depth around different-shaped bridge abutments. *Proceedings of the Institution of Civil Engineers – Water Management* **177(5)**: 308–326, https://doi.org/10.1680/jwama.22.00087.

Durap A (2023) A comparative analysis of machine learning algorithms for predicting wave runup. *Anthropocene Coasts* **6(1)**: 17, https://doi.org/10.1007/s44218-023-00033-7.

Gao Y, Jiang Z and Wang Y (2024) Research on stage–discharge relationship model based on random forest algorithm. *Proceedings of the Institution of Civil Engineers – Water Management* **177(6)**: 375–382, https://doi.org/10.1680/jwama.23.00029.

Gray PC, Boss E, Prochaska JX, *et al.* (2024) The promise and pitfalls of machine learning in ocean remote sensing. *Oceanography* **37(3)**: 52–63, https://doi.org/10.5670/oceanog.2024.511.

Hou J, Zhu M and Hou B (2024) Comparison of deep learning models to extract silt storage dams from remote sensing images. *Proceedings of the Institution of Civil Engineers – Water Management* **177(5)**: 327–338, https://doi.org/10.1680/jwama.22.00094.

Jacox MG, Alexander MA, Siedlecki S *et al.* (2020) Seasonal-to-interannual prediction of North American coastal marine ecosystems: forecast methods, mechanisms of predictability, and priority developments. *Progress in Oceanography* **183**: 102307, https://doi.org/10.1016/j.pocean.2020.102307.

Kabootarkhani MR, Kermani SG, Aldallal A and Zounemat-Kermani M (2024) Forecasting river daily discharge using decision tree and time series methods. *Proceedings of the Institution of Civil Engineers – Water Management* **177(5)**: 294–307, https://doi.org/10.1680/jwama.22.00079.

Kazemipour S, Kabiri-Samani A and Asghari K (2024) Numerical modelling of flow field at shaft spillways with the marguerite-shaped inlets. *Proceedings of the Institution of Civil Engineers – Water Management* **177(6)**: 413–424, https://doi.org/10.1680/jwama.22.00058.

Li R, Zhang J and Guo Z (2024) Impacts of the flexible net on riverbed evolution in degrading channels. *Proceedings of the Institution of Civil Engineers – Water Management* **177(6)**: 383–396, https://doi.org/10.1680/jwama.23.00018.

Liu Z, Zhou J, Yang X, Zhao Z and Lv Y (2024) Research on water resource modeling based on machine learning technologies. *Water* **16(3)**: 472, https://doi.org/10.3390/w16030472.

Maslej N, Fattorini L, Perrault R, *et al.* (2024) *The AI Index 2024 Annual Report*. AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA.

Nandi B and Das S (2024) Equation for time-dependent local scour at pier-like structures with eccentric in-line arrangements. *Proceedings of the Institution of Civil Engineers – Water Management* **177(6)**: 361–374, https://doi.org/10.1680/jwama.23.00006.

Richards CE, Tzachor A, Avin S and Fenner R (2023) Rewards, risks and responsible deployment of artificial intelligence in water systems. *Nature Water* **1(5)**: 422–432, https://doi.org/10.1038/s44221-023-00069-6.

Sanchez Banda GF, Alarcon VJ and Carvajal SA (2024) Management of suspended solids accumulation on a tidally inundated stormwater canal. *Proceedings of the Institution of Civil Engineers – Water Management* **177(6)**: 397–412, https://doi.org/10.1680/jwama.23.00035.

Water Source (2024) Addressing the risks of AI in the water sector, Australian Water Association website, See, https://www.awa.asn.au/resources/latest-news/addressing-the-risks-of-ai-in-the-water-sector (accessed: 16/10/2024).

Wu H and Qiao R (2021) Physics-constrained deep learning for data assimilation of subsurface transport. *Energy and AI* **3**: 100044, https://doi.org/10.1016/j.egyai.2020.100044.