



# AHP-based spatial analysis of water quality impact assessment due to change in vehicular traffic caused by highway broadening in Sikkim Himalaya

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## Abstract

Spatial analysis of water quality impact assessment of highway projects in mountainous areas remains largely unexplored. A methodology is presented here for Spatial Water Quality Impact Assessment (SWQIA) due to highway-broadening-induced vehicular traffic change in the East district of Sikkim. Pollution load of the highway runoff was estimated using an Average Annual Daily Traffic-Based Empirical model in combination with mass balance model to predict pollution in the rivers within the study area. Spatial interpolation and overlay analysis were used for impact mapping. Analytic Hierarchy Process-Based Water Quality Status Index was used to prepare a composite impact map. Model validation criteria, cross-validation criteria, and spatial explicit sensitivity analysis show that the SWQIA model is robust. The study shows that vehicular traffic is a significant contributor to water pollution in the study area. The model is catering specifically to impact analysis of the concerned project. It can be an aid for decision support system for the project stakeholders. The applicability of SWQIA model needs to be explored and validated in the context of a larger set of water quality parameters and project scenarios at a greater spatial scale.

**Keywords** Analytic hierarchy process · Environmental impact assessment · Geographic information systems · Sensitivity analysis · Water pollution · Highway

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## Introduction

Highways are essential for the development and security of a region. However, understanding the detrimental effects of highway projects is pivotal for environmentally appropriate decision making. Environmental impact assessment (EIA) involves the assessment of impacts of a development project on the environmental attributes, including water resources (Barthwal 2012; Canter 1995). Conventional EIA can be time consuming, expensive, and subjective (Glasson et al. 2005; Takyi 2012). Moreover, conventional EIA focuses mainly on the temporal aspect of the impacts and undermines the importance of their spatial distribution. Geographic information systems (GIS) can overcome these limitations and provide an unbiased and easily interpretable EIA (Agrawal 2005).

A highway is essentially a non-point source of water pollution. Construction and post-construction conditions of a highway generate pollutants, which degrade the water quality and affect the habitat of the nearby water bodies (Wu et al. 1998). Highway runoff contains relatively high

concentration of pollutants as compared to the adjacent river (USEP 1996; Bingham et al. 2002; Gan et al. 2008). Statistical models suggest that traffic volume, rainfall characteristics, highway pavement type, and properties of pollutants and seasons are important determinants of road runoff composition (Aldheimer and Bennerstedt 2003; Forsyth et al. 2006; Granato 2013; Kayhanian et al. 2003; Kim et al. 2006; Li and Barrett 2008; Pagotto et al. 2000; Tong and Chen 2002; USEP 1996; Yannopoulos et al. 2004, 2013). These models mostly cater to highway projects of developed countries. Applicability of these models in developing countries remains largely unexplored. Depending upon the nature of the highway runoff study, traffic volume can be considered in two broad ways, namely, as average daily traffic and vehicles during storm. Average daily traffic is a good predictor of water pollutants like Chemical Oxygen Demand (COD), Total Suspended Solids (TSS), and Zinc (Zn), while it poorly predicts the levels of lead, copper, and oil and grease (Thomson et al. 1997; Venner 2004). In contrast, oil and grease has a significant relationship with the vehicles during storm rather than average daily traffic (Stenstrom et al. 1982; Venner 2004). Correlation studies of river water have shown COD is strongly correlated to percent Dissolved Organic Carbon, Dissolved Oxygen, and Total Dissolved Solids (TDS). Moreover, TSS is strongly associated with pH and TDS (Bhandari and Nayal 2008; Waziri and Ogugbuaja 2010).

A wide variety of water quality indices are used in the impact assessment of a highway project. However, except for Water Quality Status Index (WQSI), all other water indices involve predetermined weight or the importance of water pollutants, which cannot be manipulated to see the impact of the change in water pollutant weight on the overall impact on water quality. (Karbassi et al. 2011; Mushtaq et al. 2015; Li et al. 2009; Yan et al. 2015). The weight of a pollutant can be determined using Multi-criteria Decision-Making (MCDM) methods like Delphi Method and Analytic Hierarchy Process (AHP) that use expert opinion-based criteria weighing (Mushtaq et al. 2015; Kumar and Alappat 2009). AHP decomposes the decision process into several levels of hierarchy. Based on a pairwise comparison of criteria for alternatives, a comparison matrix is made for the evaluation of criteria weights (Saaty 1980, 1990; Saaty and Vargas 1994). The data requirement for AHP is less data-intensive than classic statistical methods, which are based on historical data (Arriaza and Nekhay 2008). Use of AHP-based weighing of pollutants helps in giving due importance to the characteristics and conditions of the study area, which may not be reflected in non-expert opinion-based criteria weighing (Karbassi et al. 2011).

Limited literature is available on GIS-based water quality impact assessment of highway projects (Agrawal 2005; Banerjee and Ghose 2016; Brown and Affum 2002). These

studies do not provide a clear methodology to perform Spatial Water Quality Impact Assessment (SWQIA). In addition, the reliability of these models is arguable as they lack appropriate model validation criteria. Moreover, none of them have discussed the importance of individual water pollutants on the overall value of a spatial water quality score or index. Spatial analysis of water quality usually involves interpolation of individual water pollutants in the study area, followed by combining their thematic maps using appropriate water quality index (Gajendra 2011; Yan et al. 2015; Zhou et al. 2007). Studies show that kriging is an effective interpolation method (Fallahzadeh et al. 2016; Ostovari et al. 2012; Sadat-Noori et al. 2014).

Spatial Explicit Sensitivity Analysis (SESA) is progressively becoming an essential component of spatial model validation. It is the measurement of variation in the model outputs explained by the variation in the model inputs (Chen et al. 2010, 2011; Crosetto et al. 2000; Feizizadeh et al. 2014; Lilburne and Tarantola 2009; Qi et al. 2013; Xu and Zhang 2013). The outputs of a robust spatial model show marginal perturbations to changes in the model inputs. However, the computational cost associated with SESA is a major constraint for its inclusion in spatial analysis.

The aim of this study is to address the lack of appropriate understanding and methods to assess the spatiotemporal impact of highway construction on water quality in a developing country. The SWQIA model performs a project-specific spatiotemporal assessment of traffic-induced water pollution in East Sikkim. With further validation, in terms of a wider study area and comprehensive water quality parameters, it can be used in developing countries to assess impacts of highway construction on water quality. It acts as a geovisualization and temporal extrapolation tool for traffic-induced water pollution. Moreover, SWQIA model can capture people's perception of the project impacts. The results of the model are encouraging and show that it is a robust model with good prediction capability.

## Materials and methods

### Study area

The study area stretches from Rangpo ( $27^{\circ}10'31.26''$  N,  $88^{\circ}31'44.43''$  E, Elevation 300 m) to Ranipool ( $27^{\circ}17'28.74''$  N,  $88^{\circ}35'31.11''$  E, Elevation 847 m) in the East district of Sikkim, a stretch of 27 km along the route of NH 10 highway. It is the main route which connects Sikkim with the rest of India. In 2008–09, the broadening of NH 10 had commenced to promote defence and economic growth in Sikkim. The highway has been broadened from its present width of 7–12 m. This broadening of the highway will cause an increase in traffic volume. The project stretches from Sevok

in West Bengal to North Sikkim. However, the road corridor chosen for the study is relatively much smaller than the actual stretch of the highway because of its relatively homogenous geography. A drainage area of 147 km<sup>2</sup> was delineated to include all the micro-catchments providing runoff to the highway/rivers (Machado et al. 2017; Siqueira et al. 2017). Furthermore, the project impact area of 7.4 km<sup>2</sup> was demarcated by merging 50 m buffers around the rivers and the highway. The rationale of considering the project impact area was based on the accessibility of the river water/road runoff by the wildlife and humans living near the river/highway (Antunes et al. 2001; Geneletti 2004). The study area has steep elevations, which is predominated by subtropical vegetation, interspersed with small human habitations, traditional farming areas, and towns like Rangpo, Singtam, and Ranipool. The highway closely follows river Teesta and Rani Khola (Fig. 1). It is also worth noting that Sikkim has high biodiversity and it is home to a large number of endemic species (Arrawatia and Tambe 2011). Moreover, it has a unique culture which gives high value to its natural resources. Therefore, unabated water pollution can severely affect the ecological and cultural sanctity of this area.

