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REVIEW PAPER

Land use impacts on surface water quality by statistical approaches

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ABSTRACT: Surface waters are the most important economic resource for humans which provide water for agricultural, industrial and anthropogenic activities. Surface water quality plays vital role in protecting aquatic ecosystems. Unplanned urbanization, intense agricultural activities and deforestation are positively associated with carbon, nitrogen and phosphorous related water quality parameters. Multiple buffers give robust land use land cover and water quality model and highlight the impacts of land use land cover characteristics on water quality parameters at various scales which will guide watershed managers for particular application of best management practices to enhance stream health. Traditionally, water quality data collections are based on discrete sampling and were analyzed through statistical techniques which were designed for spatially isolated measurements. Traditional multivariate statistical approaches uncover hidden information in water quality data but they are unable to expose spatial relationship. The complexity of information in water quality data needs new statistical approaches which uncover spatiotemporal variability. This review briefly discusses influences of land use land cover characteristics on surface water quality, effects of spatial scale on land use land cover- water quality relationship, and water quality modeling using various statistical approaches. Every statistical method has unique purpose, application and solves different problems. This review article pinpoints that how statistical approaches in combination with spatial scale can be applied to develop statistically significant land use land cover- water quality relationship for better water quality evaluation.

KEYWORDS: *Agricultural activities; Land use land cover (LULC); Statistical approach; Urbanization; Water quality.*

INTRODUCTION

Evaluating land use land cover (LULC) and water quality relationship is valuable because it will give an idea about freshwater protection which would help us in fulfilling the growing demand of water in various sectors including industrial usage, agricultural consumption, municipal usage, potable water supply, and recreational use. LULC-water quality correlation can be implemented to unmonitored watershed because monitoring is time consuming and expensive. It will help the policy makers and watershed managers to make proactive steps in future land use development. Human activities have altered ecological, geochemical and hydrological processes at all scales including local, regional and global. Catchment characteristics i.e. LULC, soil texture, geomorphology, topography and socioeconomic conditions impacts the response of water quality parameters to climatic drivers (Avril, *et al.,* 2007; Khan, *et al.,* 2017; Khan, *et al.,* 2017). Mobilization and delivery of pollutants to receiving waters and its concentration at catchment scale source

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are mainly influenced by LULC, land management practices, topographic conditions, surficial geology, climatic conditions and watershed hydrology (Lintern, et al., 2017; Zhang, et al., 2017; Keesstra, et al., 2018). Hence, assessing LULC-water quality relationship is challenging task for watershed managers (Tong, et al., 2002, King, et al., 2005, Turner, et al., 2003). Besides, spatial scale is important to determine sink/source relationship at various scales which regulate the surface water quality. Spatial analysis scale is important as it highlights the area of interest which researchers want to link with physicochemical and biological characteristics of water quality parameters. Upstream land area of water quality monitoring station is responsible for water quality degradation (Lee, et al., 2009, Mehaffey, et al., 2005, Yang, et al., 2010). Generally, LULC-water quality relationship are developed via buffer and subbasin scale methods (Sliva, et al., 2001). The size of subbasin depends upon the sampling point. Riparian buffers have varying distance ranging from 8m to 200m (Li, et al., 2009, Chang, 2008, Nash, et al., 2009, Daniel, et al., 2010). Scale of the study is important for robust modeling which precisely predicts water quality parameters concentration. LULC-water quality relationship shows regionalization (Allan, et al., 1997, Zaccarelli, et al., 2008, Zhou, et al., 2012). It's challenging to find appropriate technique for a certain catchment to develop spatiotemporal LULC-water quality relationship at several spatial scales. It is obvious from literature that nonpoint-source pollution models and process based watershed hydrologic models is sophisticated in simulating complex problems (Borah, et al., 2004). The applicability of the above stated models are subjected to the long continuous historical time series dataset for model calibration, parametrization and validity. These models are usually avoided due to limited observational data because model development and calibration is based on significant amount of data and empirical parameters. Besides, some models need improvement to get good results while simulating daily and monthly extreme weather data. Keeping in mind the limitation of water quality models, statistical techniques are usually preferred over hydrologic models. Conventional statistical approaches are widely used to link water quality with land use which includes redundancy analysis (RDA) (Sliva and Williams, 2001), multiple linear regression (MLR) (Amiri, et al., 2009), ordinary least square (OLS) (Kang, et al., 2010), structure equation modeling (SEM) (Wu, et al., 2015) and principal component analysis (PCA) (Paul, 2005). Traditional statistical techniques are easy in the sense that they are simple to learn and understand, and robust in computing the influences of independent variables on dependent variable. However, the main disadvantage of these models is that they did not give any idea about spatial variations (Kang, Lee, Cho, Ki, Cha and Kim, 2010). LULC-water quality relationship is extensively quantified via empirical equations (Reimann, et al., 2009, Cunningham, et al., 2010, Utz, et al., 2011). LULC-water quality relationship can be easily evaluated via spatial analysis tools (ArcGIS, FRAGSTATS and ENVI software) (Mehaffey, Nash, Wade, Ebert, Jones and Rager, 2005, Versace, et al., 2008, Rothwell, et al., 2010, Tu, 2011). Spatiotemporal patterns and trends in water quality can be extracted by various analytical approaches to unveil the hidden information for better understanding. These methods highlight spatiotemporal variation in water quality. It can also specify variables causing water quality variations. Remote sensing datasets are spatiotemporally comprehensive. Traditional statistical approaches are usually inappropriate to uncover the hidden information in these datasets. So there is a need of new approaches which fully exploit the hidden information. Conventional statistical approaches such as OLS are unable to uncover spatial autocorrelation and local variations in model parameters. To overcome the shortcomings of traditional statistical approaches, recently statistical approaches in combination with geographic information system (GIS) have been introduced to develop statistically significant LULC-water quality relationship (Tong and Chen, 2002, Maillard, et al., 2008, Xiao, et al., 2007). To take into account spatial variations, advanced regressions techniques have been introduced to uncover the complex linkage between LULC and water quality parameters. Geographically weighted regression (GWR) approach is excessively used for modelling LULC-water quality relationship by incorporating coordinates to gauge the spatial variability. In comparison to OLS regression, GWR gives high R^2 value (Tu, et al., 2008). Spatial regression models in combination with interpolation techniques i.e. Kriging and Inverse distance weighted (IDW) are excessively applied to unveil the watershed varying conditions on water quality through spatial autocorrelation among observations (Yang and Jin, 2010, Chang, 2008). This review article primarily investigates statistical approaches which can be applied to gauge land use influences on surface water quality, differences between statistical approaches, limitations and advantages, as well as purposes and applications in order to expose the most suitable statistical method for different circumstances.

Conceptual framework for water quality evaluation

Water quality is mainly deteriorated by unplanned urbanization and intense agricultural activities. Geological, hydrological and land use percentage composition is extracted from satellite imagery using catchment and buffer series approach. The extracted variables along with water quality parameters are subjected to statistical analysis to find the relationship at several spatial scales. The results obtained from LULC and water quality evaluation will be handy in protecting freshwaters.

