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# A cost-effective and efficient framework to determine water quality monitoring network locations


Hossein Alilou[1], Alireza Mogaddam Nia[2*], Hamidreza Keshtkar[3], Dawei Han[4], Michaela Bray[5]

[1] Faculty of Natural Resources, University of Tehran, Iran.

Email: h.aliloo@ut.ac.ir

[2]Faculty of Natural Resources, University of Tehran, Iran.

(Corresponding author) Email:a.moghaddamnia@ut.ac.ir

[3] Faculty of Natural Resources, University of Tehran, Iran.

Email: keshtkar@ut.ac.ir

[4] Department of Civil Engineering, University of Bristol, Bristol, BS8 1TR, UK.

Email: dawei.han@bristol.ac.uk

Hydro-Environmental Research Center, School of Engineering, Cardiff University, UK.

Email: braym1@cardiff.ac.uk


## Abstract


A crucial part in designing a robust water quality monitoring network is the selection of appropriate water quality sampling locations. Due to cost and time constraints, it is essential to identify and select these locations in an accurate and efficient manner. The main contribution of the present article is the development of a practical methodology for allocating critical sampling points in present and future conditions of the non-point sources under a case study of the Khoy watershed in northwest Iran, where financial resources and water quality data are limited. To achieve this purpose, the river mixing length method (RML) was applied to propose potential sampling points. A new non-point source potential pollution score (NPPS) was then proposed by the analytic network process (ANP) to classify the importance of each sampling point prior to selecting the most appropriate locations for a river system. In addition, an integrated cellular automata–Markov chain model (CA–Markov) was applied to simulate future change in non-point sources during the period 2026–2036. Finally, by considering anthropogenic activities through land-use mapping, the hierarchy value, the non-point source potential pollution score values and budget deficiency in the study area, the seven sampling points were identified for the present and the future. It is not expected, however, that the present location of the proposed sampling points will change in the future due to the forthcoming changes in non-point sources. The current study provides important insights into the design of a reliable water quality monitoring network with a high level of assurance under certain changes in non-point sources. Furthermore, the results of this study should be valuable for water quality monitoring agencies looking for a cost-effective approach for selecting sampling locations.

**Keywords:** Water quality monitoring network; River mixing length; ANP; Land-use change modeling; Cost-effective siting sampling locations.

## 1. Introduction

A water quality monitoring network (WQMN) is used to interpret current situations and trends in a surface water system and to support decision-makers in realizing and managing stakeholders' health risks (Baltacı et al., 2008; Telci et al., 2009; Xiaomin et al., 2016). One of the most important keys to monitoring water quality is to design suitable locations for sampling points (Sanders et al., 1983). The frequency of sampling and the mode of data presentation and interpretation become unimportant if gathered samples are not representative of the water body (Do et al., 2012). By selecting the best locations for sampling points, time and cost, which have major effects on the process of the WQM program, can be managed more effectively (Kovacs et al., 2016; Behmel et al., 2016).

Behmel et al. (2016) reviewed and summarized prolific literature on the WQMN program. Moreover, they remarked that there is not an eminently suitable and accepted approach to designing a WQMN program. It is widely acknowledged that most recent relevant studies have chiefly concentrated on mathematical aspects for the selection of water quality sampling locations (Do et al., 2012). To select representative sampling points, entropy and fuzzy approaches (Mahjouri and Kerachian, 2011; Memarzadeh et al., 2013; Chang and Lin, 2014) have been employed. In addition, the genetic algorithm method has been applied to select representative sampling points (Telci et al., 2009; Liyanage et al., 2016). Furthermore, a combination of numerical models, experiments, and matter-element analysis has been applied to assess WQMNs (Chen et al., 2012; Keum and Kaluarachchi, 2015). Some researchers have applied geostatistical methods (Beveridge et al., 2012), multivariate statistical techniques (Ouyang, 2005; Noori et al., 2010; Wang et al., 2014), and multi-objective analysis (Ning and Chang, 2002; Khalil et al., 2011; Aboutalebi et al., 2016) to optimize and propose sampling points. Furthermore, the combination of a fuzzy logic method and the geographical information system (GIS) (Strobl et al., 2006 a) was applied to establish exact location of sampling points. However, in most of the above-mentioned studies, neither human activities nor natural processes were comprehensively considered (Do et al., 2012).

In contrast to the methods described above, some researchers have introduced alternative methods for locating sampling points and properly designing WQMN (Sharp, 1971; Sanders et al., 1983; Park et al., 2006; Do et al., 2011; Varekar et al. 2012; Varekar et al., 2015 a, b). However, there are some limitations in employing these approaches for rivers without tributaries as well as short or long rivers. Moreover, there should be reliable and regular long-term data collectetion on the water quality parameters, which is not particularly applicable to developing countries (e.g., Iran) where there are limited financial resources and incomplete hydrological data sets (Choubin et al., 2018). In turn, Do et al. (2012) pioneered in using the Sanders et al. (1983) modification of Sharp's approach and the river mixing length introduced by Day (1977) to solve the aforementioned issues in proposing sampling sites. The advantages of this method can be summarized in the following points: (i) it is mainly suitable for rivers with inaccurate or unreliable on hydraulic and flow characteristics data; (ii) it is appropriate for rivers of different lengths and without branches; (iii) it uses available watershed data to select sampling points; and (iv) it takes scale and frequency into account when there is a budget deficiency. However, in the aforementioned study, few non-point sources and water quality variables were used; furthermore, inter-relationship between criteria and sub-criteria has never been considered. In order to enhance, improve, and compensate for the shortcomings of previous studies, the analytic network process (ANP) procedure (Saaty and Takizawa, 1986) is needed. Other limitation of their study was to consider linear ground surface for buffer zone among candidate points (Varekar et al., 2015a). It is also worth mentioning that none of the literature on representing sampling points is able to predict the effect of future land-use change (non-point sources) on the location of WQMNs.

It is necessary to carefully consider land-use activities, especially, future land-use changes in order to discern and manage non-point pollution sources, particularly in modeling water quality (Sivertun and Prange, 2003; Wilson and Weng, 2011). The novelty and advantages of predicting land-use change are as follows: (i) people will adapt to future changes in environment and will have sustainable management (PETIT et al., 2001; Rounsevell et al., 2006); (ii) it is needed in making comprehensive strategies at a given watershed in order to deal with short and long term environmental problems (Wilson and Weng, 2011); (iii) the potential impacts of land-use change on water resources will be recognized. A couple of computer models have been used to simulate future land-use change (Theobald and Hobbs, 1998). However, among these scientific endeavors to forecast spatio-temporal land-use change in the future, Cellular automata-Markov chain (CA–Markov) model has played a main role (Mitsova et al., 2010; Behera et al., 2012; Subedi et al., 2013; Rimal et al., 2017). Although there are many studies in assessing and predicting future land-use change, many studies have concentrated on urban land-use change (Lopez et al., 2001; Sun et al., 2007; Yang et al., 2008; Sang et al., 2011; Mosammam et al., 2016; Aburas et al., 2017). Also, there is no literature directly identifying the impact of future land-use change on locating and relocating sampling points for WQMN in the future.

