Factors influencing Lake Surface Temperature and its trend analysis for reservoirs of the Columbia River Basin

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Abstract

Lake surface temperature (LST) is one of the key indicators required for ecological and hydrological studies and for water quality management. Satellite remote sensing of LST has high spatial and temporal coverage and can be a cost-effective method of monitoring lakes. This study explores geophysical factors that control LST. LST for one hundred and fifteen reservoirs in the Columbia River basin were studied from 2000-2022. The climatic factors like air temperature, vapor pressure deficit and surface specific humidity were found to be drivers that can explain up to 80% of the variability observed in LST. Precipitation, wind speed, wind direction, and lake bathymetry along with the lake's elevation appeared to have negligible influence on the temporal variability of LST for these Columbia basin reservoirs. Our study revealed that there is an overall increasing trend in LST. Surfaces of two-third (66%) reservoirs are warming up with a mean rate of 0.25 ºC/decade while the remaining reservoirs are cooling with mean yearly trend of 0.16 ºC/decade. The surfaces of reservoirs with smaller surface area and located at low elevations were found to be warming fastest whereas the surfaces of those reservoirs at higher elevation have cooling trend, especially if they have large surface area. The trend of LST of a reservoir was found to be insensitive to the depth of these reservoirs. Using the vantage of space and multi-decadal observations, this study presents a thorough overview of the thermal behavior of reservoir water surface in the Columbia River basin. The findings can build clear pathways to improving hydro-ecological studies and water management of the region that is drought prone and impacted by climate change.

Key words: Lakes, temperature, remote sensing, Columbia river, climate change.

Key points:

1. According to multi-decadal remote sensing data of surface temperature, 76 out of the 115 reservoirs of Columbia river basin are warming yearly with a mean rate of 0.25°C/decade, while the remaining reservoirs show a cooling yearly trend with a mean rate of 0.16°C/decade.

2. Reservoirs with smaller surface area at low elevations are warming with high rates while many large area reservoirs at high elevations appear to have a cooling trend.

3. Climatic factors like air temperature, minimum and maximum temperature, and vapor pressure deficit have a larger influence on LST as compared to reservoir parameters like depth, surface area and elevation of a reservoir.

Introduction

Lakes and reservoirs are one of the major sources of freshwater for humans. They are used to meet demand for water supply for drinking, industry, and irrigation purposes. Such surface water bodies replenish the groundwater and preserve the aquatic habitat of that area. Reservoirs, which are artificially managed lakes, can mitigate floods and droughts by storing large amounts of water. Climate change also has a severe impact on the freshwater aquatic ecosystems. Thus, lakes and reservoirs can be used as indicators of a limnological response to change climate (Sharma et al., 2007). Lake surface temperature (LST) is one of the key parameters that affects the function of the freshwater ecosystems (Sharaf et al., 2019). LST is an important index that influences physical, chemical and biological processes in the water bodies (Dörnhöfer and Oppelt, 2016). Hereafter we shall use the terms lakes and reservoirs to refer to artificially managed lakes as the focus of this study is on reservoirs. We will use the term lake surface temperature (LST) to define the surface temperature of reservoirs.

The traditional method of measuring LST is to install temperature probes and measure the temperature on site. Satellite remote sensing can also be used to estimate LST. The brightness temperature detected by passive radiometers on satellites represents radiance emitted in the thermal or microwave wavelengths. Because surface water has a near-one emissivity at those wavelengths, the brightness temperature can be conveniently converted to kinetic and skin temperature. However, the water temperature beneath the surface does not remain the same as LST when there is thermal stratification of reservoirs (Elçi, 2008). Thus, satellite LST cannot be used to represent depth-averaged temperature that captures the thermal regime of the entirety of reservoirs. Nevertheless, due to convenience afforded by satellites in terms of multi-decadal observations with global coverage, satellite LST allows the exploration of spatial and temporal patterns of water temperature changes in reservoirs and how they are affected by geophysical factors. For example, LST of reservoirs may be potentially influenced by properties of reservoirs such as average depth, surface area and elevation with respect to sea level (Wetzel, 2001).

Meteorological factors, such as precipitation, wind speed, humidity are also potential drivers of change for LST (Sharma et al., 2008). Consequently, temporal variation in LST over decades can be linked to variations in these meteorological factors over time, which in turn correlate with shifts in climate patterns due to global warming. Today, we know very little about these factors and the role they may play in controlling LST in the Columbia River basin. Understanding of this role can improve reservoir operations for better eco-system health and water management outcomes in the region as artificial reservoir operation scheme plays a vital role in temperature stratification (Buccola et al., 2016; Yearsley et al., 2019).

