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MONITORING WATER QUALITY PARAMETERS USING SATELLITE BASED REMOTE SENSING DATA

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ABSTRACT

Water quality monitoring is used to warn us of existing, continuing and emerging problems. It assesses the accuracy of drinking water requirements and protects other beneficial water uses. It is used to evaluate whether or not the laws on pollution are being implemented. Analysing and tracking water quality for a wider body of water is a real challenge with so many in-situ measurements and varying data. In this analysis, water quality is evaluated using the water quality parameters with the aid of remote sensing. ASTER data values of bands 8 and 9 are used to derive the pH value of the parameter, and with Landsat 7, the LST is derived from the relevant spectral band 6, and its values are extracted. Finally, both the in-situ and the calculated data are compared, and the Goodness of fit Chi-square test is performed to check for any major significant changes. Based on the findings, it has been proven that remote sensing is more accurate and effective in studying water quality.

Keywords: *Temperature, pH, ASTER, Landsat, Chi-square test, water quality, remote sensing*

INTRODUCTION

Water is a vital requirement for the human race to survive. Over the past few years, the consistency of open-source water has been strong enough for us to rely on directly. But now, water quality has been significantly reduced due to the rise in the discharge of domestic and industrial effluents. Over 435 million people rely on unregulated wells and springs, and around 144 million people depend on untreated surface water from rivers and streams. So, the water qualities of the sources need to be monitored & regulated. Water quality can be analysed through its physical, chemical and biological parameters. In this presented study, two physical parameters - pH and temperature are monitored to examine water quality for precise prediction. Conventional methods take a lot of time and cost to assess water quality. This is where remote sensing and Geographical Information System (GIS) come into play. Remote sensing makes it possible to collect data about an object or occurrence without interacting directly with an object, thus a preference for on-site observation. It detects and tracks the site's characteristics by measuring its reflected and emitted radiation at a distance.

There are several approaches to determine surface temperatures, and Li et. al., (2013) discussed the advantages of one over the other and the difficulties of each method. They also deduced that surface temperature from satellite products is ambiguous over a heterogeneous surface. But this study involves implementing the same approach for water bodies where the surface is homogeneous. Landsat series are highly dependable for their availability and resolution at the same time in-situ data was collected. Many researchers used Landsat 5, 7 and 8 for surface temperature derivation like Milton and Ugur (2016), Muhammad et. al., (2021), and Jakub et. al. (2013) used Landsat 5 and 7, and Jeevalakshmi et. al., (2017) used Landsat 8. Hakan (2015) used ASTER data for deriving temperature, but the study here performed atmospheric correction based on the reference and used to derive pH from the atmospherically corrected data. Several other researchers used different satellite products to derive empirical relationships through regression analysis. Osvaldo et. al., (2020) used the Landsat series to derive the pH value of lakes, Mochamad et. al. (2020) used the Landsat series to compute soil pH. Also, Peter et.al., (2015) used Copernicus and Sentinel to deduce ocean parameters and concluded that Sentinel based regression analysis provided better results. Though many works have been carried out using Landsat data, ASTER data not only has favourable bandwidth to compute pH parameters (Abdelmalik, 2018) but has a better spatial resolution. Finally, the computed and in-situ data are accounted for in the Goodness of fit Chi-square Test. It is a method used to equate the distribution of the sample observed with the predicted probability distribution.

The need for the study emanates from the fact that it is impossible to collect numerous in-situ samples and analyze them further for water quality monitoring when the water bodies are of large areal extent like Cauvery. Also, to develop a mathematical relation for the precise prediction of the data on water quality parameters throughout the area of study, this work is carried out. Considering what the study entails, the following objectives were formulated: a) to collect in-situ data on water quality parameters- pH and temperature, b) to calculate LST (Land surface temperature from Landsat 7 thermal bands, c) to derive pH values from ASTER data bands through image processing techniques and d) to evaluate the derived values accuracy by performing Goodness of fit- Chi square test.

