GEOSTATISTICAL ANALYSIS OF GROUNDWATER LEVEL IN THIRUVANANTHAPURAM DISTRICT

HARINATH A

(2019-19-005)

DEPARTMENT OF AGRICULTURAL STATISTICS
COLLEGE OF AGRICULTURE
VELLAYANI, THIRUVANANTHAPURAM – 695522
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by

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THESIS

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DECLARATION

I, hereby declare that this thesis entitled **"Geostatistical analysis of groundwater level in Thiruvananthapuram district"** is a bonafide record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title, of any other University or Society.

Place: Vellayani,

Date: 01.04.2022.

Harinath A

(2019-19-005)

CERTIFICATE

Certified that this thesis entitled "**Geostatistical analysis of groundwater level in Thiruvananthapuram district**" is a record of research work done independently by Mr. Harinath A under my guidance and supervision and that it has not previously formed the basis for the award of any degree, fellowship or associateship to her.

Place: Vellayani.
Date:01.04.2022

Dr. Pratheesh P Gopinath
(Major Advisor, Advisory Committee)
Assistant Professor
Department of Agricultural Statistics
College of Agriculture, Vellayani.

CERTIFICATE

We, the undersigned members of the advisory committee of Mr. Harinath A, a candidate for the degree of Master of Science in Agriculture with mayor in Agricultural Statistics, agree that the thesis entitled "Geostatistical analysis of groundwater level in Thiruvananthapuram district" may be submitted by Mr. Harinath A, in partial fulfilment of the requirement for the degree.

Dr. Pratheesh P Gopinath
(Chairman, Advisory Committee)
Assistant Professor,
Department of Agricultural Statistics,
College of Agriculture, Vellayani.

Dr. Brigit Joseph
(Member, Advisory Committee)
Associate Professor & Head,
Department of Agricultural Statistics,
College of Agriculture, Vellayani.

Dr. Gladis. R
(Member, Advisory Committee)
Assistant Professor,
Department of Soil Science and
Agricultural Chemistry,
College of Agriculture, Vellayani.

T. Paul Lazarus

Sri. T. Paul Lazarus
(Member, Advisory Committee)
Assistant Professor (SS) and Head,
Department of Agricultural Economics,
College of Agriculture, Vellayani.

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HARINATH A

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LIST OF ABBREVIATIONS

WRIS	Water Resource Information System
ISRO	Indian Space Research Organization
WHO	World Health Organization
POWER	Prediction Of Worldwide Energy Resources
GQI	Groundwater Quality Index
TVM	Thiruvananthapuram
GIS	Geographic Information System
Q-Q	Quantile – Quantile
et al.,	Co-workers
i.e.	That is
Etc.	et cetera
mm	Millimeter
cm	Centimeter
m	Meter
mgbl.	Meters below ground level
km	Kilometer
km^2	Square kilometer
ºC	Degree Celcius
Fig.	Figure
No.	Number
MCDM	Multi-Criteria Decision Making
AHP	Analytic Hierarchy Process
ME	Mean Error
MSE	Mean Square Error
RMS	Root Mean Square Error

RSS	Residual Sum of Squares
RMSE	Root Mean Square error
ASE	Average Standard Error
RMSSE	Root Mean Square Standardized Error
R^2	Co-efficient of determination
ESDA	Exploratory spatial data analysis
PCA	Principal Component Analysis
IDW	Inverse distance weighted
O.K.	Ordinary Kriging
NASA	National Aeronautics and Space Administration
MODIS	Moderate Resolution Imaging Spectrometer
NDVI	Normalized difference vegetation index
SNH	Standard Normal Homogeneity
ET_0	Reference Evapotranspiration
AIC	Akaike Information Criterion
EBK	Empirical Bayesian Kriging
MK	Mann-Kendall
CV	Co-efficient of variation
NO_3-N	Nitrate nitrogen

Introduction

1. INTRODUCTION

The most substantial water resource on the planet is groundwater and it is one of the nation's most imperative natural resources. It is the most common and preferred source for drinking water, agriculture, and industrial purposes in both rural and urban areas. It is estimated that groundwater provides around 80 percent of water for household consumption in rural regions and about 50 percent of water for urban and industrial areas. Groundwater resources have become vulnerable to depletion and degradation as a result of rapid population growth, urbanization, industrialization, and other developmental activities (Datta, 2005).

Groundwater is a significant source of freshwater reserve on which billions of people rely for a variety of purposes. The vulnerability of groundwater to exploitation has risen in frequency and extent in recent years, making it a global issue. Climate change, along with widespread groundwater extraction from the shallow aquifer for agriculture, industry, and other household purposes, is one of the primary causes of groundwater storage shortages and water level declines. In recent years, global warming and climate change have resulted in a precipitation shortfall and an increase in evapotranspiration as a result of a temperature rise directly impacting groundwater recharge.

Kerala state is a tiny strip of territory in India's southwest region, surrounded on the east by the Western Ghats and on the west by the Lakshadweep sea. There are 14 districts and 152 blocks that make up the state. Even though the state has abundant water resources and rainfall, the availability of water resources, particularly groundwater, is not uniform throughout the state (Shaji, 2011). It differs from one location to the next. Increasing urbanization and a growing reliance on groundwater for irrigation and industry have necessitated careful and planned groundwater resource usage. The state has both an excess and a deficit in the groundwater level. The state receives 3000 mm of annual rainfall, most of which falls during the South-West monsoon, which begins in June and lasts until September. During October to December, the state receives rain from the North-East monsoon. In the lowlands, annual rainfall varies from 900 mm in the south to 3500 mm in the north. Annual rainfall in the midland varies from 1400 mm in the south to over 6000 mm in the north. Annual rainfall in the highlands ranges from 2500 mm in the south to over 6000 mm. in the north (ENVIS Hub, 2011).

Kerala is heavily reliant on groundwater, which has significant economic and social value as well as a rôle in the maintenance of a variety of ecosystems both above and below ground. In the research study area, groundwater is the most abundant source of water supply, irrigation and industrial purposes. As a result, the growth of this essential resource is critical to satisfying these demands. The hydrologic cycle process, which includes precipitation, infiltration, evaporation, transpiration, and condensation, is interconnected with all the water resources.

Due to increasing demand for water usage and shortage of surface water resources, the management in the use of groundwater has been so important in recent decades. Understanding spatial and temporal changes in groundwater has a very important role in planning the use of groundwater as it is one of the most valuable water resource available for humankind in the world.

Groundwater is the water that exists under the earth's surface and fills all or part of the empty spaces in soils and geologic layers. To distinguish it from surface water, which is found in huge bodies such as oceans or lakes or flows overland in streams, it is sometimes referred to as subsurface water. Weak turbidity, a consistent temperature, and chemical composition, and an almost complete lack of oxygen are some of the most common features of groundwater. The composition of circulating groundwater can vary greatly, depending on the presence of pollution and other impurities (Lerner *et al.*, 1990).

Groundwater management has become increasingly essential in recent decades as a result of the rising demand for water, and the scarcity of surface water supplies. Global water consumption has considerably outstripped total available water resources, posing a major threat to food security. Changes in land use and land cover, as well as fast population expansion, are putting undue strain on the water supplies. Thiruvananthapuram district is an urban area which is getting widely populated day by day. The urbanization in the district is expanding towards the outskirts of the district also. And the impact of the increasing population is huge on the groundwater level, which needs to be studied for the betterment of the future. There are not so many prominent studies happened in the case of groundwater level variations in the Thiruvananthapuram district. According to the report on groundwater monitoring of the Kerala state, the districts of Thiruvananthapuram, Kasaragod, Kannur, and Malappuram, showed more than 10 mgbl. of groundwater level in the isolated areas. The deeper water levels (< 15 mgbl.) are found in isolated pockets in the Thiruvananthapuram district, which can be linked to local hydrogeological factors such as elevated wells (Report GW Intro.). So, a detailed study on the fluctuations of the groundwater level is a must to identify the behaviour of the groundwater level in the Thiruvananthapuram district.

Spatial statistics has a subdiscipline called geostatistics. It has been well-established and refined, during the previous three decades, and it is now widely used in environmental research and technology. Geostatistics is a collection of statistical techniques, for dealing random variables having geographical or temporal variability. The purpose of geostatistics is to forecast a geographical distribution. A map or a group of maps is frequently used to make such predictions (Corzo and Varouchakis, 2018). Geostatistical technique is a highly helpful method for better understanding, evaluating, and studying groundwater level fluctuations. It is also very much helpful for water resource management and can be used to predict the long-term groundwater changes in a specified study area.

1.1 OBJECTIVE OF THE STUDY

Analysis of the spatiotemporal variation in the groundwater level and the identification of the relationship with climatic factors and prepare a thematic map of the Thiruvananthapuram district.

1.2 SCOPE OF THE STUDY

The use of numerical models to manage groundwater resources needs knowledge of geographical distribution. By estimating model input parameters at regular grid points from data taken at random places, spatial interpolation techniques play a critical role in the long-term management of groundwater systems. Thus, the geostatistical analysis in the study area will be very much useful for identifying, managing, and controlling the depletion of groundwater level. The kriging interpolated maps prepared will be very much useful for better understanding the structure of the groundwater level in the study area.

1.3 LIMITATION OF THE STUDY

The main limitation of the study is that for over the last 30 years, only the groundwater level data was appropriately available for the ten years from 2008 to 2017. At least 20 years data are required to get an accurate picture of the water level fluctuations of a specific study area. The cost of the software available for geostatistical analysis, preparation of the thematic maps are also some constraints in this research study.

1.4 PRESENTATION OF THE THESIS

The existing study comprises five chapters namely, introduction, review of literature, materials and methods, results and discussion, and summary. In the first chapter, the introduction, importance, objectives, scope, limitations, and future aspects of the present study are counted in. A review of the past works related to the current study is included in the second chapter. The third chapter designates various statistical methods and techniques used to analyze the data. The inferences drawn from the analysis are enlightened in the fourth chapter, results and discussion. The summary of the entire research program is presented in the last chapter followed by the reference part and abstract part.

1.5 FUTURE LINE OF STUDY

The current study is restricted to Thiruvananthapuram district of Kerala. This study can be further extended to remaining districts and at different time periods to assess or understand the spatiotemporal variations in the groundwater level. Groundwater level data over many different geographical location points within the study area for at least 20 years is required in order to have good accuracy for the study. More coordinate location points are to be included for better mapping of the district.

Review of literature

2. REVIEW OF LITERATURE

The findings of previous studies pave the way to understand the methodologies that may be adopted for the present study. This chapter puts forward the critical reviews of literature related to the current study. The research works done by many research workers related to different statistical procedures and its application to real problems not only in the field of agriculture but also in other disciplines has been critically reviewed in this chapter.

The use of statistics to mine valuation in the Witwatersrand is explored, and general implications regarding the application of the lognormal curve to the frequency distribution of gold values are derived. On the other hand, an indicator of the dependability of current valuation methodologies is presented. It is demonstrated that the current overvaluation and undervaluation of blocks of ore classified as high-grade and low-grade, respectively, may be statistically explained. The application of statistical theory is suggested for the removal of such mistakes and the enhancement of the general standard of mine appraisal. (Krige, 1951).

According to Dubrule (1983), a cross-validation is a suitable tool for finding the efficiency among different spatial interpolation methods. It gives an idea that which method of interpolation is best suited for the given study area. Usually, we will be selecting the interpolation method which has the lowest mean squared error.

Curran (1988) explained in his paper that the semivariogram is a function that relates semivariance to sampling lag. This function can be assessed utilizing remotely detected information or ground information and can be represented as a plot that gives a picture of the spatial reliance of each point on its neighbor. This function relates semivariance to spatial separation and gives a brief and fair depiction of the scale and design of spatial variability in the study area. There are some important terms related to the interpretation of the semivariogram plot. The Range, which specifies the point on the height axis where the semivariance reaches maximum. The Sill, the maximum level of semivariance. And the Lag, which specifies the distance between the sampling pairs in the study area.

Abtew *et al.* (1993) conducted a study on preparing the spatial continuity of monthly rainfall in the study area. The spatial correlation and variogram models have been prepared for the monthly rainfall database. The study indicates that the best three approaches for interpolating monthly rainfall within the study region are multiquadric, kriging, and optimum interpolation. The optimal and kriging methods have the advantage of providing estimates of the error of interpolation. The study concludes that both the above methods are reliable to interpolate the monthly rainfall data in the specified study area.

The groundwater recharge function of the Hadejia-Nguru wetlands in northern Nigeria is valued using a production function technique. The groundwater recharge function aids agricultural output during the dry season, which is reliant on groundwater abstraction for irrigation. This study begins by doing an economic assessment of agricultural productivity per hectare of irrigated land using survey data. The recharge function is subsequently valued as an environmental input into dry-season agricultural output, and suitable welfare change metrics are derived. The welfare change is computed using predicted production functions and hypothetical changes in groundwater recharge and hence groundwater levels. The estimated production functions and hypothetical changes in groundwater recharge and therefore the groundwater levels are used to compute welfare change. This study demonstrates that the groundwater recharge function of wetlands is of major relevance for the floodplain by concentrating on agricultural output that is exclusively dependent on groundwater resources from the shallow aquifer. (Acharya and Barbier, 2000)

Tonkin and Larson (2001) have used the kriging method of interpolation for depicting the groundwater variations. The data were collected from the pumping wells in the respective study area. The groundwater levels measured from the locale of the pumping wells were done kriging by regional-linear and point-logarithmic drift. The drift model comes close to the principal physical process that administers the groundwater flow and finally governs the autocorrelation of the groundwater elevation data. The maps of countered water level thus obtained are more realistic and represent the physical conditions and allow for improved interpretation of measured water level data. The linear log-kriging method was also developed as an applied explanation for improving the degree of understanding possible from measured groundwater data.

In free-range aquifers flowing under the topographic gradients, the water table will be a passive duplication of the ground surface above it. And this is the key principle why we can use the secondary information derived from the digital elevation models to enhance the sparse observations from the water wells for the mapping of the phreatic surfaces. The famous geostatistical method known as kriging with an external drift (KED) is used in this experiment. And it is incorporated with the DEM-derived secondary data for the estimation of groundwater table elevations. They have proposed two different KED models based on the choice of secondary variables in the experiment. In the first one, the water table is expressed as the sum of the deterministic trend and the residual random component representing the water table depth which is measured. The depth to the water table is stated in the second as a linear function of a deterministic trend, which is supplied by the TOPMODEL topographical index and the error. (Desbarats *et al.* 2002).

Kumar and Ahmad (2003) have used the universal kriging technique with a linear drift to analyze the groundwater availability for unlike periods in one cycle during the year around. Many variogram models have been prepared with the effect of drift. And it was calculated using the directional variogram. All the variograms are checked and cross-validated for getting a final satisfactory model for all individual periods. Subsequently, two different variograms were obtained. The one is for the monsoon period and the second one for the non-monsoon period. The variogram for the monsoon period is with the presence of a recharge component and the other variogram without the recharge component. A common variogram was also prepared for representing the average of all the periods. The cross-validation tests were conducted for checking the variograms whether can reproduce the field values for the corresponding periods more satisfactorily than a single common variogram.

Ahmadi and Sedghamiz (2006) have conducted a study on spatial and temporal analysis of groundwater level variations which was supervised every month of 39 different piezometric wells during 12 years. Geostatistical tools were used to depict the spatial and temporal structure of the fluctuations in the groundwater level. The results displayed that a strong spatial and temporal structure occurred for groundwater level variations because of the low nugget effects. The ordinary kriging method and the universal kriging method with cross-validation were performed for evaluating the exactness of the selected variograms used for the estimation of variations and drops of the groundwater level in the selected area. Owing to the satisfactory performance of the kriging interpolation method in estimation, it is likely to monitor the groundwater instabilities in lengthier time intervals. And also, we can calculate approximately the values of water table level in spatial and temporal scales for unidentified locations. The nugget ratio effect imitates the spatial correlation of the groundwater level. Additionally, the results showed that kriging is a valuable and proficient tool for identifying those critical regions where more courtesies for the sustainable use of groundwater are needed.

A study conducted in East Anglia, UK, by Holman (2006) describes an integrated method to evaluate the regional implications of climatic and socio-economic change on groundwater recharge. Altering precipitation and temperature regimes, coastal floods, urbanization, forest establishment, and cropping and rotational modifications are only a few of the variables that impact future groundwater recharge. The results are reviewed in light of significant sources of uncertainty and flaws in recharge estimates. The relevance of socio-economic scenarios in examining the effects of unknown futures is underlined, as it is the unpredictability of socio-economic scenarios. Changes in soil characteristics occur across a variety of periods, thus future soils may not have the same infiltration properties as current soils. The potential consequences of presuming constant soil characteristics are discussed. Focusing solely on climate change's direct effects ignores the potentially significant influence of policy, social values, and economic processes in altering the landscape above aquifers. Hydrogeologists must increasingly collaborate with academics from other disciplines, such as socio-economists, agricultural modelers, and soil scientists, to estimate the potential effects of future changes in groundwater recharge caused by both climate and socio-economic change.

Diverse routines of water require diverse qualities of water. Therefore, monitoring the quality of water is having a vital role because clean water is necessary for human and aquatic ecosystem survival. (Babiker *et al.* 2007) suggested a GIS-based groundwater quality index (GQI) that generates various water quality data by indexing them in ascending order related to WHO guidelines. They have also introduced an impartial procedure for selecting the optimal parameter measurements for calculating the GQI. They have incorporated the characteristics of temporal fluctuations or variations for addressing the degree of usage of water. They have also familiarized the optimum index factor technique which allows the collection of the perfect combinations of the different parameters imparting the fluctuations in the groundwater quality.

Eldrandaly (2007) conducted a study for selecting the best possible GIS software package is a critical measure in the analysis of topographic data. The software itself imparts the success or failure of the experiment conducted. A multi-criteria decision-making dilemma arises while selecting the suitable GIS software package for a certain GIS project. This problem can be solved by taking the essential attention of a complete set of factors and harmonizing multiple objectives in determining the suitability of specific software for building a distinct GIS application. The multi-criteria decision-making (MCDM) technique and the analytic hierarchy process (AHP) are used to select the most appropriate and reliable GIS software for a particular application. The methods mentioned can be used by the project analysts to improve the decision-making process and to minimize the time taken for selecting the GIS software.

In the observed groundwater level data, geostatistical methods can be used to determine the values for the points where measurements are not available or are not feasible to measure because of economic considerations. Geostatistics is a set of statistical methods that may be used to analyze geographical variability and interpolation. Semivariograms are used for describing the spatial variability structure. The models with the least error will be selected as the best fit model. The kriging method provides the best linear unbiased estimation for spatial interpolation. The drift instigated in the experiment is a simple polynomial function that represents the average of the scattered points in the data. The kriging equations can be expanded so that the drift can be estimated if the surface data is not stationary. The kriging method will estimate the drift caused and the residuals from the drift at every point so that it can be mapped. Theoretically, any model other than kriging can produce the best estimates. The kriging method's effectiveness is dependent on the precise definition of a number of parameters that determine the semivariogram and the drift model. The map created without the use of kriging had sharp-lined curves because of the severe distribution of observation wells while the map created with kriging had smooth lines. (Gundogdu and Guney, 2007)

Ahmadi and Sedghamiz (2008) have conducted a study on groundwater depth mapping with the famous kriging and cokriging methods. They have applied geostatistical methods on the maximum, minimum, and mean groundwater depth of 39 different wells. They have found that geostatistical tools are more reliable for this type of analysis. It makes the cost and time-efficient of the experiments. They used kriging and cokriging methods to conduct the mapping of the groundwater depth fluctuations in different climatic conditions across the study area. The results obtained depict that the groundwater depth varies spatially in different climatic conditions. They have also mentioned that the kriging method is an exact interpolation estimator used to find the best linear unbiased estimate. The degree of precision between the two methods was estimated by Root Mean Square Error (RMSE) method. Moreover, both the methods are acceptable, but the latter one (cokriging method) showed more precise results in the mentioned study area.

Because the expenses of collecting and analysis are typically prohibitive, maps of kriged soil parameters for precision agriculture are frequently based on a variogram calculated from too few data. When there are less than 100 data points, the variogram generated using the traditional method of moments is likely to be unstable. Before sampling, compute a variogram from supplementary data, such as an aerial image of the bare soil, to determine the scale of variation in soil parameters. There will be insufficient data to construct an accurate variogram for kriging if the sample interval indicated by this is too wide in respect to the size of the field. If the data is spatially organized and the nugget: sill ratio is comparable to that of a credible variogram of the property, standardized variograms from aerial images can be utilized with sparse standardized soil data. In the absence of a precise variogram, the question of how to establish this ratio remains. For specified soil parameters, several approaches for determining the nugget: sill ratio are offered and assessed. These approaches provide standardized variograms with nugget: sill ratios that are more comparable to variograms computed from dense soil data than variograms calculated from sparse soil data. Cross-validation and mapping findings reveal that standardized variograms produce more accurate estimates and better maintain the key patterns of variation than sparse data variograms (Kerry and Oliver, 2008).

