Search String:

TITLE-ABS-KEY (("regress*" OR "support vector machine*" OR "na?ve bayes*" OR "discriminant analy*" OR "*nearest neighbor*" OR "decision tree*" OR "similarity learn*" OR "ensemble method*" OR "ensemble learn*" OR "ensemble of tree*" OR "random* forest*" OR "gradient tree boost*" OR "gradient boost*" OR "forest* of randomized tree*" OR "bootstrap aggregat*" OR "bagging" OR "boosting" OR "boosted tree*" OR "bagged tree*" OR "adaptive boost*" OR "adaboost" OR "voting regressor" OR "stacking" OR "stacked general*" OR "least absolute shrinkage and selection operator" OR "lasso" OR "elastic-net" OR "elastic net" OR "matching pursuit" OR "stochastic gradient descen*" OR "passive aggressive" OR "passive-aggressive" OR "gaussian process*" OR "cross decompos*" OR "generalized linear model*" OR "probabilistic graphical model*" OR "bayes* optimal classif*" OR "group method of data handling" OR "*neural net*" OR "deep* learn*" OR "radial basis" OR "deep belief" OR "memory net*" OR "supervised learn*" OR "supervised algorithm*" OR "supervised method*" OR "supervised technique*") AND ("groundwater" OR "ground water" OR "aquifer") AND ("model*" OR "predict*" OR "forecast*" OR "simulat*")) AND DOCTYPE (ar OR cp) AND PUBYEAR > 2009 AND (LIMIT-TO (LANGUAGE , "English"))

List of Included Articles:

1. Adamowski, J. and Chan, H.F., 2011. A wavelet neural network conjunction model for groundwater level forecasting. *Journal of Hydrology*, *407*(1-4), pp.28-40.
2. Yoon, H., Jun, S.C., Hyun, Y., Bae, G.O. and Lee, K.K., 2011. A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. *Journal of hydrology*, *396*(1-2), pp.128-138.
3. Taormina, R., Chau, K.W. and Sethi, R., 2012. Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. *Engineering Applications of Artificial Intelligence*, *25*(8), pp.1670-1676.
4. Gholami, V.C.K.W., Chau, K.W., Fadaee, F., Torkaman, J. and Ghaffari, A., 2015. Modeling of groundwater level fluctuations using dendrochronology in alluvial aquifers. *Journal of hydrology*, *529*, pp.1060-1069.
5. Zhang, J., Zhu, Y., Zhang, X., Ye, M. and Yang, J., 2018. Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas. *Journal of hydrology*, *561*, pp.918-929.
6. Moosavi, V., Vafakhah, M., Shirmohammadi, B. and Behnia, N., 2013. A wavelet-ANFIS hybrid model for groundwater level forecasting for different prediction periods. *Water resources management*, *27*(5), pp.1301-1321.
7. Mohanty, S., Jha, M.K., Kumar, A. and Sudheer, K.P., 2010. Artificial neural network modeling for groundwater level forecasting in a river island of eastern India. *Water resources management*, *24*(9), pp.1845-1865.
8. Shiri, J. and Kişi, Ö., 2011. Comparison of genetic programming with neuro-fuzzy systems for predicting short-term water table depth fluctuations. *Computers & Geosciences*, *37*(10), pp.1692-1701.
9. Banerjee, P., Singh, V.S., Chatttopadhyay, K., Chandra, P.C. and Singh, B., 2011. Artificial neural network model as a potential alternative for groundwater salinity forecasting. *Journal of Hydrology*, *398*(3-4), pp.212-220.
10. Fallah-Mehdipour, E., Haddad, O.B. and Mariño, M.A., 2013. Prediction and simulation of monthly groundwater levels by genetic programming. *Journal of Hydro-Environment Research*, *7*(4), pp.253-260.
11. Shiri, J., Kisi, O., Yoon, H., Lee, K.K. and Nazemi, A.H., 2013. Predicting groundwater level fluctuations with meteorological effect implications—A comparative study among soft computing techniques. *Computers & Geosciences*, *56*, pp.32-44.
12. Emamgholizadeh, S., Moslemi, K. and Karami, G., 2014. Prediction the groundwater level of bastam plain (Iran) by artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). *Water resources management*, *28*(15), pp.5433-5446.
13. Shirmohammadi, B., Vafakhah, M., Moosavi, V. and Moghaddamnia, A., 2013. Application of several data-driven techniques for predicting groundwater level. *Water Resources Management*, *27*(2), pp.419-432.
14. Sahoo, S. and Jha, M.K., 2013. Groundwater-level prediction using multiple linear regression and artificial neural network techniques: a comparative assessment. *Hydrogeology Journal*, *21*(8), pp.1865-1887.
15. Kurtulus, B. and Razack, M., 2010. Modeling daily discharge responses of a large karstic aquifer using soft computing methods: Artificial neural network and neuro-fuzzy. *Journal of Hydrology*, *381*(1-2), pp.101-111.
16. Sun, A.Y., 2013. Predicting groundwater level changes using GRACE data. *Water Resources Research*, *49*(9), pp.5900-5912.
17. Mohanty, S., Jha, M.K., Kumar, A. and Panda, D.K., 2013. Comparative evaluation of numerical model and artificial neural network for simulating groundwater flow in Kathajodi–Surua Inter-basin of Odisha, India. *Journal of Hydrology*, *495*, pp.38-51.
18. Behzad, M., Asghari, K. and Coppola Jr, E.A., 2010. Comparative study of SVMs and ANNs in aquifer water level prediction. *Journal of Computing in Civil Engineering*, *24*(5), pp.408-413.

19. Sahoo, S., Russo, T.A., Elliott, J. and Foster, I., 2017. Machine learning algorithms for modeling groundwater level changes in agricultural regions of the US. *Water Resources Research*, *53*(5), pp.3878-3895.
20. Gong, Y., Zhang, Y., Lan, S. and Wang, H., 2016. A comparative study of artificial neural networks, support vector machines and adaptive neuro fuzzy inference system for forecasting groundwater levels near Lake Okeechobee, Florida. *Water resources management*, *30*(1), pp.375-391.
21. Barzegar, R., Fijani, E., Moghaddam, A.A. and Tziritis, E., 2017. Forecasting of groundwater level fluctuations using ensemble hybrid multi-wavelet neural network-based models. *Science of the Total Environment*, *599*, pp.20-31.
22. Maiti, S. and Tiwari, R.K., 2014. A comparative study of artificial neural networks, Bayesian neural networks and adaptive neuro-fuzzy inference system in groundwater level prediction. *Environmental earth sciences*, *71*(7), pp.3147-3160.
23. Suryanarayana, C., Sudheer, C., Mahammood, V. and Panigrahi, B.K., 2014. An integrated wavelet-support vector machine for groundwater level prediction in Visakhapatnam, India. *Neurocomputing*, *145*, pp.324-335.
24. Nourani, V., Ejlali, R.G. and Alami, M.T., 2011. Spatiotemporal groundwater level forecasting in coastal aquifers by hybrid artificial neural network-geostatistics model: a case study. *Environmental Engineering Science*, *28*(3), pp.217-228.
25. Chang, F.J., Chang, L.C., Huang, C.W. and Kao, I.F., 2016. Prediction of monthly regional groundwater levels through hybrid soft-computing techniques. *Journal of Hydrology*, *541*, pp.965-976.
26. Ghose, D.K., Panda, S.S. and Swain, P.C., 2010. Prediction of water table depth in western region, Orissa using BPNN and RBFN neural networks. *Journal of hydrology*, *394*(3-4), pp.296-304.
27. Ebrahimi, H. and Rajaee, T., 2017. Simulation of groundwater level variations using wavelet combined with neural network, linear regression and support vector machine. *Global and Planetary Change*, *148*, pp.181-191.
28. Wunsch, A., Liesch, T. and Broda, S., 2018. Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (NARX). *Journal of hydrology*, *567*, pp.743-758.
29. Guzman, S.M., Paz, J.O. and Tagert, M.L.M., 2017. The use of NARX neural networks to forecast daily groundwater levels. *Water Resources Management*, *31*(5), pp.1591-1603.
30. Mohanty, S., Jha, M.K., Raul, S.K., Panda, R.K. and Sudheer, K.P., 2015. Using artificial neural network approach for simultaneous forecasting of weekly groundwater levels at multiple sites. Water Resources Management, 29(15), pp.5521-5532.
31. Yoon, H., Hyun, Y., Ha, K., Lee, K.K. and Kim, G.B., 2016. A method to improve the stability and accuracy of ANN-and SVM-based time series models for long-term groundwater level predictions. *Computers & geosciences*, *90*, pp.144-155.
32. Tapoglou, E., Karatzas, G.P., Trichakis, I.C. and Varouchakis, E.A., 2014. A spatio-temporal hybrid neural network-Kriging model for groundwater level simulation. *Journal of hydrology*, *519*, pp.3193-3203.
33. Rezaie-balf, M., Naganna, S.R., Ghaemi, A. and Deka, P.C., 2017. Wavelet coupled MARS and M5 Model Tree approaches for groundwater level forecasting. *Journal of hydrology*, *553*, pp.356-373.
34. Chang, J., Wang, G. and Mao, T., 2015. Simulation and prediction of suprapermafrost groundwater level variation in response to climate change using a neural network model. *Journal of Hydrology*, *529*, pp.1211-1220.
35. Nourani, V. and Mousavi, S., 2016. Spatiotemporal groundwater level modeling using hybrid artificial intelligence-meshless method. *Journal of Hydrology*, *536*, pp.10-25.
36. Alizamir, M., Kisi, O. and Zounemat-Kermani, M., 2018. Modelling long-term groundwater fluctuations by extreme learning machine using hydro-climatic data. *Hydrological sciences journal*, *63*(1), pp.63-73.

37. Choubin, B. and Malekian, A., 2017. Combined gamma and M-test-based ANN and ARIMA models for groundwater fluctuation forecasting in semiarid regions. *Environmental Earth Sciences*, *76*(15), pp.1-10.
38. Zhou, T., Wang, F. and Yang, Z., 2017. Comparative analysis of ANN and SVM models combined with wavelet preprocess for groundwater depth prediction. *Water*, *9*(10), p.781.
39. Izady, A., Davary, K., Alizadeh, A., Ghahraman, B., Sadeghi, M. and Moghaddamnia, A., 2012. Application of "panel-data" modeling to predict groundwater levels in the Neishaboor Plain, Iran. *Hydrogeology Journal*, *20*(3), pp.435-447.
40. Doglioni, A., Mancarella, D., Simeone, V. and Giustolisi, O., 2010. Inferring groundwater system dynamics from hydrological time-series data. *Hydrological Sciences Journal–Journal des Sciences Hydrologiques*, *55*(4), pp.593-608.
41. Zare, M. and Koch, M., 2018. Groundwater level fluctuations simulation and prediction by ANFIS-and hybrid Wavelet-ANFIS/Fuzzy C-Means (FCM) clustering models: Application to the Miandarband plain. *Journal of Hydro-environment Research*, *18*, pp.63-76.
42. Kisi, O., Alizamir, M. and Zounemat-Kermani, M., 2017. Modeling groundwater fluctuations by three different evolutionary neural network techniques using hydroclimatic data. Natural Hazards, 87(1), p.367.
43. Izady, A., Davary, K., Alizadeh, A., Nia, A.M., Ziaei, A.N. and Hasheminia, S.M., 2013. Application of NN-ARX model to predict groundwater levels in the Neishaboor Plain, Iran. Water resources management, 27(14), pp.4773-4794.
44. Sujay Raghavendra, N. and Deka, P.C., 2015. Forecasting monthly groundwater level fluctuations in coastal aquifers using hybrid Wavelet packet–Support vector regression. Cogent Engineering, 2(1), p.999414.
45. Jalalkamali, A., Sedghi, H. and Manshouri, M., 2011. Monthly groundwater level prediction using ANN and neuro-fuzzy models: a case study on Kerman plain, Iran. *Journal of hydroinformatics*, *13*(4), pp.867-876.
46. Barzegar, R., Moghaddam, A.A., Adamowski, J. and Fijani, E., 2017. Comparison of machine learning models for predicting fluoride contamination in groundwater. *Stochastic Environmental Research and Risk Assessment*, *31*(10), pp.2705-2718.
47. Sreekanth, P.D., Sreedevi, P.D., Ahmed, S. and Geethanjali, N., 2011. Comparison of FFNN and ANFIS models for estimating groundwater level. *Environmental Earth Sciences*, *62*(6), pp.1301-1310.
48. Huang, F., Huang, J., Jiang, S.H. and Zhou, C., 2017. Prediction of groundwater levels using evidence of chaos and support vector machine. *Journal of Hydroinformatics*, *19*(4), pp.586-606.
49. Gorgij, A.D., Kisi, O. and Moghaddam, A.A., 2017. Groundwater budget forecasting, using hybrid wavelet-ANN-GP modelling: a case study of Azarshahr Plain, East Azerbaijan, Iran. *Hydrology Research*, *48*(2), pp.455-467.
50. Chen, H., Zhang, W., Nie, N. and Guo, Y., 2019. Long-term groundwater storage variations estimated in the Songhua River Basin by using GRACE products, land surface models, and in-situ observations. *Science of the Total Environment*, *649*, pp.372-387.
51. Yadav, B., Ch, S., Mathur, S. and Adamowski, J., 2017. Assessing the suitability of extreme learning machines (ELM) for groundwater level prediction. *Journal of Water and Land Development*, (32), pp.103-112.
52. Xu, T. and Valocchi, A.J., 2015. Data-driven methods to improve baseflow prediction of a regional groundwater model. *Computers & Geosciences*, *85*, pp.124-136.
53. Rakhshandehroo, G.R., Vaghefi, M. and Aghbolaghi, M.A., 2012. Forecasting groundwater level in Shiraz plain using artificial neural networks. *Arabian Journal for Science and Engineering*, *37*(7), pp.1871-1883.
54. Kisi, O., Keshavarzi, A., Shiri, J., Zounemat-Kermani, M. and Omran, E.S.E., 2017. Groundwater quality modeling using neuro-particle swarm optimization and neuro-differential evolution techniques. *Hydrology research*, *48*(6), pp.1508-1519.

