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Future water quality analysis of the Anseongcheon River basin, Korea under climate change

Deokwhan Kim, Jungwook Kim, Hongjun Joo, Daegun Han and Hung Soo Kim*

Civil Engineering Department, Inha University, 100, Inha-ro, Michuhol-gu, Incheon City, South Korea

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Abstract. The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) predicted that recent extreme hydrological events would affect water quality and aggravate various forms of water pollution. To analyze changes in water quality due to future climate change, input data (precipitation, average temperature, relative humidity, average wind speed and sunlight) were established using the Representative Concentration Pathways (RCP) 8.5 climate change scenario suggested by the AR5 and calculated the future runoff for each target period (Reference:1989-2015; I: 2016-2040; II: 2041-2070; and III: 2071-2099) using the semi-distributed land use-based runoff processes (SLURP) model. Meteorological factors that affect water quality (precipitation, temperature and runoff) were inputted into the multiple linear regression analysis (MLRA) and artificial neural network (ANN) models to analyze water quality data, dissolved oxygen (DO), biological oxygen demand (BOD), chemical oxygen demand (COD), suspended solids (SS), total nitrogen (T-N) and total phosphorus (T-P). Future water quality prediction of the Anseongcheon River basin shows that DO at Gongdo station in the river will drop by 35% in autumn by the end of the 21st century and that BOD, COD and SS will increase by 36%, 20% and 42%, respectively. Analysis revealed that the oxygen demand at Dongyeongyo station will decrease by 17% in summer and BOD, COD and SS will increase by 30%, 12% and 17%, respectively. This study suggests that there is a need to continuously monitor the water quality of the Anseongcheon River basin for long-term management. A more reliable prediction of future water quality will be achieved if various social scenarios and climate data are taken into consideration.

Keywords: climate change; multiple linear regression analysis; artificial neural network; water quality prediction

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) predicted that the recent extreme hydrological events—increased water temperatures, floods and droughts—would affect water quality, which would eventually aggravate various forms of water pollution. Reasons may include river sediment discharge, nutrients, dissolved organic carbon, pathogens, pesticides, salt and others. Should this prediction come true, it can have negative effects on the ecosystem, human health, as well as reliability and operating costs of water-related systems.

Floods and droughts directly affect water quality in terms of the pollutant dilution and dissolution (Prathumratana *et al*. 2008, van Vliet and Zwolsman 2008). As it could reduce the number of precipitation days and increase the frequency of heavy rainfall (Brunetti *et al*. 2001, Bates *et al*. 2008), climate change could particularly have a negative impact on water quality (Rehana and Mujumdar 2012). More specifically, spatial changes in regional snowfall or summer precipitation due to climate change affect the interactions between surface water quality, biogeochemical process, land use change and acid deposition, thereby influencing water quality in river basins (Park *et al*. 2010). This means that time series variations of temperature and precipitation play a very important role in determining water quality criteria (Parmar and Bhardwaj 2013a, b, Damodhar and Reddy 2013). Moreover, this has an impact on water resources that people generally use. It has been found that climate change alters pollutants and biological parameters, which causes the deterioration of drinking water quality and results in increased potential health risks (Delpla *et al*. 2009). Taking into consideration that climate change-induced water quality degradation adversely affects human life, it is thus important to predict water quality.

Mainly, modeling is used to predict water quality. Kim *et al*. (2011) estimated long-term runoff using the Hydrologic Modeling System (HEC-HMS). In the aforementioned study, input data was established on the observed water level, weather, water temperature, total nitrogen and total phosphorus and to apply the Environmental Fluid Dynamics Code (EFDC) model, water depth was divided into three layers to make a three-dimensional grid of 5,634 lattices. Using that as the basis, changes in the water quality of the Unam Lake were spatiotemporally simulated. Kim *et al*. (2013) conducted a rainfall-runoff analysis using the Soil and Water Assessment Tool (SWAT) model to determine how climate change impacts the ecological habitat of Rhynchocypris kumgangensis in Pyungchang River. Main methods of water quality prediction include statistical evaluation

*Corresponding author, Ph.D.
E-mail: sookim@inha.ac.kr

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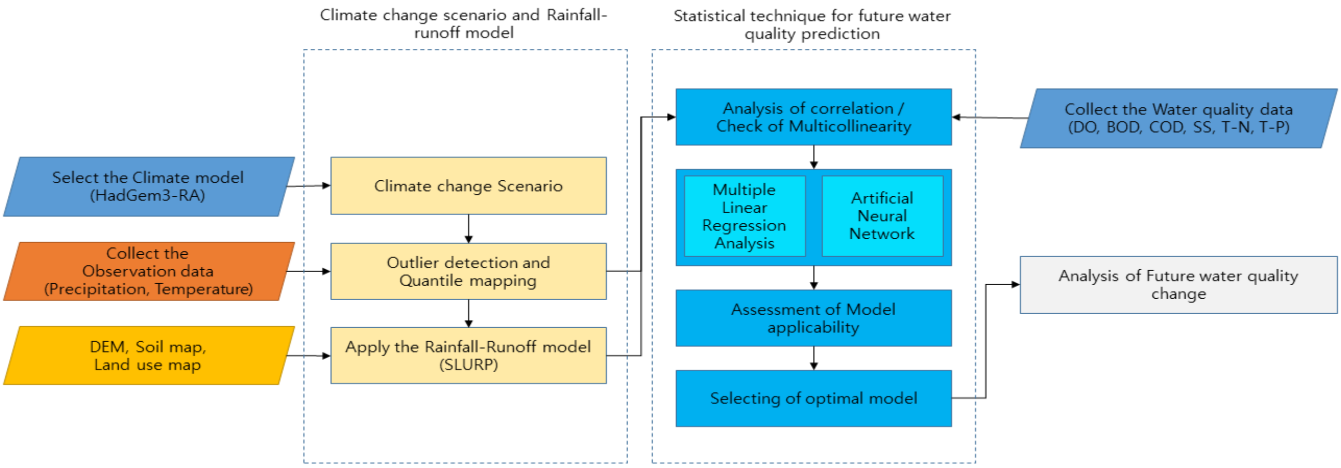


Fig. 1 Study flow

methodologies—multiple linear regression analysis (MLRA), structural equations, trend and time series analysis and others—and water quality modeling based on hydrochemical data (Attah and Bankole 2012, Chenini and Khemiri 2009, Huang *et al*. 2010, Su *et al*. 2011, Prasad *et al*. 2013, Seth *et al*. 2013). In particular, Parmar and Bhardwaj (2014) validated the model through a statistical evaluation approach and estimated future water quality parameters using the autoregressive integrated moving average (ARIMA) model.