STUDY AREA

The Cauvery delta has its significance to the agricultural production of Tamil Nadu, and the nation is important. But, undeniably, the irrigation in this area is highly inefficient, the services are poorly designed, and thus the productivity per litre of input used is low. Weather patterns and the subsequent shift in monsoon trends and extreme coastal occurrences have a cumulative impact on farmers in the delta. Tamil Nadu's major tributaries, such as Bhavani, Noyyal, Amaravathi and Kodaganaru, are highly contaminated due to industrial effluent discharge. The towns along with the river spill domestic waste into the river. Sand mining on the riverbed kills the riverbed, riverbed filtration, and aquifers violently. Therefore, there is a strong need to monitor the water quality.

Figure 2.1. Cauvery river from Mettur dam to Erode

Monitoring offers the credible data required to make sound decisions on water quality management both today and in the future. The study area is the Cauvery River, which extends from the Mettur dam to Erode. The highlighted area in Figure 2.1 represents the study area. Cauvery river flows through the states of Karnataka and Tamil Nadu. It rises at Talakaveri in the Brahmagiri range in the Western Ghats, Kodagu district of Karnataka. The stretch of the Cauvery River from Mettur to Erode is about 100 kilometres.

MATERIALS & METHODS

Data & Software

Landsat 7 was launched on 15 April 1999, and it is the seventh satellite of the Landsat programme. The data is used in a wide range of applications such as agriculture, forestry, mining, etc. ASTER was launched into the earth orbit by NASA in 1999, and it provides high-resolution images of the earth in

14 different bands. ASTER data is used to create detailed maps of land emissivity reflectance, elevation, and surface temperature.

The outline of the Cauvery River, which extends from the Mettur dam to Erode, is taken using Earth explorer. Band 6 of Landsat 7 data (25 February 2007) is used to derive LST, and bands 8 and 9 of ASTER data derive pH. ArcGIS (version 10.5) software is used to pre-process Landsat 7 data, estimate LST, and thematic mapping of calculated data. ERDAS Imagine for index calculation of pH. RStudio is used for checking the Goodness of fit by Chi-square test.

Methodology

The flow of the process is depicted in detail in figure 3.1. The extent of the study area was mapped using the Google earth image. Then the procured Landsat and ASTER are clipped to the study area extent, and the data are processed to derive the required water quality parameters. Finally, using in-situ data, the derived parameters are assessed for their accuracy by Chi-square Goodness of fit test.