55. Mukherjee, A. and Ramachandran, P., 2018. Prediction of GWL with the help of GRACE TWS for unevenly spaced time series data in India: Analysis of comparative performances of SVR, ANN and LRM. *Journal of hydrology*, *558*, pp.647-658.
56. Yan, Q. and Ma, C., 2016. Application of integrated ARIMA and RBF network for groundwater level forecasting. *Environmental Earth Sciences*, *75*(5), p.396.
57. Alagha, J.S., Said, M.A.M. and Mogheir, Y., 2014. Modeling of nitrate concentration in groundwater using artificial intelligence approach—a case study of Gaza coastal aquifer. *Environmental monitoring and assessment*, *186*(1), pp.35-45.
58. He, Z., Zhang, Y., Guo, Q. and Zhao, X., 2014. Comparative study of artificial neural networks and wavelet artificial neural networks for groundwater depth data forecasting with various curve fractal dimensions. *Water resources management*, *28*(15), pp.5297-5317.
59. Jalalkamali, A. and Jalalkamali, N., 2011. Groundwater modeling using hybrid of artificial neural network with genetic algorithm. *African Journal of Agricultural Research*, *6*(26), pp.5775-5784.
60. Chen, L.H., Chen, C.T. and Lin, D.W., 2011. Application of integrated back-propagation network and self-organizing map for groundwater level forecasting. *Journal of Water Resources Planning and Management*, *137*(4), pp.352-365.
61. Chitsazan, M., Rahmani, G. and Neyamadpour, A., 2015. Forecasting groundwater level by artificial neural networks as an alternative approach to groundwater modeling. *Journal of the Geological Society of India*, *85*(1), pp.98-106.
62. Karthikeyan, L., Kumar, D.N., Graillot, D. and Gaur, S., 2013. Prediction of ground water levels in the uplands of a tropical coastal riparian wetland using artificial neural networks. *Water resources management*, *27*(3), pp.871-883.
63. Afzaal, H., Farooque, A.A., Abbas, F., Acharya, B. and Esau, T., 2020. Groundwater estimation from major physical hydrology components using artificial neural networks and deep learning. *Water*, *12*(1), p.5.
64. Nourani, V., Alami, M.T. and Vousoughi, F.D., 2016. Hybrid of SOM-clustering method and wavelet-ANFIS approach to model and infill missing groundwater level data. *Journal of Hydrologic Engineering*, *21*(9), p.05016018.
65. Sattari, M.T., Mirabbasi, R., Sushab, R.S. and Abraham, J., 2018. Prediction of groundwater level in Ardebil plain using support vector regression and M5 tree model. *Groundwater*, *56*(4), pp.636-646.
66. Jeong, J. and Park, E., 2019. Comparative applications of data-driven models representing water table fluctuations. *Journal of Hydrology*, *572*, pp.261-273.
67. Yu, H., Wen, X., Feng, Q., Deo, R.C., Si, J. and Wu, M., 2018. Comparative study of hybrid-wavelet artificial intelligence models for monthly groundwater depth forecasting in extreme arid regions, Northwest China. *Water resources management*, *32*(1), pp.301-323.
68. Guzmán, S.M., Paz, J.O., Tagert, M.L.M., Mercer, A.E. and Pote, J.W., 2018. An integrated SVR and crop model to estimate the impacts of irrigation on daily groundwater levels. *Agricultural systems*, *159*, pp.248-259.
69. Bowes, B.D., Sadler, J.M., Morsy, M.M., Behl, M. and Goodall, J.L., 2019. Forecasting groundwater table in a flood prone coastal city with long short-term memory and recurrent neural networks. *Water*, *11*(5), p.1098.
70. Lee, S., Lee, K.K. and Yoon, H., 2019. Using artificial neural network models for groundwater level forecasting and assessment of the relative impacts of influencing factors. *Hydrogeology Journal*, *27*(2), pp.567-579.
71. Nakhaei, M. and Nasr, A.S., 2012. A combined Wavelet-Artificial Neural Network model and its application to the prediction of groundwater level fluctuations. *Geopersia*, *2*(2), pp.77-91.
72. Khaki, M., Yusoff, I. and Islami, N., 2015. Simulation of groundwater level through artificial intelligence system. *Environmental Earth Sciences*, *73*(12), pp.8357-8367.
73. Granata, F., Saroli, M., de Marinis, G. and Gargano, R., 2018. Machine learning models for spring discharge forecasting. *Geofluids*, *2018*.

74. Yesilnacar, M.I. and Sahinkaya, E., 2012. Artificial neural network prediction of sulfate and SAR in an unconfined aquifer in southeastern Turkey. *Environmental Earth Sciences*, *67*(4), pp.1111-1119.
75. Djurovic, N., Domazet, M., Stricevic, R., Pocuca, V., Spalevic, V., Pivic, R., Gregoric, E. and Domazet, U., 2015. Comparison of groundwater level models based on artificial neural networks and ANFIS. *The Scientific World Journal*, *2015*.
76. Raghavendra, N.S. and Deka, P.C., 2016. Multistep ahead groundwater level time-series forecasting using gaussian process regression and ANFIS. In *Advanced computing and systems for security* (pp. 289-302). Springer, New Delhi.
77. Tian, J., Li, C., Liu, J., Yu, F., Cheng, S., Zhao, N. and Wan Jaafar, W.Z., 2016. Groundwater depth prediction using data-driven models with the assistance of gamma test. *Sustainability*, *8*(11), p.1076.
78. Kasiviswanathan, K.S., Saravanan, S., Balamurugan, M. and Saravanan, K., 2016. Genetic programming based monthly groundwater level forecast models with uncertainty quantification. *Modeling Earth Systems and Environment*, *2*(1), p.27.
79. Khaki, M., Yusoff, I., Islami, N. and Hussin, N.H., 2016. Artificial neural network technique for modeling of groundwater level in Langat Basin, Malaysia. *Sains Malaysiana*, *45*(1), pp.19-28.
80. Sahoo, S. and Jha, M.K., 2015. On the statistical forecasting of groundwater levels in unconfined aquifer systems. *Environmental Earth Sciences*, *73*(7), pp.3119-3136.
81. Demirci, M., Unes, F., Kaya, Y.Z., Mamak, M., Tasar, B. and Ispir, E., 2017, March. Estimation of groundwater level using artificial neural networks: a case study of Hatay-Turkey. In *10th International Conference „Environmental Engineering "*.
82. Guzman, S.M., Paz, J.O., Tagert, M.L.M. and Mercer, A.E., 2019. Evaluation of seasonally classified inputs for the prediction of daily groundwater levels: NARX networks vs support vector machines. *Environmental Modeling & Assessment*, *24*(2), pp.223-234.
83. Wen, X., Feng, Q., Deo, R.C., Wu, M. and Si, J., 2017. Wavelet analysis–artificial neural network conjunction models for multi-scale monthly groundwater level predicting in an arid inland river basin, northwestern China. *Hydrology Research*, *48*(6), pp.1710-1729.
84. Rakhshandehroo, G., Akbari, H., Afshari Igder, M. and Ostadzadeh, E., 2018. Long-term groundwater-level forecasting in shallow and deep wells using wavelet neural networks trained by an improved harmony search algorithm. *Journal of Hydrologic Engineering*, *23*(2), p.04017058.
85. Yan, S.F., Yu, S.E., Wu, Y.B., Pan, D.F. and Dong, J.G., 2018. Understanding groundwater table using a statistical model. *Water Science and Engineering*, *11*(1), pp.1-7.
86. Ghadampour, Z. and Rakhshandehroo, G., 2010. Using artificial neural network to forecast groundwater depth in union county well. *World Academy of Science, Engineering and Technology*, *62*(1), pp.957-960.
87. Roshni, T., Jha, M.K., Deo, R.C. and Vandana, A., 2019. Development and evaluation of hybrid artificial neural network architectures for modeling spatio-temporal groundwater fluctuations in a complex aquifer system. *Water Resources Management*, *33*(7), pp.2381-2397.
88. Wang, X., Liu, T., Zheng, X., Peng, H., Xin, J. and Zhang, B., 2018. Short-term prediction of groundwater level using improved random forest regression with a combination of random features. *Applied Water Science*, *8*(5), pp.1-12.
89. Huang, X., Gao, L., Crosbie, R.S., Zhang, N., Fu, G. and Doble, R., 2019. Groundwater recharge prediction using linear regression, multi-layer perception network, and deep learning. *Water*, *11*(9), p.1879.
90. Alagha, J.S., Seyam, M., Said, M.A.M. and Mogheir, Y., 2017. Integrating an artificial intelligence approach with k-means clustering to model groundwater salinity: the case of Gaza coastal aquifer (Palestine). *Hydrogeology Journal*, *25*(8), pp.2347-2361.
91. Chen, C., He, W., Zhou, H., Xue, Y. and Zhu, M., 2020. A comparative study among machine learning and numerical models for simulating groundwater dynamics in the Heihe River Basin, northwestern China. *Scientific reports*, *10*(1), pp.1-13.

92. Tapak, L., Rahmani, A. and Moghimbeigi, A., 2014. Prediction the groundwater level of Hamadan-Bahar plain, west of Iran using support vector machines. *Journal of research in health sciences*, *14*(1), pp.82-87.
93. Sudheer, C., Shrivastava, N.A., Panigrahi, B.K. and Mathur, S., 2011, December. Groundwater level forecasting using SVM-QPSO. In *International conference on swarm, evolutionary, and memetic computing* (pp. 731-741). Springer, Berlin, Heidelberg.
94. Seeboonruang, U., 2015. An application of time-lag regression technique for assessment of groundwater fluctuations in a regulated river basin: a case study in Northeastern Thailand. *Environmental Earth Sciences*, *73*(10), pp.6511-6523.
95. Kouziokas, G.N., Chatzigeorgiou, A. and Perakis, K., 2018. Multilayer feed forward models in groundwater level forecasting using meteorological data in public management. *Water Resources Management*, *32*(15), pp.5041-5052.
96. Yang, Q., Hou, Z., Wang, Y., Zhao, Y. and Delgado, J., 2015. A comparative study of shallow groundwater level simulation with WA–ANN and ITS model in a coastal island of south China. *Arabian Journal of Geosciences*, *8*(9), pp.6583-6593.
97. Yang, Q., Hou, Z., Wang, Y., Zhao, Y. and Delgado, J., 2015. A comparative study of shallow groundwater level simulation with WA–ANN and ITS model in a coastal island of south China. *Arabian Journal of Geosciences*, *8*(9), pp.6583-6593.
98. Gong, Y., Wang, Z., Xu, G. and Zhang, Z., 2018. A comparative study of groundwater level forecasting using data-driven models based on ensemble empirical mode decomposition. *Water*, *10*(6), p.730.
99. Moghaddam, H.K., Moghaddam, H.K., Kivi, Z.R., Bahreinimotlagh, M. and Alizadeh, M.J., 2019. Developing comparative mathematic models, BN and ANN for forecasting of groundwater levels. *Groundwater for Sustainable Development*, *9*, p.100237.
100. Zhang, N., Xiao, C., Liu, B. and Liang, X., 2017. Groundwater depth predictions by GSM, RBF, and ANFIS models: a comparative assessment. *Arabian Journal of Geosciences*, *10*(8), p.189.
101. Supreetha, B.S., Nayak, K.P. and Shenoy, K.N., 2015. Groundwater level prediction using hybrid artificial neural network with genetic algorithm. *International Journal of Earth Sciences and Engineering*, *8*(6), pp.2609-2615.
102. Li, H., Lu, Y., Zheng, C., Yang, M. and Li, S., 2019. Groundwater level prediction for the arid oasis of Northwest China based on the artificial bee colony algorithm and a back-propagation neural network with double hidden layers. *Water*, *11*(4), p.860.
103. Salem, G.S.A., Kazama, S., Shahid, S. and Dey, N.C., 2017. Impact of temperature changes on groundwater levels and irrigation costs in a groundwater-dependent agricultural region in Northwest Bangladesh. *Hydrological Research Letters*, *11*(1), pp.85-91.
104. Malekzadeh, M., Kardar, S., Saeb, K., Shabanlou, S. and Taghavi, L., 2019. A novel approach for prediction of monthly ground water level using a hybrid wavelet and non-tuned self-adaptive machine learning model. *Water Resources Management*, *33*(4), pp.1609-1628.
105. Liu, D., Li, G., Fu, Q., Li, M., Liu, C., Faiz, M.A., Khan, M.I., Li, T. and Cui, S., 2018. Application of particle swarm optimization and extreme learning machine forecasting models for regional groundwater depth using nonlinear prediction models as preprocessor. *Journal of Hydrologic Engineering*, *23*(12), p.04018052.
106. Shamsuddin, M.K.N., Kusin, F.M., Sulaiman, W.N.A., Ramli, M.F., Baharuddin, M.F.T. and Adnan, M.S., 2017. Forecasting of Groundwater Level using Artificial Neural Network by incorporating river recharge and river bank infiltration. In *MATEC Web of Conferences* (Vol. 103, p. 04007). EDP Sciences.
107. Sudheer, C. and Shashi, M., 2012. Groundwater level forecasting using SVM-PSO. *International Journal of Hydrology Science and Technology*, *2*(2), pp.202-218.
108. Nie, S., Bian, J., Wan, H., Sun, X. and Zhang, B., 2017. Simulation and uncertainty analysis for groundwater levels using radial basis function neural network and support vector machine models. *Journal of Water Supply: Research and Technology—AQUA*, *66*(1), pp.15-24.
109. Banadkooki, F.B., Ehteram, M., Ahmed, A.N., Teo, F.Y., Fai, C.M., Afan, H.A., Sapitang, M. and El-Shafie, A., 2020. Enhancement of groundwater-level prediction using an integrated machine learning model optimized by whale algorithm. *Natural resources research*, *29*(5), pp.3233-3252.