Cay and Uyan (2009) applied geostatistical methods to study the changes in the groundwater level in the specified study area. They have collected the data from 91 wells for 5 years. The spatial and temporal changes in the groundwater level were assessed by the application of the ordinary kriging method with cross-validation leading to estimation of groundwater levels. They said that the spatial analysis based on the kriging method was much useful and operative for assessing the unknown groundwater levels from the known groundwater level data. The modeling results have shown that the kriged groundwater levels exposed approximately harmonized the actual values. The errors estimated in the experiment can be useful in the future for selecting the new observation wells.

Nikroo *et al.* (2009) conducted the study to predict the depth and elevation of groundwater level in the study area. Both the groundwater depth and elevation are predicted by different kriging methods to find the most suitable interpolation method. The acceptable kriging methods are those with low statistical error parameters. The data collected should be normally distributed. The semi-variograms are prepared. The study had concluded that to better interpolate the groundwater position, it should be interpolated on both the groundwater depth and elevation. Interpolation of both of these variables will advance the interpolation in different aspects and suitability criteria.

Salah (2009) have collected the groundwater data of 95 different wells in the study area. The groundwater data collected were not normally distributed. They have done appropriate transformations to make the data normal. The exploratory spatial data analysis

(ESDA) was done in ArcGIS software for the water level to study the distribution of data, global and local outliers in the data, and the trend of the water level. Then they have performed the spatial interpolation by the kriging method. The variograms and semi-variograms are also prepared to fit the best model. The spherical model showed the best fit variogram model for the water level data. The cross-validation method was used for finding out the best fit model. Surface generation was performed to produce the water level map that shows the groundwater level variations in the study area.

The main objective of the study was to assess the spatial and temporal variations in the groundwater level during a period from 2001 to 2005. The data from 31 fairly distributed wells are collected and applied to the geostatistical methods. The good data were subjected to descriptive data analysis for better understanding. The data analysis was followed in four different stages. The first stage was done to determine the type of distribution of the data set. The second stage deals with the characterization of the determined distribution types. The third stage contains the semi-variance analysis, which involves the construction of semivariograms in all directions to test the anisotropy. Forecasting potentials for management purposes were attempted using autocorrelation analysis. (Ta'any *et al.* 2009)

Zang *et al.* (2009) studied the spatial and temporal structure of the groundwater level by geostatistical methods. The findings showed that groundwater drop and groundwater fluctuations are having spatial and temporal structure rendering to nugget effects. The accuracy of the chosen variograms in the estimation of groundwater drop and groundwater fluctuation obtained was evaluated by using ordinary and universal kriging methods with cross-validation. The low Root-Mean-Square (RMS) values obtained from the cross-validation reflect that the chosen variograms are the best and the estimations are appropriate. The low nugget effects in the study validate that the groundwater level fluctuation is strictly time-correlated and illustrates a strong temporal structure. The study concludes that by applying geostatistics to the spatial and temporal analysis, we can obtain a better vision of the water resources systems and can propose suitable solutions to the critical conditions in which water resources are in danger.

Principal component analysis (PCA) is a multivariate PCA is a multivariate way to evaluate a data table in which observations are defined by a large number of quantitative dependent variables that are inter-correlated. Its purpose is to extract the key data from the table, represent it as a collection of new orthogonal variables known as principal components, and display the pattern of similarity between the observations and variables as dots on maps. Cross-validation procedures like the bootstrap and the jackknife may be used to assess the PCA model's quality. In order to manage qualitative variables, PCA may be generalized as correspondence analysis, and in order to handle heterogeneous sets of variables, it can be generalized as multiple component analysis. PCA is based on the eigen-decomposition of positive semi-definite matrices and the singular value decomposition of rectangular matrices in terms of mathematics (Abdi and Williams, 2010).

Different geostatistical methods were used to examine the geographical variations in groundwater nitrate concentrations utilizing data from 119 groundwater wells. Geostatistical approaches have been widely employed as a useful tool for making decisions about the management of hydrochemical parameter behaviour in groundwater. GIS is used to analyze the geographical variations in nitrate concentrations in groundwater, which leads to the estimate of groundwater nitrate concentrations using the universal kriging technique with cross-validation. According to the nugget to sill ratio, nitrate concentrations followed a log-normal distribution and showed a considerable spatial dependency (60 percent). A spherical model best matches the observed variogram of groundwater nitrate concentrations. The level of cross-validation mistakes is acceptable (Uyan and Cay, 2010).

In the geostatistical literature, there is a muddled situation: some writers use the term variogram, while others use the term semivariogram. The numbers represented in a variogram are full variances of observations at a particular geographic separation, according to a formula for the empirical variance that corresponds to pairwise differences. As a result, they should not be referred to as semivariances, nor should the name semivariogram be used. Instead of the misleading semivariance, it is recommended to use the word gamma variance to designate a variogram value (Bachmaier and Backes, 2011).

Moslemzadeh *et al.* (2011) performed this study to find the accuracy of kriging and co-kriging methods in estimating the groundwater level. Both the methods are from the statistical category which makes use of magnitude, distance, and vectorial information for the estimation. Before geostatistical estimation, a precise model is required to calculate the variogram values for each sampling interval. The accuracy, adequacy, and efficiency of different variograms prepared can be tested by the cross-validation technique. The results gave low errors for both the kriging and co-kriging method, which indicates they are unbiassed linear estimators. Among both these interpolation methods, the co-kriging method is having higher accuracy than the kriging method although the increased accuracy is not so significant.

The study conducted by Pareta (2011) is mainly concentrated on groundwater investigation by using remote sensing techniques. Thus, topographic and surficial features are mapped to determine the flow of water from different places in the area under study. The data were utilized from IRS-P6 LISS-IV Mx (5.8 m). For the betterment of the study, the Remote Sensing techniques were utilized because it is more reliable, much effective, and are now being widely used for land resource surveys. Many thematic maps are prepared and integrated with appropriate ratio scales by using ArcGIS software.

Recognizing temporal and geographical fluctuations in groundwater levels and quality has become a precondition for developing and implementing plans for the long-term development and use of water resources. From 1999 to 2008, data from 51 observation wells of depth to groundwater and 30 sample wells of hydrochemical properties of groundwater in the Minqin oasis were collected for this study. All of the data had a normal or log-normal distribution, according to the Kolmogorov–Smirnov test. A set of well-structured semivariograms also revealed that the data was spatially dependent in a moderate to the strong way (Chen and Feng, 2013a).

Chen and Feng (2013bH) collected the data from 51 different observation wells for 10 years. The normality of the data is tested by the Kolmogorov-Smirnov test, and the result showed that the data follows a normal or log-normal distribution. They used the ordinary kriging interpolation method in different periods to attain the thematic maps. The study reveals the declining trend of the groundwater table in the study area.

Dashtpagerdi *et al.* (2013) have applied disjunctive kriging (DK) and radial basis function (RBF) for zoning the groundwater levels. The condition to apply the kriging method is the normality of the data set. But the data collected were not normally distributed and was found out by data histogram and Q-Q Plot methods. Thus, the data were transformed to logarithmic data though it obeys the normal distribution. Different models like spherical, exponential, and gaussian are used in the kriging interpolation method. Among these models, the exponential model was selected because it gives the minimum level of error comparing other models in the study. The comparison of errors was analyzed in the ArcGIS 9.3 software.

Noori *et al.* (2013) In the present study, groundwater level variations were analyzed spatially, and the SPI (drought index) was used to identify different climatic conditions in the study area over 11 years. Different geostatistical methods were performed on the maximum, mean and minimum groundwater level elevations of 59 observation wells. The semivariograms are also fitted and resulted that, the Gaussian model is having the lowest error and high R^2 (coefficient of determination) value in both kriging and co-kriging method. The study illustrates that whatever the depth of groundwater level is lower, estimation accuracy will be more precise. Although all the interpolation techniques have shown appropriate results, the co-kriging method had a better performance for predicting the groundwater level. Lastly, the results depict that the geostatistical approach could be a useful method in creating groundwater level maps.

Adhikary *et al.* (2014) collected the groundwater level data obtained from 25 monitoring wells for 13 years. They divided each year into two seasons, wet and dry seasons. Variograms are calculated for each set of data, therefore a total of 26 variograms have been prepared. In the study, they have fitted three variogram models, Exponential, Gaussian, and Spherical variogram models. The best variogram model is selected from each set of data. The selected variograms are used for the ordinary kriging interpolation method in ArcGIS software to estimate the groundwater level fluctuations. The result depicted that there exists a strong spatial structure for the groundwater level fluctuation because of very low nugget effects. The accuracy of the estimation by the ordinary kriging interpolation method for groundwater level fluctuations for spatial scales is measured by the cross-validation method. The groundwater level fluctuations are also carried out by the general Inverse Distance Weighting (IDW) method. But the results showed up increased errors in this method. So, they have concluded that the ordinary kriging method is more reliable than the IDW method for estimating the groundwater level fluctuations in the specified study area.

Mini *et al.'s* (2014) studied the Spatio-temporal variations in the groundwater level. The study was augmented with the GS+ and geostatistical module of ArcGIS 9.3 software. The variograms and thematic maps were prepared for both pre-monsoon and post-monsoon seasons of 10 years. The results of the variogram analysis showed that the groundwater level has a nugget-to-sill ratio less than 0.25, representing that the groundwater level is having a high degree of spatial dependence. The selection of variograms was done by measuring the accuracy of each. The adequacy and validity of the models were tested by the cross-validation method. Overall, the study concludes that the geostatistical analysis is giving a reliable result in explaining the critical regions where control measures needed to be executed.

Pranuthi *et al.* (2014) described that the Mann-Kendall and linear regression tests were used to assess long-term trends and the cumulative deviation. The Mann Kendall test indicated that just one region, which has a larger urbanizing area than the others, had a substantial increase in rainfall. Rainfall trend variation in the city is also a result of anthropogenic activity and development. In the examined Indian cities, a tendency of rising rainfall is seen throughout the monsoon season. Precipitation patterns, both geographical and temporal, are important for a region's future growth and long-term management of its water resources.

Groundwater potential zones are demarked with the help of remote sensing and Geographic Information System (GIS) procedures. (Waiker and Nilawar, 2014) The thematic maps are created by using GIS tools and the data required for detecting the groundwater potential zones were obtained from the satellite data sources. The collected data were integrated with the weighted overlay technique in ArcGIS. Suitable ranks were given to the different parameters following the storage capacity of groundwater. And this information can be useful for operative identification for extraction of groundwater.

In an Indian state like Gujarat, groundwater is essential for agricultural purposes. The Gujarat government invested in a variety of large-scale and small-scale water facilities to supplement existing agricultural water sources. Greater knowledge of the consequences of previous WIs is required to enhance water storage and groundwater recharge, as well as to justify more expenditures in water infrastructure. This study estimates water storage before and after increased investment in water infrastructures using data from NASA's Gravity Recovery and Climate Experiment (GRACE) and soil moisture data from the Global Land Data Assimilation Systems. In addition, data from the Moderate Resolution Imaging Spectrometer (MODIS) sensor's Normalized Difference Vegetation Index (NDVI) sensor was utilized to illustrate variations in seasonal cropped regions throughout the same period. During the era of intensification in infrastructures for water storage and groundwater recharge in Gujarat, the results show a large net increase in water storage and a rise in agricultural crop area. The findings also show that certain districts have larger net water storage, although the cropped area duration - PCDI has not grown much. The findings of this study can help people better grasp the potential of this and give useful advice on how to expand the cultivated area in Gujarat's high-water-storage zones. (Chinnasamy *et al.*, 2015)

Given the impact of climatic variability on water availability, irrigation demand, agricultural production, and other aspects of life, research of change detection and trend on monthly, seasonal, and yearly historical series of several climatic variables in the study region were conducted. Pettitt's test, von Neumann ratio test, Buishand's range test, and standard normal homogeneity (SNH) test were used for change detection, while non-parametric tests such as linear regression, Mann-Kendall, and Spearman rho tests were used for trend analysis. The changes occurred because of the period's industrialization and urbanization. Trend analysis was used for three distinct periods, namely: P-1, P-2, and P-3 for the entire series of the period. The significantly growing trend in the summer and rainy months in case of minimum temperature, and the winter months in case of maximum temperature during the periods P-2 and P-3 may distress water accessibility and water difficulties in the region. (Jaiswal *et al.* 2015)

The reference evapotranspiration (ET_0) is a critical quantity in agrohydrological systems, but its regional estimation is constrained by its geographical variability. This research examines two methods for creating geographical distribution maps of ET_0 in Iran's Mazandaran region. ET_0 was derived using climatic data and the Hargreaves-Samani equation in weather station sites in the first method and then interpolated. The components of the Hargreaves-Samani equation were interpolated in the second technique, and then ET_0 maps were created using the Hargreaves-Samani equation and appropriate GIS commands. Over Mazandaran province, 10-year climatic data for 51 weather stations were collected. Semivariograms were generated, and the optimal semivariogram model was chosen based on the lowest Residual Sum of Squares value (RSS). The Nugget to Sill ratio was used to compare the geographical correlation of the data. The data were interpolated using the Ordinary Kriging method, and the interpolation error was calculated using the Root Mean Square Standardized Error (RMSSE). Invalidation stations, the projected ET_0 values were compared to the computed ET_0, and a sensitivity analysis was performed. The results demonstrate that the second strategy had a greater spatial correlation and smaller interpolation error, with no significant difference between the two approaches. As a result, the technique of producing ET_0 matters more than the type of meteorological data being interpolated when it comes to the accuracy of the ET_0 maps (Kamali *et al.*, 2015).

In hydrological modeling, the groundwater level is crucial information. The free surface of an aquifer is frequently mapped using geostatistical techniques. The choice of the best variogram model is critical for the best method performance in geostatistical analysis utilizing Kriging techniques. The least-squares sum technique, the Akaike

Information Criterion, and the Cressie's Indicator are compared in this study to examine the theoretical variogram that matches the experimental one and investigate the influence on prediction outcomes. Furthermore, the distance between data is calculated using five distinct distance functions (Euclidean, Minkowski, Manhattan, Canberra, and Bray-Curtis), which impacts both the variogram computation and the Kriging estimator. Using a separate distance measure and the aforementioned three variogram fitting criteria successively, cross-validation analysis in terms of Ordinary Kriging is performed. Classic variogram models are used to investigate the geographical dependency of the observations in the tested dataset. (Theodoridou *et al.* 2015)

The choice of a semivariogram model truly affects the results of a kriging survey at both endpoints and the adequacy of the range of the evaluated values. In any case, the course of a variety of interpolated values is independent of the semivariogram model. Different semivariogram models produce different maps but, the ranges of least and greatest values remain unaltered. A standard guideline to select the most suitable model, using mean error (ME), mean square error (MSE), root mean square error (RMSE), average standard error (ASE), and root mean square standardized error (RMSSE), is proposed. (Aretouyap *et al.* 2016)

The main constraint on agricultural development in the region is the unpredictability and irregular distribution of precipitation, as well as a lack of governmental water resource planning. Using a monthly precipitation data series from 18 meteorological stations, the geographical and temporal variability in precipitation in the state was investigated in this study. Theil and Sen slope estimator tests were performed to estimate the amount of change across the whole time series, and autocorrelation and Mann–Kendall/modified Mann–Kendall tests were employed to find probable trends. The Pettitt–Mann–Whitney test was used to identify the most likely change point, and the full-time series was split into two parts: before and after the change point. The geographical patterns of the trends were assessed using Arc-Map 9.3 software throughout the whole state. (Chandniha *et al.* 2016)

The study conducted by Hussain *et al.* (2016), reveals the performance and application of newly established Empirical Bayesian Kriging (EBK) for the spatiotemporal groundwater fluctuation analysis additionally to the prevailing methods. In this study, spatial prediction thematic maps of groundwater levels were created using the kriging method. Here, we have used both the ordinary kriging method and Empirical Bayesian Kriging (EBK) method. The advantage of using the EBK method over ordinary is that the semivariogram models created need not be fit manually with the experimental semivariogram models. The data collected should be normally distributed. The normality of the data is tested by histogram plot, normal Q-Q plot, Kurtosis, Skewness, and Anderson-Darling test. The semivariogram was then fitted with the most common standard models and the best-fitted model with the experimental model was selected for the ordinary kriging method. The results showed that the EBK method was more accurate and efficient than the ordinary kriging method.

Monthly precipitation data from 16 sites in the study area were used to investigate spatial and temporal precipitation variability. The double-mass curve technique was used to assess the homogeneity of precipitation data, and the presence of serial correlation was determined using the lag-1 autocorrelation coefficient. To find trends, linear regression analysis, the traditional Mann–Kendall (MK) test and Spearman's rho were used, as well as Sen's slope to estimate the slope of the trend line. Precipitation variability was studied using the coefficient of variation (CV). Kriging method was used to perform spatial interpolation in ArcGIS 9.3. Sen's slope test revealed a declining trend in annual and monsoon precipitation for all locations except some sites. (Meshram *et al.* 2016)

Using multivariate statistical analysis and the kriging method, this study delineates the features and regulating elements of groundwater pollution. Groundwater pollution was found mostly in the central and southern regions, as well as in the southwestern and northern regions, according to GIS spatial maps. To categorise the groundwater samples and determine the geochemical processes and sources that govern groundwater geochemistry, geostatistical approaches were used. At 85 m of well height, the scatter diagrams of factor score vs topographic elevation and groundwater level showed that saline water and NO3-N impacted groundwater. The spatial distribution maps of factor scores vs groundwater level revealed the locations and degrees of groundwater pollution. The kriging approach proved helpful in creating distribution maps that showed the extent and location of groundwater pollution. As a result, geostatistical approaches such as factor analysis, cluster analysis, and the kriging method were critical in assessing groundwater pollution and locating contamination sources (Venkatramanan *et al.*, 2016).

Xiao *et al.* (2016) collected the groundwater level data of 30 different locations from the study area. The decline of groundwater level is estimated by using geostatistical theory and ArcGIS geostatistical modules. Seven different methods were adopted for interpolating the groundwater level in the study. The accuracy of the seven different methods was evaluated by cross-validation, absolute error, and coefficient of determination (R^2). The thematic maps of different interpolation methods on groundwater levels in the study area were prepared and evaluated. The correlation between the predicted value and the actual value is measured using the coefficient of determination. Semivariograms are used to describe the spatial variability of the groundwater levels. The kriging method syndicates the effects of both distance and direction parameters such that it signifies a spatially continuous and irregular change of variables. Thus, the interpolation effect of the simple kriging method is giving the best fit. The spatial variability analysis of groundwater level was also conducted in the study.

The study conducted by Chandan and Yashwant (2017) illuminates the application of the geostatistical method to augment the current network of observation wells. The groundwater level fluctuations from different wells are compared with the parameters and analyzed in GIS using simple, ordinary, disjunctive, and universal kriging methods. The best fit theoretical model with the experimental model was found out by comparing the semivariograms fitted for all kriging methods separately. The spatial analysis accomplishes that the exponential semivariogram model attained from the kriging method gives the best fit model among all others. The study depicts that the ordinary kriging method gives the ideal solution for monitoring the groundwater level.

The effects of human-made landscape changes on groundwater recharge rates, locations, and processes are examined. Conversion of land for agriculture and urbanization are the two primary kinds of change investigated, both of which have a substantial influence on groundwater recharge. The methods for recognizing and quantifying changes in recharge as a result of these consequences are addressed. In many semi-arid locations throughout the world, land clearing for agriculture and surface water transfer for irrigation has resulted in orders of magnitude increases in recharge rates, generating continuous land and water salinization and water-logging concerns. While increased irrigation return flow recharge may help to alleviate shallow groundwater depletion in some cases, the effect of unsaturated zone thickening, which reduces the fraction of potential recharge that becomes actual recharge and may result in new water quality risks like nitrate contamination, complicates the situation. Expansion of urban and peri-urban areas, as well as related surface and sub-surface infrastructure, causes complicated water balance changes that redistribute groundwater recharge locations, affect recharge mechanisms, and have varying consequences on recharge rates and quality. (Han, *et al.*, 2017)

The study presents a trend analysis of monthly rainfall data for the Raipur, district for 102 years. The trend analysis is done using the statistical non-parametric tests i.e. Mann-Kendall test and Sen's slope method. The non-parametric tests are performed over the parametric tests because the problems produced due to data skewness can be sidestepped. Man-Kendall test is frequently used for testing the trend analysis of any hydro-climatic series for examining the spatial variation and temporal variation. Sen's slope estimator test is also used to determine the magnitude of the trend. (Swain *et al.* 2018)

Pandey and Sharma (2019) have conducted a study on geostatistical analysis of spatial and temporal variations in groundwater level of the Bhilwara district in Rajasthan. They have analyzed pre and post-monsoon water level and rainfall data to show the spatial distribution of groundwater level in that district for a period of 10 years (2007 – 2016). They have collected Satellite data, water level data, and rainfall data from the available resources. Then they have generated the point data from excel data and prepared the district boundaries also. Then, they have prepared a continuous surface using the Kriging interpolation method, and the relation between water level and rainfall is studied. They have studied the relationship between the rainfall, pre and post-monsoon season groundwater level according to different geographical locations in that district. Charts with two groundwater level series were plotted with average rainfall in that specific geographical location. And the results showed that the surge in the groundwater level is sustained at a satisfactory level till 2016.

