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RESEARCH ARTICLE

# Relationship between anthropogenic factors and freshwater quality in Hainan Province, south China

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## Abstract

Water resource security directly or indirectly affects the development of society, economy, and the environment, and is of massive significance for regional sustainable development. This study addresses whether anthropogenic activities, especially from tourism, significantly affect the freshwater quality in Hainan Province, China. The freshwater quality in Hainan Province was generally good in 2012 to 2015 (at level II, GB3838-2002). Agriculture, fishery, animal husbandry, and chemical oxygen demand discharge mainly affect freshwater quality in the Nandu and Changhua rivers. Water quality in Wanquan River is more susceptible to tourism in comparison with the Nandu and Changhua rivers. DO content in the Wanquan River fluctuated greatly. It remains necessary to closely monitor negative changes in water quality due to increasing tourism, especially in Wanquan River and eastern Hainan Province. The developed radial basis function neural network shows that the changes in water quality are predicted accurately in comparison with experimental values in the present study. Our results suggested that current anthropogenic factors had a modest effect on water quality on Hainan Island, while tourism had a perceptible effect in eastern Hainan. Our findings provide a reference for the interplay of water quality, people's livelihood, and economic development (tourism and port construction) in Hainan Province.

**Keywords** Anthropogenic activities · Freshwater quality · Hainan Province · Tourism · Radial basis function neural network

## Abbreviations

| | |
|---|---|
| GDP by region | Gross domestic product by region |
| WW discharge | Wastewater discharge |
| Total AABM | Total afforested area in barren mountain |
| ECPU GDP | Energy consumption per unit of gross domestic product |
| GOVA | Gross output value of agriculture |
| GOVF | Gross output value of forestry |
| GOVAH | Gross output value of animal husbandry |
| GOV of Fishery | Gross output value of fishery |
| GIO | Gross industrial output |

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| | |
|---|---|
| PDUA | Population density of urban area |
| Annual average of NOV | Annual average of number of overnight visitors |
| COD | Chemical oxygen demand |
| NH+ 4-N | Ammoniacal nitrogen |
| DO | Dissolved oxygen |

## Introduction

With the rapid economic growth in China, increasing discharges of industrial, agricultural, and domestic wastewater are accelerating eutrophication of lakes (Lin et al. 2021; Pu et al. 2021). Due to these human activities, water quality has declined at varying degrees in several areas in China (Luo et al. 2021). To date, the rate of damage to aquatic environments is far greater than their ability to recover (Hand and Cusick 2021). With regard to eutrophication globally, excessive loading of the growth limiting nutrients nitrogen and phosphorus into slow-flowing water bodies (including lakes, reservoirs, estuarine, and coastal ecosystems) can lead to rapid propagation of harmful algal blooms, which decreased dissolved oxygen levels leading to increased mortality of resident fauna ( Li et al. 2020a; Menberu et al. 2021; Mironga et al. 2012). Knowledge of environmental drivers and their impacts on water quality is essential for obtaining a better understanding of mechanism of eutrophication and to allow for implementation of mitigation steps to protect inland freshwater resources.

The Nandu, Changhua, and Wanquan rivers are major rivers on Hainan Island, China, with a combined catchment area of more than 3000 $km^2$, accounting for 47% of the island's area. The island's unique geographical factors, including landform by marine erosion, volcanic activity, mineral spring activity, tectonic denudation, karst cave, and stone forest, lead to relatively fragile ecological conditions. It can also lead to insufficient and inhomogeneous water resources (Li et al. 2020b) and lead to imbalances of species distributions in impacted waters. Therefore, reversing eutrophication represents a major challenge. In the Chinese coastal waters near Hainan Island, Zhang et al. (2020) described the spatiotemporal variation, composition of DIN, and its role in eutrophication. According to the findings, DIN concentrations ranged from 0.008 mg/L to 0.384 mg/L, with an average of $0.114 \pm 0.087$ mg/L. In all seasons, areas with high DIN concentrations (> 0.2mg/L) were found in the coastal waters near Haikou City and the Qiongzhou Strait. Jia et al. (2012) reported that the Shamei lagoon in Hainan Island was transformed into a freshwater environment during 1900–1950. After 1950, due to anthropogenic activities, freshwater phytoplankton biomass increased and became the major source of sedimented organic matter (Jia et al. 2012). Beyond this finding, there are few studies concerning the investigation of inland water quality in Hainan Province.

With rapid economic development in Hainan, various sources of pollution, especially agricultural non-point sources, have increased pressure and impacts on its rivers' water quality (Yu et al. 2020). Despite this, it has been demonstrated that river water quality can be improved through an increase of environmental investment, specifically to improve industry and agricultural practices (Barrington et al. 2014; Xiao et al. 2020). Zhou et al. (2017) reported that during the past decade, water quality of Chinese inland waters has improved markedly since Chinese government financed investments in environmental restoration and reforestation. They found that GDP-normalized COD and ammonium concentrations significantly and exponentially decreased. Zhou et al. (2020) showed that population size and agriculture declined to varying degrees at the end of the study period, although the urbanization continued to challenge acceptable water quality. Ma et al. (2020) showed that water quality improved markedly and was maintained at acceptable levels nationwide because of reduced discharges in the industrial, rural, and urban residential sectors. Unfortunately, growing discharges from the agricultural sector threaten to negate these gains. Consequently, it appears that several indexes, e.g., industrialization, agriculture, population, and per capita GDP, may significantly impact inland water quality. In this study, we will investigate on the relationship between these factors and water quality in the three major rivers of Hainan Island.

Artificial neural network is a mathematical model simulating biological neural network for information processing (Ma et al. 2020). It is based on the physiological connections within the brain, and its purpose is to simulate some mechanisms of the brain and achieve several specific functions (Wu et al. 2020). At present, ANN has been applied in numerous fields, including environmental monitoring and assessment of inland waters (Aghav et al. 2011; Wu et al. 2021). Shi et al. (2021) used the back propagation artificial neural network, a self-adapting algorithm, to assess cumulative risks to aquatic ecosystems. Abdel Daiemet al. (2021) utilized two radial basis function neural networks (a conventional and based on particle swarm optimization) in combination with submerged biofilter media to accurately predict the removal of COD from polluted water streams. The variables studied included temperature, flow rate, and influent COD.