110. Zhang, J., Zhang, X., Niu, J., Hu, B.X., Soltanian, M.R., Qiu, H. and Yang, L., 2019. Prediction of groundwater level in seashore reclaimed land using wavelet and artificial neural network-based hybrid model. *Journal of Hydrology*, *577*, p.123948.
111. Rahman, A.S., Hosono, T., Quilty, J.M., Das, J. and Basak, A., 2020. Multiscale groundwater level forecasting: coupling new machine learning approaches with wavelet transforms. *Advances in Water Resources*, *141*, p.103595.
112. Bhanja, S.N., Malakar, P., Mukherjee, A., Rodell, M., Mitra, P. and Sarkar, S., 2019. Using satellite-based vegetation cover as indicator of groundwater storage in natural vegetation areas. *Geophysical Research Letters*, *46*(14), pp.8082-8092.
113. Hosseini, Z. and Nakhaie, M., 2015. Estimation of groundwater level using a hybrid genetic algorithm-neural network. *Pollution*, *1*(1), pp.9-21.
114. Wang, L.Y. and Zhao, W.G., 2010. Forecasting groundwater level based on Relevance Vector Machine. In *Advanced Materials Research* (Vol. 121, pp. 43-47). Trans Tech Publications Ltd.
115. Colombani, N., Giambastiani, B.M. and Mastrocicco, M., 2017. Impact of climate variability on the salinization of the coastal wetland-aquifer system of the Po Delta, Italy. *Journal of Water Supply: Research and Technology—AQUA*, *66*(7), pp.430-441.
116. Seifi, A., Ehteram, M., Singh, V.P. and Mosavi, A., 2020. Modeling and uncertainty analysis of groundwater level using six evolutionary optimization algorithms hybridized with ANFIS, SVM, and ANN. *Sustainability*, *12*(10), p.4023.
117. Zhang, Z., Yang, X., Li, H., Li, W., Yan, H. and Shi, F., 2017. Application of a novel hybrid method for spatiotemporal data imputation: A case study of the Minqin County groundwater level. *Journal of Hydrology*, *553*, pp.384-397.
118. Roshni, T., Jha, M.K. and Drisya, J., 2020. Neural network modeling for groundwater-level forecasting in coastal aquifers. *Neural Computing and Applications*, pp.1-18.
119. Kim, Y., Yoon, H. and Kim, G.P., 2016. Development of a novel method to monitor the temporal change in the location of the freshwater–saltwater interface and time series models for the prediction of the interface. *Environmental Earth Sciences*, *75*(10), p.882.
120. Tang, Y., Zang, C., Wei, Y. and Jiang, M., 2019. Data-driven modeling of groundwater level with least-square support vector machine and spatial–temporal analysis. *Geotechnical and Geological Engineering*, *37*(3), pp.1661-1670.
121. Huang, M. and Tian, Y., 2015, October. Prediction of groundwater level for sustainable water management in an arid basin using datadriven models. In *International Conference on Sustainable Energy and Environmental Engineering (SEEE), Bangkok*.
122. Hong, Y.M., 2017. Feasibility of using artificial neural networks to forecast groundwater levels in real time. *Landslides*, *14*(5), pp.1815-1826.
123. Rakhshandehroo, G., & Ghadampour, Z., 2011). A combination of fractal analysis and artificial neural network to forecast groundwater depth. *Iranian Journal of Science And Technology Transaction B- Engineering*, 35(C1), pp. 121-130.
124. Natarajan, N. and Sudheer, C., 2020. Groundwater level forecasting using soft computing techniques. *Neural Computing and Applications*, *32*(12), pp.7691-7708.
125. Soltani Mohammadi, A., Sayadi Shahraki, A. and Naseri, A.A., 2017. Simulation of groundwater quality parameters using ANN and ANN+ PSO Models (Case Study: Ramhormoz Plain). *Pollution*, *3*(2), pp.191-200.
126. Wu, J., Li, Z., Zhu, L., Li, G., Niu, B. and Peng, F., 2018. Optimized BP neural network for dissolved oxygen prediction. *IFAC-PapersOnLine*, *51*(17), pp.596-601.
127. Demırcı, M., Üneş, F. and Körlü, S., 2019. Modeling of groundwater level using artificial intelligence techniques: a case study of Reyhanli region in Turkey. *Applied Ecology and Environmental Research*, *17*(2), pp.2651-2663.
128. Moravej, M., Amani, P. and Hosseini-Moghari, S.M., 2020. Groundwater level simulation and forecasting using interior search algorithm-least square support vector regression (ISA-LSSVR). *Groundwater for Sustainable Development*, *11*, p.100447.
129. Zare, M. and Koch, M., 2016, July. Using ANN and ANFIS Models for simulating and predicting groundwater level fluctuations in the Miandarband Plain, Iran. In *Proceedings of the 4th IAHR Europe Congress. Sustainable Hydraulics in the Era of Global Change, Liege, Belgium* (p. 416).

130. Ghose, D., Das, U. and Roy, P., 2018. Modeling response of runoff and evapotranspiration for predicting water table depth in arid region using dynamic recurrent neural network. *Groundwater for Sustainable Development*, *6*, pp.263-269.
131. Weesakul, U., Watanabe, K. and Sukasem, N., 2010. Application of soft computing techniques for analysis of groundwater table fluctuation in Bangkok area and its vicinity. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies*, *1*(1), pp.53-65.
132. Mayilvaganan, M.K. and Naidu, K.B., 2011, September. Application of artificial neural network for the prediction of groundwater level in hard rock region. In *International Conference on Computational Science, Engineering and Information Technology* (pp. 673-682). Springer, Berlin, Heidelberg.
133. Doglioni, A. and Simeone, V., 2017. Evolutionary modeling of response of water table to precipitations. *Journal of Hydrologic Engineering*, *22*(2), p.04016055.
134. Li, Z., Yang, Q., Wang, L. and Martín, J.D., 2017. Application of RBFN network and GM (1, 1) for groundwater level simulation. *Applied Water Science*, *7*(6), pp.3345-3353.
135. Das, U.K., Roy, P. and Ghose, D.K., 2019. Modeling water table depth using adaptive Neuro-Fuzzy Inference System. *ISH Journal of Hydraulic Engineering*, *25*(3), pp.291-297.
136. Yadav, B., Gupta, P.K., Patidar, N. and Himanshu, S.K., 2020. Ensemble modelling framework for groundwater level prediction in urban areas of India. *Science of The Total Environment*, *712*, p.135539.
137. Iqbal, M., Naeem, U.A., Ahmad, A., Ghani, U. and Farid, T., 2020. Relating groundwater levels with meteorological parameters using ANN technique. *Measurement*, *166*, p.108163.
138. SOEKARNO, I., Hadihardaja, I.K. and Cahyono, M., 2013. The prediction of groundwater level on tidal lowlands reclamation using extreme learning machine. *Journal of Theoretical & Applied Information Technology*, *56*(1).
139. Goyal, M.K., Sharma, A. and Katsifarakis, K.L., 2017. Prediction of flow rate of karstic springs using support vector machines. *Hydrological Sciences Journal*, *62*(13), pp.2175-2186.
140. Das, U.K., Samantaray, S., Ghose, D.K. and Roy, P., 2019. Estimation of aquifer potential using BPNN, RBFN, RNN, and ANFIS. In *Smart Intelligent Computing and Applications* (pp. 569-576). Springer, Singapore.
141. Hosseini, Z., Gharechelou, S., Nakhaei, M. and Gharechelou, S., 2016. Optimal design of BP algorithm by ACO R model for groundwater-level forecasting: A case study on Shabestar plain, Iran. *Arabian Journal of Geosciences*, *9*(6), p.436.
142. Cobaner, M., Babayigit, B. and Dogan, A., 2016. Estimation of groundwater levels with surface observations via genetic programming. *Journal-American Water Works Association*, *108*(6), pp.E335-E348.
143. Ying, Z., Wenxi, L., Haibo, C. and Jiannan, L., 2014. Comparison of three forecasting models for groundwater levels: a case study in the semiarid area of west Jilin Province, China. *Journal of Water Supply: Research and Technology—AQUA*, *63*(8), pp.671-683.
144. Zanotti, C., Rotiroti, M., Sterlacchini, S., Cappellini, G., Fumagalli, L., Stefania, G.A., Nannucci, M.S., Leoni, B. and Bonomi, T., 2019. Choosing between linear and nonlinear models and avoiding overfitting for short and long term groundwater level forecasting in a linear system. *Journal of Hydrology*, *578*, p.124015.
145. Zhao, W.G., Wang, H. and Wang, Z.J., 2011. Groundwater level forecasting based on support vector machine. In *Applied Mechanics and Materials* (Vol. 44, pp. 1365-1369). Trans Tech Publications Ltd.
146. Khedri, A., Kalantari, N. and Vadiati, M., 2020. Comparison study of artificial intelligence method for short term groundwater level prediction in the northeast Gachsaran unconfined aquifer. *Water Supply*, *20*(3), pp.909-921.
147. Vetrivel, N. and Elangovan, K., 2016. Prediction and forecasting of groundwater level fluctuation by ann technique. *International Journal of Civil Engineering and Technology (IJCIET)*, *7*(5).

148. Brédy, J., Gallichand, J., Celicourt, P. and Gumiere, S.J., 2020. Water table depth forecasting in cranberry fields using two decision-tree-modeling approaches. *Agricultural Water Management*, *233*, p.106090.
149. Ping, J., Qiang, Y. and Xixia, M., 2013. A combination model of chaos, wavelet and support vector machine predicting groundwater levels and its evaluation using three comprehensive quantifying techniques. *Information Technology Journal*, *12*(15), p.3158.
150. Cao, Y., Yin, K., Zhou, C. and Ahmed, B., 2020. Establishment of landslide groundwater level prediction model based on GA-SVM and influencing factor analysis. *Sensors*, *20*(3), p.845.
151. Mirarabi, A., Nassery, H.R., Nakhaei, M., Adamowski, J., Akbarzadeh, A.H. and Alijani, F., 2019. Evaluation of data-driven models (SVR and ANN) for groundwater-level prediction in confined and unconfined systems. *Environmental Earth Sciences*, *78*(15), pp.1-15.
152. Jeihouni, E., Mohammadi, M., Eslamian, S. and Zareian, M.J., 2019. Potential impacts of climate change on groundwater level through hybrid soft-computing methods: a case study—Shabestar Plain, Iran. *Environmental monitoring and assessment*, *191*(10), pp.1-16.
153. Mardookhpour, A., 2013. Utilizing artificial neural network for forecasting groundwater table depths fluctuations. *World Journal of Engineering*.
154. Gemitzi, A. and Lakshmi, V., 2018. Estimating groundwater abstractions at the aquifer scale using GRACE observations. *Geosciences*, *8*(11), p.419.
155. KazemBijari M, GolkarHamzee H, Tavousi M (2015) Evaluation of artificial neural network models and time series in the estimation of hydrostatic level (Case study: South Khorasan Province-Birjand Aquifer). J Mater Environ Sci 6(12):3539–3547.
156. Supreetha, B.S., Nayak, K.P. and Shenoy, K.N., 2019. Hybrid artificial intelligence based abc-pso system for ground water level forecasting in udupi region. *Journal of Engineering Science and Technology*, *14*(2), pp.797-809.
157. Supreetha, B.S., Shenoy, N. and Nayak, P., 2020. Lion algorithm-optimized long short-term memory network for groundwater level forecasting in Udupi District, India. *Applied Computational Intelligence and Soft Computing*, *2020*.
158. Nejat, Z., Reza, N.H., Alireza, S. and Farshad, A., 2020. Prediction of the karstic spring flow rates under climate change by climatic variables based on the artificial neural network: a case study of Iran. *Environmental monitoring and assessment*, *192*(6).
159. Ebrahimi, F., Nakhaei, M., Nassery, H.R., Khodaei, K. and Kisi, O., 2019. Light non-aqueous phase liquids simulation using artificial intelligence models: Esmaeilabad aquifer case study. *Groundwater for Sustainable Development*, *8*, pp.245-254.
160. Kim, I. and Lee, J., 2019. Proposed Correlation Model for Groundwater Level Prediction Based on River Stage Considering Changes in Hydrological and Geological Conditions. *Journal of Hydrologic Engineering*, *24*(10), p.04019042.
161. Vetrivel, N. and Elangovan, K., 2017. Application of ANN and ANFIS model on monthly groundwater level fluctuation in lower Bhavani River Basin.
162. Yang, Q., Wang, Y., Zhang, J. and Martín, J.D., 2015. Stochastic simulation of groundwater dynamics based on grey theory and seasonal decomposition model in a coastal aquifer of South China. *Journal of Water Supply: Research and Technology—AQUA*, *64*(8), pp.947-957.
163. Rani, R. and Elangovan, K., 2017. An emerging intuitionistic fuzzy based groundwater level prediction.
164. Zhao, T., Zhu, Y., Ye, M., Mao, W., Zhang, X., Yang, J. and Wu, J., 2020. Machine-Learning Methods for Water Table Depth Prediction in Seasonal Freezing-Thawing Areas. *Groundwater*, *58*(3), pp.419-431.
165. Fan, Y., Hu, L., Wang, H. and Liu, X., 2020. Machine learning methods for improved understanding of a pumping test in heterogeneous aquifers. *Water*, *12*(5), p.1342.
166. Sharafati, A., Asadollah, S.B.H.S. and Neshat, A., 2020. A new artificial intelligence strategy for predicting the groundwater level over the Rafsanjan aquifer in Iran. *Journal of Hydrology*, *591*, p.125468.
167. Darivianakis, N., Katsifarakis, K.L. and Vafeiadis, M., 2015. Measurement and prediction of Karstic spring flow rates. *Global NEST Journal*, *17*(2), pp.257-270.
168. Hajji, S., Hachicha, W., Bouri, S. and Dhia, H.B., 2012. Spatiotemporal groundwater level forecasting and monitoring using a neural network-based approach in a semi arid zone. *International Journal of Hydrology Science and Technology*, *2*(4), pp.342-361.