### Data collection

Based on the changes in Annual Average Daily Traffic (AADT) and landuse & landcover (LULC), three time frames were considered for the study, viz. the year 2004 as pre-project scenario, 2014 as project implementation

scenario, and 2039 as post-project scenario (Fig. 3). The changes considered from 'pre-project' to 'project implementation' scenarios included changes in AADT and LULC. While only change in AADT was considered for 'post-project year' scenario. AADT for 'post-project year' scenario was calculated based on annual growth rates for traffic, provided by Border Roads Organization. LULC in 'pre-project' and 'project implementation' scenarios was estimated using satellite images, whereas such an estimation was not possible for 'post-project' scenario. Five water pollutants were considered for the study (Table 1) mainly based on the ability of the empirical model to predict their concentration in the road runoff, and second, on the availability of a complete data set of historical water quality of the rivers near the highway. Keeping in view of the ecological and cultural sensitivity of the local water bodies, drinking water quality standards of US Public Health Service (USPH 1962) were considered, except pH, where Bureau of Indian Standards (BIS 2012) standard was considered for the present study. Various inputs for SWQIA model were prepared, as mentioned in Table 2.

### AHP model

A structured questionnaire on pairwise comparison of water pollutants and project alternatives was administered to a panel of experts, based on a numerical scale having values ranging from 1 to 9 as suggested by Saaty (2000) (Table 3). The expert choice software was used for the preparation of comparison

Fig. 1 Study area



**Table 1** Description of water quality parameters

Name	Meaning	Relation with road runoff <sup>a</sup>	Environmental impact
Chemical oxygen demand (COD)	Indicative measure of amount of organic matter present in the water	Oil, dirt and grease generated by vehicles and areas close to the road	A high COD causes, anaerobic condition in the water body, suffocation of aquatic organisms and loss of biodiversity
pH	Indicative measure of acidity or alkalinity of water	Release of oxides of Sulphur and Nitrogen from incomplete combustion of fuel from vehicles	At low pH, bioavailability of heavy metals causes metal toxicity of aquatic organisms. In contrast, a high pH causes loss of aquatic organisms due to ammonia toxicity
Total dissolved solids (TDS)	Aggregate measure of organic and inorganic ions present in water	Dissolved materials generated from traffic, rainfall and construction sites settle down on the road	A high concentration in water causes hardness, toxicity and eutrophication
Total suspended solids (TSS)	Aggregate measure of sediment particles suspended in water	Atmospheric dust fall, dust carried by vehicles from construction sites, untarred roads and damaged fraction of the road	A high TDS causes, turbidity or cloudiness of water. This hampers aquatic photosynthesis and respiration of aquatic organisms
Heavy metals (Zn)	Relatively dense metals or metalloids, example Zinc	Generated as traces from fuel combustion, galvanization of steel, preparation of negative plates in electric batteries and vulcanization of rubber. A strong correlation has been found between average daily traffic and zinc concentration in road runoff (Venner 2004)	Biomagnification of heavy metals like zinc in food chain. At high concentration, zinc interrupts the normal metabolism of aquatic organisms and causes birth defects

<sup>a</sup>Doamekpor et al. (2016)

**Table 2** Data types, source, and processing method for SWQIA model

Data type	Data source	Data processing
AADT <sup>a</sup>	BRO, MoRTH	Direct input
DEM	bhuvan.nrsc.gov.in	Direct input
LULC <sup>b</sup>	Sikkim State Remote Sensing Applications Centre	Supervised image classification
Meteorological parameters	Rahman et al. (2012)	Direct input
Slope Percent	DEM from bhuvan.nrsc.gov.in	ArcGIS Spatial Analyst
Soil Texture	CISMHE (2008b)	Georeferencing, vectorization, rasterization
Water quality profile of Teesta and Rani Khola rivers for year 2004	CISMHE (2008a)	Direct input
Water quality profile of Teesta and Rani Khola rivers for year 2014	Bhutia (2015), Gurung et al. (2015)	Direct input

<sup>a</sup>Courtesy: MoRTH, Traffic data of NH 31A (nearest town, Singtam) collected on July 2004 and December 2004 by Ministry of Road Transport and Highways, Govt. of India. Downloaded from <http://morth.nic.in/writereaddata/sublinkimages/sikkim2987772247.htm> accessed on 18/05/2014. BRO, Traffic data of NH 31A (nearest town, Rangpo) collected from 29/06/2012 to 06/07/2012 by Border Roads Organization, Govt. of India. The AADT was projected for 2014 and 2039 based on annual growth rates (in percent) for traffic estimated by BRO

<sup>b</sup>LISS III accessed from <http://bhuvan.nrsc.gov.in/data/download/index.php> under Resourcesat-I satellite image on 18/12/2014

**Table 3** Importance scale used in AHP

Scale of importance	Description
1	Both decision elements are equally important
3	First element is slightly more influenced than the second
5	First element is stronger than the second
7	First element is significantly stronger than the second
9	First element is extremely significant than second
2,4,6,8	Judgement values between equally, slightly, strongly, very strongly and extremely
Reciprocals	When the $i$ th criterion is compared to the $j$ th criterion, $a_{ij}$ , then $1/a_{ij}$ is the judgement value when the $j$ th criterion is compared with the $i$ th, i.e., $a_{ij} = 1/a_{ji}$ .

matrix and calculation of the weight of the pollutants. Two project alternatives were considered for the AHP model, viz. ‘with project’ and ‘without project’, for comparison of the impacts. The ‘with project’ alternative assumed that the highway had been broadened and traffic volume had increased, while ‘without project’ alternative assumed no change in the highway width and the traffic volume remains unchanged. In AHP, the elements of the comparison matrix,  $a_{ij} > 0$ , express the expert’s evaluation of the preference of the  $i$ th criterion in relation with the  $j$ th. It is worth noting that  $a_{ij} = 1$  whenever  $i = j$  and  $a_{ij} = 1/a_{ji}$  for  $i \neq j$ . The total number of pairwise comparisons by expert is  $n(n-1)/2$ , where ‘ $n$ ’ is the total number of criteria under consideration. The eigenvector,  $\mathbf{w}$ , matching the maximum eigenvalue,  $\lambda_{\max}$ , of the comparison matrix is the preferred solution of the AHP model, that is

$$\mathbf{A}\mathbf{w} = \lambda_{\max}\mathbf{w}. \quad (1)$$

or

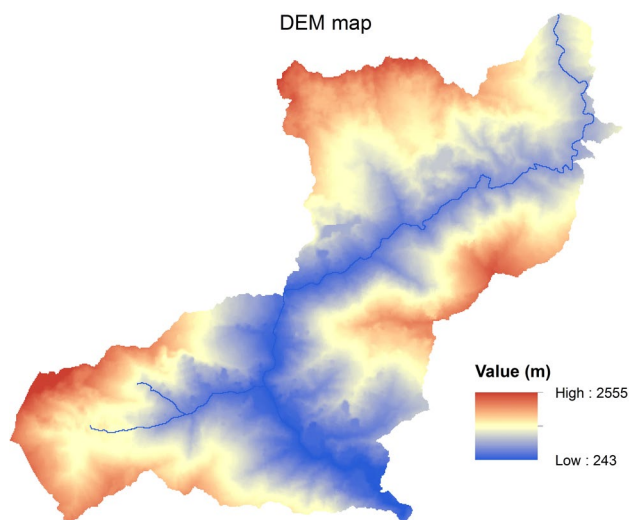
$$\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \begin{pmatrix} w_1 \\ \vdots \\ w_n \end{pmatrix} = \lambda_{\max} \begin{pmatrix} w_1 \\ \vdots \\ w_n \end{pmatrix}, \quad (2)$$

where  $\mathbf{A}$  is the comparison matrix. The elements of  $\mathbf{w}$  must fulfill the condition,  $\sum_{i=1}^n w_i = 1$ , and under ideal condition,

$\lambda_{\max} = n$ . The reliability of the AHP model is assessed by consistency ratio,  $CR = CI/RI$ , where Consistency Index,  $CI = (\lambda_{\max} - n)/(n - 1)$ , and Random Consistency Index,  $RI$ , that is obtained by a large number of simulation runs. It varies upon the order of the comparison matrix (Saaty 2000; Taha 2010). An inconsistency value not more than 0.1 is acceptable for an AHP model.