Several studies have also predicted the effects of climate change on hydrology and water quality using long-term runoff models. Varanou *et al*. (2002) developed nine climate change scenarios based on the three general circulation models (GCMs) data using a downscaling technique and subsequently analyzed water quality changes such as river runoff and sediment discharge. Bouraoui *et al*. (2002) developed six different climate change scenarios for the Ouse River watershed in Yorkshire, Northern England and applied them to the SWAT model, concluding that with climate change, total nitrogen (T-N) and total phosphorus (T-P) loadings could increase from 6% to 27% and from 5% to 34%, respectively. According to Bouraoui *et al*. (2004), the annual average nutrient load and winter runoff would increase while the snow-covered area would decrease with climate change. Nearing *et al*. (2005) estimated and compared the runoff and soil loss from the SWAT model and six other models.

Aside from the modeling methodologies described above, statistical techniques have also been used recently to predict water quality. For example, Palani *et al*. (2008) estimated the quantitative characteristics of water bodies using the artificial neural network (ANNs) and predicted water quality using salinity, temperature, dissolved oxygen (DO) and chlorophyll as variables. Jiang *et al*. (2013) conducted a water quality risk assessment through ANNs. Altenburger *et al*. (2015) also estimated the future water quality for water resources management and showed the potential of ANNs in predicting water quality parameters.

Due to industrialization and urbanization, river water quality has been continuously deteriorating. However, previous research studies tend to focus on predicting water quality based on long-term runoff models and statistical techniques, rarely taking into consideration the effects of climate change. This study thus estimated future runoff using the reliable semi-distributed land use-based runoff processes (SLURP) model with climate change taken into account. To analyze changes in water quality that might occur in the future, the correlation between runoff and water quality was estimated using the MLRA and ANN models and predicted river water quality (e.g., biological oxygen demand (BOD), DO, T-N and T-P), which may be affected by changes in the flow rate. Fig. 1 shows the analysis procedure for this study.

Table 1 Comparison of RCP and SRES Scenarios

Scenarios	RCP Scenarios				SRES Scenarios		
CO2 (ppm)	2.6	4.5	6.0	8.5	B1	A1B	A2
	420	540	670	940	550	720	830

*Current CO2 concentration in Korea: About 440 ppm (2010).

2. Climate change scenarios and the SLURP model

Future rainfall that takes climate change into consideration is required for future runoff simulation, which can be used for future water quality analysis. Future rainfall can be obtained using climate change scenarios. Climate change scenarios and the SLURP model for runoff simulation are briefly described in the following sections.

2.1 Climate change scenarios

IPCC reported Representative Concentration Pathway (RCP) scenarios in their AR5, which was published in 2014. These scenarios consist of four possible future climates that depend on how much greenhouse gases would be emitted in the future. These were compared with the Special Report on Emissions Scenarios (SRES) reported in the Fourth Assessment Report (AR4) in 2010 (see Table 1). The comparison in Table 1 is based on CO_2 concentration and the numbers of RCP scenarios represent the values of radiative forcing in 2100. AR5 demonstrated that an increase in temperature and the occurrence of

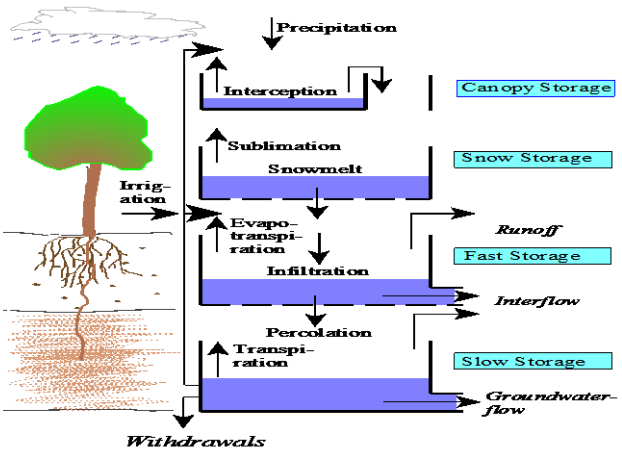


Fig. 2 Schematic diagram of vertical water balance

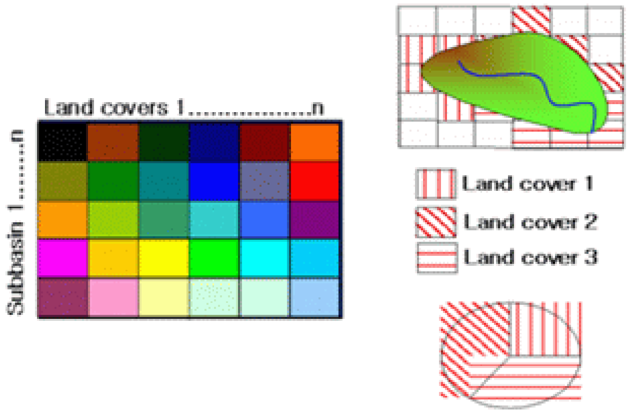


Fig. 3 A concept of ASA

extreme events, such as flood and drought, will affect water quality. Future prospects also reveal that water quality would worsen.