169. Hsieh, P.C., Tong, W.A. and Wang, Y.C., 2019. A hybrid approach of artificial neural network and multiple regression to forecast typhoon rainfall and groundwater-level change. *Hydrological Sciences Journal*, *64*(14), pp.1793-1802.
170. Kang, M.G. and Maeng, S.J., 2016. Gray models for real-time groundwater-level forecasting in irrigated paddy-field districts. *Journal of Irrigation and Drainage Engineering*, *142*(1), p.04015036.
171. El ibrahimiM, A. and Baali, A., 2018. Groundwater Level Predicted in the Sawss Plain (Northern Morocco) using Artificial Intelligence Techniques. *International Journal of Ecology & Development*, *33*(1), pp.125-137.
172. Ibrahimi, A.E. and Baali, A., 2017. Comparative Study of the Three Models (ANN-PMC),(DWT-ANN-PMC) and (MLR) for Prediction of the Groundwater Level of the Surface Water Table in the Saïss Plain (North of Morocco). *International Journal of Intelligent Engineering and Systems*, *10*(5), pp.220-230.
173. Pratama, H., Sutikno, S. and Yusa, M., 2020, March. Modeling of groundwater level fluctuation in the tropical peatland area of Riau, Indonesia. In *IOP Conference Series: Materials Science and Engineering* (Vol. 796, No. 1, p. 012037). IOP Publishing.
174. Kumar, A.R., Kale, R., Babu, B.M., Sathishkumar, U., Reddy, G.V. and Kulkarni, P.S., 2019. A hybrid-wavelet artificial neural network model for monthly water table depth prediction. *Current Science (00113891)*, *117*(9).
175. Husna, N.E.A., Bari, S.H., Hussain, M.M., Ur-rahman, M.T. and Rahman, M., 2016. Ground water level prediction using artificial neural network. *International Journal of Hydrology Science and Technology*, *6*(4), pp.371-381.
176. Jahanara, A.A. and Khodashenas, S.R., 2019. Prediction of ground water table using NF-GMDH based evolutionary algorithms. *KSCE Journal of Civil Engineering*, *23*(12), pp.5235-5243.
177. Volf, G., Žic, E. and Ožanić, N., 2018. Predicition of groundwater level on Grohovo landslide using ruled based regression. *Engineering Review: Međunarodni časopis namijenjen publiciranju originalnih istraživanja s aspekta analize konstrukcija, materijala i novih tehnologija u području strojarstva, brodogradnje, temeljnih tehničkih znanosti, elektrotehnike, računarstva i građevinarstva*, *38*(1), pp.51-61.
178. Yoon, H., Kim, Y., Lee, S.H. and Ha, K., 2019. Influence of the range of data on the performance of ANN-and SVM-based time series models for reproducing groundwater level observations. *Acque Sotterranee-Italian Journal of Groundwater*, *8*(1).
179. Application of Soft and Hard Computing Tools for the Estimation of Groundwater Recharge
180. Barahmand, N. and Sabetfard, M., 2017. Estimation of ground water level in Jahrom plain, using Artificial Neural Networks. *INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND NETWORK SECURITY*, *17*(6), pp.72-75.
181. Wang, Q., Tian, T. and Li, C., 2015. The Comparison of Four Different Groundwater Level Prediction Models in Baoding City.
182. Sreedevi, P.D., Sreekanth, P.D. and Ahmed, S., 2012. Predicting groundwater level using the soft computing tool: an approach to precision enhancement. *Environ Eng Res*, *17*, pp.569-574.
183. Chen, N., Qu, J. and Li, Y., 2010, December. Improved PSO Algorithm Trained BP Neural Network: Application to Groundwater Table Prediction. In *2010 International Conference on Computational Intelligence and Software Engineering* (pp. 1-4). IEEE.
184. Kumar, D., Roshni, T., Singh, A., Jha, M.K. and Samui, P., 2020. Predicting groundwater depth fluctuations using deep learning, extreme learning machine and Gaussian process: a comparative study. *Earth Science Informatics*, *13*(4), pp.1237-1250.
185. Modelling qualitative and quantitative parameters of groundwater using a new wavelet conjunction heuristic method: wavelet extreme learning machine versus wavelet neural networks
186. Agoubi, B. and Kharroubi, A., 2019. Groundwater depth monitoring and short-term prediction: applied to El Hamma aquifer system, southeastern Tunisia. *Arabian Journal of Geosciences*, *12*(10), pp.1-10.

187. Mallikarjuna, B., Sathish, K., Krishna, P.V. and Viswanathan, R., 2021. The effective SVM-based binary prediction of ground water table. *Evolutionary Intelligence*, *14*(2), pp.779-787.
188. Hasda, R., Rahaman, M.F., Jahan, C.S., Molla, K.I. and Mazumder, Q.H., 2020. Climatic data analysis for groundwater level simulation in drought prone Barind Tract, Bangladesh: Modelling approach using artificial neural network. *Groundwater for Sustainable Development*, *10*, p.100361.
189. Bozorg-Haddad, O., Delpasand, M. and Loáiciga, H.A., 2020. Self-optimizer data-mining method for aquifer level prediction. *Water Supply*, *20*(2), pp.724-736.
190. Goodarzi, M., 2020. Application and performance evaluation of time series, neural networks and HARTT models in predicting groundwater level changes, Najafabad Plain, Iran. *Sustainable Water Resources Management*, *6*(4), pp.1-10.
191. Thomas, B.F. and Vogel, R.M., 2010. The Impact of Stormwater Recharge Practices on Boston Groundwater Levels. In *World Environmental and Water Resources Congress 2010: Challenges of Change* (pp. 2352-2361).
192. Meng, J. and Ju, Y., 2012, March. Underground water level dynamic prediction based on hybrid genetic algorithm and the least square support vector model. In *International Conference on Automatic Control and Artificial Intelligence (ACAI 2012)* (pp. 2243-2246). IET.
193. Kombo, O.H., Kumaran, S., Sheikh, Y.H., Bovim, A. and Jayavel, K., 2020. Long-term groundwater level prediction model based on hybrid KNN-RF technique. *Hydrology*, *7*(3), p.59.
194. Bahmani, R., Solgi, A. and Ouarda, T.B., 2020. Groundwater level simulation using gene expression programming and M5 model tree combined with wavelet transform. *Hydrological Sciences Journal*, *65*(8), pp.1430-1442.
195. Neeta, K. and Gopal, P., 2017. Determination of Suitable ANN Architecture for Groundwater Fluoride Prediction. In *Advances in Computational Intelligence* (pp. 81-88). Springer, Singapore.
196. Imani, K., Zamani, M., Amiribesheli, R. and Gilanilarimi, M., 2014. Predicting the ground water level with artificial neural network: a case study of Talar watershed in Ghaemshahr, Iran. *Advances in Environmental Biology*, pp.372-377.
197. Samantaray, S., Sahoo, A. and Ghose, D.K., 2019, June. Assessment of Groundwater Potential Using Neural Network: A Case Study. In *International Conference on Intelligent Computing and Communication* (pp. 655-664). Springer, Singapore.

Figures:

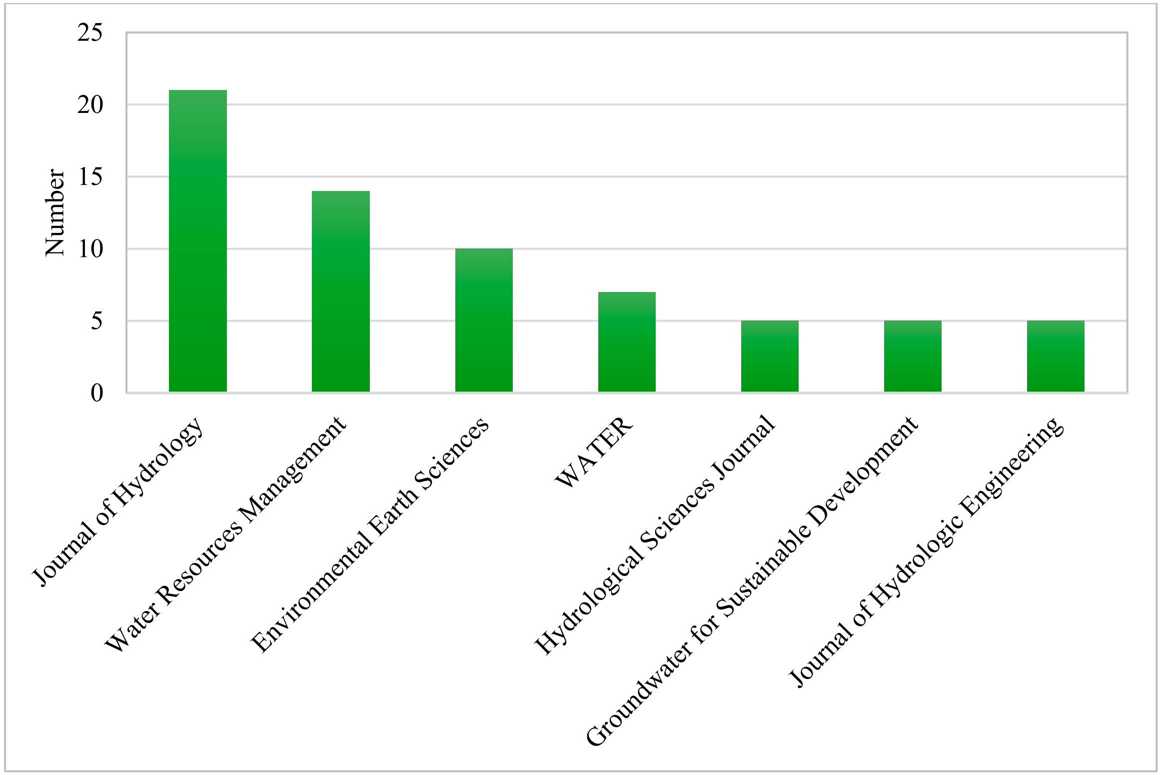

Figure S1. Journals with high numbers of included records

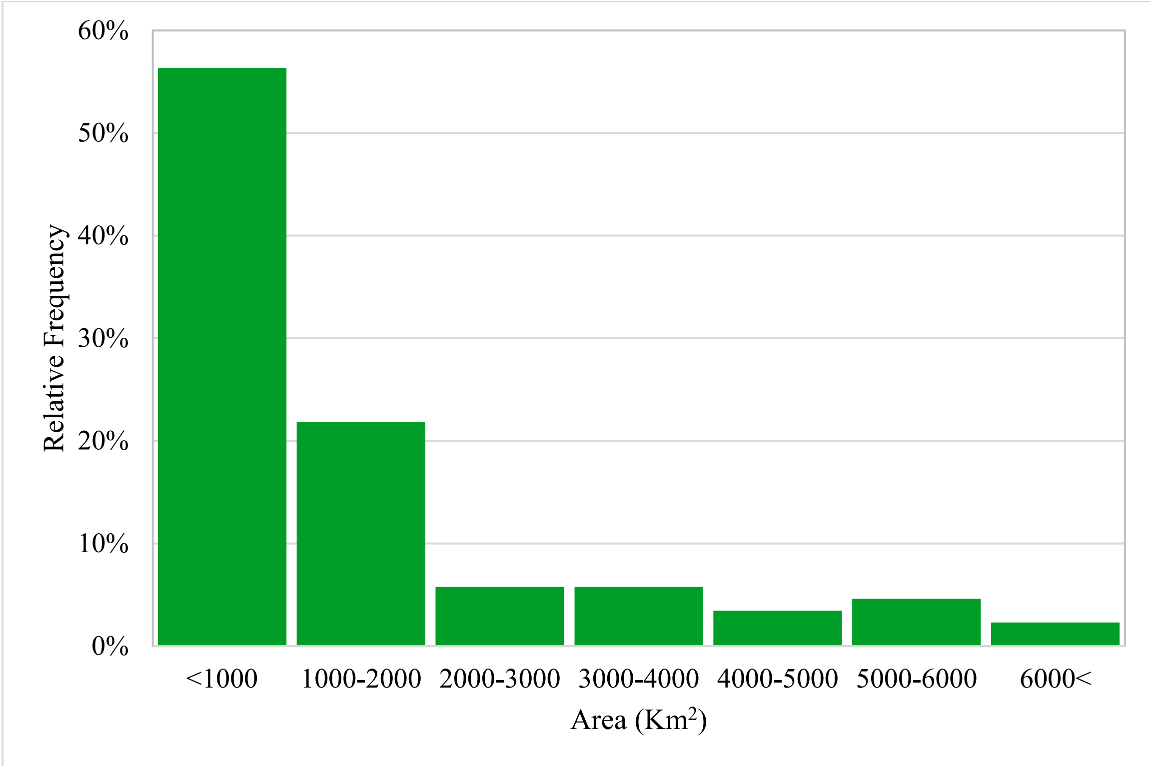

Figure S2. Percentage of reviewed articles based on the area of their case study

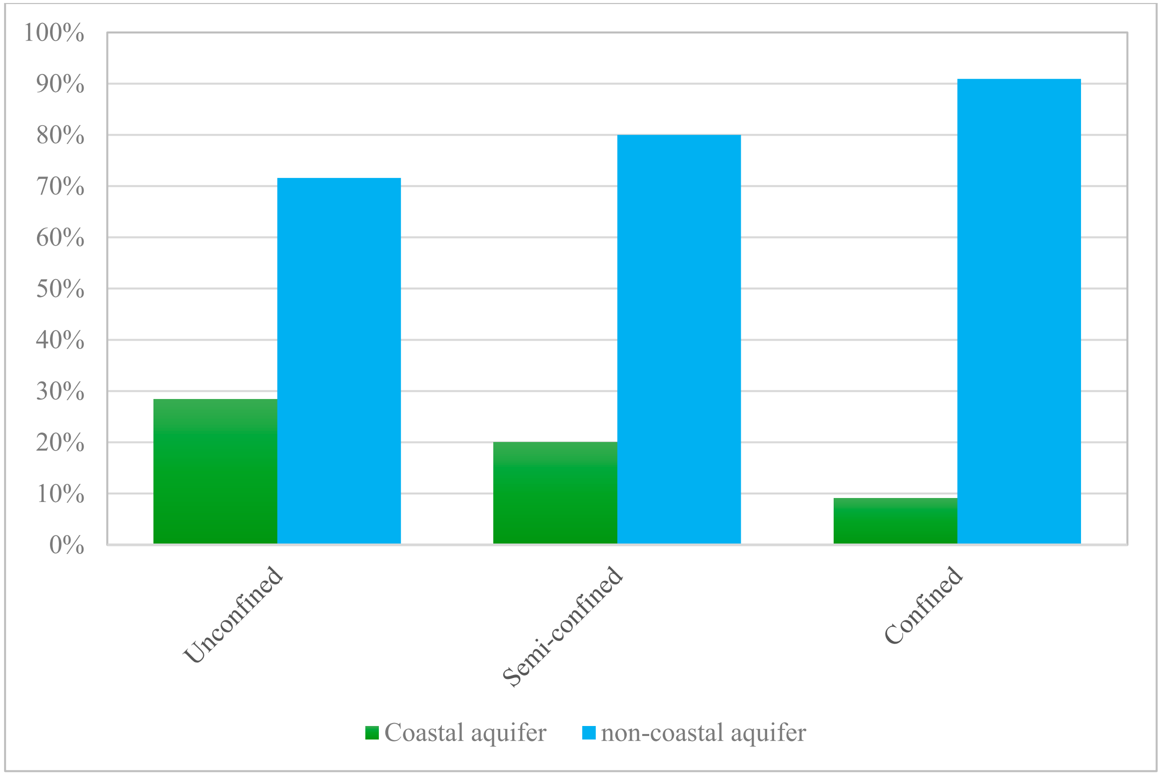

Figure S3. Proportion of the reviewed articles' case studies

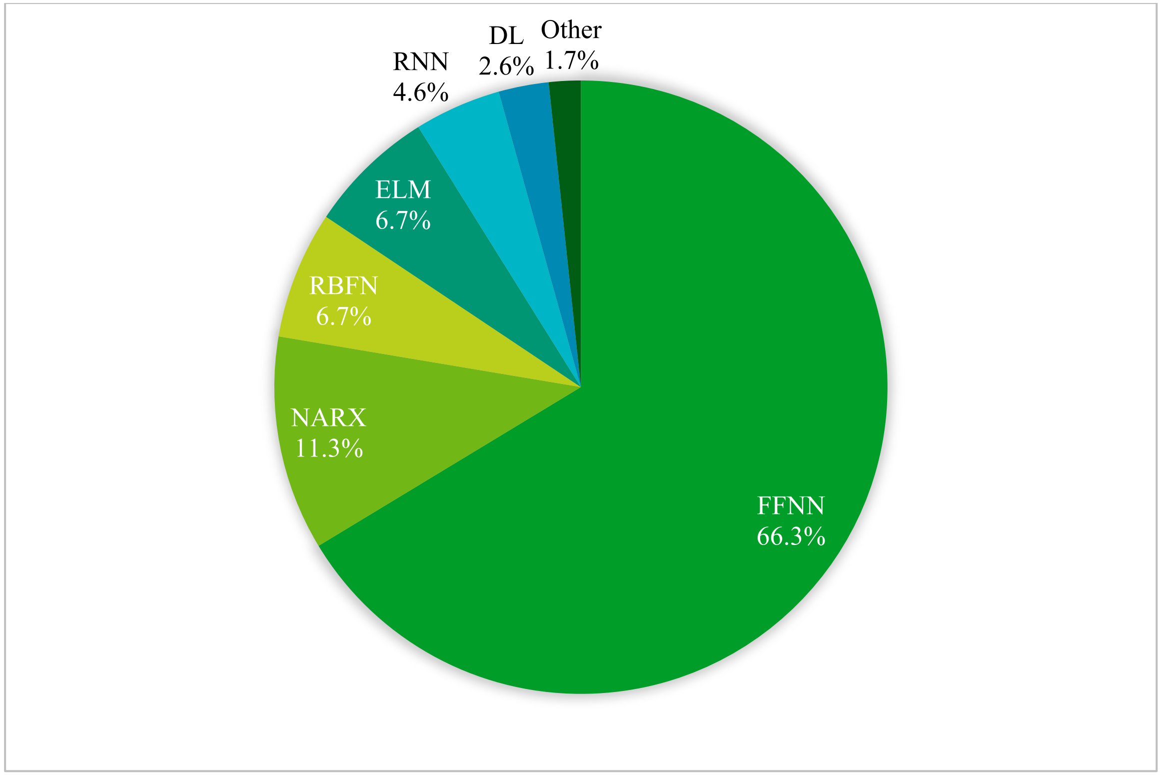

Figure S4. Percentage of network architectures for the reports employing ANN as their machine learning method

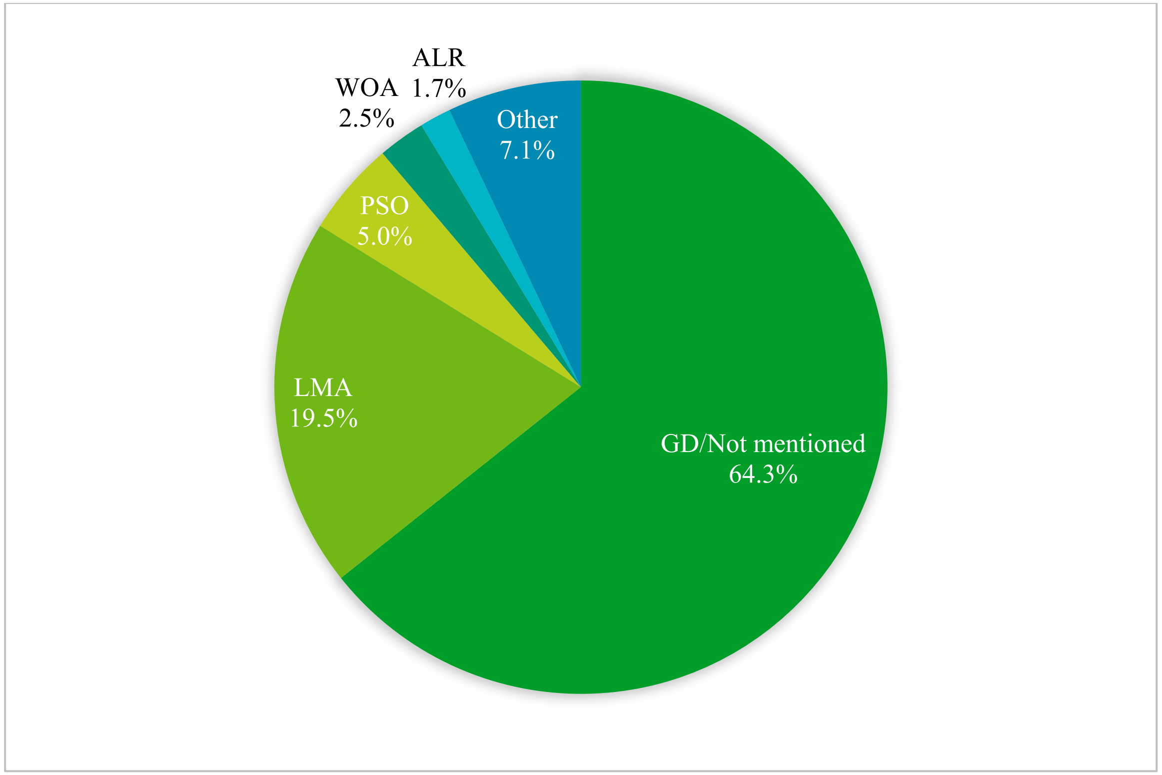

Figure S5. Percentage of optimization algorithms for ANN methods

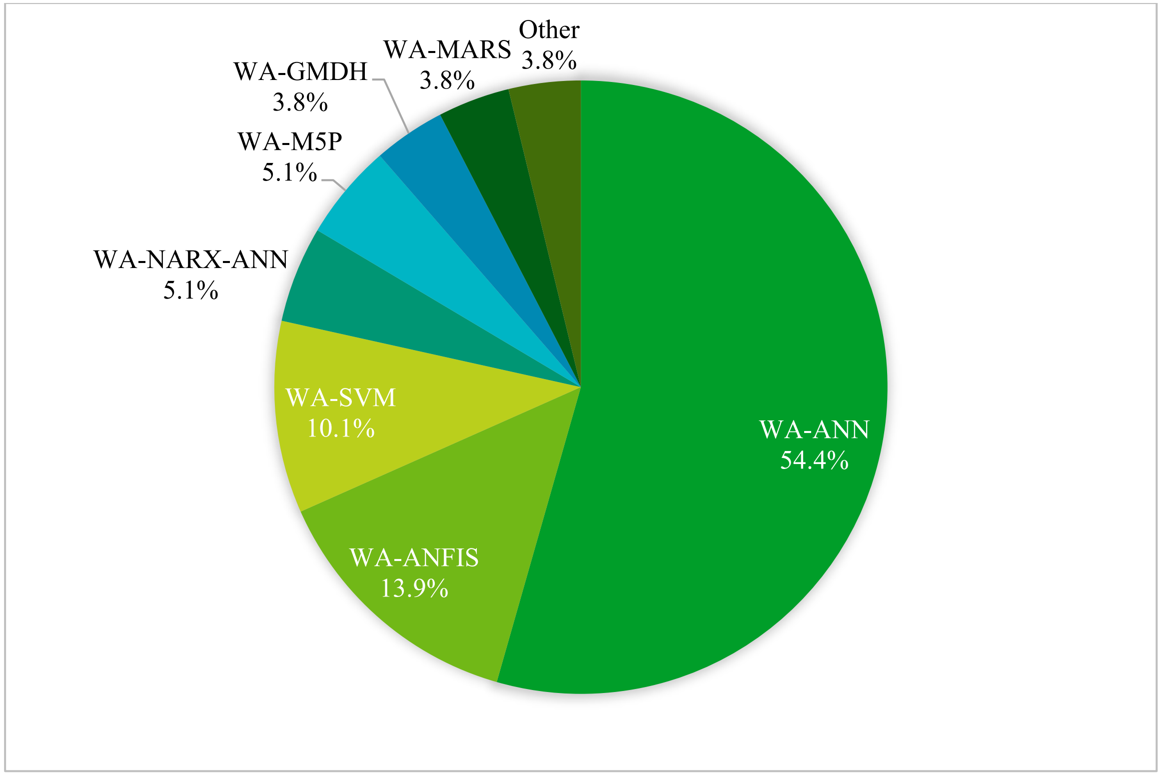

Figure S6. Proportion of the reports using wavelet transform with machine learning methods

