AN INTEGRATED HYDROLOGIC BAYESIAN MULTI-MODEL FRAMEWORK FOR WATER QUALITY ANALYSIS

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Abstract

Water is a prime element responsible for life on earth. Declining environmental water quality directly restricts the availability of water regionally, and accelerates the degradation of aquatic ecosystems. For regional water resources and ecological environmental security, it is necessary to characterize the overall status of the water quality quantitatively, and to guide water use planning based on comprehensive quantitative water quality evaluation. The MCMC modelling estimated the impact of DO, TC and EC as quality indicators in drinking water quality of the Brahmani River. The correlation between water pollution and the indicators are determined by the beta (β) and mu (μ) coefficients in prior estimations. Considering the conjugate and non-informative priors, standard value of water pollution is lower by 0.50% and 0.40% respectively. In case on non-informative priors, the pollution in water grows by 13.21% in absence of DO, 85.60% in presence of EC and 98.88% with the existence of TC as a water quality indicator. Correspondingly, the pollution level elevates by 14% with less amount of DO. Whereas, the pollution level diminishes by 86.13% and 98.83% with the presence of EC and TC.

Keywords: MCMC, prior, water quality, DO, EC and TC

1.0 INTRODUCTION

Water is a prime element responsible for life on earth. Declining environmental water quality directly restricts the availability of water regionally, and accelerates the degradation of aquatic ecosystems. For regional water resources and ecological environmental security, it is necessary to characterize the overall status of the water quality quantitatively, and to guide water use planning based on comprehensive quantitative water quality evaluation. No uniform method for the water quality evaluation has been developed to date, mainly because a large number of water quality evaluation factors complicate the nonlinear relationships that operate among factors and water quality types. Previously, the most commonly used water quality evaluation methods were single-factor evaluation methods, and aggregative index evaluation methods. These methods used clear concepts and were easy to operate. Some other water quality evaluation methods were established based on the grey box theory and systems theories, to reflect fuzziness (the nonlinear and uncertain characteristics of water quality evaluations). These methods include the fuzzy mathematics evaluation method, the grey system evaluation method, the artificial neural network method, and the principal component analysis method.

Water quality evaluation is based on inference decisions, and uses multiple types of information to infer possibilities statistically. As a statistical classification method that uses known information to infer probabilities, the Bayesian method has drawn much attention in recent years. This method uses objective probability estimates, or statistical analyses, to indicate the probability of unknown states with incomplete information. Next, this method is used to find the most likely reasons for the occurrence of a certain event, by using probabilistic logic that is based on the Bayesian theory. This method requires only simple calculations, and reliable results can be obtained for small samples data. Thus, the Bayesian method has been used widely for water quality evaluations of rivers, estuaries, lakes and reservoirs.

2.0 REVIEW OF LITERATURE

Shlens (2003) stated Principal component analysis (PCA) was a mainstay of modern data analysis - a black box that was widely used but poorly understood. The goal of this paper was to dispel the magic behind this black box.

Juahir et al. (2004) discussed the development of Artificial Neural Network (ANN) model in estimating water quality index (WQI). The ANN model had been developed and tested using data from 30 monitoring stations.

Ouyang et al. (2006) assessed seasonal changes in surface water quality was an important aspect for evaluating temporal variations of river pollution due to natural or anthropogenic inputs of point and non-point sources. The principal component analysis technique was employed to evaluate the seasonal correlations of water quality parameters, while the principal factor analysis technique was used to extract the parameters that were most important in assessing seasonal variations of river water quality.

Boyacioglu (2006) proposed the factor analysis technique and was applied to surface water quality data sets obtained from the Buyuk Menderes River Basin, Turkey, during two different hydrological periods.
Jha et al. (2007) used river water quality models for biochemical oxygen demand; BOD and dissolved oxygen; DO simulations are mainly based on advection, decay, settling, and loading functions. Newton–Raphson technique is used to optimize the model parameters during calibration and the performance of different models are evaluated using error estimation, viz. standard error and mean multiplicative error, and correlation statistics r².

Najah et al. (2009) applied Artificial Neural Network (ANN) for embedded spatial and unsteady behaviour in the investigated problem using its architecture and nonlinearity nature compared with the other classical modelling techniques.