2.2 SLURP model

SLURP is a semi-distributed physical model that can take into consideration the precipitation of rainfall and snow. The model simulates the runoff with a daily time step by dividing an entire watershed into small ones called aggregated simulation areas (ASAs). It then uses physiographic parameters (mean elevation of ASA, channel length, land cover characteristics and others), time series (temperature, precipitation and others) and physical factors (Manning's roughness, infiltration and others) as the input data. Physiographic parameters are estimated through TOpographic PArametriZation (TOPAZ), a digital terrain analysis tool. The runoff is obtained at the outlet of the entire watershed through channel routing on each ASA after the vertical water balance analysis for the ASAs. The vertical water balance of the SLURP model consists of four layers and the main factors are the initial contents of slow storage, maximum infiltration, Manning's roughness coefficient, retention constant of fast storage, retention constant of slow storage, maximum capacity of slow storage, precipitation factor, snow melting temperature and so on. Figs. 2 and 3 show the vertical water balance structure of the SLURP model and the concept of ASA (Kite 2008).

3. Statistical methods for water quality prediction

The purpose of this study is to predict water quality components, the response variables of the MLRA and ANN models that include hydrometeorological components as explanatory variables.

3.1 MLRA model

A simple linear regression model can be established by a single response variable or dependent variable and a single explanatory variable or independent variable. If the model has more than two independent variables, it is called MLRA (see Eq. 3.1).

$$y_1=\beta_o+\beta_1x_1+\ldots+\beta_pX_p+\varepsilon_1 \qquad (3.1)$$

y^i is the i^{th} value of dependent variables, p is the number of independent variables, β_0, ..., β^p are the regression coefficients, x_i is the i^{th} value of independent variables and ε_i is the error term, which is a normal distribution with a mean zero and variance σ^2. A correlation analysis and a multicollinearity analysis may be performed to investigate the correlations among independent variables.

3.2 ANN method

The structure of an ANN consists of an input layer, the receiver of external input; a hidden layer, located between the input layer and the output layer and not visible from the outside; and an output layer, which displays the processed result. A processing element accepts input from a number of other processing elements, calculates a net input value using a connection weight and determines an output value through an activation function.

This study adopted the backpropagation algorithm based on the steepest descent method, which is used to estimate the connection strength between layers in a way that minimizes errors. The difference between the measured value and the result value is processed in reverse.

3.3 Methods for selecting optimal prediction techniques

Typical outlier detection methods include the scatter plot, box plot, Dixon test, Grubb's test, Barnett and Lewis test and others. In this study, the box plot was used.

The method for evaluating the accuracy of the outlier detection result is presented in Table 2. Ways to examine reliability and validity include the mean absolute error (MAE), root mean square error (RMSE), relative root mean square error (RRMSE), model efficiency (EF) and others.

4. Water quality forecasting model using hydrometeorological data

4.1 Selection of the study basin

The Anseongcheon River basin is located in the mid-

Table 2 Type of accuracy assessment technique

Accuracy assessment technique	
Mean Absolute Error (MAE)	$\mathrm{MAE} = \frac{\sum_1^n \lvert O_i - S_i \rvert}{n}$
Root Mean Square Error (RMSE)	$\mathrm{RMSE} = \sqrt{\frac{\sum_1^n (O_i - S_i)^2}{n}}$
Relative Root Mean Square Error (RRMSE)	$\mathrm{RRMSE} = \frac{100}{\bar{O}} \times \sqrt{\frac{\sum_1^n (O_i - S_i)^2}{n}}$
Model Efficiency (EF)	$\mathrm{EF} = 1 - \frac{\sum_1^n (O_i - S_i)^2}{\sum_1^n (O_i - \bar{O})^2}$

western part of the Korean Peninsula. The area of the basin is 1,658.66 km^2 and the length of the river is 70 km. There are three meteorological stations (Suwon, Cheonan and Icheon) and seven water level stations (Songsan, Hoeryong, Donyeongyo, Pyeongtaek, Yangpyeong, Gongdo and Anseong) in the Anseongcheon River basin (Figs. 4 and 5).

Taking into consideration that urbanized and/or dry areas around the river basin are rapidly increasing due to large-scale development projects since the 1980s and climate change, which has been causing water quality problems, it is necessary to analyze the water quality changes in this region for water quality management.

4.2 Daily runoff estimation using the SLURP model

In this study, daily runoff was estimated by applying hydrometeorological data (rainfall, temperature, relative humidity, daylight hours and average wind speed measured in the weather stations in Suwon, Cheonan and Icheon from 1989 to 2015) to the SLURP model.

For the initial content of slow storage (mm), there was no significant change in the minimum value, but the baseline flow rate was found to be low at the maximum value. It was also observed that the baseline flow decreases as the maximum infiltration rate (mm/day) increases. Moreover, the retention constants of fast storage (day) did not show significant changes in their maximum and minimum values, but infiltration, evapotranspiration and runoff tended to occur more often as the values decreased.

For the maximum capacity of fast storage (mm), it was found that runoff was quite substantial at the minimum value and only occurred at the maximum value occasionally when the rainfall reached a certain level.

In addition, the initial runoff increased significantly at the minimum value for the retention constant of slow storage (day), which is a parameter related to evaporation, intermediate runoff and groundwater. Lastly, for the maximum capacity of slow storage (mm), the baseline runoff was high at the maximum value.

The parameters of the model were calibrated and tested based on their sensitivity described above. After the calibration, the Nash-Sutcliffe model efficiency coefficient increased from 0.32 to 0.61. The test result was 0.60, thus confirming the reliability of the model; the runoff from 1989 to 2015 was simulated using the calibrated model (Table 3).