Data collection

Water quality data collection mainly depends upon the research parameters, research questions, research outcomes, and scale of the study area. Traditional monitoring techniques provide reliable and accurate water quality information but usually limited in space and time. Various analysis techniques are required to extract the underlying spatiotemporal patterns. These approaches are applied for particular purpose and produce different outcomes. Number of variables and historical record of data depends upon the modeling technique. Different researchers used different water quality and LULC variables which are demonstrated by Table 1. Urban, agriculture and forest land uses are excessively analyzed. Some researcher worked at finer scale at the above mentioned land uses considering impervious surface area (parking lots), commercial area, residential area and recreational spots, crop agriculture, animal agriculture, mixed forest, evergreen forest to unveil the complex linkage between LULC and water quality. Water bodies and industrial land are also tried.

Water quality explanatory variables identification

Spatial scale identifies the portion of land use which will be linked with the physicochemical properties of water quality monitoring station. Two methods are usually used which includes watershed scale and buffer (concentric and parallel) scale as demonstrated by Fig. 1. The above stated techniques are tried by various researchers which are demonstrated in Table 2.

Watershed scale for water quality explanatory variables identification

In watershed scale method whole area of the catchment is linked with physicochemical properties of water quality monitoring station. It highlights the influences of whole catchment on water quality. This technique measure LULC effects on water quality at whole catchment scale (only one spatial scale). It suggests land use management practices at whole catchment level. It is obvious from literature that watersheds have stronger impacts on water quality in comparison to buffer zone because it consider nearer and distant pollution emission sources (Sliva and Williams, 2001, Nash, Heggem, Ebert, Wade and Hall, 2009, Sonoda, *et al.,* 2001, Delpla, *et al.,* 2014). Buck et al. (2004) exposed that buffer scale is the weaker predictor of fecal coliforms as compared to entire catchment scale (Buck, *et al.,* 2004). This method has some limitation in larger catchments due to longer traveling distance which influences LULC-water quality relationship owing to in stream dilution, soil, vegetation and plants absorption (Lee, Hwang, Lee, Hwang and Sung, 2009, Li, Gu, Tan and Zhang, 2009, Gardner, *et al.,* 2009). Furthermore, studies on large scale may face spatial variability due to environmental determinants which change with space.

Buffer scale for water quality explanatory variables identification

Buffer scale method includes two types of buffers i.e. concentric (various radii circles around water quality monitoring station) and parallel (runs parallel along the stream at various distances). In this method water quality is linked with various land uses at multiple spatial scales. The above stated technique enables us to judge, that how LULC-water quality relationship changes as distance increases from water quality monitoring station. It point out land use conservative efforts at particular spatial scale. Hurley and Mazumder (2013) noted that nearby land use to surface water bodies elucidates higher variability in water quality in comparison to entire (Hurley, *et al.,* 2013). Dosskey *et al.* (2010) found that riparian area adjacent to water bodies are helpful in declining surface water pollution from point and

Table 1: Various water quality parameters and land use variables used in previous studies

LULC variables	Water quality parameters	Spatial scale	hypotheses of the study	Outcomes of the study	References
IND,URB,GRA,AGR,FOR	DO, COD_{Mn}, NH_3N, TN, TP, Phenol and Oil.	Multiple concentric buffer technique	Influences of LULC on water quality vary with spatial scale	IND and URB area degrade water quality at both scales i.e. smaller and larger.	(Zhao, *et al*., 2015)
URB,AGR,FOR,WET	EC,DO,NN,Ph,TP,TS, Temperature	Parallel buffer	LULC influences on water quality alter with scale, season and regression method.	Water quality variables showed temporal patterns. GWR give stronger results than OLS.	(Pratt, *et al*., 2012)
ISA, Mixed forest, Evergreen forest, Pasture	Cl^-,NO_3^-,SO_4^{-2},Na^+,NH_4^+, K^+,TP,DOC,FC	Watershed scale	Extent of ISA impacts stream health	Watersheds with ISA (>24%) have higher concentration of fecal coliform and nutrients.	(Schoonover, *et al*., 2006)
FOR, farmland, URB, village area, bare land, WAT	DO,COD,TN,NO_3-N,TP,PO_4P	Subbasin	LULC-water quality relationship changes in space.	Both nitrogen and phosphorous parameters are positively and negatively linked with URB and village, and forest land use respectively.	(Zhang, *et al*., 2012)
WAT,FOR,bareland, rangeland, Other land uses	BOD, COD, EC, NO_3^-,P, Na^+, DO,K^+, Ca^{+2}, Cl^-, SO_4^{-2}, HCO_3^-, pH and TDS	Subbasin	LULC-water quality relationship changes in space.	Degradation of rangeland and ED badly impacts water quality.	(Bateni, *et al*., 2013)
FOR, AGR, GRA,URB and WAT	DO, pH, BOD,SS, Escherichia coli, TN and TP	Catchment and buffer scale	LULC-water quality relationship changes with scale.	Integrated approach at whole catchment and buffer zone give robust model	(Amiri, *et al*., 2008)
High-density urban, medium- to low-density urban, crop agriculture, animal agriculture, FOR, GRA/shrub, water, WET and barren/disturbed.	TP, SRP,NO_3-N+NO_2-N	Subbasin	Changes in land use are associated with impaired water quality.	N and P parameters are closely linked with urban and agricultural activities.	(Rothenberger, *et al*., 2009)
FOR, AGR, URB and bare lands	pH, EC, turbidity, DO, COD_{Mn}, NO_3^--N, NH_4^+-N, Cl^-,$SO_4^{2-}$$HCO_3^-$,K^+, Ca^{+2}, Na^+, Mg^{+2}	Parallel riparian zone	LULC-water quality relationship changes in space especially riparian zone.	Major ions are primarily linked with LULC in riparian zone and showed spatiotemporal variability.	(Li, Gu, Tan and Zhang, 2009)
FOR, farmland, developing, IND, commercial, park, low and high residential area & others	Na^+, K^+, Mg^{2+}, Ca^{2+}, Cl-,NO_3^-, SO_4^{2-}, pH, EC, HCO_3^-, TMI	Sub-watershed	Land use impacts major inorganic ions in riparian zone during base flow conditions.	IND, URB and residential area have positive while forest land use has negative correlation with water quality.	(Bahar, *et al*., 2008)
URB, agro-pastoral, vegetation, planted FOR, barren, WAT	DO, FC, pH, BOD, Nitrate, Phasphate,Temperature, Turbidity, TDS	Parallel riparian zone	Impacts of land use on water quality changes with seasonal variations at riparian scale.	Dry season is the better choice for modeling correlation between LULC and fecal coliform, turbidity, nutrients parameters.	(Maillard and Santos, 2008)
(ISA), population density	BOD,TSS,TKN,NO_3+NO_2, TN,TDP, oil and grease,Pb and Zn	Sub drainage basin	URB area has strong relation with degraded water quality.	Population density and ISA are strongly associated with water quality.	(Xian, *et al*., 2007)
Cultivated land, FOR, grass land, WAT & built up land	TN,TP,NH_3-N,COD,DO	Subbasin	Changes in LULC effects water quality.	FOR and GRA negatively while built up area is positively linked with water quality.	(Huang, *et al*., 2013)
AGR, Open canopy, roads, Residential, Commercial, FOR & WET	NH_3-N,TKN,COD,DO	Subbasin and buffer scale	Variations in land use, scale, and hydrologic conditions influences water quality.	The results highlight the importance of scale. Forest land use is negatively linked with COD at watershed scale.	(Boeder, *et al*., 2008)
FOR, URB, AGR and field	NH_4, Alkalinity, Cl, Cu, DO, PO_4, TS, NO_3, Temp	Catchment and buffer scale	Landscape influences water quality at whole catchment and buffer scale.	Impacts of URB were severe on water quality. FOR played protecting role.	(Sliva and Williams, 2001)
Farmland, orchard, FOR, built-up land and WAT	pH, DO, BOD, COD, NH_3-N, DTP, TN	Multiple buffer	LULC-water quality relationship changes with season and space.	Scale and season play important role in impacting water quality.	(Xiao, *et al*., 2016)