The objective of the current study is to propose and select sampling points for WQM under present and future conditions of non-point sources using an Iranian watershed as a case study. Firstly, the modified approach (Do et al., 2012) was employed to select potential sampling points based on existing data and budget limitations of the regional water authority. Secondly, land-use maps (1995, 2006, and 2016) were used to simulate the spatial distribution of land-use categories from 2016 to 2036 using the CA–Markov model. Thirdly, using the ANP method, relative pollution weight for each land-use category was calculated according to the review literature and professional questionnaire. Finally, non-point source potential pollution scores (NPPS) were identified for each candidate sampling point in order to prioritize and select sampling points for the years 2016, 2026, and 2036.

## 2. Material and methods

### 2.1. Study area

The Khoy watershed is located in West Azerbaijan province, northwest of Iran (Fig. 1). It has a drainage area of about 3166 $km^2$ and; its elevation varies significantly from about 938m to 3670m above sea level, with an average slope of 23.16 %. Köppen-Geiger climate classification system classifies its climate as cold semi-arid with the mean annual precipitation of 281.92 mm, which decreases from approximately 400 mm in the west with high elevation to about 190 mm in the north east. The study area is a mountainous area comprising three main rivers: (1) Qutor Chai (110.13 km long); (2) Gazan Chai (around 40 km long); and (3) Qudox Bogan (98 km long). During the last decade, mismanagement, heavy use of the land (e.g., overgrazing), industrialization, urbanization around these rivers, and currently irregular data collection and inappropriate location of existing hydrometric stations (Fig. 1) have created an urgent need for a robust WQMN in the study area based on current and future conditions.(financial issues)

**Fig. 1** SOMEWHERE HERE

### 2.2. Designation of representative sampling points

To determine representative sampling point locations, the RML method introduced by Do et al. (2012) was applied. In this approach, rivers and branches are divided into small segments, which are equal to the mixing lengths of rivers. They proposed that the middle of each segment can be considered as sampling points. River mixing length describes a distance over which an upstream water parcel will hold its original properties before it is mixed with the surrounding downstream water (Day, 1977). We first determined the mixing lengths for each branch or river only by using a single geometric parameter, the mean flow width, using a simple equation, L = 25W (Day, 1977; Do et al., 2012).

Therefore, we first used Google earth to measure the stream width because of its spatial resolution (15m-15cm) (http://earth.google.com). Then, to ensure the accuracy of the measured stream width, 100 bridges over the rivers were measured by field trips (Telci et al., 2009). In this study, ArcGIS 9.3 is used to divide a river system into small segments with different lengths which are equal to the river mixing length. Eq. (1) was then employed to identify the total number of segments of a branch or river. Finally, the total number of segments for an entire river network or the number of total potential points is achieved by applying Eqs. (2) (Do et al., 2012).

$$N_j = \frac{l_j}{L_j} = \frac{l_j}{25W_j} \quad (1)$$

$$N = \frac{1}{25}\sum_{i=1}^{n}\frac{l_j}{W_j} \quad (2)$$

where Nj is the total number of segments of river j; lj is the total length of river j; Lj shows river's mixing length of each segment; Wj is the stream width, and N is the total number of potential sampling points.

In the second step, based on existing stations and budget limitations of the regional water authority, Eq. (3) introduced by Sanders et al., (1983) was used to determine the number of stations needed in the study area. In this study, i is assumed as four.

$$S_i = 2^i - 1 \quad (3)$$

where $S_i$ is the number of stations and *i* is hierarchy of sampling points; i is a natural number. A high-hierarchy value point has a lower priority than a low-hierarchy value point in selecting sampling points (Sanders et al., 1983) (Fig. S. 1.).

In the third step, the location of sampling points with different $i^{th}$ hierarchy values should be determined. Therefore, Eqs. (4) – (5) were employed to identify the major centroid where $i^{th}$ hierarchy point is to be positioned in a segment whose magnitude is the closest (Do et al., 2012):

$$M_i = \frac{p_i + 1}{2} = \frac{\left(\frac{1}{25}\sum_{i=1}^{n}\frac{l_j}{w}\right) - k + 1}{2} \tag{4}$$

$$M_i + 1 = \frac{M_i + 1}{2} \tag{5}$$

where K is the total number of junctions and M*i* is the river mixing length's magnitude at the $i^{th}$ hierarchy. Segments that should be placed as sampling points with a different $i^{th}$ hierarchy are named "candidate sampling points".

### 2.3. Contributing area

Typically, the land unit areas being far away from the river cannot have pollution potential for surface water bodies (Sivertun and Prange, 2003). As a result, Sivertun and Prange (2003) proposed that pollutants produced at a distance of more than 1000 meters cannot reach the river or influence the river's water quality (contributing area). Therefore, a buffer zone 1000 m from the rivers is used. To remove the linear surface ground problem (simple buffer zone), the flow length of each land unit area (cell) is considered. The distance from any point in the river basin to the basin outlet is described by the flow length. The digital elevation model (DEM) is employed to measure the distance. To do this, the polyline of the rivers was first divided into points with approximately 30-meter intervals because of resolution of the DEM (30×30 meters). Then, for each point (outlet), its watershed was delineated and the flow length of each cell at any given watershed was computed. Finally, those cells having less than 1000 meters as flow length were considered as the buffer zone. The buffer zone between the candidate points was divided into catchments with different pollution sources affecting changes to water quality.

## 2.4. Modeling future land-use change

In this section, the trend of land-use change in the study area was monitored in order to simulate future changes in the years 2026 and 2036. To do so, the cellular-automata, Markov chain and remote sensing techniques were integrated to predict forthcoming changes in land-use. The framework proposed in this study consisted of five steps: (a) land-use mapping of 1995, 2006 and 2016 using the classification of Landsat TM and OLI images derived from the Maximum Likelihood method (b) calculation of the transition area matrix using a Markovian process; (c) generation of transition potential maps using multi-criteria evaluation (MCE), analytic hierarchy process (AHP), and fuzzy membership functions; (d) model evaluation based on the Kappa index; and (e) simulation of future land-use maps using the CA–Markov model.

### 2.4.1. land-use data

In the present study, Landsat data from the years 1995 (Landsat 5), 2006 (Landsat 5), and 2016 (Landsat 8) for path/row 169/33 were acquired from the United States Geological Survey (USGS) archive (http://earthexplorer.usgs.gov/) and used to generate land-use maps. To eliminate geometric distortion and atmospheric interference, first order polynomial and dark-object subtraction approaches were used, respectively (Wilson and Weng, 2011). Due to the lack of field observations at the time of the imaging, ground truth data was collected by visual interpretation of the high-resolution Quickbird images available in Google Earth (http://earth.google.com). This method has been reported in other studies, for example Keshtkar et al. (2017). The supervised classification method (Maximum Likelihood) was used to obtain the land-use maps corresponding to different years. Finally, six land-use classes (Residential, Agriculture, Rangeland, Forest/Wooded, Highway/Road, Water bodies) were introduced.

#### 2.4.2. CA–Markov model

The CA–Markov has been widely used to understand and measure urban expansion (Rimal et al., 2017) and landscape dynamics (Keshtkar and Voigt, 2016a). In the current study, the transition potential matrix was calculated based on land-use conditions during the periods 1995–2006, 2006–2016, and 1995–2016. To produce transition potential maps of urban areas, four general agents (distance to main roads, distance to water bodies, distance to urban areas, and slope) were set as driving factors. The ancillary data was chosen based on similar previous studies (Keshtkar and Voigt, 2016b; Moghadam and Helbich, 2013; Rimal et al., 2017). Fuzzy membership functions were applied to rescale driver maps into the range of 0–1, where 0 represents unsuitable locations and 1 represents ideal locations. Also, the AHP model was run to determine the weight of driving factors with the use of pair-wise evaluations. The individual weights and control points are listed in Table 1. Then, the performance of the CA–Markov model was evaluated using actual (derived from satellite image) and predicted (simulated using transition area matrix of 1995–2006) maps of the year 2016 based on the Kappa index. Finally, the land-use map of 2016 was used as the base map to simulate land-use maps for the years 2026 and 2036 by calculating the transition area matrix of 2006–2016 and 1995–2016, respectively.