### Modelling of seasonal peak storm runoff

Rainfall occurs almost the entire year in Sikkim (IMD 2014). However, there is a substantial drop in rainfall in the non-monsoon months, which is from November to March. While April–October gets a relatively high proportion of annual average rainfall (Rahman et al. 2012). Thereby, the non-monsoon months were considered as antecedent dry period and the highest daily rainfall was considered as maximum intensity rainfall. The drainage area and micro-catchments feeding the road runoff/rivers in the study area were



**Fig. 2** Digital elevation model of the study area

demarcated using Digital Elevation Model (DEM) (Machado et al. 2017; Siqueira et al. 2017) (Fig. 2). HEC-GeoHMS, a geospatial hydrological extension of ArcGIS, was used to prepare Soil Conservation Service-Curve Number (SCS-CN) maps for ‘pre-project and project implementation’ scenarios (Merwade 2012; Flemming and Doan 2013). For this, satellite images from LISS III were converted to LULC rasters using maximum likelihood method under image classification extension of ArcGIS (Fig. 3a, b). LULC rasters were reclassified into water, agriculture, forest, and medium residential areas. Furthermore, soil texture map of the drainage area was prepared from secondary sources (CISMHE 2008b) (Fig. 4). It was further reclassified into Hydrologic Soil Groups (HSG), based on the soil texture types (USDA 2007). CN maps were used to prepare Maximum recharge capacity maps (*S* Maps) based on the relation:

$$S = \frac{25400}{CN} - 254. \quad (3)$$

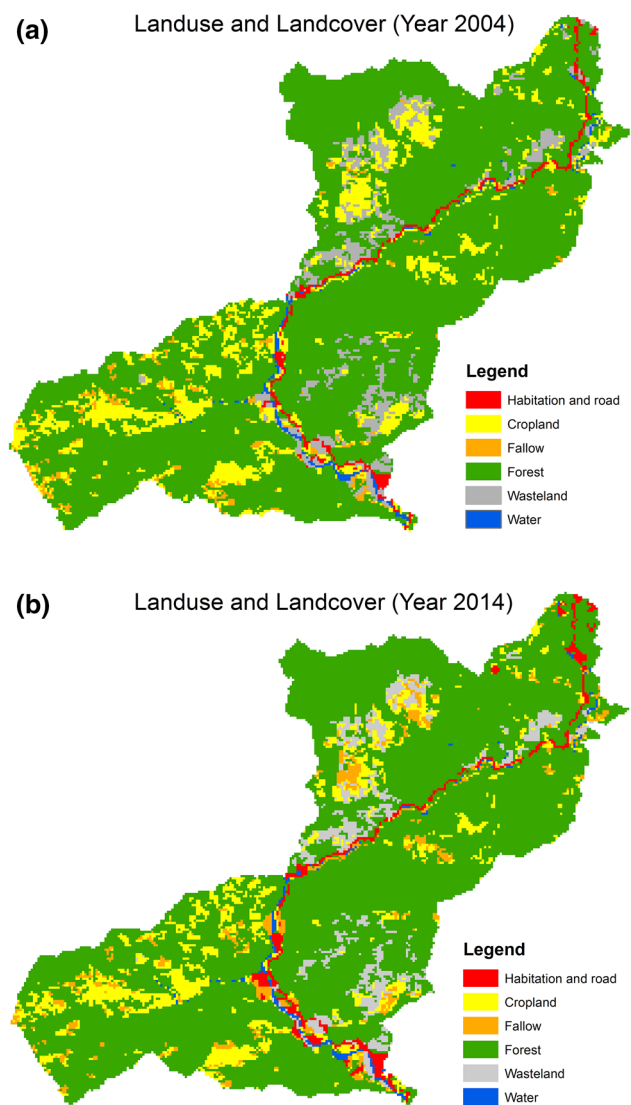
Runoff from each micro-catchment was estimated using the relation:

$$Q = \begin{cases} 0 & \text{if } P < 0.2 \times S \\ \frac{(P-0.2 \times S)^2}{P+0.8 \times S} & \text{if } P \geq 0.2 \times S \end{cases}, \quad (4)$$

where  $Q$  is the runoff and  $P$  is the maximum intensity rainfall (Vojtek and Vojteková 2016).

### Multiple linear regression model for traffic-induced water pollution

The empirical model developed by Kayhanian et al. (2003) was used in calculating the traffic-induced water pollutants

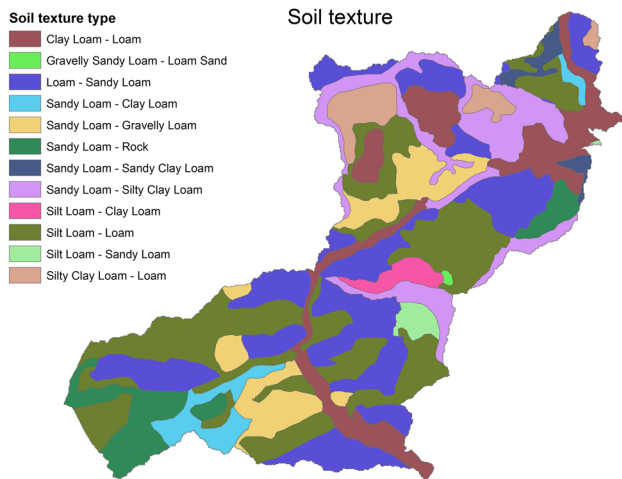


**Fig. 3** Landuse and Landcover map of **a** pre-project scenario (2004) and **b** project implementation scenario (2014)

concentration in the highway runoff (Eq. 5). It is reliable in predicting road runoff concentration of conventional water pollutants like COD, pH, TSS, and TDS, while it is unable to predict turbidity and dissolved oxygen:

$$C_i^H = \exp\left(b_i + \sum_{j=1}^6 a_j x_j\right), \quad (5)$$

where  $C_i^H$  is the concentration in the highway  $H$  and  $b_i$  is the y-intercept of the  $i$ th water pollutant,  $a_j$  is the proportionality coefficient, and  $x_j$  is value of the  $j$ th predictor variable. The predictor variables include Event Rainfall as  $x_1$ , Maximum Intensity Rainfall as  $x_2$ , Antecedent Dry Period as  $x_3$ , Cumulative Seasonal Rainfall as  $x_4$ , watershed area as  $x_5$ ,



**Fig. 4** Soil texture map

and AADT as  $x_6$ .  $a_j$  is the coefficient of  $x_j$ . However, for the year 2039, except for AADT, the values of all other predictor variables were not available. As a result, the most reliable estimate of water pollutants given by Kayhanian et al. (2003) for AADT > 30,000 was considered for the year 2039.

### Estimation of water pollutant concentration in the project impact area using mass balance model

The concentration of water pollutants due to traffic-induced pollution at various locations of the rivers within the project impact area was estimated using the mass balance model (Barthwal 2012; Davie 2008):

$$C_i^R = \frac{Q_D C_i^H + \sum_{j=1}^n Q_j C_{ij}}{Q_D + \sum_{j=1}^n Q_j}, \quad (6)$$

where  $C_i^R$  is the downstream concentration of the  $i$ th water pollutant in the river,  $Q_j$  and  $C_{ij}$  are the upstream discharge rate in l/s and concentration of the  $i$ th water pollutant in mg/l for the  $j$ th stream or river. The runoff from the micro-catchment area,  $Q_D$ , was calculated using SCS-CN method (Eqs. 3 and 4). The concentration of the water pollutant in the highway runoff,  $C_i^H$ , was calculated using empirical model (Eq. 5). The concentration of water pollutant  $C_i^R$  at Rangpo was taken as the model output and it was compared with the observed data using model validation criteria. (Palwal and Srivastava 2014). A correlation matrix of water

pollutants estimated by the mass balance model was used to assess their nature of association.

