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Machine Learning in Dam Water Research: An Overview of Applications and Approaches

Farashazillah Yahya[1]*, Bashirah Fazli[2], Hasimi Sallehudin[3], Mohd Izham Mohd Jaya[4]

[1] Faculty of Computing and Informatics, Universiti Malaysia Sabah, Kota Kinabalu, Sabah Malaysia
[2] National Hydraulic Research Institute of Malaysia (NAHRIM), Selangor, Malaysia.
[3] Faculty of Technology and Science Technology, Universiti Kebangsaan Malaysia, Selangor, Malaysia
[4] Faculty of Computing, Univiersiti Malaysia Pahang, Kuantan, Malaysia

ABSTRACT

Dam plays a crucial role in water security. A sustainable dam intends to balance a range of resources involves within a dam operation. Among the factors to maintain sustainability is to maintain and manage the water assets in dams. Water asset management in dams includes a process to ensure the planned maintenance can be conducted and assets such as pipes, pumps and motors can be mended, substituted, or upgraded when needed within the allocated budgetary. Nowadays, most water asset management systems collect and process data for data analysis and decision-making. Machine learning (ML) is an emerging concept applied to fulfill the requirement in engineering applications such as dam water researches. ML can analyze vast volumes of data and through an ML model built from algorithms, ML can learn, recognize and produce accurate results and analysis. The result brings meaningful insights for water asset management specifically to strategize the optimal solution based on the forecast or prediction. For example, a preventive maintenance for replacing water assets according to the prediction from the ML model. We will discuss the approaches of machine learning in recent dam water research and review the emerging issues to manage water assets in dams in this paper.

Key words: dam, dam water, machine learning, water asset

1. INTRODUCTION

A standard practice to minimize the owning and operational cost of managing water assets in dams involves a series of process [1]. The processes involved are systematic in a way to tackle specific requirements for dams according to the approved service level agreements [2]. A sustainable dam can make sure the dam operation and system in working order while delivering the desired service. Many dam operation centres utilize a computerized system that records detail assets inventories, scheduled maintenance tasks and the associated cost that comes along the way. These computerized system records and store data about the water assets such as details of the asset lifecycle (purchase or installation info, condition, and preemptive maintenance schedule), replacement plans and costs based on the analysis. In Malaysia, dams may serve to fulfil single or multi-purpose objectives. Some dams serve as a single-purpose dam while some have multi-purposes [3]. An example for single-purpose dams; hydropower dam (Chenderoh, Bakun and Pergau), irrigation dam (Pedu) or water supply dam (Batu and Sembrong). Multi-purpose dams include dams that supply waters and mitigates floods (Klang Gate), water supply and irrigation (Ahning), and have three purposes; supply waters, irrigation, mitigates floods (Timah Tasoh) [3]. Dams that runs to fulfil several purposes requires a complex process in dam operation and management. The paper intends to outline the recent approaches in machine learning for dam water research and the surrounding issues in this research domain.

The paper is outlined below. The next section outlines the recent machine learning approaches in dam water research. We briefly outline the previous researches in dam water research using machine learning approaches. Later, we summarize the machine learning approaches applied based on the area or domain of dam engineering application. The next section discusses the surrounding issues of the application for machine learning in dams followed by a concluding remark in the final section.

2. MACHINE LEARNING APPROACHES

There are various ways an algorithm can model a data or issue according to the information or data set. Some research identifies patterns for water and soil [4], prediction in agriculture [5] and determine disaster management index [6]. Generally, machine learning approaches can be grouped based on learning styles or similarity in form of function [7] presented in Table 1. There are three main categories in ML based on learning style; supervised, unsupervised and semi-supervised learning [7].

The first learning style is known as supervised learning algorithms. The predictions are prepared through the training phase. The training phase is repeated until a desired target or objective is met. The input training data has known labelled such as spam/not-spam etc. Classification and regression problems are example of supervised learning. The next learning style is unsupervised learning. On the other hand, the data in an unsupervised learning is not labelled. The model is prepared based on reasoning, such as extracting general rules or through a dimension reduction using mathematical calculations, or similarity-grouping. The example of tasks includes clustering, association rule and dimension reduction. The final learning style is the semi-supervised learning. Like both the supervised and unsupervised learnings; the data can be labelled and unlabelled. A problem is identified but the model learns through the structures to make predictions. Classifications and regression are example of problem.