The appropriate management of groundwater resources can be done by identifying, modeling, and predicting the level of groundwater level in the plains for long-term planning and optimal use of the potential of water. For accomplishing these factors, we need to have a broad study of approximately all the locations in the study area. Thus, the interpolation techniques are used to achieve continuous, integrated maps and to predict the unknown values within the study area. The disparities in the groundwater level from 2001-2016 were found out by different interpolation techniques like the classic statistical interpolation methods, deterministic interpolation methods, and geostatistical methods. The accuracy of the interpolation methods was assessed by the cross-validation method and the three indices, co-efficient of determination (R^2), the root mean squared error, and mean absolute error were used to compare the interpolation method. The results of the geostatistical methods exposed that the groundwater level is a regionalized variable and there is a high spatial structure ratio between groundwater level data. According to the results obtained from the cross-validation methods, the geostatistical interpolation method is having high accuracy and minimal error, and the classical statistical interpolation method is having the least accuracy and maximum error. Thus, the geostatistical interpolation method is the optimal method for interpolation procedure. (Shahmohammadi-Kalalagah and Taran, 2021)

Materials and methods

3. MATERIALS AND METHODS

This chapter analyzes the important methodologies used to carry out this research. It gives information about the research work so that the process can be repeated. The present study aims to analyze the spatiotemporal variations in the groundwater level of Thiruvananthapuram district. The geostatistical methods are used to analyze the spatiotemporal variations in groundwater level. The normality of the collected data was tested using Shapiro Wilk's normality test. The spatial interpolation within the district boundary was done by the Kriging interpolation method.

This chapter is divided into different sections:

3.1 Study area

3.2 Data

3.3 Examination of the data

3.4 Semivariogram

3.5 Kriging interpolation technique

3.6 Principal component analysis

3.1 **Study area**

Thiruvananthapuram district is located at the southernmost part of Kerala state and is the capital of Kerala. The coordinates of the district are 8.48° north latitude and 76.94° east longitude. The total geographical area of the district is 2192 km^2. It is bounded in the north by the Kollam district, the east is bounded by the Tamil Nadu state, and the west by the Arabian Sea. The district is having a coastline of 78 km with the Arabian Sea. The graphical representation of the study area is shown in Fig. 1.

In the present study the data of groundwater, rainfall, and temperature were collected for about 29 different locations from the study area. The details of the selected geographical sites of data collection are provided in the Table 1.

Table 1: Selected geographical sites from the study area

Sl. No.	Site Name	Latitude (°)	Longitude (°)
1	Ariyanadu	8.58061	77.08611
2	Attingal	8.69721	76.81671
3	Attingal Sub	8.69311	76.82221
4	Balaramapuram	8.42501	77.04721
5	Chengal	8.35831	77.10941
6	Chirayinkil	8.65831	76.78891
7	Edavai	8.76111	76.70001
8	Kallar	8.70831	77.13081
9	Kariavattom	8.56531	76.89031
10	Kattakkada	8.50691	77.08331
11	Kochuveli	8.50281	76.90141
12	Kulathoor	8.32641	77.10971
13	Maruthamoola	8.67501	77.12781
14	Neyyattinakara	8.41111	77.08061
15	Palode	8.72081	77.03191
16	Pangode	8.76531	76.96941
17	Parassala	8.34031	77.15691
18	Parassala Sub	8.34171	77.15281
19	Pattom	8.51941	76.94031
20	Peringamala	8.72781	77.04721
21	Pirappankod	8.65561	76.92221
22	Pothencode	8.63891	76.89721
23	Sasthanthala	8.38611	77.07501
24	Sreekariyam	8.55001	76.91671
25	Udayankulangara	8.37921	77.12471
26	Vamanapuram	8.71941	76.90001

27	Varkala	8.73111	76.71671
28	Vellarada	8.44111	77.19721
29	Vengod	8.65561	76.86671

3.2 Data

The analysis is based on the secondary data of the groundwater level for ten years which is collected from different wells situated in the study area as a part of the Water Resource Information System (WRIS) project. The depth of the groundwater in each well is represented in mgbl. (meters below ground level). The geographical location points (Latitude and Longitude) were collected from the LandSat-8 satellite data. The district boundary shapefile data required for the analysis was collected from the ISRO website. The study also analyzes the relationship of groundwater level variations with the annual rainfall and annual temperature. The rainfall and the temperature data for ten years were collected from the NASA Prediction Of Worldwide Energy Resources (POWER) data access viewer. The rainfall data is collected in millimeters and the temperature data in degree Celsius (°C).

3.3 Examination of the data

The important condition to apply the kriging interpolation technique is the normality of the data set. (Nikroo *et al.*, 2009, Dashtpagerdi *et al.*, 2013, Hussain *et al.*, 2016). The groundwater data, rainfall data, and temperature data should be checked whether they are normally distributed or not for the better accuracy of the research. The normality measure of the specific data set is checked by plotting the Normal Q-Q plots or by drawing the histograms. The statistical test called Shapiro-Wilk's test is also used for checking the normality of the given data set.

3.3.1 *Normal Q-Q plot*

The Q-Q plot, also known as the Quantile-Quantile plot, is an exploratory graphical tool used to test the validity of a distributional assumption for a data collection. On the *x*-

axis, we draw the theoretical quantiles, or standard normal variate (a normal distribution with mean zero, and a unit standard deviation), and on the y-axis, we plot the ordered values for the random variable. We cannot establish a link between the x and y axes if the points at the ends of the curve produced from the points do not lie on a straight line but are substantially scattered from the locations, indicating that our ordered values that we wanted to compute are not normally distributed. The points on the Q-Q plot will fall roughly on a straight line if the data follows the expected distribution. A 45-degree reference line is drawn in the graph. We can plainly claim that this distribution is Normally distributed if all of the points shown on the graph properly lie on a straight line since it is equally aligned with the standard normal variate, which is the basic principle of the Q-Q plot. The normal Q-Q plot of a randomly selected data is represented in Fig. 2.

3.3.2 ***Histogram***

A histogram is a graphical representation of the distribution of a univariate data collection. The histogram graphically depicts the following: the data's center, spread, skewness, outliers, and existence of several modes. These characteristics point to the correct distributional model for the data. The distributional model may be verified using a probability plot or a goodness-of-fit test. A histogram is a graphical representation that separates a set of data points into user-defined ranges. The histogram, which resembles a bar graph in appearance, condenses a data series into an easily understandable visual by grouping many data points into logical ranges or bins. Splitting the data range into equal-sized classes yields the most common version of the histogram. The number of points from the data set that fall into each class is then tallied for each class. That is, the frequency is on the vertical axis, and the response variable is on the horizontal axis. The model histogram is represented in the Fig.3.

3.3.3 *Shapiro-Wilk test*

Testing for distributional assumptions in general, and normality in particular, has been a key focus of theoretical and practical statistical study. Many statistical techniques have been devised based on certain distributional assumptions, particularly those of normality, which might explain the continuing interest. Although the procedures are often more resilient than the assumptions that underpin them, knowing that the underlying assumption is erroneous may moderate the methods' use and application.

The Shapiro-Wilk test generates a W statistic that determines whether a random sample $x_1, x_2, x_3, \dots x_n$, is drawn from a normal distribution or not. The test statistic is obtained by dividing the square of an appropriate linear combination of the sample order statistics by the standard symmetric estimate of variance. Since this ratio is consistent in both size and origin, it may be used to test the composite hypothesis of normality.

The W statistics can be mathematically defined as,

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3.1}$$

Where, $x_{(i)}$ are the ordered sample values and the a_i are constants generated from the means, variances, and covariances of the order statistics of a sample of size n from a normal distribution (Shapiro and Wilk, 1965).

3.4 Semivariogram

Tobler's First Law of Geography states that "everything is related to everything else, but near things are more related than distant things (Tobler, 1970).

Semivariogram is a function that connects semivariance with the sampling lag. The function can be effectively estimated using the remotely sensed data or the ground data and represented as a graph (plot) that gives a depiction of the spatial dependence of each point on its neighbour. This function relates semivariance to spatial separation and provides a concise and unbiased description of the scale and pattern of the spatial variability (Curran,

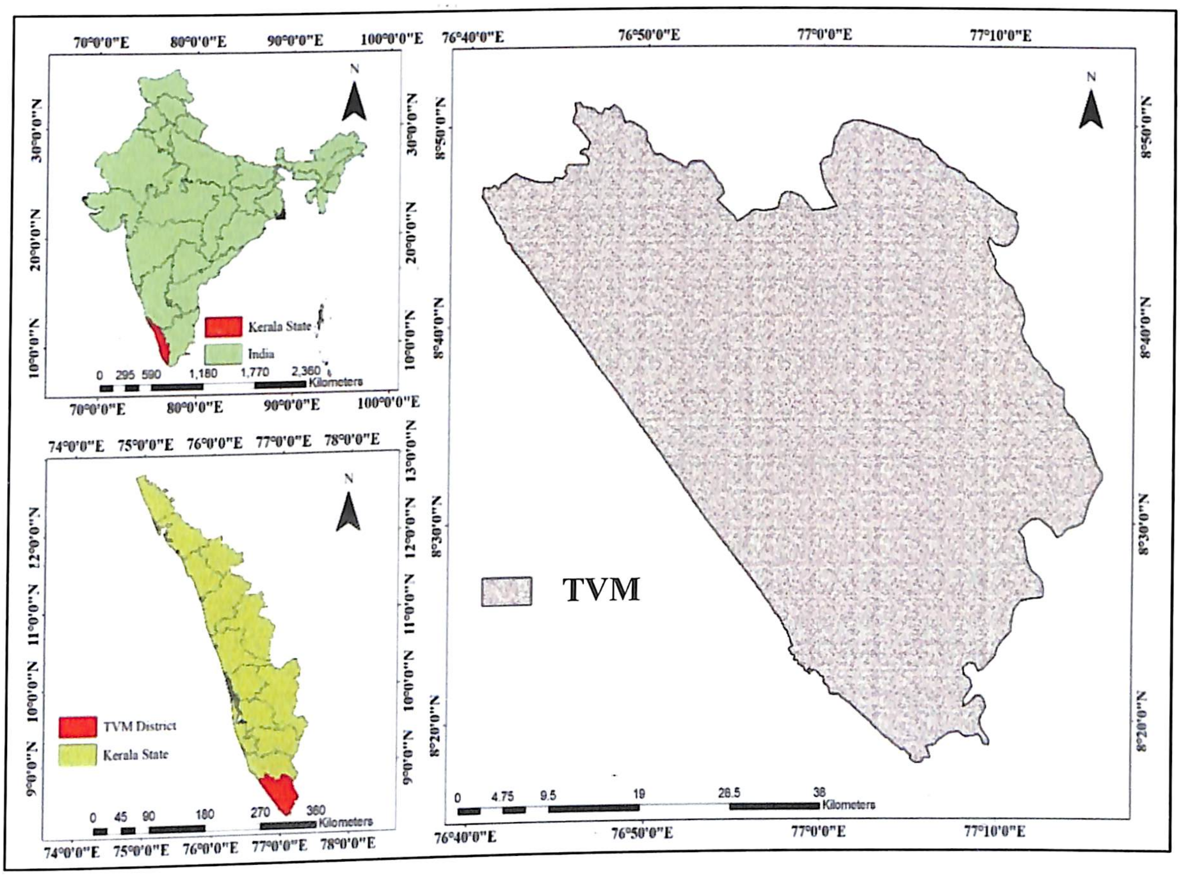

Fig. 1: Geographical representation of the study area (TVM – Thiruvananthapuram)

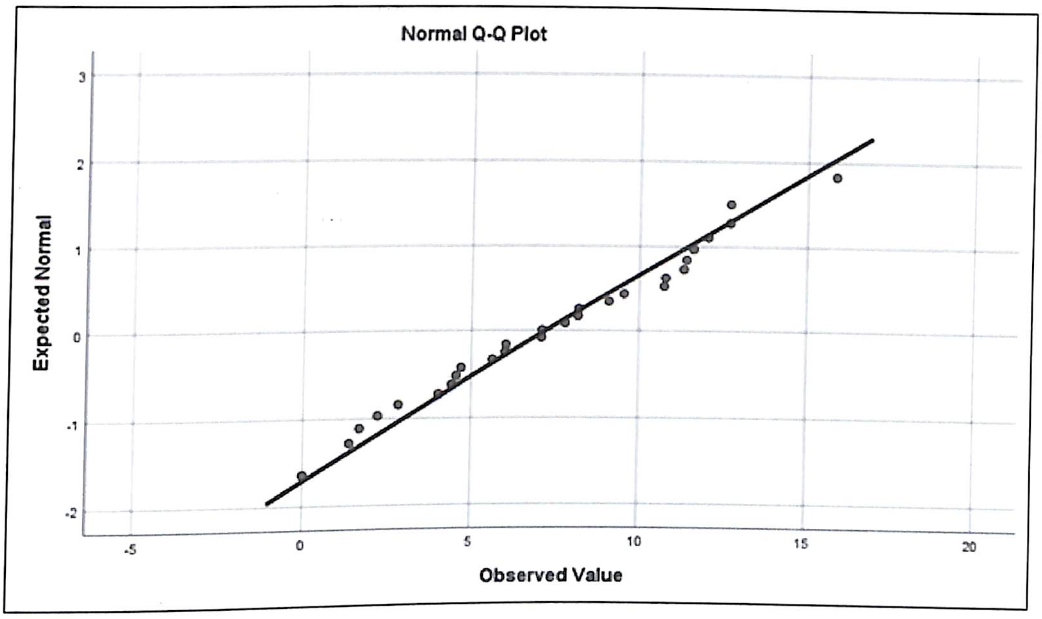

Fig. 2: Normal Q-Q plot of a random sample (For illustration purpose only)

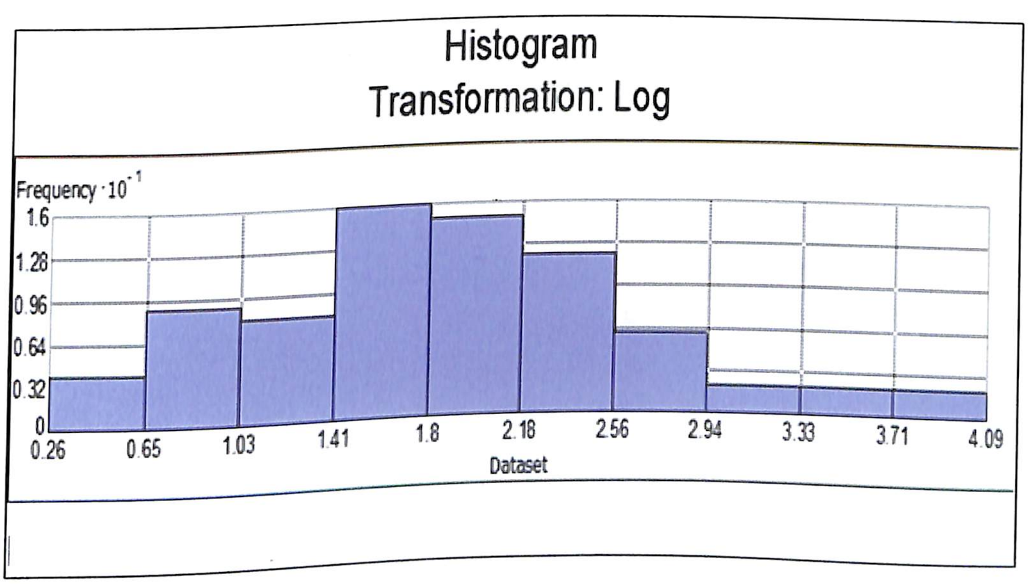

Fig. 3: Histogram of a random sample (For illustration purpose only)

P. J., 1988). Closer items are more predictable and have less fluctuation in a semi-variogram. Things that are far away are less predictable and have fewer connections.

The semivariogram defines the spatial autocorrelation of the measured sample points in the study area. It quantifies the assumption that the things nearby tend to be more similar than the things which are far apart. The semivariogram contains all of the structural information about a regionalized variable:

(1) the size of the zone of effect surrounding a sample,

(2) the variable's isotropic character,

(3) the variable's continuity over space.

The semivariogram gives the concept of sample dependency. Mathematically, the zone of influence is the n-dimensional sphere whose radius is the smallest distance L, such that $var[Y(x)] - \gamma(L) \leq e$, where e is any small number and x is a random point inside the sphere. The semivariogram's range is defined by the parameter L. The sill refers to the portion of the semivariogram to the right of the range portion. All samples with distances less than or equal to L from the point to be estimated give information about the point. All samples beyond the neighborhood described by L are independent observations with respect to the point to be estimated and may be ignored because they give no information about the point (Matheron, 1963).

The definition of the semivariogram is mathematically explained as,

$$= \hat{\gamma}(\vec{h}) = \frac{1}{2}E[\{Z(\vec{x}+\vec{h}) - Z(\vec{x})\}^2] \quad (3.2)$$

$$= \hat{\gamma}(\vec{h}) = \frac{1}{2}Var[\{Z(\vec{x}+\vec{h}) - Z(\vec{x})\}] \quad (3.3)$$

Where, $\vec{x}$ and $\vec{x} + \vec{h}$, are representing the spatial positions separated by a vector $\vec{h}$.

$Z(\vec{x})$ and $Z(\vec{x} + \vec{h})$ signifies the random variable, $\hat{\gamma}(\vec{h})$ is assumed to be dependent only on the separation vector represented as $lag(\vec{h})$, and is independent on the locational vector $\vec{x}$ (Bachmaier and Backes, 2011).

3.4.1 *Range, sill and nugget of the semivariogram*

By observing a typical semivariogram model, it can be observed that the curve levels out at a certain distance. There are different parameters like range, sill, nugget for the better interpretation of the semivariogram. The model graph of a semivariogram is represented in Fig.4. The different parameters of the semivariogram are briefly discussed below.

- The *range* is the distance at which the model begins to flatten out. Spatial autocorrelation exists between sample locations separated by distances less than the range, but not between places farther apart than the range.
- The *sill* is the value that the semivariogram model achieves at the range. The partial sill is the same as the original sill, but without the nugget. When the nugget value is subtracted from the original sill, partial sill is obtained.
- The *nugget* is the value at which the semivariogram intercepts the y-axis.

3.4.2 *Mathematical models of semivariogram*

There are different mathematical models for the semivariogram. The best fitted one will be selected among them. Consider h as the lag distance, c as the sill, r as the range, a as the effective range and ω as an integer. The predominant models of semivariogram are explained briefly below:

3.4.2.1 *Linear model*

This model is the most basic of all the others. The model will not have the sill value and will have a straight linearly rising trend as the distance increases.

$$\gamma(h) = cr;\ r = |h| \leq 0 \tag{3.4}$$

3.4.2.2 *Spherical model*

The model is also known as the "Matheron model," since it has a modest polynomial expression. Its pattern indicates a steady climb up to a distance equal to the range, then a flattening out.

$$\gamma(h) = \begin{cases} c\left(1.5\frac{r}{a} - 0.5\frac{r^3}{a^3}\right); r = |h| \leq a \\ c\,; \qquad\qquad\qquad\quad r = |h| > a \end{cases} \tag{3.5}$$

3.4.2.3 *Exponential model*

It is termed as an exponential model since it has an asymptotic trend when it hits the threshold value. The range is defined as the distance at which the γ – value agrees with the threshold value by 95 percent. The model can be defined as:

$$\gamma(h) = \begin{cases} c\left(1 - e^{-|r|/a}\right); r = |h| \leq a \\ c\,; \qquad\qquad\qquad r = |h| > a \end{cases} \tag{3.6}$$

3.4.2.4 *Gaussian model*

This model is used in the case which is of extremely continuous phenomena. The gaussian model can be defined as:

$$\gamma(h) = \{c\left(1 - e^{-r^2/a^2}\right); r = |h| \leq 0 \tag{3.7}$$

3.4.2.5 *Power model*

The power model is characterized by the parabolic trend, it can be defined as:

$$\gamma(h) = \{cr^{\omega}; \quad r = 0 < \omega < 2 \tag{3.8}$$

The different models of the semivariogram are represented in the Fig. 5 for better understanding (Mazzella and Mazzella, 2013).