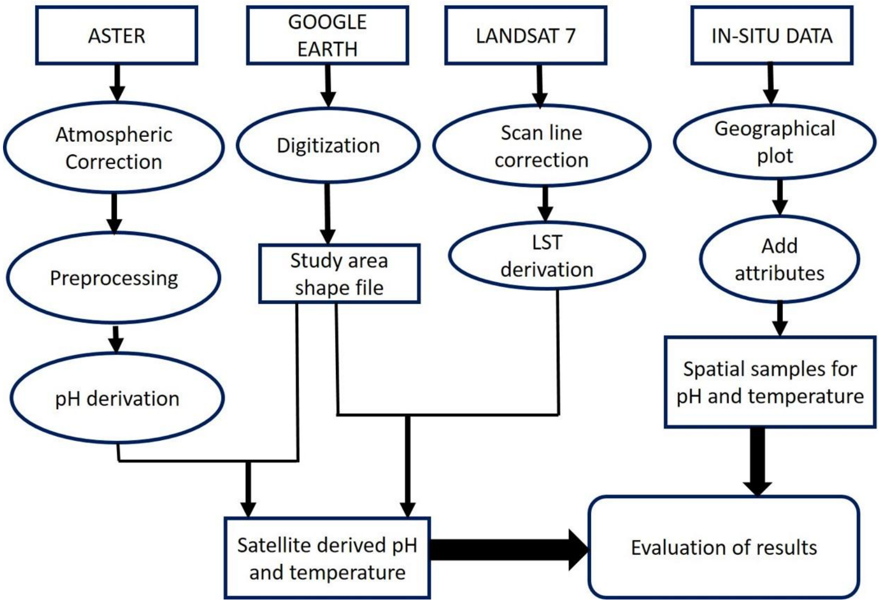

Figure 3.1. Methodology Flowchart

3.2.1. Temperature from Landsat 7

The surface temperature can be easily determined using the thermal bands of the electromagnetic spectrum. Like Javed et.al., (2008), for this study, Landsat 7 ETM + (Enhanced Thematic Mapper Plus) data was used because of the data available that coincide with the time of in - situ data collection. The data is pre-processed to remove atmospheric errors, and scan line correction is applied to rectify the gaps. The Scan-Line Corrector assembly is used to eliminate the motion of the zigzag pattern of the imagery field view created by the combination of the along and across track motion.

The Enhanced Thematic Mapper Plus line of sight now traces a zigzag pattern through the satellite ground track without running Scan Line Corrector.

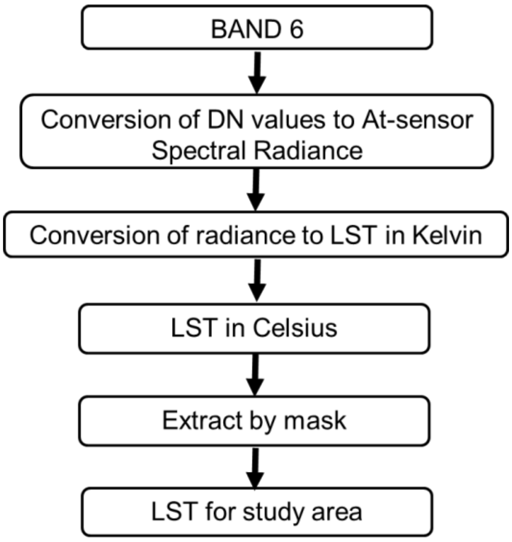

Figure 3.2. Derivation of the surface temperature using Landsat 7 ETM+ data

Then band six, the thermal band of spectral width10.40 µm - 12.5 µm, was used to compute Surface temperature, as shown in figure 3.2. The recorded DN value of the band is first converted to spectral radiance at sensor L_λ using the conversion relationship given below (Sundara et. al., 2012 and Anandbabu et. al., 2018)

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{Q_{cal\ max} - Q_{cal\ min}}\right)(Q_{cal} - Q_{cal\ min}) + LMIN_\lambda$$

Q_{cal} denoted the DN value, $Q_{cal\ max}$is maximum calibrated pixel value of 255, and Qcal minis minimum calibrated pixel value of 1. Also, $LMAX_\lambda$ represents at-sensor radiance scaled to $Q_{cal\ max}$, and $LMIN_\lambda$ denotes at-sensor radiance scaled to $Q_{cal\ min}$. This conversion is performed using a raster calculator. The LMIN and LMAX values are available in the metadata that comes with the downloaded satellite data. The estimated spectral radiance is then used to calculate the surface temperature on the Kelvin scale. The relationship between at sensor radiance $L_\lambda$and the surface temperature in kelvin (T) is given as below (Fuqin et. al., 2004)

$$T = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda} + 1\right)}$$

Where K1 and K2 are thermal conversion constants available in the metadata file, the above conversion is performed using a raster calculator. Then unit conversion from Kelvin to Celsius is done using the formula (Abduwaist, 2019).

$$T\ (celsius) = T\ (kelvin) - 273.15$$

3.2.2. PH from ASTER

The ASTER data downloaded is pre-processed using the process flow as shown in figure 3.3. Two tiles cover the study area, and so the covering tiles are mosaicked before which no data values are removed to avoid mishaps when computing pH. Then the atmospheric correction is performed in two steps (Alistair, 2009);