On the other hand, there are several groups if the machine learning algorithms are grouped based on similarity in form of function[7]. Basically, the ML approaches can be group into 12 similarity functions. Regression models the relationship between variables by repeating the refined measure of error from the modelled predictions. Regression methods is supported by statistics and opted as a statistical machine learning.

Next, instance-based learning models a decision problem and construct its hypothesis using instances in the training data. In predicting class for a new instance, the model computes distance or similarities between the new instance and instances in the training data. Another approach is known as regularization. Regularization is an extension made to other approaches such as regression. The model looks into the complexity for generalization.

Decision tree approach constructs a model based on decisions of actual values in the data and useful for both classification and regression task. The constructed decision tree splits data using decision rules based on learnt data features. On the other hand, the Bayesian approach are models that apply the Bayes' Theorem to calculate probability distribution for instances in the dataset. In ML, Bayesian approach can be applied to solve classification and regression task. Another approach, namely the clustering, worked by dividing data into groups with maximum commonalities. Group is determined based on similarities and dissimilarities between the data.

In the context of ML, rules extracted can describe the key relation between the data variables investigated to uncover the hidden correlation. This approach is known as the association rule learning. Moreover, the extracted rules also help to identify associations and multidimensional data variables relations. Another approach called Artificial Neural Network (ANN) are models motivated by the function of biological neural networks. The model groups pattern based on regression and classification problems. An extension work of ANN that is concerned more on developing a more complex ANN is known as deep learning approach. In current research work, deep learning approach is adopted in analyzing a very large dataset contained image, text. audio, and video.

The dimensionality reduction approach seeks the inherent structure in the data set and expose a set of principal variables that is important to maintain the structure and information in the original data set. The number of random variables which are not important is then reduced. Dimensionality reduction approach is useful to visualize high dimensional data by reducing data dimensions and increase analysis accuracy in classification and regression task. Lastly, the ensemble approach model is composed of multiple independently trained models to make the overall prediction. There are other machine learning approaches for specialty tasks such as feature selection, accuracy evaluation, performance measures, optimization algorithms and many more.

Table 1: Overview of Machine Learning Approaches [7]

ML Group	Categories	Algorithms
Learning Styles	Supervised	Logistic Regression and the Back Propagation Neural Network.
	Unsupervised	Apriori algorithm and K-Means
	Semi-supervised	Classification, Regression
Similarity in Form of Function	Regression	Ordinary Least Squares Regression (OLSR), Linear Regression, Logistic Regression, Stepwise Regression, Multivariate Adaptive Regression Splines (MARS), Locally Estimated Scatterplot Smoothing (LOESS).
	Instance-based	k-Nearest Neighbor (KNN), Learning Vector Quantization (LVQ), Self-Organizing Map (SOM), Locally Weighted Learning (LWL), Support Vector Machines (SVM)
	Regularization	Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net, Least-Angle Regression (LARS)
	Decision Tree	Classification and Regression Tree (CART), Chi-squared Automatic Interaction Detection (CHAID), Decision Stump, Conditional Decision Trees

ML Group	Categories	Algorithms
Similarity in Form of Function	Bayesian	Naive Bayes, Gaussian Naive Bayes, Multinomial Naive Bayes, Averaged One-Dependence Estimators (AODE), Bayesian Belief Network (BBN), Bayesian Network (BN)
	Clustering	k-Means, k-Medians, Expectation Maximisation (EM), Hierarchical Clustering
	Association Rule	Apriori algorithm, Eclat algorithm
	Artificial Neural Network	Perceptron, Multilayer Perceptron (MLP), Back-Propagation, Stochastic Gradient Descent, Hopfield Network, Radial Basis Function Network (RBF or RBFN)
	Deep Learning	Convolutional Neural Network (CNN), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Stacked Auto-Encoders, Deep Boltzmann Machine (DBM), Deep Belief Networks (DBN)
	Dimensionality Reduction	Principal Component Analysis (PCA), Principal Component Regression (PCR), Partial Least Squares Regression (PLSR), Sammon Mapping, Multidimensional Scaling (MDS), Projection Pursuit, Linear Discriminant Analysis (LDA), Mixture Discriminant Analysis (MDA), Quadratic Discriminant Analysis (QDA), Flexible Discriminant Analysis (FDA)
	Ensemble	Boosting, Bootstrapped Aggregation (Bagging), AdaBoost, Weighted Average (Blending), Stacked Generalization (Stacking), Gradient Boosting Machines (GBM), Gradient Boosted Regression Trees (GBRT), Random Forest