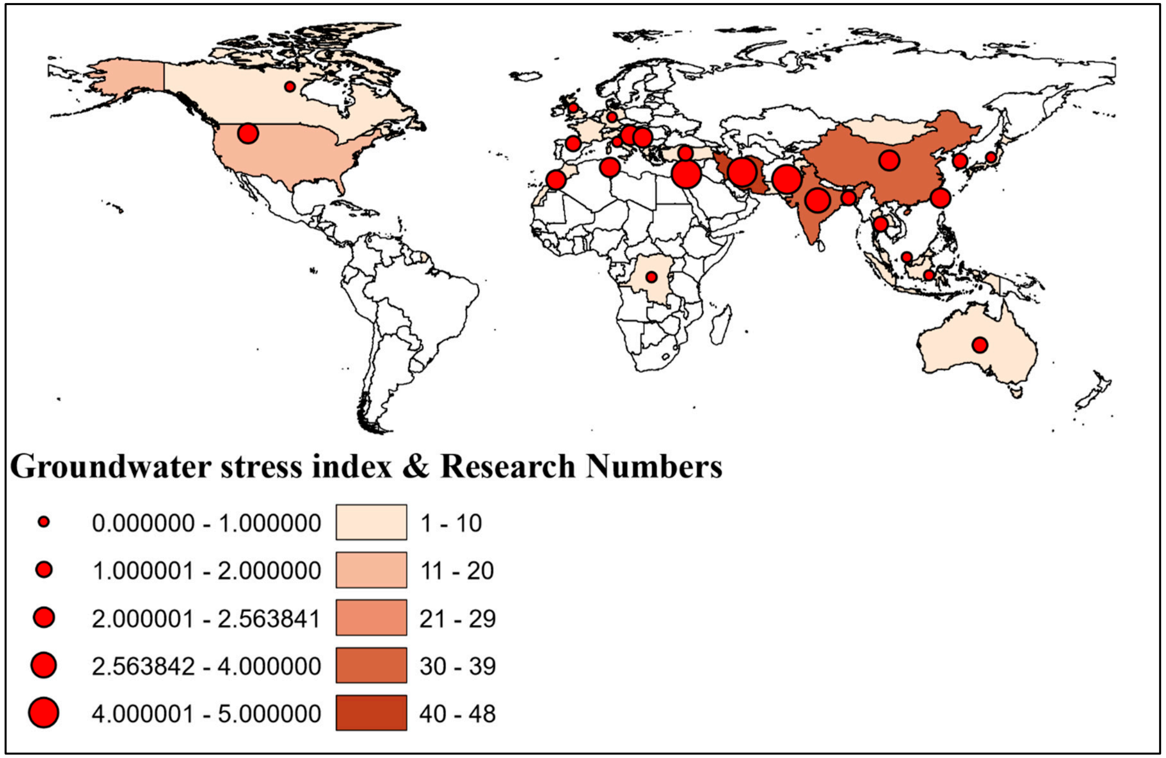

Figure S7. The relationship between groundwater stress and the number of articles in different countries

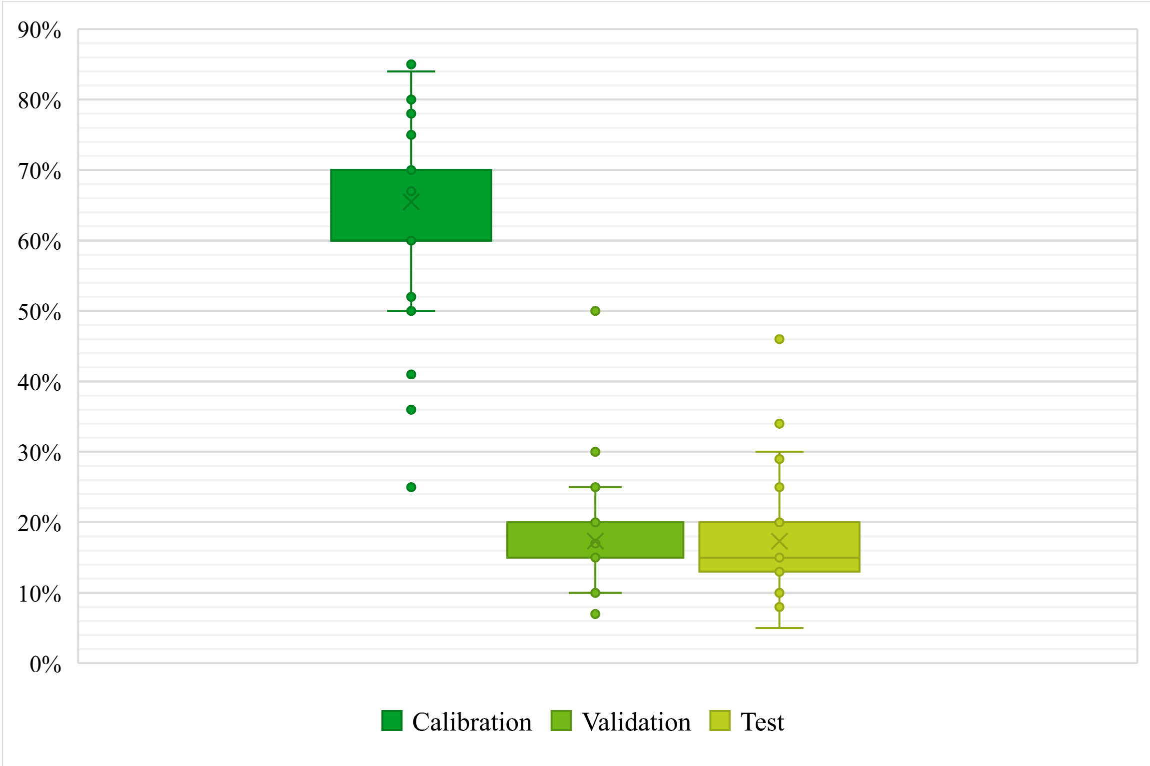

Figure S8. Frequency of data division strategies for articles having three subsets

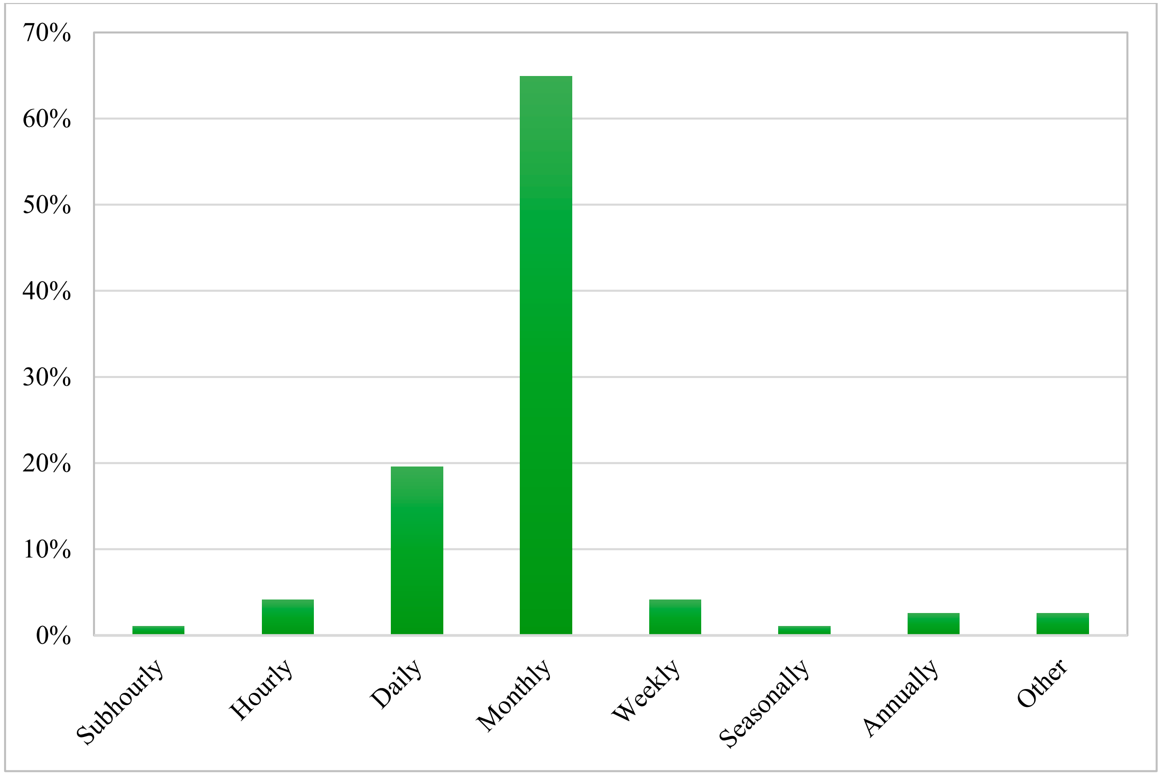

Figure S9. Percentage of articles based on their input data temporal resolution

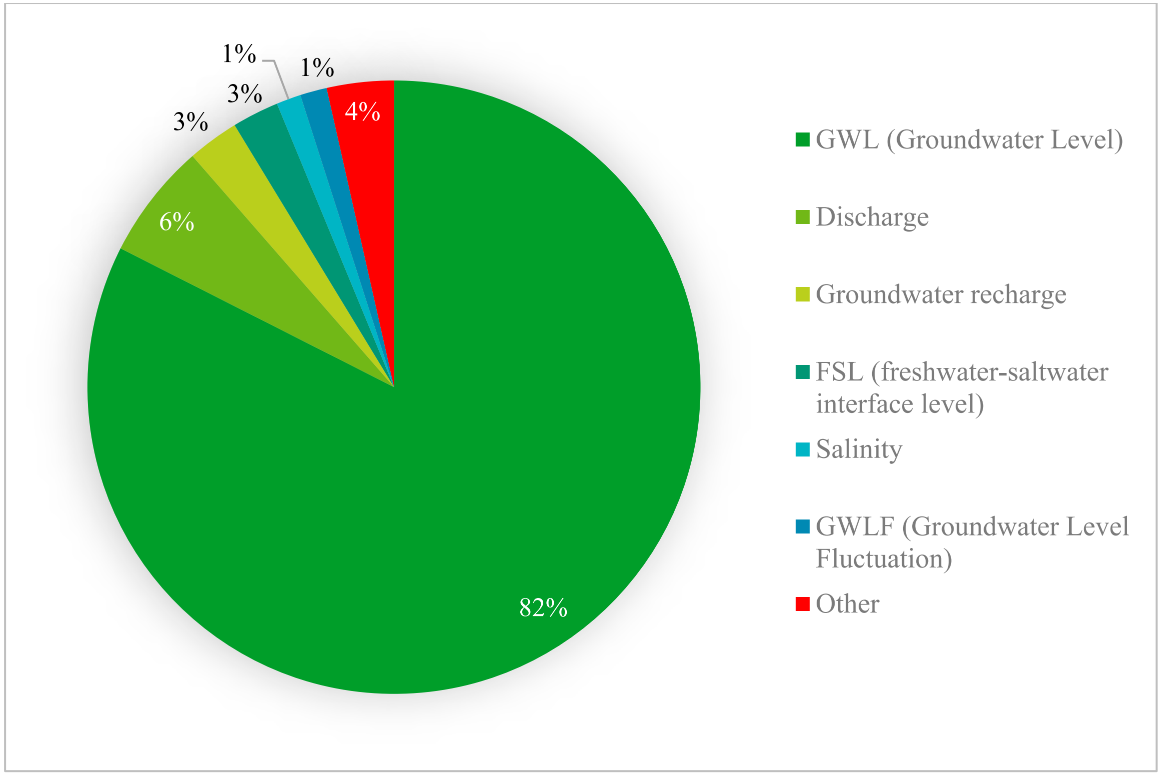

Figure S10. Groundwater characteristics predicted using machine learning algorithms