Fig. 4: Diagrammatic representation of a typical semivariogram model

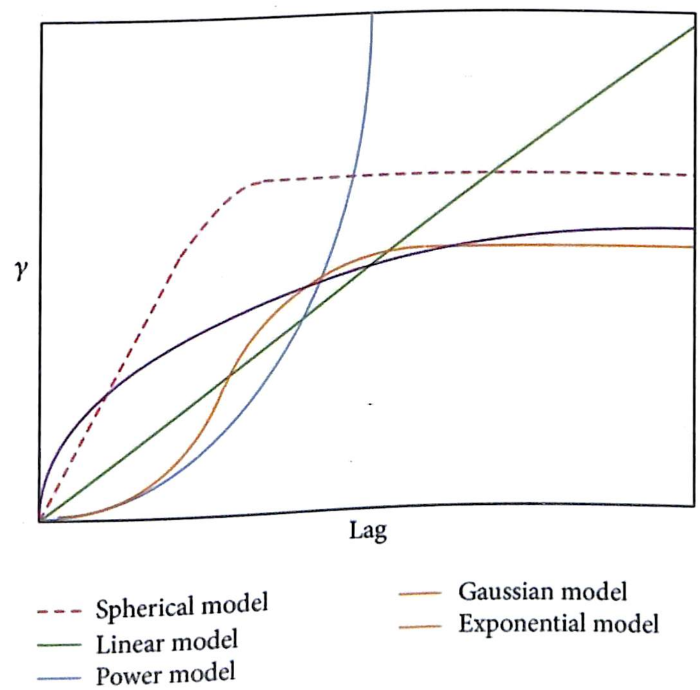

Fig. 5: Semivariogram theoretical models

3.5 **Kriging interpolation technique**

Surfaces integrating the statistical characteristics of the observed data are created using geostatistical techniques. As geostatistical analysis is based on statistics, these approaches generate both prediction and error or uncertainty surfaces, providing the user a sense of how accurate the forecasts are.

Kriging is separated into two parts, measuring the data's spatial structure and making a forecast. Variography is the process of quantifying the geographic data structure by fitting a spatial-dependence model to the data. Kriging will utilize the fitted model from variography, the spatial data configuration, and the values of the measured sample points surrounding the prediction site to create a prediction for an unknown value for a given place. Many tools are given by Geostatistical Analyst to assist in determining which parameters to use, and defaults are also provided so that a surface may be rapidly constructed.

Geostatistics encompasses a wide range of techniques, although they all fall under the kriging family. In Geostatistical analysis, you may do ordinary, simple, probability, universal, disjunctive, and indicator kriging, as well as multivariate cokriging technique.

Depending on the measurement error model, kriging is a relatively fast interpolator that is reliably more accurate or smoothed. It is quite versatile, allowing the user to study spatial autocorrelation graphs. Kriging employs statistical models to provide a wide range of map outputs, including predictions, prediction standard errors, indicator standard errors, and probability. Kriging's versatility might need a lot of decision-making. Kriging is based on the assumption that the data is generated by a stable stochastic process. Ordinary, simple, and universal kriging are examples of techniques that assume normally distributed data.

Kriging weights the adjacent measured values to provide a prediction for an unmeasured site in the nearby location. The general formula for interpolation is formed as a weighted sum of the data,

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \tag{3.9}$$

Where, $Z(s_i)$ is the measured value at the i^{th} location, λ_i is an unknown weight for the measured value at the i^{th} location, s_0 is the prediction location and N is the number of measured values.

The thematic maps of spatiotemporal variation are performed with the kriging interpolation technique in ArcGIS 10.4 software.

3.6 **Biplot and Principal component analysis (PCA)**

PCA (Principal Component Analysis) is a multivariate approach that is mostly used to reduce the number of dimensions in a big data collection. With the aid of orthogonal transformation, it is a statistical technique that turns observations of correlated characteristics into a collection of linearly uncorrelated data. The principal components are the newly altered characteristics. It is a method for extracting strong patterns from a dataset by lowering variances. PCA provides an objective method for finding indices of this type, allowing for the simplest data variance accounting. Principal components give information on the most essential characteristics of a data set as a whole, enabling data reduction with little loss of original data.

The biplot, which includes both the principal component scores and the loading vectors in a single biplot display, is a common approach to visualize PCA findings. The observations are represented as points in a plane defined by two primary components in the plot.

Results and discussion

4. RESULTS AND DISCUSSIONS

The research study entitled "Geostatistical analysis of groundwater level in Thiruvananthapuram district" has been carried out at the Department of Agricultural Statistics, College of Agriculture, Vellayani, Thiruvananthapuram district during the years 2019 – 2021. Different geostatistical methods were applied to describe the spatiotemporal variations in the groundwater level within the study area. The relationship of groundwater level with rainfall and temperature was also identified. The semivariogram models were built to check the spatial continuity of the groundwater level. The results of the statistical analysis performed during research are presented below in this chapter.

The groundwater level data of 29 different locations within the study area are collected for about ten years, 2008 to 2017 from the WRIS [Water Resource Information System] website. The selection of data points was based on the even spatial distribution such that all the locations in the district are entirely covered. The rainfall and temperature data were also collected for the 29 different locations for ten years from the NASA satellite website.

The kriging interpolation technique was performed in the study area to estimate the spatiotemporal variations in the groundwater level. The kriging technique is more effective when the data sets are normally distributed (Zhang *et al.*, 2013). Thus, the data points were subjected to exploratory data analysis to test the normality of the data sets. The results are presented here.

The results of the research are presented by the subheadings as given below:

4.1 Exploratory data analysis

4.2 Relationship of groundwater level with rainfall and temperature.

4.3 Semivariogram fitting for groundwater level drop.

4.4 Semivariogram fitting of groundwater level over the years.

4.5 Semivariogram fitting of the average groundwater level over the years.

4.6 Spatiotemporal variation in the groundwater level.

4.7 Spatiotemporal variations in Temperature and rainfall.

4.8 Biplot analysis of the groundwater level

4.1 Exploratory data analysis

The mean, median, and standard deviation of the groundwater level, temperature, and rainfall for ten years are represented in the table.

4.1.1 Exploratory data analysis of groundwater level data

Table 2: Exploratory data analysis of groundwater level data

Sl. No.	Year	Mean	Median	SD
1	2008	8.36	7.1	7.83
2	2009	7.81	7.22	4.65
3	2010	8.78	7.3	8.71
4	2011	7.58	6.95	4.69
5	2012	7.79	6.8	4.78
6	2013	10.85	9.21	9.16
7	2014	9.59	8.04	7.05
8	2015	9.03	7.62	6.74
9	2016	9.87	7.37	8.85
10	2017	10.09	8.96	6.18

Table 3: Shapiro-Wilk's normality test results of the groundwater data

Sl. No.	Year	p – value[a]	Normality
1	2008	0.611	Normal
2	2009	0.564	Normal
3	2010	**0.025**	Not Normal
4	2011	0.654	Normal
5	2012	0.439	Normal
6	2013	0.066	Normal
7	2014	0.265	Normal
8	2015	0.106	Normal
9	2016	0.300	Normal
10	2017	**0.026**	Not Normal

H_0: The population is having a normal distribution

H_a: The population does not have a normal distribution

a – p-value of the Shapiro-Wilk's test.

From the Shapiro-Wilk's normality test represented in the Table 3, it can be identified that the years 2010 and 2017 are not normally distributed as the null hypothesis is rejected at 5 percent level of significance. Thus, log transformation is performed to the data sets which are not normally distributed and have proceeded further.

4.1.2 Exploratory data analysis of temperature data

Table 4: Exploratory data analysis of temperature data

Sl. No.	Year	Mean	Median	SD
1	2008	26.02	26.18	0.662
2	2009	26.59	26.61	0.304
3	2010	26.61	26.62	0.298
4	2011	26.49	26.42	0.337
5	2012	26.79	26.78	0.301
6	2013	26.63	26.66	0.295
7	2014	26.68	26.73	0.306
8	2015	26.66	26.74	0.348
9	2016	26.98	26.94	0.255
10	2017	26.86	26.84	0.252

Table 5: Shapiro-Wilk's normality test results of the temperature data

Sl. No.	Year	p – value[a]	Normality
1	2008	0.00	Not Normal
2	2009	0.00	Not Normal
3	2010	0.00	Not Normal
4	2011	0.00	Not Normal
5	2012	0.00	Not Normal
6	2013	0.00	Not Normal
7	2014	0.00	Not Normal
8	2015	0.00	Not Normal
9	2016	0.00	Not Normal
10	2017	0.00	Not Normal

H_0: The population is having a normal distribution

H_a: The population does not have a normal distribution

a – p-value of the Shapiro-Wilk's test

From the Shapiro-Wilk's normality test represented in the Table 5, it can be inferred that all the years are not normally distributed.

4.1.3 Exploratory data analysis of rainfall data

Table 6: Exploratory data analysis of rainfall data

Sl. No.	Year	Mean	Median	SD
1	2008	1864.32	1665.2	260.82
2	2009	1525.6	1332.58	259.67
3	2010	1796.82	1551.87	325.67
4	2011	1369.84	1163.86	266.34
5	2012	1098.68	969.41	177.93
6	2013	1652.61	1391.91	342.24
7	2014	1752.36	1549.94	262.3
8	2015	1856.34	1683.39	232.56
9	2016	1080.11	889.88	270.88
10	2017	1598.31	1377.55	313.89

Table 7: Shapiro-Wilk's normality test results of the rainfall data

Sl. No.	Year	p – value[a]	Normality
1	2008	0.00	Not Normal
2	2009	0.00	Not Normal
3	2010	0.00	Not Normal
4	2011	0.00	Not Normal
5	2012	0.00	Not Normal
6	2013	0.00	Not Normal
7	2014	0.00	Not Normal
8	2015	0.00	Not Normal
9	2016	0.00	Not Normal
10	2017	0.00	Not Normal

H_0: The population is having a normal distribution

H_a: The population does not have a normal distribution

a – p-value of the Shapiro-Wilk's test

From the Shapiro-Wilk's normality test, it can be observed that all the years are not normally distributed and to make the data normal, the log transformation is performed.

4.2 Relationship of groundwater with rainfall and temperature

The correlation between groundwater and temperature, and between groundwater and rainfall are computed to find the linear relation between the variables. And the result of the correlation analysis is shown in Table 8.

Table 8: Correlation analysis of groundwater with climatic factors (Temperature and Rainfall)

	Correlation	t value	p value
GW vs T	0.181	3.12	0.002*
GW vs RF	0.023	0.34	0.734

Here, from the correlation analysis, it can be inferred that there is a positive correlation between groundwater and temperature, as the correlation between them is significant at 5 percent level of significance. But there is no significant correlation at 5 percent level of significance between groundwater and rainfall.

4.3 Semivariogram fitting for groundwater level drop

The semivariogram fitting to the groundwater level drop for each location is done inorder to find the temporal structure of the groundwater level in the study area. The groundwater drop was found out for each location by taking the difference between the groundwater levels of 2008 and 2017 inorder to find the temporal variations. The positive drop refers to the depletion in the groundwater level and the negative drop refers the increment in the groundwater level for each different location.

Table 9: The groundwater level drop for 29 different locations

Sl. No.	Location	Latitude	Longitude	Groundwater level drop
1	Ariyanadu	8.58061	77.08611	-0.83
2	Attingal	8.69721	76.81671	5.66

3	Attingal sub	8.69311	76.82221	-1.28
4	Balaramapuram	8.42501	77.04721	3.33
5	Chengal	8.35831	77.10941	7.57
6	Chirayinkil	8.65831	76.78891	2.03
7	Edavai	8.76111	76.70001	-0.47
8	Kallar	8.70831	77.13081	0.6
9	Kariavattom	8.56531	76.89031	0.43
10	Kattakkada	8.50691	77.08331	-0.4
11	Kochuveli	8.50281	76.90141	1.15
12	Kulathoor	8.32641	77.10971	2.06
13	Maruthamoola	8.67501	77.12781	0.46
14	Neyyattinakara	8.41111	77.08061	2.61
15	Palode	8.72081	77.03191	2.45
16	Pangode	8.76531	76.96941	0.96
17	Parassala	8.34031	77.15691	-0.06
18	Parassala sub	8.34171	77.15281	-0.25
19	Pattom	8.51941	76.94031	-2.44
20	Peringamala	8.72781	77.04721	-1.99
21	Pirappankod	8.65561	76.92221	2.14
22	Pothencode	8.63891	76.89721	7.99
23	Sasthanthala	8.38611	77.07501	2.22
24	Sreekariyam	8.55001	76.91671	1.58
25	Udayankulangara	8.37921	77.12471	0.8
26	Vamanapuram	8.71941	76.90001	2.14
27	Varkala	8.73111	76.71671	2.76
28	Vellarada	8.44111	77.19721	1.51
29	Vengod	8.65561	76.86671	0.42
30	Ariyanadu	8.58061	77.08611	-0.83

After fitting the semivariogram, the nugget effect found was 0.467, the sill measured was 1.272, and the nugget to sill ratio obtained was 0.367, resulting that the groundwater drop is having a relatively strong temporal dependence. And also, the rate of the groundwater level drop is 1.49 meters. The positive drop for the study area indicates that there is an overall depletion in the groundwater level.

4.4 Semivariogram fitting of groundwater level over the years

The semivariogram model is fitted for the groundwater level data for all the years. The best-fitted model is selected by comparing the adjusted R^2 values between the models.

Table 10: The adjusted R^2 values for semivariogram models for different years

Year	Gaussian	Spherical	Exponential	Best fit model
2008	0.699	0.842	0.543	Spherical
2009	0.439	0.679	0.689	Exponential
2010	0.439	0.641	0.667	Exponential
2011	0.637	0.822	0.574	Spherical
2012	0.668	0.623	0.486	Gaussian
2013	0.293	0.641	0.492	Spherical
2014	0.367	0.892	0.695	Spherical
2015	0.601	0.596	0.367	Gaussian
2016	0.583	0.755	0.461	Spherical
2017	0.583	0.698	0.771	Exponential

The model having the highest adjusted R^2 will be selected as the best fit model. After identifying the best fit model, their nugget, sill, and range is identified. The nugget to sill ratio is also identified to check the spatial dependency of the groundwater level in the study area.

Table 11: The best fitted model, range, nugget, sill and Nugget to sill ratio for different years.

Year	Model	Range	Nugget	Sill	N/Sill
2008	Spherical	0.056079	0.150	0.504	0.298
2009	Exponential	0.048608	0.228	0.443	0.515
2010	Exponential	0.071168	0.166	0.594	0.279
2011	Spherical	0.016144	0.063	0.451	0.141
2012	Gaussian	0.053469	0.193	0.427	0.452
2013	Spherical	0.031655	0.293	0.411	0.714
2014	Spherical	0.028777	0.174	0.323	0.539
2015	Gaussian	0.019655	0.141	0.354	0.399
2016	Spherical	0.042133	0.053	0.419	0.126
2017	Exponential	0.020614	0.185	0.331	0.561

If the ratio is less than 0.25, the variable has a high spatial dependency and if the ratio is between 0.25 and 0.75, the variable has moderate spatial dependence, otherwise, the variable has weak spatial dependence (Cambardella *et al.*, 1994). Here, when examining the table, it can be inferred that the years 2011 and 2016 are having the nugget to sill ratio less than 0.25, thus it can be concluded that they are very much spatially dependent and all the remaining years are moderately spatially dependent.

4.5. Semivariogram fitting of the average groundwater level over the years

The semivariogram is fitted for the average groundwater level over the years to identify the spatial dependence. The range, nugget, sill is identified. The nugget to sill ratio is 0.483, which can be referred that the groundwater level drop is having a moderate spatial dependence.

4.6. Spatiotemporal variation in the groundwater level

The thematic maps of the groundwater level variations for the ten years are represented below. From the maps given below, the trend of the groundwater level fluctuations yearly from 2008 to 2017 can be observed clearly.

