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Sensitivity Analysis of Stream Water Quality and Land Cover Linkage Models Using Monte Carlo Method

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ABSTRACT: Sensitivity analysis might be considered as one of inevitable steps in modelling since it would help to determine the behaviour of model, which was developed for further application. Sensitivity analysis was not paid much attention in studies that have been conducted for modelling the relationship between stream water quality and land cover except machine learning techniques such as artificial neural networks was applied for specifying the possible relationship between alteration in area (%) of land cover types and changes in water quality variable. Two linkage models for predicating stream water total nitrogen (r^2= 0.70, p<0.01) and total phosphorus (r^2=0.47, p<0.01) concentrations were developed using multiple regression approach in twenty-one river basins in the Chugoku district of west Japan. Application of Monte Carlo method-based sensitivity analysis indicated that TN regression model would be able to predict stream water concentration between 0.4-3.2 mg/L without any possibility for generation of negative value. For the TP regression model, predicting capacity would vary between 0.04, 0.32 mg/L. The results revealed that the Monte Carlo method-based sensitivity analysis would provide reliable information for determining output space in which the model would accurately respond.

Key words: Sensitivity analysis, Stream, Water, Quality, Nitrogen, Phosphorus

INTRODUCTION

Rivers and their catchments are very important part of our natural heritage. Rivers have been utilized by humankind over the centuries to the extent that are very few, if any, now in their natural condition because of pollution loads (Ngoye and Machiwa, 2004). Water quality in rivers is generally linked with land use in the basin that can affect the quantity and quality of runoff during and following rainfall. Forestry, agriculture, industrialization and urbanization modify watershed cover characteristics that influence runoff quantity and quality (Richards and Host, 1994). Many problems of water pollution are caused by changes in land use pattern on the catchment as population pressure and economic activities increase (Lee and Bastemeijer, 1991). Agricultural activities have been identified as major sources of nonpoint pollution (Viessman and Hammer, 1993) and are known to have major impacts on water quality. Urban areas have the potential to generate large amount of Non Point Source (NPS) pollution from storm water discharge (Basnyat *et al.*, 1999). Due to the relationship between pollution loading and composition of the land uses in the river basin (Perry and Vanderkilen, 1996), there would be a potential for improving water quality with proper land use management if the role of different land use combination is known (Basnyat *et al.*, 1999). Although numerous studies have been carrying out on this matter, categorization of the land use and stream water quality linkage studies (Johnson *et al.*, 1997) indicated that these kinds of studies have been conducted in three progressive steps

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as follows: The first generation of stream water quality-land use linkage studies had been commenced since early 1960's in order to investigate the effects of morphometric features of catchments (area, elongation, gradient, drainage network density and so on) on turbidity, dissolved oxygen and temperature (Hynes *et al.*, 1960); (Kuehne , 1962), (Kuehne, 1966), (Harrel, 1968). The second generation of these studies had been merged in 1970's focusing on understanding elemental dynamics and quantifying diffuse sources of pollutants in the catchments (Bormann *et al.*, 1969; Likens *et al.*, 1970; Omernik 1976; Burton *et al.*, 1977a; Burton *et al.*, 1977b and Correll *et al.*, 1977). The fourth generation of the catchments studies have been used the advantages of remote sensing, GIS and multivariate analysis to explore the land use and suspended sediment (Thomas *et al.*, 1974; Hill, 1981; Allan *et al.*, 1997; Bolstad and Swank, 1997; Jones *et al.*, 2001; and Ahearn *et al.*, 2005) and nutrients (Arheimer and Liden, 2000; Osbourne, 1988; Pekarova and Pekar, 1996, Sliva and Williams, 2001; Tong and Chen, 2002).