### Preparation of water quality status index maps

The project impact area map was overlaid upon the micro-watershed map and 100 random points were created within the project impact area. These points were populated with concentration of water pollutants of various years derived from mass balance model as attributes. The attributes of these points were based on their position with respect to the micro-watershed feeding their runoff to the rivers. These points were considered as known points for spatial interpolation of pollutant concentrations over the project impact area.

Empirical Bayesian Kriging (EBK) is a robust and straightforward spatial interpolation technique. Unlike other types of kriging, EBK considers uncertainty in spatial parameters. The algorithm behind EBK generates several semivariogram models to minimize the prediction error generated from the uncertainty of model parameters. Each semivariogram gets a weight, based on Bayes' rule, which predicts how likely the observed data can be generated from a semivariogram (Banerjee et al. 2016; Cui et al. 1995; Krivoruchko 2012; Pilz and Spöck 2008). Hence, EBK was used for spatial interpolation of the water pollutants. Cross-validation criteria were used to assess the quality of spatial model made from the spatial interpolation. Mean Standardized Error and Standardized Root Mean Square Error were used as cross-validation criteria for the interpolation of the year 2014 (Chang 2017; Lloyd 2009). Pollutant maps prepared from spatial interpolation were converted to Single Factor Pollution Index (SFPI) maps using Eq. 6:

$$P_{ijk} = \frac{C_{ijk}}{S_j} \quad (7)$$

where  $P_{ijk}$  is the SFPI value and  $C_{ijk}$  is the measured concentration at the  $i$ th location for the  $j$ th water pollutant of the  $k$ th year.  $S_j$  is the standard value of the  $j$ th water pollutant. The SFPI maps were further reclassified based on Table 4.

$P_{ijk} < 1$  is an indication of low pollution level, while  $P_{ijk} > 1$  indicate moderate-to-high pollution level depending on how low or how high the SFPI value is from one (Li et al. 2009; Yan et al. 2015). The reclassified SFPI maps were used to prepare WQSI maps for various years using the relation:

$$WQSI_{ijk} = \frac{\sum_{j=1}^n W_j P_{ijk}}{\left[ \sum_{j=1}^n W_j P_{ijk} \right]_{\max}}, \quad (8)$$

**Table 4** Standard of SFPI

$P_i$	$\leq 0.4$	$0.4 \sim 1.0$	$1.0 \sim 2.0$	$2.0 \sim 5.0$	$> 5.0$
Pollution levels	Not-polluted	Slight polluted	Medium polluted	Heavy polluted	Serious polluted

where  $W_j$  is the weight of the water pollutant calculated from AHP model and  $P_{ijk}$  is calculated from Eq. 7.  $\left[ \sum_{j=1}^n W_j P_{ijk} \right]_{\max}$

is the maximum value in the set of  $W_j P_{ijk}$ . The WQSI varies from 0 to 1. A WQSI value close to zero indicates no impact, while a value close to 1 implies high adverse impact. The WQSI was further reclassified using natural break classification (Table 5) (Mushtaq et al. 2015).

### Spatially explicit sensitivity analysis

SA of project alternatives was done with respect to change in water pollutant weight for the AHP model. ‘One-At-a-Time’ is a relatively simple SA method, which mainly involves changing one input variable at a time to see its effect on the model output. Its major limitation is that it does not capture the effect of simultaneous variation of input variables on the model output (Murphy et al. 2004). OAT-based SESA was performed on WQSI of the year 2014 as a case study, by changing the water pollutant weight. The water pollutant weight was changed for a range of  $\pm 20\%$  with a step size of  $\pm 2\%$  for each water pollutant considering a uniform probability distribution within a range of 0–1. The WQSI run maps were generated using Eq. 9:

$$WQSI_{it\alpha} = \frac{W_t P_{it} + \sum_{j \neq t}^n (1 - W_t) \frac{W_j}{\sum_{j \neq t}^n W_j} P_{ij}}{\left[ W_t P_{it} + \sum_{j \neq t}^n (1 - W_t) \frac{W_j}{\sum_{j \neq t}^n W_j} P_{ij} \right]_{\max}}, \quad (9)$$

Subject to the condition:

$$\sum_{j=1}^n W_j = 1 \quad (10)$$

where  $WQSI_{it\alpha}$  is dependent on the  $t$ th water pollutant and step size,  $\alpha$ .  $W_t$  is the changed weight, and  $(1 - W_t) \frac{W_j}{\sum_{j \neq t}^n W_j}$  is

the adjusted weight for the  $j$ th water pollutant. Other variables hold the same meaning, as given in Eqs. 6, 7, and 8 (Chen et al. 2011; Xu and Zhang 2013). To evaluate the change in the WQSI value per pixel per step size, a change function was used:

$$CR_{it\alpha} = \frac{WQSI_{it\alpha} - WQSI_{it0}}{WQSI_{it0}} \times 100, \quad (11)$$

where  $CR_{it\alpha}$  is the change rate of WQSI at the  $i$ th location for the  $t$ th WQI at the  $\alpha$ th step size. Mean Absolute Change Rate

(MACR), a summary sensitivity index, was used to assess the overall sensitivity of the entire study area with change in water pollutant weight:

$$MACR_{it\alpha} = \frac{1}{N} \sum_{i=1}^N \left| \frac{WQSI_{it\alpha} - WQSI_{it0}}{WQSI_{it0}} \right| \times 100 = \frac{CR_{it\alpha}}{N}, \quad (12)$$

where  $MACR_{it\alpha}$  is the mean absolute value of change rate of WQSI value due to change in the weight of water pollutant and  $N$  is the total number of pixels. Equation 11 was also used to assess the temporal change in WQSI over various project scenarios.  $MACR_{it\alpha} \geq \alpha$  indicate that the SWQIA model is sensitive to the  $i$ th water pollutant weight at the  $\alpha$ th step size, while  $MACR_{it\alpha} < \alpha$  implies an insensitivity. In other words, if a change of say  $\pm 10\%$  of a model input brings a  $\geq 10\%$  change in model output, the MACR curve slope will be  $\geq 45^\circ$ . In such cases, the model will be considered as sensitive to the model input (Longley et al. 2010). The overall methodology is illustrated in Fig. 5.

## Results

### AHP weight of water pollutants

The order of AHP weight was found to be: Zn > COD > TSS > TDS > pH. The inconsistency value of the AHP model was within acceptable limit ( $CR = 0.01 < 0.1$ ) (Table 6). The analysis showed that the ‘with project’ alternative had a higher priority of 0.727 as compared to the ‘without project’ alternative priority score of 0.273. Moreover, the project alternatives, viz. ‘with project’ and ‘without project’, did not change the order of priority level at various OAT weight change combinations in a range of  $\pm 20\%$ . This proved that the alternatives were insensitive to the water pollutant weight, as each instances of weight change did not yield an equal or above change in the project alternatives (Banerjee and Ghose 2017; Longley et al. 2010). Thereby, the AHP model was robust.