*Nitrogen nitrate (NN),Fecal coliform(FC),Total phosphorous(TP), Total nitrogen(TN), Dissolved oxygen(DO), Chemical oxygen demand(COD), Biochemical oxygen demand(BOD),Suspended solids(SS), Total dissolved solids(TDS), Total major ion(TMI), Total Kjeldahl nitrogen (TKN), Total nitrates and nitrites (NO_3+NO_2), Total dissolved phosphorus (TDP), Soluble Reactive Phosphate (SRP),

** Industrial(IND), Urban(URB), Grass area(GRA), Agricultural(AGR), Forest(FOR), Wetland(WET), Water body(WAT), Impervious surface area density(ISA)

*** Edge density(ED), patch density(PD), Interspersion and Juxtaposition Index(IJI), Shannon's Diversity Index (SHDI),Shannon's Evenness Index (SHEI), Landscape Division Index (DIVISION), Percentage of landscape(PLAND), Number of patches(NP), Largest patch index(LPI), Total edge(TE) and Landscape shape index(LSI).

diffuse pollution sources (Dosskey, *et al.,* 2010). Watershed managers should focus on a particular spatial scale (riparian zone) to improve water quality (Cunningham, Menking, Gillikin, Smith, Freimuth, Belli, Pregnall, Schlessman and Batur, 2010). Undisturbed vegetation in riparian zone (river and streams bank) can improve surface water quality through the process of absorption, deposition and denitrification by removing pollutants total solids and nutrients (Peterjohn, *et al.,* 1984, Zhang, *et al.,* 2009, Smart, *et al.,* 2001). Removing parking lots adjacent to stream will allow surface runoff to percolate into the soil and join stream water (Pratt and Chang, 2012). Major water quality variables are strongly correlated with land use characteristics at riparian scale (Li, Gu, Tan and Zhang, 2009).

It is obvious from the above discussion that both spatial analysis techniques have merits and demerits. Watershed scale approach takes into account distant pollutant emission sources while buffer scale only considers local scale variation in water quality. Watershed scale technique face risk of pollutants absorption due to long travelling distance while buffer scale approach minimize the risk of decay due to shorter travelling distance. Multiple buffers explain LULC-water quality empirical relationship at several spatial scales which give better robust model with higher R^2 value having higher explanatory power. It also highlights the influence of LULC change on LULC-water quality relationship at various scales which will guide watershed managers for particular application of best management practices to improve stream health. Study area scale selection is subjected to the covered area.

Influences of land use on water quality impairment

Diffuse pollution is the principal environmental problem for researchers owing to its disperse origin and varying nature which changes with LULC characteristics and climatic conditions (Sharpley, *et al.,* 1994, Griffith, 2002). Literature shows that various kinds of land uses which include urbanization and intense agricultural activities are the main causes of NPS production.

Influences of agricultural activities on water quality

Intense agricultural activities usually enhance N-parameters, P-parameters and chemical oxygen demand (COD) in surface waters, coming from whole catchment and riparian zone (Lee, Hwang, Lee, Hwang and Sung, 2009, Tu, 2011, Sonoda, Yeakley and Walker, 2001, Howarth, *et al.,* 2000, Ahearn, *et*

Table 2: Different spatial scale techniques tried to extract land use variables

Spatial scale	Scale effects on water quality	Comments	Reference
Concentric buffer technique was used creating concentric circles of 100, 200, 400, 800 and 1500 m from water quality monitoring station.	Industrial area is strongly associated with water quality at smaller scale while urban and forest land uses at larger scale.	Industrial parks are located at smaller scale while urban and forest is located at wide spread area producing non-point source pollution	(Zhao, Lin, Yang, Liu and Qian, 2015)
100m parallel buffer (riparian zone) was created.	Multiple regression models (R^2) for sectioned watershed are superior to buffer scale.	Wider area should be considered to take all the non-point source pollutants	(Pratt and Chang, 2012)
Whole catchment was delineated into sub basins.	Strong relationship with water quality variables.	Large scale takes into account distant non-point source pollutants.	(Zhang and Wang, 2012)
Whole catchment was delineated into sub basins.	Landscape characteristics are strongly linked with water quality.	It accounts for large scale pollution.	(Bateni, Fakheran and Soffianian, 2013)
Whole catchment and 30-m buffer zone analysis.	Integrative application of both scales gives more robust models.	Take both near and distant pollution sources.	(Amiri and Nakane, 2008)
Whole catchment was delineated into sub basins.	Significant linkage between water quality and LULC.	Large scale quantifies distant non-point source pollutants.	(Rothenberger, Burkholder and Brownie, 2009)
100m parallel buffer (riparian zone) was created.	Major ions are significantly linked with water quality at riparian scale.	It is due to local variation in pollutants emission.	(Li, Gu, Tan and Zhang, 2009)
Sub basin plus multiple of 30m width buffers were created up to a maximum of 510m to each sampling point.	Relationship depends upon water quality parameters.	Scale depends upon the main activities responsible for water quality parameters.	(Maillard and Santos, 2008)
Whole catchment and 100 buffer zone approach	Urban land use significantly impact water quality at smaller scale while forests and field land uses at whole catchment scale.	Depends upon the source of pollution.	(Sliva and Williams, 2001)
100m, 500m, 1000m and 2000m buffer	At smaller scale, built up land significantly impacts on water quality.	Depends on domestic and industrial waste water	(Xiao, Wang, Zhang and Zhang, 2016)

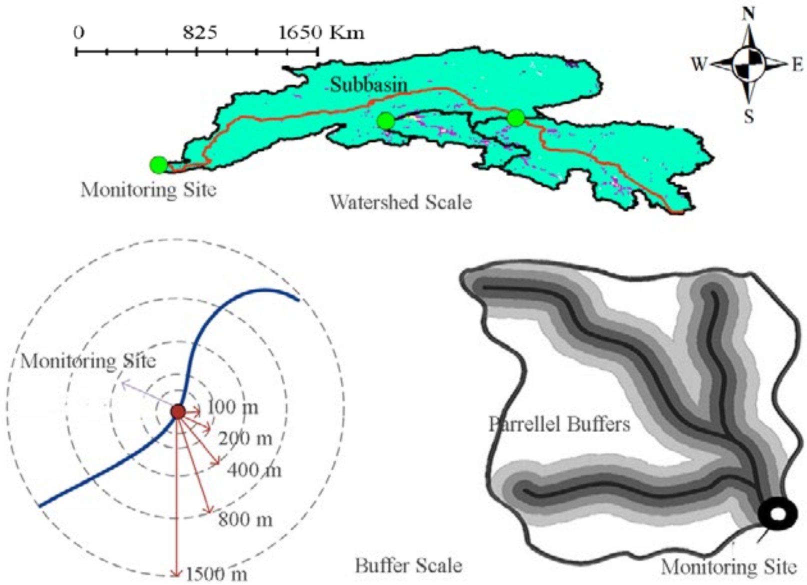

Fig. 1: Watershed scale and buffer scale techniques used for water quality explanatory variables identification