Singkran et al. (2010) evaluated water quality in the north eastern rivers of Thailand by computing the water quality index of each river in the wet and dry seasons.

Mishra (2010) approached multivariate statistics for interpretation of large and complex data matrix. The dataset was treated using Principal Component Analysis (PCA) to extract the parameters that were most important in assessing variation in water quality.

Noori (2010) proposed the determination of principal and non-principal monitoring stations was carried out using principal component analysis (PCA) technique. Canonical correlation analysis (CCA) was also used to determine relationship between physical and chemical water quality parameters.

Sahu et al. (2011) proposed an efficient methodology such as adaptive network fuzzy inference system (ANFIS) for the prediction of water quality.

Akkaraboyina and Raju (2012) assembled different water quality parameters into single number leads an easy interpretation of an index.

Mangukiya et al. (2012) suggested Groundwater is a natural resource for drinking water. The calculation of Water Quality Index (WQI) was done by Weighted Arithmetic Index method.

Enjei et al. (2012) investigated the spatial and temporal variation in water Analysed water quality parameters using MANOVA and discriminant analysis.

Mahapatra et al. (2012) applied an empirical approach was for classification of water samples based on 10 quality parameters. Q-mode principal component analysis had been applied to classify the water samples.

Duan (2012) realised by raising likelihood function of the data. The power prior Bayesian Analysis has been proven to be useful class of informative in Bayesian inference.

Pohlert et al. (2012) analysed the internal fluxes and cycles of nitrogen pointed out considerable weakness in the models conceptualisation of the nitrogen modules which will be improved in future research.

Saatsaz and Sulimanin (2013) evaluated spatio-temporal distributions of groundwater quality using multivariate statistical techniques and Multivariate Analysis of Variance technique (MANOVA) and Cluster analysis (CA) were performed to measure significant effects of spatial, seasonal and annual differences.

Yong et al. (2013) applied a Bayesian Approach to river water quality modelling (WQM) for load and parameter estimation. A distributed Source model (DSM) was used as a basic model.

Borsuk et al. (2013) estimated both global and system specific parameters using Baye's Theorem.

Dilks et al. (2013) used a new technique, Bayesian Monte Carlo (BMC), is used to quantify errors in water quality models caused by uncertain parameters. BMC also provides estimates of parameter uncertainty as a function of observed data on model state variables.

Sahoo et al. (2014) proposed an efficient methodology such as adaptive Neuro fuzzy inference system (ANFIS) for the prediction of water quality in Brahmani River. The water quality parameters used to assess are usually inter correlated with each other and this makes an assessment unreasonable.

Fangbing et al. (2014) applied a Bayesian statistical method to evaluate the water quality comprehensively. The normal distribution sampling method was used to calculate likelihood, and the entropy weight method was used to determine indicator weights for variables of interest in to the study.

The objectives for the current research after the critical review are:

1. To identify the trends of water quality indicators in Brahmani River by the application of Cumulative WQI Method.
2. To develop a Bayesian method for evaluation of water quality using Maximum Likelihood (ML) estimates for likelihood estimation.
3. To develop prior and posterior distributions of water quality indicators before and after estimation of weights by entropy weight method.
4. To estimate the final water quality comprehensively by the proposed Bayesian method.
5. To determine the posterior probability distributions of the quality of water with presence of conjugate priors and non-informative priors by Markov Chain Monte Carlo through the application of Bayesian Inference.
6. To develop an application of power prior Bayesian analysis to improve priors in Bayesian Inference.
7. To analyse the uncertainty analysis and risk analysis of water quality indicators in developed Bayesian water quality Model.

8. To analyse the impact of changes in the indicators and random factors on the errors of the Bayesian Models.

2.1 Scope of the Research work

This research is intended to illustrate the applicability of the Bayesian belief network (BBN) as a means by which multi-scale habitat risk assessment may be accomplished. The BBN is a useful communication tool for representing influences on wildlife habitat that combines in a graphical model empirical data with expert judgement. It can be used to express the likelihoods of risk where uncertainty or bias in expert judgement and where deficiencies in empirical data exists. There are several primary assumptions required to construct a BBN. First, a BBN represents a “causal web” of ecological influences and can further reflect cumulative risks to habitat and ecological function. It further states that not intended to replace empirical research but rather offers a method for “analysing planning alternatives”. Unlike other types of ecological risk assessments, this method accounts for subjectivity and uncertainty in the data.