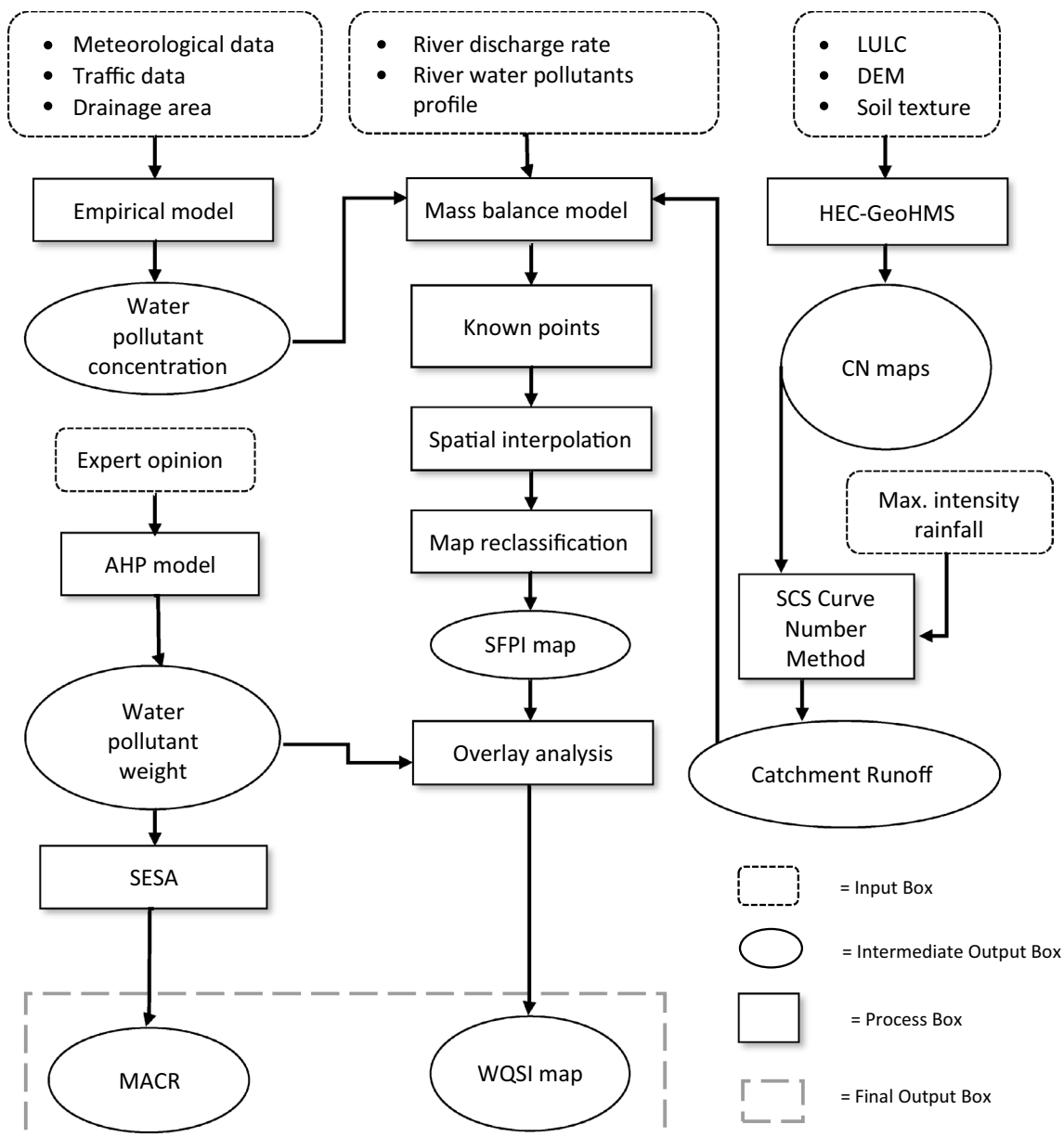
### Runoff estimation, outputs of mass balance model, and thematic maps of water pollutants

CN maps for pre-project and project implementation scenarios were used to estimate runoff from the micro-catchments (Fig. 6a, b). Water pollutants generated at various sections of the highway intersecting with various micro-catchments were estimated using Empirical model (Supplementary Figure S1,

**Table 5** Impact category of WQSI

Range	$\leq 0.55$	$0.55 \sim 0.70$	$0.70 \sim 0.85$	$> 0.85$
Pollution levels	No impact	Slight adverse impact	Moderate adverse impact	High adverse impact





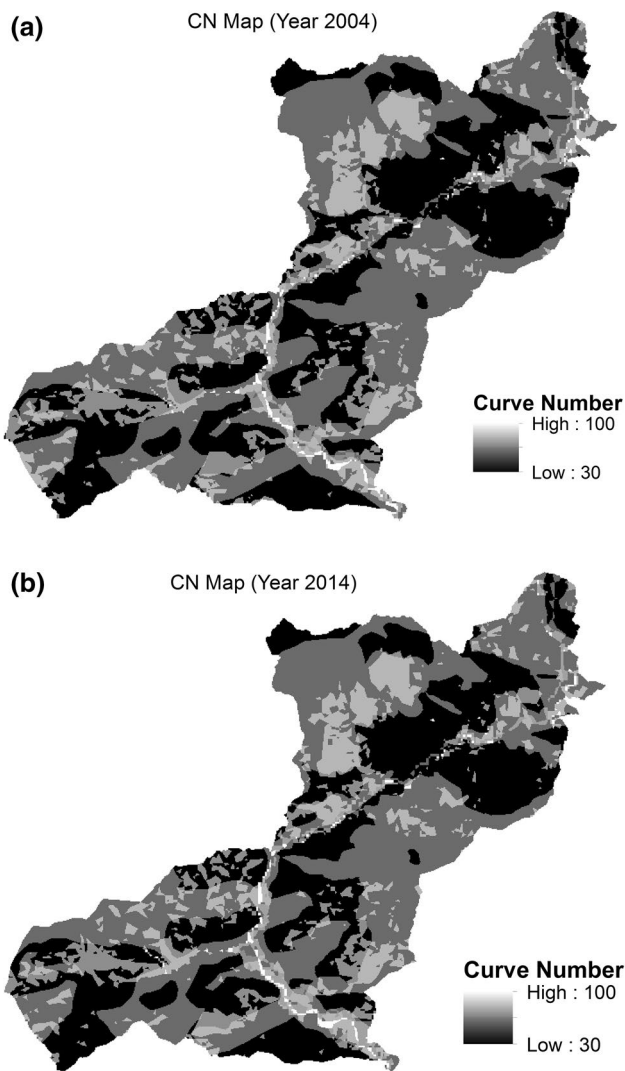
**Fig. 5** Flowchart of spatial water quality impact assessment model

**Table 6** HP weight

Parameter	COD	pH	TDS	TSS	Zn
Weight	0.197	0.161	0.150	0.163	0.329

Tables S1–S3). The outputs of the Empirical model, rivers discharge rates and their pollutant profiles (Supplementary Table S4) were fed into the Mass balance model. The contribution of pollution load from the highway runoff along each micro-catchment was then estimated (Supplementary Tables S5–S7). Traffic-induced water pollution contributed

significantly to the water quality along the Rani Khola impact area as compared to nominal contribution along the Teesta area (Supplementary Tables S8–S10). The pollutants concentration estimated by mass balance model was compared with the downstream water pollutant profile at Rangpo for model validation (Supplementary Table S11). The model validation criteria showed satisfactory results (Table 7). The correlation matrix of water pollutants for 2004 showed a significant relationship between all the water pollutants. TDS had a moderate correlation with TSS and Zn. In 2014, except for Zn, the remaining water pollutants, namely, COD, pH, TDS, and TSS, showed strong association amongst each other (Table 8).



**Fig. 6** **a** SCS-CN map of pre-project scenario (2004). **b** SCS-CN map of project implementation scenario (2014)

**Table 7** MBM validation criteria

Criterion	Fractional bias	Normalized mean square error	Correlation coefficient	Index of agreement
Ideal value	0	0	1	1
Result	0.003	0.041	0.997	0.961

Cross-validation criteria showed satisfactory results for EBK interpolation (Table 9). SFPI maps of water pollutants showed a sharp change in concentration at three locations viz. Ranipool, Martam, and Singtam. Under 2004 and 2014 scenarios, COD maps showed heavy pollution along Rani Khola and seriously polluted condition along Teesta. However, for 2039 scenario, except for impact area above

Ranipool, the entire impact area was seriously affected due to COD pollution (Fig. 7a). pH maps of 2004 showed slight pollution all over the project impact area. In contrast, in 2014 and 2039, the impact area along Rani Khola showed slight pollution, while moderate pollution along Teesta (Fig. 7b). TDS in all scenarios remained at a Not-polluted level (Fig. 7c). On the other hand, TSS levels under 2004 and 2014 scenarios remained largely under seriously polluted level except for an upper fraction of the impact area up to Martam. Furthermore, under 2039 scenario, almost the entire impact area was seriously polluted under TSS pollution (Fig. 7d). Zn level under all the scenarios was within the not-polluted level (Fig. 7e).

