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Water quality big data analysis of the river basin with artificial intelligence ADV monitoring

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Abstract. 5th Assessment Report of the Intergovernmental Panel on Climate Change Weather (AR5) predicts that recent severe hydrological events will affect the quality of water and increase water pollution. To analyze changes in water quality due to future climate change, input data (precipitation, average temperature, relative humidity, average wind speed, and solar radiation) were compiled into a representative concentration curve (RC), defined using 8.5. AR5 and future use are calculated based on land use. Semi-distributed emission model Calculate emissions for each target period. Meteorological factors affecting water quality (precipitation, temperature, and flow) were input into a multiple linear regression (MLR) model and an artificial neural network (ANN) to analyze the data. Extensive experimental studies of flow properties have been carried out. In addition, an Acoustic Doppler Velocity (ADV) device was used to monitor the flow of a large open channel connection in a wastewater treatment plant in Ho Chi Minh City. Observations were made along different streams at different locations and at different depths. Analysis of measurement data shows average speed profile, aspect ratio, vertical position Measure, and ratio the vertical to bottom distance for maximum speed and water depth. This result indicates that the transport effect of the compound was considered when preparing the hazard analysis.
Keywords: artificial neural network; climate change; estimation of water quality; multiple linear regression analysis

1. Introduction

A clear sign of global warming is the increase in average earth and ocean temperatures, the widespread melting of ice and glaciers, and the rise of sea levels on land, all of which are measured and measured, including applied management (Qiu *et al.* 2022a, b, Feng *et al.* 2021), and nature physics (Yue *et al.* 2021, Quan *et al.* 2021, Zhang *et al.* 2019, Gao *et al.* 2021, Liu *et al.* 2022, Longo *et al.* 2019, Yin *et al.* 2022a, b, Zhou *et al.* 2021a, b, c, Yang *et al.* 2021, Xu *et al.* 2022, Zhao 2021a, b), and engineering application (Shen *et al.* 2022, Wang *et al.* 2021,. 2022, Fang *et al.* 2021, Liu *et al.* 2016, Chen *et al.* 2022, Zhao *et al.* 2020, Zhan *et al.* 2022, Ban *et al.* 2022, Miao *et al.* 2022, Gu *et al.* 2022, Zhu *et al.* 2022, Yang *et al.* 2022) *et al*. Freshwater supplies in Central, South, East and Southeast Asia are expected to decline by 2050. Areas near major rivers are particularly affected (IPCC Fourth Assessment Report Preparation, 2007). In fact, evidence of climate change has been found around the world in recent decades, with many scientists documenting the frequency and extent of floods and droughts. Studies are being actively conducted in many countries around the world to assess the impact of climate change on their water supply systems. Christensen *et al*. (2004) evaluated the effects of climate change on Colorado River water resources. They use RCM to analyze hydrological phenomena and the effects of changes in water resources. They (2003) analyzed the effects of climate change on water flow in the upper Mississippi River. A similar study is also being conducted in South Korea. SNURCM is a climate model developed by Seoul National University and the Ministry of Environment (2006) to predict and evaluate the effects of climate change on the water cycle. In addition, the 21st Century Research and Development Project (Sejong University and Ministry of Science and Technology 2007) has established a system to assess the impact of climate change on water resources. However, in Vietnam, most water research focuses on climate change itself and uses techniques to predict changes in climate factors based on global climate models. As a result, there is little quantitative assessment of the impact of climate change on water supply systems.

Computer-based methods have been developed for many scientific and engineering disciplines (e.g., Zyada *et al*. 2011, Rosloniec 2010, Pezeshki *et al*. 2010, Baranoski 2008, Narayanan 2008, de Espindola *et al*. 2010, Erenturk 2010, Mehrabian and Yousefi -Koma, 2011, Landolsi *et al*. 2011). For example, in water resources research, artificial neural networks have long been used to predict flow (Chang and Chen 2003) and facilitate reservoir management (Chang and Chang 2001). Efforts have been made to apply artificial neural networks to fluid dynamics problems (Milano and Koumoutsakos 2002, Hocevar *et al*. 2004), but

