GIS-BASED ASSESSMENT OF GROUNDWATER QUALITY IN TANK CASCADE LANDSCAPE IN SRI LANKA: A STUDY IN ULAGALLA CASCADE

スリランカにおける GIS に基づいたタンクカスケードの地下水水質評価：ウラガラカスケードにおける研究

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ABSTRACT

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Sri Lanka is divided into three major climatic zones based on the rainfall received; wet zone, intermediate zone, and dry zone. Though the dry zone contributes largely to agricultural production, the rainfall occurs in the dry zone is confined into two or three months of the year, resulting in long dry spells. Hence, the tank cascade system (TCS) in the lowlands within the dry and intermediate zone has evolved, in order to manage the surface water resources in a sustainable manner. Recently, it has been recognized as a globally important agricultural heritage site by the Food and Agriculture Organization of the United Nations (FAO).

As a convenient substitute for insufficient surface water resources in the dry zone of Sri Lanka, groundwater use has dramatically increased during the last three decades, coinciding with changes in agriculture and livelihoods. Accordingly, the TCS is endangered along with overexploitation and quality deterioration. Therefore, we aimed to assess spatial and temporal variations in both irrigation and drinking water quality in the tank cascade landscape.

Interpolation methods are extensively used to map the spatial distribution of water quality parameters. However, the selection of the most appropriate method is a critical issue in environmental studies. We assessed the relative performances of deterministic and geostatistical methods in explaining the spatiotemporal variation of water quality parameters/indices in the Ulagalla tank cascade landscape using root mean square error (RMSE) in a leave-one-out cross-validation. Empirical Bayesian kriging (EBK) performed well for most parameters throughout the study period and we recommended EBK as the best method to interpolate water quality parameters/indices in the Ulagalla cascade and other tank cascade landscapes in Sri Lanka and similar environments.

We sampled groundwater from 29 wells to give a homogeneous distribution within the Ulagalla cascade, during both Yala (dry) and Maha (wet) seasons, the two main cropping seasons in Sri Lanka. We collected the samples for consecutive 12 months starting from April 2016. We evaluated the suitability of groundwater for irrigation using the analytic hierarchy process and GIS. Water quality did not vary notably between seasons. However, it deteriorated with the onset of high-intensity heavy rain, especially during the Maha season. A water quality zoning map indicated that groundwater in 4% and 96% of the study area is suitable and moderately suitable for irrigation, respectively.

Since Chronic kidney disease of unknown etiology (CKDu) is a major health concern in the north central province, we tried to assess the suitability of groundwater for drinking by integrating the Sri Lankan standards of drinking water quality parameters and GIS. Based on the overall suitability, we found that the major portion falls under doubtful and unsuitable categories during both seasons. Hence, urgent attention is required to introduce proper long term drinking water treatment technology.

We established new protocols to classify groundwater suitability for both irrigation and drinking for the first time in the tank cascade landscape in Sri Lanka. Hence, irrigation and drinking water quality in tank cascade landscapes and similar environments can be assessed using these methodologies and results.

Keywords: AHP, CKDu, EBK, Geostatistical methods, GIS, Hardness, Salinity, Tank cascade system

要約

スリランカは、降雨量により 3 つの主要な気候帯(湿潤帯、中間帯、乾燥帯)にわけられる。乾燥地帯は農業生産に大きく貢献するが、降雨期間は 1 年の 2、３か月に限られ、長い乾燥期間となる。そのために、地表水資源を持続可能な方法で管理するために、乾燥地帯および中間地帯内の低地におけるタンクカスケードシステム（TCS）が進化した。最近、このシステムは FAO により、世界的に重要な農業遺産として認められた。

スリランカの乾燥帯において不十分な地表水の代用として、この 30 年で農牧畜の変化とともに地下水利用が劇的に増加している。そのため、TCS は過剰利用と水質低下が危惧されている。そこで、本研究では、TCS における灌漑および飲用水水質の時間空間的変化について評価した。

水質パラメータの空間分布のマッピングに内挿法が使われる。しかし、どの方法が適しているかについては環境研究において重要な課題である。そこで、ウラガラ TSC の水質指標の空間変化説明における決定論的手法と地理統計的指標の適用性の評価を行なった。その結果、経験ベイズクリギング(EBK)がほとんどのパラメータに関して良い適用性を示した。これより、EBK をウラガラ TSC やスリランカの類似した環境での水質指標の空間内挿に最適手法であると結論した。

主な耕作期間である Yala(乾燥期)と Maha(湿潤期)に、ウラガラカスケードで均一に分布する 29 の井戸において地下水を 2016 年 4 月からの 12 カ月間サンプリングした。地下水の灌漑への適性を AHP と GIS により評価した。その結果、水質は季節間で大きく変わることはなかったが、高降雨強度により特に Maha 期に水質が悪化することが認められた。水質のゾーニングでは、灌漑水として 4%が最適で 96%が適しているという結果となった。

中北部では原因不明の腎臓病(CKDu)が問題となっているため、スリランカ飲料水水質基準と GIS を用いて地下水の飲用水としての適性について評価した。全体的な適性として、両シーズンにおいて不適であるという結果となった。したがって、適切な飲料水処理技術の導入が急務である。

以上より、本研究では、スリランカのTCSに関して初めて地下水の灌漑および飲用水としての適性について分類する方法が示された。そして、スリランカにおける類似環境にあるTCSでは、本研究の手法および結果を適用することが可能であると考える。

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LIST OF ABBREVIATIONS

AHP	Analytic hierarchy process
As^{3+}	arsenic
APHA	American public health association
BCE	Before the common era
Ca^{2+}	Calcium
Cd^{2+}	Cadmium
Cl^{-}	Chloride
CO_3^{2-}	Carbonate
CR	Consistency ratio
CV	Coefficient of variance
EBK	Empirical Bayesian kriging
EC	Electrical conductivity
ESRI	Environmental systems research institute
EVnB	Extreme values near boundaries
F^{-}	Fluoride
FAO	Food and agriculture organization
GIS	Geographic information system
GPI	Global polynomial interpolation
GPS	Global positioning system
HCO_3^{-}	Bicarbonate
IDW	Inverse distance weighted
K^{+}	Potassium
KR	Kelly's ratio
LPI	Local polynomial interpolation
MAR	Magnesium adsorption ratio
Mg^{2+}	Magnesium
MI	Moran's index
Na^{+}	Sodium
NH_4-H	Ammonium nitrogen
NO_3-N	Nitrate nitrogen
OK	Ordinary kriging
p	Probability
PO_4^{3-}	Phosphate
RBFs	Radial basis fuctions
RI	Random consistency index
RMSE	Root mean square error
RSC	Residual sodium carbonate

SK	Simple kriging
SO_4^{2-}	Sulfate
TCS	Tank cascade system
TDS	Total dissolved solids
TH	Total hardness
UK	Universal kriging
USA	United States of America
WEKA	Waikato environment for knowledge analysis
WHO	World health organization

1.0 General Introduction

Sri Lanka is a tropical island in the Indian subcontinent and located at $5^0$54’-$9^0$52’N $79^0$39’-$81^0$53’. The total extent of the island is 6,570,134 ha. The central highlands (more than 2500 m above mean sea level) are surrounded by broad lowland plains and characterized by both wet and dry climates (Geekiyanage and Pushpakumara, 2013). Based on the rainfall received, the country is divided into three major climatic zones; wet zone (>2500 mm), intermediate zone (1750-2500 mm) and dry zone (<1750 mm). The rainfall is mainly governed by the monsoon, and on average, the rainfall of dry zone exceeds 1000 mm (Madduma Bandara, 1985). However, high evaporation ranges from 1700-1900 mm, and seasonal changes of rainfall occur in the dry zone implies the water stress condition during dry periods (Panabokke et al., 2002). This spatial and temporal variation of rainfall has led the ancient farming communities to invent tank cascade systems (TCS), which can act as a sustainable water management system.

TCS is an unique water storage and supply system used in the intermediate and dry zones of Sri Lanka. The system has been in use since the third century BCE (Madduma Bandara, 1985), mainly for irrigation and domestic water use. The main principle behind the TCS is re-use and recycling of water through a connected series of tanks. Hence, the TCS is defined as a connected series of tanks arranged within a micro- (or meso-) catchment of the dry zone landscape for storing, conveying, and utilizing water from an ephemeral rivulet (Madduma Bandara, 1985). TCS provides cooler micro-climate which enhance the plant and animal biodiversity while providing habitat for endangered elephants, resident, and migrant water birds. (Bebermeier et al., 2017; Bitterman et al., 2016; Van Meter et al., 2016).

During the last few decades, the usage of groundwater in the dry zone of Sri Lanka has rapidly increased owing to the inability of surface water resources to cater to growing demand, hastening the deterioration of water quality in the tank cascade landscape (Bebermeier et al., 2017). Thus, an increasing amount of attention has been given to sustainably managing water resources in the tank cascade landscapes, and several monitoring studies of groundwater in this landscape have been conducted (Wijesundara et al., 2012; Gunarathna et al., 2016a,b; Kumari et al., 2016). However, no appropriate continuous monitoring system has been put in place, because continuous monitoring of groundwater over a large area for an extended duration is expensive and labor-intensive. Therefore, a suitable method for estimating groundwater availability and quality is needed that requires a minimum number of sampling sites in order to better manage the water resources in the tank cascade landscapes.

Spatial interpolation in ArcGIS has been used to understand the spatial and temporal variation of natural resources (Chai et al., 2011; Gunaalan et al., 2018). Deterministic and geospatial interpolation techniques are considered as the major two types of spatial interpolation methods. Deterministic interpolation techniques include inverse distance weighted (IDW), radial basis functions (RBFs), global polynomial interpolation (GPI), and local polynomial interpolation (LPI) methods; geostatistical interpolation techniques include kriging/co-kriging (ordinary kriging [OK], simple kriging [SK], universal kriging [UK], etc.), areal interpolation, and empirical Bayesian kriging (EBK) (Bao et al., 2014; Kumar et al., 2007; Uyan and Cay, 2013). Since the interpolation accuracy depends on sample size (Stahl et al., 2006), area (Gunaalan et al., 2018; Mirzaei and Sakizadeh, 2016), spatial distribution (Güler, 2014), normality of the data set (Wu et al., 2016), grid size (Hengl, 2007) and interpolation method (Luo et al., 2008; Xie et al., 2011), it is vital to assess the relative performance of interpolation methods and select the best interpolation method to predict the groundwater quality in tank cascade system.

Groundwater quality is mainly influenced by the physical and chemical characteristics of the aquifer, characteristics of chemical interaction with mineral surfaces, anthropogenic contaminants, and the length of time water spend in the groundwater (Domenico and Schwartz, 1998). Since good water quality is important to maintain a healthy ecosystem, it is required to assess the groundwater resources. A large number of water quality parameters have led to creating confusion in terms of water quality. As a result, water quality indexes (WQI) have been developed by a number of researchers (Chandrajith et al., 2011a; Science and Banerjee, 2009). In recent years multi-criteria decision-making tools (MCDM) have been successfully used in disaster management and environmental management studies (Üstün and Barbarosoğlu, 2015). However, the analytic hierarchy process (AHP), one of the MCDM techniques is widely used for environmental studies (Jozaghi et al., 2018; Machiwal et al., 2011; Pramanik, 2016).

Chronic kidney disease of unknown aetiology (CKDu) is considered as one of the major health problems in the dry zone, especially the north-central province of Sri Lanka. A special feature of this disease is the patients with CKDu do not exhibit the common causative factors of kidney disease such as diabetes or hypertension or the aging population (Athuraliya et al., 2011). Since the available surface water resources are limited in this area, people rely heavily on the extraction of groundwater from shallow regolith aquifer and the fractures in the hard rock. The tanks available at the tank cascade system has significant control of the recharge of shallow regolith aquifer (Chandrajith et al., 2011b; Mahatantila et al., 2011). Among the 3500-4000 cascade systems, most are clustered in the north-central province, especially in the Anuradhapura district (Cooray et al., 2019). People use dug wells (maximum depth of 15 m build on shallow regolith aquifer) and tube wells (maximum depth of 60 m build on hard rock aquifers) to fulfill the drinking water requirement. However, the World Health Organization (WHO) recommended that the provision of safe drinking water is very important to prevent CKDu. Hence reverse osmosis plants were established in these areas since 2011.

The Ulagalla cascade is a major TCS located near Anuradhapura city, in the dry zone of Sri Lanka. Although the cascade has not been studied comprehensively, elevated concentrations of nutrients were observed in the adjacent Thirappane and Mahakanumulla cascades (Wijesundara et al., 2012), showing that not only the quantity but also the quality of irrigation water poses problems for sustainable farming. However, no scientific protocol has yet been developed to assess the suitability of groundwater for irrigation and drinking purposes in the tank cascade landscapes or similar environments.

1.1 General objective of the study

To develop a GIS-based protocol to assess the groundwater quality in the tank cascade landscape in Sri Lanka.

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2.0. Interpolation Methods for Groundwater Quality Assessment in Tank Cascade Landscape

2.1. Introduction

The tank cascade system (TCS) is a unique water storage and supply system used in the intermediate and dry zones of Sri Lanka. The system has been in use since the third century BCE (Madduma Bandara, 1985), mainly for irrigation and domestic water use. The main principle behind the TCS is re-use and recycling of water through a connected series of tanks. Hence, the TCS is defined as a connected series of tanks arranged within a micro- (or meso-) catchment of the dry zone landscape for storing, conveying, and utilizing water from an ephemeral rivulet (Madduma Bandara, 1985). As can be seen in Figure 2.1, the major elements of TCS are categorized as meso-catchment, micro-catchment (catchment area of the individual tanks within the cascade), the main valley, side valleys and irrigated paddy lands. It has been recognized as a globally important agricultural heritage site by the Food and Agriculture Organization of the United Nations (FAO).

The dry zone of Sri Lanka receives an annual rainfall less than 1750 mm whereas, annual evaporation ranges from 1700-1900 mm, which implies the water stress condition during dry periods (Panabokke et al., 2002). This area is characterized by a short rainy period (from September to January), which receives 80% of the total rainfall and long dry period (from February to October). As this area is dominated by reddish-brown earth with low water retention capacity, the water scarcity problem is intensified in this area (Panabokke et al., 2002). This spatial and temporal variation of rainfall has led the ancient farming communities to invent TCS, which can act as a sustainable water management system. TCS provides cooler micro-climate which enhance the plant and animal biodiversity while providing habitat for endangered elephants, resident, and migrant water birds. Though it is not totally similar to Sri Lankan tank cascade systems, comparable environments are in use for paddy irrigation in India (Bebermeier et al., 2017; Bitterman et al., 2016; Van Meter et al., 2016).

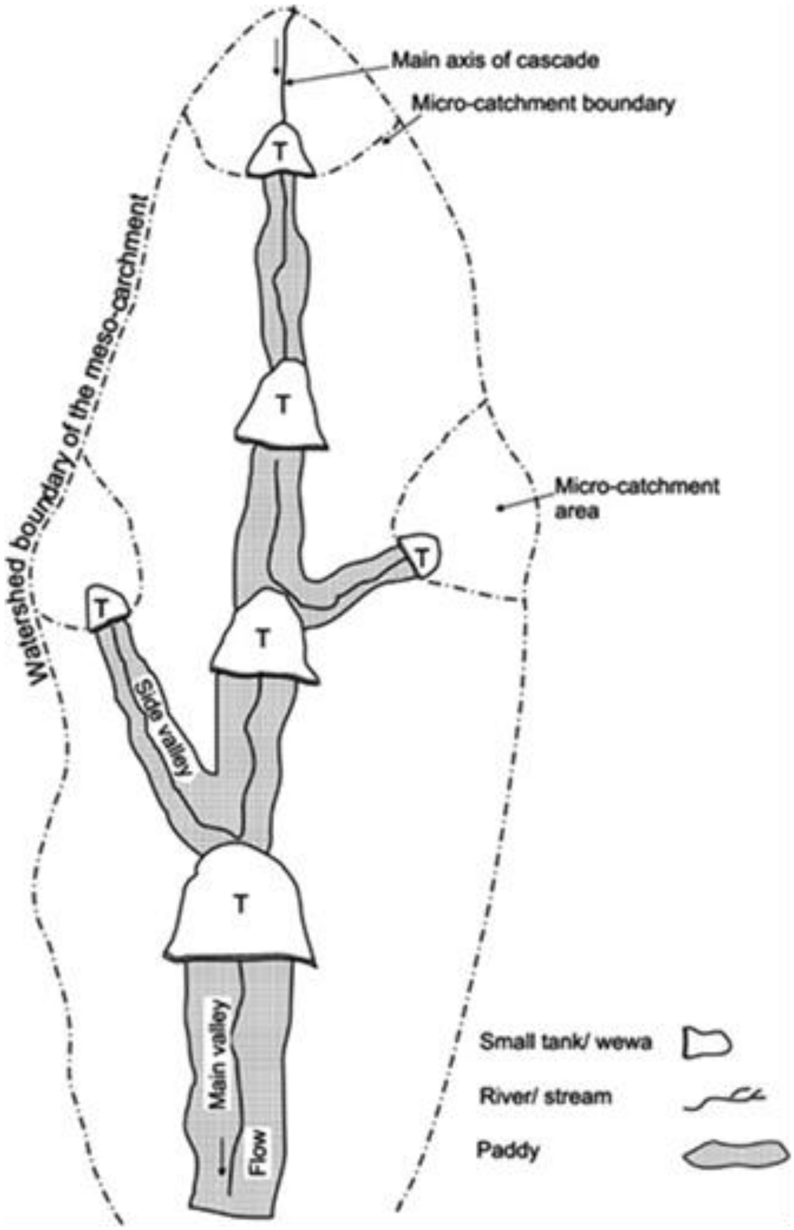

Figure 2.1. Schematic representation of tank cascade system in dry zone of Sri Lanka (adapted from Panabokke et al., 2002)

As a convenient substitute for insufficient surface water resources in the dry zone of Sri Lanka, groundwater use has dramatically increased during the last three decades, coinciding with changes in agriculture and livelihoods (Jayakody, 2006; Kumari et al., 2013). Moreover, a close relationship between the groundwater and surface water has been identified in the tank cascade landscape (Bebermeier et al., 2017). Hence, the sustainability of the tank cascade landscape is endangered along with the overexploitation and quality deterioration of groundwater. Thus, an increasing amount of attention has been given to sustainably managing water resources in the tank cascade landscapes, and several monitoring studies of groundwater in this landscape have been conducted (Wijesundara et al., 2012; Gunarathna et al., 2016a,b; Kumari et al., 2016). However, no appropriate continuous monitoring system has been put in place, because continuous monitoring of groundwater over a large area for an extended duration is expensive and labor-intensive. Therefore, a suitable method for estimating groundwater availability and quality is needed that requires a minimum number of sampling sites in order to better manage the water resources in the tank cascade landscapes. Spatial interpolation, including deterministic and geostatistical interpolation techniques in ArcGIS, has been used to understand the spatial and temporal variation of natural resources, including groundwater, and related environmental concerns (Chai et al., 2011; Gunaalan et al., 2018). Deterministic interpolation techniques include inverse distance weighted (IDW), radial basis functions (RBFs), global polynomial interpolation (GPI), and local polynomial interpolation (LPI) methods; geostatistical interpolation techniques include kriging/co-kriging (ordinary kriging [OK], simple kriging [SK], universal kriging [UK], etc.), areal interpolation, and empirical Bayesian kriging (EBK). The ArcGIS Geostatistical Analyst extension can fill the gap between geostatistics and GIS analysis and has been used to characterize the spatial variability of variables in detail (Bao et al., 2014; Kumar et al., 2007; Uyan and Cay, 2013).