al., 2005, Hill, 1981, Haidary, et al., 2013, Liu, et al., 2012, Sun, et al., 2013, Wan, et al., 2014) as obvious from Fig. 2. It highlights that agricultural activities degrade surface water quality. Longer growing seasons and excessive plowing enhance sediment load via irrigation tail water discharges and surface runoff which effects oxygen concentration and water temperature resulting in unfavorable condition for aquatic organisms (Malone, 2009). Intense application of fertilizers and insecticides for high crop yield can impair nearby water bodies. Surface runoff and leaching sweep excessive phosphorous and nitrogen from agricultural fields to nearby water bodies which increase nutrient concentration enhancing algal blooms and eutrophication resulting in aquatic organisms death (Carpenter, 2008, Pärn, et al., 2012). Nitrate concentration in surface is attributed to over fertilization and excessive ploughing which loosen the soil structure making condition suitable for surface runoff (Tong and Chen, 2002, King, Baker, Whigham, Weller, Jordan, Kazyak and Hurd, 2005, Unwin, et al., 2010). There are three main transport mechanisms for nutrients including dissolution (soil mineralization, adsorption-desorption, enzyme hydrolysis, saturated soil nutrients solubilisation which leads to leaching), physical (soil erosion, and transport), and incidental (short-term displacement of fertilizer, manure or animal feces) (Haygarth, et al., 1997). Source to sink transport of nutrients (N and P parameters) is a complex phenomenon and relies on micro-scaled processes including climatic drivers, form (dissolved or particulate) of the nutrient, flow pathways, flow-path length, soil, runoff, erosion and leaching (Soranno, et al., 2015).

Influences of urban activities on water quality

It is obvious from literature that urban sprawl has strong positive association with N-parameters, P-parameters and COD (Tong and Chen, 2002, Lee, Hwang, Lee, Hwang and Sung, 2009, Li, Gu, Tan and Zhang, 2009, Zhao, Lin, Yang, Liu and Qian, 2015, Ahearn, Sheibley, Dahlgren, Anderson, Johnson and Tate, 2005, Hill, 1981, Haidary, Amiri, Adamowski, Fohrer and Nakane, 2013) as demonstrated by Fig. 2. Human interference at urban communal level badly effects surface water quality (Li, et al., 2015). Change in physical landscape and paved surface area alters watershed hydrology which badly impacts surface water quality (Kennen, et al., 2010). Anthropogenic activities at urban communal level produce various kinds of NPS including nutrients (Emmerth, et al., 1996, Rose, 2002, Lee, et al., 2000), heavy (metals) (Norman, 1991, Callender, et al., 2000, Hunter, et al., 1979), sediments (Waller, et al., 1986, Wahl, et al., 1997), bacteria (Gregory, et al., 2000, Mallin, et al., 2000), and other contaminants. Paved surface

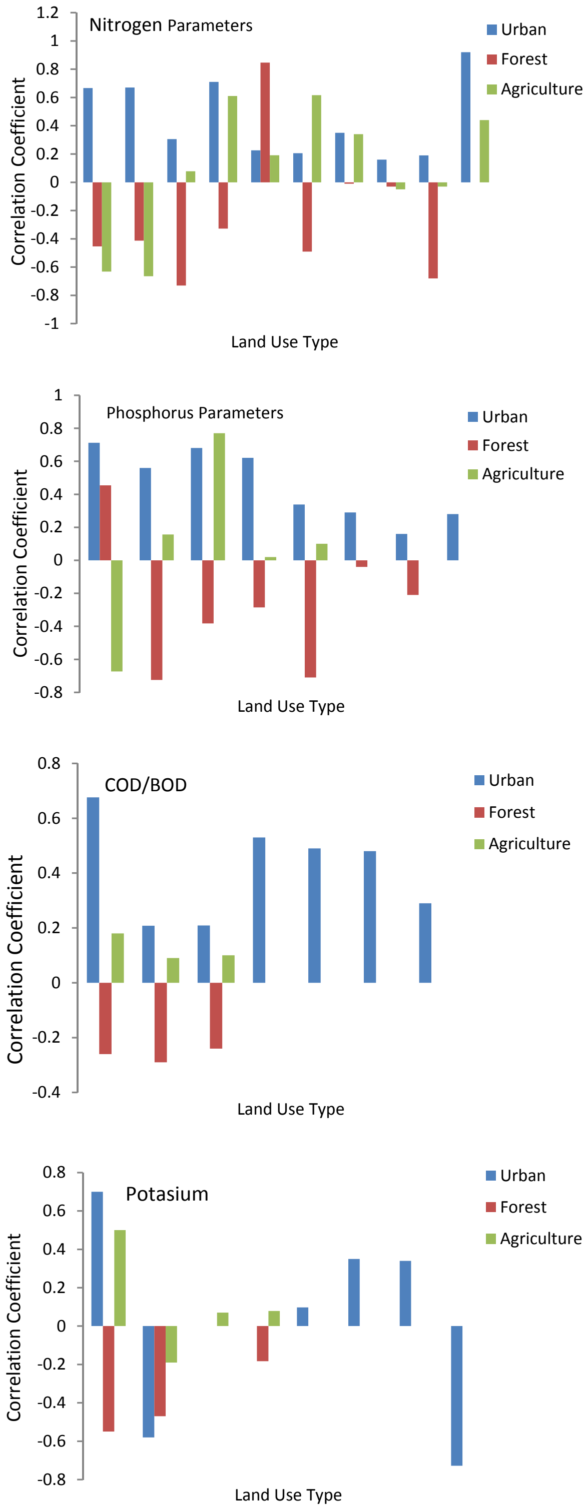

Fig. 2: Correlation between urban, forest and agriculture land uses with N-Parameters, P-Parameters and COD

plays major role in surface water impairment at urban communal level due to reduce infiltration, short time of concentration and high flow volume *(Arnold Jr, et al.,* 1996, Paul, *et al.,* 2001, Morse, *et al.,* 2003) which fuels soil erosion, in stream silting etc. Surface runoff sweeps point and diffuse pollutants (White, *et al.,* 2006). Untreated sewage and industrial effluent due to shortage of treatment facilities also enhance surface water pollution (Sun, *et al.,* 2013, Ho, *et al.,* 2001, Dudgeon, 1992, Ding, *et al.,* 2015). Combined sewage overflow and leachate from failing septic tanks in urban area are the principle cause of nutrients. Nutrients are transported to nearby water bodies via surface runoff, erosion and leaching (Ding, Jiang, Fu, Liu, Peng and Kang, 2015).