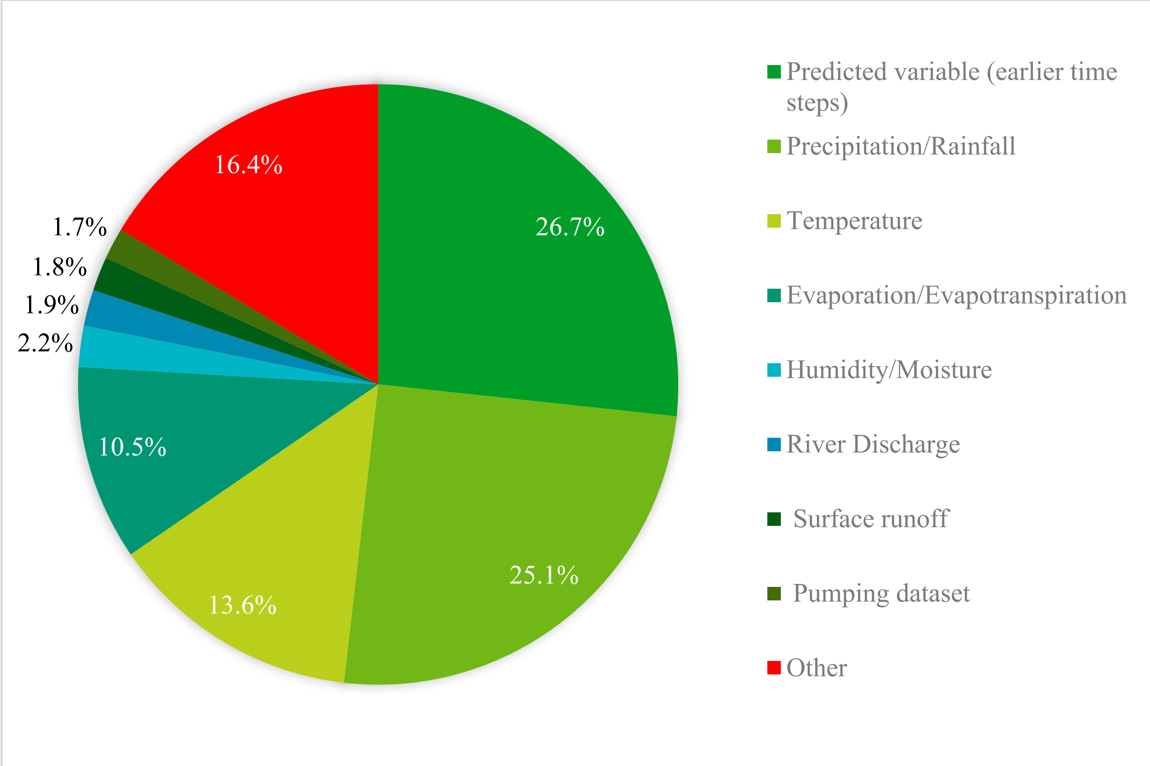

Figure S11. Proportion of input variables to predict groundwater level

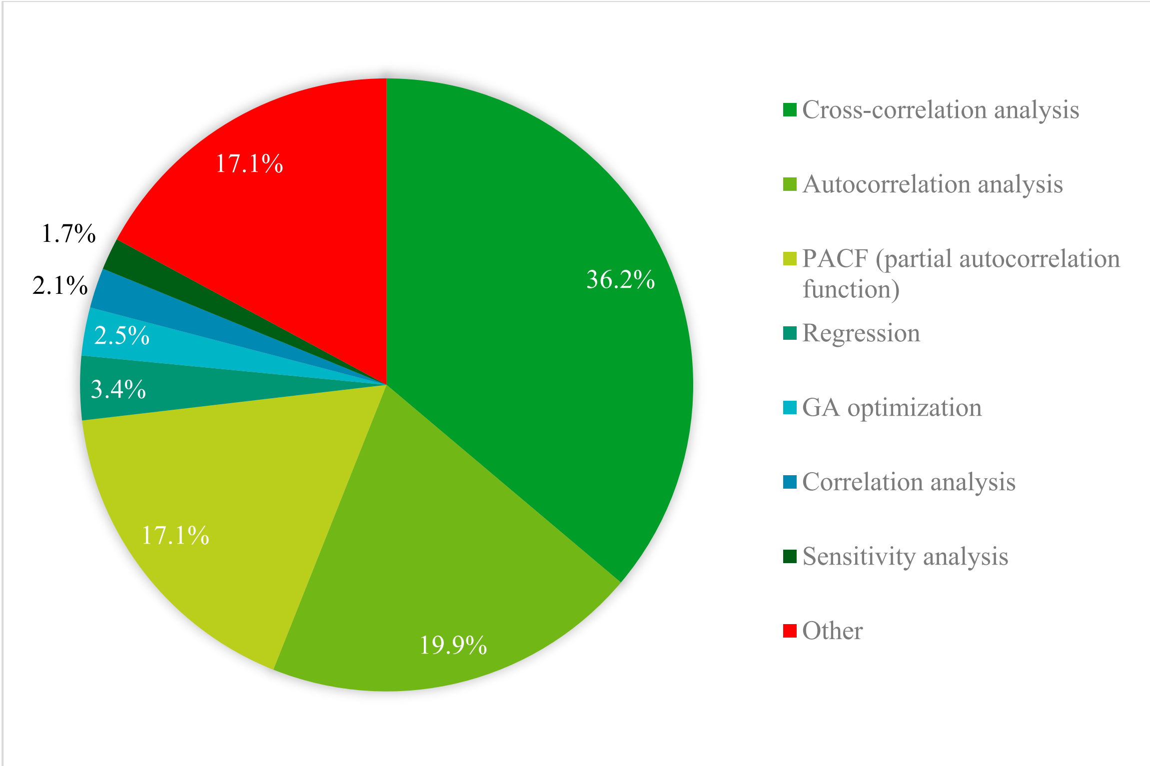

Figure S12. Percentage of most adopted input variable selection techniques

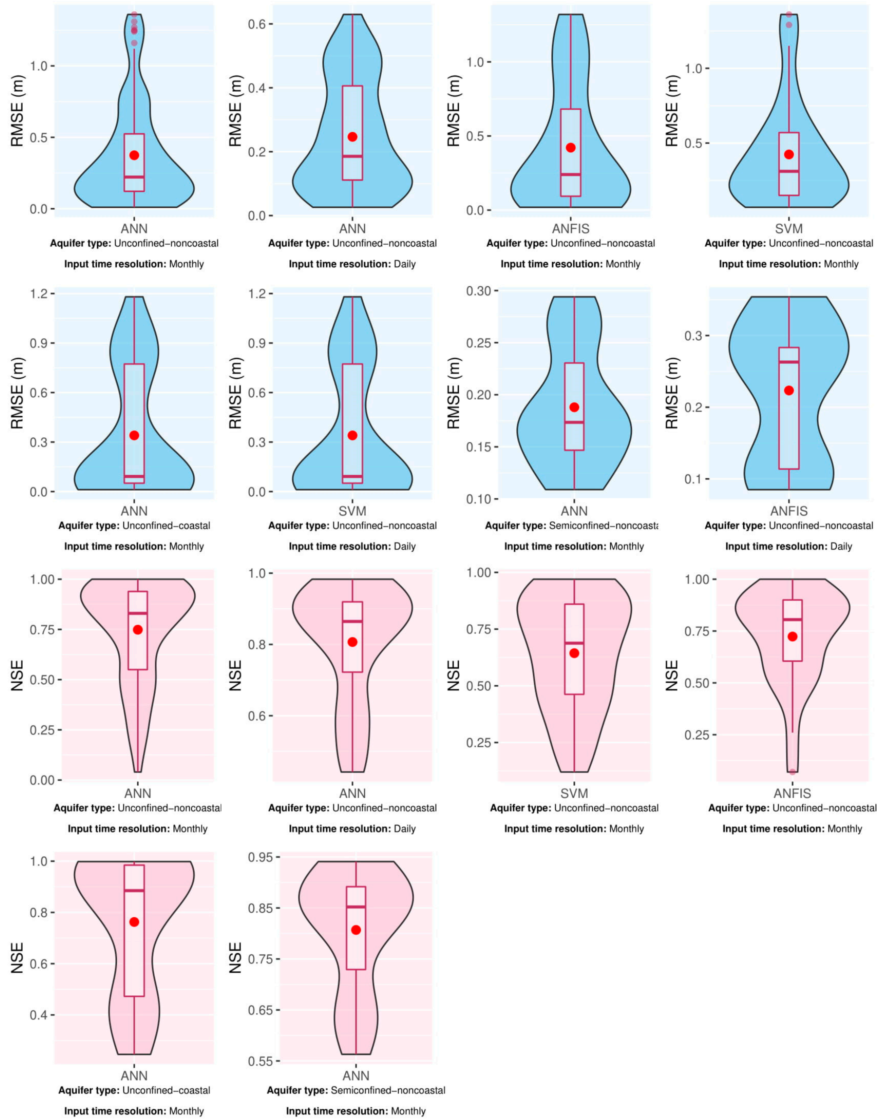

Figure S13. Results of meta-analysis for subcategories combination

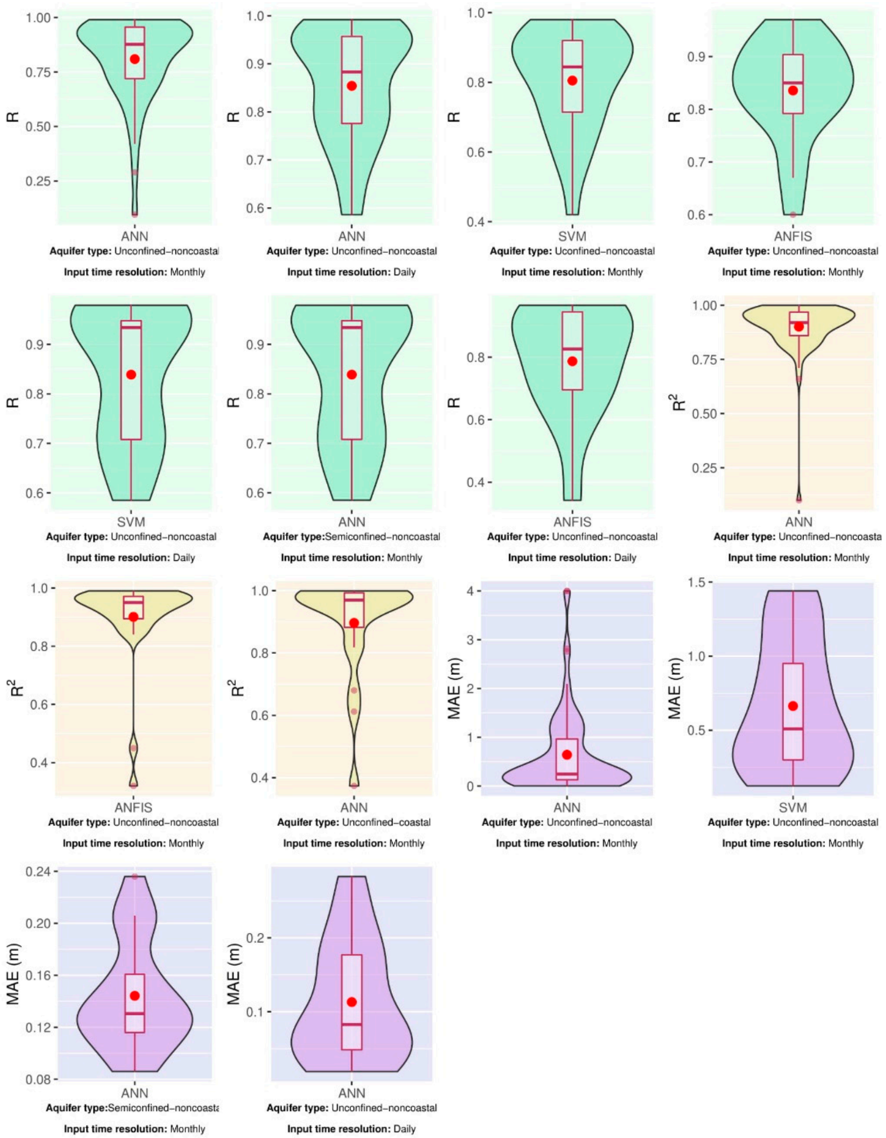

Figure S14. Results of meta-analysis for subcategories combination

Tables:

Table S1. Input variables for predicted characteristics

Predicted Characteristic	1st input	2nd input	3rd input	4th input
Discharge	Precipitation/Rainfall (46.3%)	Predicted variable (earlier time steps) (33.6%)	GWL (Groundwater Level) (5.6%)	Predicted variable (adjacent wells/other places) (3.7%)
Groundwater recharge	Precipitation/Rainfall (32.9%)	Temperature (32.9%)	Evaporation/Evapotranspiration (12.9%)	Exploitation/Extraction (12.9%)
FSL (freshwater-saltwater interface level)	Tide level (50%)	GWL (Groundwater Level) (33%)	Predicted variable (earlier time steps) (17%)	
Salinity	Predicted variable (earlier time steps) (17%)	Temperature (13%)	Evaporation/Evapotranspiration (13%)	

Table S2. Statistics of groundwater level's violin plots depicted in Figure 11

Index	**RMSE (m)**	**NSE**	**R**	**R^2**	**MAE (m)**	**MSE (m^2)**
Number of records	546	374	288	270	202	68
Q_1	0.11	0.56	0.77	0.83	0.11	0.00
Q_2	0.26	0.83	0.87	0.92	0.24	0.05
Q_3	0.62	0.92	0.95	0.97	0.91	0.71
Mean	0.52	0.72	0.84	0.86	0.60	1.19
Min	0.00	-1.85	0.10	0.09	0.00	0.00
Max	8.98	1.00	0.99	1.00	4.22	9.57
Low Whisker	0.00	0.03	0.52	0.62	0.00	0.00
High Whisker	1.38	1.00	0.99	1.00	2.11	1.78

Table S3. Statistics of other characteristics' violin plots illustrated in Figure 12

Index	**Discharge**			**Groundwater recharge**		**Freshwater saltwater interface**
	RMSE (m^3/s)	**MAE (m^3/s)**	**R^2**	**RMSE (mm)**	**R^2**	**RMAE**
Number of records	50	44	38	23	17	21
Q_1	0.01	0.03	0.83	0.19	0.48	0.80
Q_2	0.04	0.04	0.92	19.46	0.77	1.27
Q_3	0.05	0.05	0.97	49.00	0.91	1.39
Mean	0.05	0.26	0.87	80.34	0.70	1.11
Min	0.00	0.01	0.39	0.10	0.04	0.48
Max	0.53	1.89	1.00	479.00	0.97	1.42
Low Whisker	0.00	0.01	0.62	0.10	0.04	0.48
High Whisker	0.10	0.09	1.00	122.22	0.97	1.42