Majority of the studies, which have been conducted in field of stream water quality and land use linkage modelling, validation of the models were carried out based on either residual approach (i.e. applying the same data set for modelling and validation tasks) or cross-validation approach. In the later approach, data set is divided into two distinctive groups as training and testing data subsets in proportion to 70% and 30%. The cross validation method is often used in those studies, which are benefited of large data sets. Otherwise, small number of data set will not be able to provide reliable information with features of the models, which were developed.The main purpose of validation of the models might be to determine their limitations or behaviours under different conditions from what the models were developed. Nevertheless, lack of access to sufficient data set would be considered as a bottleneck for carrying out the validation or sensitivity analysis of the models during modelling process. Although sensitivity analysis of the models might be considered as one of critical steps in modelling process, only a few studies, which took advantage of some techniques of environmental informatics such as artificial neural networks (e.g. see Lek *et al.*, 1996, Noori *et al.*, 2009), have analysed the sensitivity of the developed models. Main purpose of present study was to investigate the possibility of the application of the sensitivity analysis as an option in case of accessing few data sets in number for determining the limitation or behaviours of the stream water quality and land use linkage models. The objectives of this study are as follows:

1) Developing the multiple regression models to represent the relationship between alterations in area (%) of land cover types, and changes in stream water total nitrogen and total phosphorus
2) Analysing the sensitivity of the developed model in order to specify their limitation or predictive capacity of the stream water quality and land use linkage models in case of lack of access to sufficient database.

MATERIALS & METHODS

The present study was carried out in the Chugoku district of Japan that is located in the West of Honshu island within (130° 55' 16'' and 133° 12' 11'') longitude and (33° 57' 40'' and 35° 23' 34'') latitude. It includes five Prefectures (Hiroshima, Yamaguchi, Tottori, Shimane and Okayama), and covers 32,000 km2. The underlying geology is largely volcanic (andesite and rhyolite) in central and the northern parts, Mesozoic sedimentary formations (sandstone/ shale/ pudding stone) in the west and quaternary sedimentary formations (gravel and clay) in the low lands of the study area. Dystric regosols, fluvic gleysols, gleysols, humic cambisols, ochric cambisols and rhodic arcsols are the dominant soil types that can be observed in each catchment. The spatial analysis of land cover map indicated that a high percentage (79.34%) of the study area is covered by forest. Other land cover classes including urban, agriculture, grassland and water body make up 5.15, 8.33, 6.63 and 0.46% of the study area, respectively (Table 1). There are 7,732,499 inhabitants in the study area. There are 54 major rivers in the Chugoku district, out of which 21 were selected as our study area.

Total Nitrogen (TN) and Total Phosphorus (TP) were selected as the factors representing the water quality of the rivers (Table 2). The water quality data were obtained from the five Prefecture offices (Hiroshima, Yamaguchi,

Table 1. Physical features, land cover and population density in the catchments of the Chugoku district

Basin Number	River Name	Area (km^2)	Land uses (%)					Population density ($Person/Km^2$)
			Urban	Forest	Agriculture	Grassland	Water body	
1	Awano	182	1.97	86.61	5.62	5.89	0.28	63
2	Kakefuchi	85	4.36	71.94	16.35	5.42	1.04	106
3	Fuka	72	6.39	84.17	5.01	4.27	0.10	150
4	Misumi	67	1.36	88.41	5.05	4.18	0.00	70
5	Hamada	253	8.48	78.59	3.72	6.87	1.01	176
6	Gonoo	2622	1.79	83.89	7.44	6.61	0.27	72
7	Shizuma	174	2.46	84.23	5.39	10.05	0.22	150
8	Kando	495	7.09	78.16	11.84	2.76	0.14	222
9	Numata	627	4.42	65.6	24.74	5.04	0.21	165
10	Kamo	98	3.79	78.92	7.62	9.63	0.00	211
11	Kurose	282	10.8	57.61	20.64	10.1	0.75	819
12	Ota	1700	4.74	85.22	4.29	4.71	0.29	386
13	Oze	354	3.01	86.91	3.31	6.15	0.56	183
14	Nishki	932	1.04	91.76	2.76	3.72	0.71	165
15	Shimada	284	5.91	77.75	8.14	7.72	0.43	267
16	Saba	572	2.62	88.35	2.89	5.61	0.53	225
17	Washino	300	13.99	72.84	6.96	5.89	0.30	434
18	Kotou	416	3.8	75.64	8.83	10.91	0.79	253
19	Ariho	98	9.23	72.76	9.24	8.34	0.44	477
20	Asa	226	6.24	78.09	7.14	7.94	0.52	109
21	Koya	299	4.67	78.67	7.97	7.46	1.07	362
Max.			13.99	91.76	24.74	10.91	1.07	819.00
Min.			1.04	57.61	2.76	2.76	0.00	63.00
Mean			5.15	79.34	8.33	6.63	0.46	241.19