3. MACHINE LEARNING APPLICATIONS IN RECENT DAM WATER RESEARCH

Comprehensive management of data, simulation and optimization are required for a multi-purpose objective analysis dam water management. Most dam water management is supported by a computerized model to satisfy multi-objective decision making. Machine learning (ML) supports continuous requirements towards a smart decision-making process in a dynamically varying setting. This paper presents recent researches in machine learning applications for dam water research and the overview is presented in Table 2.

A research investigates the techniques for monitoring the dam health and detecting anomalies in passive seismic incidents. by developing a workflow using machine learning. Geophysical data are obtained from sensors at the surface of the levee. The experiments were conducted using SVM to data retrieved from sensors. The data extracts features based on time series data [8]. Dam health monitoring using statistical models has been used for many types of research. Usually, there are three main indicators for dam structural; dam water level, temperature and period of deformation. Dam with concrete structures relies highly on ambient temperature. In order to support such requirements, a dam health monitoring model is modelled by emphasizing on the temperature indicators. The researcher presented a monitoring model that predicts based on air temperature. Kernel extreme learning is used to show the nonlinear relationship during the simulation experiment. The kernel extreme learning has shown speed in accuracy and performance. The simulation was also undertaken in real dam concrete gravity and the results are feasible to application [9].

Another research looked into the prediction and monitoring of the level of an underground dam water in South Africa. The performance between two single classifiers are compared; KNN and RBF and two multiple classifiers; random forest and stacking. The results show that for dam water level prediction results, RBF performed better than the other three ML techniques. RBF shows the maximum score for performance measures than other techniques [10]. A researcher also developed a time series regression forecasting model to select variables with complete variables, the result shows that it gives a better forecast result than the SVM model [11].

Research focusing on dam behaviour by discovering abnormalities patterns to establish whether an inconsistency is normal or abnormal. The boosted regression tree is the ML technique applied for the research. Early detection of anomalies is performed to a time series data collected from a 100m high arch dam [12].

Dam safety analysis estimates the dam data. If a given data is compared with actual measurement, the dam safety levels can be estimated based on the results and conclusion drawn from the analysis. In the dam safety analysis, a hybrid model that applies engineering practice, hydrostatics-season-time is implemented together with other ML technique; artificial neural network and support vector machine. The researcher emphasis on dam typology and issues on data validation. The overall results are promising although future work suggests validation and generalization capability such as data pre-processing and model evaluation [13]. Another research that looks in dam safety analysis develops a framework able to analyze the reliability of the dam gravity. The dam gravity analysis is used to predict natural disaster such as floods and earthquake. The research uses three kinds of ML technique; KNN, SVM and Naive Bayes classifier. The data modelled are a variety of dam classes, levels of dam waters, scale Richter and rate of degradation. The results suggest a specialized function for dams hydrological hazard [14].

A dam operation rule for water release and water demand at Aswan High Dam was developed and the performance was compared between shark machine learning algorithm (SMLA) and genetic algorithm (GA). The performance indicators are reliability, resiliency and vulnerability. The optimal dam operation rule using SMLA has better performance according to the final result [15]. Another research that intends to improve water management and stabilize the needs between the environment and industry was undertaken in Timah Tasoh Dam, Malaysia. The generated dam operation rule was examined by looking at the pattern using radial basis function neural network (RBF-NN) and support vector regression (SVR). The results showed significant indicators based on the simulation of the model performance [16]. An extension of this research was undertaken by adding more indicators; spatial and temporal [17]. The improved dam operation model applied three approaches; RBF-NN, SVR and SMLA to predict the water flow of the dam monthly. The purpose of the model is to lessen the gap between the water need and water supply. The simulated result compared three of the approaches. In terms of dam inflow, SVR is better RBF-NN. Instead, in terms of resiliency, reliability and vulnerability, SMLA is better than the other models [17].