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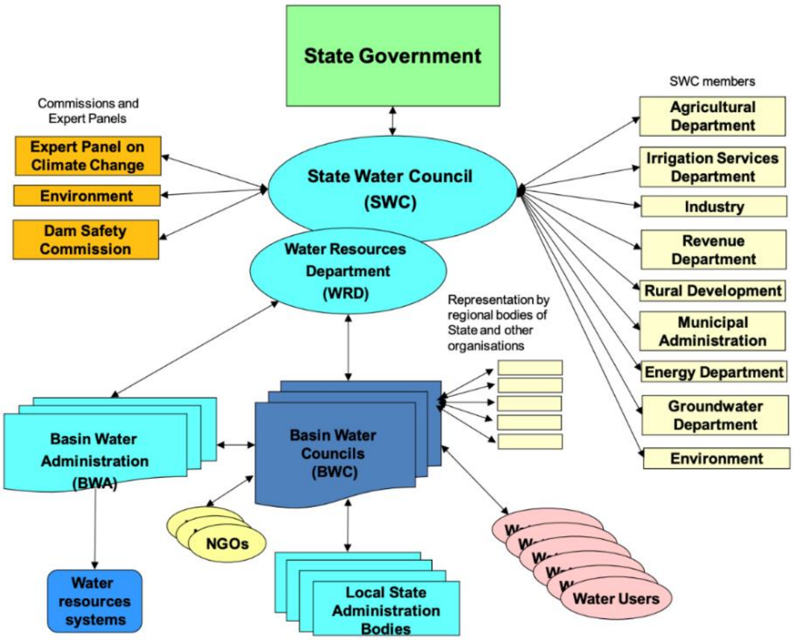

Fig. 1 Water resources planning and assessment process in the K-WEAP model

the method is rarely used for open channel simulations (Omid *et al*. 2005). Previous studies have shown that neural network results agree well with chaotic velocity and intensity distributions of open channel currents that deviate from the smooth boundary of the laboratory circuit. Current conditions can be accurately predicted under research conditions (Chang *et al*. 2008).

The main objectives of this study are: (1) to assess the impact of climate change on drought in the Mekong region. For research purposes, climate factors simulated by climate change models were analyzed using the SLURP model of distributions corresponding to long-term circulation patterns. Due to the high uncertainty about future water demand, 3 scenarios are proposed: low demand, medium demand, and high demand. For each scenario, 50 different emission values (results from the SLURP model) were used as input to the K-WEAP model to estimate future water shortages for each scenario. (2) obtain and display high-quality experimental 3D flow data using an acoustic Doppler velocimeter (ADV) in a large open channel connected to a stream of multiple flow rates and frame rates, (3) use the multi-layer neural network (MFLN) method to simulate the performance and explore the use of artificial neural networks.

2. Multilayer Functional Link Network (MFLN) and its basic theory

K-WEAP is a model developed by the "Sustainable Water Supply Technology Development Project Group" in the “Upstream Water Balance Master Plan and Technology Development Project” implemented in the 21st century. Research and development projects. The model is part of a joint study by the Water Resources Research Department of the Korea Institute of Building Technology and the Boston Environmental Center in Stockholm.

K-WEAP is based on water balance analysis and can be applied to water supply and demand systems in agricultural areas, small watersheds or river basins. In addition, K-WEAP can be used for water demand analysis, water resource protection, prioritization and allocation of water rights, water and groundwater modeling, water reservoir management, hydropower generation, pollution monitoring, water level monitoring for ecological analysis, etc. It can cover a wide range of topics.

K-WEAP is implemented in several steps, as shown in Fig. 1. First, analyze the main elements of the water supply system, such as the target year of the plan, the geographic scope of the target area, the water supply situation and regional demand, network, etc. Second, the current water supply system is at the expected level, taking into account the actual water demand, the amount of pollution, the local water supply and distribution sources, especially the water sources and waste water treatment plants. Third, future scenarios and options are developed taking into account factors such as policies, costs, technological development or demand, pollution and distribution that affect hydrological conditions. Finally, K-WEAP can assess the sensitivity of each scenario to uncertainties in key parameters, such as water scarcity, pollution load, water use for water maintenance, and water availability.

For drought and water scarcity in the Mekong River Basin, the study will follow the steps shown in Figure 2. First, create a water demand scenario based on climate change. Card. The current climate change situation and the climate change situation to support environmental water needs in the medium to long term. Then, we applied the SLURP model to the K-WEAP water resource assessment and planning model based on flow data from 50 climate change scenarios to overcome the uncertainty of climate change. Finally, water scarcity in small river basins (medium-sized areas on the water map) is assessed against scenarios and targets.