Interpolation accuracy is sensitive to the precise demarcation of boundaries and areas (Gunaalan et al., 2018; Mirzaei and Sakizadeh, 2016), the effectiveness of predicting parameters of unknown locations using known values, sample size (Stahl et al., 2006), spatial distribution of sampling sites (Güler, 2014), normality of the dataset (Wu et al., 2016), grid size or resolution (Hengl, 2007), and interpolation method (Luo et al., 2008; Xie et al., 2011). Moreover, if the distribution of sampling locations or wells does not appropriately represent the spatial variation of water quality parameters, any biases will be intensified (Heistermann and Kneis, 2011; Wagner et al., 2012). However, different interpolation methods tend to provide similar predictions at low (Mirzaei and Sakizadeh, 2016) and very high sampling densities (Gunnink and Burrough, 1996). In most cases, interpolation methods have been used without proper assessment of their accuracy. Only a few assessments of accuracy have been conducted. Mirzaei and Sakizadeh (2016) evaluated three interpolation methods to estimate a water quality index and found EBK to be the best method. Xie et al. (2011) stated that the best interpolation method to explain the spatial variation of heavy metals in soil varied with the size of the polluted area. Seyedmohammadi et al. (2016) compared five interpolation methods to estimate the spatial variation of electrical conductivity (EC) in groundwater and reported that OK was superior to the others. Based on the relative performance of four interpolation methods to interpolate EC, total dissolved solids (TDS), and pH, EBK was found as the best method (Gunarathna et al., 2016a, b).

2.1.1 Objectives of the study

To date, no study has evaluated these interpolation methods with an extensive number of parameters covering all contaminant groups (anions, cations, nutrients) and water quality indices along with temporal effects. Because the assessment of spatial and temporal variation of groundwater is essential in sustainable management of water resources, the objective of this study was to describe and predict the relative performance of deterministic (IDW, LPI, GPI, and RBFs) and geostatistical (UK, OK, and EBK) interpolation methods and to select the best interpolation method to explain the spatial and temporal variation of groundwater quality in the Ulagalla cascade, Sri Lanka. Many physicochemical parameters were studied, including anions, cations, nutrients, and other water quality indices, as well as temporal effects. The relationships between characteristics of datasets and those of different interpolation methods were also examined.

2.2. Materials and Methods

2.2.1. Study Area

Ulagalla cascade covers approximately 51 km^2 in the Anuradhapura district of Sri Lanka (8°5'–8°14'N; 80°31'–80°34'E). The economy of this area is based on agriculture, which comprises tank-based paddy cultivation and rainfed or irrigated upland crop cultivation using groundwater. The mean annual rainfall in Anuradhapura is 1255 mm, and there is a distinct dry period from May to September. The monthly average maximum and minimum temperatures in the dry zone range from 25.0 to 37.7 °C and 17.4 to 26.8 °C, respectively (Abeysekara and Punyawardena, 2016; Gunarathna and Kumari, 2013a). A shallow regolith aquifer of the hard rock region is the main aquifer type in the study area. Groundwater potential is comparatively limited because of the low groundwater storage capacity and transmissivity of the underlying crystalline basement (Sirimanne, 1952a).

2.2.2. Data collection and Data Preparation

The total cascade area was divided into 1-km^2 cells, and one agro-well was purposely selected to represent each cell so as to evaluate the quality of groundwater in the study area. Within the existence of agro-wells and the availability of water in the agro-wells throughout the study period, a total of 29 wells were selected (Figure 2.2). Three replicates from aforesaid 29 wells were collected monthly from April 2016 to March 2017 to measure the water quality parameters using standard procedures (APHA, 2005). All the chemical analyses were carried out at the laboratory of soil and water sciences, Department of Agricultural Engineering and Soil Science, Faculty of Agriculture, Rajarata University of Sri Lanka. Sodium adsorption ratio (SAR) (Wilcox, 1955) and total hardness (TH) (Todd and Mays, 2005) were calculated from measured data. The following 12 water quality parameters or indices were used: electrical conductivity (EC); pH; concentrations of sodium (Na^+), potassium (K^+), calcium (Ca^{2+}), magnesium (Mg^{2+}), chloride (Cl^-), nitrate (NO_3-N), phosphate (PO_4^{3-}), and bicarbonate (HCO_3^-); sodium adsorption ratio (SAR); and total hardness (TH).

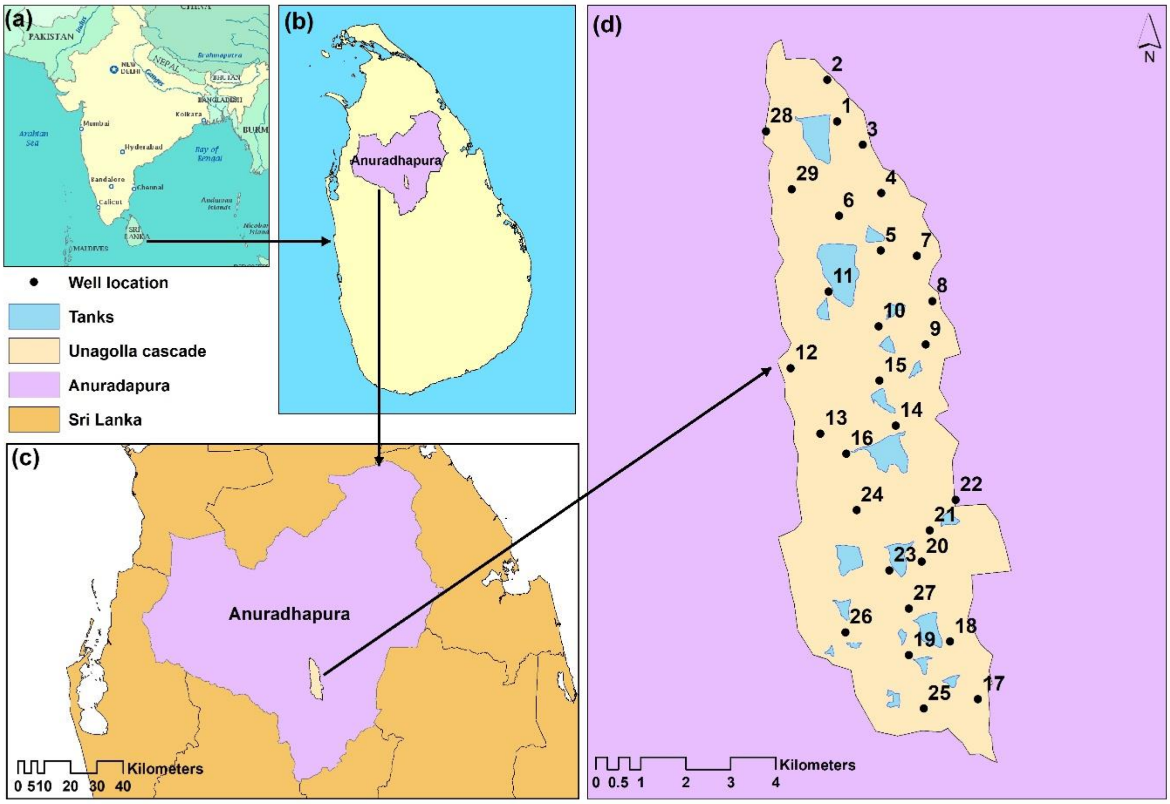

Figure 2.2. Location of the study areas: (a) South Asia; (b) Sri Lanka; (c) Anuradhapura district; (d) Groundwater sampling locations in Ulagalla cascade

Attribute data containing information about the physicochemical parameters/indices were joined with geographic coordinates obtained with a handheld global positioning system (GPS) receiver (eXplorist 510, Magellan, USA) of each sampling point (Appendix Table A1). ArcGIS 10.2 (ESRI, California, USA) and R statistical software (R Foundation for Statistical Computing, Vienna, Austria) (Team R, 2016) were used for the interpolation analysis and statistical analysis, respectively.

2.2.3. Interpolation Methods

2.2.3.1. Inverse Distance weighted (IDW)

In IDW, the interpolation weights are calculated as a function of the observed sampling point and the prediction point (Gunnink and Burrough, 1996). The accuracy of IDW depends on the number of closest neighboring sampling points (Yao et al., 2013). The values for unknown points are estimated with Equation 2.1:

$$Z(x_0) = \frac{\sum_{i=1}^{n} \frac{x_i}{h_{ij}^{\beta}}}{\sum_{i=1}^{n} \frac{1}{h_{ij}^{\beta}}} \qquad (2.1)$$

Where $Z(x_0)$ is the interpolated value, x_i is the i^{th} data value, β is the user-defined exponent for weighting, n is the total number of sampling data values, and h_{ij} is the distance between the known point and the unknown point (Seyedmohammadi et al., 2016).

2.2.3.2. Global Polynomial Interpolation (GPI)

The GPI method positions a plane between sample points by fitting a polynomial formula to the points. Using a value on the plane that relates to the prediction location, the unknown point is determined by minimizing the errors (Webster and Oliver, 2008) With the use of low order polynomials GPI creates slowly while describing the physical processes. However, with complex polynomials, it is difficult to ascribe physical meaning to GPI (Johnston et al., 2003).

2.2.3.3. Local polynomial Interpolation (LPI*)*

Whereas GPI fits one polynomial to the entire surface, LPI fits many polynomials, each within specified overlapping local neighborhoods. Although this method produces smooth surfaces, it is best suited for use only with data that have a narrow range of variation. LPI creates a surface from many different polynomial formulas, each of which is optimized for a specified neighborhood, neighborhood shape, and maximum and minimum number of points. LPI is sensitive to the neighborhood distance, and the sample points in a neighborhood can be weighted by their distance from the prediction location. Because LPI is sensitive to neighborhood distance and a small search neighborhood may create empty areas in the prediction surface, the method shows better results with grid-based sampling data than with random point sampling (Hani et al., 2011; Johnston et al., 2003).

2.2.3.4. Radial Basis Functions (RBFs)

RBFs are a form of artificial neural networks with a series of exact interpolation techniques. They use an equation derived from the distance between an interpolated point and the sampling points (Aguilar et al., 2005; Lin and Chen, 2004). The method consists of five deterministic interpolation techniques: thin-plate spline, spline with tension, completely regularized spline, multi-quadratic function, and inverse multi- quadratic function. The RBF method is used mainly to create smooth surfaces from a large number of data points. Although RBFs give good results for areas with gently varying surfaces, the method will not provide accurate results if there are any large variations in the surface within a short horizontal distance (Johnston et al., 2003). The most commonly used RBF technique, completely regularized spline was used for this analysis.

2.2.3.5. Kriging

Kriging is a linear interpolation method that assumes that the parameter to be interpolated can be modeled by random processes with spatial autocorrelation. Hence, kriging techniques are widely used to describe and model spatial patterns and predict values at unmeasured locations. Three types of kriging were evaluated in this study: ordinary kriging, universal kriging, and empirical Bayesian kriging.

2.2.3.5.1. Ordinary Kriging (OK)

OK is the most widely used kriging method. It uses an average of a subset of neighboring points to produce a particular interpolation point. OK can use either semivariograms or covariances to explain the autocorrelation and can use transformations to avoid trends (Johnston et al., 2003), but the semivariance function plays a major role in deriving weights of OK (Johnston et al., 2003). The empirical semivariance function can be used to estimate the parameters of the semivariogram function and the nugget effect as expressed in Equation 2.2:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(x_i) - Z(x_i + h) \right]^2 \tag{2.2}$$

where γ is the semivariance, $N(h)$ is the number of data pairs within a given class of distance and direction, h is the lag distance, and $Z(x_i)$ and $Z(x_i + h)$ are the sample values at two points separated by the distance interval h (Xie et al., 2011).

2.2.3.5.2. Universal Kriging

UK can be used to produce prediction, quantile, probability, or standard error maps. The method is used to estimate the spatial means when the data have a strong trend, and the trend is modeled using simple functions. The use of UK is limited to large surfaces, such as a large country because it is difficult to follow a trend along the direction of spreading (Kis, 2016).

2.2.3.5.3. Empirical Bayesian Kriging (EBK)

EBK is different from other classical kriging methods because the parameters are automatically optimized using a number of semivariogram models instead of a single semivariogram. The following steps are used in EBK: (1) A semivariogram model is estimated using available data. (2) A new value is simulated for each input data location using the semivariogram model. (3) Based on the simulated data, a new semivariogram model is estimated. Bayes's rule is then used to calculate the weight of the new semivariogram model. By repeating steps 2 and 3, the semivariogram estimated in step 1 is used to simulate a new set of values at the input locations (Krivoruchko, 2012).

2.2.4. Data Processing

Because the Kriging methods require the sample distribution to be normal, the Shapiro Wilk test was performed for all 144 datasets (12 water quality parameters/indices × 12 months) to check the goodness-of-fit of the data ($P < 0.05$). The results showed that K^+, Mg^{2+}, NO_3-N, Cl^-, and EC were not normally distributed at any time, and the other parameters and indices were normally distributed only for several months. Hence, datasets that were not normally distributed were log-transformed, and thereafter except very few, all the other data sets were normally distributed.

2.2.5. Validation and Model Evaluation

Cross-validation and validation with an independent dataset are the most common methods used to compare different interpolation methods, whereby the data are divided into a training set and a validation set. The validation set is used to test the model acquired from the training set. Those allowed us to assess the goodness-of-fit of interpolation methods and the appropriateness of the neighborhood (Dashtpagerdi et al., 2013; Gunarathna et al., 2016a,b). Because the number of sampling points was limited, we used leave-one-out cross-validation (Gunarathna et al., 2016a) to estimate the spatial variation of water quality parameters/indices in the study area, removing one data point from the known dataset and estimating its value from the other known values. If a model has a standardized mean error close to 0, the RMSE and average standard error are as small as possible as compared with other models, which means the model provides the most accurate predictions. Hence, we used RMSE (Equation 2.3) to compare the models:

$$RMSE = \sqrt{\frac{1}{n}\left(Z_i - \hat{Z}_i\right)^2} \tag{2.3}$$

Where; $\hat{Z}_i$ is the estimated value, Z_i is the measured value at sampling point i (i = 1,.., n), and n is the total number of observations.

The coefficient of variance (CV), which is the ratio of the standard deviation to the mean of each parameter/index, was used to study the relative variability of the dataset. We used the local Moran's Index (MI), one of the most commonly used criteria for spatial autocorrelation of quantitative data (Moran, 1950), to estimate the level of spatial autocorrelation of water quality parameters/indices in the Ulagalla cascade.

2.3. Results and Discussion

2.3.1. Relative Performance of Deterministic and Geostatistical Interpolation Methods

The RMSE values of cross-validation for the 12 water quality parameters/indices during 12 consecutive months are summarized in Appendix Tables A2–A13. Note that the RMSE values of the OK and UK interpolation methods were similar to each other for all the parameters/indices, and are considered together as kriging (KR). EBK was superior to all other interpolation methods in estimating spatial variation of K^+, Mg^{2+}, NO_3-N, and EC in all 12 months (Table 2.1; Appendix Tables A4, A6, A7, A11); of Na^+, HCO_3^-, Cl^-, and TH in 11 months (Table 2.1; Appendix Tables A3, A9, A10, A13); of SAR in 10 months and of pH and PO_4^{3-} in 7 months (Table 2.1; Appendix Tables A12, A2, A8). EBK was outperformed in only 6 months in the interpolation of Ca^{2+} (Table 2.1; Appendix Tables A5). Overall, EBK was the best method for interpolating groundwater quality parameters/indices in 121 out of the 144 incidences.

Based on the number of success incidences obtained from the cross-validation results, the interpolation methods can be sorted, as EBK > LPI > GPI > IDW > KR > RBF (Table 2.1). This ranking supports the findings of Gunarathna et al., (2016a,b) and Mirzaei and Sakizadeh (2016), who also found EBK to be superior to other interpolation methods with the use of a limited number of variables. Even though EBK recorded the lowest RMSE value for most of the parameters/indices, that was not the case with Ca^{2+} and PO_4^{3-}, for which several methods had the lowest RMSE during different months (Table 2.1). Hence, we selected Ca^{2+} (Table 2 .2) and PO_4^{3-} (Table 2.3) to elucidate differences in the methods.

Table 2.1. Summary of selected best interpolation methods for different parameters/indices during the study period

	pH	**Na^+**	**K^+**	**Ca^{2+}**	**Mg^{2+}**	**NO_3^--N**	**PO_4^{3-}**	**HCO_3^-**	**Cl^-**	**EC**	**SAR**	**TH**
Apr	EBK	EBK	EBK	GPI	EBK	EBK	EBK	EBK	KR	EBK	RBF	EBK
May	EBK	EBK	EBK	EBK	EBK	EBK	KR	EBK	EBK	EBK	KR	EBK
Jun	EBK	EBK	EBK	EBK	EBK	EBK	EBK	EBK	EBK	EBK	EBK	EBK
Jul	IDW	EBK	EBK	EBK	EBK	EBK	RBF	EBK	EBK	EBK	EBK	EBK
Aug	GPI	EBK	EBK	EBK	EBK	EBK	RBF	EBK	EBK	EBK	EBK	EBK
Sep	EBK	EBK	EBK	GPI	EBK	EBK	KR	EBK	EBK	EBK	EBK	EBK
Oct	EBK	EBK	EBK	LPI	EBK	EBK	EBK	EBK	EBK	EBK	EBK	LPI
Nov	EBK	IDW	EBK	GPI	EBK	EBK	RBF	EBK	EBK	EBK	EBK	EBK
Dec	GPI	EBK	EBK	EBK	EBK	EBK	RBF	KR	EBK	EBK	EBK	EBK
Jan	LPI	EBK	EBK	GPI	EBK	EBK	EBK	EBK	EBK	EBK	GPI	EBK
Feb	LPI	EBK	EBK	LPI	EBK	EBK	EBK	EBK	EBK	EBK	RBF	EBK
Mar	EBK	EBK	EBK	EBK	EBK	EBK	RBF	EBK	EBK	EBK	RBF	EBK

Table 2.2. Summary statistics of calcium concentration in Ulagalla cascade

	Apr	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**
Mean	*182.9*	*38.2*	*63.6*	*70.4*	*35.3*	*49.7*	*30.1*	*35.0*	*92.2*	*86.4*	*84.5*	*37.3*
Standard deviation	*89.7*	*28.4*	*30.3*	*47.2*	*19.5*	*25.1*	*20.6*	*17.5*	*44.0*	*36.5*	*53.8*	*23.1*
CV (coefficient of variance)	49	74	48	67	55	50	69	50	48	42	64	62
Moran's Index (MI)	−0.19	−0.12	−0.39	0.04	−0.18	−0.30	0.13	−0.26	−0.26	−0.22	−0.03	−0.07
P-value of MI	0.31	0.57	0.02	0.60	0.32	0.08	0.22	0.13	0.12	0.22	0.96	0.79
Skewness (original data)	*0.40*	*1.28*	*0.62*	*0.91*	*1.45*	*0.84*	*1.99*	*0.81*	*1.22*	*0.22*	*1.62*	*1.66*
Skewness (after log transformation)	0.4	0.07	0.62	−0.18	0.33	0.84	−0.19	0.81	−1.04	0.22	−0.43	−0.07
Range	*350*	*114*	*117*	*161*	*85*	*106*	*100*	*80*	*226*	*129*	*264*	*100*
Lowest RMSE	**GPI**	**EBK**	**EBK**	**EBK**	**EBK**	**GPI**	**LPI**	**GPI**	**EBK**	**GPI**	**LPI**	**EBK**
2nd lowest RMSE	**LPI**	**KR**	**KR**	**GPI**	**KR**	**EBK**	**EBK**	**LPI**	**GPI**	**EBK**	**EBK**	**KR**
3rd lowest RMSE	**KR**	**LPI**	**GPI**	**LPI**	**GPI**	**KR**	**RBF**	**EBK**	**LPI**	**LPI**	**GPI**	**GPI**
4th lowest RMSE	EBK	GPI	LPI	KR	LPI	LPI	IDW	KR	KR	KR	KR	LPI
5th lowest RMSE	IDW	RBF	IDW	IDW	RBF	IDW	KR	IDW	IDW	IDW	IDW	RBF
6th lowest RMSE	RBF	IDW	RBF	RBF	IDW	RBF	GPI	RBF	RBF	RBF	RBF	IDW
Well numbers with extreme values		1		10, 14	1	10	27, 28	10	10		10	1, 10

As inexact interpolators among the selected methods, GPI and LPI showed quite similar results compared to other methods used in the present study, and this was supported by Wang et al. (2014). Xiao et al. (2016) also confirmed that GPI is suitable only when the variability of the dataset is relatively small. Although GPI can be used to analyze the surface trend of regionalized variables, it is not accurate when extreme values are present (Mutuna and Kurima 2012; Wang et al., 2014). LPI is also capable of simulating a narrow range of variability with high accuracy (Xiao et al., 2016). GPI was ranked in the top three methods during 10 months of the study period, and the CV was relatively small in 6 of those 10 months (Table 2.2). Moreover, no extreme values were recorded near the boundaries in those 6 months. In the other 4 months, the variation of the dataset was moderate, and no extreme values were recorded near the boundaries (Table 2.2). According to the summary statistics of phosphate concentration (Table 2.3), the conditions of low variation and no extreme values near boundaries were met in only 3 months, and GPI was ranked among the top three only once.