Table 2. Descriptive statistics of the annual mean of TN & TP in stream water of the study area

	TN (mg/L)			TP (mg/L)		
Catchment No.	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
1	0.470	0.31	0.58	0.0255	0.02	0.05
2	0.658	0.49	0.82	0.0412	0.03	0.07
3	0.612	0.53	0.71	0.0325	0.02	0.07
4	0.753	0.59	0.93	0.0238	0.02	0.04
5	0.435	0.23	0.98	0.062	0.03	0.09
6	0.620	0.37	0.90	0.032	0.01	0.08
7	0.685	0.45	0.83	0.071	0.06	0.09
8	0.475	0.39	0.57	0.039	0.06	0.08
9	0.882	0.71	1.10	0.042	0.03	0.06
10	0.570	0.15	1.10	0.025	0.01	0.01
11	1.900	1.30	2.90	0.046	0.03	0.06
12	0.670	0.46	1.00	0.021	0.01	0.03
13	0.700	0.50	0.89	0.032	0.03	0.04
14	0.492	0.41	0.64	0.012	0.01	0.02
15	0.736	0.56	0.88	0.038	0.02	0.07
16	0.562	0.40	0.77	0.045	0.03	0.06
17	1.846	1.03	3.06	0.164	0.08	0.28
18	0.753	0.54	0.94	0.045	0.02	0.09
19	1.875	0.78	5.55	0.054	0.03	0.08
20	0.741	0.56	0.89	0.054	0.03	0.10
21	0.699	0.50	1.00	0.079	0.03	0.13

Shimane, Tottori and Okayama) in the study area that could be defined as secondary database (Sliva and William, 2001). Water sampling of the stream and analysis are carried out monthly based on Japanese Industrial Standard (TN/TP: JIS K0102 45.2, 45.3). Details of sampling method and analysis procedures would be found in JSA JIS K 0102 (Japanese Standard Association, 1998). Annual mean of water quality data in 2001 were calculated using monthly data without data transformations for this study. Population data was obtained from the population census in 2000 that carried out by Japanese Statistic Bureau of Ministry of Internal Affairs and Communication. The present study was conducted using whole-catchments land use approach (Sliva and Williams, 2001). This approach uses the results of spatial analysis for the land use or land covers in whole catchments as variable in the multivariate analysis. In order to facilitate the spatial analysis and determination of morphological attributes, Geographical Information System was established using the ArcView 3.2 (ESRI, 1999). For all water sampling stations, upstream catchments boundaries were hand digitized by using JGSI topographic quadrangle maps (1:200 000). All databases were transformed into a common digital format, projected onto a common coordinate system (UTM, zones 52 and 53). Human Population density map was firstly generated by linking county-scale population database with the digital map of counties. It was then overlaid by the catchments map and aggregated in order to find the catchments-scale population density map in the study area and was transformed into spatial data. For generating land cover map in the study area, two scenes of NASA Landsat-5 TM (2000) were used. The satellite images were geo-referenced by the affine procedure. The supervised classification method was applied to classify land uses, which included forest, agriculture, grassland, urban and water body (wetland, natural and artificial lake). Finally, the generated land cover map was verified using JGSI maps. Preparation, interpretation and analysis of the satellite data were carried out using Integrated Land and Water Information System (ILWIS, 2004). The generated land cover map was then superimposed by catchments map for calculating the real extend of each land cover for each catchment, which subsequently divided by the catchments area to drive the percentage of the catchments covered by each type.