Fig. 4 Meteorological stations in Anseongcheon river basin

Fig. 5 Water level stations in Anseongcheon river basin

Table 3 Result of calibration and validation of SLURP model

Period of calibration and verification	2006-2007 Before calibration	2006-2007 After calibration	2010 Validation
Daily average simulated runoff (m^3/sec)	9.06	13.04	15.05
Daily average observed runoff (m^3/sec)	11.06	11.06	13.05
Nash-Sutcliffe Efficiency	0.32	0.61	0.60

Table 4 Obtained prediction models for each water quality components by MLRA

Prediction model	Gongdo station	Dongyeongyo station
DO	DO = 11.265 –0.028 × precipitation – 0.131 × temperature + 0.017 × discharge	DO = 8.172 – 0.193 × precipitation –1.669 × discharge
BOD	BOD = 7.334 – 0.0089 × discharge	BOD = 12.524 – 5.311 × discharge
COD	COD = 7.227 × 0.053 × temperature – 0.046 × discharge	COD = 14.782 – 4.930 × discharge
SS	SS = 9.374 + 0.466 × temperature + 0.078 × discharge	SS = 18.404 + 0.847 × precipitation + 0.387 × temperature – 9.039 × temperature + discharge
T-N	T-N = 9.534 + 0.518 × temperature	T-N = 12.196 – 0.096 × precipitation – 0.184 × temperature – 0.360 × discharge
T-P	T-P = 0.0280 – 0.003 × discharge –0.001 × temperature	T-P = 0.722 – 0.010 × precipitation – 0.010 × temperature

4.3 Establishment of a water quality prediction model

Taking into consideration that a decrease in the river flow rate will significantly impact water quality in the future, this study aims to predict water quality by determining the relationship between water quality and meteorological factors—rainfall, runoff, temperature and others—and using the MLRA and ANN models.

In the Anseongcheon River basin, water quality monitoring began from January 1989 at the Dongyeongyo and from March 1992 at Gongdo stations. The water quality data used in the analysis include DO, BOD, chemical oxygen demand (COD), suspended solids (SS), T-N and T-P.

4.3.1 MLRA-based prediction model

The analysis was conducted using the enter, stepwise, remove, backward and forward models of the MLRA method. The comparison between the regression models was carried out using the MSE of the residuals of the validation period, which was estimated in the training period (Table 4).

The MLRA results for Gongdo showed the following: DO (using the enter model) has a negative correlation with rainfall and temperature and a positive correlation with runoff; BOD (remove) has a negative correlation with runoff; COD (stepwise) has a positive correlation with temperature and a negative correlation with runoff; SS (stepwise) has a positive correlation with temperature and runoff; T-N (remove) has a negative correlation with temperature; and T-P (enter) has a positive correlation with temperature and a negative correlation with temperature and runoff.

Table 5 Layer and components of ANN-based prediction model

Layer	Layer component
Input layer	Monthly average precipitation, monthly average temperature, monthly runoff
Hidden layer	10
Output layer	DO, BOD, COD, SS, T-N, T-P

The results for Dongyeongyo indicated the following: DO (stepwise) has a negative correlation with rainfall and a positive correlation with runoff; BOD (remove) and COD (backward) have a negative correlation with runoff; SS (enter) has a positive correlation with rainfall and temperature and a negative correlation with runoff; T-N (enter) has a negative correlation with rainfall, temperature and runoff; and T-P (stepwise) has a negative correlation with rainfall and temperature.

4.3.2 ANN-based prediction model

The analysis used daily rainfall, daily mean temperature and daily runoff (see Table 5). The interlayer processing elements of ANN is generally calculated as 2d or 2d+1 when the number of input layer processing elements is d. Here, the numbers of the interlayer and the output layer were 10 and 1, respectively. Observation data from January 1992 to December 2015 and from January 1989 to December 2015 were used for the Gongdo and Dongyeongyo, respectively, to build an optimal ANN model. The parameters between the input and hidden layers and between the hidden and output layers were estimated by applying data from the beginning of the observation period until the end of 2012 as the training period. Model applicability was validated based on the data from the validation period of the recent three years (2013-2015) using the connection strength estimated during the analysis. Connection strength, a value that shows the state of each layer as a parameter, indicates the correlation between the input and output of each element and the degree of influence between the connected processing elements.

The ANN-based prediction results for each water quality factor are described by the training and validation periods in Fig. 6 (Gongdo) and Fig. 7 (Dongyeongyo).

For DO at Gongdo, there was no significant gap between the observation data and the data estimated through the ANN and the validation confirmed this result. However, for BOD, a spike of 75.2 was found on February 10, 1995, so the researchers looked up details surrounding the occurrence: Meteorological data of that day did not show any abnormality and the news reports did not also reveal anything noteworthy such as an external, point source pollution. Although the researchers could have excluded the value by judging that it was an outlier, it was retained in the analysis despite the higher error it would cause as it was a true value provided by the Water Information System. For COD, an abnormal value of 32.2 was observed on April 8, 1994 and its cause was not also identified. This value was again included in the analysis for the same reason as the previous case. For SS, a sudden spike of 149.5 was found

Fig. 6 Water quality prediction using ANN (Gongdo station)