The aim of this study is three-fold: (1) identify which of the geophysical factors of a reservoir influence its LST; (2) quantify the relative influence of all factors (geophysical and meteorological); and, (3) quantify the long-term trend of reservoir LST as observed by two decades of satellite thermal record to understand the impact of climate change. This study aims to improve our understanding of the relationship between LST and physical and meteorological factors of reservoirs. Because satellite temperature observations of terrestrial water bodies are relatively underutilized (Malakar et al., 2018; Calamita et al., 2024) in the study of reservoirs for lake management, our study hopes to broaden the application of LST to hydro-ecological studies and water management applications (Zhang et al., 2023). For example, changes in fish count in lakes can be related with the changes in satellite based LST or knowledge of how air temperature affects LST can aid in predicting thermal stratification patterns within the reservoir, which is crucial for maintaining suitable conditions for aquatic life. Similarly, understanding the impact of wind speed on LST can inform decisions related to wind-driven mixing and nutrient cycling, which are vital for ecosystem health.

Study Region

The reservoirs located in the Columbia River basin were selected for this study. Columbia river basin is in the Pacific Northwest region of North America. Columbia River pours more water into the Pacific Ocean than any other river in North or South America. The basin covers 668,000 km^2 of drainage area. The basin exhibits diverse bioclimatic conditions, encompassing both wet and dry regions with varied hydrographs influenced by rain and snow. Wet winters and dry summers contribute to significant seasonal fluctuations in streamflow. Since the 1950s, extensive water management has been implemented through a network of over 60 large dams and reservoirs on major tributaries. These modifications aim to facilitate hydropower generation, flood control, irrigation, recreational activities, water supply, and the preservation of habitat for endangered fish species (Jones and Hammand, 2020).

Climate change is anticipated to have repercussions on hydroelectric power generation, flood risk management, agricultural water supply, and ecosystems within the Columbia River Basin (Osborn, 2012). Although regional warming is an evident consequence of heightened greenhouse gas (GHG) concentrations, alterations in precipitation may vary significantly in direction and magnitude across different regions and seasons due to thermodynamic and dynamic factors (Seager et al., 2010). Additionally, anthropogenic activities are exacerbating hydrological drought in this region (Huang et al., 2016).

To study the impact of changing climate on LST in the Columbia River basin, 115 major reservoirs were selected that are associated with large dam. The relationship of LST with the meteorological factors was analyzed. The selected reservoirs are shown in figure 1 with the Columbia River basin boundary. Geo-location of reservoirs were extracted from Global Reservoir and Dam (GRAND) database (Lehner et al. 2019).

Data

Data from three different sources were collected and combined for this analysis (Table 1). The first data source used in this study is reservoir data from the GRAND database (version 1.3) (Lehner et al., 2019) which includes reservoir physical properties (Lehner et al. 2011). The geophysical factors extracted from this database were: depth in meters, surface area (hereafter referred to as 'area') in square Kilometers and elevation of the dam in meters. The second data source was the satellite-based LST time series data, which were collected by processing Landsat-7 and 8 thermal infrared band data (Jimenez-Munoz et al., 2008). The time series data for LST were collected for each reservoir spanning a two-decade period at a frequency of 16 days. The third data source was the meteorological data time series at a daily timestep from GRIDMET database (Abatzoglou, J.T. 2013). The data variables used are specified in Table 1. These three types of data were extracted for each reservoir site for the two-decade period from January 2000 to November 2022.

The climate data from GRIDMET database was averaged over all the pixels inside the reservoir's shapefile (obtained from GRanD) for each reservoir at a daily timestep. It was then matched to the remote sensing derived LST by using date. For those dates when LST was not available, the climate data was also discarded for unbiased analysis.

LST was estimated using Landsat-7 and 8 optical and thermal infrared (TIR) imagery. For each image, the visible, thermal and near infrared bands were cropped according to the reservoir shape polygons (obtained from GRanD database) in Google Earth Engine (GEE) (Gorelick et al., 2017) and then, a cloud filter was applied using the cloud mask extracted from quality assessment data and using the GEE's 'SimpleCloudScore' algorithm (Donchyts et al., 2017; Gorelick et al., 2017; Wang et al., 2017; Bonnema et al., 2020 and Attiah et al., 2023). After applying the cloud filter 33,910 images were left which represents almost 57% of the entire dataset. Using Dynamic Surface Water Extent (DSWE) method for water classification, the pixels were classified as water or non-water (Jones, 2015). Single channel algorithm was used to estimate the surface temperature of each water pixel from the TIR brightness temperature (Jiménez-Muñoz et al., 2008). This method involves applying the corrections for atmospheric effects. The atmospheric vapor content for calculation of the atmospheric functions was derived from National Center for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR) Reanalysis data for days corresponding with sensing data of each Landsat image (Kalnay et al., 1996).