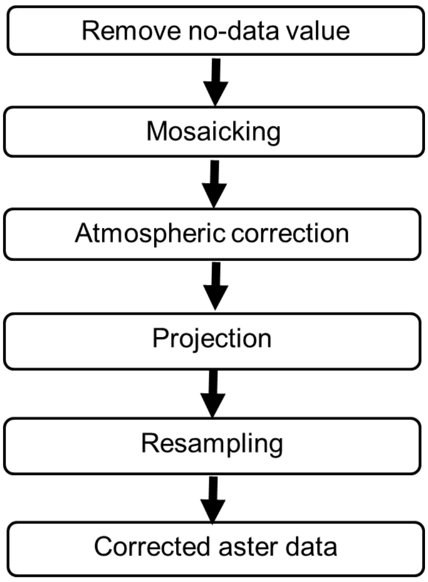

Figure 3.3. Process flow of pre-processing ASTER data

a) Calculation of radiance: (Lrad)

$$Lrad = (DN - 1) * Unit\ Conversion\ Coefficient$$

b) Calculation of reflectance at top of atmosphere (RTOA)

$$RTOA = (\pi * Lrad * i * d2)/ESUNi * COS(z))$$

ESUNi is the mean solar exo-atmospheric irradiance, and z is the solar zenith angle. D is the earth-sun distance given by

$$d = (1 - 0.01672 * COS(0.9856 * (Julian\ Day - perihelion\ day)))$$

The metadata files provided the necessary details and the constants. After atmospheric correction, the data is projected to match the Landsat data projection. We multiple ASTER bands for computation, and to have the same cell size, resampling is performed as both the parameter derivation involves a cell-based operation. The final product is then used to compute pH values.

Of all the bands of ASTER, band 9 (2.360 µm to 2.430µm) and band 8 (2.295 µm to 2.365 µm) are highly responsive. Hence Abdelmalik (2018) correlated pH value to bands 8 and 9 and formulated the equation below based on regression analysis.

$$y = -10.083\ (band\ 9/band\ 8)^2 + 26.022\ (band\ 9/band\ 8) - 8.3195$$

The above equation is implemented in calculating pH value using a model maker. The empirical equation applies to our study area as the material and parameter studied are the same and have significant variance as there are no external influences.

3.2.3. Evaluation of Results

The in-situ data is collected for the year 2007. There are four stations, namely Mettur, Bhavani, Pallipalayam and Erode, that falls within the area under study, and the details are tabulated below (Table 3.1.).

Table 3.1. In-situ temperature and pH measurements within the study area

S.NO	Station Name	Latitude	Longitude	Temperature (°C)			pH		
				Min	Max	Mean	Min	Max	Mean
1	METTUR	11°46'58.33"N	77°48'10.29"E	24	30	27	7.1	8.7	7.8
2	BHAVANI	11°26'51.90"N	77°41'2.22"E	27	31	29	6.9	8.2	7.7
3	PALLIPALAYAM	11°21'46.06"N	77°44'32.18"E	26	30	27	7.3	8.6	7.9
4	ERODE	11°20'38.23"N	77°45'4.03"E	28	31	30	7	7.9	7.5

Source: *http://cpcbenvis.nic.in/waterpollution/2007/cauvary.htm*

These stations are located as point data, and the same computed values of temperature and pH are tabulated. Then we perform a goodness of fit Chi-square test with the null hypothesis "There is no significant difference between observed and expected or computed value". If the p-value is less than 0.05, we reject the hypothesis, inferring a significant difference, and if the p-value is more than 0.05, there is no significance. The test was performed in R-studio using R-script (figure 3.4 and 3.5) using the chisq.test function.

```
cat("Correlation between measured and calculated values of temperature\n")
mettur <- c(21.86, 27)
bhavani <- c(27.363, 29)
pallipalayam <- c(23.859, 27)
erode <- c(24.867, 30)
dframe <- data.frame(mettur, bhavani, pallipalayam, erode)
rownames(dframe) <- c("Observed", "Expected")
cat("Temperature values: calculated vs measured\n\n")
print(dframe)
m <- chisq.test(dframe)
cat("\nThe p-value is ", m$p.value, "\n")
```