3.0 STUDY AREA AND DATA COLLECTION

The Study area of the proposed research work is the Brahmani River basin. The basin is an interstate basin lies between latitudes of 20° 28’ North to 25° 35’ North and longitudes of 80° 52’ East to 82° 30’ East. The river is formed by two major tributaries namely Sankh and Koel, originated in the state of Jharkhand and spreads across the states of Chhattisgarh, Jharkhand and Odisha. The river gets its name below the confluence point of Sankh and Koel at Vedvyas in Sunderagarh district of Odisha. The length of the river is 446 km. The map of Brahmani River is shown in Figure 1.

![Figure 1: Study Area showing the Brahmani River Basin](image)

3.1 River System

The River basin has a total drainage area of 39,268 km², out of which 22,516 km² is in Odisha state, 15,405 km² in Jharkhand state and 1347 km² in Chhattisgarh state. In Odisha, eight districts are included within the river basin such as Sundergarh, Keonjhar, Sambalpur, Deogarh, Angul, Dhenkanal, Jajpur and Kendrapada. The river is formed by two principal tributaries the South Koel and Sankh, originated from the state of Jharkhand. The river referred as Brahmani River at the confluence point near Vedvyas, in Odisha at an elevation of 200 m above mean sea level. Below the confluence point, the river heads its way to southeast direction up to Bay of Bengal and traverses a length of 461 km.

Five gauging stations in the state of Odisha are selected for the proposed study in the Brahmani River Basin. Those are Panposh down-stream at Sundergarh, Talcher up-stream at Angul, Kamalanga down-stream at Dhenkanal, Aul and Pottamundai stations are included in Kendrapada district in Odisha. Panposh down-stream includes 5,717.77 km², Talcher up-stream takes 4,235.38 km², Kamalanga down-stream includes 3,968.66 km², Aul and Pottamundai include 1,114.41 km² areas within the River basin.

3.2 Data Collection and Analysis

The monthly water quality parameters are collected and analysed from five selected gauging stations of Odisha during the months of January to December from 2004 to 2013. Eleven physical, chemical and biological water quality parameters are selected for the analysis, the parameters are Dissolved Oxygen (DO), Biological Oxygen Demand (BOD), Nitrogen as nitrate (Nitrate-N), Chemical Oxygen Demand as Manganese (COD. Mn), Nitrogen as ammonia (NH₄-N), Total Alkali as CaCO₃ (TA as CaCO₃), Total Hardness as CaCO₃ (TH as CaCO₃). The collected water quality parameter data are tested, analyzed and
validated with the data of Central water Commission (CWC) and Odisha Pollution Control Board (OPSC) in the Environmental laboratory of National Institute of Technology, Rourkela.

4.0 METHODOLOGY

4.1 Water Quality Evaluation

Water Quality evaluation without consideration of all water quality indicators is of no meaning. Quality of each and every indicator is analysed within the range from Excellent to Unsuitable for use before considering the aggregative index method or Bayesian method for water quality evaluation. Assessment of water quality can be utilized for many purposes, to define whether water meets designated uses, to identify specific indicators and sources of pollution to the river water, to determine the changing trends of quality of water and to scrutinize the excessive levels of indicator for impairment.

The overall WQI is calculated on monthly basis for each gauging station, i.e., one WQI value is evaluated for each time step of one month. Considering all the water quality indicators WQI can be grouped as excellent, Very good, Good, poor, Very Poor, and Unsuitable for drinking and domestic purposes when it lies in the range of $0–10$, $11–25$, $26–50$, $51–65$, $65–75$ and $>75$ respectively.

4.2 Maximum Likelihood (ML) estimates by Normal Probability Density Function

ML maximises a likelihood function, which in turn increases the compatibility between the model and data. Here, the likelihood function is acquired by appraising the probability density function (PDF) not as a function of the sample variable, but as a function of distribution’s parameters (dst2, 2004). Let us consider $W_1,...,W_n$ be the water quality indicators with $W_i \sim N(\mu, \sigma^2)$.