Influences of deforestation on water quality

Literature shows that forests play protective role in safeguarding stream health as obvious from its negative linkage with N-parameters, P-parameters and COD (Tong and Chen, 2002, Lee, Hwang, Lee, Hwang and Sung, 2009, Li, Gu, Tan and Zhang, 2009, Zhao, Lin, Yang, Liu and Qian, 2015, Ahearn, Sheibley, Dahlgren, Anderson, Johnson and Tate, 2005, Hill, 1981, Haidary, Amiri, Adamowski, Fohrer and Nakane, 2013) as shown in Fig. 2. Forests mainly effects watershed hydrology and water quality. Forest soil biological and physico-chemical characteristics have the ability to filter pollutants from water and recycle nutrients. In forests, subsurface flow is comparatively higher than overland flow reduces surface runoff which decline soil erosion (Neary, *et al.,* 2009, Baillie, *et al.,* 2015, O'Loughlin, 1994, Cooper, *et al.,* 1988, Foley, *et al.,* 2005, Quinn, *et al.,* 1997). Water temperature is the direct consequence of air temperature fueled by deforestation (Allan, *et al.,* 2007, Collier, *et al.,* 2003). Deforestation practices causes water quality problems which includes decrease in dissolved oxygen (DO) concentration (Baillie, *et al.,* 2005), enhancement of soil erosion (Fahey, *et al.,* 2006, Fransen, *et al.,* 2001, Marden, *et al.,* 2006), increase in nutrient concentration (disruption of nutrient cycling, sediment transport and increased leaching) (Hartman, 2004, Pike, *et al.,* 2010) and enhancement in periphyton production (increased solar radiation and nutrients) (Boothroyd, *et al.,* 2004, Death, *et al.,* 2006, Reid, *et al.,* 2010, Thompson, *et al.,* 2009). Deforestation fuels nitrate (NO_3) concentration in nearby surface water bodies due to reduced uptake of nutrients by vegetation and decomposition of decayed plants material. Nitrate concentration in deforested catchment is 50 times as compared to forested catchment (Falkenmark, *et al.,* 1989, Brooks, *et al.,* 2012). Forests improve water quality owing to lower human intrusion and higher biological nutrients retention capacity (plant and microbial assimilation) (Gardner and McGlynn, 2009, Ding, Jiang, Fu, Liu, Peng and Kang, 2015). LULC is the principal determinant which degrades surface water quality. Identification of pollution sources originating from various types of land use and its transport mechanism are extremely complex due to multifactor context. LULC-water quality relationship can give idea about the pollution sources. LULC-water quality relationship can be exposed using various statistical approaches. Numerous statistical techniques are available which can be used to solve different questions. The applications of appropriate technique for LULC-water quality relationship are essential for robust modelling which will help for better water quality management.

Statistical modeling techniques to analyze water quality problems

Various multivariate statistical techniques are available to make relation between LULC and water quality. Different statistical approaches details are shown in Fig. 3. Among these techniques, some are applicable to remote sensing observations while the other to discrete samples data. Conventional statistical approaches are widely used to uncover structure, association in multivariate variables and to predict responses (Vega, *et al.,* 1998, Helena, *et al.,* 2000, Liu, *et al.,* 2003, Reghunath, *et al.,* 2002, Simeonov, *et al.,* 2003, Alberto, *et al.,* 2001). In contrast, some techniques are restricted to address spatial relationships and variability which includes geographically weighted regression (Atkinson, *et al.,* 2001, Wooldridge, *et al.,* 2006). Statistical modeling needs small amount

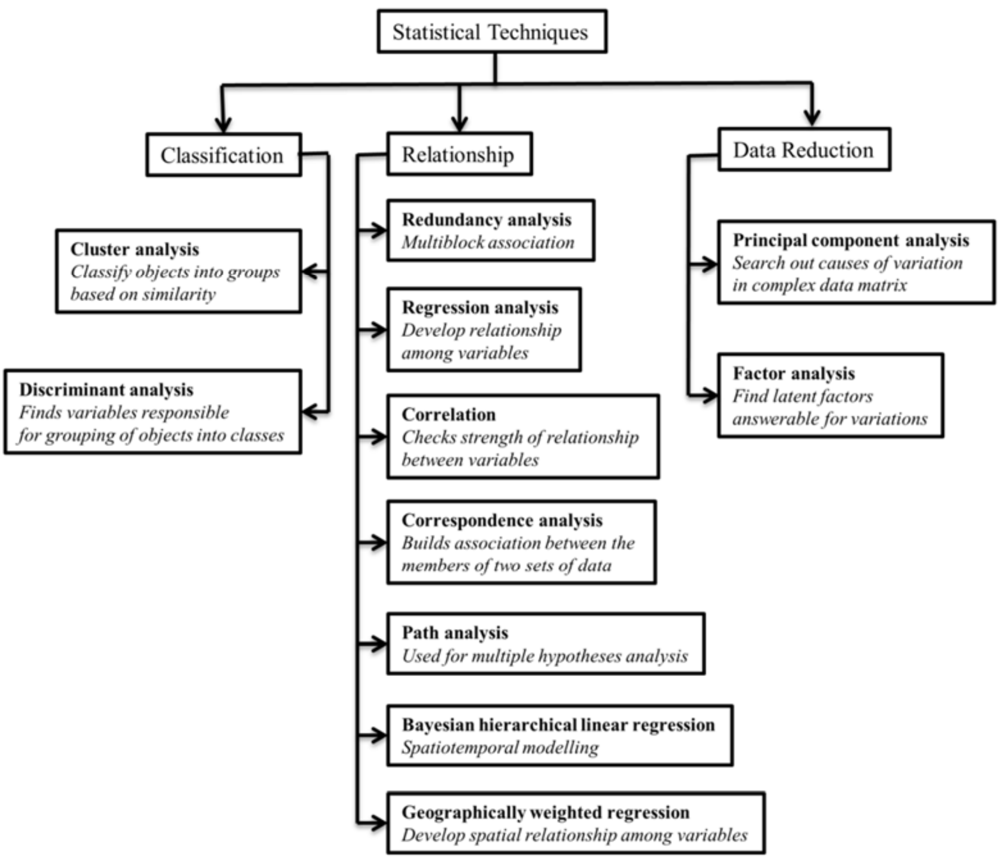

Fig. 3: Summary of different statistical techniques along with their purposes and applications

of dataset as compared to water quality models. Commonly used statistical methods for LULC-water quality relationship are demonstrated by Fig. 4.

Statistical approaches used for classification

Cluster analysis (CA)

CA is widely used in spatiotemporal classification of water quality data which helps in data interpretation and pattern identification as obvious from Fig. 4 (Singh, *et al.,* 2004, Shrestha, *et al.,* 2007). Principal limitation of CA technique is that it assess spatiotemporal differences but did not give any details of these differences (Alberto, del Pilar, Valeria, Fabiana, Cecilia and de los Ángeles, 2001, Yang, *et al.,* 2009). The group characteristics may be find after water quality data analysis which is not known in advance (Zhao, *et al.,* 2009, McNeil, *et al.,* 2005). McNeil *et al.* (2005) classified water quality data into nine groups which shows that natural processes impact surface water chemistry. Moreover, CA is used for spatiotemporal classification in various case studies: Suquia River in Argentina (Alberto, del Pilar, Valeria, Fabiana, Cecilia and de los Ángeles, 2001); Pisuerga River in Spain (Vega, Pardo, Barrado and Debán, 1998); Fuji River in Japan (Shrestha and Kazama, 2007) ; Gomti River of India (Singh, Malik, Mohan and Sinha, 2004); and the Mahanadi River in India (Panda, *et al.,* 2006).

Discriminant analysis (DA)

In comparison to CA, DA has limited application in surface waters. Literature shows that DA has the ability to significantly reduce multivariate data matrix by highlighting water quality variables responsible for spatiotemporal variations (Singh, Malik, Mohan and Sinha, 2004, Shrestha and Kazama, 2007, Yang, Linyu and Shun, 2009, Singh, *et al.,* 2005, Koklu, *et al.,* 2010). DA highlights few variables associated with biggest variation in water quality dataset via dimension reduction (Alberto, del Pilar, Valeria, Fabiana, Cecilia and de los Ángeles, 2001). Kowalkowski *et al.* (2006) used DA for the confirmation of grouping formed by CA. The main demerit of using DA is that it does not give any idea about differences among the groups.