IDW is widely used in the field of environmental sciences, but it is rarely recommended as the best interpolation method in comparison studies (Li and Heap, 2011). In their review, Li and Heap (2011) reported that IDW is highly sensitive to sample density and data variation (CV). The poor performance of IDW in our study could be attributed to the high spatial data variation and relatively low sample size. In the classification using Ca^{2+} and PO_4^{3-}, IDW was never the best-fit model when the CV was high. Therefore, we do not recommend the use of IDW to interpolate spatial variation of groundwater quality parameters/indices in the tank cascade landscapes unless the data show low spatial variation and have a higher sample density with an evenly distributed sampling pattern.

Table 2.3. Summary statistics of phosphate concentration in Ulagalla cascade

	Apr	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**
Mean	0.04	0.05	0.06	0.57	0.58	0.06	0.11	0.16	0.09	0.04	0.32	0.70
Standard deviation	0.04	0.06	0.05	0.24	0.27	0.08	0.16	0.15	0.12	0.05	0.06	0.78
CV (coefficient of variance)	97	119	87	42	47	135	139	91	134	106	20	111
Moran's Index (MI)	0.33	0.26	0.37	0.43	0.36	0.25	0.17	0.26	0.25	0.23	0.03	0.20
P-value of MI	0.00	0.02	0.00	0.00	0.00	0.03	0.14	0.04	0.04	0.06	0.61	0.09
Skewness (original data)	*2.2*	*2.9*	*2.4*	*1.9*	*1.9*	*2.4*	*2.2*	*2.0*	*2.1*	*2.0*	*−2.1*	*2.7*
Skewness (after log transformation)	0.8	0.8	0.2	1.0	0.5	0.8	0.5	1.2	0.5	0.7	−2.6	1.0
Range	0.15	0.26	0.26	0.99	1.30	0.34	0.63	0.57	0.44	0.17	0.26	3.69
Lowest RMSE	**IDW**	**RBF**	**RBF**	**EBK**	**RBF**	**RBF**	**EBK**	**EBK**	**EBK**	**EBK**	**EBK**	**EBK**
2nd lowest RMSE	**EBK**	**KR**	**EBK**	**KR**	**EBK**	**KR**	**RBF**	**GPI**	**RBF**	**RBF**	**LPI**	**LPI**
3rd lowest RMSE	**RBF**	**LPI**	**IDW**	**RBF**	**KR**	**LPI**	**IDW**	**KR**	**KR**	**KR**	**GPI**	**GPI**
4th lowest RMSE	LPI	EBK	KR	IDW	IDW	EBK	LPI	LPI	IDW	IDW	IDW	KR
5th lowest RMSE	GPI	IDW	GPI	LPI	LPI	IDW	GPI	RBF	LPI	GPI	RBF	RBF
6th lowest RMSE	KR	GPI	LPI	GPI	GPI	GPI	KR	IDW	GPI	LPI	KR	IDW
Well numbers with extreme values	14, 16, 12	14, 16	2, 14	14, 16	1, 2, 14, 15, 16	1, 2, 11, 14, 15, 16	14, 16, 11	11, 14, 16, 25	14, 16, 11	14, 11	14, 16, 11	16, 15, 11

Kriging (KR) is one of the most widely used interpolation methods in the field of environmental sciences, and it has been recommended in comparison studies (Li and Heap, 2011). Basic assumptions of KR are spatially autocorrelated observations (a function of the distance between observations) and normally distributed data (Zimmerman et al., 1999). Therefore, KR has a strong ability to predict the overall trend of groundwater contamination when a dataset is autocorrelated (Ahmed, 2002; Mutuna and Kurima, 2012; Nas, 2009; Xie et al., 2011; Zehtabian et al., 2013). As shown in Table 2.3, KR was ranked on the first three for six months when the data was significantly autocorrelated in 8 months and was in the top three in 5 of those eight months. This characteristic was also observed in the Ca^{2+} dataset, where KR performed well in June when the data were autocorrelated.

Because EBK divides the dataset into subsets and simulates a semivariogram for each subset to reduce the uncertainty relative to that in KR, it provides relatively better interpolation accuracy on small datasets and non-stationary datasets than KR (ESRI, 2015). In Tables 2.2 and 2.3, EBK was listed in the top three in 21 of 24 incidences. This shows that EBK performs well irrespective of CV, MI, extreme values near boundaries (EVnB), and skewness (SK). However, when the dataset was less variable, showed autocorrelation, and had no EVnB, other interpolation methods performed better than EBK. Hence, we recommend using EBK when data show high variability and no autocorrelation, and extreme values near boundaries and are not normally distributed.

As the quality of the dataset determines the accuracy of different interpolation methods, we assessed the importance of CV, MI, SK, and EVnB (characteristics that show the quality of a dataset) to the success of each method using an attribute evaluation option available in the CORElearn package (Robnik-Sikonja and Savicky, 2017) of R software (Table 2.4). The relative importance of the characteristics can be sorted as EVnB > CV > SK > MI for GPI and EVnB > SK > CV > MI for LPI. These results confirm the sensitivity of GPI and LPI to CV and EVnB. The relative importance for RBF was CV > EVnB > SK > MI, demonstrating that RBF is sensitive to the variability of the dataset and EVnB. The relative failure of RBF in this study can be explained by the high spatial variation of the water quality parameters/indices. The relative importance for IDW was EVnB > CV > MI > SK, confirming its sensitivity to dataset variability and extreme values. The relative importance for KR was EVnB > MI > CV > SK, confirming that KR can be successfully used when the dataset is autocorrelated with low variability while lacking extreme values near boundaries.

Table 2.4. The relative importance of attributes on different interpolation methods

	Relative importance					
Attributes	**GPI**	**LPI**	**RBF**	**IDW**	**KR**	**EBK**
CV	0.013	0.036	0.181	0.274	0.013	0.025
MI	−0.031	0.010	0.010	0.243	0.052	0.009
SK	−0.02	0.081	0.050	0.730	0.001	−0.013
EVnB	0.262	0.093	0.077	0.422	0.218	0.154

CV –coefficient of variance, MI- Moran's Index, SK- Skeweness, EVnB- extreme values near the boundary

2.3.2. Distribution pattern of observed and simulated data using the EBK method

Figure 2.3 shows the boxplot diagrams of the observed and EBK-predicted values of the 12 parameters/indices. The measured and predicted values of almost all the parameters/indices were right-skewed except pH, showing that the majority of the values are clustered below the median and the means are greater than the median. Further, it can be noted that EBK was unable to properly predict extreme values, but there were no significant differences between observed and predicted values. The final spatial distribution maps of water quality parameters/indices prepared using the EBK interpolation method for the mean values of the 12 parameters/indices are shown in Figure 2.4. It was observed that the concentration of most parameters/indices was comparatively low at the upper part of the cascade, and it has increased at the lower part of the cascade due to the accumulation effect.

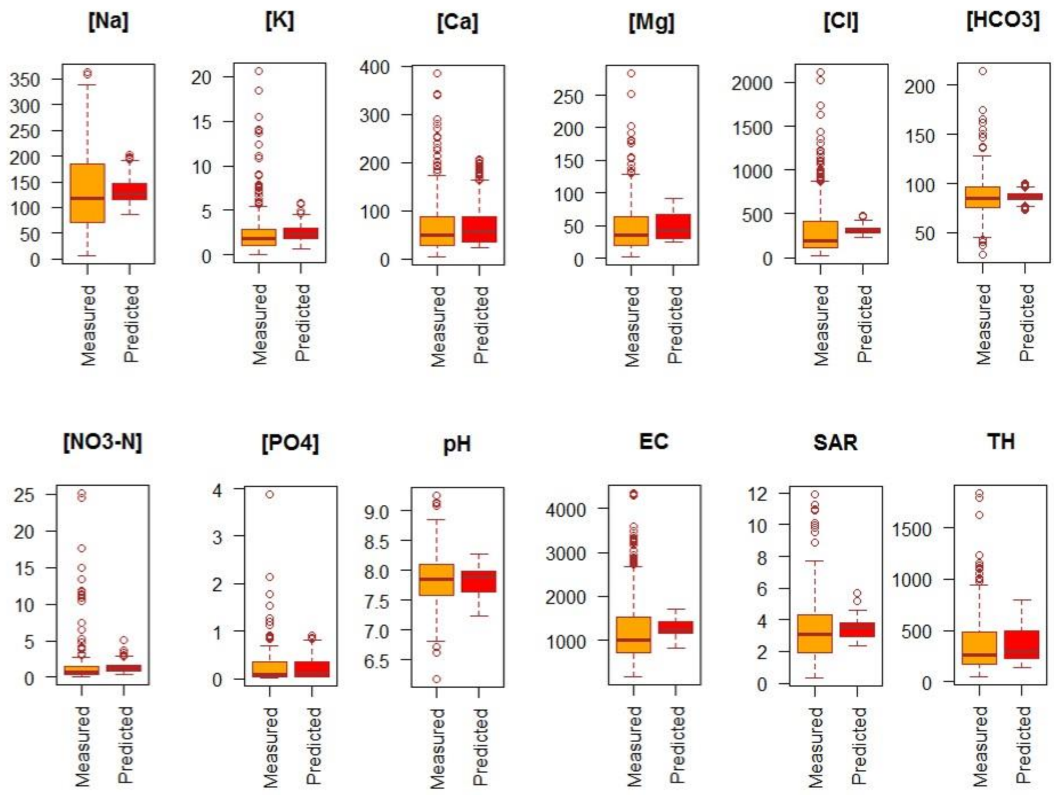

Figure 2.3. Boxplot diagrams of observed and EBK-predicted values of (a) Na^{+} (mg/L) (b) K^{+} (mg/L) , (c) Ca^{2+}(mg/L), (d) Mg^{2+} (mg/L) , (e) Cl^{-} (mg/L) , (f) HCO_3^{-} (mg/L), (g) NO_3-N (mg/L) , (h) PO_4^{3-} (mg/L) , (i) pH , (j) EC (µS/cm) , (k) SAR and (l) TH (mg/L) in Ulagalla cascade

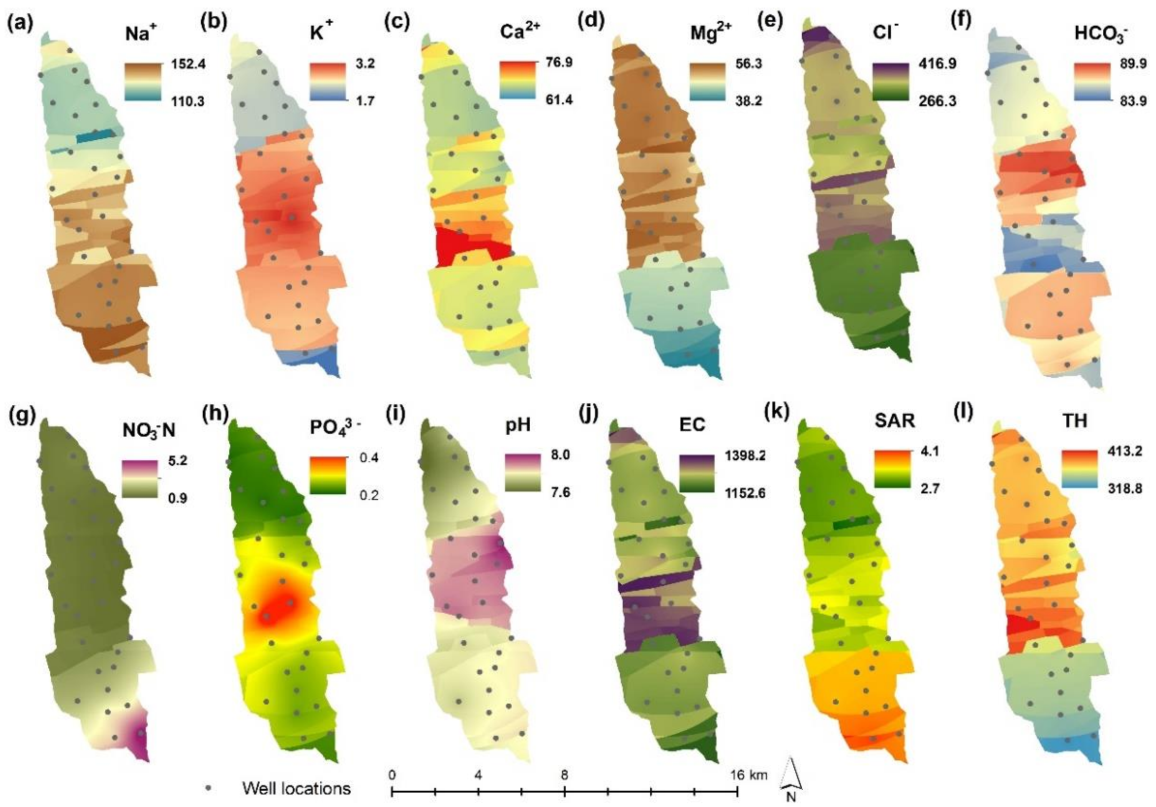

Figure 2.4. Spatial distribution of (a) Na^+ (mg/L), (b) K^+ (mg/L) , (c) Ca^{2+}(mg/L), (d) Mg^{2+} (mg/L) , (e) Cl^- (mg/L) , (f) HCO_3^- (mg/L), (g) NO_3-N (mg/L) , (h) PO_4^{3-} (mg/L) , (i) pH , (j) EC (µS/cm) , (k) SAR, and (l) TH (mg/L) in Ulagalla cascade

2.4. Conclusions

A clear understanding of spatial and temporal variation in water quality parameters/indices is a key issue in agriculture as well as in environmental studies. At present, many algorithms are used with the aim of selecting the best interpolation method for delineation of the spatial distribution of water quality parameters/indices. We investigated the interpolation accuracy of a variety of methods in a tank cascade landscape.

The EBK method proved superior to deterministic and other geostatistical methods in interpolating groundwater quality parameters (anions, cations, and nutrients) and indices associated with tank cascade landscapes. Kriging interpolation was successful when the dataset was autocorrelated with low variability. IDW had the worst results in estimating the spatial distribution of water quality parameters/indices. Better performance was obtained with the GPI and LPI methods when the dataset was less variable and had no extreme values near boundaries.

Because groundwater monitoring is labor-intensive and expensive, it is important to use optimum sampling density and to choose the design in a methodical way. Furthermore, it is advisable to decide on the interpolation method before sampling and then schedules sample density and design accordingly. This study can be used as a guide for such decision making for groundwater monitoring in a tank cascade landscape.

In general, the preparation of a composite water quality zonation map for the Ulagalla cascade with the integration of the EBK method and water quality indices/parameters can be carried out. Future research can be conducted to find out the optimum number of sampling points to obtain a precise estimation of water quality in the tank cascade landscape.

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Appendix

Appendix Table A1. Longitude and latitude of the sampling locations

Well no.	**Longitude**	**Latitude**	**Well no.**	**Longitude**	**Latitude**
1	80° 32' 28" E	8° 13' 35" N	16	80° 32' 35" E	8° 9' 34" N
2	80° 32' 21" E	8° 14' 5" N	17	80° 34' 11" E	8° 6' 36" N
3	80° 32' 47" E	8° 13' 18" N	18	80° 33' 51" E	8° 7' 18" N
4	80° 33' 1" E	8° 12' 43" N	19	80° 33' 21" E	8° 7' 8' N
5	80° 33' 0" E	8° 12' 1" N	20	80° 33' 30" E	8° 8' 16" N
6	80° 32' 30" E	8° 12' 27" N	21	80° 33' 36" E	8° 8' 38" N
7	80° 33' 27" E	8° 11' 58" N	22	80° 33' 55" E	8° 9' 0" N
8	80° 33' 38' E	8° 11' 25" N	23	80° 33' 7" E	8° 8' 9" N
9	80° 33' 33" E	8° 10' 53" N	24	80° 32' 43" E	8° 8' 53" N
10	80° 32' 59" E	8° 11' 6" N	25	80° 33' 32" E	8° 6' 29" N
11	80° 32' 23" E	8° 11' 32" N	26	80° 32' 35" E	8° 7' 24" N
12	80° 31' 55" E	8° 10' 36" N	27	80° 33' 21" E	8° 7' 42" N
13	80° 32' 16" E	8° 9' 49" N	28	80° 31' 37" E	8° 13' 28" N
14	80° 33' 11" E	8° 9' 54" N	29	80° 31' 56" E	8° 12' 46" N
15	80° 32' 60" E	8° 10' 27" N			

Appendix Table A2. Accuracy of different methods at predicting pH

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	0.422	0.421	0.442	0.440	0.482	0.482	0.393
May	0.294	0.269	0.294	0.276	0.270	0.270	0.266
June	0.406	0.430	0.425	0.438	0.409	0.409	0.402
July	0.303	0.314	0.319	0.310	0.313	0.313	0.306
August	0.401	0.392	0.412	0.400	0.413	0.413	0.404
September	0.468	0.456	0.486	0.469	0.499	0.499	0.451
October	0.417	0.395	0.426	0.406	0.440	0.440	0.391
November	0.397	0.398	0.408	0.405	0.398	0.398	0.370
December	0.394	0.356	0.397	0.357	0.395	0.395	0.377
January	0.373	0.358	0.375	0.352	0.367	0.367	0.359
February	0.355	0.373	0.359	0.344	0.351	0.351	0.347
March	0.257	0.249	0.252	0.246	0.243	0.243	0.236