### WQSI maps

High adverse impact due to water pollution was observed from Martam all the way to Rangpo under 2004 and 2014 scenarios. While the remaining fraction of the impact area above Martam suffered a moderate adverse impact. Under 2039 scenario, almost the entire impact area had a high adverse impact, except for the impact area above Ranipool which had a moderate adverse impact (Fig. 8). Change in WQSI value from 2004 to 2014 showed marginal change of 5% occurred along Teesta, while no change occurred along Rani Khola area. In contrast, a substantial change in WQSI value from 2004 to 2039 occurred in the entire impact area, except for few pockets of no change in WQSI value. The changes were most prominent along the Rani Khola impact area. Comparing WQSI value from 2039 with 2014, significant change in WQSI was observed along Rani Khola, with 19% change from Ranipool to Martam, while 12% change from Martam to Singtam (Fig. 9).

### Spatially explicit sensitivity analysis

MACR of WQSI over the change in water pollutant weights showed an approximately linear curve with varied slopes and intercept at zero. Second, MACR curves showed symmetry over y-axis, implying that the absolute value of change rate is the same for equal and opposite change in water pollutant weights. Slopewise the order of water pollutants was found to be,  $Zn > COD > TSS > TDS > pH$ , implying that the sensitivity of WQSI to water pollutant weights was in harmony with the order of AHP weights (Fig. 10). Moreover, the slopes of sensitivity were much flatter indicating a low sensitivity of WQSI to change in water pollutant weights.

Figure 11 illustrates the locationwise change rate of the WQSI value of project implementation scenario at 16% increase of all the water pollutant weights. Change in COD and TSS weights led to a slight rise in WQSI value all along the project impact area. A greater change was observed

**Table 8** Correlation matrix of water pollutants under ‘without’- and ‘with’-project scenarios ( $n = 14$ )

	COD (2004)	COD (2014)	pH (2004)	pH (2014)	TSS (2004)	TSS (2014)	TDS (2004)	TDS (2014)	Zn (2004)	Zn (2014)
COD	1	1	0.900	0.921	0.951	0.952	0.663	0.695	0.994	– 0.675
pH			1	1	0.888	0.904	0.866	0.862	0.845	– 0.392*
TSS					1	1	0.550	0.572	0.937	– 0.734
TDS							1	1	0.589	0.062*
Zn									1	1

Correlation is significant at the 0.05 level (2-tailed)

\* $p > 0.05$ . No significant  $p$  value

**Table 9** Cross-validation criteria of empirical Bayesian kriging

Map name	Mean standardized error	Standardized root mean square error
Ideal value	0	1
COD 2014	0.003	0.769
pH 2014	0.012	0.884
TSS 2014	0.002	0.850
TDS 2014	0.016	0.963
Zn 2014	0.007	0.819

along Teesta area in case of COD, while it was greater along Rani Khola (from Singtam to Martam) in case of TSS. Change in pH weight led to a marginal change in WQSI value with almost 1% drop in WQSI value between Singtam and Martam. The slight decline in WQSI occurred all through the impact area with the rise in TDS weight. Moderate fall in WQSI value occurred with an increase in Zn weight. A fall of 5% occurred along the Teesta area, while 4% fall occurred in the remaining impact area. On comparing Figs. 7 with 11, it can be inferred that a greater positive change rate was observed for areas with higher concentration of water pollutants like COD, while a greater negative change was observed for areas with a lower concentration of WQP like Zn. These arguments are further emphasized using Fig. 12. It can be seen that an increase or decrease of Zn, COD, and TSS weight by 18% led to equal but opposite change in WQSI value. For instance, an increase in COD weight led to increase in change rate in areas with higher COD concentration, while a decrease in COD weight caused lower change rate in areas with higher COD concentration.

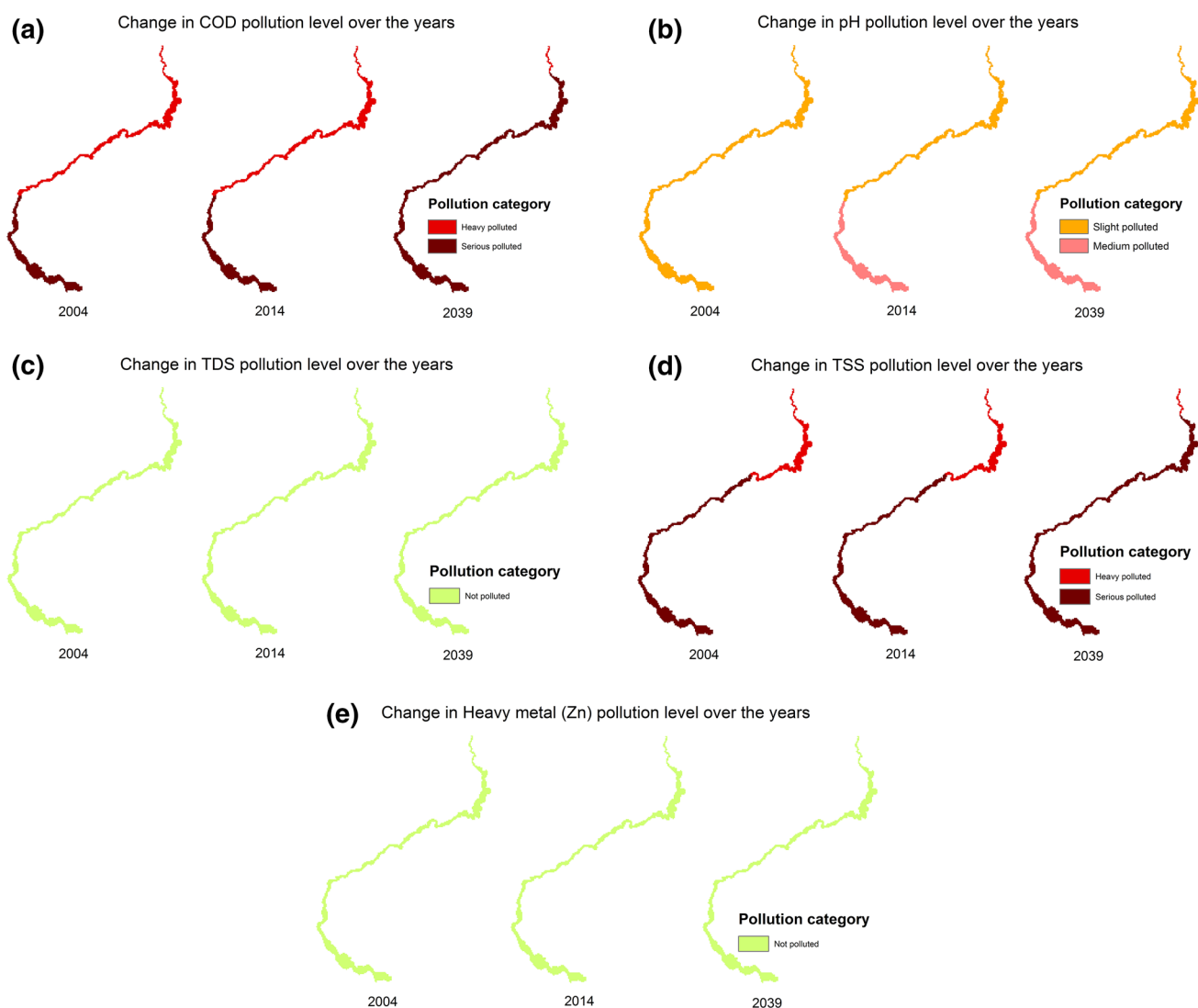
## Discussion

One of the main objectives of this study was to perform an SWQIA for road-broadening-induced vehicular traffic increase. The study revealed that the traffic volume had a major effect on water pollution in the project impact area.

The major contributors to water pollution were COD, TSS, and to some extent pH.