Table 1.SOMEWHERE HERE

### 2.4. Relative potential pollution weight for non-point sources

Non-point pollution sources have been recognized as having a significant effect on the quality of runoff water (Baird et al., 1996). The areas with higher potential pollution will impact water quality; therefore, they should be strictly monitored (Chang and Lin, 2014). In this study, the ANP method was applied as a multi-criteria evaluation to determine relative potential pollution weights for non-point sources. Among multi-criteria decision-making (MCDM) approaches (e.g., AHP, DEA, and TOPSIS), the ANP method is the most appropriate method (Saaty and Vargas's, 2006; Kucukaltan et al., 2016), as it takes into account the criteria's dependencies and the calculation of their relative weights (Lin et al., 2009). Subsequently, event mean concentrations (EMC) of each non-point source are used to precisely calculate and determine relative potential pollution weight for non-point sources, which are located in the contributing area (Table 2). In this study, unlike the previous studies, six non-point sources, i.e. residential, agriculture, rangeland, forest/wooded, water bodies, and highway/road were used as criteria. In addition, more water quality variables, including total suspended solids (TSS), total phosphorus (TP), total nitrogen (TN), biochemical oxygen demand (BOD), and nitrate nitrogen (NO3-N), were employed as sub-criteria (Table 2). The relative weights of each criterion were achieved by the ANP method, implemented with SuperDecisions software, as the following steps:

1. Determining those criteria and sub-criteria (alternatives) with the greatest impact on establishing WQMN, and distinguishing the relationship between them using expert opinions and literature (Fig. S.2. and Table S.1). Non-point sources and water quality variables were recognized as criteria and sub-criteria, respectively (Table 2). In addition, their interaction were determined using the EMC values for each non-point sources (Table 2) and correlation matrix for water quality variables (Table S.1).This step is known as building the network (see Fig. S. 2. in Supplementary information) (Kucukaltan et al., 2016).

2. Designing the questionnaire, constructing pair-wise comparison matrixes, and consistency (Lin et al., 2009). In this step, the designed questionnaires were given out to ten hydrologist experts within and outside of Iran (see Fig. S. 3. in Supplementary information). After taking the experts' preferences and judgments between1–9 into account, the comparison matrix was constructed with Super Decision software. Then, the inconsistency of the comparison matrix was measured by the consistency ratio (C.R.); the proper consistency was equal to or less than 0.1. Further details can be found in (Saaty, 2005).

3. Finally, by calculating the un-weighted and weighted super matrix and limited matrix, respectively, the priority and relative weights of both criteria and sub-criteria were obtained (Morteza et al., 2016; Aragonés-Beltrán et al., 2017).

**Table 2** SOMEWHERE HERE

### 2.6. Scoring candidate sampling points

In this study, to prioritize and select sampling points in the years of 2016 and 2036, the weighted method, which has been used for solving the multiple criteria evaluation issues (Chang and Lin, 2014), is selected. Therefore, new potential pollution scores for non-point sources was introduced (Eq. (6)). The smaller value of the NPPS demonstrates that the candidate point's priority is low. In contrast, the larger value of the NPPS shows the greater need and priority for a given candidate point to be selected as a water quality monitoring network.

$$NPPS = \sum_{i=1}^{6} W_i * A_i \qquad (6)$$

where NPPS is the non-point source potential pollution scores ; $W_i$ is the potential pollution weight of each non-point source/criterion calculated by ANP method; $A_i$ is the percentage of each non-point sources/criterion between candidate sampling points in the buffer zone.

Finally, to select the most appropriate sampling point during the periods 2016 and 2036, low values of the hierarchy and high values of the NPPS is combined. A point with low hierarchy value has a higher priority than a point with high hierarchy value (Sanders et al., 1983). In addition, a sampling point which is located in an area of high anthropogenic activities has high priority than others to be selected as a sampling point (Do et al., 2012). It means that high-NPPS value point has higher priority than low-NPPS value point. Fig. 2 shows an outline of the full study.

**Fig. 2** SOMEWHERE HERE

## 3. Results and discussion

### 3.1. Location of potential sampling points and their contributing areas

To find the total number of potential sampling points, the main rivers with differences in width were divided into different reaches. The average widths for the Gudox Bogan and Gazan Chai rivers were 26.4 m and 19.0 m, respectively. Guotor Chai, the main river in the watershed, was divided into three different sections (upstream, middle, and downstream) with average river widths of 33.5 m, 74.6 m, and 28.1 m, respectively. According to Eqs. (1) − (2), the total number of 360 potential sampling points and their locations were determined (Fig. 3). Eq. (3) was used to determine the number of candidate sampling points, which was 15 at i=4 based on the existing stations and considering the budget deficiency in the study area. To identify the location of 15 candidate sampling points at a different $i^{th}$ hierarchy and Mi, Eqs. (4) – (5) were applied (Fig. 3).

The findings are in agreement with Sanders et al. (1983) and Do et al. (2012); that the proposed sampling points were evenly distributed in both the downstream and upstream sections of the watershed under study. Also, they are situated in both natural areas (Wooded/Forest and Rangeland) and highly anthropogenic activities area (Urban and Agriculture).

In contrast with linear surface ground buffer zone, for example, the results demonstrate that contributing areas achieved by flow length were reduced 27% and 17% in C4 and C1, respectively. The results are not similar to the findings of the work done by Do et al. (2012) that simple buffer zone is sufficient for determining contributing area. Therefore, the findings emphasized that contributing areas in buffer zone between candidates points should be achieved by considering the flow length of each land unit area. It means that the values of NPPS (Eq. 6), which is related to the percent of contributing area, for candidate points were accurately calculated and priorities of candidate points were more precisely determined. The catchments between candidate points identified by flow length are shown in Fig. 3.

**Fig. 3** SOMEWHERE HERE

### 3.2. Land-use change analysis

The accuracy of the classification was assessed by the kappa coefficient in order to apply the derived maps for further change analysis and to find different pollution sources among the candidate points (buffer zone). About 30% of all ground truth points were used to assess the accuracy. Overall accuracies for the land-use maps of 1995 (92.2%), 2006 (94.9%), and 2016 (92.7%) showed that the classified remote sensing images are suitable for the reliable and effective modeling of future land-use change (see Table S.2 in Supplementary information).

Finally, land-use maps of the whole study area as well as of the buffer zone were generated (Fig. 4).