Appendix Table A3. Accuracy of different methods at predicting sodium concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	92.45	92.48	95.10	94.76	96.52	96.52	90.46
May	78.64	79.38	79.95	81.00	81.91	81.91	77.20
June	72.20	64.76	74.33	67.48	63.97	63.97	63.13
July	69.93	64.29	70.40	67.04	64.68	64.68	62.25
August	76.94	71.68	80.03	74.68	77.974	77.974	70.36
September	78.63	76.92	78.91	79.49	82.32	82.32	70.71
October	59.37	57.47	60.22	59.78	62.48	62.48	52.50
November	59.40	61.57	60.22	59.60	60.392	60.392	60.15
December	101.53	101.44	103.13	104.55	104.267	104.267	98.98
January	66.72	66.66	65.96	68.75	67.62	67.62	63.51
February	91.87	94.39	93.75	97.04	94.024	94.024	91.52
March	77.68	77.91	79.63	78.36	82.09	82.09	71.69

Appendix Table A4. Accuracy of different methods at predicting potassium concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	2.497	2.512	2.509	2.461	2.435	2.435	2.413
May	2.094	2.149	2.099	2.131	2.095	2.095	2.040
June	3.008	2.922	2.954	2.847	2.886	2.886	2.841
July	2.853	2.805	2.872	2.783	2.818	2.818	2.693
August	2.272	2.311	2.297	2.256	2.187	2.187	2.190
September	1.873	1.907	1.881	1.842	1.810	1.810	1.795
October	1.509	1.566	1.528	1.553	1.486	1.486	1.453
November	1.710	1.712	1.707	1.703	1.707	1.707	1.652
December	3.669	3.686	3.694	3.674	3.659	3.659	3.500
January	2.753	2.719	2.777	2.710	2.661	2.661	2.558
February	3.300	3.482	3.324	3.307	3.249	3.249	3.198
March	1.043	1.041	1.040	1.016	1.075	1.075	1.011

Appendix Table A5. Accuracy of different methods at predicting calcium concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	99.562	90.209	100.446	91.437	93.295	93.295	94.296
May	32.981	30.199	32.803	30.184	29.581	29.581	28.213
June	36.401	32.650	37.321	33.056	32.387	32.387	31.622
July	49.471	47.518	50.900	47.606	49.863	49.863	45.759
August	23.423	20.558	23.355	20.890	20.212	20.212	19.383
September	29.037	26.220	29.319	26.744	26.700	26.700	26.594
October	20.529	21.708	20.212	17.601	20.772	20.772	20.183
November	19.873	17.981	20.212	18.285	18.807	18.807	18.682
December	49.393	45.419	49.848	45.836	46.767	46.767	43.777
January	41.396	38.672	42.099	38.988	39.115	39.115	38.914
February	55.709	53.134	56.238	51.639	54.282	54.282	52.781
March	25.096	23.094	25.008	23.289	22.864	22.864	22.832

Appendix Table A6. Accuracy of different methods at predicting magnesium concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	52.09	48.59	51.09	49.33	51.61	51.61	46.22
May	38.74	35.86	38.09	36.70	36.62	36.62	33.58
June	33.33	30.96	33.06	31.05	30.94	30.94	29.02
July	48.02	48.26	46.85	46.06	45.52	45.52	43.98
August	21.45	19.44	21.72	19.79	22.28	22.28	18.13
September	20.26	18.93	19.76	19.02	19.11	19.11	17.84
October	19.94	19.19	19.09	18.96	19.80	19.80	18.59
November	24.27	23.11	23.92	23.12	23.69	23.69	21.57
December	59.82	57.08	58.69	57.28	59.94	59.94	53.49
January	37.24	37.04	35.26	36.30	36.45	36.45	34.28
February	55.12	56.53	53.29	53.73	54.51	54.51	52.07
March	25.35	23.85	25.07	24.16	24.28	24.28	23.55

Appendix Table A7. Accuracy of different methods at predicting nitrate nitrogen concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	3.449	3.572	3.563	3.526	3.349	3.349	3.192
May	3.035	2.890	3.188	2.884	2.794	2.794	2.735
June	2.519	2.349	2.527	2.449	2.256	2.256	2.170
July	2.684	2.685	2.829	2.670	2.529	2.529	2.490
August	0.801	0.840	0.773	0.805	0.778	0.778	0.750
September	2.334	2.395	2.416	2.382	2.247	2.247	2.119
October	4.982	5.147	5.200	5.209	4.904	4.904	4.718
November	4.537	4.770	4.691	4.694	4.344	4.344	4.299
December	2.162	2.195	2.265	2.157	2.039	2.039	1.969
January	2.181	2.246	2.260	2.217	2.067	2.067	2.027
February	2.166	2.190	2.267	2.148	2.049	2.049	1.985
March	3.316	3.147	3.507	3.164	3.052	3.052	2.906

Appendix Table A8. Accuracy of different methods at predicting phosphate concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	0.0383	0.0411	0.0393	0.0400	0.0419	0.0419	0.0387
May	0.0550	0.0579	0.0429	0.0539	0.0522	0.0522	0.0544
June	0.0521	0.0554	0.0510	0.0561	0.0547	0.0547	0.0519
July	0.2372	0.2508	0.2351	0.2505	0.2299	0.2299	0.2289
August	0.2376	0.2847	0.2137	0.2559	0.2203	0.2203	0.2185
September	0.0791	0.0845	0.0665	0.0772	0.0761	0.0761	0.0784
October	0.1630	0.1643	0.1583	0.1641	0.1666	0.1666	0.1543
November	0.1601	0.1547	0.1578	0.1577	0.1561	0.1561	0.1456
December	0.1233	0.1252	0.1184	0.1251	0.1214	0.1214	0.1165
January	0.0511	0.0513	0.0494	0.0514	0.0505	0.0505	0.0478
February	0.0644	0.0642	0.0660	0.0638	0.0678	0.0678	0.0609
March	0.8531	0.8177	0.8526	0.8143	0.8521	0.8521	0.7667

Appendix Table A9. Accuracy of different methods at predicting bicarbonate concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	7.635	8.537	7.152	7.084	7.484	7.484	7.791
May	10.472	12.321	10.672	10.795	10.583	10.583	10.177
June	25.261	25.468	25.984	26.111	25.386	25.386	23.049
July	26.454	28.259	27.438	28.560	27.723	27.723	25.567
August	26.394	25.871	27.128	26.459	25.518	25.518	23.879
September	21.248	21.488	21.703	21.815	21.398	21.398	20.118
October	24.846	24.494	24.940	24.767	26.945	26.945	22.679
November	37.413	36.044	36.765	36.308	36.299	36.299	33.808
December	23.242	22.315	23.540	22.811	21.880	21.880	22.271
January	23.791	22.593	24.270	23.372	22.774	22.774	21.953
February	13.513	13.121	13.770	13.571	13.889	13.889	13.124
March	16.755	16.211	16.609	16.734	16.073	16.073	15.043

Appendix Table A10. Accuracy of different methods at predicting chloride concentration

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	523.00	472.00	514.00	479.00	473.57	473.57	474.63
May	437.00	399.00	432.00	405.00	397.85	397.85	377.13
June	299.00	260.00	303.00	266.00	256.10	256.10	243.52
July	339.00	295.00	340.00	303.00	292.21	292.21	275.89
August	340.00	310.00	340.00	316.00	301.81	301.81	290.23
September	380.00	352.00	380.00	358.00	349.04	349.04	331.90
October	349.00	320.00	349.00	324.00	317.13	317.13	301.21
November	348.00	323.00	350.00	327.00	319.33	319.33	302.74
December	467.00	426.00	473.00	433.00	423.95	423.95	401.40
January	347.00	321.00	351.00	327.00	322.52	322.52	304.87
February	366.00	341.00	368.00	347.00	341.23	341.23	325.94
March	332.00	301.00	336.00	308.00	301.53	301.53	288.31

Appendix Table A11. Accuracy of different methods at predicting electrical conductivity

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	556.00	522.00	562.00	533.00	511.68	511.68	485.51
May	1014.00	972.00	1020.00	991.00	954.44	954.44	900.32
June	901.00	789.00	915.00	809.00	781.29	781.29	733.61
July	889.00	775.00	894.00	796.00	760.98	760.98	717.11
August	966.00	861.00	974.00	883.00	846.27	846.27	800.76
September	20.00	24.00	19.00	19.00	19.22	19.22	18.55
October	1048.00	980.00	1049.00	999.00	961.50	961.50	907.20
November	1052.00	985.00	1057.00	1002.00	961.89	961.89	914.46
December	771.00	719.00	775.00	732.00	703.45	703.45	669.21
January	843.00	797.00	849.00	812.00	779.35	779.35	739.80
February	598.00	560.00	602.00	571.00	549.77	549.77	522.34
March	824.00	764.00	817.00	780.00	762.11	762.11	719.89

Appendix Table A12. Accuracy of different methods at predicting sodium adsorption ratio

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	1.571	1.667	1.446	1.546	1.459	1.459	1.639
May	2.298	2.442	2.197	2.306	2.110	2.110	2.231
June	1.394	1.367	1.435	1.421	1.449	1.449	1.311
July	2.046	1.950	2.118	2.040	2.057	2.057	1.886
August	2.458	2.420	2.526	2.475	2.779	2.779	2.269
September	2.568	2.591	2.601	2.673	2.564	2.564	2.372
October	2.177	2.187	2.217	2.261	2.253	2.253	2.012
November	2.027	2.122	2.047	2.086	2.225	2.225	1.949
December	2.150	2.186	2.160	2.196	2.142	2.142	2.100
January	1.788	1.749	1.843	1.817	1.829	1.829	2.148
February	1.921	2.008	1.622	1.872	1.781	1.781	1.694
March	2.168	2.319	2.097	2.157	2.104	2.104	2.159

Appendix Table A13. Accuracy of different methods at predicting total hardness

	RMSE						
	IDW	**GPI**	**RBF**	**LPI**	**OK**	**UK**	**EBK**
April	364.00	338.00	363.00	339.00	357.00	357.00	349.00
May	228.00	207.00	225.00	210.00	208.57	208.57	195.55
June	202.00	185.00	204.00	186.00	183.93	183.93	170.94
July	290.00	295.00	288.00	283.00	275.66	275.66	267.19
August	134.00	120.00	135.00	122.00	117.87	117.87	113.19
September	143.00	131.00	141.00	132.00	132.02	132.02	123.10
October	117.00	117.00	111.00	103.00	114.81	114.81	110.32
November	139.00	130.00	138.00	131.00	137.79	137.79	122.21
December	344.00	325.00	340.00	325.00	336.25	336.25	307.04
January	227.00	223.00	220.00	220.00	228.00	228.00	222.00
February	338.00	339.00	331.00	324.00	332.00	332.00	318.69
March	158.00	146.00	156.00	148.00	146.53	146.53	144.43

3.0 Classification of Groundwater Suitability for Irrigation in Tank cascade landscape by GIS and Analytic Hierarchy Process

3.1. Introduction

Fresh surface water resources are unevenly distributed throughout the world and are becoming scarce owing to rapid population growth, industrialization, and human activities (Annapoorna and Janardhana, 2015). So people have turned to groundwater as a major source for drinking, domestic, and irrigation purposes (Jalali, 2008). Although the quality is important as availability, it is often ignored, especially in developing regions. Since the irrigation water with poor quality harms both the soil and crop productivity (Gunarathna et al., 2016b; Raychaudhuri et al., 2014), various studies have evaluated the quality of groundwater for irrigation (Kumari et al., 2016; Nag and Suchetana, 2016; Sarath Prasanth et al., 2012). Quality is determined through the use of several parameters and indices, namely electrical conductivity (EC), total dissolved solids (TDS), nitrate-nitrogen (NO_3-N), ammonium nitrogen (NH_4-N), sodium adsorption ratio (SAR), total hardness (TH), magnesium adsorption ratio (MAR), Kelly's ratio (KR), and chloride (Gunarathne and Kumari, 2014; Kumari et al., 2013; Subramani et al., 2010; Thapa et al., 2018). A comprehensive assessment of groundwater suitability for irrigation requires the integration of these indices.

Geographical information system (GIS) is a powerful tool for assessing the environmental changes, quality, and availability of water and for managing water resources (Gunaalan et al., 2018). Spatial analysis extension in GIS allows us to interpolate environmental parameters between known values through the use of techniques such as inverse-distance-weighted, ordinary kriging, universal kriging, empirical Bayesian kriging

(EBK), spline, and trend surface analysis (Estoque et al., 2017; Gunarathna et al., 2016c, 2016a; Ranagalage et al., 2018).

Multi-criteria decision-making tools can support the resolution of complex problems by evaluating activities using multiple criteria, as in disaster management and environmental management studies (Üstün and Barbarosoğlu, 2015). In recent years, a tool named the analytic hierarchy process (AHP), developed by Saaty (1987), has been used in environmental planning and management studies (Jozaghi et al., 2018; Machiwal et al., 2011; Pramanik, 2016).

The tank cascade system (TCS), used mainly in the dry and intermediate zones of Sri Lanka since the third century BCE, is considered as one of the most efficient traditional water management systems in the world and is still an essential element of water management for agriculture in Sri Lanka (Abeywardana et al., 2018; Bebermeier et al., 2017). The key concept of the TCS is recycling and reuse of water through a network of tanks organized within micro-catchments to store and convey water (by gravitational flow) originating from ephemeral rivulets (Madduma Bandara, 1985). TCSs collect rainwater, maintain the water content of the soil and groundwater, control soil erosion, and maintain the ecological balance (Gunarathne and Kumari, 2014). During the last few decades, the usage of groundwater in the dry zone of Sri Lanka has rapidly increased owing to the inability of surface water resources to cater to growing demand, hastening the deterioration of water quality in the tank cascade landscape (Bebermeier et al., 2017).

The Ulagalla cascade is a major TCS located near Anuradhapura city, in the dry zone of Sri Lanka. Although the cascade has not been studied comprehensively, elevated concentrations of nutrients were observed in the adjacent Tirappane and Mahakanumulla cascades (Wijesundara et al., 2012), showing that not only the quantity but also the quality of irrigation water poses problems for sustainable farming. This highlights the need to examine water quality comprehensively, and to pay more attention to continuous monitoring and management of groundwater quality in tank cascade landscapes. However, no scientific protocol has yet been developed to assess the suitability of groundwater for irrigation in the tank cascade landscapes or similar environments.

Although mapping is used worldwide to demarcate areas with suitable groundwater for irrigation in regions with a continuous water table (Kavurmaci and Üstün, 2016; Rabeiy, 2018), regions without a continuous water table have been neglected. Further, no attempt has been made to map irrigation water suitability zones in the tank cascade landscapes or similar environments.

3.1.1. Objectives of this study

To model spatial and temporal variations in irrigation water quality in tank cascade landscape using AHP and GIS, and to establish a protocol to classify the groundwater suitability for irrigation.

3.2. Materials and Methods

3.2.1. Study area

The Ulagalla cascade is a linear cascade in the low country dry zone (DL_{1b}) in the north-central province of Sri Lanka, located at 8°5'–8°14'N latitude and 80°31'–80°34'E longitude, covers about 51 km^2 of area. The cascade comprises 19 interconnected small tanks (Figure 3.1).

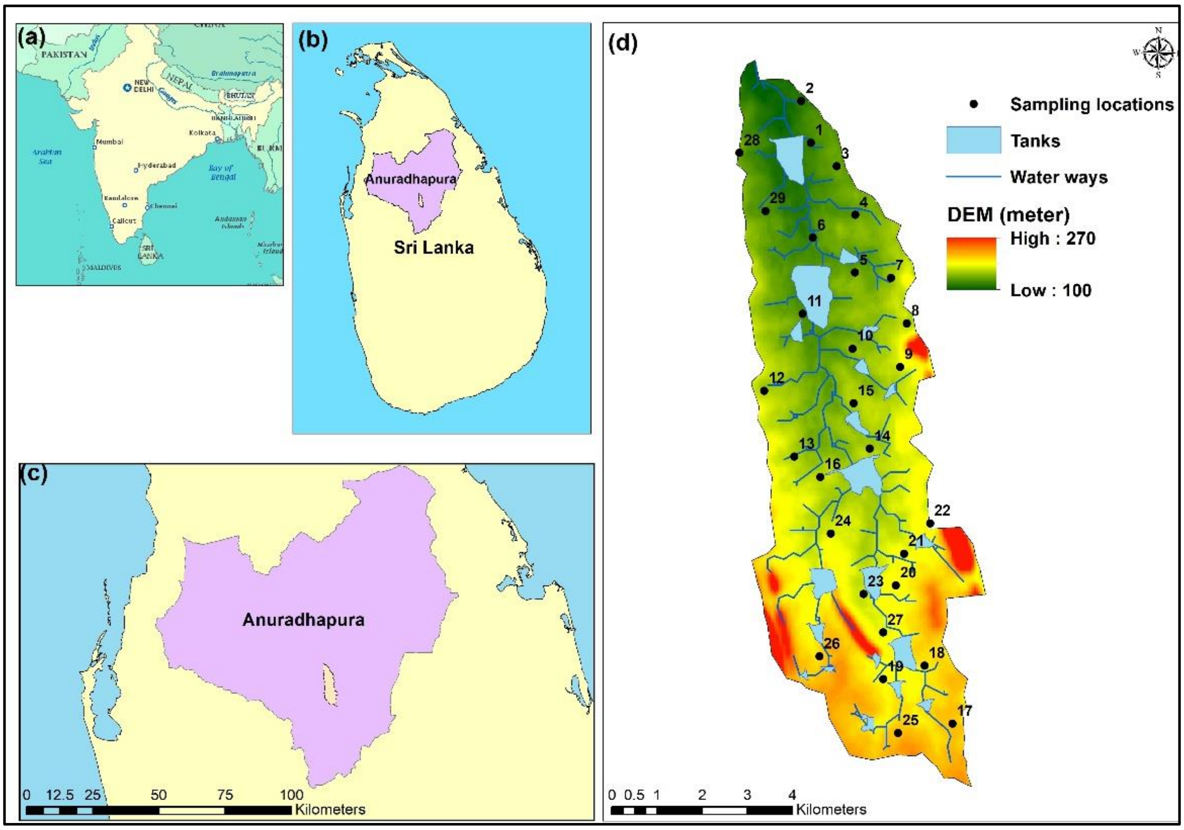

Figure 3.1. Location map of the Ulagalla cascade: (a) South Asia; (b) Sri Lanka; (c) Anuradhapura district; (d) sampling locations

The study area is underlain by charnockite, granitic gneiss, and undifferentiated Highland Series rocks (Figure 3.2a). The major aquifer type in the tank cascade landscape is a shallow regolith aquifer with 2–10 m in thickness. The groundwater potential is limited owing to a low groundwater storage capacity and the transmissivity of the underlying crystalline basement (Sirimanne, 1952) and also recognized that there is no continuous body of groundwater with a single water table but as separate pockets of groundwater (Figure 3.3). The groundwater is found in both weathered rock zone (2-10 m thickness) and deeper fracture zone of the basement rock (30-40 m) (Panabokke and Perera, 2005).