A prediction model can effectively identify dam crack behaviour for dam safety monitoring. The extreme learning machine (ELM) and bootstrap confidence intervals were performed to identify concrete dam crack behaviour. An extreme learning machine model was modelled based on the characteristic vector of crack behaviour. The result demonstrated highly accurate prediction able to recognize dam cracks behaviour [18].

Dam gully erosion is modelled for Ekbatan Dam to assist in identifying the high-risk areas of gully erosion. The model, named GESM (gully erosion susceptibility map) was developed and compared four approaches; RF, SVM, NB and GAM. Each model was evaluated based on the accuracy ranging from excellent (NB, GAM) to outstanding (RF, SVM). In overall, all models were quite stable for developing GESM. The samples are calibrated and validated using cross-validation technique. Based on GESM, the results show that the most important variables are distance from rivers, calcium carbonate equivalent (CCE), and topographic position index (TPI) [19].

A critical indicator reflecting a dam operation is the displacement monitoring and forecasting. A research proposed a model that applies GRP-based model [20]. The data modelled are based on hydraulic, thermal, irreversible factors associated with the displacements of the dam. The result compared among several machine learning approaches; MLR, RBFN and SVM. The model was able to overcome over-learning issues faced by RBFN and SVM improves the accuracy of the prediction. Besides, the model has simplified training and able to offer probabilistic output [20]. On the other hand, a research studied the dam displacement monitoring of dam deformation [21]. The research proposed a new prediction approach based on the probability and optimization of concrete dam displacement using ORVM approach. The data modelled are based on several indicators such as the effect of hydrostatic, seasonal and irreversible time period on the dam deformation process. The research compared the ORVM model with four other machine learning approaches; SVM, RBF-NN, ELM and HST-MLR. Based on the ORVM simulation results, the proposed model has the best performance for predicting displacement compared with the aforementioned four models. Besides, the ORVM model has presented an acceptable confidence index for dam safety monitoring [21].

Table 2: A Review of Machine Learning Approaches in Dam Water Research

Dam Area	ML Techniques	Authors
Dam health monitoring	Support Vector Machine (SVM)	[8]
	Kernel Extreme Learning Machines	[9]
Dam water level	K-Nearest Neighbour (KNN), and Radial Basis Function (RBF), Random Forest (RF), Stacking	[10]
	Time Series Regression forecasting model	[11]
Dam behavior (crack)	Boosted Regression Trees (BRT)	[12]
	Extreme Learning Machines (ELM)	[18]

Dam Area	ML Techniques	Authors
Dam safety analysis	Artificial Neural Network (ANN), Support Vector Machine (SVM)	[12]
	K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Naive Bayes Classifier	[14]
	Extreme Learning Machines (ELM)	[18]
Dam operation	Shark Machine Learning Algorithm (SMLA)	[22]
	Radial Basis Function Neural Network (RBF-NN), Support Vector Regression (SVR)	[16]
	SMLA, Radial Basis Function Neural Network (RBF-NN) And Support Vector Regression (SVR)	[17]
Dam gully erosion	Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes (NB), And Generalized Additive Model (GAM)	[19]
Dam displacement forecasting and monitoring	Gaussian Process Regression (GPR), Multiple Linear Regression (MLR), Radial Basis Function (RBF), Support Vector Machine (SVM)	[20]
	Optimized relevance vector machine (ORVM), Support Vector Regression (SVR), Radial Basis Function Neural Network (RBF-NN), Extreme Learning Machine (ELM) And The HST-Based Multiple Linear Regression (HST-MLR)	[21]

In the next section, we discuss the challenges and opportunities to overcome the challenges in dam water researches.

4. DISCUSSION

Emerging researches in dam waters is increasing in numbers and generally focusing in several areas such as dam health monitoring, dam water level, dam behavior, dam safety analysis, dam operation, dam gully erosion and diam displacement (forecasting and monitoring). Dam operation centres are facing with difficulties to enforce regulation have limited resources to achieve their operational tasks automatically. Therefore, applying machines learning approach enable dam operators to improve efficiency in decision making even with limited data [23]. The challenges in dam water assets research is mainly; data [24], [25] and the machine learning modelling itself [24]. Historical (temporal) data including environmental form, physical structure, disaster recovery, operation and maintenance plays a critical role in predicting any failures or conducting risk assessment) [3]. Machine learning depends highly on reliable data and when modelled, helps to suggest strategies and recommendations of necessary action.