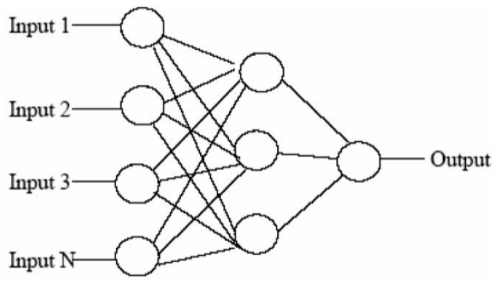

Fig. 3 MFLN architecture and learning process

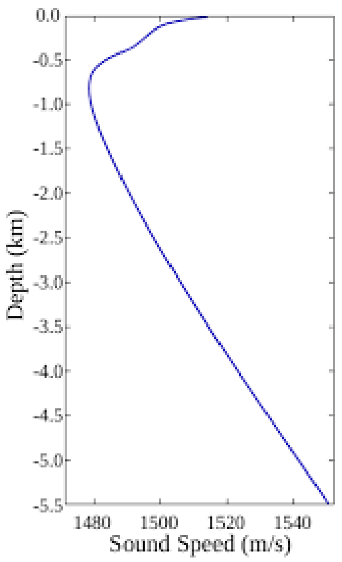

Fig. 4 Arrangement of test equipment for section measurement and speed measurement of profile points

The K-WEAP water balance model is used to predict future water supply and demand in the Mekong River Basin. To develop the K-WEAP model, it is necessary to determine the level of water supply of the Mekong River Basin in the future. This study used the national standard map - the water resource unit map. The area of the Han Basin (Great Basin) can be divided into four basins. This study takes the upper area of the Mekong River basin as the center, and the average area of the basin map is used as the simulation unit to generate the information of the Mekong River basin. According to the K-WEAP model, the Mekong river water supply system includes 17 lines, 38 rivers, 4 reservoirs, 67 bridges, 100 transmission lines. and 63 water return pipes.

Adapting the MFLN follows the error reduction function (Fig. 3). Use the delta rule to adjust the weights w_{lj} directly, specifying the output unit size directly .

$$\Delta w_{lj} = w_{lj}^{new} - w_{lj}^{c} = \eta_0(d_l - y_l)f'_0(net_l)x_l \qquad (1)$$

$$net_l = \sum w_{lj}x_l \qquad (2)$$

current weight w_{lj}^{new}, $w_{lj}^{c}d_l$ and y_l are *the components of the target cell and the output cell* . η_0 is the learning rate. is the derivative of the nonlinear function f_0 on the network . f'_0 The net is the sum of the weights l. The output unit. Learning is repetitive. Each loop has a propagation step that modifies the process weights to minimize the cost function. Standard propagation procedures are described in Ham and Kostanic (2001).

3. Materials and test methods

Collect data on the release of open channels at 90 intersections at the Ho Chi Minh City drainage station by the Ministry of Water Resources of Vietnam. °A schematic diagram of the experimental setup is shown in Fig. 4. The channel consists of 200 m one long main channel, eight inlet channels (each 20 m long), and two outlet channels (each 20 m long). The passage on both sides is 1 m wide and 1 m deep. The side bed 1.0 mis above the main hall bed. The main channel has a slope of 0.1%, a depth of 4.2 m1 4.2 m and a width of 1 2.2 m. The bed and side walls are made of concrete slabs. Fig. 2 shows 0.25 m the 1.72 m measurement 1.22 m section 2.72 m. 3.72 m. The speed of each section is obtained from 10 points with different y values.

Velocity was measured using a three-component Acoustic Doppler Velocimeter (ADV). Operating temperature 0°from C to C, the device 40° can measure 0.1 mm3D current from 0 to /s with accuracy Details of /s 2.5 m. The sampling frequency of each measurement point is 20 Hz. The number of samples per recording rate exceeds 600. Due to the limitations of the conditions of use, it is necessary to develop audio equipment that operates according to the principle of Doppler ratio measurement. A Vector 3D ADV probe from Nortek AS was used. For a more detailed review of ADV, see Kraus *et al.* (1994), Voulgaris and Trowbridge (1998), and Chanson *et al.* (2008). The aspect ratio or aspect ratio (W/H) is between 1388 and 1438. The Reynolds number (Re = U_{mA} R /) νvaries from $\frac{U_{m-A}}{\sqrt{gH}}$ approximately 4.2×10^5 to 7.7×10^5 and the Froude number is Fr = . 5 The test conditions are shown in Table 1. Where H = water depth of the main channel, T = water temperature, and Q = flow measured in the test section. U_{mA} = Q/A = average flow velocity of the main channel, A = cross-sectional area, B = width of the main channel of the upper stream. R = radius of water, νKinematic viscosity, g = gravitational acceleration.