Water quality data including TN and TP and area (%) of land cover types were tested for normality using the Sharpio-Wilk test with a p-value of less than 0.05 (Table 3). For determination of linkage between land cover and stream water qualities, Multiple Linear Regression (MLR) modelling was applied using stepwise approach. Inter-variable co-linearity of the models was investigated referring to Variance Inflation Factor (VIF). It measures the impact of co-linearity among the X's in a regression model on the precision of estimation. VIF expresses the degree to which co-linearity among the predictors degrades the precision of an estimate. (Chatterjee *et al.,* 2000). Normality of residuals of the models were then examined by Anderson-Darling test with a p-value<0.05. For a given water quality variable, the appropriate model was selected based on regression statistics (*r*2, *p*-value) and considering the significance of the coefficients of the model provided that the residuals of the model was normally distributed. Finally, the goodness-of-fit of the statistically significant models was evaluated by scatter plot and simple linear regression of observed *versus* equivalent model prediction (Ahearn *et al.,* 2005). All descriptive statistics and other statistical analysis were completed using Excel Add-ins (XLSTATTM 2006) and SPSS for Windows Release10. In environmental modelling, it is very important to know to what extend the independent variables contri1bute in explaining the variations of the dependent variable (Lek *et al.,* 1999). Sensitivity analysis was considered by some researchers (e.g. see, Maier and Dandy 2001; Lek *et al.,*1996; Lek *et al.,*1999 ;Spitz and Lek, 1999) whom took advantage of some techniques in environmental informatics such as artificial neural networks for specify how much changes in the input variables would contribute in explaining the variations in the model output.

Table 3. Results of normality test for TN and compositional attribute of land covers

Variable	Sharpio-Wilk statistics	
	Statistic	Sig.
TN	0.655	**0.010**
TP	0.731	**0.010**
Population density	0.918	**0.336**
Urban	0.893	**0.167**
Forest	0.915	**0.313**
Agriculture	0.873	**0.079**
Grassland	0.939	**0.475**
Water body	0.961	**0.746**

***All bold values are significant at *p* <0.05**

As a part of the sensitivity analysis, each of the inputs is increased by a certain percentage (5%) in turn, and the change in the output caused by the change in the input is calculated (Maier and Dandy, 2001). In applying this approach, which is classified as mathematical sensitivity analysis, a critical point should be kept in mind that all the variables of the model should be independent. In our case, mathematical sensitivity analysis was not seemed to be possible since structure of land use types within a given river basin is inter-related so that making change in the percentage of a land use type (e.g. increase of the urban area) should be in expense of other one (e.g. decrease in agricultural area) in a given river basin. Therefore, a stochastic sensitivity analysis was paid attention for this study. Considering the number of rivers that their water quality data were available (21 basins), it seemed that number of rivers that should be kept for testing the models would be very few (3 basins). In this case, reliable information will not be provided for judging on the calibrated models. Application of testing data subset was avoided for testing the calibrated models, which was real but few in numbers. For dealing with the shortage of the testing data set, it was decided to use Monte Carlo Method for sensitivity analysis of the calibrated models. According to the Monte Carlo Method, 5000 random numbers were generated using random number generator command in Microsoft Excel for six variables consisting of area (%) urban, forest, agriculture, grassland and water body, and human population density. Table 4 summarized the statistics of this randomly generated data set. The calibrated models were tested using the generated random number data set based on the Monte Carlo procedure. In generating random number, three conditions were considered as follows:

1) random numbers should vary between 0-100; 2) summation of five variables for land use type to be equal to 100%, and 3) random numbers for each variable should follow a known distribution.