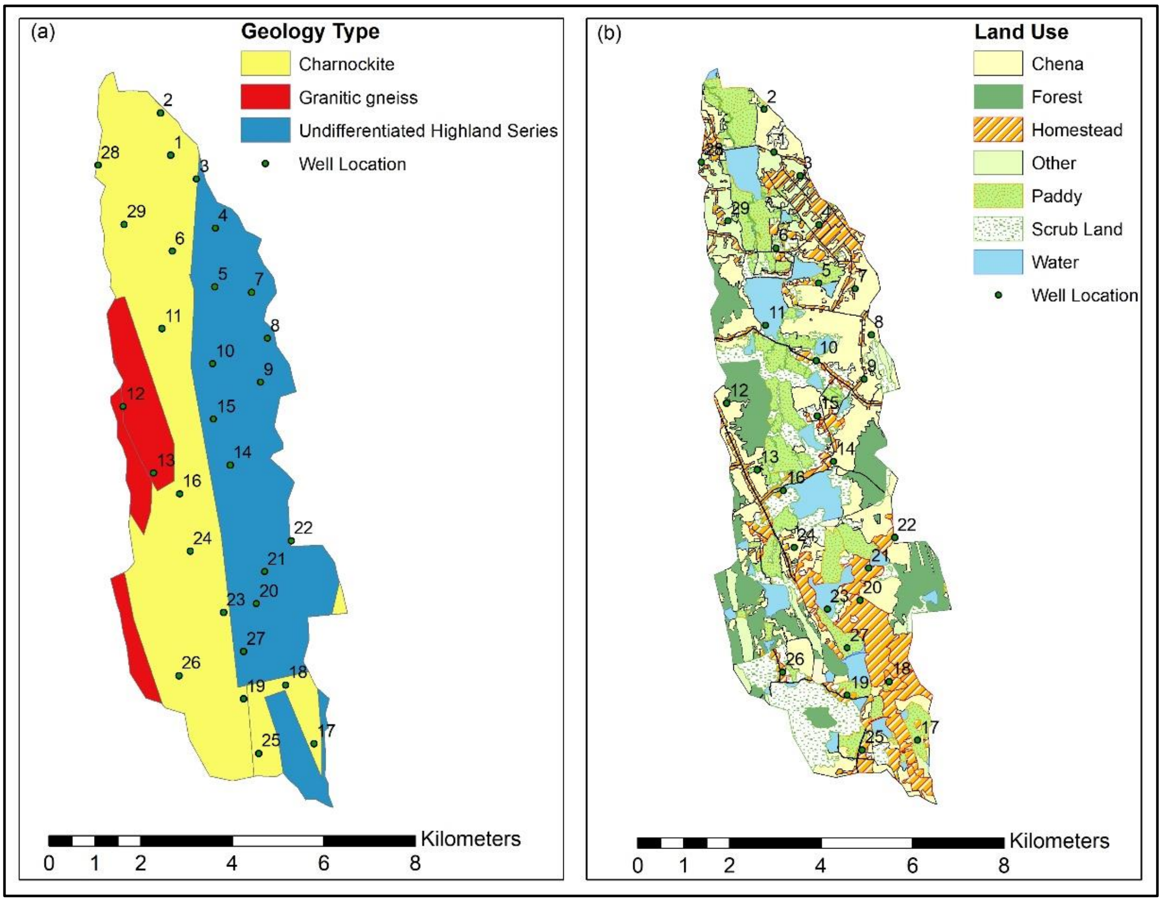

Figure 3.2. (a) Geological map and (b) land use map of Ulagalla cascade

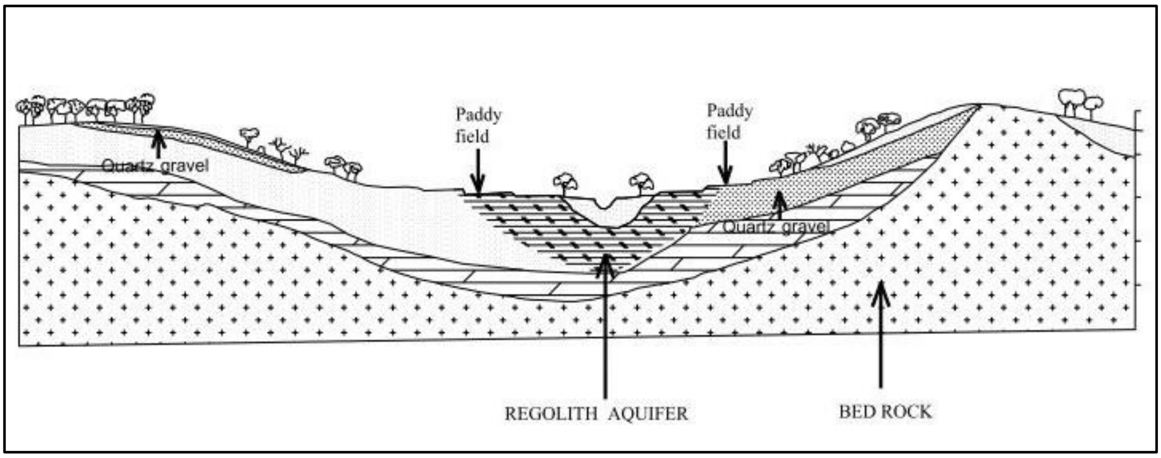

Figure 3.3. The cross-sectional view of regolith aquifer

Groundwater has been extracted for irrigation and domestic purposes for more than 2000 years from dug wells (Panabokke and Perera, 2005). The farmers in the dry zone draw irrigation water from large-diameter "agro-wells", as agricultural activities are prominent in this area. Commonly grown upland crops (e.g. chilli, eggplant, okra, banana, etc.) are grown under rainfed "*chena*" cultivation. Other mainland uses are paddy, forest, and homestead (Figure 3.2b). Two major growing seasons are recognized in Sri Lanka: the Maha (wet) season and the Yala (dry) season. The Maha season from October to February receives rainfall from the second inter-monsoon (depression and cyclonic storms in the Bay of Bengal) and north-east monsoon. The Yala season from April to August receives rainfall from first inter-monsoon (Convective type) and the south-west monsoon (Gunarathna et al., 2019; Gunarathna and Kumari, 2013). We assessed groundwater quality parameters over 12 months to investigate seasonal variations in irrigation water quality.

The study area contains a moderately deep to deep, imperfectly drained soil (SRCANSOL, 2009). The depth of the soil layer is around 1.2 m in the study area. Figure 3.4 shows the soil profile of the tank cascade system in the dry zone of Sri Lanka (Perera, 2017a).

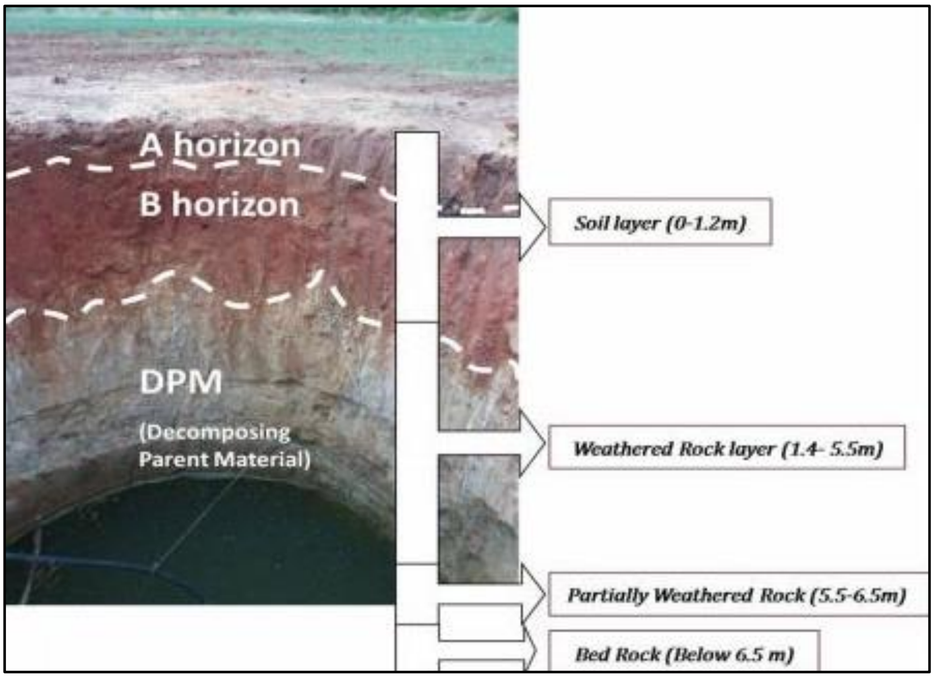

Figure 3.4. The typical soil profile of an agro-well in Tank cascade landscape

3.2.2. Cascade boundary demarcation and groundwater sampling

To demarcate the extent of the Ulagalla cascade boundary, we used 1:50000-scale topographic sheets published by the Survey Department of Sri Lanka and the Shuttle Radar Topography Mission 30-m digital elevation model (Ahmadi et al., 2014).

We randomly selected 29 active agro-wells to give a homogeneous distribution within the study area (Figure 3.1), and samples were collected for 12 consecutive months starting from April 2016. Samples were collected in acid-cleaned high-density polyethylene bottles rinsed several times with the groundwater to be sampled. The bottles were tightly closed, labelled, and transported out of direct sunlight to the laboratory, where they were stored at 4 °C. They were analyzed by standard procedures (APHA, 2005). pH, EC, and TDS were measured *in situ* with an HQ 40d multiparameter analyzer (Hach, Colorado, USA). Sodium (Na^+), potassium (K^+), magnesium (Mg^{2+}), and calcium (Ca^{2+}) ions were determined by inductively coupled plasma optical emission spectrometry (iCAP 7400 ICP-OES, Thermo Scientific, Cambridge, UK). Alkalinity as $CaCO_3$ was analyzed by acid-base titration. Chloride (Cl^-) was determined by standard $AgNO_3$ titration. Available phosphorus (PO_4^{3-}) was determined by the ascorbic acid method (Olsen et al., 1954). Nitrate-nitrogen (NO_3-N) was analyzed by the salicylic acid method (Cataldo et al., 1975). Sulfate (SO_4^{2-}) concentration was measured by method 8051 SulfaVer 4 (powder pillows) (Hach, 2005). The research methodology is presented in Figure 3.5.

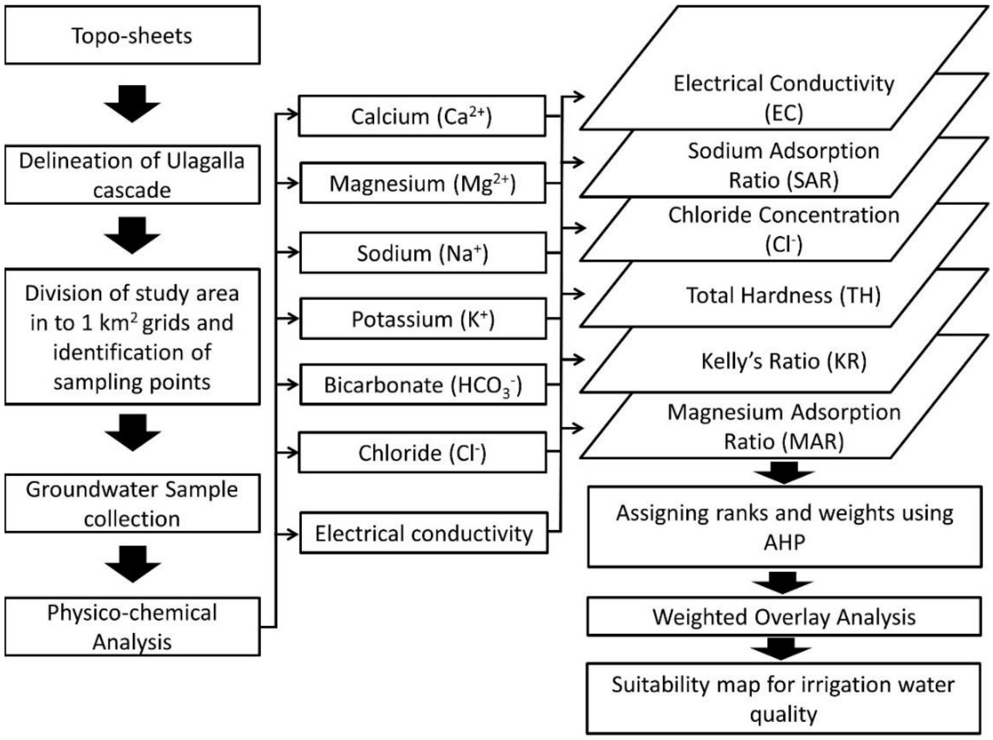

Figure 3.5 Flow chart of the methodology used in this research

3.2.3. Indices of irrigation water quality

We selected six water quality indices important for field crops grown in the study area. We estimated chloride concentration, electrical conductivity (EC), sodium adsorption ratio (SAR) (Equation 3.1) (Wilcox, 1955), magnesium adsorption ratio (MAR) (Equation 3.2) (Raghunath, 1987), Kelly's ratio (KR) (Equation 3.3) (Todd and Mays, 2005) and total hardness (TH) (Equation 3.4) (Kelly, 1963) as:

$$SAR = \frac{\mathrm{Na}^{+}}{\sqrt{(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+})/2}} \tag{3.1}$$

$$MAR = \frac{Mg^{2+} * 100}{Ca^{2+} + Mg^{2+}} \tag{3.2}$$

$$KR = \frac{Na^{+}}{Ca^{2+} + Mg^{2+}} \quad (3.3)$$

$$\text{TH }(\text{CaCO}_3)mg/L = 2.49(Ca)mg/L + 4.1(Mg)mg/L \quad (3.4)$$

where all concentrations in Equations 1–3 are expressed in meq of solute per L of solvent.

3.2.4. Spatial interpolation

Kumari et al. (2018) compared the performance of deterministic and geostatistical methods used to interpolate irrigation water quality in the tank cascade landscape. They reported EBK as the best interpolation method for the Ulagalla cascade. Gunarathna et al. (2016a, c) also reported that EBK was the best method to interpolate irrigation water quality based on EC, pH, and TDS. Since EBK is a straightforward and robust method that uses a number of semivariograms instead of just one (Krivoruchko, 2012), we used it here.

3.2.5. Analytic hierarchy process (AHP)

The AHP is recognized as a powerful decision support tool in natural resource management studies. It structures complex problem hierarchically and examine each level of the hierarchy individually. It uses pairwise comparison matrices to compare all possible pairs of criteria and determine which criterion has the highest priority (Bozdag, 2015). Criteria are scaled from 1 to 9 (Table 3.1), where 1 indicates equal importance, and 9 indicates the highest priority. A reciprocal value (e.g., 1/9) indicates the reciprocal comparison. To confirm the consistency of the priority ratio, the consistency index (CI) is calculated (Equation 3.5).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (3.5)$$

where, λ_{max} is the largest or principle Eigenvalue of the matrix, and *n* is the number of criteria in the matrix. To ensure that the pairwise comparison matrix is consistent, the consistency ratio (CR) is calculated (Hsu and Hu, 2008) as:

$$CR = \frac{CI}{RI} \tag{3.6}$$

where the value of the random consistency index (RI) is given by Saaty (2004) (Table 3.2). If CR ≤ 10%, it is acceptable. If CR ≥ 10%, the AHP may not give meaningful results, and the subjective judgment of the pairwise ranking must be revised (Saaty, 1987).

We used six criteria that influence irrigation water quality: EC, SAR, MAR, TH, Cl^-, and KR. Since each criterion relies on different measured parameters and reflects a different aspect of water quality, they need to be given weights, which must be assigned with great care. As the AHP has proved a powerful decision support tool in this regard (Bozdag, 2015), we invited ten experts in irrigation water quality from universities and the Department of Agriculture in Sri Lanka to prioritize these criteria for upland crops commonly grown in the study area in an AHP Excel template (www.scbuk.com/ahp.html). The names of the criteria or requirements were entered in the template, and the experts were asked to work through the matrix, comparing criteria in pairs. Once the pairwise ranking was completed, a normalized matrix was calculated, and the consistency was checked with the CR. All the CR values were within the acceptable limit (ranged from 2- 9 %), so the computed weights were valid. As the experts' opinions are likely to be subjective, we used the average values of the respective weights as the final weights.

Next, we divided water quality parameters and indices into subgroups and assigned ranks according to Ayers and Wescot (1994) (Table 3.3). Considering the effect of each parameter or index on irrigation water quality, we ranked subgroups on a scale of 1 to 3 as follows: 1, no harmful effect on irrigation water quality; 2, moderate effect; and 3, harmful effect. EC < 0.7 dS/m has no unfavorable effect on irrigation water quality, so it is ranked

1; $0.7 \leq EC \leq 3$ dS/m is moderately suitable, so it is ranked 2, and EC > 3 dS/m is unsuitable, so it is ranked 3. MAR and KR have only two classes: MAR < 50 and KR < 1 are ranked 1, and MAR > 50 and KR > 1 are ranked 3. TH has four classes (Ayers and Wescot, 1994); hence, TH < 75 is ranked 1, values of 75–150, and 150–300 are ranked 2, and TH > 300 is ranked 3. The values of all wells for each criterion were spatially distributed in ArcGIS software using the EBK interpolation method and reclassified as above ranks. All reclassified layers were combined, and the weighted overlay method was performed. The cell values of each reclassified layer were multiplied by their weights obtained by AHP. Irrigation suitability maps (monthly variation, seasonal variation, and overall) of the study area was obtained by calculating the total irrigation water suitability score (IW) as

$$IW = \sum_{i=n}^{i=1} F_i * W_i \tag{3.7}$$

where F_i is the value of the reclassified layer of respective water quality criterion, W_i is the weight of the respective criterion obtained from AHP, and *n* is the total number of criteria. The irrigation suitability maps showed areas as suitable (IW = 1.00–1.33), moderately suitable (IW = 1.34–2.33), or unsuitable (IW = 2.34–3.00).

Table 3.1. Relational scale for pairwise comparisons (adopted from Bozdag, 2015)

Importance	Description	Explanation
1	Equal importance	Two criteria contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one criterion over the other
5	Strong importance	Experience and judgment strongly favor one criterion over the other
7	Very strong importance	Experience and judgment very strongly favor one criterion over the other
9	Extreme importance	The evidence favoring one criterion over another is of the highest possible validity
2, 4, 6, 8	Intermediate values	When compromise is needed
Reciprocals	Values for inverse comparison	If criterion *i* had one of the above numbers assigned to it when compared with criterion *j*, then *j* has the reciprocal value when compared with *i*

Table 3.2. Random consistency indices (RI) for different numbers of criteria (adopted from Saaty, 2004)

Number of criteria	Random consistency index
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49
11	1.51
12	1.54
13	1.56
14	1.57
15	1.59

Table 3.3. Irrigation water quality restriction classes and ranks of irrigation criteria in Ulagalla cascade

Irrigation criterion	Range	Water class/restriction	Rank
EC	<0.7	none	1
	0.7–3	slight to moderate	2
	>3	severe	3
SAR	<3	none	1
	3–9	slight to moderate	2
	>9	severe	3
Cl^-	<140	none	1
	140–350	slight to moderate	2
	>350	severe	3
MAR	<50	suitable	1
	>50	unsuitable	3
KR	<1	suitable	1
	>1	unsuitable	3
TH	<75	soft	1
	75–150	moderate	2
	150–300	hard	2
	>300	very hard	3

3.3. Results and Discussion

3.3.1. Hydrochemistry of groundwater in Ulagalla cascade

The pH, EC, and major ions of the groundwater samples in the Ulagalla cascade are summarized in Table 3.4. Most of the parameters recorded a wide range and a high SD. The groundwater in all of Sri Lanka except the far north is drawn mainly from hard metamorphic aquifers. Hence, the mineral composition depends mainly on the metamorphic rocks. This indicates the influence of mineral dissolution associated with seasonal rainfall and anthropogenic activities (Rubasinghe et al., 2015).

Cl^- content showed wide variation (20 to 2120 mg/L; Table 3.4). Cl^- is one of the important parameters that govern groundwater quality. Generally, weathering of silicaterich rocks, excess application of fertilizer, seawater intrusion, and animal and human waste contribute Cl^- to groundwater (Singh and Khan, 2011). Since charnockite is prominent in the study area (Figure 3.2a), it can contribute to Cl^- through mineral dissolution. Since a major portion of the cascade is still under a rural settlement with lowland and upland cropping and lacks urban settlements and industry, the effect of industrial effluent on groundwater quality is minimal. The wells with elevated Cl^- concentration occurred in coconut plantations and home gardens. Hence, fertilizer (KCl) applied for coconut cultivation, and the improper disposal of household wastewater might be the main sources. Nutrient concentrations, notably NO_3-N and phosphate, are not yet problematic, but the continuous application of excess fertilizer can lead to problems. Hence, continuous monitoring and good management practices are essential.