The objective of the present study is to (1) investigate the dynamic of water quality of the three major rivers on Hainan Island; (2) elaborate on the relationship between socioeconomic factors and inland water quality in the three major rivers of Hainan Island; (3) assess water quality of water basin as affected by tourism from 2012 to 2015 in Hainan Island; and (4) simulate the inland water quality in the three major rivers of Hainan Island based on 2013–2015 to predict future changes.

## Materials and methods

### Study area

The Nandu River, Changhua River, and Wanquan River are the three major rivers in Hainan Province. Due to being tropical island type rivers, they exhibit unique hydrological characteristics. Firstly, as island rivers, they are relatively short in length, slow in flow rate, and small in basin area. This is due to the limitation of island area.

Furthermore, Hainan Island is high in middle and lower in its around gradually until sea surface. Therefore, the river forms a divergent structure and multi-level stepped terrain from the center to the edge, presenting a divergent water system with an initial multi-level structure. Thirdly, Hainan Island is a southeast monsoon and typhoon type river, mainly supplied by rainwater. The length of Nandu River is 333 km, with a flow of 209 $m^3$/s (Longtang) and a drainage area of 7022 $km^2$. The total amount of runoff of Nandu River is 6.12 billion $m^3$, which flows into Qiongzhou Strait. The length of Changhua River is 231 km, with a flow of 122 21 $m^3$/s (Baoqiao) and a drainage area of 5150 $km^2$. The total amount of runoff of Changhua River is 3.71 billion $m^3$, which flows into the Beibu Gulf. The length of Wanquan River is 156 km, with a flow of 166 $m^3$/s (Jiaji) and a drainage area of 3693 $km^2$. The total runoff volume of Wanquan River is 5.097 billion $m^3$, which flows into the South China Sea. The sampling points (Fig. 1) are shown for the Nandu River (110°24′40″E, 19°59′8″N), Changhua River (108°41′7″E, 19°19′58″N), and Wanquan River (110°24′13″E, 19°12′25″N).

### Data sources and water quality evaluation standards

Socioeconomic parameters in the present study used the sum of the single indices for the through cities by a basin. The socioeconomic parameters were acquired from the official website of the Hainan Provincial Bureau of Statistics (http://stats.hainan.GOV.cn/). DO, COD, and NH+ 4-N were used to assess freshwater quality from January 2012 to December 2015, and relevant data were provided by Department of ecological and environmental protection of Hainan Province (http://hnsthb.hainan.GOV.cn/). According to the water quality standards for surface waters in China (GB3838-2002), water quality was classified as five grades in Table 1.

### Statistical analyses

Radial basis function neural network (RBFNN) is an artificial neural network, and its output of a radial basis function network is a linear combination of the input radial basis function and neuron parameters. The hidden node of RBF neural network uses the distance between the input mode