**Fig. 4** SOMEWHERE HERE

All in all, analysis of land-use change showed an upward trend in the number of build-up areas (Table S.3). The figures indicated that residential areas had increased from 2.53% to 4.93% from 1995 to 2016, in other words, around 1000 hectares changed to residential lands in this period. Mistova et al. (2011), Keshtkar et al. (2017), and Rimal et al., 2017, reported such a high rate of growth in the build-up areas between the years 1995 to 2016. Moreover, highway/road increased from 288.99 ha (0.69%) to 307.52 (0.79 5) between 1995 and 2006; then there were no changes in the number of highway/road until 2016. According to Table S.3, the figures for wooded/forest lands dropped from 125.87 ha (1995) to 74.53 ha (2006), then it rose to 87.96 ha in 2016. Agriculture and rangeland continuously declined 29%–27.38% and 67%–66%, respectively, during the study period. It shows the fact that a growth in built-up area could be explained as a decrease in natural lands (Lambin and Meyfroidt, 2011). Expansion of residential areas into rangeland and agricultural are reported by several studies (López eta al., 2001; Araya and Cabral, 2010; Moghadam, and Helbich, 2013; Keshtkar et al. 2016 a, b; Mosammam et al., 2017), as it effects a wider vegetated riparian buffer zone. Therefore, it leads to decreasing travel time and distance for runoff, infiltration opportunities, and deposition of eroded soil material, as well as increase in nutrient removal (Mistova et al., 2011). For the period between 1995 and 2016, the area of water bodies significantly dropped from 184 ha to 2.12 ha. It comes from mismanagement and overuse of water in agriculture during last two decades.

### 3.3. Modeling and validation of land-use change from 2016 onwards

Kappa variations were applied to evaluate the model by comparing the real land-use map of 2016 with the simulated map of 2016. The accuracy of the models, which was more than 80%, determined them to be potent predictive tools (Araya and Cabral, 2010; Keshtkar and Voigt, 2016a). In the present study, Kno, Kstandard, and Klocation were used to validate the model. To assess the overall accuracy of the model, using the value of Kno is better than using the value of Kstandard (Pontius, 2000). The Kno and Kstandard values were 0.97 and 0.90, respectively, which verified the accuracy of the model. The Klocation value shows a reasonable representation of the location by the model and was 0.91. Thus, according to the results obtained from Kappa values, the CA–Markov model is a strong predictive tool for simulating future land-use changes.

To tackle inherent limitations and add special characters to the model, the Markov model required integration with the CA–Markov model (Keshtkar and Voigt, 2016a). Effectively, the prediction of future changes in 2026 and 2036 requires the definition of the 2016 land-use map (Fig. 4), conditional probability images derived from the Markov model, suitability maps from MCE analysis (Fig. S. 4.), transition area matrices (2006–2016), and selection of a contiguity filter (5×5 Moore neighborhood kernel). The predicted land-use maps for 2026 and 2036 in the buffer zone are illustrated in Fig. 4 and Fig. S. 5.

According to the findings (see Table S.3 in Supplementary information), the whole of the study area has been occupied with agricultural and rangeland areas, respectively, with 27.38% and 66.76% in 2016, which is estimated to decrease to 26% and 64.73% by 2036. In contrast, residential areas will increase by 4% and reach 8% of the entire study area. The figures also show that the quantities for the Wooded/Forest lands will rise from 87.97 ha to 114.45 between 2016 and 2036.The rest of the land-use categories did not illustrate marked variation (Table S.3).

The findings are similar to the findings of the work done by (Araya and Cabral, 2010; Mistova et al., 2011; Moghadam, and Helbich, 2013; Keshtkar et al. 2016 a, b; Mosammam et al., 2017) that the CA–Markov model is an effective method to simulate future land-use changes. Land-use changes in the future in this model are the basis of land-use patterns that have been distinguished in the past. However, land-use alterations are always affected by regional and national government policy and unpredictable events (e,g., floods and fires) (Keshtkar et al. 2016 a). It should be considered that this issue would cause uncertainty in the simulation of land-use changes.

### 3.4. Results of the ANP method for relative weights

Table 3 shows the relative weights of the criteria and sub-criteria which were obtained based on the pair-wise comparison matrix in the ANP method. The weights were consistent based on the consistency ratio of the pair-wise comparison matrix (0.016) (Table 3). The relative priorities among criteria in the same cluster were indicated using the normalized-by-cluster matrix (Aragonés-Beltrán et al., 2017). Taking all the influences in the network into account, relative potential pollution weights for non-point sources varied significantly. Residential area stood out with far more relative pollution weight than the other non-point sources with the normalized weight of 0.25. Agricultural area represented the second relative weight (0.22) and was followed closely by highway/road with the weight of 0.20. Of the six non-point sources in Table 3, the relative weights for rangeland, wooded/forest, and water bodies were 0.15, 0.11, and 0.07, respectively. In addition, among the sub-criteria for non-point sources, BOD and TSS accounted for the highest relative weights with totals of 0.23 and 0.22, respectively.

**Table 3**SOMEWHERE HERE

The result showed that inclusion of experts in the weighting process was beneficial as they provide knowledge needs on prioritizing sampling points (Chang and Lin, 2014). Do et al., (2012) reported the high relative pollution weights for residential and agricultural areas. Nevertheless, they calculated the relative weights by the AHP method. Moreover, the present study applied more criteria and sub-criteria (e.g. highway/road, NO3-N), most importantly, interdependency between sub-criteria was considered by the ANP method. A basic concept of non-point sources' role and the complicated relationship between the sub-criteria for non-point sources were revealed by simply using the ANP approach (Lin et al., 2009). Therefore, it can be concluded that the high weights of BOD and TSS are the consequence of a good correlation with the other water quality variables (Chapman, 1996; Ouyang, 2005) (Table 3 and Table S. 1).Thus, it can be seen that considering inter-relationship between sub-criteria is of vital importance because they have significant effect on the relative weight of non-point sources/criteria.

### 3.5. Selection and prioritization of sampling points for 2016 and the future

15 sampling points are recognized purely by mathematics and required to be combined with anthropogenic activities data through land use mapping to select the most appropriate sampling points. After considering potential catchment pollution using Eq. (6), anthropogenic activities through land-use mapping, the hierarchy and M values, and taking budget deficiency and the existing stations into account, seven sampling points in the study area were proposed for water quality monitoring in 2016 and the future (Table 4).

**Table 4**SOMEWHERE HERE

The sampling points proposed for 2016 are C4, C6, C8, C12, C13, C14, and C15, and the NPPS of these seven points are 20.53, 17.73, 20.24, 18.92, 21.31, 21.32, and 20.13, respectively.

Hierarchy values of the sampling points are 2, 3, 1, 2, 4, 3, and 4, respectively. Moreover, we proposed two sampling points (C1 and C2) for enhancing a robust WQMN in the study area. These sampling points are located in the upstream and in the downstream of the three main rivers (Fig. 5).

**Fig. 5** SOMEWHERE HERE

On the other hand, the NPPS of the aforementioned sampling points will have different scores based on the percentage of changes for 2016–2036 which were achieved using the predicted changes of the land-use map in 2036 (Table 4). The results indicated that around 4.5% of NPPS is expected to decrease at catchments C7 and C8 by 2036. This is the result of the decreasing trend in agricultural areas (e.g., dry farming). Another significant fall in the values of NPPS is related to C4 (about 3.6%). In contrast, the NPPS of C6 will rise by 2.9% in 2036, which can be interpreted by increasing the residential areas in this catchment. Based on the results, it is not expected that selected sampling locations will be changed in 2036, because there are no significant changes in their number of NPPS in the future.