The major cations of the groundwater in Ulagalla cascade decreased in the order of $Na^+ > Ca^{2+} > Mg^{2+} > K^+$, and the major anions decreased in the order of $Cl^- > HCO_3^- > SO_4^{2-} > NO_3\text{-N} > PO_4^{3-}$, during both seasons.

Table 3.4. Descriptive statistics of chemical parameters in groundwater during Yala and Maha seasons

Water quality parameter [a]	Yala season Max	Min	Mean	SD	Maha season Max	Min	Mean	SD
pH	8.8	6.2	7.7	0.4	9.3	6.8	7.9	0.4
EC	4300.0	172.4	1267.1	787.4	4310.0	337.0	1274.4	803.0
Na^+	329.4	5.9	130.4	70.6	363.8	23.0	139.3	80.5
K+	15.5	0.2	2.4	2.5	20.7	0.2	2.9	2.8
Ca^{2+}	386.2	6.4	78.1	73.2	280.1	4.3	65.6	45.7
Mg^{2+}	202.6	1.5	46.3	39.0	284.2	5.1	55.7	44.6
HCO_3^-	175.0	37.5	87.4	20.4	215.0	27.5	84.9	23.2
Cl^-	2020.0	20.0	312.9	340.1	2120.0	40.0	351.2	334.9
SO_4^{2-}	84.0	1.0	30.6	15.2	94.0	2.0	34.7	18.7
NO_3-N	17.6	0.1	1.5	2.5	25.2	0.1	1.4	3.3
PO_4^{3-}	1.5	0.0	0.3	0.3	0.6	0.0	0.1	0.1

[a]mg/L except EC, µS/cm; Max-maximum, Min-minimum, SD-standard deviation.

3.3.2. The weighting of criteria for irrigation water quality

The relative weights assigned by each expert for each criterion were averaged, and the average relative weights were used (Table 3.5) to generate the irrigation suitability maps of Ulagalla cascade.

Table 3.5. Average relative weights assigned to irrigation criteria in Ulagalla cascade

Irrigation criteria	EC	SAR	Cl^-	MAR	KR	TH
Average relative weights	0.27	0.25	0.16	0.11	0.11	0.10

Salinity, measured as EC, is considered the most influential water quality criterion (Ravikumar et al., 2011). It has been identified as the major constraint in the dry zone of Sri Lanka, where it reduces crop productivity (Najim and Jayakody, 2008). The group of experts gave it the highest weight, of 0.27. SAR indicates soil alkalinity and has a direct relationship with Na adsorption to soil; a high value indicates decreased infiltration (Gunatilake et al., 2014). It was given the second-highest weight. High concentrations of Cl^- can be toxic to sensitive crops such as citrus and leafy field crops (Murkute et al., 2005). As Cl^- is not adsorbed to the soil, the Cl^- in irrigation water readily moves with soil water. It causes leaf burn and drying, and in severe conditions leaf drop (Gunatilake et al., 2014). The Cl^- concentration was given a weight of 0.16. Both MAR and KR were given a weight of 0.11, and TH was given a weight of 0.10. Although hardness of irrigation water does not have any direct effect on crop growth, hardness triggered by HCO_3^- affects soil, ultimately it can affect crop growth.

3.3.3. Irrigation water quality zoning in Ulagalla cascade

No major difference in water quality zoning was observed between seasons. Most of the cascade falls in the moderate suitability category (Figure 3.6).

Understanding the seasonal variation of groundwater quality is important in management decisions. However, for planning or policy decisions, we need an overall idea about the groundwater quality of the area. Hence, we developed the overall irrigation water suitability map of the cascade by overlaying the 12 months irrigation suitability maps (Figure 3.8) to demarcate suitable, moderately suitable, and unsuitable areas for irrigation. In the overall irrigation water suitability map, 4% of the cascade is suitable, and 96% is moderately suitable for irrigation (Figure 3.7).

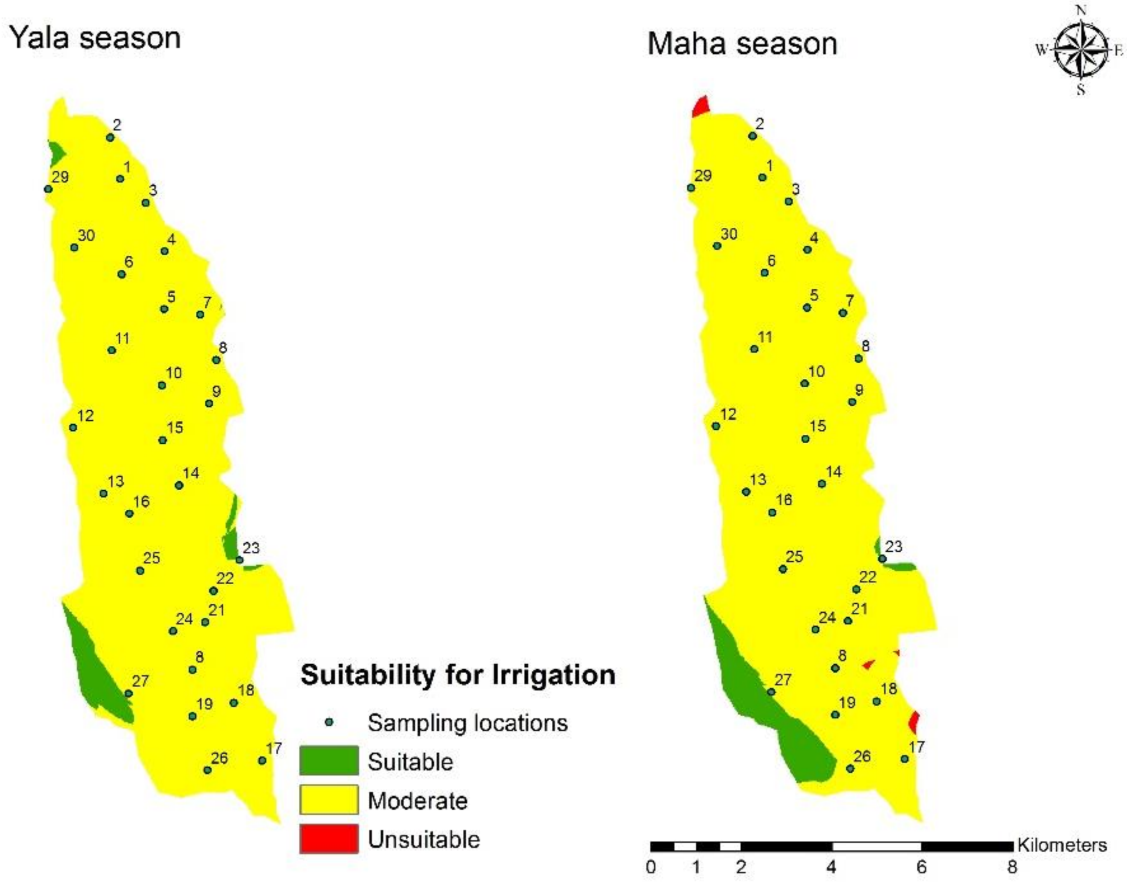

Figure 3.6. Comparison of irrigation water quality in Ulagalla cascade between Yala and Maha seasons

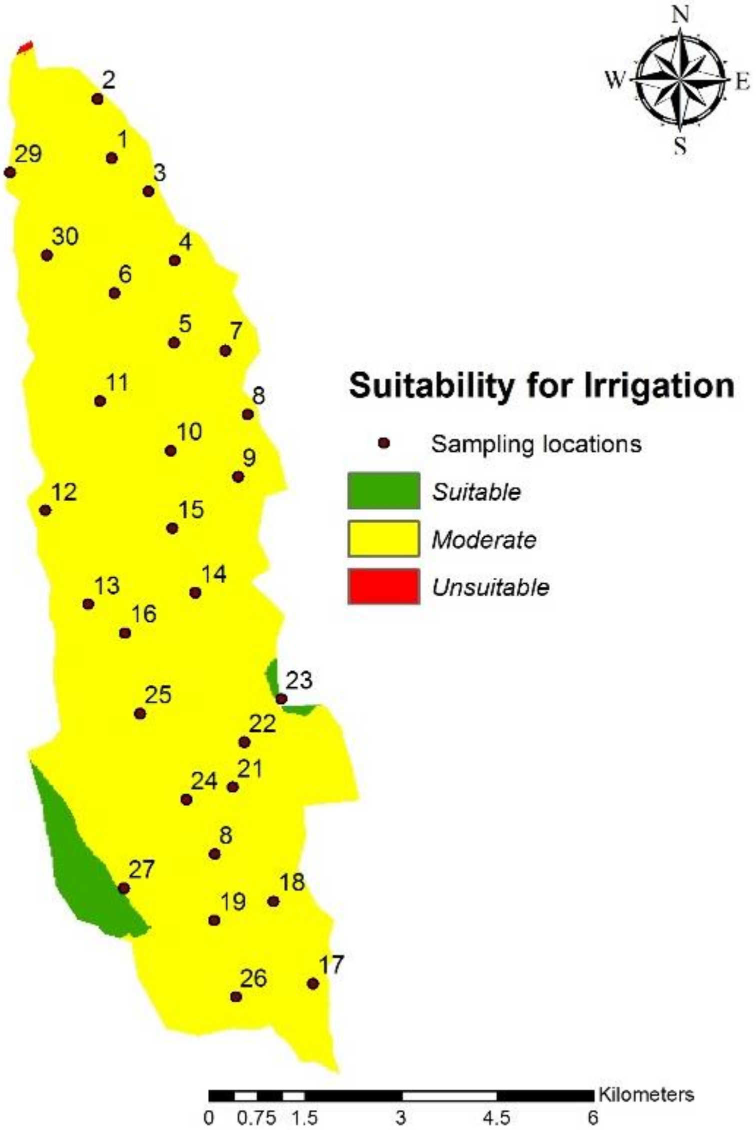

Figure 3.7. Overall irrigation water suitability map of Ulagalla cascade

Although there was no major difference in irrigation water quality between seasons, the monthly zoning maps showed greater variation in several months of the Maha season than in the Yala season (Figure 3.8).

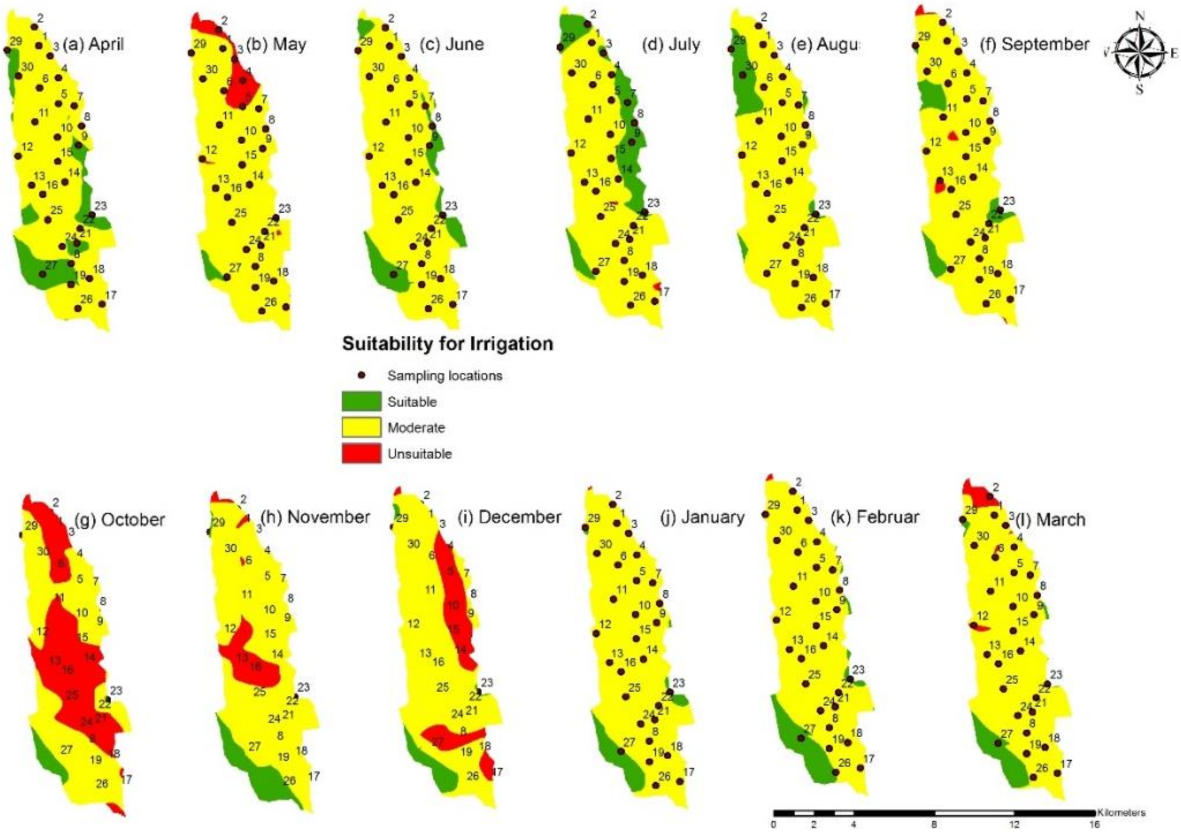

Figure 3.8. Monthly variation in irrigation water quality in Ulagalla cascade

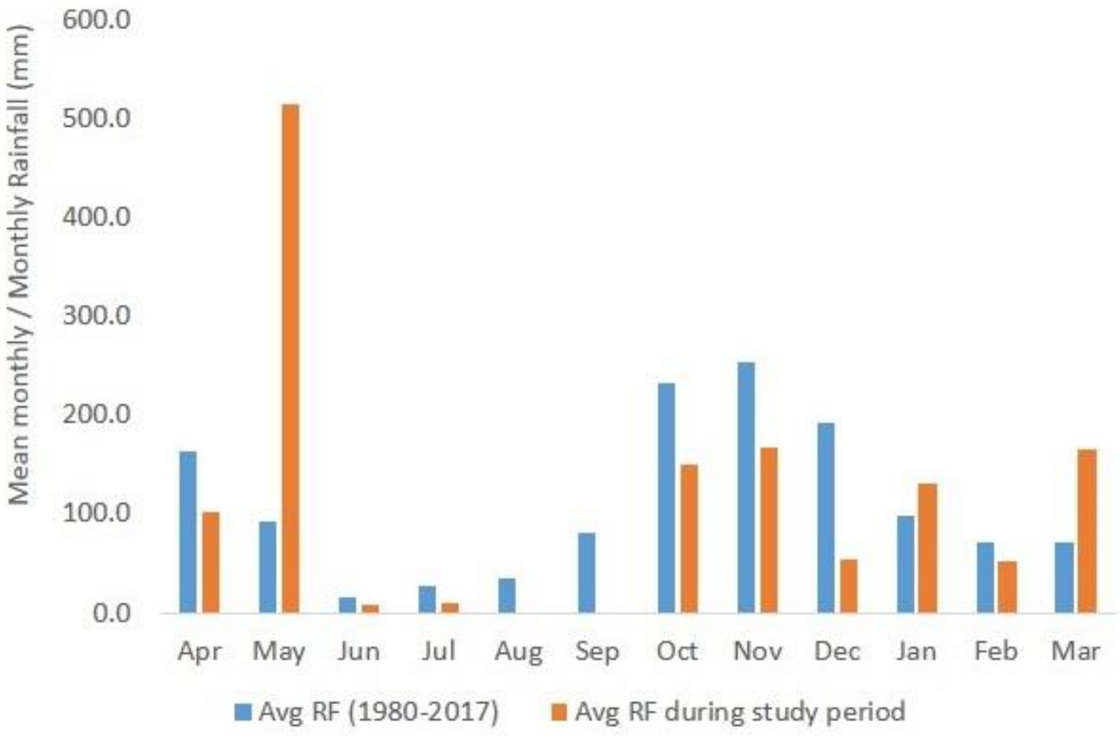

Figure 3.9. Monthly average rainfall (RF) during 1980–2017 and monthly rainfall during the study period

Since irrigation water quality is directly affected by rainfall, we examined the rainfall pattern and found that the pattern during the study period differed from the monthly average over the period of 1980–2017 (Figure 3.9). The Maha season begins in October with second inter-monsoonal rainfall occurs due to the influence of weather systems like depression and cyclonic storms in the Bay of Bengal. It contributes around 38% of the annual rainfall in Anuradhapura (Gunarathna and Kumari, 2013). October typically features high-intensity rainfall, and the subsequent runoff can explain the deterioration in irrigation water quality (Figure 3.8). This result shows the “first-flush” phenomenon. Particularly in dry zones, salts tend to accumulate on the soil surface with evaporation (Rubasinghe et al., 2015). This situation was aggravated at the end of the Yala season, as no rainfall was recorded in August or September (Figure 3.8). These accumulated salts washed off in the heavy rain during October–November, when heavy rain can fall in thunderstorms on many parts of the island (Rubasinghe et al., 2015), causing a clear deterioration in irrigation water quality (Figure 3.8).

A similar pattern was observed during the Yala season also. In general, the Yala season receives less rainfall than the Maha season (Gunarathna and Kumari, 2013). However, during the study period, it received more rainfall than the Maha season. From April to August (except in May), most of the groundwater in the Ulagalla cascade was moderately suitable for irrigation (Figure 3.8a–e). In May, high-intensity heavy rainfall caused substantial runoff with a high concentration of contaminants (Figure 3.8b), reducing irrigation water quality at the bottom (northern end) of the cascade. These results confirm that irrigation water quality in this area is influenced by heavy rainfall rather than by total rainfall, not only at the beginning but also in the middle of the rainy season.

During sampling, we noted that wells 1, 2, 5, 9, 15, and 19 were unlined. Lined wells are typically ringed with a brick or concrete wall (1.0–1.5 m height) (Perera, 2017b). Unlined wells can be contaminated through direct runoff. Farmers should be encouraged to build at least a brick wall around their agro-wells to exclude runoff and improve irrigation water quality.

3.3.4. Groundwater quality for irrigation: Present status and future implications in the tank cascade landscape

Since groundwater in most of the cascade is only moderately suitable for irrigation (Figure 3.7), urgent attention is required to manage this valuable resource sustainably. Salinity is the major constraint in dry zones (Kumari et al., 2016; Mikunthan et al., 2013). However, water hardness is higher in dry zones than in wet zones (Piyasiri and Senanayake, 2016; Rubasinghe et al., 2015), and during the study period, it varied from 47 to 1842 mg/L. Therefore, special care should be taken when micro-irrigation systems such as drip irrigation are introduced as clogging has already demotivated the farmers in the area. Farmers must be trained in the maintenance and operation of drip irrigation systems (Karunaratne and Pathmarajah, 2002), so extension officers have to pay attention to irrigation suitability maps when introducing new irrigation methods or crops, and need to alert farmers to salinity control measures.

A groundwater management policy needs to be implemented soon to assure the sustainable use of the resource. Attention must be given to continuous monitoring and management of groundwater quality, especially in areas with restrictions for irrigation purposes. The systematic evaluation of all major cascade systems will help the sustainable use of groundwater resources. Our approach can be used to develop a system of irrigation water suitability classification in Sri Lanka, and researchers can use it in developing techniques for mapping irrigation water quality zones.