Figure 3.4. The R Script of Chi-square test performed for temperature

```
cat("Correlation between measured and calculated values of pH\n")
mettur <- c(7.6, 7.8)
bhavani <- c(7.6, 7.7)
pallipalayam <- c(7.6, 7.9)
erode <- c(7.6, 7.5)
dframe <- data.frame(mettur, bhavani, pallipalayam, erode)
rownames(dframe) <- c("Observed", "Expected")
cat("pH values: calculated vs measured\n\n")
print(dframe)
m <- chisq.test(dframe)
cat("\nThe p-value is ", m$p.value, "\n")
```

Figure 3.4. The R Script of Chi-square test performed for pH

RESULTS & DISCUSSIONS

The below section discusses the estimated surface temperature and the pH and tests how good the calculated values conform with the in-situ measurements.

Temperature derivation

The data were corrected for scan line gaps and atmosphere induced error. This is done because the DN values of the pixels were further used to derive the surface temperature. Using the formula discussed in methodology, the temperature was derived in kelvin scale converted to the standard unit of temperature, i.e., degree Celsius. Final temperature data was mapped for the Cauvery extent within the area under study (figure 4.1). The temperature range falls between 20.2609 ^{o}C to 33.5985 ^{o}C for the Cauvery river within the study area. As the middle of the river is indicated by green and outer by red, it is concluded that the middle of the river has low temperature and high temperature at the outer edges.