Statistical approaches used for data reduction

Factor analysis (FA) and principal component analysis (PCA)

PCA and FA are excessively practiced for water quality dimension reduction to expose the underlying structure which elucidates maximum variance (Bahar, Ohmori and Yamamuro, 2008, Vega, Pardo, Barrado and Debán, 1998, Simeonov, Stratis, Samara, Zachariadis, Voutsa, Anthemidis, Sofoniou and Kouimtzis, 2003, Shrestha and Kazama, 2007, Ling,

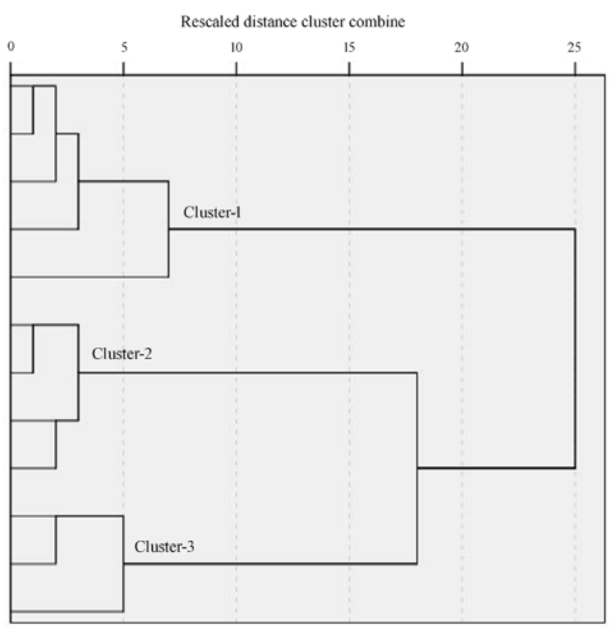

Fig. 4: Dendrogram showing pattern of objects homogeneity

et al., 2017). Md. Mezbaul Bahar (2008) carried out PCA to find out groups of LULC characteristics in O-Hori river watershed, Japan. PCA and FA identify main variables which causes variations in water quality (Yang, Linyu and Shun, 2009). PCA identify reduced number of latent factors which helps in the identification of temporal (climatic and seasonal) and spatial (originated from human activities) pollution sources (Vega, Pardo, Barrado and Debán, 1998, Simeonov, Stratis, Samara, Zachariadis, Voutsa, Anthemidis, Sofoniou and Kouimtzis, 2003, Shrestha and Kazama, 2007, Ling, Soo, Liew, Nyanti, Sim and Grinang, 2017). PCA explains similar characteristics water quality variables by only one factor (Singh, Malik, Mohan and Sinha, 2004, Boyacioglu, *et al.,* 2008, Kannel, *et al.,* 2007, Kowalkowski, *et al.,* 2006). Loss of information occurs, unable to explain 100% variability, while using FA and PCA which is its major drawback.

Statistical approaches for relationship identification

Redundancy analysis (RDA)

RDA is a multi-block analysis which is excessively practiced to evaluate LULC-water quality relationship (Grieu, *et al.,* 2005, De Jonge, *et al.,* 2008, Uthicke, *et al.,* 2008, Ye, *et al.,* 2009). Jun Zhao (2015) tried this technique to model LULC-water quality relationship (Zhao, Lin, Yang, Liu and Qian, 2015). Literature shows that LULC-water quality relationship changes with scale and seasons (Sliva and Williams, 2001, Chen, *et al.,* 2016). Direct gradient analysis isolates highly polluted monitoring station from the remaining better water quality monitoring sites (Sliva and Williams, 2001, Schoonover and Lockaby, 2006, Zeilhofer, *et al.,* 2010).

Correspondence analysis

Correspondence analyses finds out categories and distinguish them by separating. Same category variables are plotted close to one another while different categories variables are plotted far apart (Damanik-Ambarita, *et al.,* 2016). Jun Zhao *et al.* (2015) expose that water quality of industrial area is worse as compared to urban land and sub urban areas (Zhao, Lin, Yang, Liu and Qian, 2015). Correspondence analysis helps in the identification of water contamination sources impairing water quality at particular monitoring stations (Šmilauer, *et al.,* 2014, Tanrıverdi, *et al.,* 2010).

Correlation analysis

It is obvious from literature that significant correlation exists between water quality variables and LULC characteristics as shown in Fig.3.

Regression analysis

Literature shows that regression is extensively used for modeling LULC-water quality relationship, as obvious from Table 3, to expose the complexity of associations. The most commonly used regression analysis techniques are described in Table 3.

MAXR analysis

MAXR regression develop model from any possible combination of independent variables. Model selection is based on increasing number of independent variables i.e. one independent variable model (highest R^2), best two independent variables model, the process continues till entire independent variables model (Cody, *et al.,* 1997). Best predictive model selection is based on Mallow's Cp (sum of square errors) and R^2 value. Best predictive model has high R^2 and low Cp value (Yu, 2000, Moore, *et al.,* 2003). Jon E. Schoonover and B. Graeme Lockaby (2006) used the above stated technique to make relationships between land use variables and bacteriological parameters and abiotic variables (Schoonover and Lockaby, 2006).

Partial least square regression (PLSR) technique

PLSR technique analyze response variable based on a set of independent variables which has highest predicting power (Abdi, 2010). This technique produces comparatively good results (predictions) because it uses the most significant linear association (Ai, *et al.,* 2015). The above stated technique uses the outcomes of MLR and PCA. Shortcomings of the conventional multivariate regression methods in analyzing noisy and multi-collinear dataset is covered by the approaches based on multivariate statistical projection i.e. PLSR (Abdi, 2010). PLSR is very useful in situation when samples to variables ration is lower (Lindberg, *et al.,* 1983). Du Plessis *et al.* (2015) used PLSR regression model to gauge the LULC-water quality relationship (du Plessis, *et al.,* 2015). Fang et al. (2015) identify main variables controlling sediment yield from agricultural watershed using 4 different PLSR models (Fang, *et al.,* 2015).