A 10-100 m negative buffer (based on the size of reservoir) was applied to remove the effect of mixing of lake pixels with land surface pixels (Attiah et al., 2023). The estimated temperatures were then averaged across all water pixels within the reservoir polygon shape to provide single average temperature estimate for the whole reservoir from a single time-stamped Landsat image. The estimates were averaged for each reservoir for overlapping time periods. Unrealistically high and low temperatures were automatically removed to get the final time-series of daily LST. This technique to extract LST from Landsat images has been widely adopted and validated by other studies (Simon et al., 2014; Sharaf et al., 2019; Bonnema et al., 2020 and Attiah et al., 2023).

Methodology

To understand the effect of different reservoir geophysical factors (depth, area and elevation) on LST, the statistical distribution of reservoirs with respect to each factor was analyzed using histogram plot (figure 2-a, b and c) and boxplot (figure 3-a, b and c). As most of the reservoirs have area less than 30 Km^2 (figure 3 b), the histogram plot of area on the log-scale was analyzed to better understand the distribution of area. Reservoirs were categorized into two groups based on each reservoir factor. The threshold for categorizing the reservoirs in case of each morphological factor (shown by dotted red line on the histogram plots) was selected close to medians rather than means so that each group had almost equal number of reservoirs. Reservoirs were categorized as 'shallow' for depths less than 20 m and 'deep' for depths greater than 20 m. Similarly, 'small' and 'large' reservoirs were divided with a threshold of 1 Km^2 area and 'high' or 'low' elevation reservoirs were divided using a threshold of 800 m elevation above mean sea level.

The Pearson correlation matrix was employed to quantify the linear relationships between different variables in the dataset. This matrix comprises a square array of correlation coefficients, each indicating the magnitude and direction of the linear relationship between pairs of variables. These coefficients were computed using the Pearson correlation coefficient, 'r,' which spans from -1 to 1. A positive 'r' value signifies a positive linear relationship, whereas a negative value denotes a negative linear relationship (Kijsipongse et al., 2011).

Analysis of Variance (ANOVA):

Analysis of Variance (ANOVA) is a statistical technique that is used to determine if the means of two or more groups are statistically different from each other (Bewick, V. et al., 2004). ANOVA estimates F statistic by taking the ratio of variance between sample means and variance within the samples. If the p-value associated with this F-statistic is less than 0.05 then the group means are statistically different with 95% confidence. As ANOVA assumes that the underlying distribution of the dependent variable (LST) should be normally distributed, skewness of LST was also measured, and it was estimated to be -0.38. Negative skewness is also visible in the histogram plot of LST (figure 4a). Distributions with skewness between -0.5 to 0.5 can be assumed close to normal and symmetrical (Hatem et al., 2022). The following transformation was applied to make the LST more normally distributed so that the ANOVA results can be trusted.

$$X' = [(Max(X) + 4.5) - X]^{\frac{1}{2.5}} \tag{1}$$

After transformation the skewness was reduced to 0.04 and the histogram of transformed LST looks more symmetrical (figure 4b). ANOVA test was performed for each reservoir factor with both the original LST values and the transformed LST values.

Contribution Analysis (Dominance Analysis)

To determine the influence of each morphological and meteorological factor, dominance analysis (Azen and Budescu, 2003) was performed. This method involves training multiple models using every conceivable combination of predictors (meteorological and morphological factors) to predict the dependent variable (LST). Subsequently, for each predictor, the models where that predictor is included are compared to those where it is excluded while keeping the rest of the predictors constant. The importance of that predictor is measured by estimating the increase in R^2 when it is included in the model compared to when it is not, keeping the rest of the predictors unchanged. Then this incremental R^2 is averaged for all the instances of that predictor.

The average incremental R^2 is standardized to sum to 1 for all predictors and therefore can be considered as the relative contribution or importance of that predictor in predicting/influencing the dependent variable (LST). The python package called 'dominance analysis' was used in this study to perform contribution analysis. All the meteorological and morphological variables listed in Table 1 except latitude and longitude were used as predictors to predict the LST for all the reservoirs.