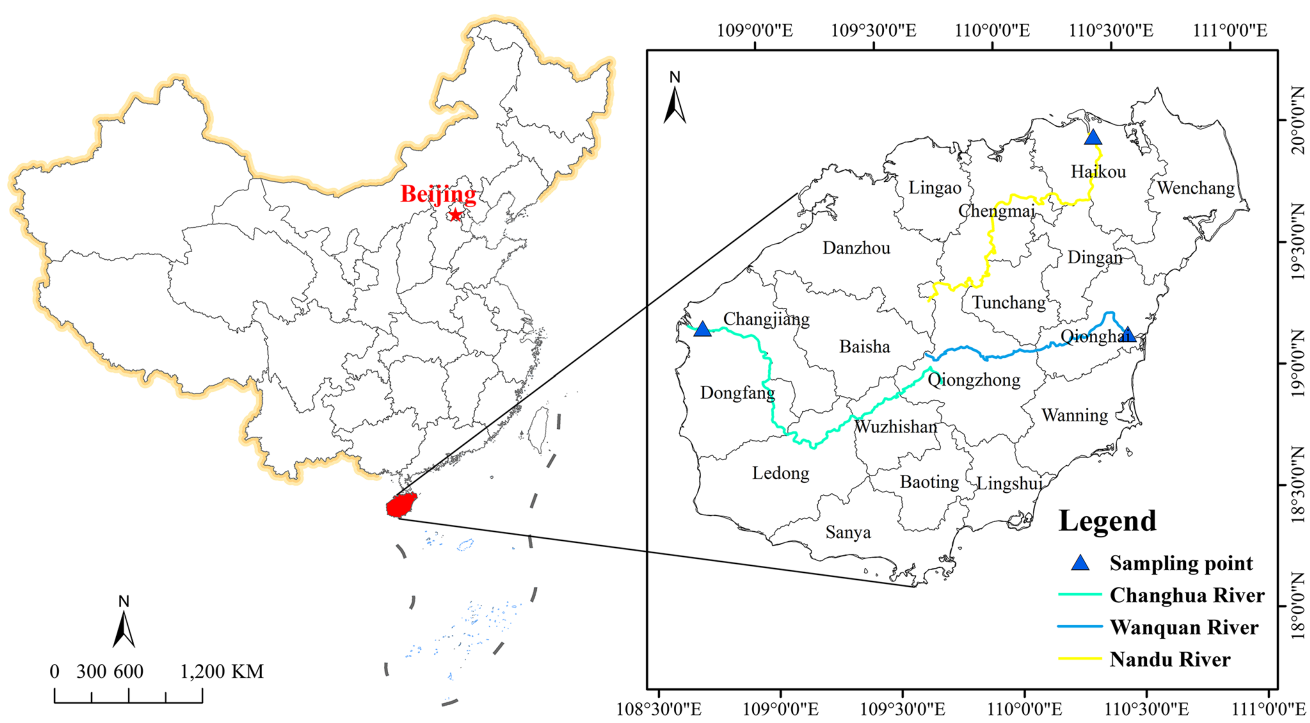


**Fig. 1** Sampling information in the Nandu River, Changhua River, and Wanquan River

**Table 1** The grade of water quality

| COD | $NH_4^+$-N | DO | Grade |
|---|---|---|---|
| COD ≤ 2.0 mg/L | $NH_4^+$-N ≤ 0.15 mg/L | DO ≥7.5 mg/L | I |
| 2.0 mg/L<COD≤ 4.0 mg/L | 0.15 mg/L<$NH_4^+$-N≤ 0.5 mg/L | 6.0 mg/L<DO≤ 7.5 mg/L | II |
| 4.0 mg/L<COD≤ 6.0 mg/L | 0.5 mg/L<$NH_4^+$-N≤ 1.0 mg/L | 5.0 mg/L<DO≤ 6.0 mg/L | III |
| 6.0 mg/L<COD≤ 10.0 mg/L | 1.0 mg/L<$NH_4^+$-N≤ 1.5 mg/L | 3.0 mg/L<DO≤ 5.0 mg/L | IV |
| 10.0 mg/L<COD≤ 15.0 mg/L | 1.5 mg/L<$NH_4^+$-N≤2.0 mg/L | 2.0 mg/L<DO≤ 3.0 mg/L | V |

and the center vector (such as Euclidean distance) as the independent variable of the function, and uses the radial basis function (such as Gaussian function) as the activation function. (Ayala et al. 2019; Hong et al. 2020). Their calculated equations are provided by Wu et al. (2020). Statistical analyses, including mean values, standard deviation, *t* test, and linear correlations, were conducted using Origin 2017. Spatial distribution of water quality related parameters was determined with ArcGIS 10.1 software. The Bayesian neural network was used to determine the relationship between the macro index and water quality using Python 3.6.0. The RBFNN was performed by MATLAB R2012a software.

## Results

### General water quality conditions in the Nandu, Changhua, and Wanquan rivers

Figure 2 shows the concentrations of pH, COD, DO, and ammonium in Nandu, Changjiang, and Wanquan rivers from August 2012 to December 2015. During the investigation period, pH of the surface layer of Nandu River was 7.36 ± 0.29, ranging from 6.95 to 7.94, with maximum values occurring in January and February 2015. The DO content in surface of Nandu River ranged from 5.29 to 8.44 mg/L, with an average of 6.64 ± 0.83 mg/L, and the maximum and minimum occurring in February 2014 and July 2015, respectively. The range of COD in the surface layer of Nandu River is 1.95–4.60 mg/L, and the average value was 3.18 ± 0.58 mg/L, with maxima and minima appearing in February 2014 and July 2015, respectively. Ammonium concentration in the surface layer of Nandu River ranged from 0.085 to 0.295 mg/L, with an average value of 0.16 ± 0.05 mg/L, with maxima and minima appearing in January 2014 and September 2012, respectively. For the Changhua River, average pH was 7.49 ± 0.23, ranging from 6.97 to 8.07, with maximum values in July 2013 and March 2014. The COD content in the surface layer of the Changhua River ranged from 1.13 to 3.53 mg/L, with an average of 1.94 ± 0.60 mg/L, with maxima and minima appearing in October 2014 and March 2013, respectively. DO content in the surface layer of the Changhua River ranged from 5.41 to 8.10 mg/L, with an average value of 6.88 ± 0.590 mg/L, with maxima

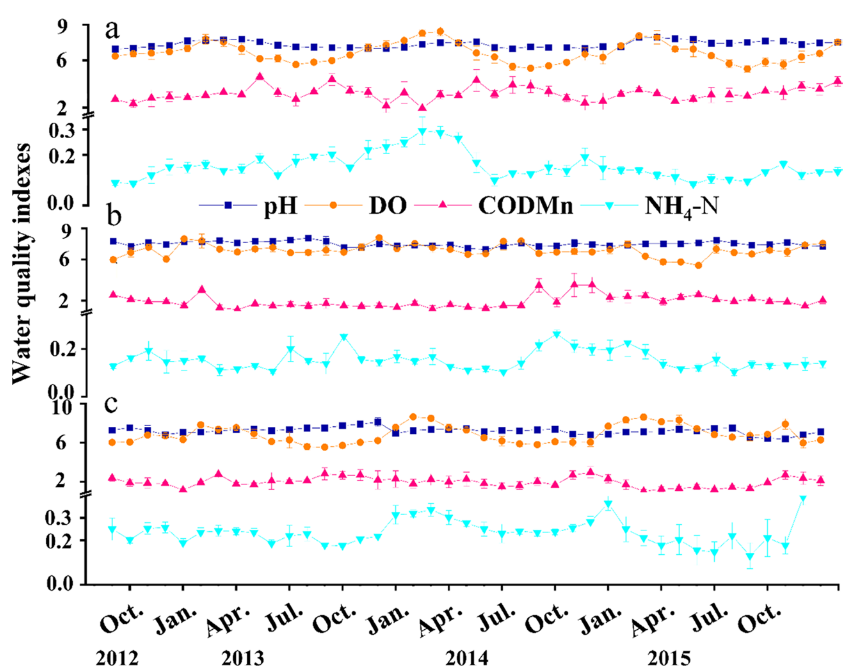


**Fig. 2** Water quality parameters (pH, DO, COD, and $NH_4^+$-N) in Nandu River (**a**), Changhua River (**b**), and Wanquan River (**c**) from 2012 to 2015

and minima occurring in November 2013 and May 2015, respectively. The range of ammonium content in the surface layer of Changjiang River is 0.105–0.265 mg/L, with an average of 0.16 ± 0.04 mg/L in September 2013 and July 2015, respectively. Surface pH of the Wanquan River was 7.22 ± 0.34, ranged from 6.39 to 8.13, with the maximum values in January and February 2014. The DO concentration in the surface of the Wanquan River ranged from 5.56 to 8.66 mg/L, with an average of 6.86 ± 0.91 mg/L, with the maximum and minimum appearing in January 2014 and August 2013, respectively. COD content in the surface layer of Wanquan River ranged from 1.05 to 2.96 mg/L, with the average content 1.98 ± 0.49 mg/L, and the maximum and minimum appearing in November 2014 and February 2015, respectively. Surface ammonium content of Wanquan River ranged from 0.13 to 0.43 mg/L, with an average of 0.24 ± 0.06 mg/L, with the maximum and minimum values occurring in December 2015 and August 2015, respectively.