Table 3: Regression equation between water quality indicators and land use

Regression equation	Reference
Ln (TN) = - 0.086 (F) - 0.057 (Village) + 0.301 (U) + 0.7 (WAT) + 0.954 NO_3- N = -0.083 (F) - 0.240 (Village) +0.794 (U) +1.209 (Bare) + 2.819	(Zhang and Wang, 2012)
log Cl- = - 0.04 (IS) - 0.06 (M) - 0.09 (E) - 0.06 (Ag) + 8.22 log K+ = 0.007(IS) - 0.02 (M) + 1.21 TP = - 0.005 (IS) - 0.005 (M) - 0.005 (E) - 0.004 (Ag) + 0.54 log FC = 0.06 (IS) + 4.85	(Schoonover and Lockaby, 2006)
Na = 6.591 + 0.158 (BAR)−0.075 (VEG) Cl^- = 26.414−0.337 (VEG) NO_3^--N = 0.724 + 0.102 (BAR)	(Li, *et al.*, 2008)
Whole watershed Ln(NO_3^-)= -0.516 (FOR) – 25.244 (RES) + 3.851 (AGR) – 7.679 (Orchards) (R^2 = 0.1861 P = 0.14) Contributing zone Ln(NO_3^-)= -3.402 (FOR) + 22.355 (RES) + 1.624 (AGR) + 5.15 (Orchards) (R^2 = 0.959 P = 0.01)	(Basnyat, *et al.*, 2000)
Buffer Wet season EC= 0.974 (URB) + 58.896 pH= 0.031 (StDev slope) + 0.006 (URB) + 6.024 TP= 0.042 (URB) + 4.486 TS= 0.533 (URB) + 83.439 Temp= 0.03 (URB) – 0.089 (StDev slope) + 0.005 (Mean elevation) + 5.615 Dry season EC= 0.486 (URB) – 0.124 (Mean elevation) + 139.099 DO^a= 627.083 (Mean slope) + 10,871.260 (SFR age) – 11,571.635 NN^b= −0.003 (Mean elevation) – 0.008 (%SFR) + 0.59 pH= 0.295 (SFR age) – 0.002 (Mean elevation) + 0.029(StDev slope) + 6.963 TP= −0.017 (Mean elevation) + 0.346 (Streets) + 9.713 TS= −0.409 (Mean elevation) + 5.63 (Mean slope) – 6.176(StDev Slope) + 186.291 Temp= −0.01 (Mean elevation) + 0.191 (StDev slope) – 0.017(%SFR) – 0.096 (Mean slope) + 15.06	(Pratt and Chang, 2012)
Dry season Buffer= 300 m Turbidity= -5.985(C) -3.98E-03(RF) + 0.180(B) - 4.75E-04(S) + 7.740E-02(F) + 8.868E-02(AP) + 8.433E-02(PF)+ 5.728E-02(URB) Buffer= 510 m Nitrate= -3.294(C) -2.53E-02(RF) + 2.486E-02(B) + 1.032E-02(S) + 5.234E-02(F) + 8.074E-02(AP) + 6.804E-02(PF) + 2.976E-02(URB) Nitrite= -0.313(C) - 4.28E-04(RF) - 3.49E-03(B) + 4.368E-04(S) + 6.766E-03(F) + 8.894E-03(AP) + 7.811E-03(PF) + 3.259E-03(URB) Buffer= 90 m Fecal coliform= -179283(C) + 2386.6(RF) + 7513.6(B) - 1899.4(S) + 1563.0(F) + 2078.3(AP) + 5116.4(PF) + 1717.7(URB) Wet season Buffer= 90 m Nitrate= 1.186E-02(C) - 1.18E-04(RF) + 1.756E-04(B) - 6.32E-04(S) - 3.42E-04(F) + 4.045E-04(AP) - 7.82E-04(PF) + 9.974E-04(URB) Phosphorus= - 0.661(C) + 1.50E-02(RF) + 1.958E-02(B) + 11.133E-03(S) + 5.976E-03(F) - 3.57E-03(AP) + 1.720E-02 + 3.856E-03(URB)	(Maillard and Santos, 2008)
1-km Buffer zone. Zn = 0.0204 (population density) + 1.9156 Cu = 0.0112 (population density) + 2.7478 Oil Grease = 0.3241 (population density) + 54.79 TSS = 10.994 (population density) + 1981.2 NO_3-NO_2 = 0.1511(population density) + 62.037 Zn = 0.4196 (ISA density) - 2.8776 Cu = 0.212 (ISA density) + 0.9196 Oil Grease = 6.2325 (ISA density) -3.0067 TSS = 223.13 (ISA density) - 466.39 NO_3-NO_2 = 2.7353 (ISA density) + 42.175	(Xian, Crane and Su, 2007)

C= constant, RF= Riparian Forest, B= Barren, S= Savanna, F= Forest, AP= Agro-Pastrol, PF= Planted Forest, URB= Urban, AGR= Agricultural, IS = % Impervious surface, M = % Mixed forest, E = % Evergreen forest, Ag = % Pasture, VEG= Vegetation, SFR= Single family residential, SFR age= Average building age of SFR homes, %SFR= % area of SFR, RES= Residential area

a= Exponentially transformed.

b= Log 10 transformed.

Linear mixed effect model

Linear mixed effect model is based on fixed and random effects. Fixed effects are related with independent variables while random effects are based on the interaction between the variable of interest and its collection location. Seilheimer et al. (2013) used this technique to find LULC type which is highly associated with phosphorus concentration (Seilheimer, *et al.,* 2013). Linear mixed effect model was used for predicting fecal coliforms and turbidity (Delpla and Rodriguez, 2014). LULC-water quality relationship can be strengthen by feeding terrestrial determinants (Taka, *et al.,* 2015). Linear mixed effect model develops association between TSS, nitrate-N flux and LULC to isolate the most significant model using backwards stepping approach as obvious from previous studies (Ahearn, Sheibley, Dahlgren, Anderson, Johnson and Tate, 2005). Soranno *et al.* (2015) found 3 factors impacting land use-lake nutrient relationships i.e. hydrologic connectivity, region and spatial extent (Soranno, Cheruvelil, Wagner, Webster and Bremigan, 2015).

Stepwise multiple linear regression (SMLR)

SMLR technique filters out highly significant independent variables by dropping the less significant explanatory variables to find the highest correlated variables with dependent variable. Pratt and Chang (2012) used SMLR technique to identify the most significant independent variables which were highly related to surface water pollution (Pratt and Chang, 2012). Xiao *et al.* (2016) used SMLR to investigate LULC variable which has significant correlation with water quality parameters at multiple scales (Xiao, Wang, Zhang and Zhang, 2016). Mustapha and Abdu (2012) used SMLR to find best predictor variable which causes variations in water quality (Mustapha, *et al.,* 2012).

Path analysis

Path analysis is the extended format of multiple linear regression used for identifying the strength and underlying mechanism of cause- effect association between the interacting webs (Grace, 2006)2006. Path analysis assesses causal linkage. It quantifies the effects (direct, indirect and total) of independent variables on dependent variable. Literature shows that this approach models the association between social, terrestrial, hydrologic and water quality variables (Wu, Stewart, Thompson, Kolka and Franz, 2015, Lewis, *et al.,* 2007).

Ordinary least square (OLS)

OLS is a well-known regression technique which tries to assess relations between two or more variables. It has the ability to develop association between independent variable and water quality variables at large scale (creates a single regression equation). This technique highlight the most significant variables in regression equation (Sun, *et al.,* 2014). OLS regression is advantageous using Arc GIS because it gives residual for each monitoring site, facilitating the watershed managers to easily check spatial autocorrelation among residuals (Pratt and Chang, 2012).

Geographically weighted regression (GWR)

GWR examines LULC-water quality relationship by incorporating coordinates in regression equation (Atkinson and Tate, 2001). Classical regression techniques are independent of spatial variation because it assumes constant relationship over the study area (Atkinson and Tate, 2001). Local parameters are computed by traditional regression while GWR weights are assigned based on the distance from the water quality monitoring station (Huang, *et al.,* 2015). GWR is the advance form of traditional regression equation which captures spatial variations by developing different regression equations between variables at various spots in space (Wooldridge, Brodie and Furnas, 2006). Local coefficient of GWR evaluates the strength of water quality-independent variables relationship (Sun, Guo, Liu and Wang, 2014). Simply, GWR models have the ability to compare independent variable-water quality parameters relationships at local scale.