Trend Analysis

Theil-Sen Slope (Sen, 1968) is used to study the trend in LST over the past two decades from 2000 to 2022. Theil-Sen slope is a non-parametric method of estimating the best fit line for a set of points. It is estimated by taking the median of the slopes of all the lines generated by considering all possible pair of points. It can be expressed by using equation 2 where x_i and x_j are the series data at time t_i and t_j and if n is the length of series data, then $1 \leq j < i \leq n$ (Yang, Yu and Luo, 2020). Theil-Sen slope estimation is a robust method which is insensitive to outliers and works great for climate data variables (Chervenkov and Slavov, 2019).

$$TS\ slope = median\ (\frac{x_i - x_j}{t_i - t_j}) \quad (2)$$

Monthly, seasonal and yearly trend analysis was completed for each reservoir and its relationship with the different factors was analyzed. For monthly trend analysis, monthly mean LST time series was generated. Due to low temporal frequency of Landsat (16 days) and due to cloud cover, there were months where no LST was observed using satellite data. For instance, figure 5 shows the monthly LST at Yale lake (shown in figure 1). To overcome this issue, a gradient boosting-based machine learning model was trained on 90% of the monthly LST time series and all meteorological variables (monthly means) were used to predict the monthly LST (Wagle et al., 2020; Jia et al., 2022). The model was tested on the remaining 10% of the data. The trained model was used to estimate the missing values in the monthly LST time series. In seasonal trend analysis, the seasons are defined as follows: Spring spans from March to May, Summer from June to August, Autumn from September to November, and Winter from December to February.

The Mann-Kendall test (Mann 1945, Kendall 1975) is widely recognized as a prominent nonparametric technique for analyzing hydrological and meteorological time series data. One of the key strengths of the Mann-Kendall method is its applicability to time series that do not adhere to a specific distribution. Additionally, the method is advantageous due to its minimal susceptibility to extreme values (Khaneshan et al., 2014). The original MK test has been used to test the statistical significance of yearly trend of 115 reservoirs.

Results

The correlation matrix calculated to understand the correlation between the various morphological and climatic factors is shown in figure 6. The darker color shades show high positive or negative correlation and lighter shades show less or no correlation. Morphological factors have almost no correlation among themselves or with the meteorological variables. Climatic factors like minimum and maximum temperature, vapor pressure deficit and surface specific humidity have high correlation with each other which is expected. High correlation among these variables signifies that their influence on LST should be similar.

Analysis of Variance (ANOVA):

The results of the ANOVA test are summarized in table 2. The p-value for Depth is more than 0.05 whereas for Area and Elevation the p-value is less than 0.05 which shows that the 'large' and 'small' reservoirs have statistically different mean LST. Similarly, 'high' and 'low' elevated reservoirs are statistically different from each other with respect to mean LST. Thus, depth of a reservoir does not affect LST whereas surface area of a reservoir and the elevation at which it is located do affect the LST of a reservoir.

Contribution Analysis (Dominance Analysis)

The incremental R^2 for each meteorological and morphological factor is shown in figure 7a in the form of a bar chart. Maximum air temperature is one of the major factors that affects LST. Vapor pressure deficit and minimum air temperature were also found to affect LST, which is intuitive. The least affecting factors for LST were wind speed, wind direction and precipitation among the meteorological variables. All geophysical factors (depth, area and elevation) also have less influence on LST. This finding is in agreement with another study by Sharma et al. (2008) who reported that on a broader scale, lake surface temperature is influenced and affected largely by climatic factors rather than lake's physical attributes. From figure 7b, it can be easily seen that more than 80% of LST is influenced by air temperature (minimum and maximum), vapor pressure deficit, surface specific humidity and downwelling surface solar radiation which have also high correlation among themselves.

Trend Analysis

The trained machine learning model had a mean absolute error (MAE) of 2.24°C on the test set. Figure 8 shows scatter plot of the predicted LST vs Actual LST for the 10% of the data that was not used for the training of the model. It shows that the model can explain the variability well and can be used to estimate missing values. Figure 9 shows that the trained model performs robustly in filling missing values for the monthly LST for the Yale Lake.

Figure 10 shows Theil-Sen trend slope for yearly LST of one of the lakes (Green Peter Lake, shown in figure 1). In the same figure, 95% confidence interval for the slope is also shown. Similarly, the slope was estimated for every reservoir and for monthly, seasonal and yearly LST. For monthly trend analysis, boxplots of the trend slopes of shallow and deep reservoirs were plotted month wise (Figure 11a). No difference in trend was visible for the shallow and deep reservoirs which indicates that the LST trend is not controlled by the depth of the reservoir. Similarly figures 11-b and c show box plots for small and large and low and high elevated reservoirs respectively. The trend of surfaces of smaller reservoirs is to warm at higher rate during the summer months as compared to larger reservoirs. This is likely due to the thermal inertial of large and deep reservoirs that require more thermal energy to heat up. However, for the rest of the months surfaces of small and large reservoirs almost have similar trends. Surfaces of low elevation reservoirs are warming up at higher rate during summer months and at a lower rate during autumn months whereas surfaces of reservoirs located at higher elevations are warming up during June with the highest rate and the rate of warming goes down from July. Thus, area and elevation have some influence on the LST trend.