Overall, water quality of the Nandu, Wanquan, and Changhua rivers was level II. For pH of the three rivers, Changhua River > Wanquan River > Nandu River. Among the three main rivers in Hainan Province, the order of COD content is Nandu River > Wanquan River > Changhua River. The DO contents of Changhua River and Wanquan River were similar, but higher than those occurring in the Nandu River. The content of ammonia nitrogen in Wanquan River was highest, followed by Nandu River and Changhua River.

## Relationships between water quality and human-driven socioeconomic indices

Table 2 shows the degree of impact on water quality under socioeconomic indexes by Bayesian network. The weight value that GOV of agriculture, GOV of fishery, GOV of animal husbandry, and COD discharge greatly influence DO content, with their weight values being 0.35, 0.35, 0.20, and 0.19, respectively. GOV of fishery, GOV of agriculture, total AABM, and GOV of animal husbandry strongly influenced COD content in Nandu River, and their weighted values were 0.60, 0.60, 0.41, and 0.41, respectively. The weighted values of GOV of fishery, GOV of agriculture, total AABM, and GOV of animal husbandry were 0.60, 0.61, 0.41, and 0.40, respectively. In general, GOV of fishery, GOV of agriculture, total AABM, and GOV of animal husbandry strongly influenced water quality of the Nandu River. GOV of agriculture has been increasing each year, GOV of animal husbandry and GOV of fishery showed little change, and total AABM decreased on a yearly basis. Table 3 shows that the correlations of GOV of agriculture, GOV of fishery, GOV of animal husbandry, and total AABM to the annual increasing trend were 0.88, 0.85, 0.62, and 0.77, respectively.

In the Changhua River, the major impact on DO content was ammonia nitrogen discharge, GOV of animal husbandry, GOV of forestry, and GOV of fishery, and the weight values were 0.79, 0.64, 0.62, and 0.61, respectively. Cultivated land, population density of urban area, and GDP by region and EC per unit of GDP had a large influence on COD content in Changhua River, and their weight values were 0.59, 0.40, 0.40, and 0.39, respectively. The weight values of cultivated land, waste discharge, population density of urban area, ammonia nitrogen discharge, total AABM and GOV of agriculture were 0.39, 0.39, 0.38, 0.38, 0.38, and 0.38, respectively. In general, cultivated land, GOV of fishery, GOV of agriculture, total AABM, and GOV of animal husbandry strongly impacted water quality of Nandu River. GOV of agriculture is increasing yearly, GOV of animal husbandry, GOV of fishery, and cultivated land changed

**Table 2** The weight of socioeconomic parameters in Nandu, Changhua, and Wanquan rivers

| Socioeconomic indicators | Nandu River | | | Changhua River | | | Wanquan River | | |
|---|---|---|---|---|---|---|---|---|---|
| | $NH_3$-N | COD | DO | $NH_3$-N | COD | DO | $NH_3$-N | COD | DO |
| Cultivated land | 0.39 | 0.39 | 0.19 | 0.39 | 0.59 | 0.23 | 0.34 | 0.19 | 0.35 |
| ECPU GDP | 0.36 | 0.36 | 0.19 | 0.21 | 0.39 | 0.23 | 0.39 | 0.39 | 0.2 |
| Total AABM | 0.41 | 0.41 | 0.18 | 0.38 | 0.2 | 0.23 | 0.34 | 0.39 | 0.2 |
| $NH_3$-N discharge | 0.36 | 0.36 | 0.19 | 0.38 | 0.12 | 0.79 | 0.37 | 0.64 | 0.19 |
| COD discharge | 0.36 | 0.36 | 0.19 | 0.21 | 0.12 | 0.12 | 0.41 | 0.19 | 0.39 |
| WW discharge | 0.39 | 0.39 | 0.19 | 0.39 | 0.17 | 0.12 | 0.64 | 0.19 | 0.39 |
| GDP by region | 0.4 | 0.4 | 0.18 | 0.15 | 0.4 | 0.12 | 0.63 | 0.19 | 0.39 |
| Population | 0.39 | 0.39 | 0.19 | 0.21 | 0.12 | 0.1 | 0.61 | 0.18 | 0.39 |
| GOV of fishery | 0.6 | 0.6 | 0.35 | 0.15 | 0.17 | 0.61 | 0.37 | 0.65 | 0.2 |
| PDUA | 0.36 | 0.36 | 0.19 | 0.38 | 0.4 | 0.1 | 0.64 | 0.19 | 0.39 |
| GIO | 0.41 | 0.36 | 0.19 | 0.15 | 0.12 | 0.1 | 0.65 | 0.19 | 0.39 |
| GOVAH | 0.36 | 0.41 | 0.21 | 0.11 | 0.16 | 0.64 | 0.37 | 0.65 | 0.2 |
| GOV fo Forest | 0.39 | 0.39 | 0.19 | 0.11 | 0.16 | 0.62 | 0.2 | 0.63 | 0.37 |
| GOVA | 0.6 | 0.6 | 0.35 | 0.38 | 0.16 | 0.1 | 0.4 | 0.4 | 0.19 |