Initially, six variables were defined in the Microsoft Excel. 5000 random numbers were generated for each variable using the related command (rand between (bottom)(top)) in it for meeting the first condition. Each row stands for a hypothetical river basin, which consisted of five variables for land use types (urban, forest, agriculture, grassland and water body areas in percent) and the last variable for human population density. For meeting the second condition, summation of five land use variables was calculated and each land use variable divided by the summation since in a real situation for a given river basin, land use types as land use variable can not be independent and any change in one land use type should be in expense of other ones. Based on the Monte Carlo Procedure, statistical distribution of variable(s) should be known before they are used for further analysis. Distribution fitting approach was applied in order to specify what statistical distribution every randomly generated variable follows. It was carried out by computing the Maximum Likelihood test with maximum 100 iterations and accuracy of 10-4 . For goodness of fit, the Kolmogrov-Smirnov test was carried out. The results of the distribution fitting of the input variables were summarized in Table 6. Following on from that, this data set was entered into LR models that were developed for the TN and TP separately. The output of each model was then computed. For the output of MLR models, the distribution fitting was carried out one more time in order to determine what statistical distribution the output of the models follow? Moreover, another purpose for distribution fitting was to specify the probability of the event such as *Pr* (output< 0), since only positive values make sense in relation with the water quality variables in general and for TN and TP in particular. For materializing aforementioned purpose, the estimated cumulative distribution curve was plotted for the output of TN and TP models, which were developed.

RESULTS & DISCUSSION

All water quality data and area (%) of land use types except that attribute (%) of agricultural land cover and human population density followed normal distribution according to the Sharpio-Wilk test (p<0.05) (Table 3). A stepwise approach was applied for determining a final model representing

Table 4. Summary of the statistics of the data set used for sensitivity analysis of the ANN model

Statistics	Urban	Forest	Agriculture	Grassland	Water body	Human Population Density
Mean	19.86	19.82	20.23	19.82	20.27	438.57
Standard Error	0.16	0.16	0.16	0.16	0.16	3.11
Median	19.80	19.82	20.18	19.83	20.18	441.00
Mode	0.00	0.00	0.00	0.00	0.00	404.00
Standard Deviation	11.32	11.52	11.61	11.53	11.63	219.79
Sample Variance	128.16	132.73	134.76	133.04	135.15	48305.84
Kurtosis	-0.30	0.07	-0.20	0.15	-0.09	-1.21
Skewness	0.29	0.39	0.32	0.42	0.36	-0.01
Range	61.29	72.26	70.00	71.43	72.07	754.00
Minimum	0.00	0.00	0.00	0.00	0.00	63.00
Maximum	61.29	72.26	70.00	71.43	72.07	817.00
Count	5000	5000	5000	5000	5000	5000
Confidence Level (95.0%)	0.31	0.32	0.32	0.32	0.32	6.09

Table 5. Results of MLR-based TN and TP models0

Variable			Statistics			Normality test	
Dependent	Independent	S.E.	r^2	*P*	VIF	Statistics	Sig.
TN model			0.7	0.001		0.985	0.966
	Cons.		0.111				
	P				1.868		
	U		0.024		1.868		
TP model			0.48	0.001		0.911	0.058
	Cons.		0.1				
	U		0.02		1.000		

the linkage between land cover and stream water quality variables (TN and TP, in this case) at catchment level. For each model, the preliminary fixed variables were *human population density*, compositional attribute (%) of land cover variables (*urban, forest, agriculture, grassland and water bodies*). The results of multiple regression modelling were summarized in Table 5, which are described as follows:

In the TN model (Eq. 1), (r^2=0.70, p<0.01), the compositional attribute (%) of *urban area*, out of five land covers and human population density could play a significant role for explaining TN variations in the river water as shown in Eq. 1.

$$TN = 0.219+1.375*10^{-3}P+5.151*10\text{-}^{2}U \qquad (1)$$

where TN is concentration of total Nitrogen in mg/L in the river, and P stands for human population density (person/km2) in the catchment, and U is urban area (%) in the catchment. Eq. 4 indicates that increasing the proportion of urban area (%) would increase total nitrogen level in the rivers. It is confirmed by the findings of Tong & Chen (2002) on the strong relationship between the total nitrogen levels and residential (urbanized area). The TP model (Eq. 2), (r^2=0.47, p<0.01), only compositional attribute (%) of urban area was introduced into the regression model as significant variable. Others were excluded during the stepwise regression modelling process.