The trend distribution exhibits greater variability in the summer months, while it is more consistent during winter, indicating similar behavior among reservoirs during colder periods. Other studies conducted by Sahoo et al. (2011), Luo et al. (2019), and Yang et al. (2020) have also noted significantly higher rates of surface temperature change during the months of summer and autumn compared to months of other seasons. Increasing trends imply heightened evaporative loss during the summer season under continued climate change scenarios compared to those without climate change.

LST trend variation with depth of the reservoir shows no clear pattern in figure 12a. Figure 12b however shows that the reservoirs at low elevations (denoted by small markers) warm up during summer and have a cooling trend in autumn whereas reservoirs in high elevation (denoted by large markers) have a warming trend during autumn. A better insight is gained on why reservoirs in eastern region of Columbia basin behave differently from western reservoirs. The reason behind this from a data based perspective seems to be due to the elevation difference, warranting further investigation in future research endeavors.

Figure 13 shows the actual shape of reservoirs and the yearly trend seen in the last two decades. Most low elevation small reservoirs (towards west) are found to be warming whereas high elevation and small reservoirs (towards the eastern region) are cooling. Large reservoirs are also found to be warming. A yearly trend of warming is exhibited by 76 reservoirs at the mean rate of approximately 0.25°C/decade. The remaining reservoirs have a cooling trend of LST with the mean rate of approximately 0.16°C/decade. These trend rates align with those reported in prior studies conducted by Woolway et al. (2017), Wan et al. (2018), Dokulil et al. (2021), and Xie et al. (2022).

Mann-Kendall test results on yearly trend revealed that 20 reservoirs out of 115 exhibited statistically significant trend with a confidence of 90% (figure 14). The mean rate of change in yearly LST for these 20 reservoirs is found to be approximately 0.34°C/decade. The uncertainty in the yearly trend is least as comparable to the monthly or seasonal trend as yearly trend is calculated using yearly LST which is calculated as the average of monthly LST for all months in a year. Further, estimating the trend on a decadal scale reduces the MAE of 2.24°C in monthly LST to MAE of 0.019°C/decade in the yearly trend.

Discussion and Conclusion

This study provides a comprehensive analysis to demonstrate that remotely sensed lake surface temperature, even if it only represents the skin temperature of a lake, can still reveal insights on trends necessary to understand the impact of global warming at the local scale. For example, climate change can affect the characteristics of lake's thermal stratification as more carbon dioxide in the atmosphere can increase the duration of thermal stratification (Stefan et al., 2001; Adrian et al., 2009; Yaghouti et al., 2023). Such studies can be done by studying the variation of LST as a proxy of climate change along with the depth averaged temperature of the lakes.

Remotely sensed LST data though available globally, has a low temporal resolution which can be further reduced due to the presence of clouds. This inherent paradox (high spatial resolution but low temporal resolution) necessitates the understanding of the driving factors of LST so that a more continuous estimate of LST over time can be generated for a wide range of lake management applications. Our study helps better understand how surface temperature of reservoirs may be influenced by geophysical and meteorological factors, which in turn has implications for the proper functioning of aquatic ecosystems. Warmer reservoir temperatures can alter lake mixing regimes, availability of fish habitat and biological uptake of nutrients which purifies water and protects downstream ecosystems (Meyer et al., 1999; Petersen and Kitchell, 2001).

What emerges from our study is that an increasing upward trend of lake surface temperature in most of the Columbia River reservoirs may be one of the direct effects of global warming as indicated by previous research (Schmid et al., 2014). A technical report published by US Army Corps of Engineers (O'Connor, 2021) found that a substantial portion, between 25 and 50%, of the observed warming trends in water temperature corresponded with rising air temperatures. Furthermore, contribution analysis reinforces the significant impact of air temperature on LST, with minimum and maximum air temperatures combined explaining approximately 43% of the variance in LST.