**Table 3** Socioeconomic parameters and its trends in Nandu, Changhua, and Wanquan rivers

| Rivers | Indicators | 2012 | 2013 | 2014 | 2015 | Time-normalized | Correlation |
|---|---|---|---|---|---|---|---|
| Nandu | Total AABM (ha) | 5901 | 3835 | 2156 | 2703 | $y = -1127.3x + 2E+06$ | $R^2 = 0.77$ |
| | GOVA (10,000 RMB) | 827,191 | 1,313,266 | 1,482,143 | 1,575,876 | $y = 241{,}493x - 5E+08$ | $R^2 = 0.88$ |
| | GOVAH (10,000 RMB) | 478,187 | 886,725 | 888,252.9 | 899,492 | $y = 126{,}544x - 3E+08$ | $R^2 = 0.62$ |
| | GOVF (10,000 RMB) | 565,105 | 866,441 | 947,620.5 | 1,004,181 | $y = 139{,}841x - 3E+08$ | $R^2 = 0.85$ |
| Changhua | Total AABM (ha) | 7257 | 4384 | 2921 | 1923 | $y = -1746.5x + 4E+06$ | $R^2 = 0.94$ |
| | GOVA (10,000 RMB) | 683,713 | 1,139,406 | 1,367,490 | 1,527,057 | $y = 275{,}812x - 6E+08$ | $R^2 = 0.94$ |
| | GOVAH (10,000 RMB) | 136,349 | 251,013 | 269,065.7 | 292,961 | $y = 48{,}789x - 1E+08$ | $R^2 = 0.82$ |
| | GOVF (10,000 RMB) | 119,887 | 189,525 | 219,458 | 229,338 | $y = 35{,}829x - 7E+07$ | $R^2 = 0.88$ |
| | Cultivated land (ha) | 101,827 | 102,181.4 | 105,060 | 105,686 | $y = 1445.6x - 3E+06$ | $R^2 = 0.90$ |
| Wanquan | Total AABM (ha) | 25,915 | 25,943 | 25,940 | 25,586 | $y = -99x + 225183$ | $R^2 = 0.54$ |
| | NN discharge (10,000 t) | 1504 | 1590 | 1657 | 1608 | $y = 37.9x - 74808$ | $R^2 = 0.59$ |
| | GOVAH (10,000 RMB) | 130,120 | 242,821 | 251,135.3 | 264,768 | $y = 41{,}226x - 8E+07$ | $R^2 = 0.73$ |
| | GOVF (10,000 RMB) | 76,828 | 129,653 | 146,864 | 153,106 | $y = 24{,}605x - 5E+07$ | $R^2 = 0.84$ |
| | GIO (10,000 RMB) | 70,894 | 70,894 | 47,746 | 49,669 | $y = -8682x + 2E+07$ | $R^2 = 0.76$ |
| | WW discharge (10,000 t) | 1617 | 1639 | 2106 | 1786.7 | $y = 97.6x - 194686$ | $R^2 = 0.31$ |

slightly, and total AABM is decreased on a year-by-year basis. Table 3 shows that the correlations of GOV of agriculture, GOV of fishery, GOV of animal husbandry, total AABM, and cultivated land to the annual growth trend were 0.88, 0.85, 0.62, 0.90, and 0.77, respectively.

For the weighted values, population, GDP by region, waste discharge, gross industrial output, and population density of urban area strongly influence DO content, with their weight values being 0.39, 0.39, 0.39, 0.39, and 0.39, respectively (Table 2). GOV of animal husbandry, GOV of fishery, total AABM, and ammonia nitrogen discharge strongly influenced COD content in Nandu River, with their weighted values being 0.65, 0.65, 0.44, and 0.64, respectively. The weighted values of gross industrial output, waste discharge, population density of urban area, and GDP by region were 0.65, 0.64, 0.64, and 0.63, respectively. In general, GOV of fishery, GOV of agriculture, total AABM, and GOV of animal husbandry influenced water quality of the Nandu River. The annual changes of the above indicators are analyzed in Table 3. GOV of agriculture is increasing year by year, GOV of animal husbandry and GOV of fishery showed little change, and total AABM decreased year by year.

## Monthly average reception of overnight guests, GOV of agriculture, and GOV of fishery in 2012, 2013, 2014, and 2015

An obvious increase for annual average of NOV occurred from 2012 to 2015 (Table 4). Among them, Haikou City and Sanya City accounted for the highest proportion for the entire province of annual average of NOV in 2012, corresponding to 29.80% and 31.92%, respectively. Thereafter, the proportion of Haikou City for the entire province of annual average of NOV in 2013, 2014, and 2015 decreased year after year, being 28.47%, 27.94%, and 27.28%, respectively. However, the ratio of Changhua County was improved during the survey period, reaching 5.44%, 5.67%, 5.94%, and 6.22%, respectively. The proportion in Qionghai City to the entire province of annual average of NOV was between 1.48% and 1.80% from 2012 to 2015. In general, the annual average of NOV in the east of Hainan Province was higher than of the west. For the annual gross value of agricultural output, the proportion in Haikou to the entire province was gradually reduced during the study period, and their respective values were 7.71%, 7.70%, 7.08%, and 6.74%. The ratio of Changhua County to the entire province varied little from 2012 to 2015, corresponding to 3.22%, 3.23%, 3.21%, and 3.30%, respectively. The proportion in Qionghai City changed slightly, ranging from 10.34 to 10.90% during the investigation period. Generally, the gross value of AO successively focused on Qionghai City, Ledong County, Sanya City, Chengmai County, Wenchang City, Haikou City, Danzhou City, and Dongfang City, and their sum of proportion in the gross value of AO reached at 74.38%. In addition, the proportion of gross value of fishery is relatively less in comparison with the Hainan Province between 2012 and 2015, and reached at 3.21, 3.09, 3.01, and 3.14, respectively. The ratio of gross value of fishery in Changhua County to Hainan Province gradually increased in 2012 to 2015, and ranged from 3.24 to 3.31%. Similarly, the proportion for Qionghai City increased little during the study period, being 4.31%, 4.63%, 4.66%, and 4.65%, respectively. On the whole, the gross value of fishery in the west was higher than that of east of Hainan Province, especially for the higher ratio for gross value of fishery in Lingao County and Danzhou City to the entire province.