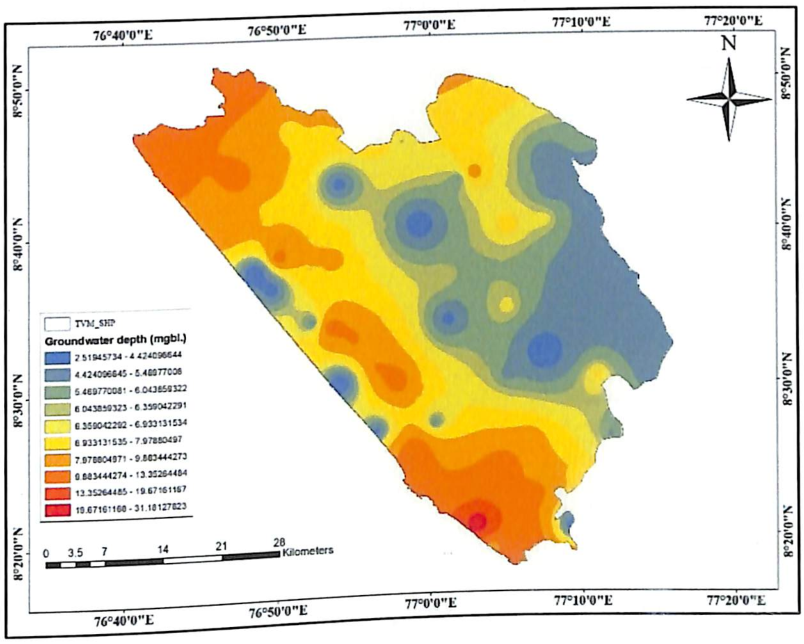

Fig. 6 – Map of groundwater level fluctuation in the year 2008

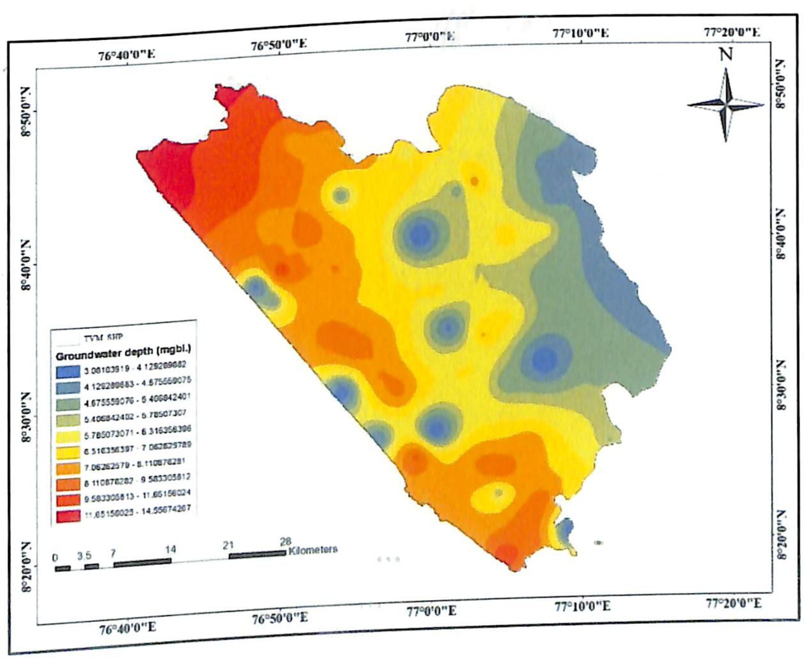

Fig. 7 – Map of groundwater level fluctuation in the year 2009

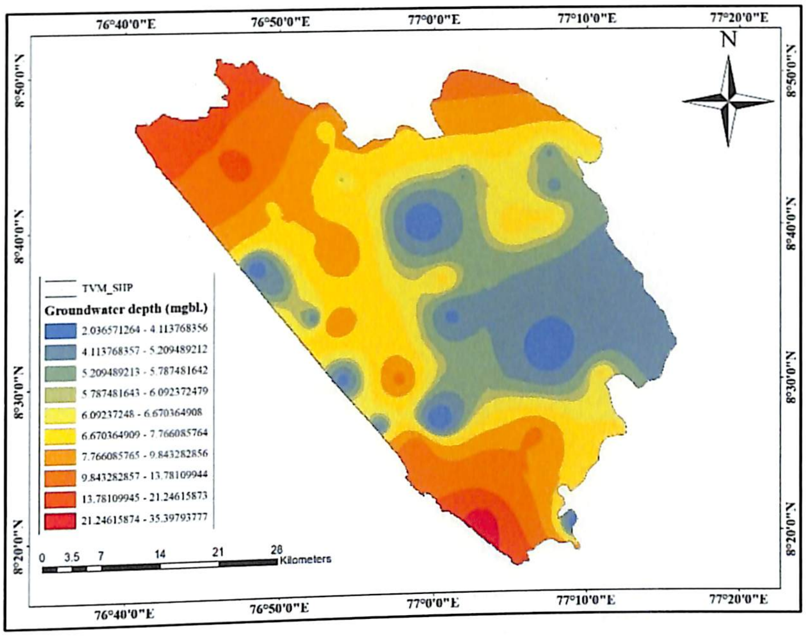

Fig. 8 – Map of groundwater level fluctuation in the year 2010

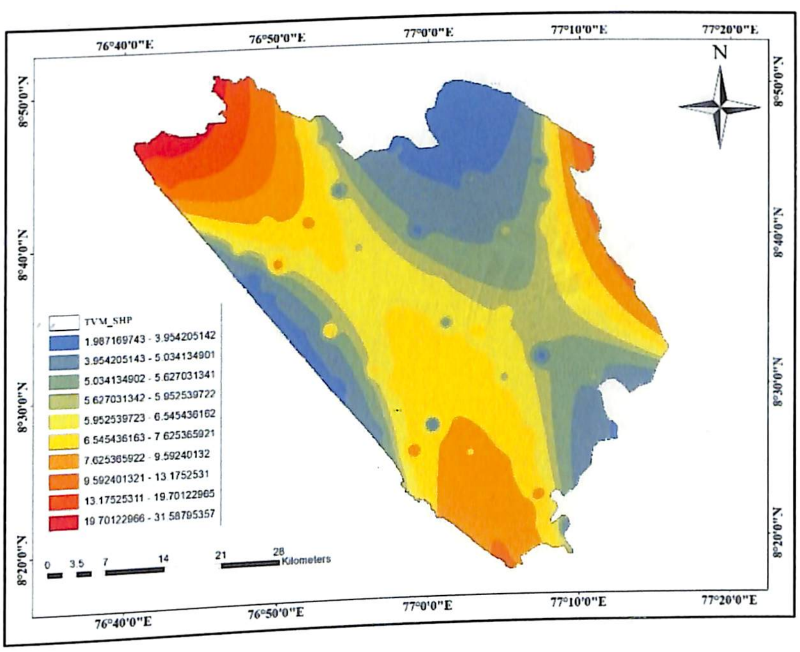

Fig. 9 – Map of groundwater level fluctuation in the year 2011

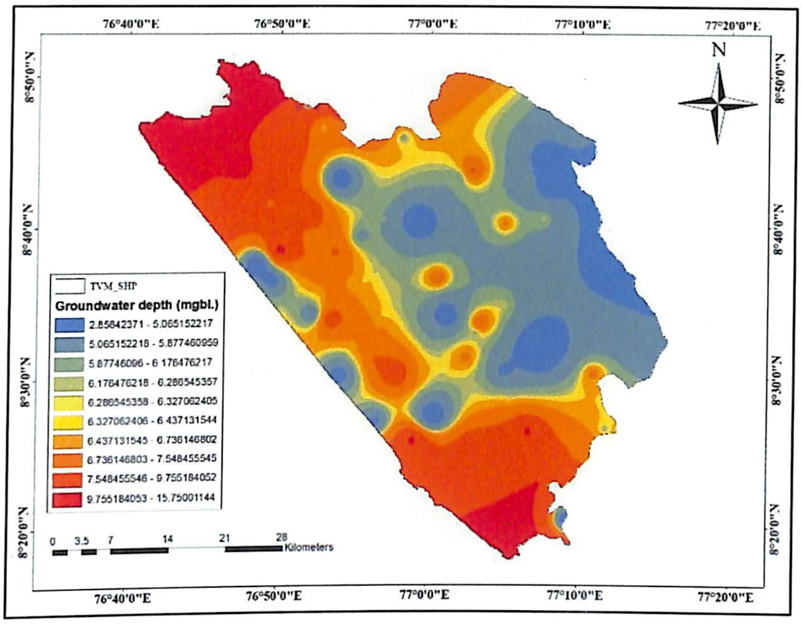

Fig. 10 – Map of groundwater level fluctuation in the year 2012

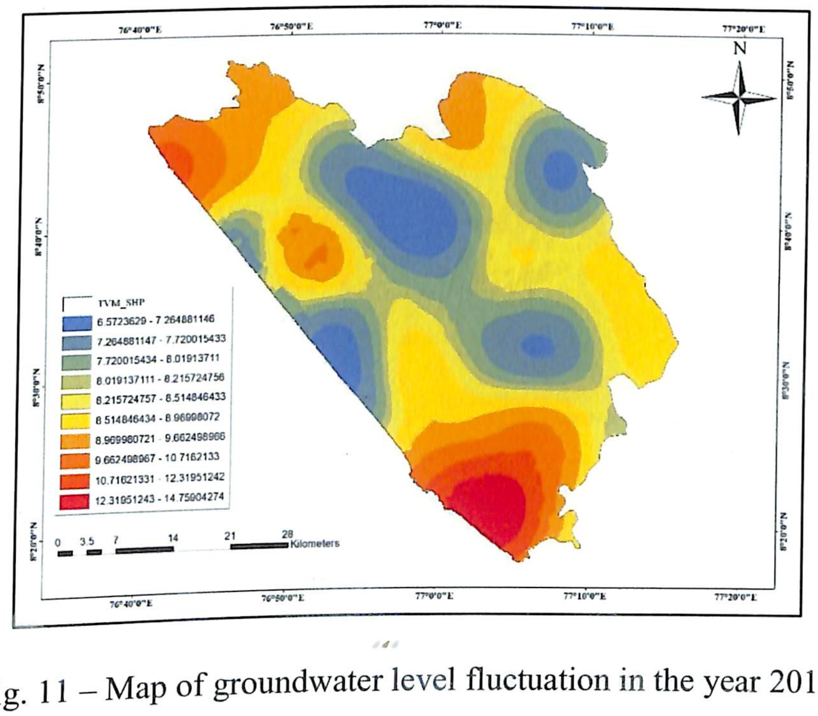

Fig. 11 – Map of groundwater level fluctuation in the year 2013

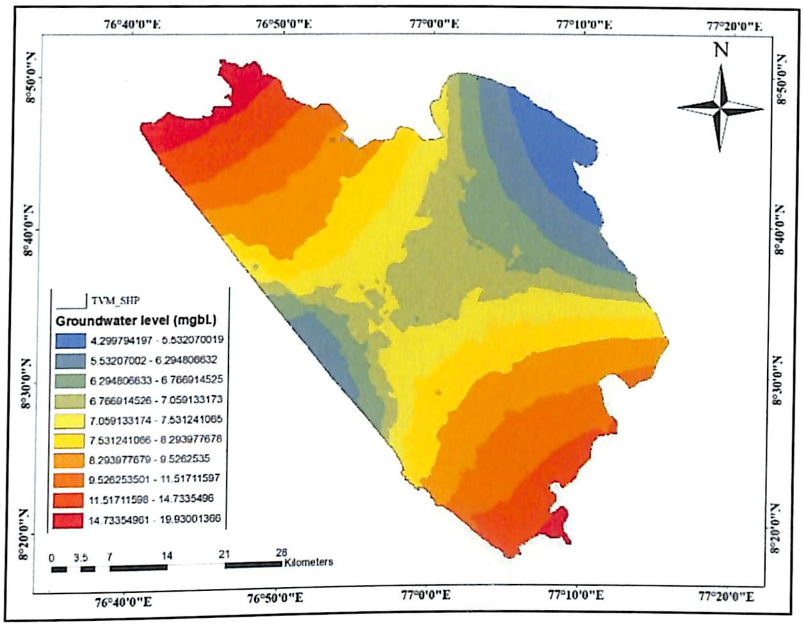

Fig. 12 – Map of groundwater level fluctuation in the year 2014

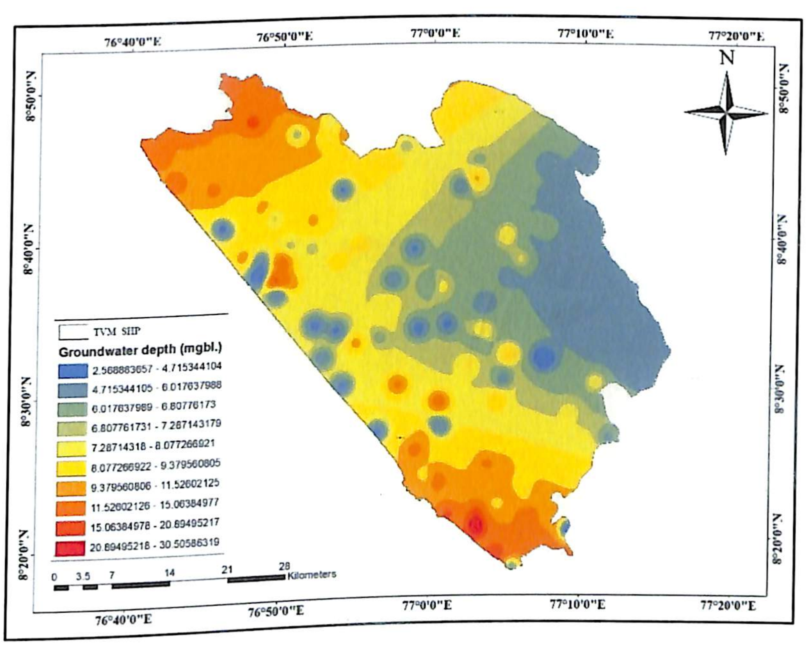

Fig. 13 – Map of groundwater level fluctuation in the year 2015

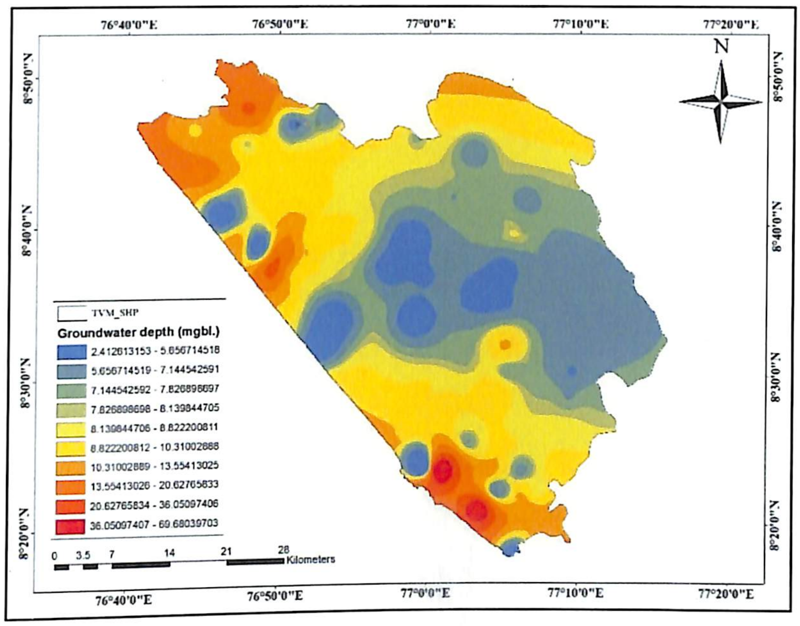

Fig. 14 – Map of groundwater level fluctuation in the year 2016

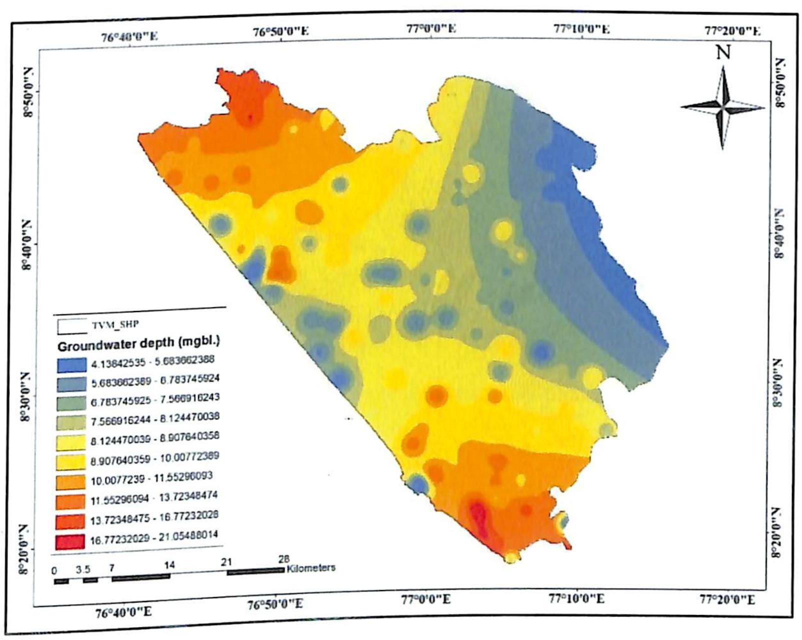

Fig. 15 – Map of groundwater level fluctuation in the year 2017

These are the thematic maps for the spatiotemporal variations in the groundwater level in the study area. The red color in the map indicates the highest drop in the groundwater and the blue color indicates the region with less drop in the groundwater level. So, it can be concluded that the areas with blue color is having a good amount of groundwater level.

By investigating the thematic maps prepared, it can be inferred that in the year 2008, the groundwater level ranges from 2.5 mgbl. to 31.2 mgbl. Chirayinkeezhu, Azhoor, Mangalapuram, Vamanapuram, Palode, Nedumangadu, Pothencode, Kazhakoottam, and Thiruvananthapuram regions are having a good amount of groundwater level, which is represented in the blue color on the map. The places surrounding the Neyyar dam is also having a good amount of groundwater in the year 2008. But towards the Parassala region, which is near Tamil Nadu state is having a less amount of groundwater level. The places, Pulluvila, Karumkulam, Nochur also have less amount of groundwater level. The Varkala region, which is the northern side of the Thiruvananthapuram district, is also having a decreased amount of groundwater level.

In the case of the year 2009, the groundwater level ranges from 3.08 mgbl. to 14.56 mgbl. There it can be observed that the Vamanapuram, Pallichal region is having an increased level of groundwater. And the places, Chirayinkeezhu, Azhoor, Aruvikkara, is having a small decrease in the groundwater level. Whereas, the places like Vithura and Ariyanadu, the groundwater level is maintained as the previous year. And there were no such noticeable drastic changes.

While investigating the year, 2010, the range of groundwater level variation is from 2.03 mgbl. to 35.41 mgbl. in the study area. The groundwater depletion was observed in the Peringamala, Chenkal, Vanniyur, Amaravila regions. But it can be observed that there is a noticeable increase in the groundwater level in Aruvikkara, Vellanad, Ariyanadu, and Kuttichal regions.

In the year 2011, the groundwater level variation ranges from 1.98 mgbl. to 31.58 mgbl. within the study area. The Peringamala, Pangode, Kallara, Manjappara, Palode, Kaniyapuram, Veli regions are having a desirable amount of groundwater level. The Bonacaud region, bound to the Tamil Nadu state border at the east side does not have much amount of groundwater level, same as the case in the south side of the district. The Parassala, Nochur, Poovar, Amaravila regions are having a moderately sufficient amount of groundwater level. The Peroorkada, Nedumangadu, Alamcode regions are having moderately less amount of groundwater levels. Edavai, Varkala, Ariyur, Kappil regions are showing the least level of groundwater.

In the year 2012, the groundwater level variation ranges from 2.90 mgbl. to 15.78 mgbl. While observing the thematic map, it is found that there is a noticeable groundwater level decrease in the region near to the Kollam district and the Parassala region. But a noticeable increment in the groundwater level at Vithura and Neyyar regions are observed.

In the year 2013, the groundwater level variation ranges from 6.57 mgbl. to 14.76 mgbl. From the map it can be identified that in the north side of the district, Edavai region, Varkala region, and the south side, Pulluvila, Karumkulam, Poovar regions are also having a decreased amount of groundwater level. But the Vamanapuram, Palode, Peringamala, Venjaramoodu, Veli, Palayam, Ponmudi, Neyyar, Aruvikkara regions are having a decent amount of groundwater level. The major decline is seen in the Attingal region.

The groundwater level drop of the year 2014 ranges from 4.30 mgbl. to 19.93 mgbl. The northern part of the district, which is near the Kollam state like the Varkala region, and the southern region near to Tamil Nadu state like Parassala, has a decrement in the groundwater level. Whereas, the eastern region near the Tamil Nadu and the western region near to the coastline are having a decent amount of groundwater.

While investigating the year 2015, it can be identified that the groundwater level variation ranges from 2.57 mgbl. to 30.50 mgbl. There is a small increase in the groundwater level for the Kazhakoottam region and Thiruvananthapuram region. The Ponmudi, Bonacaud, Aruvikkara, Vithura, Ariyanadu, Kuttichal, Neyyar regions are having a good amount of groundwater level. The northern part of the district, the Varkala region, and the southern part, the Pulluvila region is showing the maximum drop in the groundwater level. The water level is maintained in the Vamanapuram, Peringamala, Venjaramoodu and Nedumangadu regions.

The groundwater level drop of the year 2016 ranges from 2.42 mgbl. to 69.68 mgbl. The highest drop in the groundwater level is observed this year at the Balaramapuram and Neyyattinakara regions. While so, there is an acceptable increase in the groundwater of Kilimanoor, Peringamala, and Pangode regions. The groundwater level is maintained in Vithura, Ariyanadu, Nedumangadu, Sreekariyam areas. While observing the map, it can be inferred that there is a decrease in Vellanad, Venganoor, Balaramapuram, and Poovar regions.

In 2017, the groundwater level drop is ranging from 4.13 mgbl. to 21.05 mgbl. The highest drop is seen in the Varkala and Parassala regions. The places bound to Tamil Nadu state is maintaining a considerable amount of groundwater level. The Kazhakoottam, Kaniyapuram, Attippara, Chirayinkeezhu regions are having a decent amount of groundwater level.