All in all, it is clear that the selected sampling points are located in the catchments, having high values of NPPS as a result of human activities (Do et al., 2011; Do et al., 2012; Varekar et al., 2015a), and low hierarchy values (Sanders et al., 1983). Except the seven selected sampling points for both the present and the future condition of the non-point sources, two points are needed, providing that the budget limitation in the regional water authority could be solved or there will be an expansion plan in the study area (Fig. 5, black and red stars). This research also highlights that the current stations are not located in appropriate locations in order for WQM in the study area (Figs. 5). Therefore, our study recommended new sampling points for setting up new monitoring stations due to changing environmental conditions (Strobl and Robillard, 2008). In general, sampling point locations are subdivided into two groups, namely macrolocations for routing monitoring and microlocations for critical points monitoring (strobl and Robillard, 2008). It is known that microlocations are functions of macroloctions, and current WQMN design is based on macroloction network designs. Therefore, 15 proposed sampling points will partially help critical point monitoring (emergency monitoring). Since, they are systematically designed and are evenly distributed in the study area, eight sampling points (C4, C5, C6, C7, C8, C13, C14, and C15) monitor water quality in the downstream especially an area of concentrated human activity, while seven sampling points (C1, , C2, C3, C9, C10, C11, and C12) monitor water quality in the upstream.

Hence, our results integrate previous findings by Sanders et al., (1983), Park et al. (2006) and Do et al. (2012), with the results that sampling points are selected for the present and the future condition of diffuse pollution loadings under the study area. Also, the findings emphasize that the sampling points are identified with high certainty via the RML approach and the NPPS. By applying the natural processes and human activities (Baird et al., 1996; Park et al., 2006; Strobl et al., 2006b), the present study suggests proper sampling points for a highly reliable WQMN in the present and the future conditions. In contrast to previous studies (Sanders et al., 1983; Chilundo et al., 2008; Karamouz et al., 2009; Telci et al., 2009; Mahjouri and Karachian, 2011; Chen et al., 2012; Varekar et al., 2015 a, b; Aboutalebi et al., 2016), our proposed method is cost-effective because it uses only available watershed data, technical and expert resources to design sampling points. The aforementioned literatures are too complicated and too case specific for a watershed manager to implement easily. They have focused on designing sampling points using extensive water quality data, extensive network of flow gauges, statistical method, and water quality modeling (Behmel et al., 2016), which are not applicable for developing countries (e.g., Iran), struggling with limited financial resources. In water quality monitoring program there should be guidance to be updated quickly using existing data sets and would make it possible for a watershed manager to obtain a timely and holistic view (Behmel et al., 2016). The proposed framework can be updated quickly using satellite data and simulation of the diffuse pollution loads in the future. If the land-uses of the study area change, it will be updated by employing satellite data and identifying its impact on sampling points. In addition, the proposed framework is highly recommended to regional water authorities seeking for a framework which is able to design sampling points for the first time, in particular, for developing countries like Iran. It is worth to mention that the mean values of the pollution concentrations in the river system will increase due to a combination of human activities with the RML procedure. Therefore, when the monitoring results illustrate that river water quality is getting worse, it is time to manage anthropogenic activities along the river system.

## 4. Conclusion

This study describes a practical methodology to propose sampling points for surface water quality monitoring under a case study of the Khoy watershed in northwest of Iran, where financial resources and water quality data are limited. Analysis in this study demonstrates that a combination of the RML method, land-use change modeling, multi-criteria evaluation, considering anthropogenic activities through land-use mapping, and the hierarchy value is a practical approach to identifying representative river water sampling points.

In this study, the RML approach is applied to identify representative sampling points. New potential pollution of non-point sources was introduced by the ANP method, helping to classify the priority of the most appropriate points for an entire river system. Moreover, in order to determine the effect of land-use changes on the location of water quality, an integrated cellular automata–Markov chain model (CA–Markov) was applied to simulate future change in non-point sources during the period 2026–2036. In particular, we show that in order to calculate contributing area in water quality changes, using flow length of each land unit area instead of linear surface ground is the accurate method. In sum, 15 sampling points are systematically recognized. Based on budget limitation, the river system, and modeling of future land-use changes, seven sampling points are proposed as the most appropriate stations for water quality monitoring in the investigated river system. Moreover, two points have been selected as the second most appropriate sampling sites for enhancing a robust WQMN if there is an expansion plan. Results from this research illustrated that it is not expected that the present locations of proposed sampling points will change in 2036 due to the forthcoming changes in non-point sources.

These notable, relevant findings can provide a novel strategic guide and practical recommendation for water quality monitoring agencies when extensive watershed information is available but there is a lack of water quality data and no cost-effective method for identifying the correct location of sampling sites and the potential impacts of land-use changes on water resources. Another advantage this study offers is that the present method is helpful and applicable to natural resources managers, land-use management organizations, and policymakers to comprehensively realize and manage the patterns of projected land-use changes. The findings further manifest that identifying sampling sites using the RML approach, natural processes, human activities, and NPPS values suggests proper sampling points for a highly reliable WQMN with a high level of certainty.

On the other hand, to eliminate the uncertainty of predicting future land-use changes and their effects on proposing sampling points, the presented approach needs more comparative analyses of the effects of unpredictable events, such as floods and fires.

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**Table 1. Extracted weights based on AHP and fuzzy standardization for urban areas**

| Factors | Function | Control points | Weights |
|---|---|---|---|
| **Slope** | Sigmoid | 0 % highest suitability | 0.19 |
| | | 0–15 % decreasing suitability | |
| | | >15 % no suitability | |
| **Distance from roads** | J-shaped | 0–10 m highest suitability | 0.28 |
| | | 10–400m decreasing suitability | |
| | | > 400 m no suitability | |
| **Distance from water bodies** | Linear | 0–10 m no suitability | 0.15 |
| | | 10–1000m increasing suitability | |
| | | > 1000 m highest suitability | |
| **Distance from built-up areas** | Linear | 0–100 m highest suitability | 0.38 |
| | | 100–2400 m decreasing suitability | |
| | | > 2400 m no suitability | |

**Table 2. Event mean concentration (EMC)**

| | TSS (mg/l) | TP (mg/l) | TN (mg/l) | BOD (mg/l) | NO3-N (mg/l) |
|---|---|---|---|---|---|
| **Residential** | 100[a],41[b], 71[c], 127[d],73[e] | 0.79[a], 0.57[b], 0.49[c],0.38[d], 0.59[e] | 3.41[a],1.82[b], 2.42[c], 2.1[d] | 15[a],25.5[b],11[c] | 0.23[b], 0.79[e] |
| **Agriculture** | 201[a],107[b],55.3[c] | 0.36[a], 1.3[b],0.34[c] | 1.56[a],4.40[b],2.32[c] | 4[a], 4[b],3.8[c] | 1.6[b] |
| **Rangeland** | 70[a],1[b],94.3[c],151[e] | 0.12[a],0.01[b],0.476[c],2.14[e] | 1.51[a], 0.7[b],2.48[c] | 6[a],5.1[c] | 0.4[b],1.30[e] |
| **Forest /Wooded** | 39[a],487[e] | 0.06[a],0.35[e] | 0.83[a] | 6[a] | 1[e] |
| **Water bodies** | 3.1[c] | 0.11[c] | 1.25[c] | 1.6[c] | ------ |
| **Highway/Road** | 50.30[c],1453[e] | 0.34[c], 0.28[e] | 2.08[c] | 5.6[c] | 1[e] |