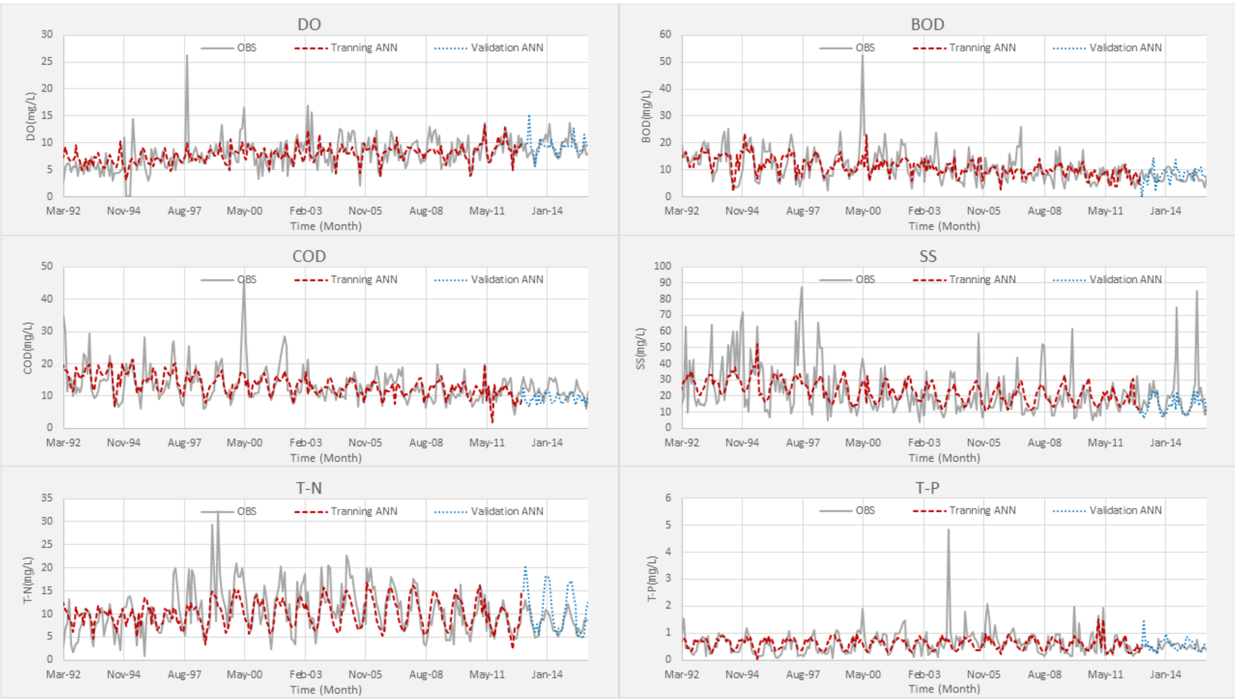


Fig. 7 Water quality prediction using ANN (Dongyeongyo station)

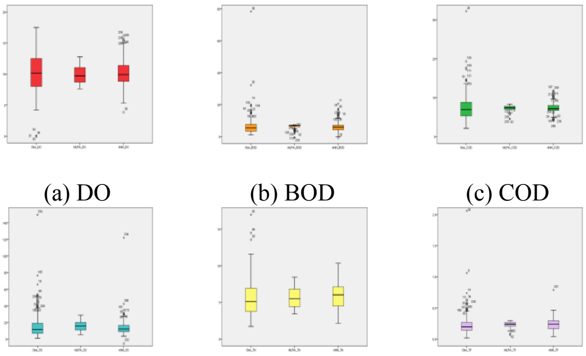
on August 22, 2011. The meteorological data showed rainfall on the same day, which made it difficult to obtain an accurate water quality measurement because of the runoff and SS increase due to the rain. For T-N, abnormalities found on April 8, 1994, April 8, 1997 and February 2, 1999, are considered as due to external, nonpoint source pollution. For T-P, an abnormal value of 2.058 was recorded on April 4, 1994—the same day that showed COD and T-N outliers—and nothing noteworthy was found in the meteorological data and news reports. Water quality data for Dongyeongyo and Gongdo were predicted through the ANN analysis.

5. Water quality prediction in consideration of climate change

5.1 Selection of the water quality prediction model through outlier detection and accuracy assessment

Table 6 Outlier of Gongdo and Dongyeongyo stations

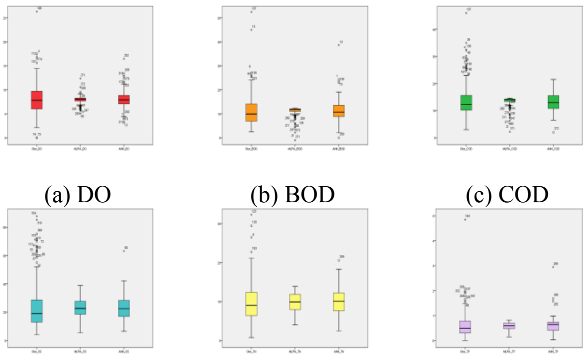
Gongdo	DO	BOD	COD	SS	T-N	T-P
Q1	8.200	3.325	5.300	6.825	3.770	0.0142
Q3	12.600	7.600	8.800	19.000	6.928	0.267
IQR	4.400	4.275	3.500	12.175	3.158	0.125
Upper limit	19.200	14.013	14.050	37.263	11.664	0.454
Lower limit	1.600	0.000	0.050	0.000	0.000	0.000
Dongyeongyo	DO	BOD	COD	SS	T-N	T-P
Q1	6.000	6.900	10.175	12.975	6.395	0.298
Q3	9.700	14.025	15.600	28.575	12.371	0.780
IQR	3.700	7.125	5.425	15.600	5.976	0.482
Upper limit	115.250	24.713	23.738	51.975	21.335	1.503
Lower limit	4.150	3.338	7.463	5.175	3.407	0.057



(a) DO (b) BOD (c) COD

(d) SS (e) T-N (f) T-P

Fig. 8 Outlier detection using box plot (Gongdo Station)



(a) DO (b) BOD (c) COD

(d) SS (e) T-N (f) T-P

Fig. 9 Outlier detection using box plot (Dongyeongyo Station)

In section 4, water quality changes were simulated through ANN analysis and MLRA of meteorological data and water quality variables. To determine which model is more accurate for water quality prediction, outlier detection and accuracy assessment were conducted.

ME, MAE, RMSE, RRMSE and EF were applied to evaluate the accuracy of water quality prediction of the MLRA and ANN models. The accuracy of the prediction models was evaluated through the predicted statistical error analysis of the water quality data (DO, BOD, COD, SS, T-N and T-P) based on the rainfall, temperature and runoff data from 1989 to 2015 and the actual water quality measurements for the same period.

Table 7 Selection of optimal model

Model	Gondo				
	Index	MAE	RMSE	RRMSE	EF
MLRA	DO	2.188	3.083	30.839	0.173
	BOD	2.993	5.578	89.557	0.032
	COD	2.171	3.038	41.138	0.029
	SS	8.413	13.196	86.249	0.129
	T-N	1.433	1.927	35.135	0.286
	T-P	0.094	0.162	70.678	0.042
ANN	DO	2.038	2.966	29.671	0.234
	BOD	2.721	5.144	82.600	0.177
	COD	1.895	2.775	37.576	0.190
	SS	7.944	13.948	91.166	0.027
	T-N	1.356	1.917	34.956	0.294
	T-P	0.093	0.153	66.722	0.147

Model	Dongyeongyo				
	Index	MAE	RMSE	RRMSE	EF
MLRA	DO	1.995	2.593	33.005	0.068
	BOD	4.016	5.012	45.514	0.080
	COD	3.372	4.196	31.675	0.083
	SS	9.032	11.336	50.762	0.174
	T-N	3.288	4.172	42.771	0.216
	T-P	0.244	0.305	54.465	0.155
ANN	DO	1.693	2.281	29.035	0.278
	BOD	3.149	4.137	37.570	0.373
	COD	2.877	3.701	27.937	0.287
	SS	8.170	10.714	47.974	0.262
	T-N	3.152	4.001	41.014	0.279
	T-P	0.233	0.298	53.170	0.194

First, outlier detection was carried out to enhance the reliability of the data predicted by either the MLRA or the ANN. Table 6 and Figs. 8 and 9 show the outliers of Gongdo and Dongyeongyo.