Table S4. Statistics of the violin plots represented in Figure 13

Index	ML method																		
	RMSE (m)					**NSE**				**R**				**R^2**			**MAE (m)**		**MSE (m^2)**
	ANFIS	**ANN**	**Decision Tree**	**GEP**	**SVM**	**ANFIS**	**ANN**	**Decision Tree**	**SVM**	**ANFIS**	**ANN**	**GEP**	**SVM**	**ANFIS**	**ANN**	**SVM**	**ANN**	**SVM**	**ANN**
Number of records	67	242	24	18	84	38	179	20	64	42	133	15	58	35	135	35	132	28	42
Q_1	0.10	0.09	0.03	0.10	0.13	0.50	0.68	0.71	0.49	0.78	0.77	0.71	0.73	0.89	0.85	0.78	0.09	0.28	0.00
Q_2	0.26	0.18	0.10	0.25	0.26	0.75	0.86	0.87	0.75	0.84	0.89	0.80	0.84	0.95	0.93	0.92	0.20	0.49	0.01
Q_3	0.62	0.45	0.38	0.32	0.46	0.89	0.94	0.93	0.88	0.92	0.95	0.96	0.94	0.97	0.97	0.96	0.47	1.10	0.05
Mean	0.38	0.30	0.29	0.22	0.35	0.69	0.78	0.75	0.69	0.82	0.84	0.81	0.83	0.91	0.90	0.84	0.47	0.69	0.08
Min	0.02	0.00	0.01	0.06	0.01	0.07	0.04	0.11	0.12	0.34	0.10	0.56	0.42	0.32	0.10	0.29	0.00	0.12	0.00
Max	1.32	1.36	1.19	0.35	1.36	1.00	1.00	0.99	0.97	0.97	0.99	0.99	0.98	0.99	1.00	0.98	4.00	2.26	0.72
Low Whisker	0.02	0.00	0.01	0.06	0.01	0.07	0.29	0.38	0.12	0.59	0.51	0.56	0.42	0.78	0.67	0.52	0.00	0.12	0.00
High Whisker	1.32	0.97	0.90	0.35	0.96	1.00	1.00	0.99	0.97	0.97	0.99	0.99	0.98	0.99	1.00	0.98	1.05	2.26	0.12

Table S4. Continued

Index	ANN type									
	FFNN	NARX	FFNN	NARX	FFNN	FFNN	NARX	FFNN	FFNN	NARX
	RMSE (m)		NSE		R	R^2		MAE (m)	MSE (m^2)	
Number of records	144	19	104	17	98	75	16	67	17	16
Q_1	0.11	0.01	0.54	0.85	0.76	0.85	0.92	0.07	0.00	0.00
Q_2	0.18	0.11	0.82	0.94	0.87	0.93	0.97	0.17	0.00	0.00
Q_3	0.46	0.46	0.91	0.98	0.95	0.97	0.98	0.48	0.05	0.13
Mean	0.31	0.24	0.73	0.91	0.83	0.89	0.93	0.43	0.03	0.14
Min	0.01	0.00	0.04	0.74	0.10	0.37	0.68	0.00	0.00	0.00
Max	0.25	0.00	0.99	1.00	0.99	1.00	1.00	2.82	0.10	0.72
Low Whisker	0.01	0.00	0.04	0.74	0.48	0.67	0.83	0.00	0.00	0.00
High Whisker	0.25	0.00	0.99	1.00	0.99	1.00	1.00	1.09	0.10	0.31

Table S5. Statistics of the violin plots represented in Figure 14

Index	Aquifer types												
	Confined	**Semi-confined**	**Unconfined**	**Confined**	**Semi-confined**	**Unconfined**	**Confined**	**Semi-confined**	**Unconfined**	**Semi-confined**	**Unconfined**	**Semi-confined**	**Unconfined**
	RMSE (m)			**NSE**			**R**			**R^2**		**MAE (m)**	
Number of records	16	47	432	18	42	304	16	19	253	32	237	22	172
Q_1	0.36	0.10	0.09	0.63	0.81	0.55	0.81	0.83	0.76	0.88	0.83	0.09	0.12
Q_2	0.47	0.15	0.22	0.83	0.87	0.82	0.91	0.93	0.86	0.93	0.92	0.13	0.27
Q_3	0.63	0.19	0.48	0.87	0.92	0.93	0.94	0.96	0.95	0.96	0.97	0.16	1.03
Mean	0.49	0.19	0.33	0.76	0.84	0.74	0.86	0.90	0.83	0.86	0.86	0.12	0.67
Min	0.01	0.00	0.00	0.38	0.25	0.04	0.37	0.76	0.10	0.29	0.09	0.00	0.00
Max	0.78	1.28	1.36	0.93	0.97	1.00	0.97	0.97	0.99	0.98	1.00	0.24	4.22
Low Whisker	0.01	0.00	0.00	0.38	0.65	0.04	0.60	0.76	0.48	0.75	0.62	0.00	0.00
High Whisker	0.78	0.33	1.05	0.93	0.97	1.00	0.97	0.97	0.99	0.98	1.00	0.24	2.39

Table S5. Continued

Index	Coastal aquifer (Y/N)									
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	RMSE (m)		NSE		R		R^2		MAE (m)	
Number of records	402	93	298	66	256	32	207	63	174	28
Q_1	0.11	0.06	0.62	0.56	0.77	0.79	0.83	0.84	0.12	0.04
Q_2	0.22	0.13	0.83	0.88	0.87	0.83	0.91	0.96	0.24	0.17
Q_3	0.43	0.64	0.92	0.98	0.95	0.95	0.96	0.99	0.90	0.99
Mean	0.32	0.33	0.74	0.77	0.83	0.86	0.85	0.89	0.59	0.64
Min	0.00	0.00	0.04	0.25	0.10	0.75	0.09	0.37	0.00	0.00
Max	1.36	1.19	1.00	1.00	0.99	0.99	1.00	1.00	4.22	2.86
Low Whisker	0.00	0.00	0.18	0.25	0.50	0.75	0.64	0.62	0.00	0.00
High Whisker	0.91	1.19	1.00	1.00	0.99	0.99	1.00	1.00	2.07	2.41

Table S5. Continued

Index	Cross Validation (Y/N)									
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	RMSE (m)		NSE		R		R^2		MAE (m)	
Number of records	401	63	287	51	249	30	226	39	175	25
Q_1	0.10	0.18	0.62	0.44	0.77	0.77	0.84	0.65	0.10	0.22
Q_2	0.20	0.38	0.85	0.73	0.87	0.85	0.92	0.84	0.21	0.33
Q_3	0.41	0.68	0.93	0.87	0.95	0.92	0.97	0.96	0.83	1.15
Mean	0.31	0.48	0.76	0.66	0.84	0.81	0.88	0.76	0.58	0.79
Min	0.00	0.03	0.04	0.11	0.29	0.10	0.10	0.09	0.00	0.00
Max	1.36	1.29	1.00	1.00	0.99	0.99	1.00	1.00	4.22	2.86
Low Whisker	0.00	0.03	0.15	0.11	0.50	0.54	0.65	0.19	0.00	0.00
High Whisker	0.89	1.29	1.00	1.00	0.99	0.99	1.00	1.00	1.93	2.56

Table S5. Continued

Index	Sample division														
	70-30	**75-25**	**80-20**	**Other**	**70-30**	**75-25**	**Other**	**70-30**	**75-25**	**Other**	**70-30**	**75-25**	**Other**	**70-30**	**Other**
	RMSE (m)				**NSE**			**R**			**R^2**			**MAE (m)**	
Number of records	56	92	23	324	74	41	238	48	76	151	38	28	196	54	128
Q_1	0.04	0.11	0.12	0.10	0.60	0.49	0.63	0.71	0.71	0.80	0.84	0.77	0.83	0.23	0.07
Q_2	0.22	0.25	0.14	0.20	0.82	0.89	0.84	0.87	0.85	0.87	0.90	0.93	0.92	1.18	0.16
Q_3	0.61	0.30	0.39	0.51	0.93	0.95	0.92	0.96	0.94	0.94	0.93	0.97	0.97	1.56	0.34
Mean	0.40	0.23	0.37	0.34	0.72	0.77	0.75	0.82	0.82	0.85	0.88	0.87	0.86	1.27	0.29
Min	0.01	0.00	0.01	0.00	0.04	0.42	0.11	0.42	0.34	0.10	0.57	0.61	0.09	0.04	0.00
Max	1.36	1.27	1.29	1.36	0.99	1.00	1.00	0.99	0.99	0.99	0.99	1.00	1.00	4.22	2.86
Low Whisker	0.01	0.00	0.01	0.00	0.11	0.42	0.18	0.42	0.37	0.58	0.70	0.61	0.62	0.04	0.00
High Whisker	1.36	0.59	0.80	1.12	0.99	1.00	1.00	0.99	0.99	0.99	0.99	1.00	1.00	3.55	0.74

Table S6. Statistics of the violin plots represented in Figure 15

Index	Input data time resolution											
	Daily	**Hourly**	**Monthly**	**Daily**	**Hourly**	**Monthly**	**Daily**	**Monthly**	**Daily**	**Monthly**	**Daily**	**Monthly**
	RMSE (m)			**NSE**			**R**		**R^2**		**MAE (m)**	
Number of records	138	24	302	68	17	251	95	175	39	212	19	173
Q_1	0.11	0.02	0.12	0.69	0.72	0.55	0.76	0.78	0.80	0.83	0.02	0.13
Q_2	0.17	0.03	0.30	0.87	0.83	0.81	0.88	0.85	0.90	0.92	0.07	0.25
Q_3	0.29	0.05	0.64	0.94	0.93	0.92	0.96	0.93	0.96	0.97	0.17	0.95
Mean	0.22	0.05	0.41	0.79	0.83	0.72	0.84	0.82	0.85	0.86	0.09	0.63
Min	0.00	0.01	0.01	0.25	0.69	0.04	0.34	0.10	0.39	0.09	0.00	0.29
Max	1.03	0.41	1.36	0.98	0.99	1.00	0.99	0.99	1.00	1.00	0.28	1.00
Low Whisker	0.00	0.01	0.01	0.32	0.69	0.04	0.45	0.54	0.56	0.63	0.00	0.29
High Whisker	0.57	0.09	1.36	0.98	0.99	1.00	0.99	0.99	1.00	1.00	0.28	1.00

Table S6. Continued

Index	Selection technique									
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	RMSE (m)		NSE		R		R^2		MAE (m)	
Number of records	311	184	214	150	184	104	167	103	151	51
Q_1	0.10	0.09	0.51	0.77	0.78	0.76	0.78	0.87	0.12	0.04
Q_2	0.20	0.23	0.77	0.88	0.85	0.92	0.91	0.94	0.23	0.25
Q_3	0.49	0.41	0.91	0.94	0.94	0.96	0.96	0.98	0.96	0.65
Mean	0.34	0.30	0.69	0.83	0.83	0.85	0.84	0.90	0.54	0.76
Min	0.00	0.00	0.04	0.38	0.10	0.34	0.09	0.10	0.00	0.00
Max	1.36	1.29	1.00	1.00	0.99	0.99	1.00	1.00	2.86	4.22
Low Whisker	0.00	0.00	0.04	0.51	0.55	0.45	0.52	0.70	0.00	0.00
High Whisker	1.07	0.88	1.00	1.00	0.99	0.99	1.00	1.00	2.22	1.57

Table S6. Continued

Index	Forecast for future									
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**
	RMSE (m)		**NSE**		**R**		**R^2**		**MAE (m)**	
Number of records	171	324	83	281	100	188	100	170	65	137
Q_1	0.09	0.10	0.71	0.56	0.79	0.77	0.80	0.84	0.17	0.09
Q_2	0.18	0.22	0.80	0.85	0.87	0.87	0.89	0.94	0.24	0.24
Q_3	0.34	0.55	0.91	0.93	0.94	0.95	0.95	0.97	0.86	0.96
Mean	0.26	0.36	0.78	0.74	0.84	0.84	0.85	0.87	0.75	0.53
Min	0.00	0.00	0.26	0.04	0.34	0.10	0.32	0.09	0.03	0.00
Max	1.29	1.36	1.00	1.00	0.98	0.99	1.00	1.00	4.22	2.86
Low Whisker	0.00	0.00	0.42	0.04	0.56	0.49	0.57	0.65	0.03	0.00
High Whisker	0.71	1.23	1.00	1.00	0.98	0.99	1.00	1.00	1.88	2.25

Abbreviations:

AIC	Akaike information criterion
ANFIS	adaptive network-based fuzzy inference system
ANN	artificial neural network
CEBC	Center for Evidence-Based Conservation
FFNN	feed-forward neural networks
GEP	gene expression programming
GP	genetic programming
GA	genetic algorithm
LMA	Levenberg–Marquardt
LR	linear regression
MAE	mean absolute error
MAPE	mean absolute percentage error
MSE	mean squared error
ML	machine learning
MLR	multiple linear regression
NARX	nonlinear autoregressive network with exogenous inputs
NRMSE	normalized root mean square error
NSE	Nash–Sutcliffe efficiency
RF	random forest
RMAE	relative mean absolute error
RMSE	root mean square error
PSO	particle swarm optimization
SST	sea surface temperature
SVM	support vector machine
SWAT	soil and water assessment tool