$$TP=1.362*10^{-2}+6.495*10^{-3}U. \qquad (2)$$

where TP is concentration of total phosphorus in mg/L in the river, and U is urban area (%) in the catchment. Eq. 2 suggests a positive relationship between the proportion of urban area (%) and concentration of total phosphorus in the rivers. It is confirmed by the findings of Tong & Chen (2002) and Ngoye & Machiwa (2004) who reported strong relationship between TP levels and urban area. The statistics value (r^2) for the TP regression model is not relatively high. It might be related to effects of other factors, which were not considered in the present study. These factors could be background sources of chemical loads from either catchment geology and soils or catchment hydrology, which plays important role in the transport of pollutants from the catchment surface to the rivers (Jarvie et al, 2003). Inter-variable co-linearity of the models was investigated by referring to VIF (Table 5). While a VIF>10 could be considered as severe co-linearity within variables in the models (Neter *et al.*, 1996; Chatterjee *et al.*, 2000), all models have revealed no co-linearity (VIF<2). Normality of residuals of the models were tested using the Anderson-Darling test with a p<0.05 whether they follow a normal distribution. The results of the test were summarized in Table 5. It suggests the residuals of all models were normally distributed at significance level of p<0.05. For validating of the goodness-of-fit of the statistically significant models, simple linear regression analysis of observed value *versus* the values predicted by the relevant models was carried out. Sensitivity analysis of TN model suggested that stream water TN concentration might be predicted between 0.4 to 3.60 mg/L using the developed model. On the other hands, upper limit, which were specified by sensitivity analysis, might not be responded accurately by the model in real situation. Besides, it seems to be no probability for *Pr* (TN<0) since

Table 6. Results of the distribution fitting of the input variables that were generated for sensitivity analysis and that of outputs of TN and TP models

Variable		Kolmogorov-Smirnov Test	
		Statistics	Statistical Distribution
Input:			
	Urban	0.0395	Normal
	Forest	0.0425	Normal
	Agriculture	0.0405	Normal
	Grassland	0.0426	Normal
	Water body	0.0404	Normal
	Human Population Density	0.0510	General Extreme Value
M.L.R. Model Output:			
	TN	0.0385	Logistic
	TP	0.0192	Normal

*** Critical value is 0.0192 for p<0.05**

the cumulative distribution curve achieved a turning point at 0.4 mg/L. It might be mentioned that the TN model would not be able to predict the targeted water quality variable in a level more than 3.6 mg/L since the cumulative distribution curve have reached a turning point at this concentration and a steady state was revealed afterward. Concerning the TP regression model, the sensitivity analysis revealed that the model might be able to predict the stream water TP concentration within a range of 0.04 to 0.4 mg/L. This model could not be used for prediction of the TP concentration beyond the upper and lower limits. Moreover, no probability for occurring the Pr (TP<0) was observed for the output of the TP model. To know the probability for Pr(x<0), which x stands for any water quality variable, would be very important since the generation of negative values by water quality predictive model would not make any sense.

CONCLUSION

Application of the sensitivity analysis, which used the randomly generated data, could provide reliable information with us for judging on the prediction abilities of the developed models stochastically. On the other hands, using the sensitivity analysis, which was based on the Monte Carlo Method could dealt with the issue of lack of access to the sufficient database in numbers. The results of this study indicated that the Monte Carlo method-based sensitivity analysis would be helpful for determination of the upper and lower limits of the prediction abilities of the models, which are developed, in case of facing with insufficient database in number. It might be noted that the prediction of the behaviour of the TN and TP regression models, which were conducted in present study, would be valid provided that input data that will use for the prediction of stream water TN and TP concentrations to be the range shown in Table 4. It will be obvious that the behaviour of the model will be in expose of uncertainty if the input data to be out of the range. Results of this study indicated that the sensitivity analysis might be considered as one of inevitable steps in model development. Its importance should not be underestimated once any effort is taking into action for investigating the linkage between land cover and stream water quality. Information, which is provided with us by the sensitivity analysis about output space of the model that was developed would be more reliable than those which is brought up by judging from initial conditions based on which the model was built.

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