It can be written as:

$$\hat{\mu} = \frac{\sum w_i}{n},$$

Similarly, for $\hat{\sigma}$, the equation can be illustrated as:

$$\frac{\partial(\ln f)}{\partial \sigma} = -\frac{n}{\sigma} + \sum \frac{(w_i - \mu)^2}{\sigma^2} = 0,$$

The above equations gives:

$$\hat{\sigma} = \sqrt{\frac{\sum (w_i - \hat{\mu})^2}{n}},$$

The mean ($\hat{\mu}$) and standard deviation ($\hat{\sigma}$) are calculated by using the above illustration for ML estimates.

4.3 Bayes Rule for Probabilistic Theory

Bayes rule can be used to combine the information in the set of data with the prior probability distribution; in particular, interest is likely to focus on posterior probability estimation (Gelman et al., 2004). The Bayes formula for the discrete set of events is used to calculate posterior probability $P(b_j/a_k)$ (Bayes, 1763, Jensen, 1996 and Fangbing et al., 2014):

$$P(b_j/a_k) = \frac{P(b_j)P(a_k/b_j)}{\sum_{a=1}^s P(a_k)P(b_j/a_k)}$$

Where $i$ is the number of water quality class ($i= 1, 2, \ldots, 6$), $j$ is the number of water quality indicators ($j = 1, 2, 3, 4, 5$), $k$ is the number of representative sites ($k = 1, 2, 3, 4, 5$), $b_j$ is the quality value of the $j^{th}$ indicator of the $k^{th}$ standard water quality type, $a_k$ is the value of $j^{th}$ indicator at the $k^{th}$ site $P(b_j/a_k)$, is the posterior probability values of every water quality indicator that belongs to a certain class, and $P(b_j)$ is the probability of the $j^{th}$ indicator that belongs to the $k^{th}$ water quality class.

4.4 Posterior Probability by Bayes Rule using Beta Prior

Using Beta prior, it can be considered as an unconventional approximation to build a density $g(p)$ on the interval $0 < p < 1$ that entitles the person’s initial beliefs. An appropriate family of densities for a proportion is the beta with kernel proportional to

$$g(p) \propto p^{a-1} (1-p)^{b-1}, 0 < p < 1.$$
where the hyper parameters $a$ and $b$ are chosen to reflect the user’s prior beliefs about $P$. The mean of a beta prior is $m = a/(a + b)$ and the variance of the prior is $v = m(1-m)/(a + b + 1)$, but it is difficult in practice for a user to assess values of $m$ and $v$ to obtain values of the beta parameters $a$ and $b$. It is easier to obtain $a$ and $b$ indirectly through statements about the percentiles of the distribution.

4.5 Entropy Weights Measure

Entropy is the course of the disorder of the system (Lee, 2013). To determine the entropy weights by calculating the value is the way of defining the weights of every water quality indicator based on the interpretation of the variation degree of every evaluated indicator value. It can be said that the quantity of information can be studied indirectly according to the degree of the reduction of uncertainty i.e., greater the entropy tends to a greater reduction of the uncertainty spatially (Shannon, 1948).

5.0 Results and Discussions

5.1 Results by Cumulative Water Quality Index Method

The water quality indices are calculated by applying the formulations and calculations as discussed before. According to the water quality indices, the level of pollution of water ranges from excellent to unsuitable for use and are varied from one gauging statin to another. Physio-chemical characteristics of surface water quality of Brahmani River depend upon the water quality indicators. Table 1 shows the categories of water quality criteria and the range of its monitoring values for each water quality indicator at five gauging sites. According to descriptive statistics, DO exceeds the permissible range varies from a mean value 8.60 mg/L in monsoon to a maximum value of 12.10 mg/L in summer. The values of BOD are within the permissible limits, but it is difficult in practice for a user to assess the reduction of uncertainty i.e., greater the entropy tends to a greater reduction of the uncertainty spatially. Nitrate-N mg/L varies in its value from 0.87 mg/L to 1.17 mg/L, which is within the permissible limit. The values of TA as CaCO$_3$ is lower than their permissible limits throughout the year. The COD$_{Mn}$ values are within the permissible range of 18-30 mg/L in all seasons. The NH$_4$-N exceeds slightly from its permissible range at summer and monsoon but exceeds a bit in winter season.