Adopted from: a (Newell et al., (1992)); b (Barid et al., (1996)); c (Harper,  (1998)); d (Baldys  et al., (1998)); e (Line et al., 2002)

**Table 3. The weights of criteria and sub-criteria using the ANP method**

| | BOD | NO3-N | TN | TP | TSS | Relative weight | Normalized by cluster |
|---|---|---|---|---|---|---|---|
| **Agriculture** | 0.03 | 0.048 | 0.045 | 0.033 | 0.061 | 0.22 | 0.22 |
| **Wooded/Forest** | 0.04 | 0.025 | 0.015 | 0.008 | 0.031 | 0.12 | 0.11 |
| **Highway/Road** | 0.055 | 0.025 | 0.025 | 0.02 | 0.062 | 0.19 | 0.20 |
| **Rangeland** | 0.04 | 0.028 | 0.025 | 0.02 | 0.038 | 0.15 | 0.15 |
| **Residential** | 0.086 | 0.023 | 0.031 | 0.044 | 0.051 | 0.23 | 0.25 |
| **Water bodies** | 0.023 | 0.016 | 0.024 | 0.01 | 0.019 | 0.09 | 0.07 |
| **Relative weight** | 0.27 | 0.17 | 0.17 | 0.13 | 0.26 | | |
| **Normalized by cluster** | 0.23 | 0.19 | 0.19 | 0.16 | 0.22 | | |
| | | | | | | | CR = 0.016 |

**Table 4. The candidate sampling point's prioritization for appropriately selecting to river water quality monitoring**

| River | **Catchments(**candidate points**)** | M_Value | i | NPPS(2016) | NPPS(2026) | NPPS(2036) | Δ %2016-2036 |
|---|---|---|---|---|---|---|---|
| Gutor Chai | C1 | 23 | 4 | 16.58 | 16.75 | 16.87 | 1.75 |
| Gutor Chai | C2 | 45 | 3 | 15.63 | 15.77 | 15.80 | 1.09 |
| Gutor Chai | C3 | 23 | 4 | 15.95 | 15.93 | 16.01 | 0.37 |
| Gutor Chai | C4 | 90 | 2 | 20.53 | 20.00 | 20.14 | -1.90 |
| Gazan Chai | C5 | 23 | 4 | 17.72 | 16.96 | 17.07 | -3.68 |
| Gazan Chai | C6 | 45 | 3 | 17.73 | 17.79 | 18.26 | 2.96 |
| Gazan Chai | C7 | 23 | 4 | 17.15 | 17.94 | 16.34 | -4.73 |
| Gutor Chai | C8 | 178 | 1 | 20.24 | 19.23 | 19.32 | -4.53 |
| Qudox Bogan | C9 | 23 | 4 | 15.56 | 15.63 | 15.65 | 0.55 |
| Qudox Bogan | C10 | 45 | 3 | 15.03 | 15.02 | 15.02 | -0.09 |
| Qudox Bogan | C11 | 23 | 4 | 15.70 | 15.78 | 15.79 | 0.60 |
| Qudox Bogan | C12 | 90 | 2 | 18.92 | 18.95 | 18.97 | 0.28 |
| Qudox Bogan | C13 | 23 | 4 | 21.46 | 20.86 | 20.98 | -2.26 |
| Qudox Bogan | C14 | 45 | 3 | 21.32 | 20.69 | 21.00 | -1.52 |
| Gutor Chai | C15 | 23 | 4 | 20.13 | 19.40 | 19.53 | -2.98 |