**Table 4** Monthly average reception of overnight guests, GOV of agriculture, and GOV of fishery in 2012, 2013, 2014, and 2015

| Cities/counties | Monthly average reception of overnight guests | | | | GOV of agriculture (billion RMB) | | | | GOV of fishery (billion RMB) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2012 | 2013 | 2014 | 2015 | 2012 | 2013 | 2014 | 2015 | 2012 | 2013 | 2014 | 2015 |
| Haikou | 85.52 | 87.03 | 94.97 | 102.10 | 3.55 | 3.74 | 4.02 | 4.13 | 0.76 | 0.85 | 0.93 | 1.02 |
| Sanya | 91.64 | 102.23 | 113.47 | 124.59 | 4.38 | 4.59 | 5.43 | 5.86 | 1.34 | 1.55 | 1.73 | 1.84 |
| Qionghai | 15.62 | 17.34 | 20.18 | 23.30 | 4.91 | 5.16 | 6.19 | 6.35 | 1.02 | 1.28 | 1.45 | 1.51 |
| Wanning | 28.54 | 27.68 | 30.49 | 32.25 | 2.91 | 3.08 | 3.86 | 4.47 | 0.92 | 1.05 | 1.22 | 1.35 |
| Wenchang | 10.97 | 11.40 | 12.73 | 14.49 | 3.61 | 3.77 | 4.33 | 4.46 | 2.27 | 2.69 | 2.59 | 2.68 |
| Wu zhishan | 4.31 | 4.38 | 4.63 | 5.20 | 0.31 | 0.32 | 0.38 | 0.42 | 0.02 | 0.02 | 0.02 | 0.02 |
| Danzhou | 9.67 | 9.87 | 11.15 | 10.31 | 3.42 | 3.62 | 4.04 | 4.27 | 5.25 | 6.11 | 6.46 | 6.91 |
| Anding | 4.31 | 4.78 | 5.64 | 9.31 | 1.87 | 2.02 | 2.35 | 2.54 | 0.08 | 0.10 | 0.13 | 0.10 |
| Dongfang | 3.65 | 4.31 | 4.92 | 4.59 | 3.19 | 3.35 | 3.85 | 4.20 | 0.42 | 0.49 | 0.54 | 0.57 |
| Lingshui | 10.66 | 11.60 | 12.66 | 9.99 | 1.86 | 1.92 | 2.32 | 2.64 | 1.51 | 1.96 | 2.28 | 2.05 |
| Changjiang | 4.02 | 4.51 | 5.55 | 6.07 | 1.48 | 1.57 | 1.82 | 2.03 | 0.77 | 0.90 | 1.01 | 1.08 |
| Tunchang | 1.76 | 2.36 | 2.67 | 2.69 | 1.48 | 1.53 | 1.81 | 1.99 | 0.12 | 0.14 | 0.16 | 0.16 |
| Baoting | 2.61 | 2.97 | 4.00 | 8.13 | 1.10 | 1.15 | 1.33 | 1.40 | 0.04 | 0.04 | 0.04 | 0.04 |
| Qiongzhong | 1.93 | 2.42 | 3.17 | 4.51 | 0.91 | 1.03 | 1.29 | 1.46 | 0.04 | 0.07 | 0.12 | 0.12 |
| Yuedong | 2.54 | 2.75 | 3.23 | 5.05 | 4.61 | 5.12 | 6.33 | 7.17 | 0.40 | 0.42 | 0.49 | 0.51 |
| Lingao | 2.13 | 2.29 | 2.40 | 2.79 | 1.77 | 1.82 | 1.99 | 2.12 | 7.17 | 8.27 | 9.89 | 10.54 |
| Chengmai | 4.89 | 5.51 | 5.88 | 5.54 | 3.69 | 3.78 | 4.42 | 4.79 | 1.45 | 1.52 | 1.76 | 1.84 |
| Baisha | 2.24 | 2.28 | 2.12 | 3.41 | 1.02 | 0.96 | 1.05 | 1.10 | 0.07 | 0.11 | 0.20 | 0.16 |

## Water quality prediction by radial basis function neural network

RBFNN can approximate any non-linear function, dealing with laws that are difficult to analyze for the system, and is also of excellent generalization ability and fast learning convergence speed. In the present study, the goal value of mean square error was set as $1 \times 10^{-10}$ and the spread value was set as 0.8. Figure 3a exhibits that the training process is terminated when the mean square error was reached at 0.0141958 with 100 iterations. Additionally, the determination coefficient ($R^2$) between the experimental and predicted values was 0.97744 after the training the developed RBFNN (Fig. 3b). For Nandu River, Fig. 4 shows that only the predicted water quality of fourth and eight weeks was not consistent with the correspondingly predicted values. For the Changhua River, the non-conformity between experimental and predicted values is only at sixth week for Changhua River. For Wanquan River, the predicted water quality differed only second and seventh weeks from the experimental values.