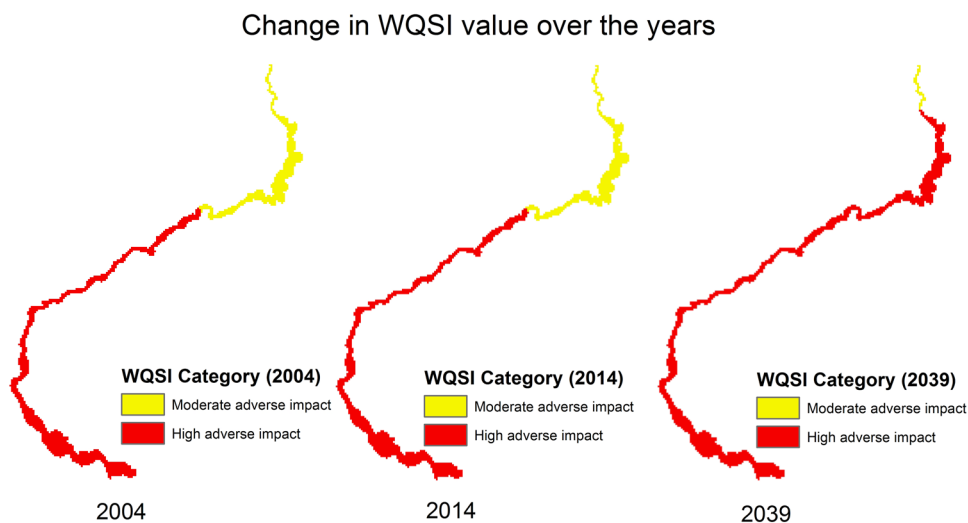
It was interesting to note that, as per the experts' opinion, heavy metal had the highest water pollutant weight, but actually, its contribution to water pollution was nominal in the impact area. This contradiction was also observed while comparing with other studies (Bingham et al. 2002). Estimates from the Empirical model partly support the previous studies. It showed that road runoff had a relatively higher concentration of COD and TSS, and it was relatively alkaline than the nearby rivers (USEP 1996; Gan et al. 2008). It is worth mentioning here that, traffic composition, high rainfall, and dense vegetation can be major players in mitigating traffic-induced heavy metal pollution in the study area (Hwang and Weng 2015; Schiff et al. 2016).

The mass balance model estimates were fairly close to the observed data. However, variations in the pollution profiles can be attributed to the higher instances of landslides, landuse change, or change in rainfall, which mass balance model is not equipped to predict. A significant correlation was observed between the water pollutants. This observation is in harmony with the previous studies (Bhandari and Nayal 2008; Waziri and Ogugbuaja 2010). The contrast of water pollutants in Teesta as compared to Rani Khola can be due to the construction of a number of small-to-medium hydel projects in Teesta such as in Dikchu area (DFEWM 2012). Satisfactory results of model validation criteria reinstate the reliability of mass balance model in SWQIA (Agrawal 2005). COD, pH, and TSS showed a higher concentration in Teesta. In terms of water quality, Teesta was much more polluted than Rani Khola. The abrupt transition of water quality at Martam and Singtam can be partly explained by relatively greater runoff contributed by large micro-catchments at specific points along the river. Moreover, the change in water quality at Singtam area was mainly due to the addition of large amount of COD and TSS into the impact area from Teesta. Cross-validation criteria of EBK showed satisfactory results validating the reliability of EBK.

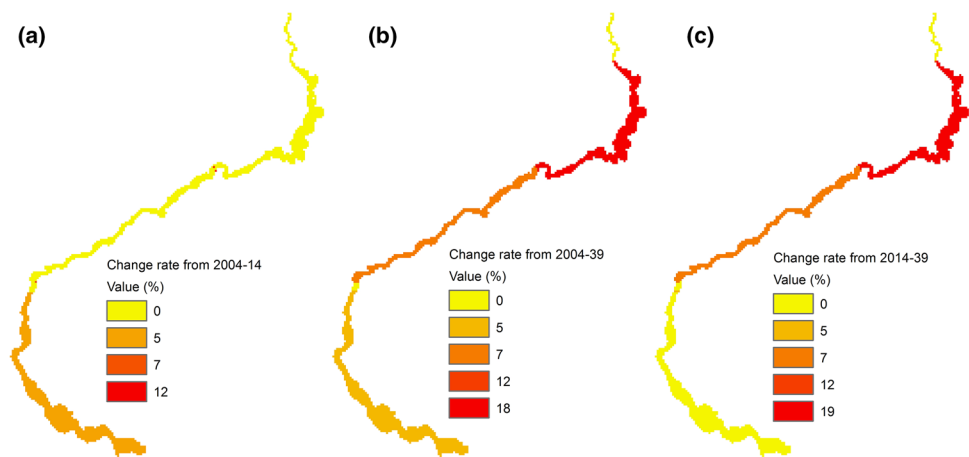


**Fig. 7** **a** Change in COD level under various project scenarios. **b** Change in pH level under various project scenarios. **c** Change in TDS level under various project scenarios. **d** Change in TSS level under various project scenarios. **e** Change in Zn level under various project scenarios

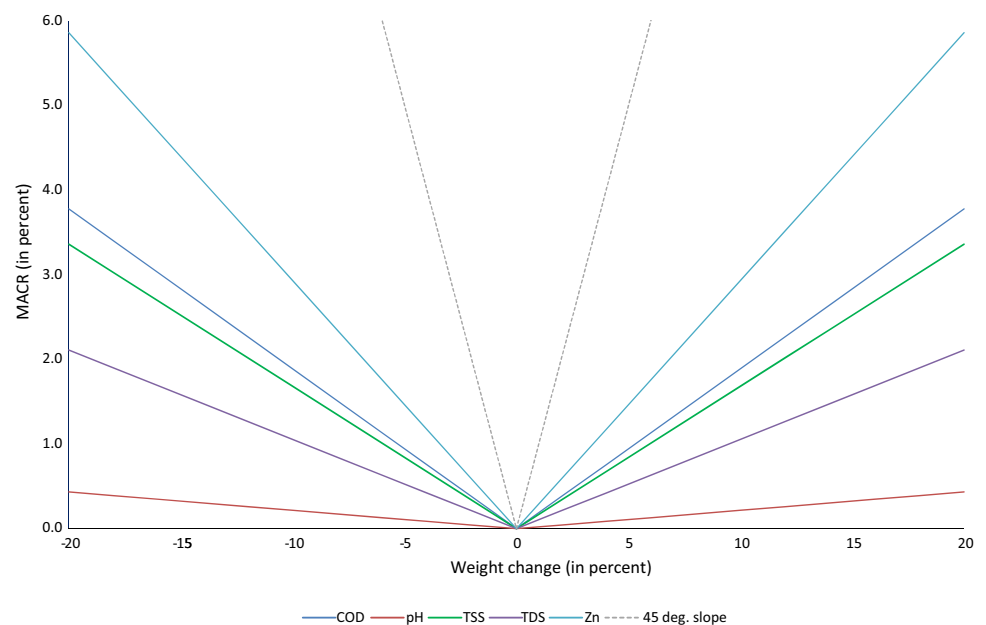
**Fig. 8** Water quality status index maps of various project scenarios



**Fig. 9** Percent change in WQSI values **a** from pre-project to project implementation scenario. **b** From pre-project to the post-project scenario. **c** From project implementation to the post-project scenario