Out of the 115 reservoirs examined in the Columbia River basin, 76 of them exhibit a warming yearly trend in LST, with a mean rate of 0.25°C/decade, while the remaining reservoirs show a cooling yearly trend, averaging 0.16°C/decade. The yearly trends were found to be statistically significant for 20 out of 115 reservoirs, warming with a mean value of 0.33°C/decade. The trends in LST appear to be influenced by the surface area and elevation of the reservoirs, factors that are closely associated with their impact on air temperature. Elevation directly influences air temperature variation, whereas surface area determines the extent of water-air interaction. Interestingly, reservoir depth does not appear to have any significant influence on LST trends. Reservoirs with small surface area or which are at low elevation tend to show higher positive LST trend during summer months (June-August) compared to reservoirs with large surface area, or which are at high elevation. In winter (December – February), all the reservoirs almost behave similarly and exhibit similar LST trends. Small reservoirs are overall warming yearly, with a higher rate for low-lying reservoirs as compared to higher elevated reservoirs whereas high elevated large reservoirs have an overall cooling yearly trend.

This study, revealing the significant differences found in mean LST between reservoirs categorized by surface area and elevation, suggests that these factors play a notable role in influencing reservoir surface temperature. The lack of significance for reservoir depth implies that this variable may have less impact on LST compared to surface area and elevation. Moreover, the dominance analysis test highlights that depth explains the least variability in LST among all the meteorological and morphological factors considered.

Lake surface temperature was found to be predominantly influenced by meteorological factors rather than lake bathymetry. Air temperature, vapor pressure deficit, surface specific humidity and downwelling surface solar radiation emerged as the topmost contributing factors for LST and they together explain 80% of the observed variation in LST. Conversely, wind direction, wind speed and precipitation were identified as the least influential climatic factors for LST explaining 0.73%, 0.57% and 0.47% of the variability, respectively. Among the factors associated with reservoir bathymetry, surface area exhibited the highest variability (0.56%), followed by elevation of the reservoir (0.33%) and depth of the reservoir (0.074%).

Our study highlights the efficacy of utilizing multi-decadal time-series of lake surface temperature (LST) from remote-sensing data to monitor evolving trends. These trends not only yield valuable insights into LST dynamics but also present opportunities to explore their implications for the hydro-ecological cycle. By correlating LST trends with ecological indicators like algae growth and fish population, we can deepen our understanding of ecosystem dynamics and inform more targeted water management strategies. For instance, identifying periods of elevated LST can prompt interventions aimed at reducing water temperatures through methods such as strategic water releases or the implementation of shading techniques. This approach contributes to the preservation of aquatic habitats and the sustainable management of water resources. Continued advancements in remote sensing based LST monitoring will further enhance our ability to assess the impacts of climate change on aquatic ecosystems. Additionally, future studies can explore the impact of factors like basin parameters and mean daily inflow in conjunction with LST.

Author Contributions

S. Minocha conceptualized the study, ran the data analyses and wrote the paper. F. Hossain edited the paper. P. Wang assisted in data collection, analysis, and the use of statistical tools. S. Khan assisted in temperature analyses code and remote sensing data. All the authors helped in discussing ideas, interpreting results, and editing the paper.

Data Availability

All data, codes and analyses used in this study are available on request.