3.4. Conclusions

We aimed to demarcate the suitable areas for irrigation in the Ulagalla cascade. We used AHP to understand the relative importance of six irrigation water quality criteria, and developed an irrigation water suitability map using a weighted overlay in GIS.

Monthly variations in irrigation water quality revealed that the first flush associated with surface runoff is prominent in the study area following high-intensity heavy rainfall in both seasons, but there was no distinct difference in quality between seasons.

Only 4% of the groundwater in the Ulagalla cascade is suitable for irrigation, and 96% is moderately suitable. Our results can be incorporated into the decision-making process of agricultural production and environmental planning in the study area. We recommend this AHP- and GIS-based water quality zoning procedure for research in the tank cascade landscapes and similar environments.

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4.0 Application of GIS-based drinking water quality index to assess the groundwater quality for drinking in CKDu affected tank cascade landscape

4.1 Introduction

Safe drinking water with acceptable quality and sufficient quantity is a basic need for good health, and it is also a basic right of humans. Although surface water and groundwater serve as drinking water sources all over the world, it is limited in many regions (Meride and Ayenew, 2016; Mukate et al., 2019). Due to the rapid increase in the population, intensive agriculture, urbanization, and climate change will increase the demand for drinking water, and it will become more limited in the next few years (Jackson et al., 2001; Meride and Ayenew, 2016).

Deterioration of drinking water quality takes place due to the introduction or removal of different substances by both natural and anthropogenic factors (Fyfe et al., 1983; Rubasinghe et al., 2015; Todd and Mays, 2005). Among the introduction of the anthropogenic factor of heavy metals, nitrate, arsenic, fluoride, and synthetic chemical emissions due to industrialization and agricultural activities play a key role (Cabrera et al., 1999; Shah et al., 2000; Wasana et al., 2017). However, drinking water quality have a great influence on public health as prolong exposure to poor quality drinking water increases the disorders in the kidney, liver, and risk of cancer, etc. Moreover, the effect of chemical contamination of drinking water has been identified as chronic rather than acute and cause the death of human in many regions of the world (Wasana et al., 2017). Water quality deterioration affects not only human health but also economic development and social prosperity. Therefore, continuous monitoring, assessment, and sustainable management of the drinking water resources are vital.

As natural purification processes like ion exchange, filtration, and aerobic decomposition take place in the soil column, groundwater has been identified as a pure form of water compared to surface water (Shabbir and Ahmad, 2015). Groundwater is identified as the most important source of drinking and irrigation water in many tropical regions, especially in rural areas. Natural groundwater chemistry is determined by aquifer lithology, weathering of rocks, seawater intrusion, and other characteristics of flow paths (Tóth, 1999). The climate also plays a key role in groundwater chemistry due to its effects on weathering of rocks, evaporation, evapotranspiration, and concentration of chemical components in groundwater. It has been identified that the composition of groundwater changes during wet and dry periods, and in some cases, several ions have reached very high levels causing several geochemical diseases. Fluoride can be considered as one example. Especially in the dry zone, it is found in excessive amounts in groundwater and causes dental and skeletal fluorosis (Dissanayake and Chandrajith, 2019). However, both natural and anthropogenic factors can deteriorate the effective use of groundwater. During the recent past, the application of agrochemicals in excessive quantities has also created greater threats in farming communities in the dry zone of Sri Lanka. WHO reported that the high level of nitrate in drinking water is linked to methemoglobinemia (blue baby syndrome) especially in infants (Sutharsiny et al., 2014).

Chronic kidney disease of unknown etiology (CKDu) has been identified as a serious global health concern. The special feature of this disease is the patients with CKDu do not exhibit the common causative factors of kidney disease such as diabetes or hypertension or the aging population (Athuraliya et al., 2011). In addition to these traditional causes, glomerular, and tubule-interstitial diseases due to infections, nephrotoxic drugs, herbal medications, and snake bites also can end up with CKD (Jayasumana et al., 2017). CKDu is evident in several countries like Mexico, Guatemala, Nicaragua, Bulgaria, Croatia, India, Sri Lanka, etc. Since the early 1990s, a rapid increase of CKDu is observed in North Central Province and the North Western Province of Sri Lanka.

Moreover, it is now appearing in Uva, Eastern, and Northern Provinces also (Elledge et al., 2014). Though the prevalence of CKDu is not well documented, some studies indicate that the no of CKDu patients has been doubling every four to five years, and now more than 15000 people are affected (Kafle et al., 2019). Fatigue, panting, nausea, lack of appetite, and anemia are the main symptoms of CKDu (Elledge et al., 2014). Agricultural workers are most affected by this disease, and among them, the majority are males in their productive working age of 30-60 years (Chandrajith et al., 2011b). Hence, CKDu has become one of the major environmental health issues in farming communities of the dry zone of Sri Lanka in both social and economic aspects.

A number of active hypotheses have been made to explain the etiology of CKDu. Among them, the consumption of groundwater or agricultural commodities made using irrigation water plays a major role. Since the irrigation water has direct contact with agrochemicals, long term exposure to these water may be responsible for CKDu. However, some authors proposed fluoride and hardness of drinking water are the causative factors for CKDu (Athuraliya et al., 2009; Chandrajith et al., 2011a, 2011b). Moreover, the excessive hardness of drinking water has aggravated the prevalence of CKDu in the dry zone of Sri Lanka. Hence proper systematic assessment of drinking water and strategic plan is required to provide safe drinking water to the CKDu affected areas.

4.1.1. Objectives of this study

The objectives of the study were to assess /investigate the groundwater quality for drinking in the tank cascade systems affected with CKDu and to establish a GIS-based water quality index to classify the suitability of groundwater for drinking.

4.2. Materials and Methods

4.2.1. Study area

The Ulagalla cascade is in the low country dry zone (DL_{1b}) in the north-central province of Sri Lanka, located at 8°5'–8°14'N latitude and 80°31'–80°34'E longitude, covers about 51 km^2 of area. The cascade comprises 19 interconnected small tanks (Figure 4.1). The major aquifer type in the tank cascade landscape is a shallow regolith aquifer with 2–10 m in thickness. The groundwater potential is limited owing to a low groundwater storage capacity and the transmissivity of the underlying crystalline basement (Sirimanne, 1952b). Groundwater has been extracted for irrigation and domestic purposes for more than 2000 years from dug wells (Panabokke and Perera, 2005).

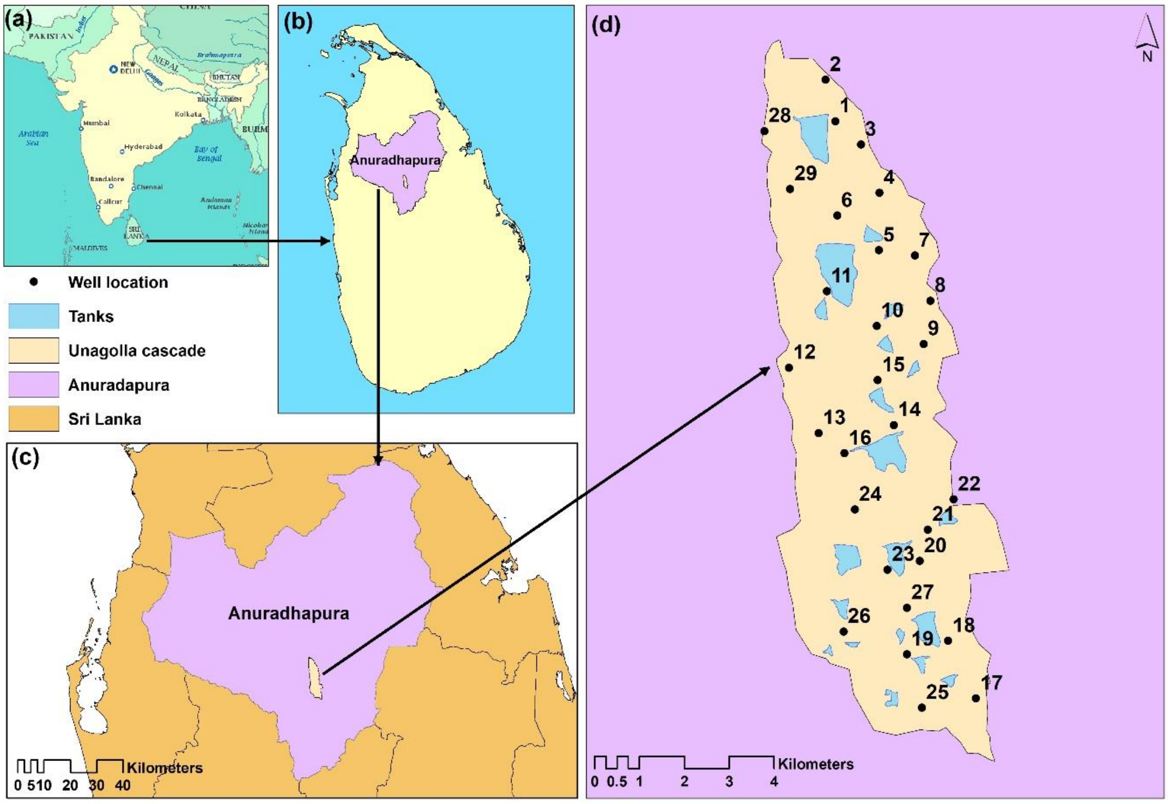

Figure 4.1. Groundwater sampling locations in Ulagalla cascade

4.2.2. Sample collection and analytical procedures

We selected a total of 29 dug wells to give a homogeneous distribution, and the samples were collected in September to represent dry season and December to represent the wet season. Groundwater samples were collected in acid-cleaned high-density polyethylene bottles rinsed several times with the groundwater to be sampled. The bottles were tightly closed, labeled, and transported out of direct sunlight to the laboratory, where they were stored at 4 °C. They were analyzed by standard procedures (APHA, 2005). pH and TDS were measured *in situ* with an HQ 40d multi-parameter analyzer (Hach, Colorado, USA). The samples collected for cation such as sodium (Na^+), magnesium (Mg^{2+}), calcium (Ca^{2+}), Arsenic (As^{3+}), and cadmium (Cd^{2+}) ions were determined by inductively coupled plasma optical emission spectrometry (iCAP 7400 ICP-OES, Thermo Scientific, Cambridge, UK). Alkalinity as $CaCO_3$ was analyzed by acid-base titration. Chloride (Cl^-) was determined by standard $AgNO_3$ titration. Available phosphorus (PO_4^{3-}) was determined by the ascorbic acid method (Olsen et al., 1954). Nitrate-nitrogen (NO_3-N) was analyzed by the salicylic acid method (Cataldo et al., 1975). Sulfate (SO_4^{2-}) concentration was measured by method 8051 SulfaVer 4 (powder pillows) (Hach, 2005). Total hardness was calculated based on the measured Ca and Mg data (Equation 4.1) (Kelly, 1963).

$$\text{TH } (\text{CaCO}_3) mg/L = 2.49(Ca) mg/L + 4.1(Mg) mg/L \quad (4.1)$$

4.2.3. Assigning weights and ranks for drinking water quality parameters

Sri Lankan standards and WHO standards for drinking water of selected drinking water quality parameters are listed below (Table 4.1). Based on the literature (Cooray et al., 2019; Shabbir and Ahmad, 2015; Vasanthavigar et al., 2010) and the views of the experts, weights were assigned for each parameter.

We assigned the maximum weight of 5 was assigned to TDS, fluoride, nitrate, cadmium, and arsenic, considering their ability to cause health problems. We assigned 1 for Phosphate, considering the least significance to human health. Meanwhile, we assigned other parameters respective weights depending on the relative significance. Subsequently, the relative weight (W_i) of the chemical parameters were computed using the following equation.

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{4.2}$$

Where, W_i is the relative weight, w_i is the weight of each parameter, and n is the number of parameters.

Table 4.1. Sri Lankan Standards, WHO standards and relative weights of drinking water quality parameters

Water quality parameter	**Sri Lankan standards**	**WHO standards**	**Weight**	**Relative weight**
pH	6.5-8.5	6.5-8.5	2	0.0392
TDS	500	500	5	0.0980
Total hardness	250	-	4	0.0784
Total alkalinity	200	120	2	0.0392
Calcium	100	75	3	0.0588
Magnesium	30	50	3	0.0588
Sodium	200	200	3	0.0588
Fluoride	1	1.5	5	0.0980
Chloride	250	250	4	0.0784
Sulfate	250	250	4	0.0784
Phosphate	2	-	1	0.0196
Nitrate nitrogen	10	10	5	0.0980
Cadmium	0.003		5	0.0980
Arsenic	0.01	0.05	5	0.0980

Next, we divided the drinking water quality parameters into two subgroups and assigned ranks (Table 4.2). Considering the effect of each parameter on drinking water quality, we ranked the subgroups on scale 1 and 2 as follows: 1, suitable for drinking, and 2, not suitable for drinking. pH between 6.5- 8.5 has no unfavorable effect on drinking. So it is ranked 1, pH less than 6.5 or more than 8.5 is unsuitable, so it is ranked 2. TDS < 500 is ranked as 1, and TDS > 500 is ranked 2. TH < 250 is ranked 1 and TH > 250 is ranked 2.

Total alkalinity < 200 is ranked 1, and total alkalinity > 200 is ranked 3. Ca^{2+} < 100 is ranked 1 and Ca^{2+} > 100 is ranked 2. Mg^{2+} < 30 is ranked 1, and Mg^{2+} > 30 is ranked 2. Na^{+} < 200 is ranked 1, and Na^{+} > 200 is ranked 2. F^{-} < 1 is ranked 1 and F^{-} > 1 is ranked 2. Cl^{-} < 250 is ranked 1, and Cl^{-} > 250 is ranked 2. Sulfate < 250 is ranked 1, and sulfate > 250 is ranked 2. Phosphate < 2 is ranked 1, and phosphate > 2 is ranked 2. Nitrate < 50 is ranked 1, and nitrate > 50 is ranked 2. Cd^{2+} < 0.003 is ranked 1, and Cd^{2+} > 0.003 is ranked 2. As^{3+} < 0.01 is ranked 1, and As^{3+} > 0.01 is ranked 2. The values of all wells for each drinking water quality parameter were spatially distributed in ArcGIS software using the EBK interpolation method and reclassified as above ranks. All reclassified layers were combined, and the weighted overlay method was performed. The cell values of each reclassified layer were multiplied by their relative weights. Drinking water quality suitability maps of the study area were obtained by calculating the total drinking water quality suitability score (DWQS) as;

$$\mathrm{DWQS} = \sum_{i=n}^{i=1} \mathrm{F_i} * W_i \tag{4.3}$$

Where F_i is the value of the reclassified layer of respective drinking water quality parameter, W_i is the relative weight of the respective parameter, and n is the total number of parameters. The drinking water suitability maps showed areas as excellent (DWQS= 1.00) or doubtful (DWQS=1-1.33) unsuitable (DWQS=1.34-2.0).

Table 4.2. Drinking water quality restriction classes and ranks in Ulagalla cascade

Water quality parameter	Range	Water class	Rank
pH	6.5-8.5	suitable	1
	<6.5 or >8.5	unsuitable	2
TDS	0-500	suitable	1
	>500	unsuitable	2
Total hardness	0-250	suitable	1
	>250	unsuitable	2
Total alkalinity	0-200	suitable	1
	>200	unsuitable	2
Calcium	0-100	suitable	1
	>100	unsuitable	2
Magnesium	0-30	suitable	1
	>30	unsuitable	2
Sodium	0-200	suitable	1
	>200	unsuitable	2
Fluoride	0-1	suitable	1
	>1	unsuitable	2
Chloride	0-250	suitable	1
	>250	unsuitable	2
Sulfate	0-250	suitable	1
	>250	unsuitable	2
Phosphate	0-2	suitable	1
	>2	unsuitable	2
Nitrate	0-50	suitable	1
	>50	unsuitable	2
Cadmium	0-0.003	suitable	1
	>0.003	unsuitable	2
Arsenic	0-0.01	suitable	1
	>0.01	unsuitable	2

4.3. Results and discussion

4.3.1. Physico-chemical analysis of groundwater

Table 4.3 shows the descriptive statistics of the groundwater in both wet and dry seasons. All the samples were slightly alkaline, and very few were more basic (9.1). TDS values varied from 74.7 to 2250 mg/L in all areas during both seasons. High TDS values indicate the mineralization of groundwater. Particularly in Anuradhapura where characterized by low rainfall, high ambient temperature, and high evaporation, groundwater tends to move upward and tend to accumulate more salts. It led to concentrate more solids in the groundwater (Gunatilake et al., 2014). Na^{+} is the highest dominant cation in the study area. Na^{+} is added to the groundwater by weathering from plagioclase bearing rocks, exchange of Ca^{2+} and Na^{+} in the surface of clay minerals and leaching of detergents used for domestic activities (Hem, 1985). Mg^{2+} concentration in the groundwater is generally less than Ca^{2+} due to the slow dissolution ability of Mg^{2+} bearing minerals and greater abundance of Ca^{2+} in the earth's crust. These two minerals act as the most common minerals that make water hard. According to the geology of the study area, charnockite and granitic genesis which contains plagioclase feldspar might be the reason for higher sodium concentration in the study area. Higher Ca^{2+} concentration was recorded due to the dissolution of carbonate minerals such as calcite and dolomite ($Ca\ Mg\ (CO_3)_2$) in limestone rocks. A high concentration of Mg was observed due to the dissolution of dolomite (Rabeiy, 2018). Accordingly, the total hardness expressed as $CaCO_3$ in the study area is much higher than the SLS and WHO standards. A higher concentration of sulfate in the cascade (33.6 mg/L in the wet season) indicates the occurrence of permanent hardness in the study area (Rubasinghe et al., 2015).

Table 4.3. Descriptive statistics of chemical parameters (all in mg/L) in groundwater during wet and dry seasons

Water quality parameters	Dry season				Wet season			
	Min	Max	Mean	St. Dv.	Min	Max	Mean	St. Dv.
pH	6.6	9.1	7.6	0.4	6.8	9.3	7.9	0.4
TDS	74.7	1912.0	656.5	395.4	224.0	2250.0	691.3	428.8
Na^{+}	5.9	268.9	119.8	63.7	23.0	363.8	131.6	76.4
Ca^{2+}	8.6	174.5	54.8	34.6	4.3	240.9	60.9	42.4
Mg^{2+}	1.5	176.0	36.0	32.5	5.1	251.5	50.9	40.8
F^{-}	0.3	1.9	1.2	0.4	0.3	1.9	1.0	0.4
Cl^{-}	20.0	1430.0	285.3	287.4	40	2120.0	358.5	337.5
Alkalinity	37.5	175.0	91.1	23.9	27.5	215.0	87.0	25.3
SO_4^{2-}	6.0	91.0	26.9	15.5	2.0	94.0	33.6	18.6
PO_4^{3-}	0.0	1.5	0.3	0.3	0	0.6	0.1	0.1
NO_3-N	0.1	13.3	1.1	2.0	0.1	25.2	1.5	3.5
Cd^{2+}	0.0	0.4	0.0	0.1	0.0	6.3	0.1	0.6
As^{3+}	0.0	1.1	0.1	0.1	0.0	0.3	0.1	0.1
TH	50.0	1156.3	298.2	214.9	46.9	1630.9	301.6	238.8

Among the main anionic constituents in groundwater chloride plays a major role as it is the most dominant anion. As charnockite is prominent in the study area, it can contribute to Cl^{-} through mineral dissolution. Moreover, the wells with elevated Cl^{-} concentration occurred in coconut plantations and home gardens. Hence, fertilizer (KCl) applied for coconut cultivation, and the improper disposal of household wastewater might be the main sources. Higher NO_3^--N concentration in groundwater was recorded during the wet season than in dry season with a maximum of 25.2 mg/L. The most probable cause for the high concentration of NO_3^--N concentration during the wet season could be the excess fertilizer leaching to the shallow groundwater. Mikunthan et al. (2013) studied the groundwater quality in Jaffna extensively and found that the nitrate level increase in groundwater due to the reaching of excess fertilizer to the shallow groundwater table. Fluoride is a major health-related contaminant that requires regulatory protocols before water consumption. On the other hand, several researchers suggested that the hardness below the threshold level correlated with good health, and the increase of iconicity above the threshold would correlate with CKDu (Dissanayake and Chandrajith, 2019). Heavy metals in small concentrations also have a nephrotoxic effect. Accordingly, long term exposure to heavy metals with low concentrations can trigger the progression of CKDu (Kulathunga et al., 2019). Hence, fluoride, heavy metals, and hardness can be considered as the most important drinking water quality parameters that affect CKDu. Many ionic concentrations were higher in the wet season than in dry season. The major anions decreased in the order of $Cl^- > SO_4^{2-} > NO_3^-N > F^- > PO_4^{3-}$ in Ulagalla cascade. On the other hand Na^+ is the most dominant cation and the cations varied as $Na^+ > Ca^{2+} > Mg^{2+} > K^+$.