**Fig. 10** MACR of WQSI over the change in water pollutant weights

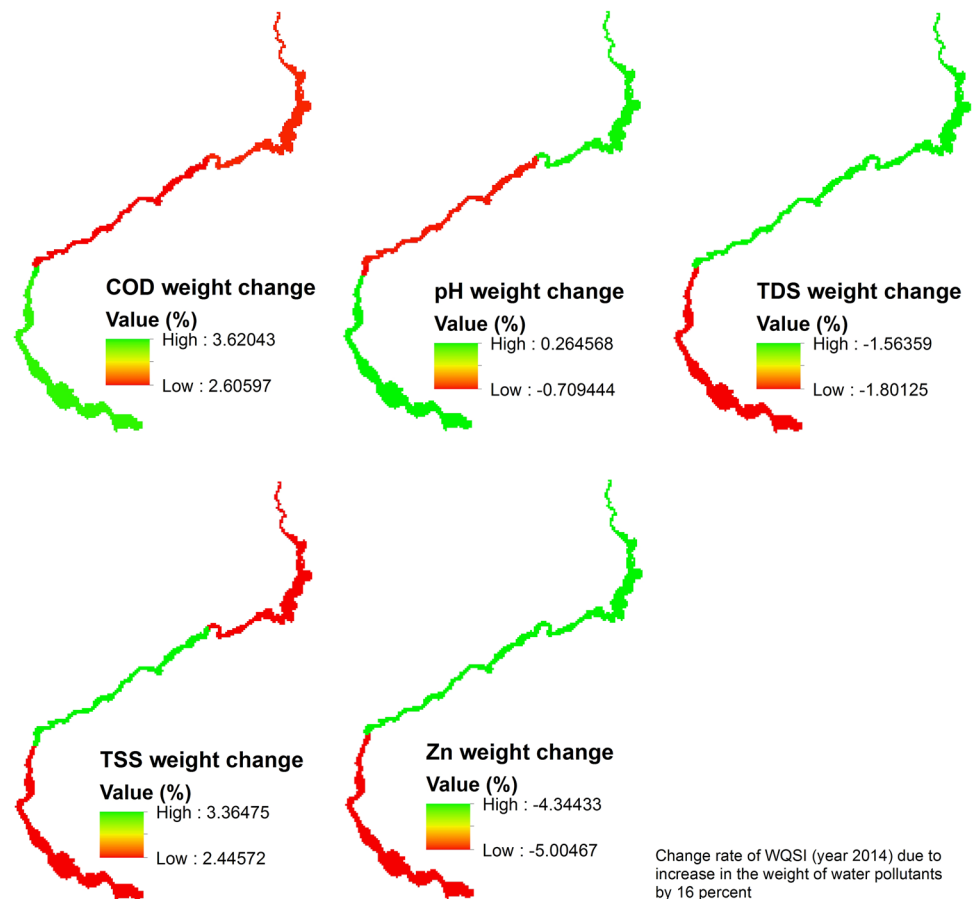


The set of water pollutants considered in this study are widely accepted for the analysis of highway runoff (Agrawal et al. 2005; Venner 2004). However, a limited number of water pollutants and a relatively small stretch of highway were considered in the present study. A wider set of water pollutants including nutrients, metals, salts, BOD, and oil and grease can improve SWQIA model. Moreover, a wider acceptance of SWQIA model demands its validation for a wider study area like a longer road section or a network of roads. Although OAT is a relatively simple SA method, its application in the present study does highlight the role of criteria weight in overall spatial impact assessment. Such an attempt has not been made in earlier SWQIA studies. The MACR outcomes were in harmony with SESA method suggested by Xu and Zhang (2013). The similarity between priority order of criteria

weight of AHP and slope of MACR, and gentle slopes of MACR ( $\leq 45^\circ$ ) showed the robustness of SWQIA model. Our study emphasized on SESA of criteria weight. However, it undermined the importance of SA of an attribute on the model (Chen et al. 2011). The present model used OAT, which is essentially a deterministic method of SA. Use of Monte Carlo simulation-based AHP can further add to the validity of the SESA method (Xu and Zhang 2013; Qi et al. 2013).

At present, hardly, any highway induced water pollution spatial models are available to serve for highway projects of developing countries, especially for hilly areas (Banerjee and Ghose 2016). Subjected to its validation in larger study areas and comprehensive water quality analysis, SWQIA model can be considered as a decision support tool for stakeholders in highway projects. Therefore, as to spatially

**Fig. 11** Change rate maps of WQSI due to increase in WQP weight by 16%



visualize and interpret, the impacts of project-induced traffic volume change on the water quality in the vicinity of the highway. Moreover, SESA can be used as a reliable tool by the impact analyst to visualize the role of criteria weights and thereby incorporate people's and experts' perceptions into impact measurement and mitigation measures. With reliable spatial and temporal data, the present model can be used for a more refined SWQIA in similar areas.

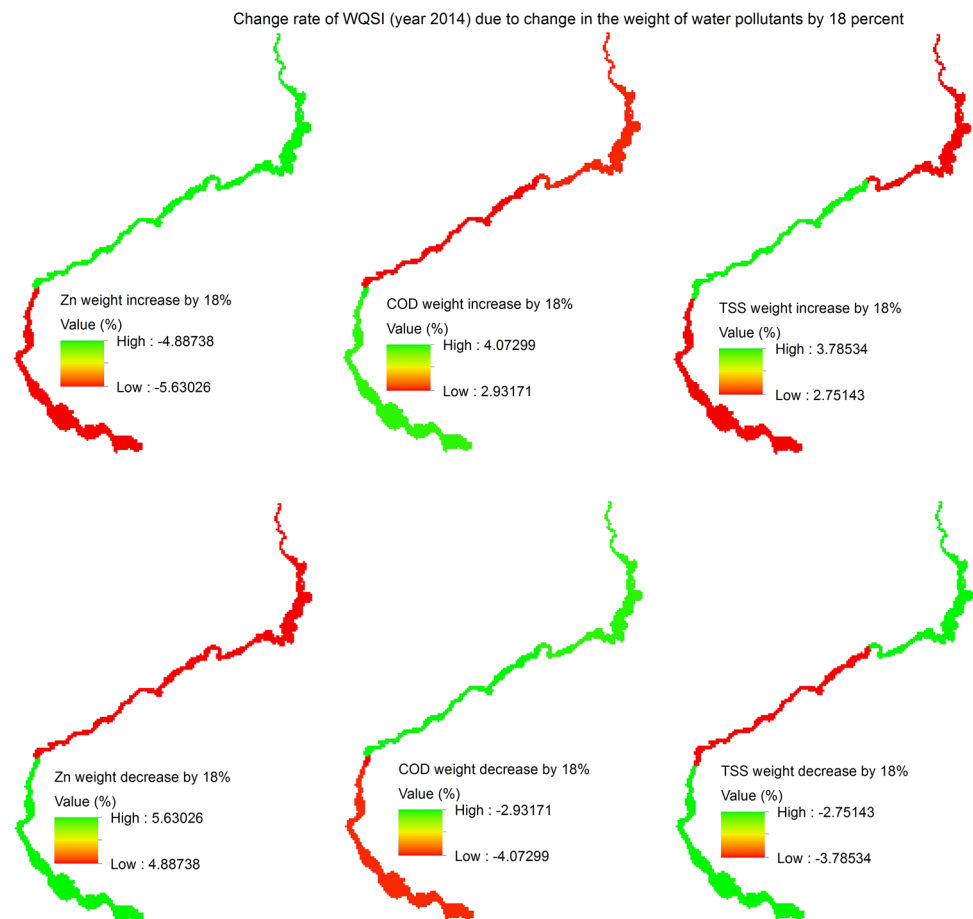
## Conclusion

Vehicular traffic is a significant contributor to water pollution to its nearby areas. SWQIA model suggested that water bodies as far as 500 m away from the highway can be affected by road runoff pollution. Spatial analysis of water quality impact due to highway projects in mountainous areas involved weighing of impact criteria and spatial impact classification. These are essential steps in combining and interpreting pollution impacts. These impacts showed high pollution level in the Teesta drainage area mainly due to COD, pH, and TSS. Temporal analysis

showed that all the project scenarios had moderate-to-high adverse impact due to water pollution. SESA showed that the overall water quality summarized by WQSI was most sensitive to heavy metal weight followed by COD. Model validation and cross-validation criteria suggested that the model has a good predictive capability and spatial reliability in pollution prediction. This model can be further improved by more detailed meteorological and spatially distributed water quality data. The inclusion of stochasticity in criteria weighing along with attribute SA can substantiate the spatial explicit SA presented here. This SWQIA methodology can also be applied to other project impact analysis by selecting appropriate theoretical models for water pollutants measurement. AHP-based capturing of experts' as well as people's perception of impact criteria, geovisualization of impacts, temporal extrapolation of impacts, and SESA can substantially facilitate the decision support system of the project stakeholders.

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**Fig. 12** Change rate maps of WQSI value due to change in Zn, COD, and TSS weights by  $\pm 18\%$



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## Compliance with ethical standards

**Conflict of interest** No potential conflict of interest was reported by the authors.

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