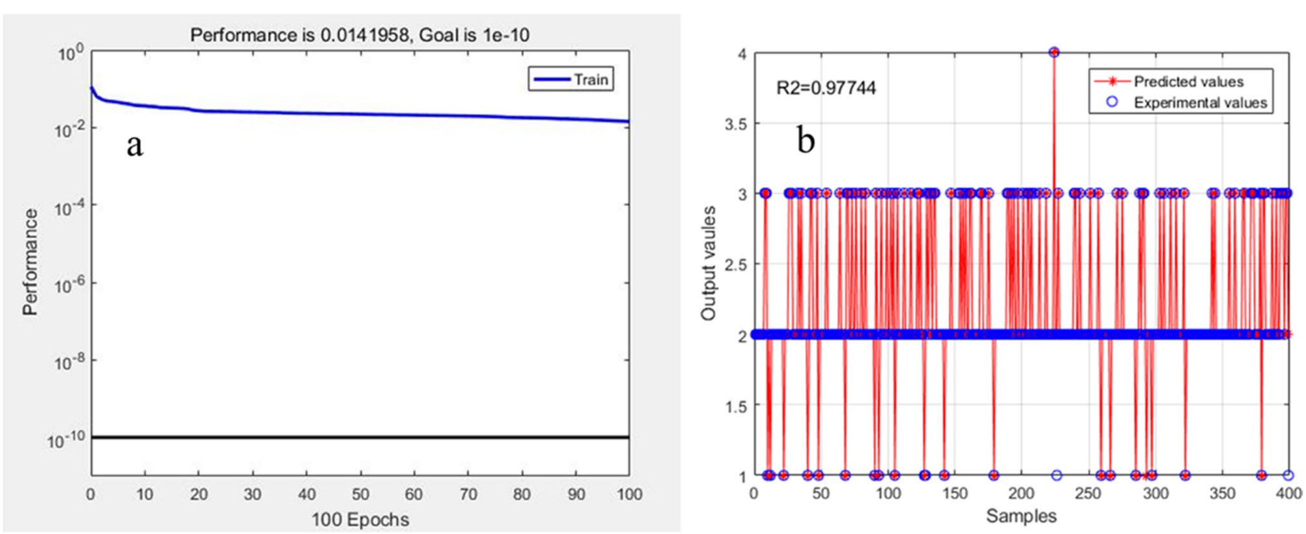


**Fig. 3** The relationship between iterations and mean square error (**a**) and between trained and experimental values (**b**)

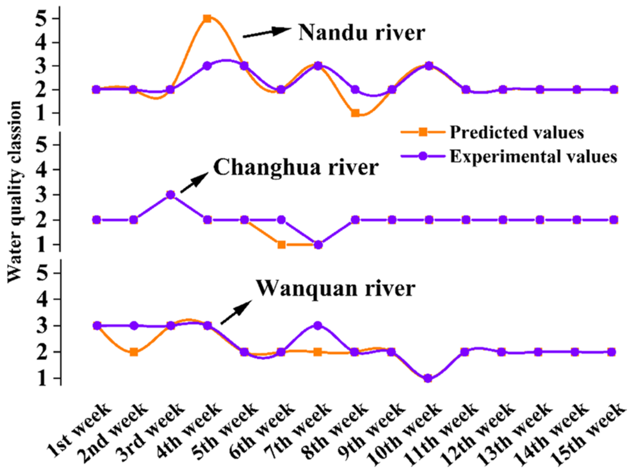


**Fig. 4** The predicted and experimental values in Nandu, Changhua, and Wanquan rivers using RBFNN

## Discussion

The degree of variation of pH values in Wanquan River was relatively higher in comparison with Nandu and Wanquan rivers. The higher and lower pH values were found at annual November to February and annual May to July, respectively. Generally, in Hainan Province, March and April, July and August, and October and November are dry, wet, and normal seasons, respectively. Zuo et al. (2015) reported that the pH value of water in the tourism development zone and the control zone was high water period > low water period > normal water period and the pH value of tourism development zone was significantly higher than that of control zone ($p < 0.05$), which coincided with the present study. Haraguchi et al. (2008) reported water utilization by local inhabitants responding to seasonal changes in water quality of river water in Central Kalimantan, Indonesia. River water chemistry showed little difference between the dry season and the rainy season in the Sigi area, whereas river and canal water in the rainy season in Paduran and Pangkoh showed lower pH than in the dry season due to a high concentration of sulfuric acid in the rainy season (Haraguchi et al. 2008). Zhang and Zhu (2023) exhibited spatial and temporal characteristics of hydrochemistry in three large drainage systems (Junggar, Yili, and Erlqis) of the north Tianshan Mountains. The pH value of the water body is weakly alkaline, and the pH change is clearly seasonal. The pH value is higher in dry season and lower in wet season. Generally, water quality in the wet season is better than that in dry season. The abovementioned studies are roughly in accord with the present study.

Overall, GOV of agriculture, GOV of fishery, GOV of animal husbandry, and COD discharge have large impacts on water quality in the Nandu and Changhua rivers in the present study. However, GDP by region, waste discharge, gross industrial output, and population density of urban area strongly influence water quality. The proportion of agricultural non-point source pollution is approximately 20~30%, which is mainly due to the release of pesticides, chemical fertilizers from farmland with runoff, and the discharge from farms (Hou et al. 2021). Yang et al. selected the Yangtze River Basin and the Yellow River Basin as research areas. They used a combination of canonical correlation analysis and a distance-based influence assessment method to quantitatively assess the influence of socioeconomic development on river water quality. Their results revealed a strong correlation between socioeconomic development and river water quality. The average degree of influence in the Yangtze River Basin was between 0.22 and 0.27, and that in the Yellow River Basin was between 0.2 and 0.36. Moreover, the degree of influence in the Yangtze River Basin in the wet season was greater than that in the dry season, whereas the opposite pattern was observed in the Yellow River Basin. By analyzing the influences of various socioeconomic indicators on water quality, we found that the main factors that influence water quality are per capita GDP and urbanization rate in the Yangtze River Basin and urbanization rate in the Yellow River Basin. Elhatip et al. (2003) demonstrated the influences of human activities on groundwater quality of Kayseri-Incesu-Dokuzpnar springs, central Anatolian part of Turkey. The results showed that agricultural activities directly and indirectly affected the concentrations of a large number of inorganic chemicals in groundwater, e.g., $NO_3^-$, $N_2$, $Cl^-$, $SO_4^{2-}$, $H^+$, K, Mg, Ca, Fe, Cu, B, Pb, and Zn, as well as a wide variety of pesticides and other organic compounds. According to the website of Hainan Provincial Bureau of Statistics, the agricultural output value was sharply increased between 2012 and 2015. Rice is the main crop in Hainan Province, and is seeded approximately in April and October, respectively. A large amount of fertilizer is needed in the process of rice sowing, and thus decreasing the water quality in approximately June and January every year, especially for Nandu River.