The accuracy of the MLRA and ANN models was assessed for the two spots to determine which model is more appropriate for water quality prediction. As a result, the data produced by the ANN model were found to be more accurate (Table 7).

Therefore, water quality was predicted using the rainfall and temperature data predicted based on the climate change scenario and the runoff data estimated by the SLURP model.

5.2 Analysis of future changes in water quality

This study used the runoff data obtained from the SLURP model, based on the RCP 8.5 climate change scenario, for long-term rainfall-runoff simulation. Outlier

Table 8 Criteria of river water quality

Grade	DO (mg/mL)	BOD (mg/mL)	COD (mg/mL)	SS (mg/mL)	T-P (mg/mL)
Excellent	>7.5	<1	<2	<25	<0.02
Very good	>5.0	<2	<4	<25	<0.04
Good	>5.0	<3	<5	<25	<0.1
Quite good	>5.0	<5	<7	<25	<0.2
Not bad	>2.0	<8	<9	<100	<0.3
Not so good	>2.0	<10	<11	Waste or not present	<0.5
bad	>2.0	>10	>11	-	>0.5

*Source: water.nier.go.kr

detection was also conducted for the results of the MLRA and ANN models to determine the optimal model. Water quality (i.e., DO, BOD, COD, SS, T-N and T-P) was predicted by month for each target period (I: 2016-2040, II:2041-2070 and III: 2071-2099) using the selected model. Future water quality was analyzed according to the water quality criteria listed in Table 8.

Fig. 10 illustrates the predicted water quality of the Gongdo and Dongyeongyo by month for each target period and Tables 9 and 10 show variations by period at each spot.

It is predicted that, for most of the periods, DO will decrease but generally increase to 7.5 or higher, which is a criterion for clean water. However, water quality is expected to deteriorate in summer. BOD and COD are predicted to decrease in target periods I and II, but not lower than 1 (for BOD) or 2 (for COD)—the "very clean" level—which indicates that more efforts are needed to make water cleaner particularly in spring, fall and winter when runoff decreases. Although SS is predicted to show a gradually increasing trend with time, most of the values will lie below 25—the "very clean" state. This also means that actions need to be taken, particularly during summer when SS could temporarily drop due to heavy rain, to maintain the current water quality level. T-N and T-P are expected to rise in target period I. Measures should thus be put in place to reduce them to 0.02 or lower—the very clean level.

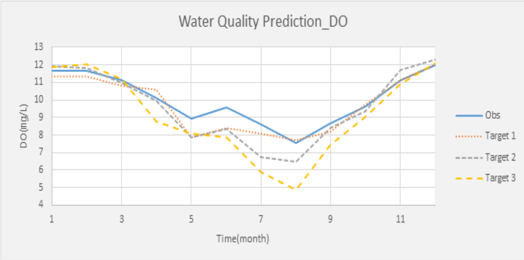
6. Conclusions

This study estimated the future runoff of the Anseongcheon River basin, with the objective to analyze potential changes in water quality due to climate change, through the application of the RCP 8.5 scenario to the SLURP model, taking into consideration the climate change policy. Runoff characteristics for the reference period (1989-2015) and the three target periods (I: 2016-2040; II: 2041-2070; and III: 2071-2099) were analyzed and compared to predict changes in runoff due to climate change. The water quality data (DO, BOD, COD, SS, T-N and T-P) by month for each target period were predicted by applying rainfall, runoff and temperature scenarios to the MLRA and ANN models.

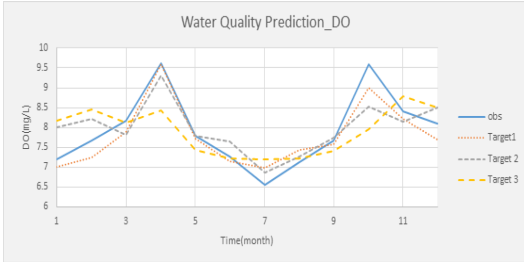
For Gongdo, DO is expected to decrease for most of target periods I and II, except in winter. However, the values would stay above 5, which is considered good. However, as this parameter could decrease below the "clean water" level of 5 in target period III due to temperature increase due to climate change, preventive measures need to be taken. BOD is predicted to rise in target period I by up to 36.2% from the current level, particularly in spring and winter. In fact, there is a need for additional efforts when it comes to BOD as it is predicted to be above 2—the upper limit for clean water—for all target periods. COD shows a trend similar to BOD—it could increase by up to 24.3%, or above 9, indicating a slightly poor water quality, in spring and fall for target period I. This also calls for proactive actions. SS is predicted to be generally high for most of the target periods compared to the current level and particularly higher in summer. However, given that the upper limit of SS for the "very clean water" criteria is 25, the predicted values are considered desirable. Although T-N is not included in the river water quality parameters, values that exceed 1.5 are considered very poor according to the water quality criteria for lakes. Both the current level and protections of T-N for Gongdo are considered very poor, which is why continuous and proactive measures are required. The T-P range will become wider from 0.30-0.15 to 0.35-0.10 in the future and the value is expected to particularly increase by up to 26.7% in spring, autumn and winter, which falls into the "poor water quality" level.

For Dongyeongyo, DO is predicted to decrease in spring and fall and increase in summer and winter. With most of the predicted values lying above 5, this parameter will be in the "good water quality" level. BOD is predicted to decrease for most of the target periods, except autumn but will still be over the upper limit of 2, indicating that extra measures are needed. COD also shows a trend similar to BOD, increasing up to 11, which is considered "very poor," in spring and fall for target period I. SS is generally predicted to be low in summer and high in spring, fall and winter, with higher values than the current level for most of the target periods. The value could drop to below 100, the limit for the "slightly poor" level, in summer but is expected to stay in "good" condition generally. Although T-N is not included in the river water quality parameters, values over 1.5 are considered very poor according to the water quality criteria for lakes. Both the current level and protections of T-N for Dongyeongyo are considered very poor, which is why continuous and proactive measures are required. In the future, the range of T-P will become wider from 0.80-0.32 to 0.85-0.21.