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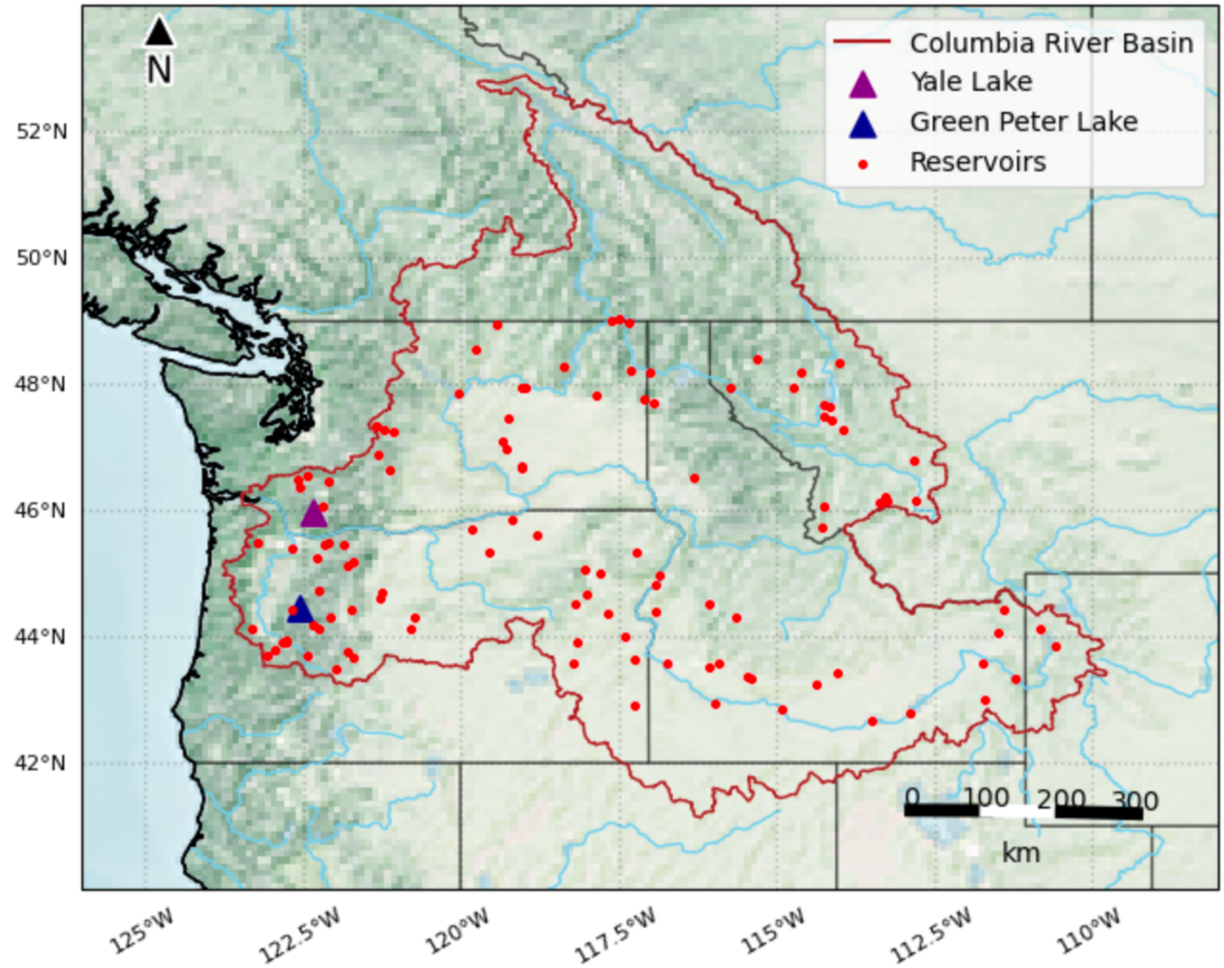


Figure 1 : *Columbia River basin as the study region and the 115 selected reservoirs. It also shows the geo-spatial location of Yale Lake and Green Peter Lake that have been referred to in the text.*

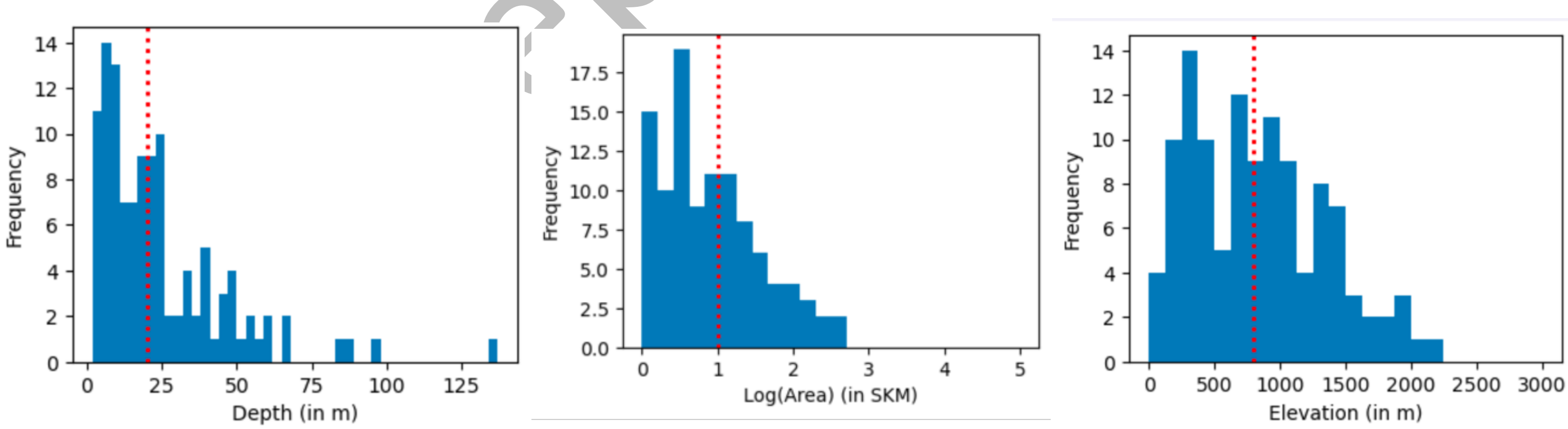


Figure 2(a, b and c): Histogram for the reservoir depth, log(reservoir surface area) and reservoir elevation of 115 reservoirs in the Columbia River basin respectively. The red dotted line shows the value used to categorize each of the variables into two groups: (1) shallow and deep for depth, (2) large and small for surface area and (3) high and low for elevation.