**Δ The NPPS percentage of changes for 2016-2036**

**The green color shows the higher priority of a candidate point in each year**

*** the least appropriate sampling points**

**** the second most appropriate sampling points**

***** the most appropriate sampling points**

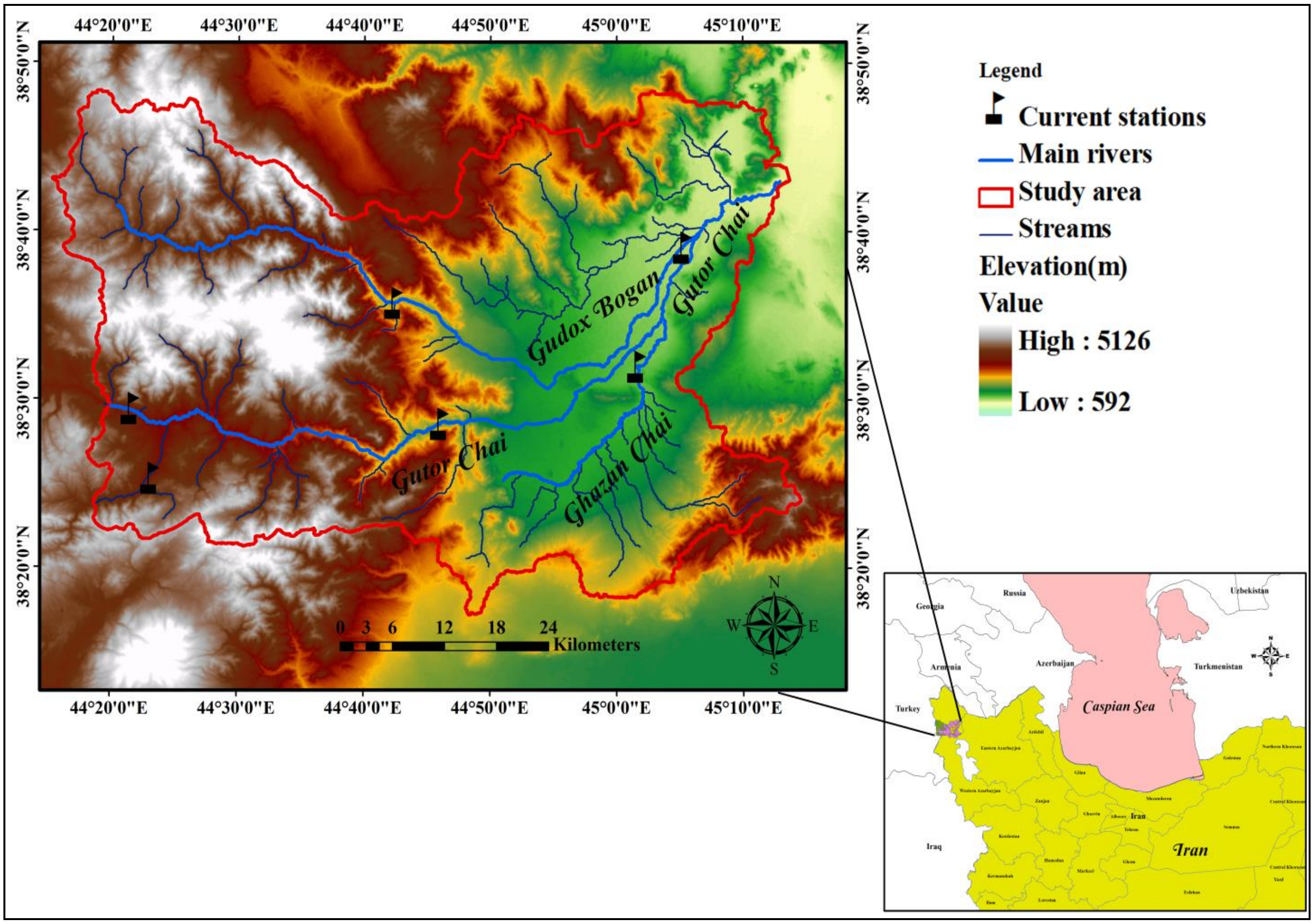


**Fig. 1. Location of the study area in Iran.**

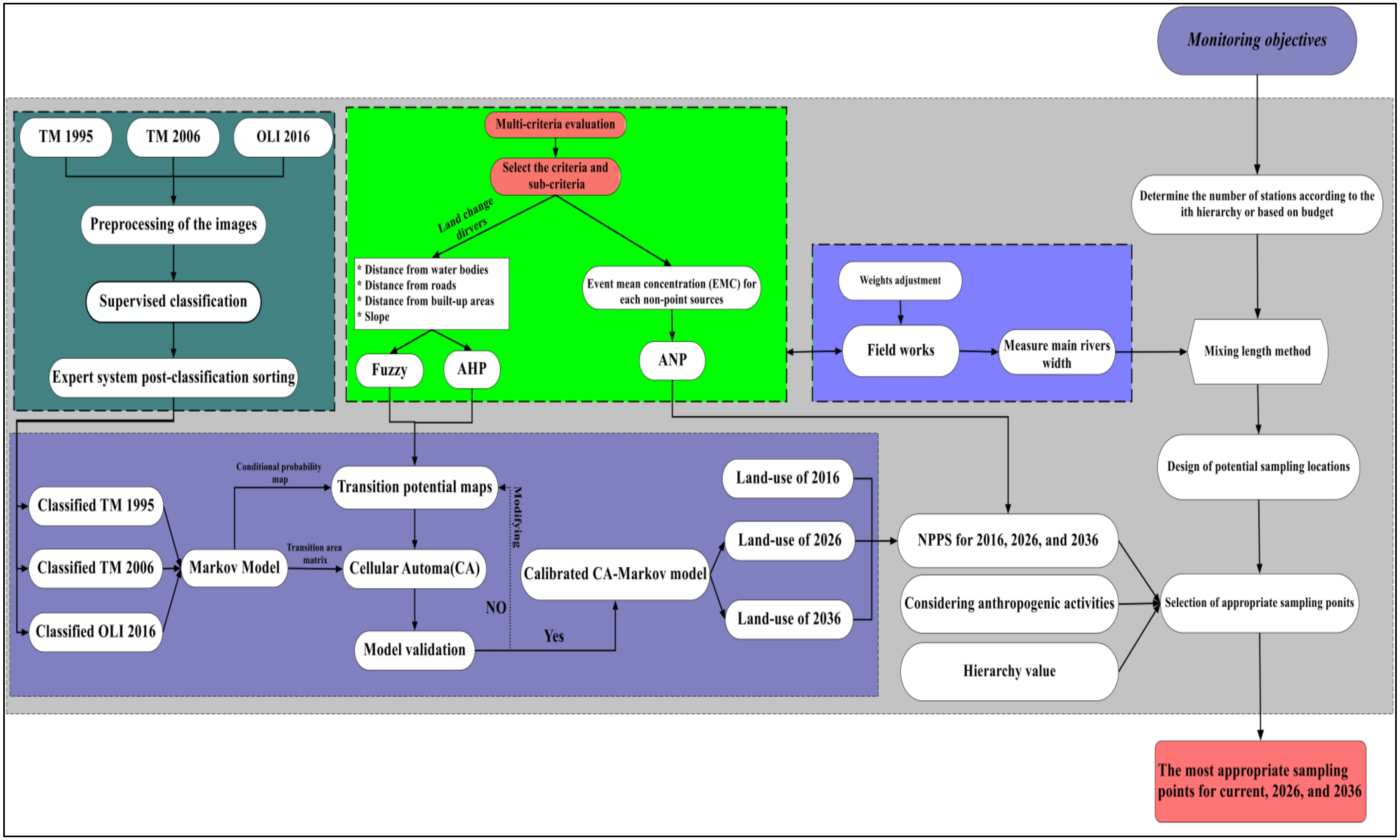