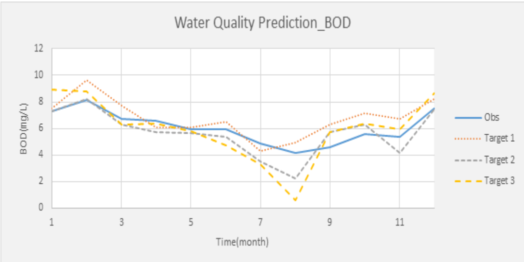
In this study, only six parameters (DO, BOD, COD, SS, T-N and T-P) were considered due to the short observation period. To enhance study reliability in the future, it is suggested that more diverse parameters of water quality should be applied. It is also important to expand the water quality networks at a national level, as well as provide data on a regular and consistent basis for statistical analysis. Moreover, an analysis of additional environmental factors using different climate change scenarios—including RCP 2.6, 4.5 and 6.0—will increase study reliability. This study is expected to be used in the future as basic data for establishing water quality measures against climate change and urbanization.



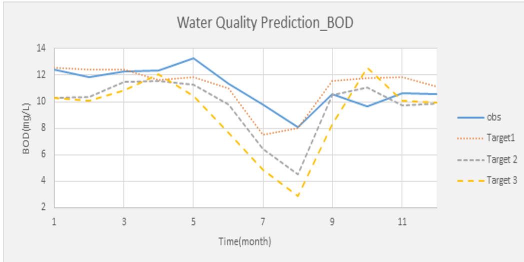
(a) DO



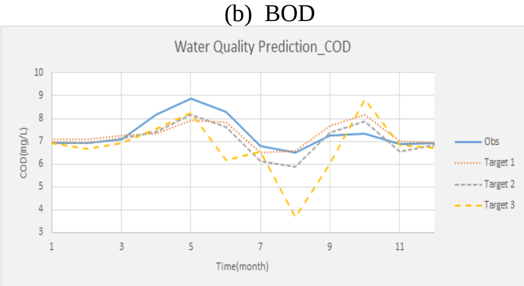
(a) DO



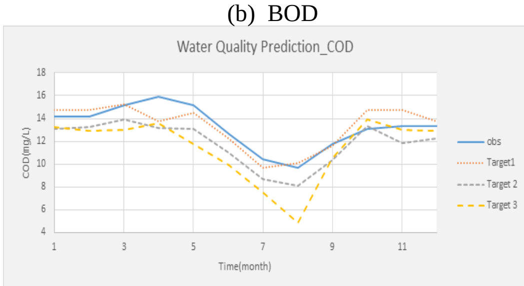
(b) BOD



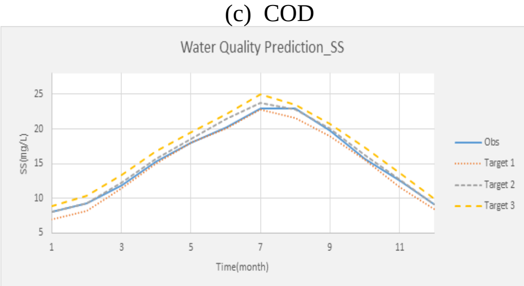
(b) BOD



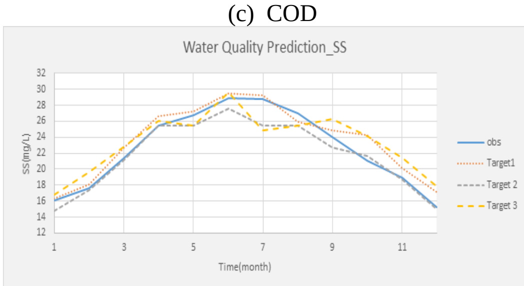
(c) COD



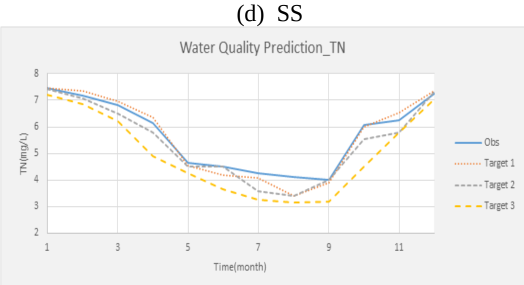
(c) COD



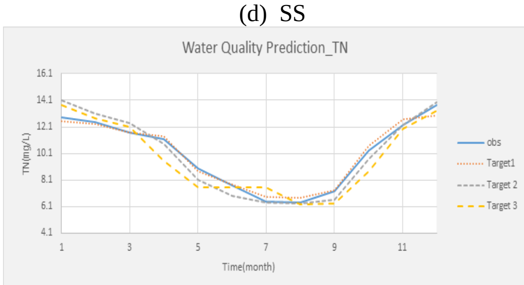
(d) SS



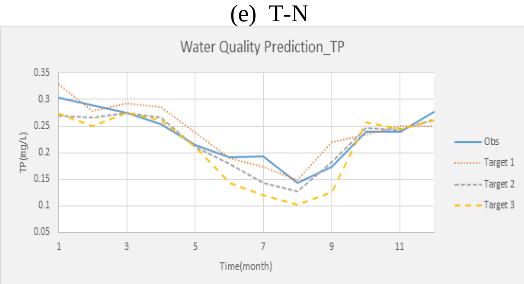
(d) SS



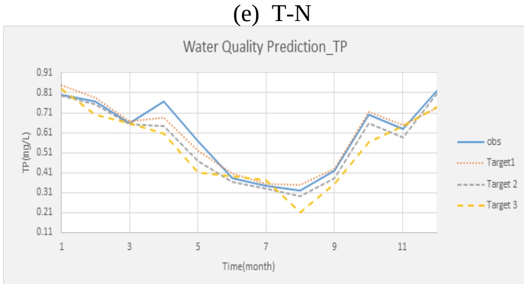
(e) T-N



(e) T-N



(f) T-P



(f) T-P

Fig. 10 Monthly water quality change in the future

Table 9 Rate of water quality change in the future (Gongdo Station)