<table>
<thead>
<tr>
<th>National Criteria</th>
<th>DO (mg/L)</th>
<th>BOD (mg/L)</th>
<th>COD$_{Mn}$ (mg/L)</th>
<th>NH$_4$-N (mg/L)</th>
<th>TA as CaCO$_3$ (mg/L)</th>
<th>Nitrate-N (mg/L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXCELLENT</td>
<td>≥ 7.5</td>
<td>≤ 2.5</td>
<td>≤ 12</td>
<td>≤ 0.15</td>
<td>≤ 35</td>
<td>≤ 4.0</td>
</tr>
<tr>
<td>VERY GOOD</td>
<td>≥ 6</td>
<td>≤ 4</td>
<td>≤ 8</td>
<td>≤ 1.5</td>
<td>≤ 40</td>
<td>≤ 4.5</td>
</tr>
<tr>
<td>GOOD</td>
<td>≥ 5</td>
<td>≤ 6.5</td>
<td>≤ 10</td>
<td>≤ 2.0</td>
<td>≤ 42</td>
<td>≤ 5.5</td>
</tr>
<tr>
<td>POOR</td>
<td>≥ 3</td>
<td>≤ 10</td>
<td>≤ 14</td>
<td>≤ 2.5</td>
<td>≤ 45</td>
<td>≤ 6.5</td>
</tr>
<tr>
<td>VERY POOR</td>
<td>≥ 2</td>
<td>≤ 12</td>
<td>≤ 16</td>
<td>≤ 3.0</td>
<td>≤ 50</td>
<td>≤ 7.5</td>
</tr>
<tr>
<td>UNSUITABLE</td>
<td>≤ 1.5</td>
<td>≥ 12.1</td>
<td>≥ 16.5</td>
<td>≥ 3.5</td>
<td>≥ 55</td>
<td>≥ 8.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Monitoring Sites</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Panposh d/s</td>
<td>4.5-12.1</td>
<td>0.2-7.0</td>
<td>0.5-44.0</td>
<td>0.0-11.7</td>
<td>14.0-108.0</td>
<td>0.01-9.3</td>
</tr>
<tr>
<td>Talcher u/s</td>
<td>5.2-10.2</td>
<td>0.3-8.9</td>
<td>3.9-41.4</td>
<td>0.0-3.9</td>
<td>34.0-87.0</td>
<td>0.0-9.7</td>
</tr>
<tr>
<td>Kamalanga d/s</td>
<td>4.2-12.5</td>
<td>0.3-9.2</td>
<td>0.5-44.7</td>
<td>0.0-12.5</td>
<td>14.0-111.0</td>
<td>0.0-7.0</td>
</tr>
<tr>
<td>Aul</td>
<td>4.2-12.0</td>
<td>0.4-8.7</td>
<td>0.7-45</td>
<td>0.0-12</td>
<td>14.1-109</td>
<td>0.0-7.5</td>
</tr>
<tr>
<td>Pottamundai</td>
<td>4.0-11.5</td>
<td>0.5-7.6</td>
<td>0.8-45.4</td>
<td>0.0-13.5</td>
<td>14.0-112</td>
<td>0.01-8.2</td>
</tr>
</tbody>
</table>

5.2. Maximum Likelihood (ML) estimates by Normal Probability Density Function

The mean or expectation ($\hat{\mu}$) and standard deviation ($\hat{\sigma}$) of every water quality indicator are calculated by ML estimates by applying the equations (10) and (12) as mentioned earlier for estimation of prior probability through Normal Probability Density Function, which can be pre-owned for the estimation of posterior probability. The two quantities $\hat{\mu}$ and $\hat{\sigma}$ are specified because, the peak of the density occur at $\hat{\mu}$ and $\hat{\sigma}$ indicates the spread or girth of the bell curve in normal distribution. Table 2 gives the information about maximum likelihood ($\hat{\mu}$ and $\hat{\sigma}$) estimates for water quality indicators.
Table 2. Maximum Likelihood estimates