4.7. Spatiotemporal variations in Temperature and rainfall

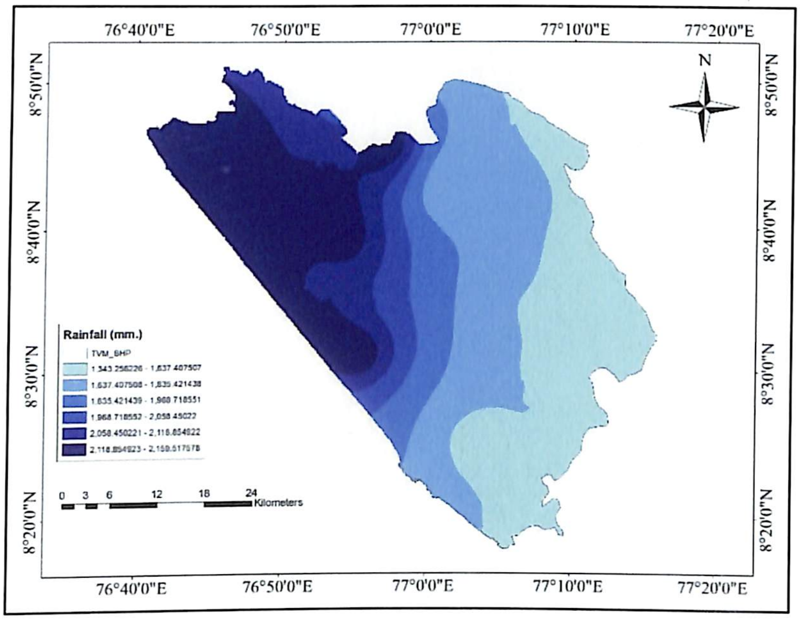

Fig. 16 – Map of rainfall distribution in the year 2008

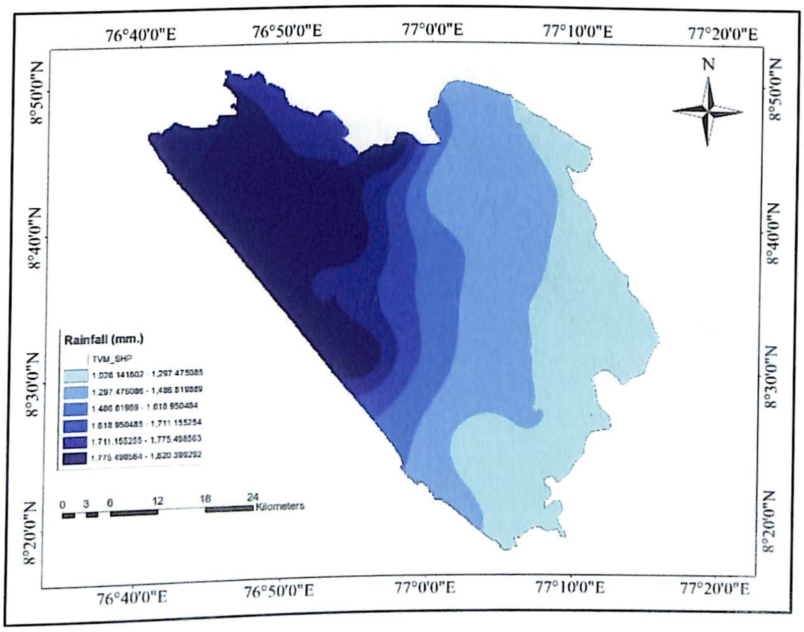

Fig. 17 – Map of rainfall distribution in the year 2009

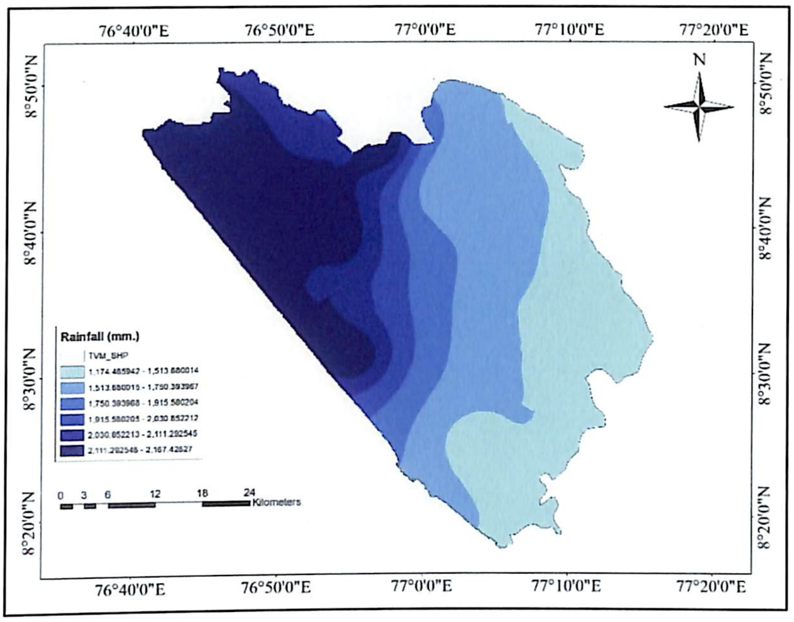

Fig. 18 – Map of rainfall distribution in the year 2010

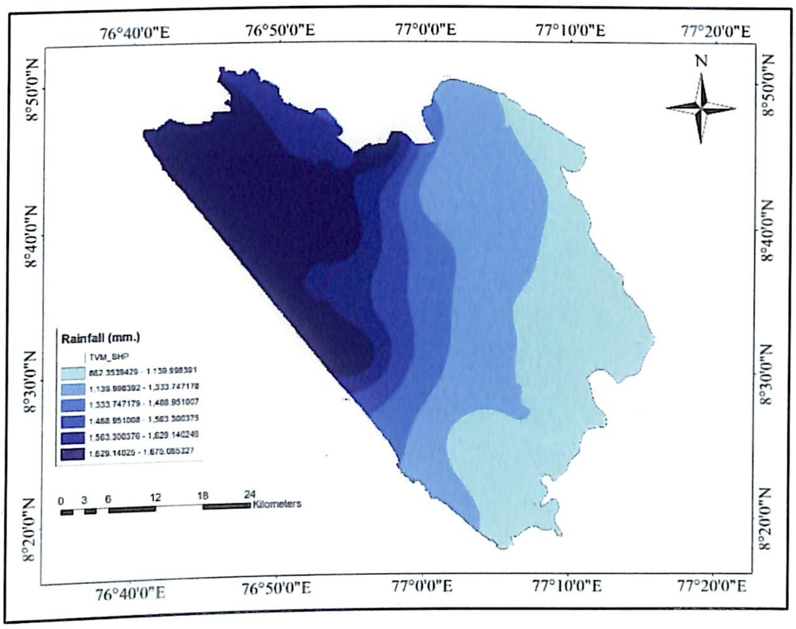

Fig. 19 – Map of rainfall distribution in the year 2011

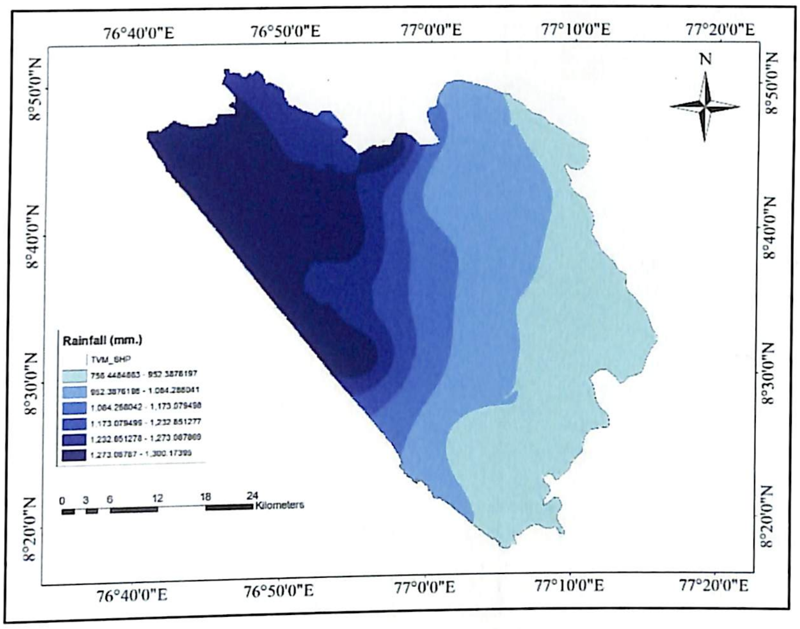

Fig. 20 – Map of rainfall distribution in the year 2012

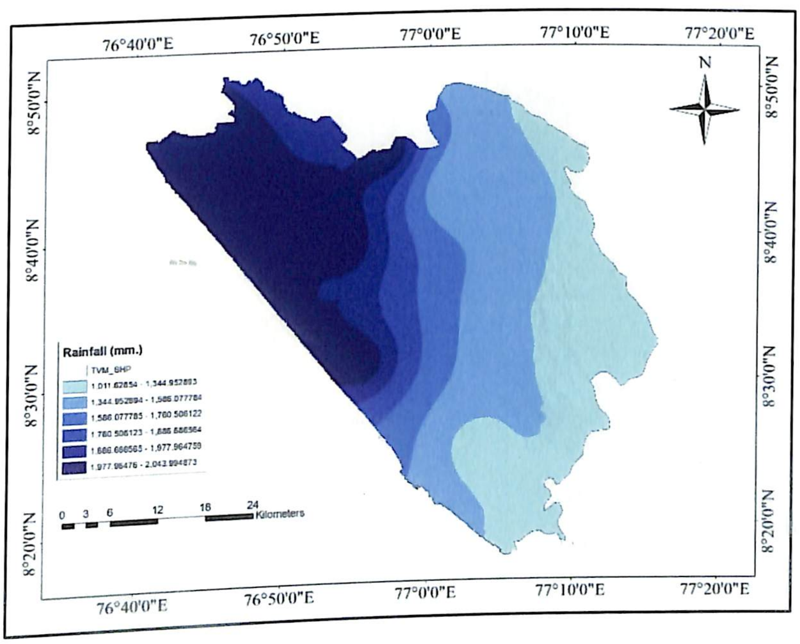

Fig. 21 – Map of rainfall distribution in the year 2013

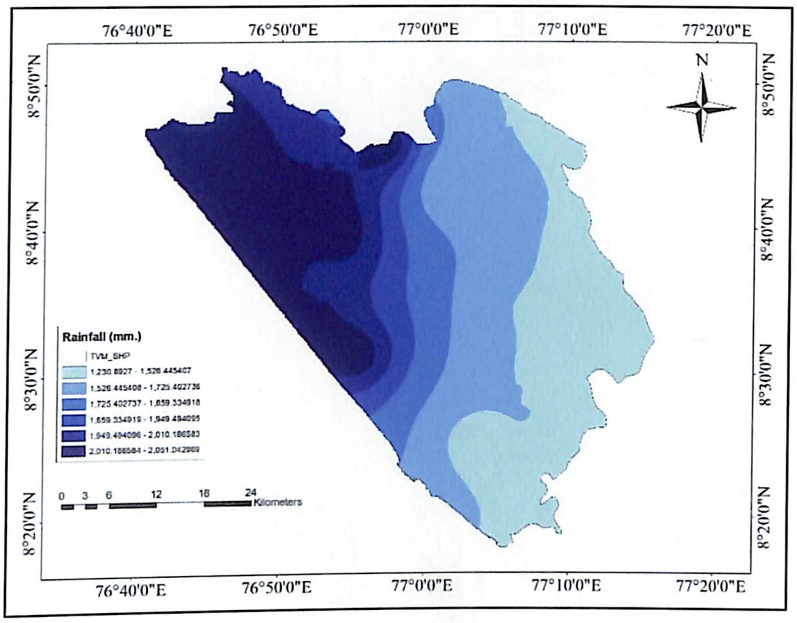

Fig. 22 – Map of rainfall distribution in the year 2014

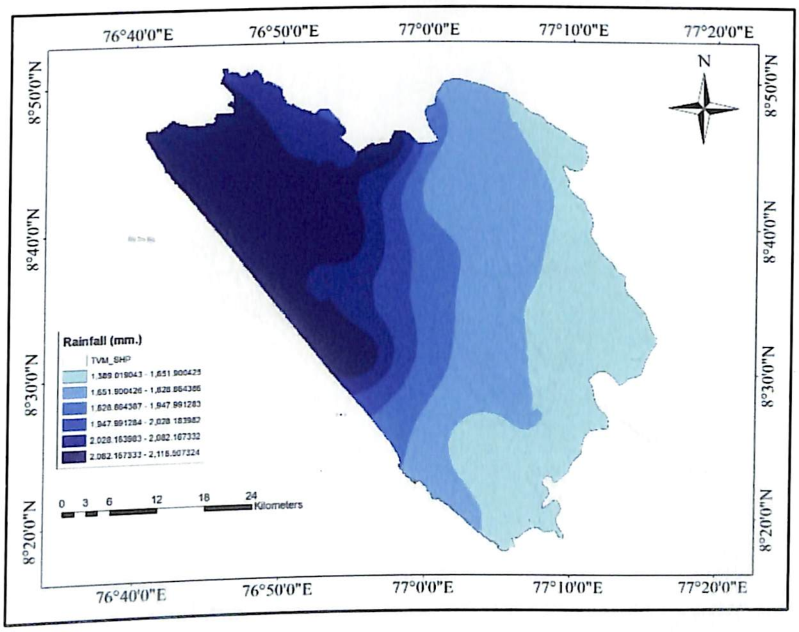

Fig. 23 – Map of rainfall distribution in the year 2015

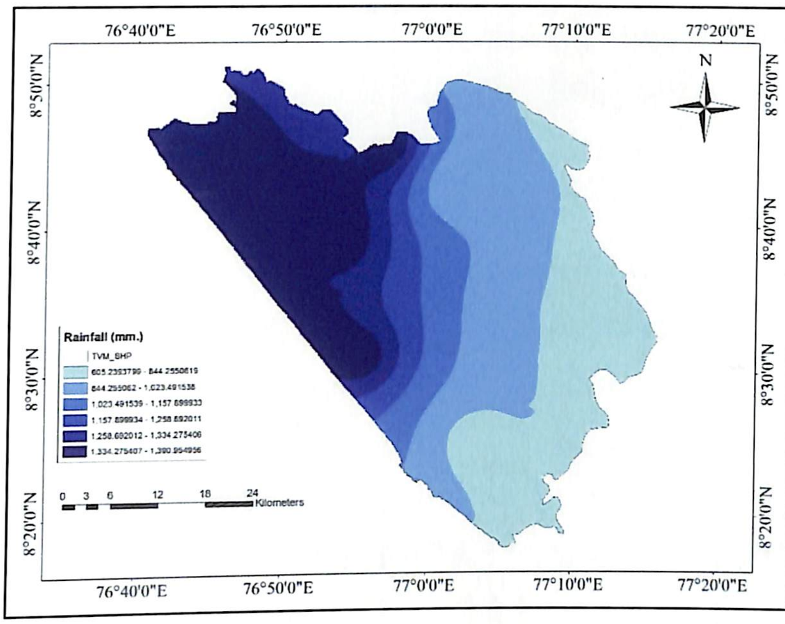

Fig. 24 – Map of rainfall distribution in the year 2016

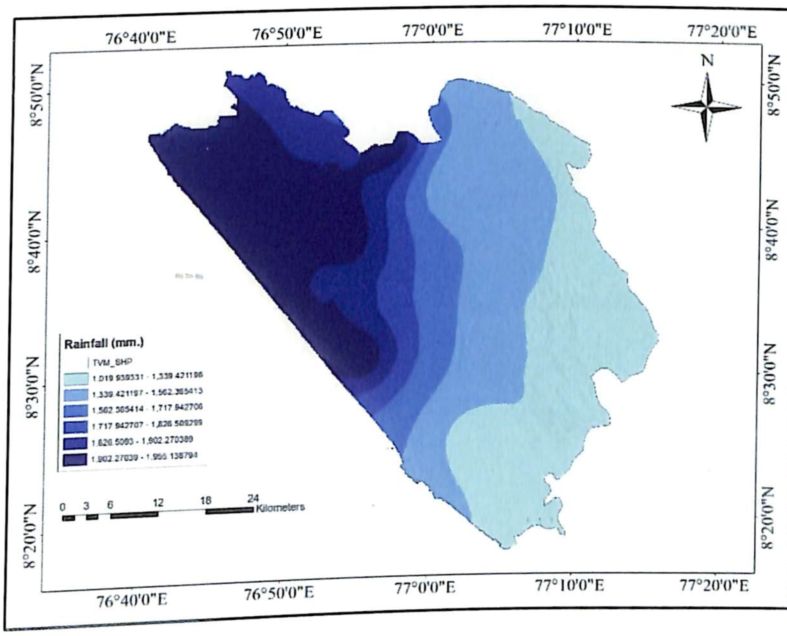

Fig. 25 – Map of rainfall distribution in the year 2017

The figures from Fig.16 – Fig. 25 represents the spatiotemporal analysis of the rainfall in the study area. According to the study, the highest rainfall is observed in the 2008, 2010, and 2015 years with 2159.51 mm., 2167.42 mm., and 2118.50 mm. respectively. The dark blue shade indicates the places where the rainfall is high and the light blue shade indicates the low rainfall areas within the study area. While observing the maps it can be observed that there did not occur many changes to the distribution of the rainfall throughout ten years. The northern region which is bound to the Kollam district and the region bound to the coastal area is having the highest amount of rainfall. But while coming to the southern part of the district, and also to the region near the Tamil Nadu state, it can be seen that there is some decrease in the amount of rainfall. And this trend is occurring similarly in all the ten years.

The spatiotemporal variations in the temperature are shown from Fig.26 to Fig.35.