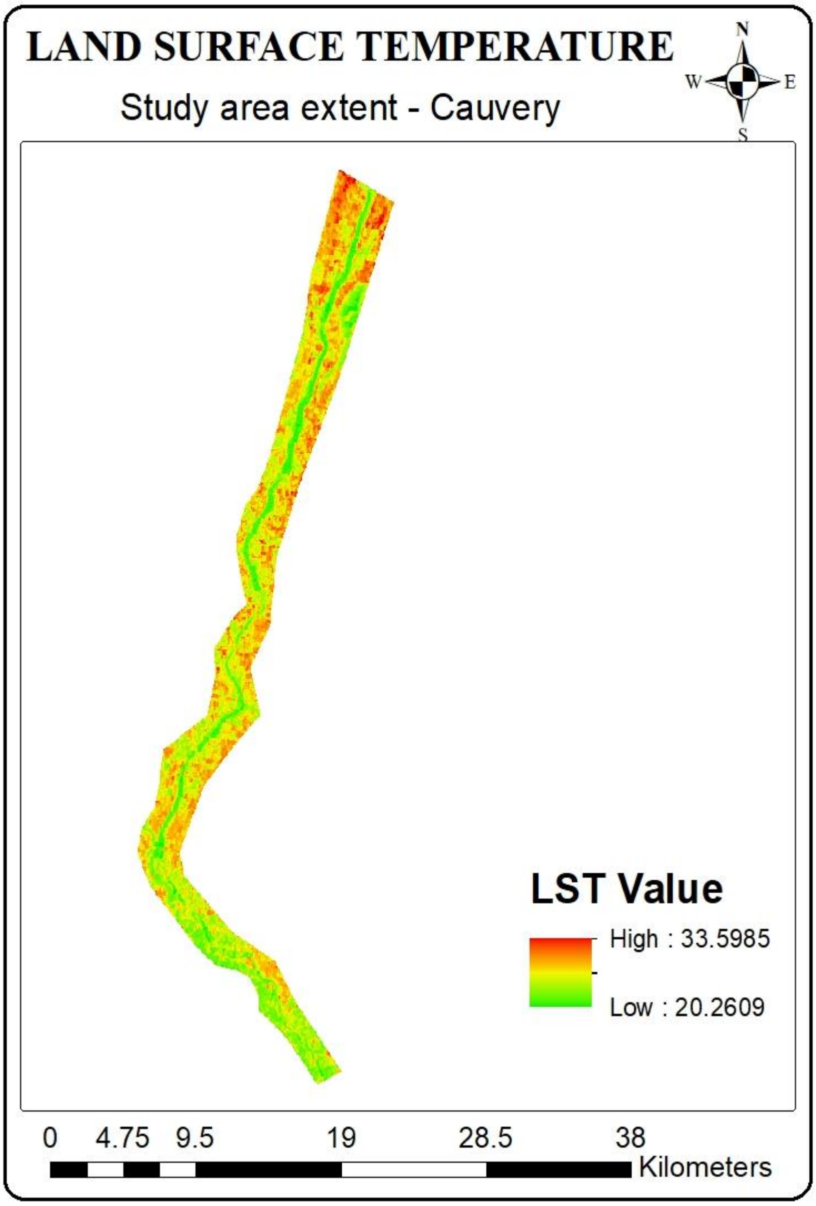

Figure 4.1. Surface temperature estimated from Landsat 7

4.2. pH derivation

The ASTER data was pre-processed, atmospherically corrected, and then used to estimate pH. The negative logarithm of [H +] ion concentration is pH. It measures the acidity and basicity of solution or fluid. It has a scale ranging from 0 to 14. The regression equation that defines the relationship between band 8 and 9 of ASTER TERRA and pH value derived by Abdelmalik (2018) was used to calculate pH values. pH value range derived from ASTER band 8 and 9 is up to 7.6195 for the study area. From figure 4.2, the white colour indicates the water and pH value is constant throughout the river as the river is running.