<table>
<thead>
<tr>
<th>Water Quality Indicator</th>
<th>$\hat{\mu}$</th>
<th>$\hat{\sigma}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DO (mg/l)</td>
<td>1.9327</td>
<td>0.8876</td>
</tr>
<tr>
<td>BOD (mg/l)</td>
<td>2.0014</td>
<td>1.0374</td>
</tr>
<tr>
<td>Nitrate-N (mg/l)</td>
<td>2.0242</td>
<td>0.987</td>
</tr>
<tr>
<td>COD.Mn (mg/l)</td>
<td>1.8992</td>
<td>0.8299</td>
</tr>
<tr>
<td>NH4-N (mg/l)</td>
<td>1.8571</td>
<td>0.8994</td>
</tr>
<tr>
<td>T. A. as CaCO3 (mg/l)</td>
<td>2.0434</td>
<td>1.0968</td>
</tr>
</tbody>
</table>

5.3 Evaluation of Posterior Probability by Bayes Rule using Beta Prior

Beta prior concludes that the sampling distribution is normal with known variance but unknown mean. Therefore, in the natural conjugate prior distributions, mean is considered to be normal. If the prior distributions for some random variable of interest and data gathering process are normal, the posterior distribution is normal. Therefore, it can be said that, a normal distribution is conjugate with respect to a normal data gathering process. The histogram is generated by histogram prior, which could suggest a normal distribution sampling method for the data that could be used for generating the likelihood functions, which can be used further in the Bayesian Inference (Press, 2003). Figure 3 and Figure 4 exhibit the prior and posterior distributions of WQI values for class type III, i.e., “Good” and class type IV and V, i.e., “Poor” and “Very Poor”.

![Figure 3: Prior and Posterior distributions of WQI values for Class type II](image)

![Figure 4: Prior and Posterior distributions of WQI values for Class type IV and V](image)

The posterior interval/credible interval/ acceptable region dispenses a very instinctive way to narrate the estimation of uncertainty. Unlike a confidence interval, a posterior interval provides the probability having a value within the interval.
interlude is established on calculating the probability of dissimilar values of the given data. Figure 5 shows the different values (identified as theta) as well as the imitated posterior interval limits (α = 0.05 in green and 0.01 in cyan colour). In other words the probability that theta is a member of the 95% credible interval is 0.95. It can be written as $P(\theta \in CI) = 0.95$. It can be concluded that the prior is informative.

The water quality class types of every water quality index are determined by application of posterior probability equation as described before in Equation 13 and the posterior probability of the multi indicator is resolved. Figure 6 shows the probability distribution box plot for each water quality class types. The figure explains that the class type of water quality belongs to type III or “Good” which is 30.2-33.1% larger than the other three class types of water quality for surface water in India.

**5.4 Calculation of Indicator Weights by Shannon’s Entropy Weight Method**

The entropy weights of WQI based on Shannon’s entropy theory are calculated for each gauging station of every months from 2004 to 2013. The entropy weights are varied from 4.006 to -4.104, which showed a Gaussian distribution. The entropy weight calculation results indicate that the Panposh downstream and Talcher upstream stations are affecting the water quality more than the other stations especially in the months of May, June, October, December, January and also in other months of the year.

**6.0 CONCLUSIONS**

1. Cumulative Water Quality Index Method categorised the overall quality of water at all monitoring station from Excellent to Unsuitable for use respectively. According to aggregative WQI, the concentration of COD$_{Mn}$ and DO affect the quality of water in Panposh downstream station.

2. The seasonal variations of six water quality indicators vary with temperature, rainfall, runoff and waste water disposal. The overall water quality of Brahmani River is gone sore during dry seasons than during wet season.
3. The comprehensive evaluation of water quality indicates that the prior-posterior probability by application of Bayes rule belongs to type III i.e. “Good” which illustrates that the water is suitable for second grade surface source protection zones and for centralized drinking water, general fish conservation areas, swimming area etc. and is 30.2-33.1%, larger than the other water quality types defined by environmental water quality standards prevailing in India.

4. The MCMC modelling estimated the impact of DO, TC and EC as quality indicators in drinking water quality of the Brahmani River. The correlation between water pollution and the indicators are determined by the beta (β) and mu (µ) coefficients in prior estimations. Considering the conjugate and non-informative priors, standard value of water pollution is lower by 0.50% and 0.40% respectively. In case on non-informative priors, the pollution in water grows by 13.21% in absence of DO, 85.60% in presence of EC and 98.88% with the existence of TC as a water quality indicator. Correspondingly, the pollution level elevates by 14% with less amount of DO. Whereas, the pollution level diminishes by 86.13% and 98.83% with the presence of EC and TC.

REFERENCES