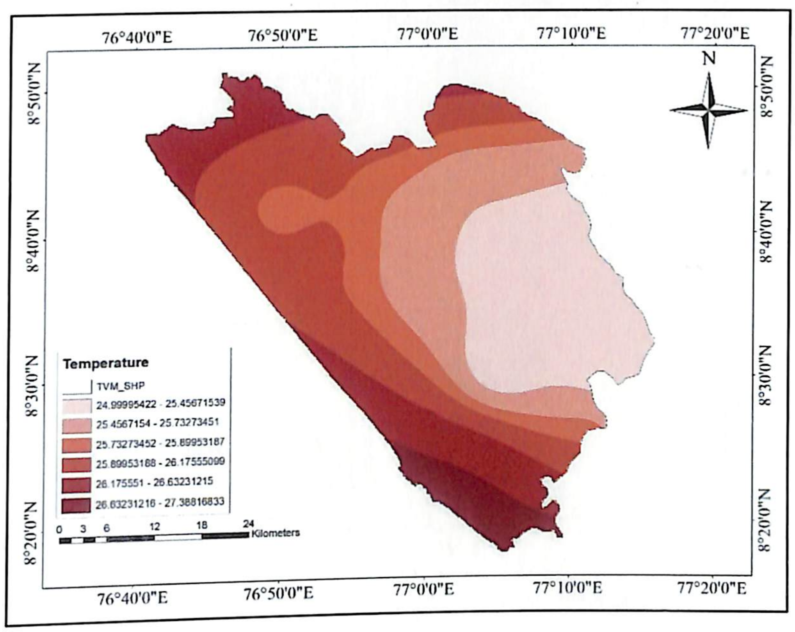

Fig. 26 – Map of temperature fluctuation in the year 2008

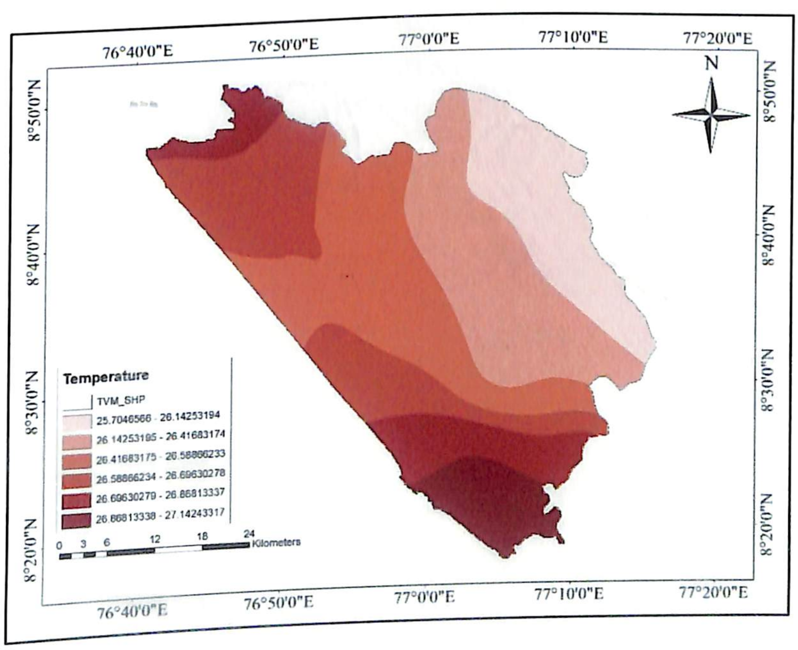

Fig. 27 – Map of temperature fluctuation in the year 2009

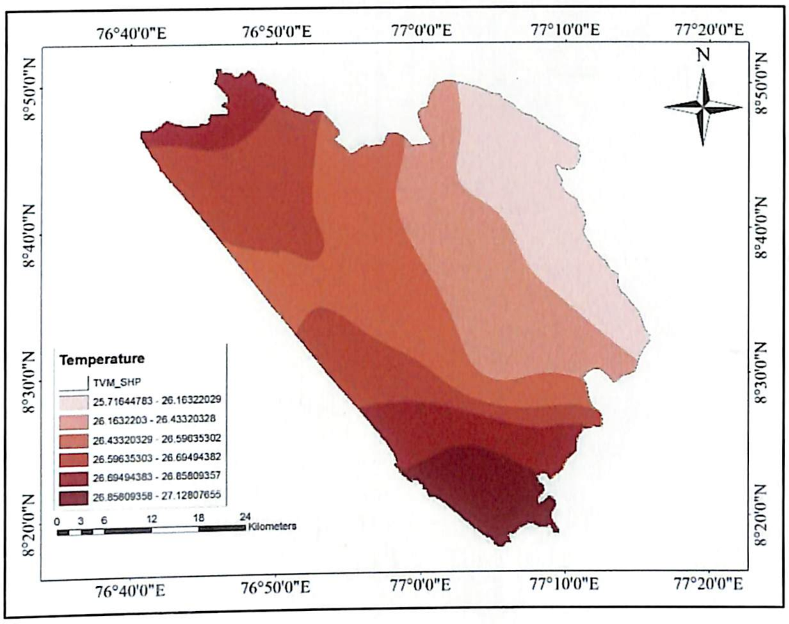

Fig. 28 – Map of temperature fluctuation in the year 2010

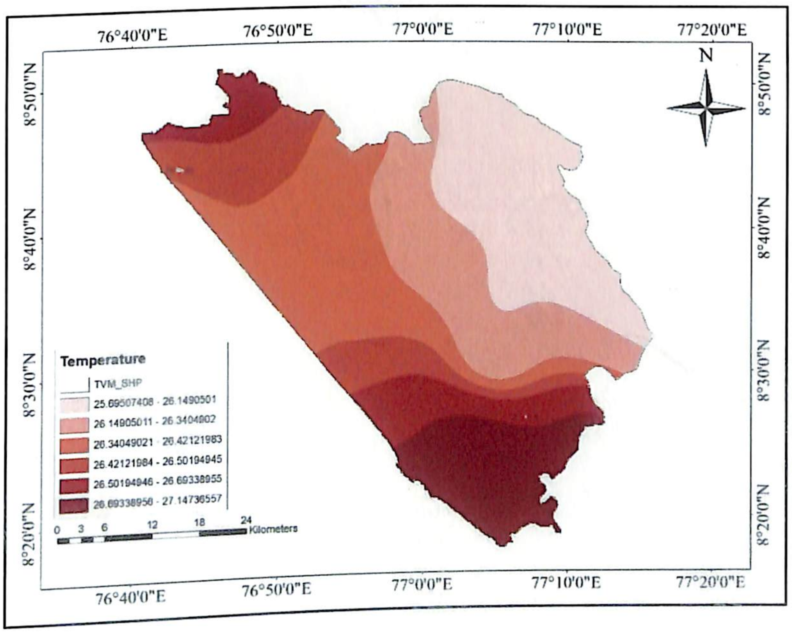

Fig. 29 – Map of temperature fluctuation in the year 2011

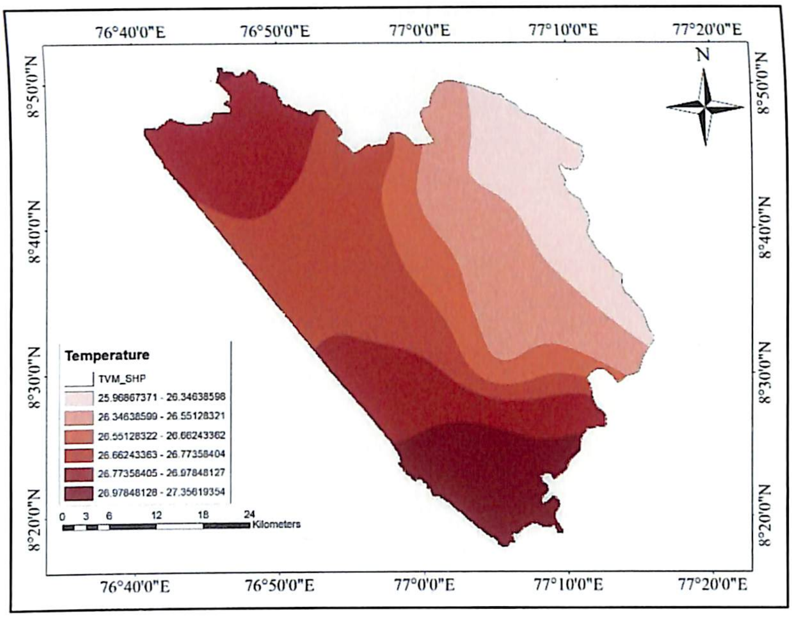

Fig. 30 – Map of temperature fluctuation in the year 2012

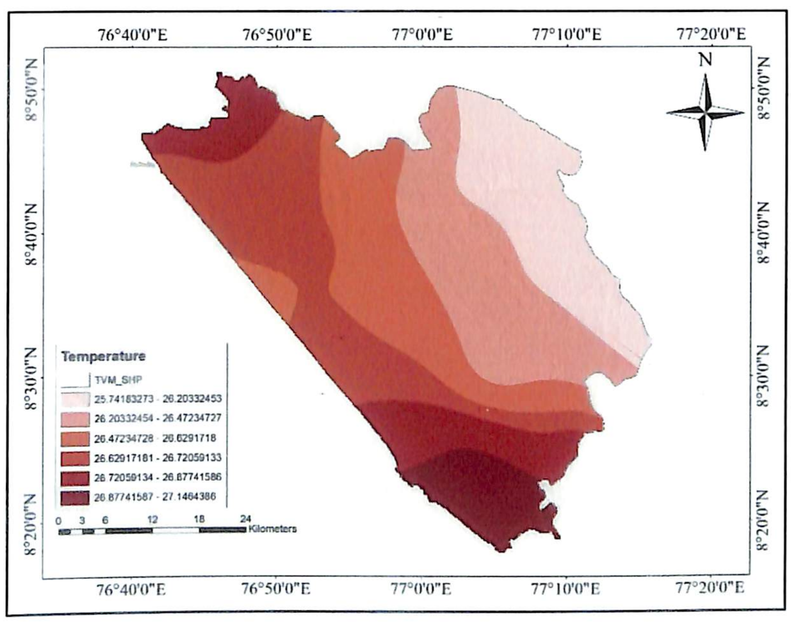

Fig. 31 – Map of temperature fluctuation in the year 2013

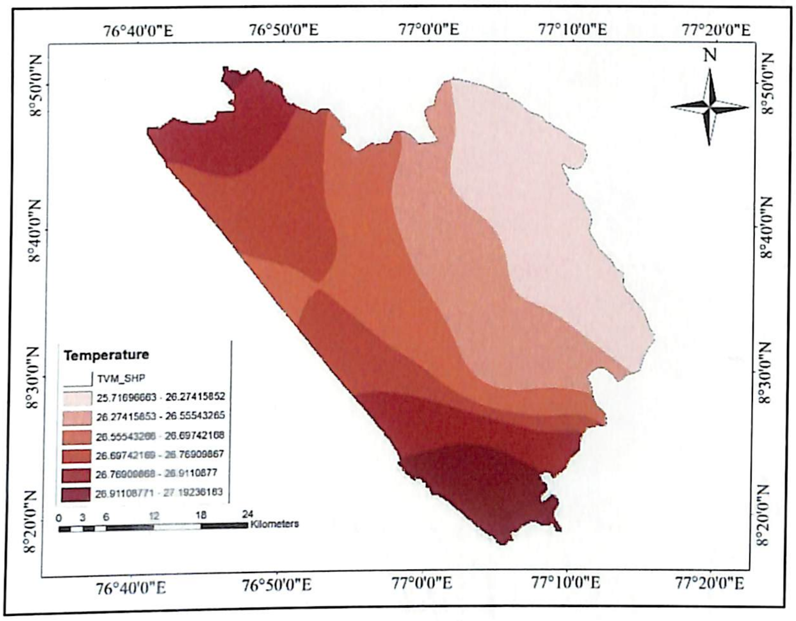

Fig. 32 – Map of temperature fluctuation in the year 2014

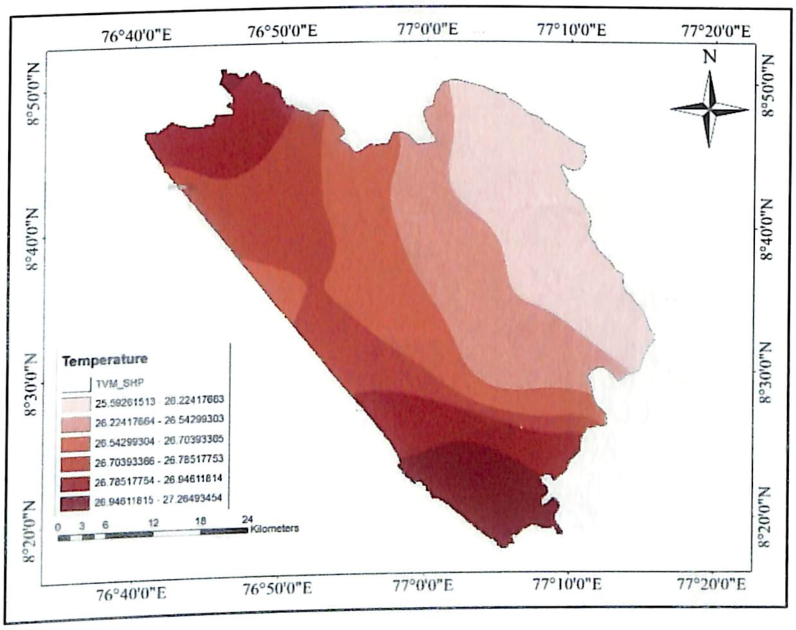

Fig. 33 – Map of temperature fluctuation in the year 2015

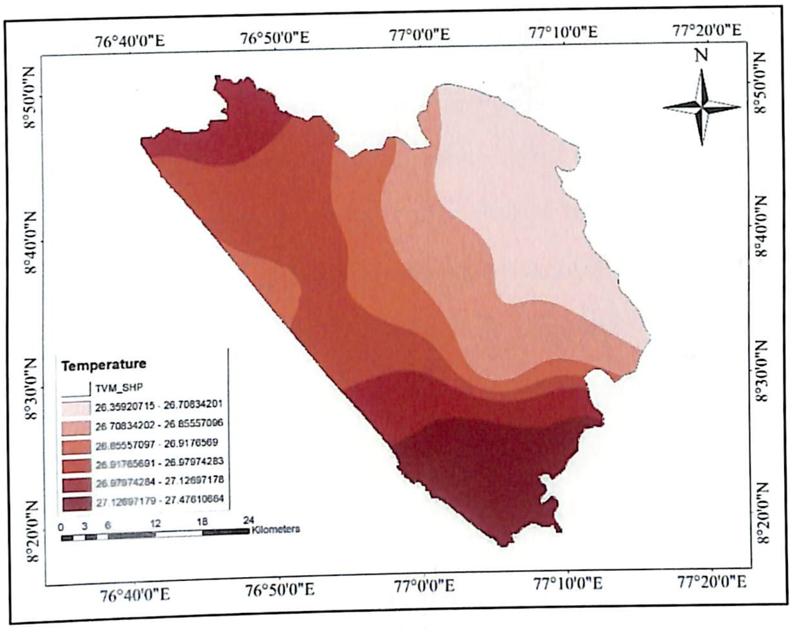

Fig. 34 – Map of temperature fluctuation in the year 2016

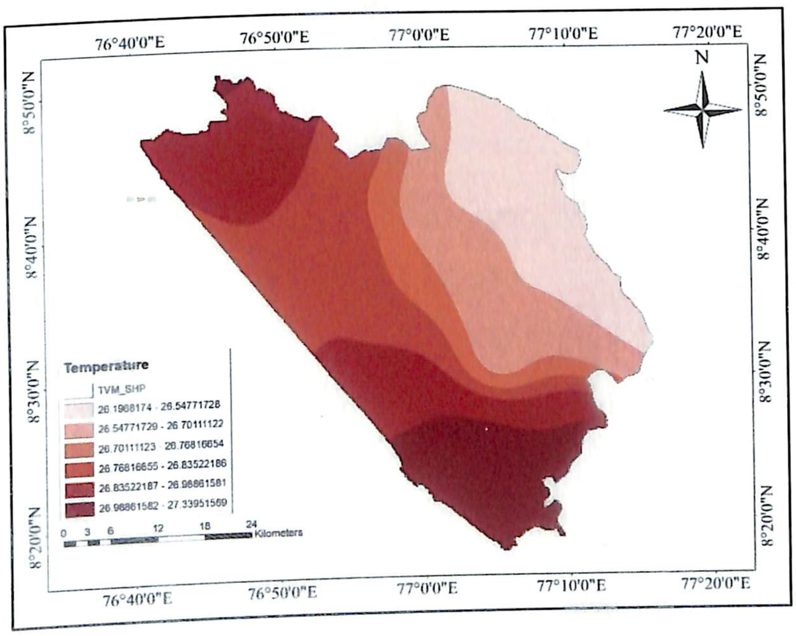

Fig. 35 – Map of temperature fluctuation in the year 2017

The average temperature of the district varies from 25°C to 28°C around a year. The dark red shade indicates the places where the temperature is comparatively high. Similarly, the light shade indicates the low temperature areas. While observing the maps, it can be inferred that the trend of the temperature variation is approximately similar in all the years. The southern part and the northern part are having an increased level of temperature. While the western regions near to the Tamil Nadu state is having low levels of temperature. And the reason for the low levels of temperature is found to be the effect of geographic elevation differences in that area.

4.8. Biplot analysis of the groundwater level.

From the biplot of groundwater for different years, it can be concluded that there is a gradual groundwater depletion is happening from 2008 to 2017. It can be seen that the years 2016 and 2017 are having relatively high temperature and also high groundwater depth which indicates a groundwater depletion. And in the years 2008 and 2009, the temperature is comparatively less and the groundwater depth is also less. From the biplot analysis and also from correlation analysis, represented in Table 8 it is clear that temperature is having a significant role in groundwater depletion.

The biplot of groundwater level in different places, represented in Fig. 37, is divided in to four clusters for better comprehension. The cluster 1 include the places Attingal, Vengod, Kariavattom, Pirappankod, Pangode, Vamanapuram, and Kochuveli. The cluster 2 includes, Varkala, Sreekariyam, Edavai, Pothencode, Pattom, and Chirayinkil. The cluster 3 includes Peringamala, Maruthamoola, Ariyanadu, Palode, Kattakkada, and Kallar regions. And in the cluster 4, includes Parassala, Vellarada, Sasthanthala, Balaramapuram, Kulathoor, Udayankulangara, Neyyattinkara, and Chengal. From the biplot, it can be inferred that the right part cluster 2 and cluster 4 is having high groundwater depth, which implies that the regions are having groundwater level depletion. And the left part of cluster 3 and cluster 1 are having low groundwater depth which concludes that the regions quoted in the clusters are having less depletion in groundwater level.

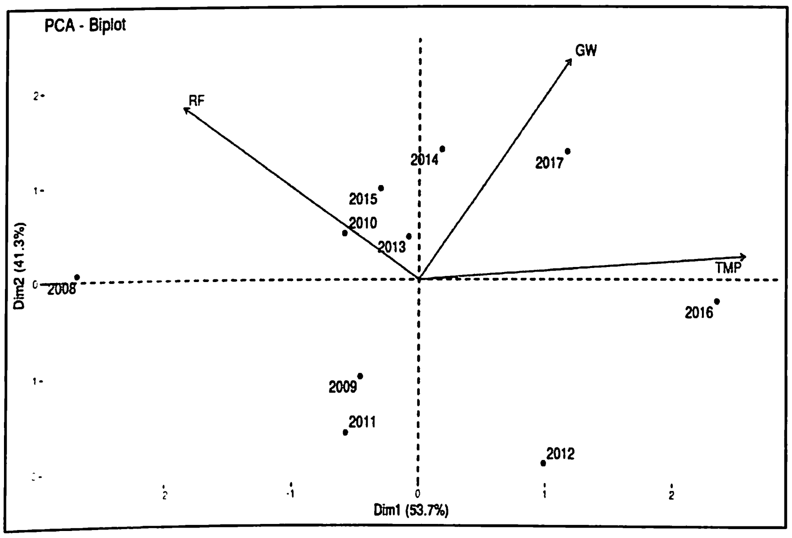

Fig. 36: Biplot of groundwater for different years

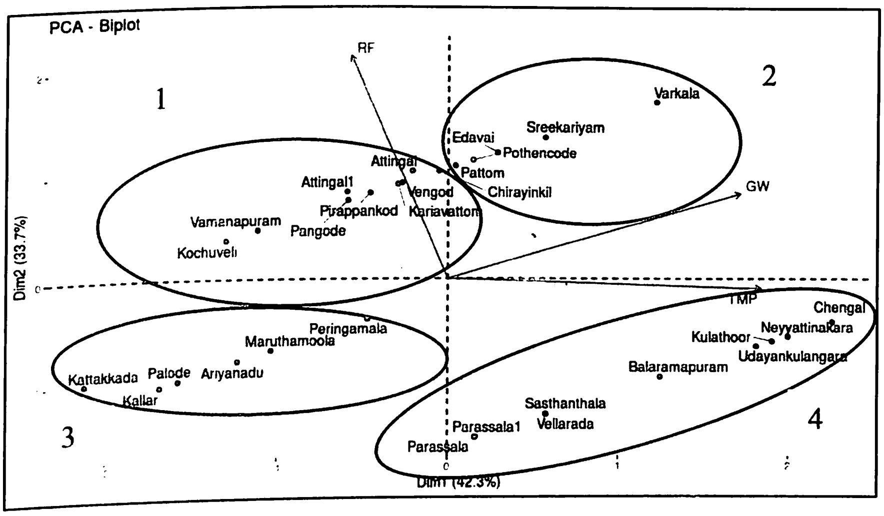

Fig. 37: Biplot of groundwater level in different places

Most of the locations are having a positive drop in the groundwater, which represents that the groundwater depletion is happening in temporal structure in the study area. Rate of groundwater level drop is 1.49 meters, which is positive, and can infer that there is depletion in the groundwater level. The highest depletion is seen in Pothencode, Varkala, Chengal, Neyyattinkara regions, which can also be concluded from the PCA biplot analysis. The nugget to sill ratio of the groundwater drop in the study area is 0.367, which can be inferred that the depletion is moderately spatially dependent.

From the correlation analysis, it can be observed that the temperature is a major factor influencing the groundwater depletion than the rainfall. Based on the PCA biplot analysis, it can be inferred that there is a gradual depleting trend in the groundwater level from 2008 to 2017. The groundwater depth of Varkala, Pothencode, Sreekariyam, Neyyattinkara, Chenkal, Kulathoor is high and at Kattakkada, Palode, Kallar, Ariyanadu have low groundwater depth which can be concluded from PCA biplot of different locations. By investigating the maps prepared for spatiotemporal analysis of the groundwater level variations, it can be observed that the groundwater level depletion is severe in the Varkala region, and the Parassala region. The groundwater level at the high ranges like Ponmudi, Bonacaud, and Neyyar regions are having a decent amount of groundwater.

Summary

5. SUMMARY

Groundwater is a major source of freshwater reserve on which billions of people rely for variety of purposes. The vulnerability of groundwater has risen in occurrence and extent in recent years, making it a global problem. Climate change, along with intensive groundwater extraction from the shallow aquifer for agriculture, industry, and other household purposes, is one of the primary causes of groundwater storage shortages and water level declines.

The study entitled "Geostatistical analysis of groundwater level in Thiruvananthapuram district" conducted in the Department of Agricultural Statistics, College of Agriculture, Vellayani during 2019 – 2021 was an attempt to identify the different fluctuations occurred in the groundwater level in the study area. The objective of the study was to analyze the spatiotemporal variations in the groundwater level, identify the relationship between groundwater and climatic factors (i.e., rainfall and temperature), and to prepare the thematic map for the study area. The variations are studied using different geostatistical methods. The secondary data of groundwater level required was collected from the Water Resource Information System (WRIS) website. The temperature data and the rainfall data were collected from NASA POWER website.

The groundwater level data, temperature data, and rainfall data of 29 different locations from the study area are collected for about a period of 10 years. The data collected was subjected to the normality test for identifying whether the data collected are distributed normally or not. The semivariogram models were fitted for identifying the spatial continuity of the groundwater level. Nugget to sill ratio is also identified for detecting the spatial dependency. The kriging interpolation technique was used to identify the spatiotemporal fluctuations in groundwater levels.

The data collected are subjected to the Shapiro-Wilk's normality test to identify whether the data are normally distributed or not. The results displayed that the years 2010 and 2017 are not normally distributed. And in case of temperature and rainfall, all the data points were not normally distributed. Thus, for the proper analysis, the log transformation was performed to the data sets which are not normally distributed and proceeded to further steps.

The correlation analysis was performed to find out the relationship between groundwater and climatic factors. The correlation analysis was performed between the groundwater and temperature and also between groundwater and rainfall. The analysis resulted that the temperature is having more dependency than the rainfall with the groundwater level in the study area.

The semivariogram fitting to the groundwater level drop for each location is done inorder to find the temporal structure of the groundwater level in the study area. The groundwater drop was found out for each location by taking the difference between the groundwater levels of 2008 and 2017 inorder to find the temporal variations. The positive drop refers to the depletion in the groundwater level and the negative drop refers the increment in the groundwater level for each different location. The three models, Spherical, Exponential and Gaussian models were fitted to the groundwater level for each year. The best fit model was selected by accounting the Adjusted R^2 value. After fitting the semivariogram, the nugget to sill ratio obtained was 0.367, resulting that the groundwater drop is having a relatively strong temporal dependence. And the rate of the groundwater level drop observed was 1.49 mgbl. The positive drop indicates that there is an overall depletion in the groundwater level within the study area.

The semivariogram model is fitted for the groundwater level data for all the ten years. The best-fitted model is selected by comparing the adjusted R^2 values between the models. The semivariogram is fitted inorder to account the spatial dependence for all the ten different years. From the semivariograms plotted, it can be concluded that the years 2011 and 2016 are having strong spatial dependence since the nugget to sill ratio is less than 0.25, and the rest of the years are having moderate spatial dependence in the groundwater level.