Bayesian hierarchical linear regression (BHLR)

BHLR technique is used for spatiotemporal analysis because it takes into account the interaction of variables in space and time (Pollice, *et al.,* 2010). BHLR method is useful for spatiotemporal modeling and has been proved suitable for handling missing data prediction (Cha, *et al.,* 2010, Pollice, *et al.,* 2010, Liu, *et al.,* 2008). BHLR can be split into three parts i.e. data model, parameter model and process model (Wan, Cai, Li, Yang, Li and Nie, 2014). Every part perform a specific function i.e. distribution of data, distribution of parameters and regression model respectively. The above mentioned models are connected via probability relationships (Wikle, *et al.,* 2003). This method is handy in evaluating the complicated LULC-water quality relationships at various scales (Wan, Cai, Li, Yang, Li and Nie, 2014).

DISCUSSION

Monitoring techniques provide useful water quality data but statistical approaches and water quality models are required to fully uncover spatiotemporal variations. Water quality models are really sophisticated but their applicability is subjected to the availability of extensive data record. On the other hand, statistical techniques are easy and need comparatively less data record. Various statistical approaches can be used to answer different research questions as earlier discussed. Traditional multivariate statistical approaches uncover hidden information in water quality data but they are unable to expose spatial relationship. These techniques assume constant relationship over the study area. Average relationships across the entire study area can hide the interesting variability of associations. This gap is filled by GWR which explains spatial relationships among water quality and land use characteristics. Moreover, BHLR has the ability to solve complex spatiotemporal variations at multiple scales. Historically water quality data collections are based on discrete sampling and were analyzed through statistical techniques which were designed for spatially isolated measurements. Statistical approaches like CA, DA, FA, PCA etc. have the capacity to extract meaningful results from data. Comprehensive data, remote sensing imagery, application for water quality monitoring, traditional multivariate techniques like CA, DA, FA, PCA etc. have passed through various stages of evolution and transferred to remote sensing imagery analysis. Statistical approaches are growing with frequent use of remote sensing imagery for water quality analyses to suite the requirement of comprehensive data. GWR is suitable for comprehensive data analyses but not solely designed for remote sensing imagery. Main merits and demerits of statistical approaches are demonstrated by Fig. 5.

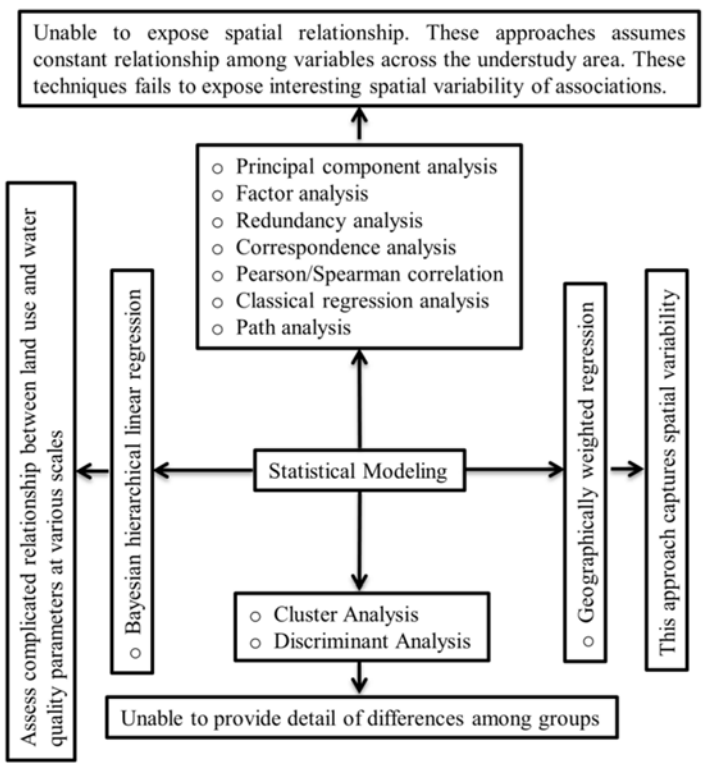

Fig. 5: Merits and demerits of statistical approaches

CONCLUSION

In this article we discussed spatial analysis techniques, LULC effects on surface water quality and various statistical techniques. This paper provides comprehensive knowledge regarding LULC-water quality relationship. Spatial analysis scale should be decided based on the watershed area to get robust LULC-water quality model for better management of surface waters. Moreover, environmental determinants vary in space which affects the pollutants load from land use. For large scale studies these factors should be considered. After studying the literature, we concluded that physical based models need large dataset. As compared to physical based water quality/ hydrologic modeling, statistical modeling is easy to understand, simple, efficient with limited experimental data set. Historically, water quality data collection is based on discrete sampling. The aforementioned data were analyzed via traditional statistical techniques which suite spatially separated measurements like PCA, regression analysis etc. Recently the application of spatial comprehensive data source i.e. remote sensing imagery has been extended to water quality monitoring. Traditional statistical techniques cannot explain the complex LULC-water quality relationship. To overcome this problem spatial statistical techniques were introduced like GWR etc. These techniques have the ability to incorporate coordinates to fully exploit the spatial variability. Moreover, BHLR has the ability to analyze LULC-water quality relationship taking into account spatiotemporal variation. All land use did not contribute equal amount of pollutant to the nearby water body. Some land use generates more while some produce less amount of pollutant. It's quite misleading to assume that all land use produce equal amount of pollutant. Area with maximum pollution production as well as with higher discharge should be identified to make robust relationship between water quality and land use. Storm runoff drains more pollutants from land as compared to dry season. It's ambiguous to assume that both seasons produce equal amount of pollutants load. Rainy season should be analyzed separately.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this manuscript.

ABBREVIATIONS

Ag	% Pasture
Agr	Agricultural
AP	Agro-Pastrol
B	Barren
BHLR	Bayesian hierarchical linear regression
BMPs	Best management practices
BOD	Biochemical oxygen demand
CA	Cluster analysis
COD	Chemical oxygen demand
DA	Discriminant analysis
Division	Landscape division index
DO	Dissolved oxygen
E	Evergreen forest
ED	Edge density
F	Forest
FA	Factor analysis
FC	Fecal coliform
For	Forest
GIS	Geographic information system
Gra	Grass area
Gwr	Geographically weighted regression
IJI	Interspersion and Juxtaposition Index
Ind	Industrial
Isa	Impervious surface area density
Lpi	Largest patch index
Lsi	Landscape shape index
LULC	Land use land cover
M	Mixed forest
Mlr	Multiple linear regression
Nn	Nitrogen nitrate
NO_3+NO_2	Total nitrates and nitrites

Np	Number of patches
Nps	Non-point source
Ols	Ordinary least square
Pca	Principal component analysis
Pd	Patch density
Percent SFR	% area of SFR
Pf	Planted forest
Pland	Percentage of landscape
Plsr	Partial least square regression
Rda	Redundancy analysis
Res	Residential area
Rf	Riparian Forest
S	Savanna
Sem	Structure equation modeling
Sfr	Single family residential
Sfr age	Average building age of SFR homes
Shdi	Shannon's Diversity Index
Shei	Shannon's Evenness Index
Smlr	Stepwise multiple linear regression
Srp	Soluble Reactive Phosphate
SS	Suspended solids
TDP	Total dissolved phosphorus
TDS	Total dissolved solids
TKN	Total Kjeldahl nitrogen
Tmi	Total major ion
TN	Total nitrogen
TP	Total phosphorous
Tp	Total edge
Urb	Urban
Veg	Vegetation
Wat	Water body
Wet	Wetland

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