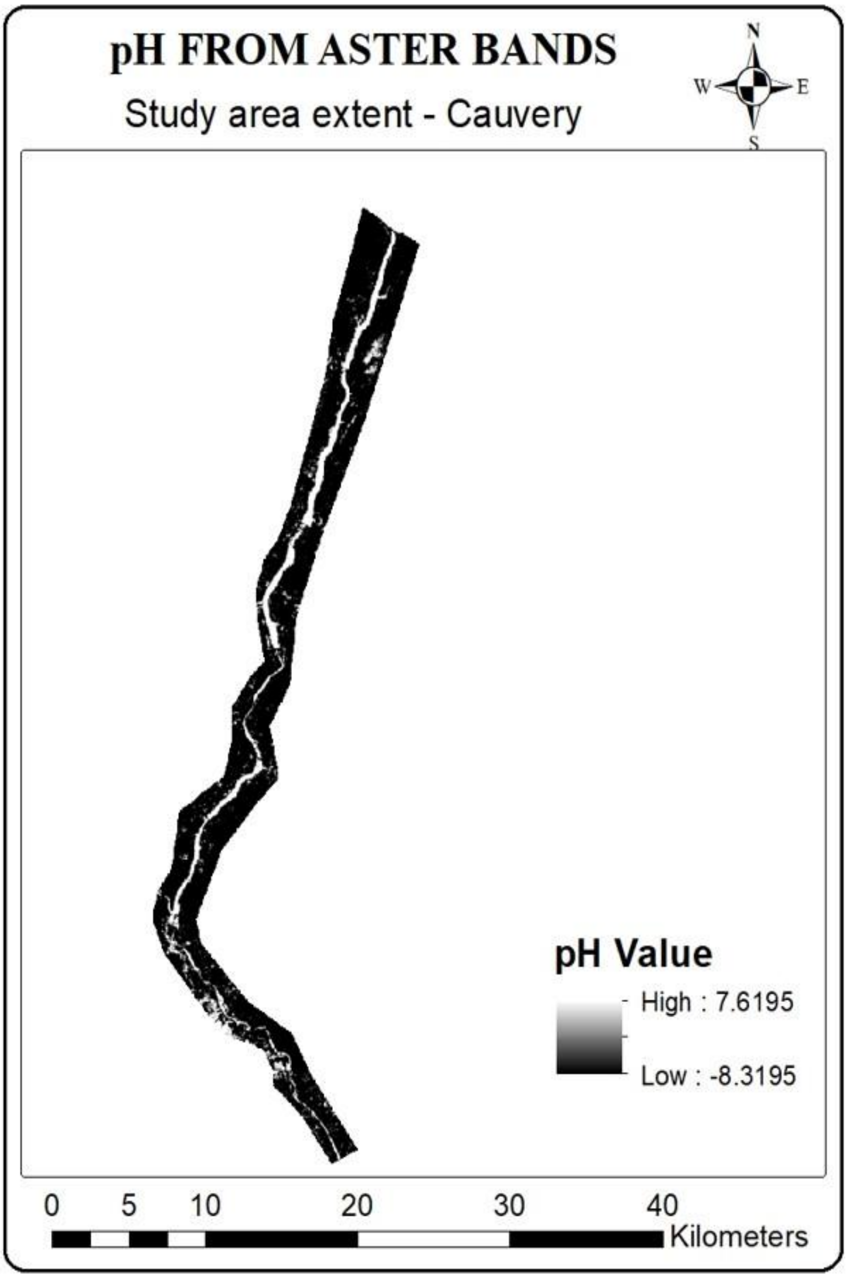

Figure 4.2. pH estimated from ASTER bands

4.3. Chi-square test

The means to measure the accuracy of the derived parameter used here was the Goodness of fit Chi-square test. It was performed in R studio with the null hypothesis that there is no significant difference between the measured and the calculated values. The test results are shown in Figures 4.3 and 4.4. It can be seen that the p-value for temperature and pH testing are 0.9792582 and 0.9998875, respectively. These values are greater than 0.5, and the null hypothesis is accepted. Hence it can be concluded that the estimated values are highly accurate.

```
> source(file = "temp.txt")
Correlation between measured and calculated values of temperature
Temperature values: calculated vs measured

         mettur bhavani pallipalayam  erode
Observed  21.86  27.363       23.859 24.867
Expected  27.00  29.000       27.000 30.000

The p-value is  0.9792582
```

Figure 4.3. Chi-square test run for temperature

```
> source(file = "pH.txt")
Correlation between measured and calculated values of pH
pH values: calculated vs measured

         mettur bhavani pallipalayam erode
Observed    7.6     7.6          7.6   7.6
Expected    7.8     7.7          7.9   7.5

The p-value is  0.9998875
```

Figure 4.4. Chi-square test run for pH

CONCLUSION

The study outcomes are the LST range derived from band 6 of Landsat 7 for the study area, which is 20.2609 to 33.5985 degrees Celsius and the pH range derived from aster band 8 and 9 is up to 7.6195 for the study area. This implies that there is no significant difference between the field data and remote sensing derived data for both temperature and pH. Thus, the water quality parameters can be derived from satellite data, having the empirical relations of the bands are known. The accuracy of the predicted values can be increased when a season study of band reflectance is performed. The results have proved that remote sensing is a convenient and inexpensive method of acquiring water quality parameters with very few in-situ data. As a future study, water quality can be further monitored and predicted with the help of hyperspectral imaging by deriving a more precise mathematical relation as it involves narrow bandwidth, and a greater number of parameters can be derived the same way.

REFERENCES

1. Sundara Kumar K, Udhaya Bhaskar P &Padmakumari (2012). "Estimation of land surface temperature to study urban heat island effect using Landsat ETM+ image", International Journal of Engineering Science and Technology, Vol 4, No. 2, pp:771 to 778.