4.3.2. Hydro-chemical facies of groundwater

Hydro-chemical facies are vital in understanding the origins and distribution of groundwater. Trilinear diagram developed by Piper (Piper, 1944) has been widely used to infer hydro-chemical facies (Glynn and Plummer, 2005; Sarkar and Shekhar, 2015). The major cations (Na^+, K^+, $Ca^{2+,}$ and Mg^{2+}) and anions (Cl^-, HCO_3^- and SO_4^{2-}) are shown by separate ternary plots. The two ternary plots are projected into a diamond which represents the origin of the water. As can be seen in Figure 4.2, thirty-one percent (31%), 45%, and 24

% of the samples were categorized as mixed Ca-Na-HCO_3 type, mixed Ca-Mg- Cl type, and Na-Cl type respectively. Calcium type groundwater is mainly distributed in southern, eastern, and north-central regions. Hence Ca type predominates in the study area. It has been observed that the Cl^- type predominates in this area due to the effect of salinity caused by excessive evaporation and salt accumulation (Dissanayake, 2005).

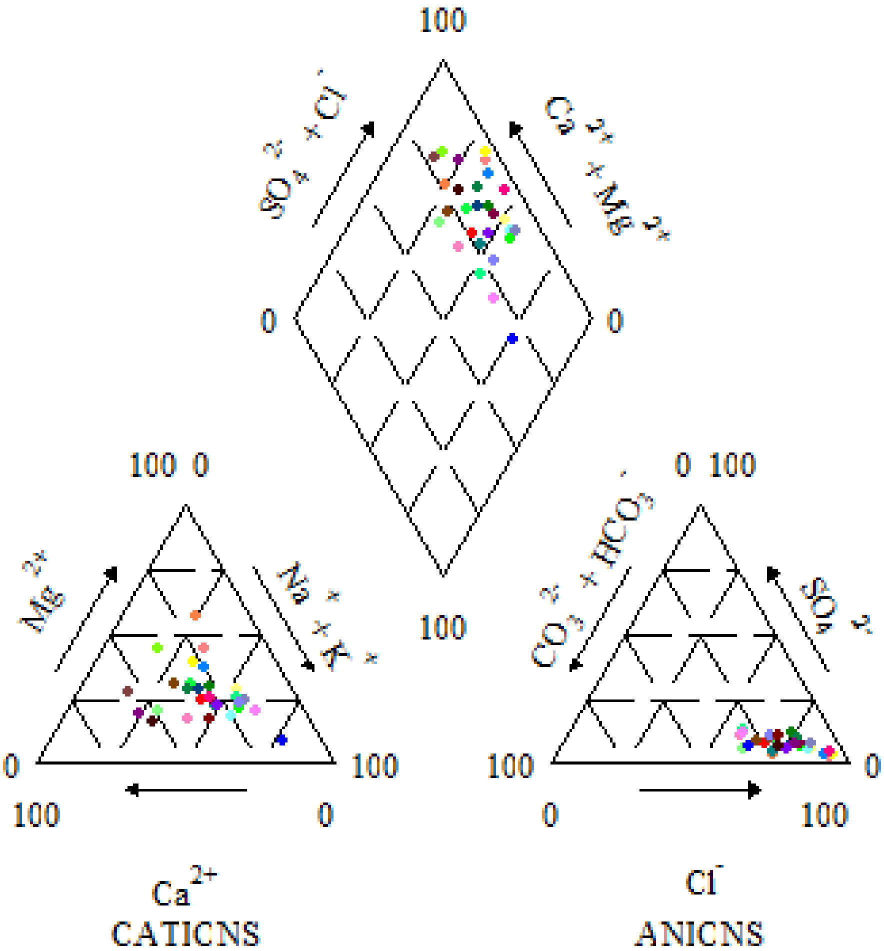

Figure 4.2. Piper diagram showing fields of different hydro-chemical facies in groundwater

4.3.3. Drinking water quality zoning in Ulagalla cascade

As discussed in the section 4.3.2, hydro-chemical facies based on Piper diagram has limited values in terms of suitability for drinking purpose. Hence, the availability of an integrated value based on the SLS permissible levels is more useful. As the first step, we ranked the drinking water quality parameters based on Sri Lankan standards. Thereby, we prepared the spatial distribution of the suitability of groundwater for drinking (Figure 4.3 and 4.4). Based on Figure 4.3 and 4.4, a major portion of the study area of TDS, Mg^{2+}, F^-, Cl^-, and TH exceed the permissible levels for drinking during both seasons. We observed the concentration of most of the ions increased during the wet season than in dry season. During the dry period, the salts tend to accumulate on the soil surface due to high evaporation, high ambient temperature, and less or no rainfall. This situation is aggravated at the end of the dry season as no rainfall was observed during August and September. With the onset of heavy rainfall, these accumulated salts might be washed off and contribute to the deterioration of groundwater in the wet season. Whereas mineral dissolution also contributes much to the water quality deterioration during the wet season.

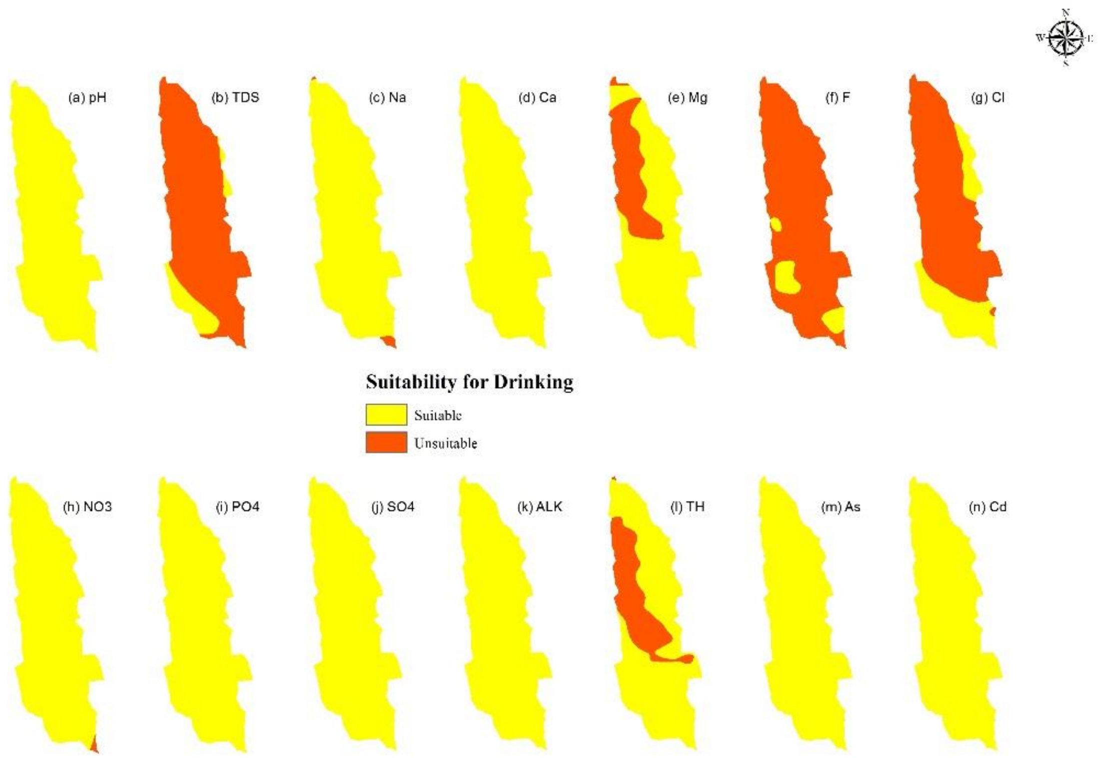

Figure 4.3. Spatial distribution of (a) pH, (b) TDS (mg/L), (c) Na^+(mg/L), (d) Ca^{2+} (mg/L), (e) Mg^{2+} (mg/L), (f)F^- (mg/L), (g) Cl^- (mg/L), (h) NO_3-N (mg/L), (i) PO_4^{3-} (mg/L), (j) SO_4^{2-} (mg/L), (k) Alkalinity, (l) TH (mg/L), (m) As^{3+} (mg/L) and (n) Cd^{2+} (mg/L) during dry season in Ulagalla cascade

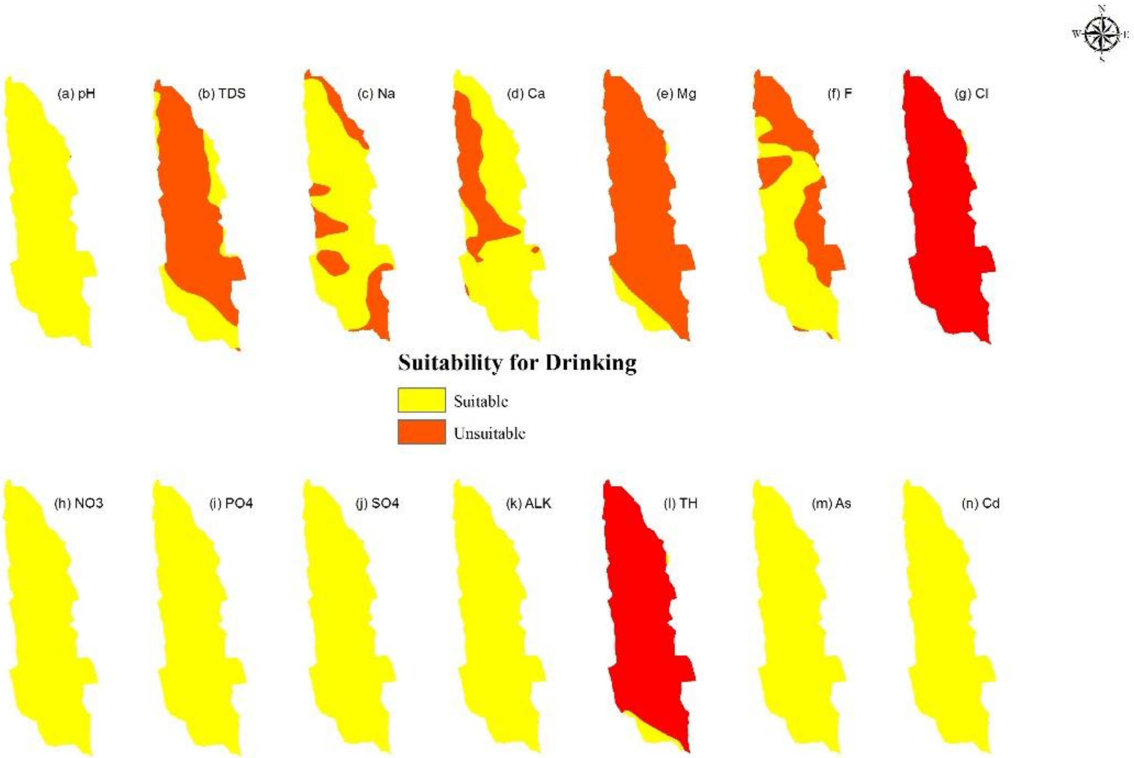

Figure 4.4. Spatial distribution of (a) pH, (b) TDS (mg/L), (c) Na^{+}(mg/L), (d) Ca^{2+} (mg/L), (e) Mg^{2+} (mg/L), (f)F^{-} (mg/L), (g) Cl^{-} (mg/L), (h) NO_3-N (mg/L), (i) PO_4^{3-} (mg/L), (j) SO_4^{2-} (mg/L), (k) Alkalinity, (l) TH (mg/L), (m) As^{3+} (mg/L) and (n) Cd^{2+} (mg/L) during wet season in Ulagalla cascade

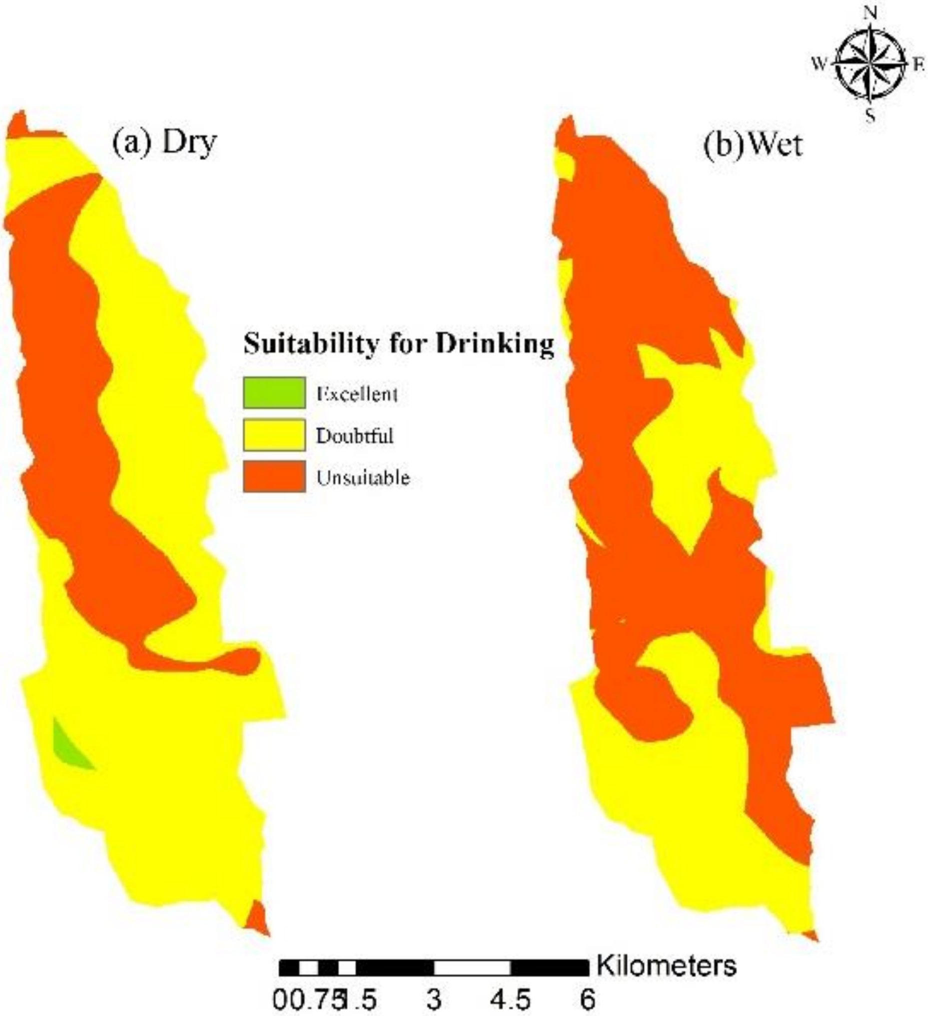

Figure 4.5. Overall drinking water suitability map during (a) dry and (b) wet season in Ulagalla Cascade

We could not observe any significant difference between overall drinking water suitability maps of the wet and dry season. All most all the cascade falls into doubtful category during both seasons (Figure 4.5). Accordingly, an appropriate drinking water treatment method is essential for the study area. Since the groundwater contains high electrical conductivity (EC), membrane-based treatment methods are successful in desalination. Installation of community-scale reverse osmosis (RO) plants based on membrane treatment, in a proper manner can be successful in CKDu prevalent areas.

4.4. Conclusions

We aimed to demarcate the suitable areas for drinking in the Ulagalla cascade. This is the first study assessing the groundwater for drinking in the tank cascade system affected with CKDu. We used Sri Lankan standards of drinking water quality parameters and developed a drinking water suitability map using a weighted overlay in GIS. Moreover, this is the first attempt of GIS-based drinking water quality assessment in Sri Lanka.

Variation of drinking water quality parameters in wet and dry season revealed that surface runoff occurs during the onset of the rainy season, and the mineral dissolution has led to increasing the ionic concentration in groundwater during the wet season. The overall suitability of groundwater for drinking varied notably between seasons. We found that the whole cascade falls under doubtful and unsuitable for drinking during the wet season. This implies the importance of the installation of proper water treatment methods. Though the community-based RO plants have been installed in the CKDu prevalent areas, better maintenance and management of these treatment plants are needed.

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5.0 General conclusions

A clear understanding of spatial and temporal variation in water quality parameters/indices is a key issue in agriculture as well as in environmental studies. Hence, this study aimed to develop a GIS-based protocol to assess the groundwater quality in the tank cascade landscape in Sri Lanka. Ulagalla cascade, located near Anuradhapura city, Sri Lanka, was selected as the study area.

Because the assessment of the spatial and temporal variation of groundwater is essential in the sustainable management of water resources, the relative performance of deterministic (IDW, LPI, GPI, and RBFs) and geostatistical (UK, OK, and EBK) interpolation methods were described and predicted. Thereby, the best interpolation method to explain the spatial and temporal variation of groundwater quality in the tank cascade landscape was selected. The EBK method was the best-fitted interpolation method in estimating groundwater quality parameters (anions, cations, and nutrients) and indices associated with tank cascade landscapes ad similar environments.

Spatial and temporal variation of irrigation water quality in the tank cascade landscape was modeled using AHP and GIS. AHP was used to understand the relative importance of six irrigation water quality criteria, and the irrigation water suitability maps were developed using weighted overlay in GIS. Irrigation was quality assessed during major growing seasons, namely Yala (dry season) and Maha (wet season) in Sri Lanka. Monthly variations in irrigation water quality revealed that the first flush associated with surface runoff is prominent in the study area following high-intensity heavy rainfall in both seasons, but there was no distinct difference in quality between seasons. GIS and AHP based classification can be successfully used to estimate groundwater quality in tank cascade landscape in Sri Lanka. Developed protocols can be incorporated in the decision-making process of agricultural production and the environmental planning of tank cascade landscape in Sri Lanka.

Suitability of groundwater for drinking in the tank cascade landscape affected with CKDu was assessed and GIS-based protocol was established to classify the suitability of groundwater for drinking. The overall suitability of groundwater for drinking varied notably between seasons. The whole cascade falls under doubtful and unsuitable for drinking during the wet season. This implies the importance of the installation of proper water treatment methods. Since the groundwater contains high electrical conductivity, membrane-based treatment methods are successful in desalination. Installation of community-scale reverse osmosis (RO) plants based on membrane treatment, in a proper manner, can be successful in CKDu prevalent areas. Moreover, better maintenance and management of these treatment plants are also needed.