With regard to aquaculture, in order to increase the output of aquatic products, fishermen add a lot of feed, or cultivate rotifers and other live bait by fertilizing, resulting in a large amount of residual bait. These substances are mainly carbohydrate (18%), fat (14~17%), and protein (46~51%), as well as a small amount of phosphorus, vitamins, and pharmaceuticals (Duan et al. 2010). A large number of residual food enters the water body, which accelerates eutrophication. In addition, excreta from aquaculture products also have an important impact on water quality. Residual food and feces accumulated on the surface of sediment and continuously oxidized and decomposed, consuming a lot of oxygen, resulting in the decrease of DO in aquaculture discharge (Duan et al. 2010). Shen and Chao (2005) reported that the comprehensive quality of eco-environment in the Yangtze River Estuary shows obvious seasonal variation, and the quality of eco-environment in summer is poor when compared to that in spring. Fortunately, with the acceleration of the construction of Hainan International Tourism Island and ecological island, the coastal aquaculture land in Hainan Province will be greatly reduced, and the coastal aquaculture space will be reduced. Additionally, the excrement of livestock and poultry can pollute surface waters via runoff, and from polluted groundwater. After livestock manure enters the surface water, it is easy to form the eutrophication in the water quality, resulting in the excessive propagation of algae, rendering the water black and smelly due to oxygen depletion, and eventually causing the death of fish and shrimp in the water (Li 2017).

Tourism has become the pillar industry of Hainan's economic development, and it is beginning to negatively impact the environment. In general, the annual average of NOV in the east of Hainan Province was higher that of west. Therefore, the $NH_4^+$-N content in Wanquan River was significantly lower than of Nandu River and Changhua River, and the DO content relatively fluctuated in comparison with the other two rivers. The ammonium content in the Wanquan River was relatively high in November to January, which is coincidentally as the high season of tourism. Surprisingly, the more tourists there are, the higher the DO value is, especially for Nandu River and Wanquan River. Jiang et al. (2016) studied the impact of ecotourism on the water body of Qilian Mountain National Nature Reserve. Their result indicated that with the increasing intensity of tourist interference, the pH value and DO content of water in the reserve decreased, and the electrical conductivity and $BOD_5$ increased, and thus increasing pollution of the water body. Aminu et al. (2015) evaluated the suitability for recreational activities and conservation in Bertam River. Seven sampling points were selected in the river and tributaries: DO, BOD and COD, TSS, $NH_3$-N, and pH were measured, and the water quality index (WQI) was computed during high and average water flow. Results show that TSS, BOD, and $NH_3$-N contribute most to water pollution. Juma et al. (2014) reported the dynamic response of water quality change to human tourism disturbance in Liupan Mountain Ecotourism area. They indicated that during the tourism season, the main indices of water quality in the tourism area are within the scope of class II water quality standard, and some indices reached at class III. However, the degree of pollution in some sections reached at the level of grade 3 and grade 4. With the change on tourism mode, the interference increased gradually, and the folk village and hotel changed the most acutely. Lin et al. (2013) exhibited the impact of water quality changes on tourism capacity at Golden Lake, China. Tourism activities of 500–600,000 people each year over last few years have greatly increased pollution to the lake, with serious negative water quality impacts. Although water quality in Hainan Province was acceptable from 2012 to 2015, it is necessary to pay close attention to water quality degraded by tourism, especially in Wanquan River and eastern Hainan Province.

The most of water quality was predicted precisely in comparison with experimental values by the developed RBF-ANN in the present study. However, the minor parts' predicted value was not absolutely match. The situation may be due to its shortcoming, e.g., the poor interpretation, unable to proceed due to insufficient data, the difficult to determine the number, and center and width of hidden layer nodes. It was also reported that RBF-ANN could well recognize the complex non-linear relationship between haloketone occurrence and the related water quality, and paved a new way for haloketone prediction and monitoring in practice (Deng et al. 2021). Hameed et al. (2017) reported that the radial basis function neural network and back propagation neural network models were used to examine and mimic the relationship of WQI with the water quality variables in a tropical environment (Malaysia). Their results are promising with high performance accuracy belonging to RBFNN model for both scenarios. Rahnama et al. (2021) compared the forecasting of SAR of water in Aras, Sepidrud, Karun, and Mond rivers, Iran, using autoregressive integrated moving average (ARIMA) time series and RBF neural network. They also compared forecast errors of the ARIMA time series and RBF neural network for SAR forecasting of Sepidrud, Karun, and Mond rivers; the results presented that RBF neural network is more reliable than ARIMA for the predicting of SAR. Zhang et al. (2012) exhibited a new PSO-RBF model for groundwater quality assessment, which was employed in the ten monitoring points of the black dragon hole. The results of this evaluation corresponded with the actual conditions, and are basically in accord with those obtained by other evaluation methods, which also showed the applicability to groundwater quality assessment. Hong et al. (2020) proposed a radial basis function artificial neural network (RBF ANN) as well as the hybrid method of RBF ANN and grey relational analysis (GRA) to predict trihalomethane levels in real distribution systems. This result demonstrates that GRA can be an effective technique to facilitate the generation of sound RBF ANN models with fewer factors. Therefore, future studies should develop RBF-ANN that is of the more accuracy and speed to employ the water quality.

## Conclusion

This study showed that freshwater quality of Hainan Province was acceptable from 2012 to 2015. Agriculture, fishery, animal husbandry, and COD discharge significantly impacted freshwater quality in Nandu and Changhua rivers.

The annual average of NOV in the east of Hainan Province was higher than that of west. In the Wanquan River, DO content fluctuated in comparison with the other two rivers, and inexplicitly, the more tourists, the higher the DO value was. However, it is still necessary to pay close attention to the water quality declines due to tourism, especially in Wanquan River and eastern Hainan Province. The predicted model showed that overall, water quality was predicted precisely in comparison with experimental values in the present study, and also indicated that the water quality will continue to improve. Our results suggest that the anthropogenic activities moderately affected water quality in Hainan Island. Agriculture, fishery, animal husbandry, and COD discharge were relatively the most important factors affecting water quality on Hainan Island, while tourism can also have an impact in eastern Hainan.

**Author contribution** J. M., Q. C., G. L., and Q. C designed the research; J. M. and Q. C. wrote the paper, performed the experiments, and performed the data analysis. All authors helped revise the manuscript.

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**Data availability** The present study data are available from the corresponding author on reasonable request.

## Declarations

**Ethical approval** All data are from the official publication and do not involve human subjects and animals.

**Consent to participate** All authors agree to participate.

**Consent for publication** All authors agree to publish.

**Conflict of interest** The authors declare no competing interests.

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