2. Javed Mallik, Yogesh Kant & Bharath B D (2008). "Estimation of land surface temperature over Delhi using Landsat – 7 ETM+", Journal of Indian Geophysical Union, Vol 12, No. 3, pp: 131 to 140.

3. Milton IsayaNdossi and Ugur Avdan (2016). "Application of Open-Source Coding Technologies in the production of Land Surface Temperature (LST) maps from Landsat: A PyQGIS Plugin", Remote Sensing 8 (431), doi:10.3390/rs8050413.

4. Zhao-Liang Li, Bo-Hui Tang, Hua Wu, Huazhong Ren, Guangjian Yan, Zhengming Wan, Isabel F. Trigo & Jose A. Sobrino (2013). "Satellite-derived land surface temperature: Current status and perspectives", Remote Sensing of Environment, Vol 131, pp: 14 to 37, https://doi.org/10.1016/j.rse.2012.12.008.

5. Fuqin Li, Thomas J. Jackson, William P. Kustas, Thomas J. Schmugge, Andrew N. French, Michael H. Cosh & Rajat Bindlish (2004). "Deriving land surface temperature from Landsat 5 and 7 during SMEX02/SMACEX", Remote sensing of Enironment, Vol 92, pp: 521 to 534. doi:10.1016/j.rse.2004.02.018.

6. Muhammad Amir Siddique, Yu Wang, Ninghan Xu, Nadeem Ullah & Peng Zeng (2021). "The spatiotemporal implications of urbanization for urban heat islands in Beijing: A predictive approach based on CA-Markov modelling (2004-2050)", Remote Sensing 13 (4697), https://doi.org/10.3390/ rs13224697.

7. Alistair M. S. Smith (2009). "How to convert ASTER radiance value to reflectance" An online guide by University of Idaho.

8. Abdelmalik, K.W. (2018). "Role of statistical remote sensing for Inland water quality parameters prediction", The Egyptian Journal of Remote Sensing and Space Science, pp 193 to 200.

9. Jeevalakshmi. D, S. Narayana Reddy & B. Manikiam, (2017). "Land Surface Temperature Retrieval from LANDSAT data using Emissivity Estimation", International Journal of Applied Engineering Research, Research India Publications, Vol 12, No. 20.

10. Hakan (2015). "A software tool for retrieving land surface temperature from ASTER imagery", Journal of Agricultural Sciences, 21, pp: 471 to 482, DOI: 10.1501/Tarimbil_0000001350.

11. Anandababu D, Purushothaman B M & S. Suresh Babu (2018). "Estimation of Land Surface Temperature using LANDSAT 8 Data", International Journal of Advance Research, Ideas and Innovations in Technology Volume 4, Issue 2, pp: 177 to 186.

12. Osvaldo J. R. Pereira, Eder R. Merino, Celia R. Montes, Laurent Barbiero, Ary T. Rezende-Filho, Yves Lucas &Adolpho J. Melfi (2020). “Estimating water pH using cloud-based landsat images for a new classification of the Nhecolandia Lakes”, Remote Sensing, 12(1090), doi:10.3390/rs12071090.

13. Mochamad Firman Ghazali, Ketut Wikantika, Agung Budi Harto & Akihiko Kondoh (2020). "Generating soil salinity, soil moisture, soil pH from satellite imagery and its analysis", Information Processing in Agriculture, 7, pp: 294 to 306

14. Peter E. Land, Jamie D. Shutler, Helen S. Findlay, Fanny Girard-Ardhuin, Roberto Sabia, Nicolas Reul, Jean-Francois Piolle, Bertrand Chapron, Yves Quilfen, Joseph Salisbury, Douglas Vandmark, Richard Bellerby & Punyasloke Bhadury (2015). "Salinity from space unlocks satellite-based assessment of Ocean acidification", Environmental Science & Technology, 49(4), pp: 1987 to 1994, https://doi.org/10.1021/es504849s.