Month	DO			BOD			COD		
	Target I	Target II	Target III	Target I	Target II	Target III	Target I	Target II	Target III
1	-2.830	2.179	1.726	2.770	0.533	22.505	2.289	0.788	-0.292
2	-3.050	1.069	3.109	18.756	1.624	7.996	2.329	-0.329	-3.719
3	-2.802	-1.262	0.351	14.917	-6.682	-6.733	1.918	0.180	-2.803
4	4.770	-1.297	-13.328	-8.073	-13.911	-3.419	-10.169	-8.853	-7.735
5	-11.746	-11.901	-9.831	2.626	-5.312	-2.417	-10.813	-8.086	-7.048
6	-12.281	-12.627	-17.664	8.853	-9.958	-20.593	-5.454	-7.848	-25.276
7	-5.944	-21.528	-31.654	-10.751	-26.991	-32.350	-4.233	-9.974	-3.933
8	2.451	-13.956	-35.540	17.375	-46.698	-85.955	1.836	-9.542	-42.956
9	-5.388	-2.939	-14.338	36.243	24.306	23.895	5.844	1.951	-17.040
10	1.010	-2.446	-5.833	28.372	12.679	14.737	11.386	7.315	20.136
11	-0.172	5.323	-1.868	25.720	-22.986	10.386	1.916	-4.940	-0.468
12	0.488	2.602	0.945	9.732	-0.154	15.392	-0.220	-1.622	-3.395
Month	DO			BOD			COD		
	Target I	Target II	Target III	Target I	Target II	Target III	Target I	Target II	Target III
1	20.227	7.722	9.482	0.148	-0.515	-3.203	7.902	-11.510	-10.022
2	18.754	27.682	42.062	2.636	-1.638	-4.267	-3.781	-8.486	-13.562
3	28.849	23.959	42.380	1.699	-4.828	-8.971	6.371	-0.481	-0.244
4	18.840	29.235	37.733	3.620	-5.705	-20.299	12.332	4.726	2.462
5	0.170	0.913	-15.315	-1.876	-3.197	-8.595	11.128	-1.644	-1.992
6	0.283	6.381	5.851	-6.672	0.028	-18.796	-1.608	-6.920	-25.130
7	5.098	17.852	41.021	-4.603	-15.905	-23.580	-10.436	-25.832	-38.157
8	-53.024	-15.303	16.241	-17.403	-17.388	-23.699	3.339	-12.277	-28.747
9	15.422	-15.767	-51.243	-2.715	0.387	-19.824	26.656	5.474	-27.442
10	5.699	11.643	35.070	-1.125	-8.868	-26.097	-2.208	2.598	7.480
11	-2.079	17.405	24.224	4.680	-7.367	-7.511	3.886	1.186	1.693
12	32.684	17.865	22.810	1.628	0.905	-2.739	-9.776	-5.513	-6.388

Table 10 Rate of water quality change in the future (Dongyeongyo Station)

Month	DO			BOD			COD		
	Target I	Target II	Target III	Target I	Target II	Target III	Target I	Target II	Target III
1	-2.537	11.353	13.461	1.230	-16.952	-17.414	4.025	-7.372	-6.706
2	-5.756	7.063	9.985	4.775	-12.535	-14.693	4.534	-6.239	-8.626
3	-3.566	-4.410	-0.712	1.381	-6.272	-11.624	0.034	-8.263	-14.380
4	-0.150	-3.066	-12.237	-5.670	-6.721	-2.594	-13.529	-17.466	-14.840
5	-0.682	0.193	-4.579	-10.552	-15.100	-21.340	-4.380	-13.838	-22.138
6	-1.735	5.255	-0.784	-2.994	-13.872	-32.537	-3.210	-13.171	-21.251
7	6.682	4.575	9.627	-23.361	-34.083	-50.224	-7.408	-16.460	-27.587
8	4.344	1.982	1.236	-0.831	-44.333	-64.642	4.334	-16.409	-49.348
9	-1.344	0.761	-3.571	9.557	-0.773	-21.813	-1.604	-12.021	-10.797
10	-5.973	-11.160	-17.115	22.198	14.441	29.904	12.339	1.460	6.510
11	-2.274	-3.038	4.597	11.316	-8.661	-5.128	10.745	-10.969	-2.581
12	-5.137	4.877	4.795	5.025	-6.872	-6.383	3.270	-7.909	-3.212
Month	DO			BOD			COD		
	Target I	Target II	Target III	Target I	Target II	Target III	Target I	Target II	Target III
1	1.171	-8.115	4.000	-1.889	10.443	7.168	6.016	-0.645	3.676
2	3.278	-1.093	11.965	-1.228	5.295	2.286	2.908	-1.775	-8.508
3	5.945	-1.257	6.536	0.155	5.817	3.803	1.214	-0.936	-0.338
4	4.428	0.056	2.167	1.993	-3.177	-14.696	-10.608	-16.057	-21.545
5	1.943	-4.617	-4.856	-1.751	-9.415	-15.263	-8.250	-17.604	-26.938
6	1.857	-4.359	2.586	0.253	-11.015	-2.110	7.153	-4.541	2.623
7	1.989	-11.342	-13.601	5.709	-0.343	16.940	1.723	-4.549	7.837
8	-4.045	-5.926	-5.777	5.899	-0.368	-2.107	7.947	-9.613	-33.966
9	3.644	-5.177	9.404	0.609	-8.863	-13.512	2.736	-8.756	-15.164
10	15.229	2.881	14.676	3.464	-6.410	-15.088	1.970	-5.881	-19.460
11	6.689	-1.261	13.613	3.411	0.055	-2.225	3.152	-6.625	1.788
12	12.111	-1.974	16.950	-5.731	1.476	-3.488	-10.444	-1.734	-9.954

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