4. Analysis and discussion

As mentioned above, one of the main goals of this study is to evaluate the potential of neural networks to simulate speed data based on existing experimental data. Velocity data is a function of aspect ratio (W/H), vertical position (Z), and depth of position y/H.

$$u = f(B/H, Z, y/H) \qquad (3)$$

where *f( )* is a non-linear function. There are 5 different discharge hoppers, each with 8 vertical posts. Each vertical configuration has 10 data points. The total number of data points is 400. This amount of data is sufficient to model the speed data and create the MFLN n. By convention, the available data is divided into two subsets, the training set and the validation set. MFLN usually begins with a mock

Table 1 Test conditions

case	H (man)	T (°3)	listen (m^3/s)	U_{m-A} (think)	B/H	relationship	Fr
R1	Chapter 2785	21.4	3 981	0.35 1	1,88	425319	0.058
R2	Chapter 2818	21.3	5,173	0.448	1,519	55220	0.027
R3	2847 __	21.5	5,87	0.516	1,448	62928	0.120
R4	Chapter 2868	21.6	6,835	0.26	1,356	729	0.12
R5	Chapter 2889	22.8	7,226	0.637	1,38	771254	0.128

Table 2 MFLNs. The result

Subgroup	γ	Raw RMSE (m/s)
Electric train	0.977	0.01 5
confirm	0.954	0.0 11

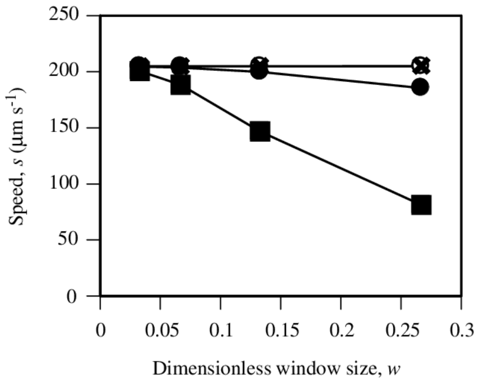

Fig. 5 Speed comparison between ADV method and MFLN method

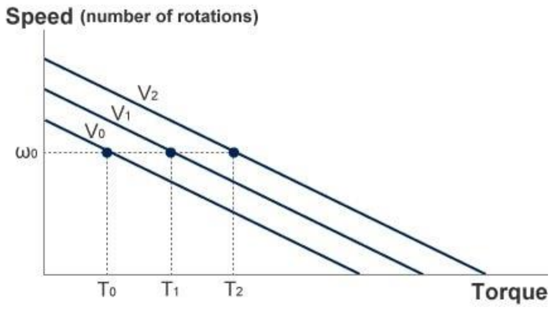

Fig. 6 Measuring the curve of speed circuit R3

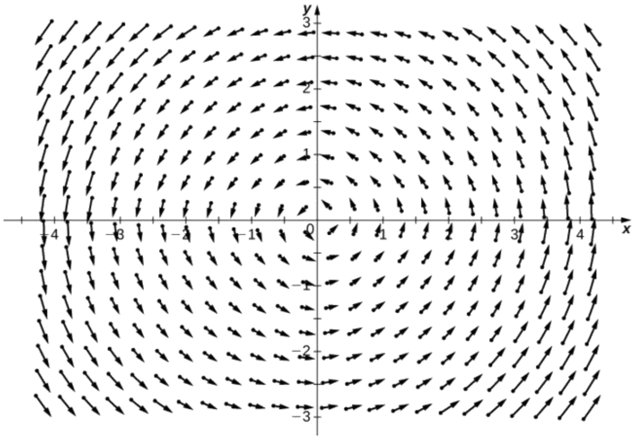

Fig. 7 Measure the vector field cross section

exam. Then we use hybrid algorithms to adjust the synaptic weights of the multilayer sensor using as many training examples as possible. Therefore, there are 16 vertical velocities, of which 160 are vertical velocities and the remaining 24 are vertical velocities (Cas. R2, R3 and R4) and 240. This training and validation dataset subsection aims to provide a general evaluation of the properties of the trained network. As shown in Fig. 3, the input layer contains 9 parameters, while the output layer has only one node that shows the velocity value at a specified position in the vertical direction y/H. Through trial and error, we have identified the best eight hidden neurons for our training data set. The learning rate is initially unitary and is multiplied by a certain number depending on whether the error function increases or decreases during the learning process. This type of activation is called a sigmoid function. Network training continues until the failure target is reached and stops after 20,000 iterations. The results of training and validation are shown in Fig. 5. All data points (observed and simulated) seem to agree. Table 2 shows the γ values and root mean square error (RMSE) for the training and validation sets. The correlation coefficient is close to 1, and the RMSE is small.

Fig. 6 shows the measurement results of the velocity envelope u R3. It can be seen that 1.5 m the maximum speed (*Umax* $_{-A)}$ *of* this part is between and 2.0 m. This result is 4.0 mdue to the reduced width of the main channel 2.0 m. In addition, because the bottom of the side channel is located at 1.0 mthe bottom 1.5 mof the main channel, the maximum speed of the flow channel can be obtained at a water depth of 1 to 1.5 m. The lateral velocity (ie, z-direction) reduces the amplitude of the main velocity (ie, x-direction). The secondary flow pattern can be understood by looking at the measured cross section of the velocity vector fields R1 and R5, as shown in Fig. 7. Looking down, you can see the wake from the right bank to the left bank in the north. There is a clockwise circle near the open water of the channel. Note that the secondary current in R1 is less than the secondary current in R5. In other words, when the channel ratio decreases, the secondary current becomes stronger, slowdown in open straits (Henderson 1965, Nezu and Rodi 1985). Therefore, the maximum speed reaches the lower region and the speed distribution is not symmetrical with the center line.