Key challenges in conducting water related research are i) spatio temporal data, ii) heterogeneity data, iii) data collection and iv) missing data [24]. Missing data is a well-known challenge in order to perform machine learning as datasets in water research are surrounded with issues of incompleteness and missing values. The data sources can transmit through machine learning algorithms to the prediction variable. This provides opportunities for researcher to leverage techniques that takes missing values into account.

Unpredictable data in spatial and temporal measures poses challenges during data analysis. Therefore, a standard resolution measure can be explored by researchers to manage the difficulties in carrying out data analysis prior to modelling the learning. Besides that, analyzing heterogeneity data also present challenges if it is stored or presented in different spaces. For an example, ocean is in 3D Euclidean space and stream flow is in 2D space. Researchers should handle the differences accordingly through understand the heterogeneous dimensional space interactions.

In dam water research, data standards and data availability are also a challenge as some data does not come in a standard format since data collection stage. Data may be collected from different sources and if not standardized according to a uniform standard will pose problems. The cause of such variations and discrepancies arises from variations in definition of terms and methods applied for data collection. Researchers can explore solutions through aggregating data from different sources including specifying the data format and standards.

5. CONCLUSION

This paper presented an overview of machine learning approaches in recent dam water research. The recent years showed, the machine learning approaches in dam water research surrounds several areas such as dam health monitoring, dam water level, dam behavior, dam safety analysis, dam operation, dam gully erosion and diam displacement (forecasting and monitoring). The approach of machine learning allows for dam operators to prioritize on the actions taken to address problems arise. ML allows monitoring and optimization of system performance. Hence, users are able to make effective decision based on the developed algorithm even with limited data. Assessment and analysis of data is relatively more accurate. Prediction made using ML in relation to policies, operation and management of dam will be more objective oriented and reduce inefficiency.

The objective of this paper is to introduce machine learning approaches and the algorithms applied in dam water research based on the dam research areas. Studies as reviewed in this paper have documented that applying ML approach is significantly promising in dam operation management.

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REFERENCES

[1] D. Ellison, T, T. Mizutani, and T. Z., "ISO - Managing water assets - Tackling the infrastructure gap," 2013. [Online]. Available: https://www.iso.org/news/2013/07/Ref1762.html.

[2] A. Palmieri, "Rehabilitation of Dams: Financial instruments, O&M and Sustainability," in *International Workshop Water Infrastructure*, 2017.

[3] B. et al. Fazli, "Improvement of Dam Management in Terms of WAM Using Machine Learning," in *In: Mohd Sidek L., Salih G., Boosroh M. (eds) ICDSME 2019. ICDSME 2019. Water Resources Development and Management.*, 2020, pp. 226–236. https://doi.org/10.1007/978-981-15-1971-0_23

[4] V. Sudha, S. Mohan, and R. M. Mohan, "A high performance on extemporize yield of horticulture crops with predictions based water and soil properties using multivariate analytics and machine learning algorithms," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 4, pp. 1706–1710, 2019. https://doi.org/10.30534/ijatcse/2019/98842019

[5] S. More and J. Singla, "Machine learning techniques with IoT in agriculture," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 3, pp. 742–747, 2019. https://doi.org/10.30534/ijatcse/2019/63832019

[6] D. Siva and P. Bojja, "MLC based Classification of Satellite Images for Damage Assessment Index in Disaster Management," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 3, pp. 10–13, 2019. https://doi.org/10.30534/ijatcse/2019/24862019

[7] J. Brownlee, *Master Machine Learning Algorithms*, V1.14. Jason Brownlee, 2016.

[8] W. D. Fisher, T. K. Camp, and V. V. Krzhizhanovskaya, "Crack detection in earth dam and levee passive seismic data using support vector machines," in *Procedia Computer Science*, 2016. https://doi.org/10.1016/j.procs.2016.05.339

[9] F. Kang, X. Liu, and J. Li, "Temperature effect modeling in structural health monitoring of concrete dams using kernel extreme learning machines," *Struct. Heal. Monit.*, 2019.