**Fig. 2. Graphical diagram of the full study in order to determine appropriate sampling points.**

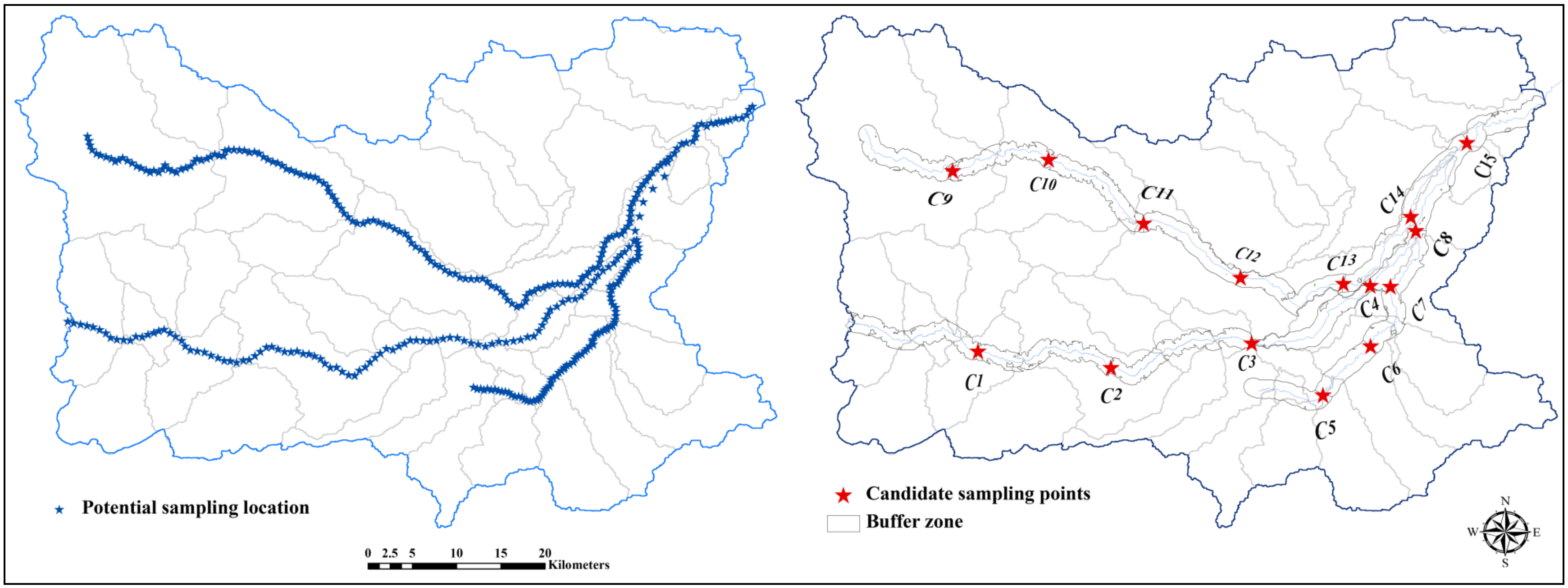


**Fig. 3. Potential and candidate sampling points.**

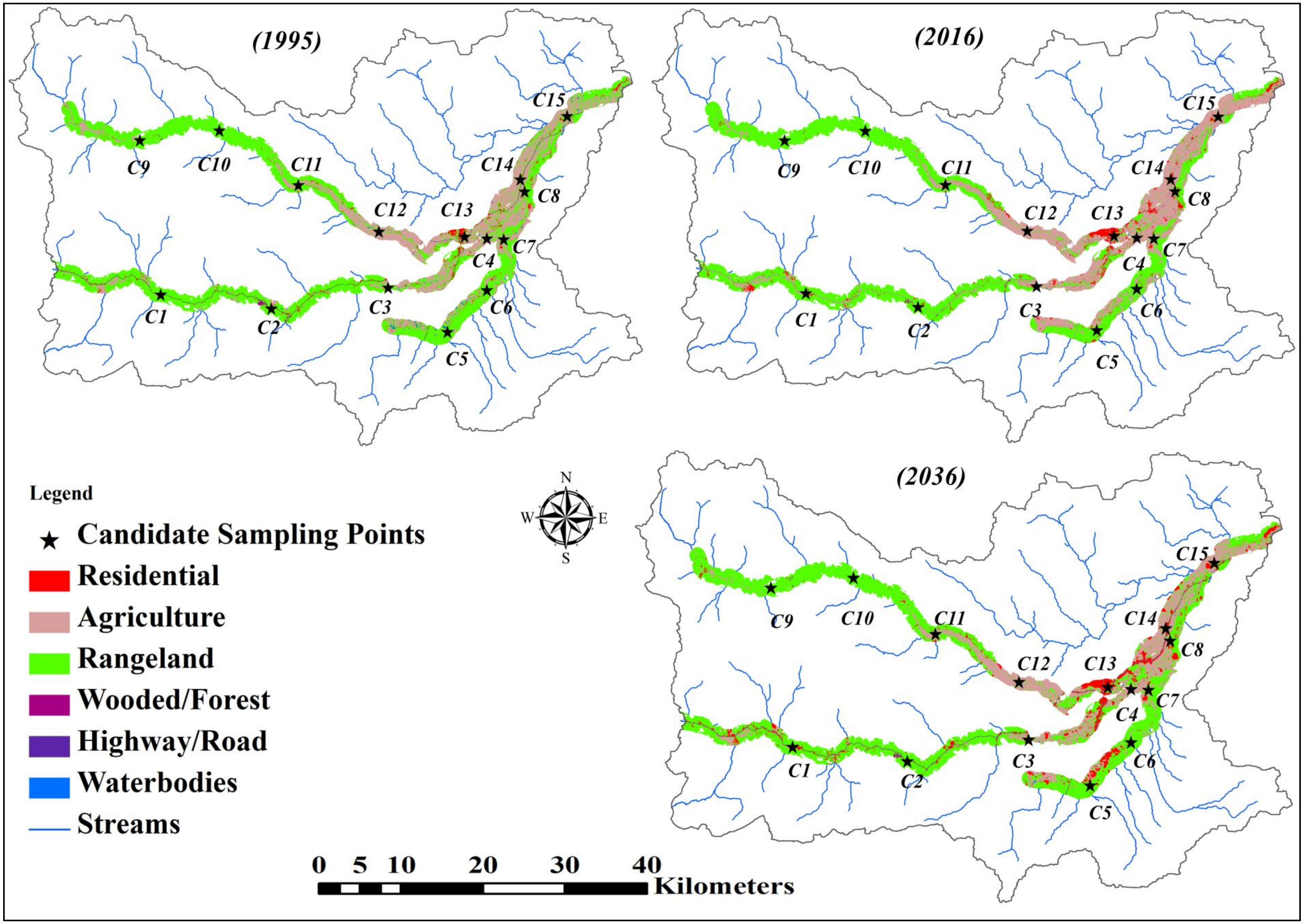


**Fig. 4. Time series of land-use maps for 1995, 2016 and 2036.**

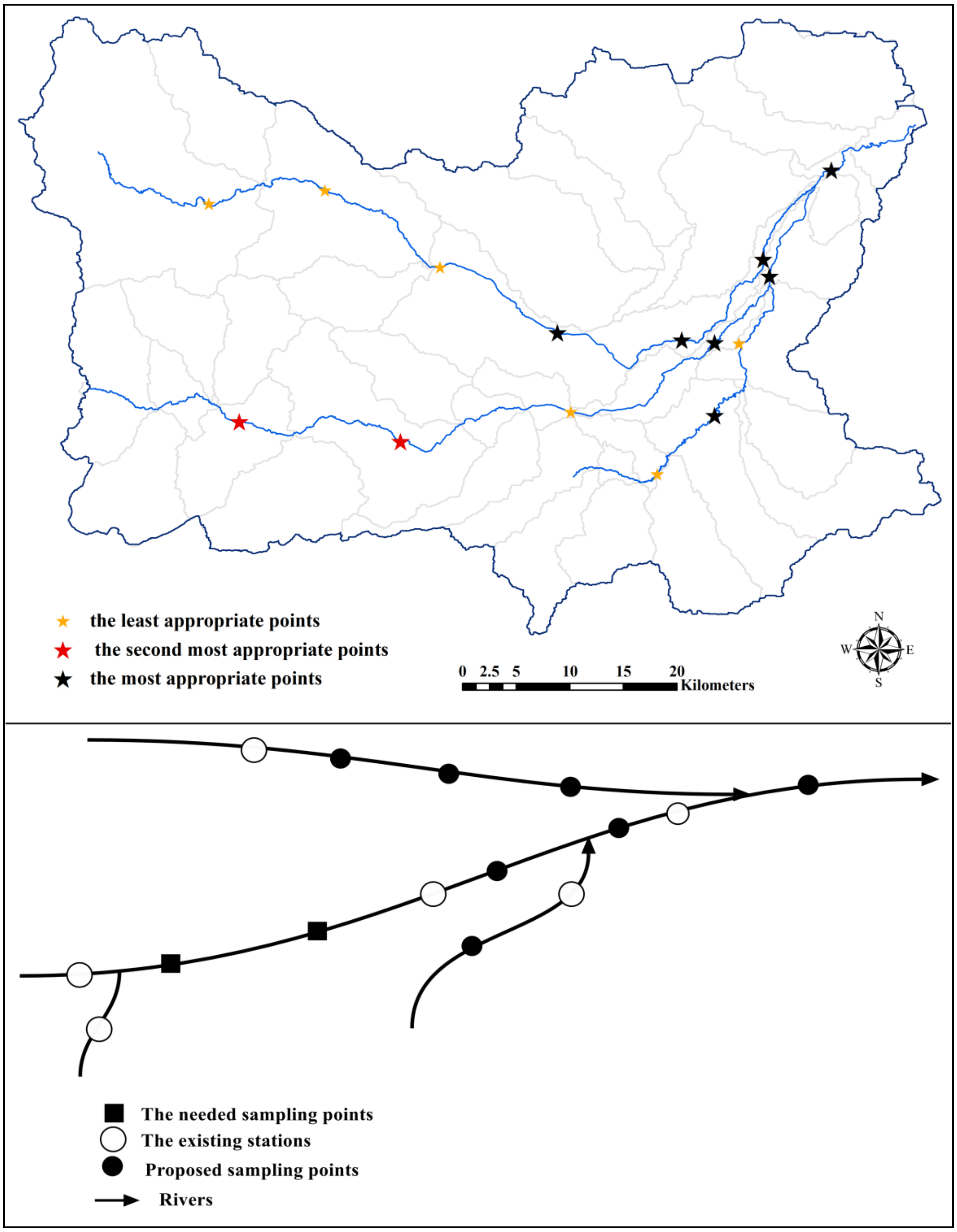


**Fig. 5. Proposed sampling points.**