To predict future water scarcity, we ran a 70-year simulation from 2020 to 2090. Select 2020-2030. as the base year, and select 2031-2060 and 2061-2090 as the base year. Estimate the water shortage in the target year. policy. To calculate the uncertainty associated with the water scarcity model, 50 streamflow sets for each sub-basin (19 central basins) were derived from the SLURP model and the annual water scarcity was calculated. Simulation. Climate change scenarios and water demand.

In 50 sets of data on water scarcity, the average is the average water scarcity per population over 50 years. To see the long-term trend of water scarcity compared to the base year, use the moving average method to calculate the annual average of the modeled water scarcity. The procedure using the 10-year moving average method shows that the water shortage in the Mekong River Basin is more and more high demand A2.

(1) Water shortages are more severe in June as the flood season moves from July, August, and September to August, September, and October.

(2) In general, less water flow leads to more weight loss.

(3) Similar budget implementation signatures are seen in 2031-2060 and 2061-2090. However, water scarcity will increase in the target years 2061-2090 due to uncertainty in emissions (levels of change).

5. Conclusions

This study assesses the vulnerability of the Mekong River region to drought and water use. Climate change scenarios and water demand were developed based on climate change scenarios applied to the K water resource assessment model, and emissions data were simulated using the SLURP model. -WEAP and pattern mode. The results of this model are used in the quantitative analysis of water scarcity in the Mekong River region. At the same time, it will also analyze the extent of water scarcity in small watersheds and suggest why. A robust and reliable hydrological risk assessment process deserves attention. Flooding and transportation of mixed materials in the powerful lava play a role in this danger and should be considered. However, the transport of the mixture is not currently systematic and is only included in the preparation of the hazard analysis. The result is the loss of the accuracy of the forecast and the risk of assessing the impact of the disaster. Flow phenomena at open junctions such as irrigation canals and sewage treatment plants are important hydrological issues. The current characteristics of open junctions at different transmission frequencies were investigated. Experimental measurements show that the maximum velocity is not a free surface under all flow conditions tested. The experimental measurements were compared with the open channel velocity distribution obtained by ADV. MFLN simulation results are better than Eq. (4). Embedded neural network models can be used as modules for estimating or generating complex average velocity profiles in open channels. Such models are powerful tools for simulating flow under similar flow conditions and can also be used to correct distorted flow data. A comparison with the regression analysis results was performed as well. In this study, an artificial neural network (ANN) was used to simulate the average speed data. The results show that the artificial neural network can accurately and reliably simulate average speed data.

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