[10] A. N. Hasan, "Evaluating the performance of single classifiers against multiclassifiers in monitoring underground dam levels and energy consumption for a deep gold mine pump station," in *IECON Proceedings (Industrial Electronics Conference)*, 2016.

[11] J. K. Wong, M. Alraih, A. N. Ahmed, C. M. Fai, A. EL-SHAFIE, and A. EL-SHAFIE, "Daily Forecasting of Dam Water Levels Using Machine Learning," *Int. J. Civ. Eng. Technol.*, vol. 10, no. 6, pp. 314–323, 2019.

[12] F. Salazar, M. Á. Toledo, J. M. González, and E. Oñate, "Early detection of anomalies in dam performance: A methodology based on boosted regression trees," *Struct. Control Heal. Monit.*, 2017. https://doi.org/10.1002/stc.2012

[13] F. Salazar, R. Morán, M. Toledo, and E. Oñate, "Data-Based Models for the Prediction of Dam Behaviour: A Review and Some Methodological Considerations," *Arch. Comput. Methods Eng.*, 2017.

[14] M. A. Hariri-Ardebili and F. Pourkamali-Anaraki, "Simplified reliability analysis of multi hazard risk in gravity dams via machine learning techniques," *Arch. Civ. Mech. Eng.*, 2018.

[15] M. F. Allawi, O. Jaafar, F. Mohamad Hamzah, M. Ehteram, M. S. Hossain, and A. El-Shafie, "Operating a reservoir system based on the shark machine learning algorithm," *Environ. Earth Sci.*, 2018.

[16] M. F. Allawi, O. Jaafar, F. Mohamad Hamzah, S. B. Koting, N. S. B. Mohd, and A. El-Shafie, "Forecasting hydrological parameters for reservoir system utilizing artificial intelligent models and exploring their influence on operation performance," *Knowledge-Based Syst.*, 2019.

[17] M. F. Allawi, O. Jaafar, F. Mohamad Hamzah, and A. El-Shafie, "Novel reservoir system simulation procedure for gap minimization between water supply and demand," *J. Clean. Prod.*, 2019. https://doi.org/10.1016/j.jclepro.2018.09.237

[18] B. Dai, C. Gu, E. Zhao, K. Zhu, W. Cao, and X. Qin, "Improved online sequential extreme learning machine for identifying crack behavior in concrete dam," *Adv. Struct. Eng.*, 2019.

[19] Y. Garosi, M. Sheklabadi, C. Conoscenti, H. R. Pourghasemi, and K. Van Oost, "Assessing the performance of GIS- based machine learning models with different accuracy measures for determining susceptibility to gully erosion," *Sci. Total Environ.*, 2019.

[20] C. Lin, T. Li, S. Chen, X. Liu, C. Lin, and S. Liang, "Gaussian process regression-based forecasting model of dam deformation," *Neural Comput. Appl.*, 2019. https://doi.org/10.1007/s00521-019-04375-7

[21] S. Chen, C. Gu, C. Lin, K. Zhang, and Y. Zhu, "Multi-kernel optimized relevance vector machine for probabilistic prediction of concrete dam displacement," *Eng. Comput.*, 2020.

[22] M. F. Allawi, O. Jaafar, M. Ehteram, F. Mohamad Hamzah, and A. El-Shafie, "Synchronizing Artificial

Intelligence Models for Operating the Dam and Reservoir System," *Water Resour. Manag.*, 2018. https://doi.org/10.1007/s11269-018-1996-3

[23] M. Hino, E. Benami, and N. Brooks, "Machine learning for environmental monitoring," *Nat. Sustain.*, pp. 583–588, 2018. https://doi.org/10.1038/s41893-018-0142-9

[24] S. M. A. Zaidi *et al.*, "Machine learning for energy-water nexus: challenges and opportunities," *Big Earth Data*, vol. 2, no. 3, pp. 228–267, 2018. https://doi.org/10.1080/20964471.2018.1526057

[25] H. Kang, "Challenges for water infrastructure asset management in South Korea," *Water Policy*, vol. 21, no. 5. pp. 934–944, 2019. https://doi.org/10.2166/wp.2019.005