The semivariogram is fitted for the average groundwater level of all the years to identify the spatial dependence. The range, nugget, and sill are identified. The nugget to sill ratio is 0.483, which can be referred that the groundwater level drop is having a moderate spatial dependence.

The thematic maps of the groundwater level variations for all the ten years are prepared in order to explain the spatiotemporal variation of the groundwater level. In the year 2008, Chirayinkeezhu, Azhoor, Mangalapuram, Vamanapuram, Palode, Nedumangadu, Pothencode, Kazhakoottam, and Thiruvananthapuram regions are having a good amount of groundwater level. The places surrounding the Neyyar dam is also having a good amount of groundwater in the year 2008. But towards the Parassala region, which is neighboring the Tamil Nadu state and the places, Pulluvila, Karumkulam, Nochur are having less amount of groundwater level. The Varkala region, which is the northern side of the Thiruvananthapuram district, is also having a decreased amount of groundwater level.

In the year 2009, it can be observed that the Vamanapuram, Pallichal region is having an increased level of groundwater. And the places, Chirayinkeezhu, Azhoor, Aruvikkara, there is a small decrease in the groundwater level. Whereas, the places like Vithura and Ariyanadu, the groundwater level is maintained as the previous year.

While investigating the year, 2010, the groundwater depletion was observed in the Peringamala, Chenkal, Vanniyur, Amaravila regions. But there is a noticeable increase in the groundwater level in Aruvikkara, Vellanad, Ariyanadu, and Kuttichal regions.

In the year 2011, the Peringamala, Pangode, Kallara, Manjappara, Palode, Kaniyapuram, Veli regions are having a desirable amount of groundwater level. The Bonacaud region, bound to the Tamil Nadu state border at the east side does not maintain a good amount of groundwater level, same as the case in the south side of the district. The Parassala, Nochur, Poovar, Amaravila regions are having a moderately sufficient amount of groundwater level. The Peroorkada, Nedumangadu, Alamcode regions are having moderately less amount of groundwater levels. Edavai, Varkala, Ariyur, Kappil regions are showing the least level of groundwater.

In the year 2012, it is found that there is a noticeable groundwater level decrease in the region bounding to the Kollam district and the Parassala region. But there is a noticeable increment in the groundwater level at Vithura and Neyyar regions.

In the year 2013, it can be identified that the north side of the district, Edavai region, Varkala region, and the south side, Pulluvila, Karumkulam, Poovar regions are also having a decreased amount of groundwater level. But the Vamanapuram, Palode, Peringamala, Venjaramoodu, Veli, Palayam, Ponmudi, Neyyar, Aruvikkara regions are having a decent amount of groundwater level. The major decline is seen in the Attingal region.

In the year 2014, the northern part of the district, which is bounding the Kollam state like the Varkala region, and the southern region bounding to Tamil Nadu state like Parassala, has a decrement in the groundwater level. Whereas, the eastern region bounding Tamil Nadu and the western region near to the coastline are having a decent amount of groundwater.

In the year 2015, it is found that there is a noticeable increase in the groundwater level for the Kazhakoottam region and Thiruvananthapuram region. The Ponmudi, Bonacaud, Aruvikkara, Vithura, Ariyanadu, Kuttichal, Neyyar regions are having a good amount of groundwater level. The northern part of the district, the Varkala region, and the southern part, the Pulluvila region is showing the maximum drop in the groundwater level. The water level is maintained in the Vamanapuram, Peringamala, Venjaramoodu and Nedumangadu regions.

In the year 2016, the groundwater level drop is observed at the Balaramapuram and Neyyattinakara regions, and there is an acceptable increase in the groundwater of Kilimanoor, Peringamala, and Pangode regions. The groundwater level is maintained in Vithura, Ariyanadu, Nedumangadu, and Sreekariyam areas. It can be observed that the groundwater is having a decrease in Vellanad, Venganoor, Balaramapuram, and Poovar regions.

In the year 2017, the highest drop is seen in the Varkala and Parassala regions. The places bound to Tamil Nadu state is maintaining a considerable amount of groundwater level. The Kazhakoottam, Kaniyapuram, Attippara, Chirayinkeezhu regions are having a decent amount of groundwater level.

The spatiotemporal analysis of the rainfall distribution and temperature were also studied using the kriging interpolation technique. The results explained that the groundwater level variations are more dependent with the temperature fluctuations than the rainfall distribution.

From the PCA biplot of years, it can be observed that the temperature is relatively high in 2016, 2017 where the groundwater level is also high. And the temperature is relatively low in 2008, 2009 where the groundwater level is also low. Thus, it can be concluded that groundwater is having some dependency with the temperature variations which was detected in the correlation analysis.

From the PCA biplot of different locations, it can be observed that the Varkala, Sreekariyam, Pothencode, Chengal, Neyyattinkara regions are having high groundwater depth. And Kattakkada, Kallar, Palode, Ariyanadu, Maruthamoola, Peringamala regions are having low groundwater depth.

References

6. REFERENCES

Abdi, H. and Williams, L. J. 2010. Principal component analysis. *Wiley interdisciplinary reviews: computational statist.* 2(4): 433-459.

Abtew, W., Obeysekera, J. and Shih, G. 1993. Spatial analysis for monthly rainfall in South Florida. *J. Am. Water Resour. Assoc. 29*(2):179-188.

Acharya, G. and Barbier, E. B. 2000. Valuing groundwater recharge through agricultural production in the Hadejia-Nguru wetlands in northern Nigeria. *Agric. Economics*, 22(3): 247-259.

Adhikary, S. K., Sharif, A. A., Das, S. K. and Saha, G.C. 2014. Geostatistical analysis of groundwater level fluctuations in the shallow aquifer of northwestern Bangladesh. In: *Proceedings of the 2nd International Conference on Civil Engineering for Sustainable Development (ICCESD)*, pp. 14-16.

Ahmadi, S. H. and Sedghamiz, A. 2007. Geostatistical analysis of spatial and temporal variations of groundwater level. *Environ. Monit. Assess.* 129(1-3): 277-294.

Ahmadi, S. H. and Sedghamiz, A. 2008. Application and evaluation of kriging and cokriging methods on groundwater depth mapping. *Environ. monitoring and assess. 138*(1): 357-368.

Arétouyap, Z., Nouck, P. N., Nouayou, R., Kemgang, F. E. G., Toko, A. D. P. and Asfahani, J. 2016. Lessening the adverse effect of the semivariogram model selection on an interpolative survey using kriging technique. *Springer Plus*, 5(1): 1-11.

Babiker, I. S., Mohamed, M. A. A. and Hiyama, T. 2007. Assessing groundwater quality using GIS. *Water Resour. Manag.* 21: 699-715.

Bachmaier, M. and Backes, M. 2011. Variogram or semivariogram? Variance or semivariance? Allan variance or introducing a new term?. *Mathematical Geosciences*, 43(6): 735-740.

Bachmaier, M. and Backes, M. 2011. Variogram or semivariogram? Variance or semivariance? Allan variance or introducing a new term?. *Mathematical Geosciences*. 43(6): 735-740.

Cambardella, C. A., Moorman, T. B., Parkin, T. B., Karlen, D. L., Novak, J. M., Turco, R. F. and Konopka, A. E. 1994. Field-scale variability of soil properties in central Iowa soils. Soil *Sci. Soc. Am. J.* 58(5): 1501-1511 (result)

Cay, T. and Uyan, M. 2009. Spatial and temporal groundwater level variation geostatistical modeling in the city of Konya, Turkey. *Water environ. Res.* 81(12): 2460-2470.

Chandan, K. S. and Yashwant, B. K. 2017. Optimization of groundwater level monitoring network using GIS-based geostatistical method and multi-parameter analysis: a case study in Wainganga Sub-basin, India. *Chinese geographical sci.* 27(2): 201-215.

Chen, L. and Feng, Q. 2013. Geostatistical analysis of temporal and spatial variations in groundwater levels and quality in the Minqin oasis, Northwest China. *Environ. earth sci.* 70(3): 1367-1378.

Chen, L. and Feng, Q. 2013. Geostatistical analysis of temporal and spatial variations in groundwater levels and quality in the Minqin oasis, Northwest China. *Environ. earth sci.* 70(3): 1367-1378.

Chinnasamy, P., Misra, G., Shah, T., Maheshwari, B. and Prathapar, S. 2015. Evaluating the effectiveness of water infrastructures for increasing groundwater recharge and agricultural production–a case study of Gujarat, India. *Agric. Water Manag.* 158: 179-188.

Corzo, G. and Varouchakis, E. 2018. *Spatiotemporal analysis of extreme hydrological events*. Elsevier, United States, 171p.

Curran, P. J. 1988. The semivariogram in remote sensing: an introduction. *Remote sensing of Environ.* 24(3): 493-507.

Dashtpagerdi, M. M., Vagharfard, H. and Honarbakhsh, A. 2013. Application of cross-validation technique for zoning of groundwater levels in Shahrekord plain. *Sci. Res.* 7(4): 5p.

Datta, P. S. 2005. Groundwater ethics for its sustainability. *Curr. Sci.* 89(5): 812-817.

Desbarats, A. J., Logan, C. E., Hinton, M. J. and Sharpe, D. R. 2002. On the kriging of water table elevations using collateral information from a digital elevation model. *J. Hydrol.* 225(1-4): 25-38

Dubrule, O. 1983. Cross validation of kriging in a unique neighborhood. *J. Int. Assoc. Mathematical Geol.* 15(6): 687-699.

Eldrandaly, K. 2007. GIS software selection: a multi criteria decision making approach, *Appl. GIS.* 3(5): 1-17.

ENVIS Hub: Kerala [Government of Kerala]. 2011. *Economic Review 2009-20* [on-line]. Available: http://www.kerenvis.nic.in/Database/WATER_820.aspx [09 Nov 2021].

Gundogdu, K. S. and Guney, I. 2007. Spatial analyses of groundwater levels using universal kriging. *J. earth system sci.* 116(1): 49-55.

Han, D., Currell, M. J., Cao, G. and Hall, B. 2017. Alterations to groundwater recharge due to anthropogenic landscape change. *J. hydrol.* 554: 545-557.

Holman, I. P. 2006. Climate change impacts on groundwater recharge-uncertainty, shortcomings, and the way forward? *Hydrogeology J.* 14(5): 637-647.

Hussain, M. M., Bari, S. H., Tarif, M. E., Rahman, M. T. U. and Hoque, M. A. 2016. Temporal and spatial variation of groundwater level in Mymensingh district, Bangladesh. *Int. J. Hydrol. Sci. Technol.* 6(2): 188-197.

Kamali, M. I., Nazari, R., Faridhosseini, A., Ansari, H. and Eslamian, S. 2015. The determination of reference evapotranspiration for spatial distribution mapping using geostatistics. *Water Resources Manag.* 29(11): 3929-3940.

Kerry, R. and Oliver, M. A. 2008. Determining nugget: sill ratios of standardized variograms from aerial photographs to krige sparse soil data. *Precision Agric.* 9(1): 33-56.

Krige, D.G. 1951. A statistical approach to some basic mine valuation problems on the Witwatersrand. *J. South. Afr. Inst. Mining and Metallurgy.* 52(6): 119-139.

Kumar, D. and Ahmed, S. 2003. Seasonal behaviour of spatial variability of groundwater level in a granitic aquifer in monsoon climate. *Curr. Sci.* 84(2): 188-196.

Lerner, D. N., Issar, A. S. and Simmers, I. 1990. Groundwater recharge. A Guide to Understanding and Estimating Natural Recharge. *International Association of Hydrogeologists*, 8: pp. 327.

Matheron, G. 1963. Principles of geostatistics. *Economic geol.* 58(8): 1246-1266.

Mazzella, A. and Mazzella, A. 2013. The importance of the model choice for experimental semivariogram modeling and its consequence in evaluation process. *J. Eng.* 10p.

Mini, P. K., Singh, D. K. and Sarangi, A. 2014. Spatio-temporal variability analysis of groundwater level in coastal aquifers using geostatistics. *Int. J. Environ. Res. Dev.* 4(4): 329-336.

Moslemzadeh, M., Salarizazi, M. and Soleymani, S. 2011. Application and assessment of kriging and cokriging methods on groundwater level estimation. *J. Am. Sci.* 7(7): 34-39.

Nikroo, L., Kompani-Zare, M., Sepaskhah, A. R. and Shamsi, S. R. F. 2010. Groundwater depth and elevation interpolation by kriging methods in Mohr Basin of Fars province in Iran. *Environ. monitoring assess.* 166(1): 387-407.

Noori, S., Ebrahimi, K., Liaghat, A. M. and Hoorfar, A. H. 2013. Comparison of different geostatistical methods to estimate groundwater level at different climatic periods. *Water and Environ. J.* 27(1): 10-19.

Pandey, N. and Sharma, C. 2019. Geostatistical analysis of spatial and temporal variations of groundwater level: A case study of Bhilwara district Rajasthan. *Int. J. Advance and Innovative Res.* 6(2): 44-57.

Pareta, K. 2011. Geo-Environmental and Geo-Hydrological Study of Rajghat Dam, Sagar (M. P.) Using Remote Sensing Techniques. *Int. J. Sci. Eng. Res.* 2(8): 1-8.

Salah, H. 2009. Geostatistical analysis of groundwater levels in the south Al Jabal Al Akhdar area using GIS. *GIS Ostrava.* 25: 1-10.

Shahmohammadi-Kalalagh, S. and Taran, F. 2021. Evaluation of the classical statistical, deterministic and geostatistical interpolation methods for estimating the groundwater level. *Int. J. Energy and Water Res.* 5(1): 33-42.

Shaji, E. 2011. Groundwater quality of Kerala–Are we on the brink?. In: Proceedings of Disaster Risk Vulnerability Conference, Mahatma Gandhi University, Kerala, pp.188-191.

Shapiro, S. S. and Wilk, M. B. 1965. An analysis of variance test for normality (complete samples). *Biometrika*, 52(3/4): 591-611.

Ta, R. A., Tahboub, A. B. and Saffarini, G. A. 2009. Geostatistical analysis of spatiotemporal variability of groundwater level fluctuations in Amman–Zarqa basin, Jordan: a case study. *Environ. geol.* 57(3): 525-535.

Theodoridou, P. G., Karatzas, G. P., Varouchakis, E. A. and Corzo Perez, G. A. 2015. Geostatistical analysis of groundwater level using Euclidean and non-Euclidean distance metrics and variable variogram fitting criteria. In: *EGU General Assembly Conference Abstracts.* p. 15340.

Tobler, W. R. 1970. A computer movie simulating urban growth in the Detroit region. *Economic Geogr.* 46. 234-240.

Tonkin, M. J. and Larson, S. P. 2002. Kriging water level with a regional-linear and point-logarithmic drift. *Ground Water* 40(2): 185-193.

Uyan, M. and Cay, T. 2010. Geostatistical methods for mapping groundwater nitrate concentrations [abstract]. In: *3rd International Conference on Cartography and GIS*; 15 – 20 June, 2010, Nessebar, Bulgaria, 7p.

Venkatramanan, S., Chung, S. Y., Kim, T. H., Kim, B. W. and Selvam, S. 2016. Geostatistical techniques to evaluate groundwater contamination and its sources in Miryang City, Korea. *Environ. Earth Sci.* 75(11): 1-14.

Waiker, M. L. and Nilawar, A. P. 2014. Identification of Groundwater Potential Zone using Remote Sensing and GIS Technique. *Int. J. Innovative Res. Sci., Eng. and Technol.* 3(5): 12163-12174.

Xiao, Y., Gu, X., Yin, S., Shao, J., Cui, Y., Zhang, Q., and Niu, Y. 2016. Geostatistical interpolation model selection based on ArcGIS and spatio-temporal variability analysis of groundwater level in piedmont plains, northwest China. *Springer Plus*. 5: 425p.

Zang, H., Wang, C., Shanzhen, Y. and Jiang, Q. 2009. Geostatistical analysis of spatial and temporal variations of Groundwater depth in Shule River. *Int. Conf. Inf. Eng*. 453-457.

Zhang, M., Li, M., Wang, W., Liu, C. and Gao, H. 2013. Temporal and spatial variability of soil moisture based on WSN. *Mathematical Comput. Modelling*, 58(3-4): 826-833.

Abstract

GEOSTATISTICAL ANALYSIS OF GROUNDWATER LEVEL IN THIRUVANANTHAPURAM DISTRICT

by

HARINATH A

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COLLEGE OF AGRICULTURE
VELLAYANI, THIRUVANANTHAPURAM – 695522
KERALA, INDIA.

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ABSTRACT

The research work entitled "Geostatistical analysis of groundwater level in Thiruvananthapuram district" was carried out at the College of Agriculture, Vellayani during 2019-2021. The objective of the study was to analyze the spatiotemporal variations in the groundwater level, identify the relationship between groundwater and climatic factors (i.e., rainfall and temperature), and to prepare the thematic map for the location. To characterize the spatiotemporal fluctuations in groundwater level within the research region, various geostatistical approaches were used. The WRIS [Water Resource Information System] website was used to collect groundwater level data for 29 different locations within the study area for 10 years, from 2008 to 2017. The selection of data points was based on the even spatial distribution such that all the locations in the district are entirely covered. The NASA satellite website data was used to collect the rainfall and temperature data for the 29 distinct sites throughout a ten-year period. The semivariogram models were fitted to assess the spatial continuity of groundwater level. The nugget to sill ratio is also identified for detecting the spatial dependency. In the research region, the kriging interpolation approach was used to assess the spatiotemporal fluctuations in groundwater levels. If the data sets are normally distributed, the kriging interpolation technique will be more successful. Thus, the data points were subjected to exploratory data analysis to test the normality of the data set.

The normality of the data sets is found out by Shapiro-Wilk's normality test. The results showed that the years 2010 and 2017 are not normally distributed as the null hypothesis of the test is rejected. And also, in the case of temperature and rainfall, all the data points were not normally distributed. Thus, for the proper analysis, the log transformation was performed to the data sets which are not normally distributed and proceeded to further steps.

The relationship of groundwater and climatic factors were accounted with the correlation analysis. The results showed that the temperature is having more dependency with the groundwater level fluctuation than the rainfall.

The semivariogram fitting were done to the groundwater level drop for each location, groundwater level over the years, and for the average groundwater level to identify the spatial and temporal variations in the study area. The drop was found out for each location by taking the difference between the groundwater levels of the years 2008 and 2017. The positive drop refers the depletion in the groundwater level and the negative drop refers the increment in the groundwater level. The nugget to sill ratio explains that the groundwater level drop is having a relatively strong spatial dependence. The three models, Spherical, Exponential and Gaussian models were fitted to the groundwater level for each year. The best fit model was selected by accounting the Adjusted R^2 value.

The spatiotemporal variation was studied by kriging interpolation method. The thematic maps were created to analyze the groundwater level variations. The maps were created in the ArcGIS 10.4 software. By investigating the maps prepared, the groundwater level depletion is observed severely in the Varkala region, and the Parassala region. The groundwater level at the high ranges like Ponmudi, Bonacaud, and Neyyar regions are maintaining a decent amount of groundwater level.

From the PCA biplots prepared, the study concluded that there is a gradual groundwater depletion happening from 2008 to 2017. And from the biplot of years, the temperature is relatively high in 2016, 2017 where the groundwater level is also high. And the temperature is relatively low in 2008, 2009 where the groundwater level is also low. Thus, it can be concluded that the groundwater is having some dependency with the temperature variations which have been detected in the correlation analysis. From the biplot of different locations, it can be analyzed that the Varkala, Sreekariyam, Pothencode, Chengal, Neyyattinkara regions are having high groundwater depth. And Kattakkada, Kallar, Palode, Ariyanadu, Maruthamoola, Peringamala regions are having low groundwater depth.

From the research performed, it can be concluded that, most of the locations are having a positive drop in the groundwater, which represents that the groundwater depletion is happening in temporal structure in the study area. The highest depletion in the groundwater is seen in Pothencode, Chengal, Varkala, Neyyattinkara regions. The rate of groundwater level drop is 1.49 meters, which is positive, and can be inferred that there is depletion in the groundwater level. The nugget to sill ratio of the groundwater level drop in the study area is 0.367, which refers that the depletion is moderately spatially dependent. From the correlation analysis, it can be concluded that the temperature is a major factor influencing the groundwater depletion than the rainfall, because there is a positive significant correlation between groundwater and temperature. The groundwater depth of Varkala, Pothencode, Sreekariyam, Neyyattinkara, Chenkal, Kulathoor is high, and at Kattakkada, Palode, Kallar, Ariyanadu have low groundwater depth which can be concluded from PCA biplot of different locations.