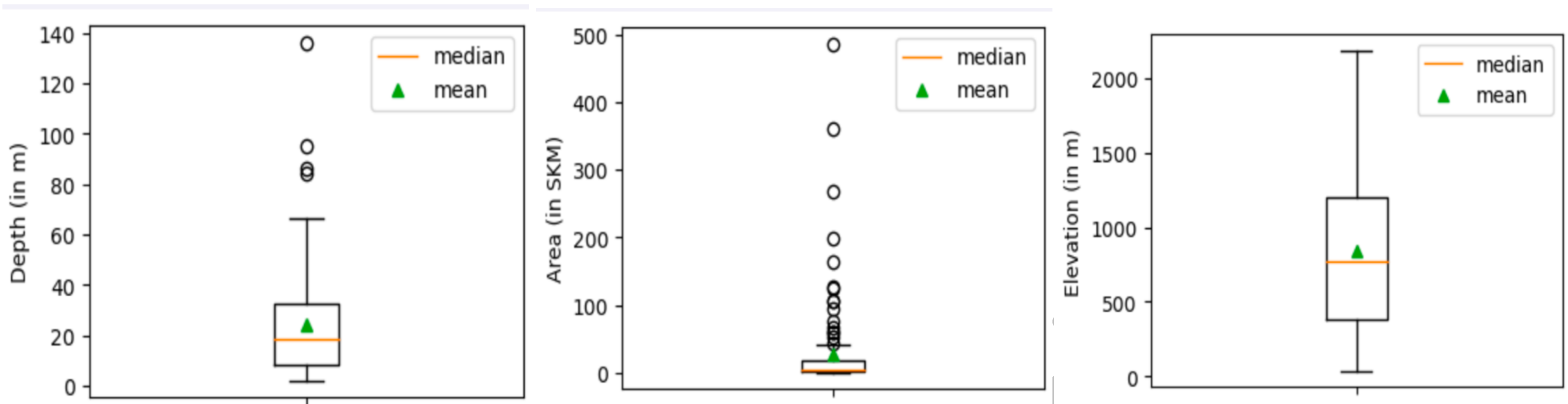


Figure 3(a, b and c): Boxplot for the reservoir depth, reservoir surface area and reservoir elevation of 115 reservoirs in the Columbia basin respectively. The green marker denotes the mean and orange line shows the median of the each of the variables.

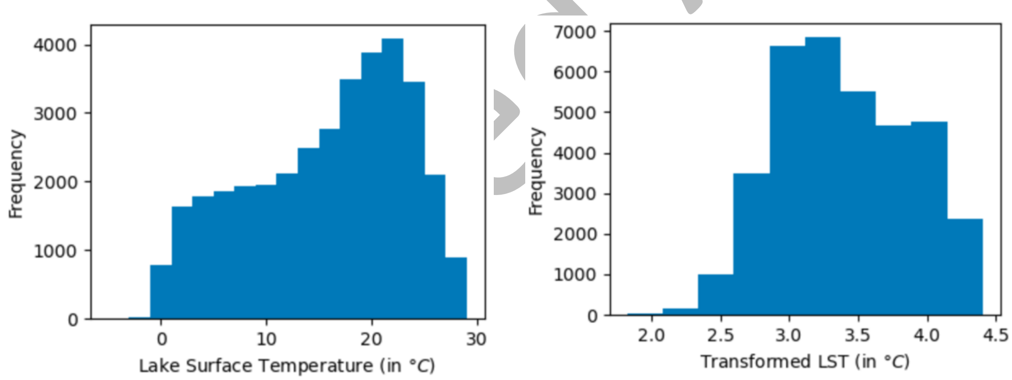
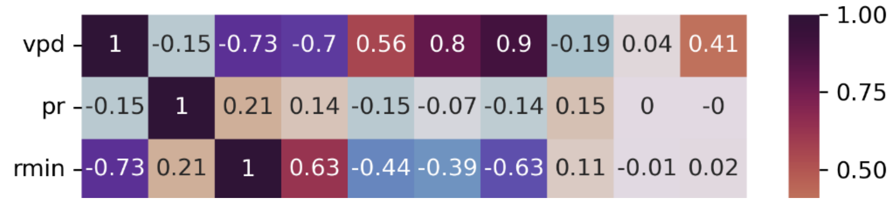


Figure 4(a and b): Histogram for daily LST and transformed LST for 115 reservoirs respectively.

Figure 5: Monthly mean LST time series for Yale Lake. Empty gaps show the missing data.



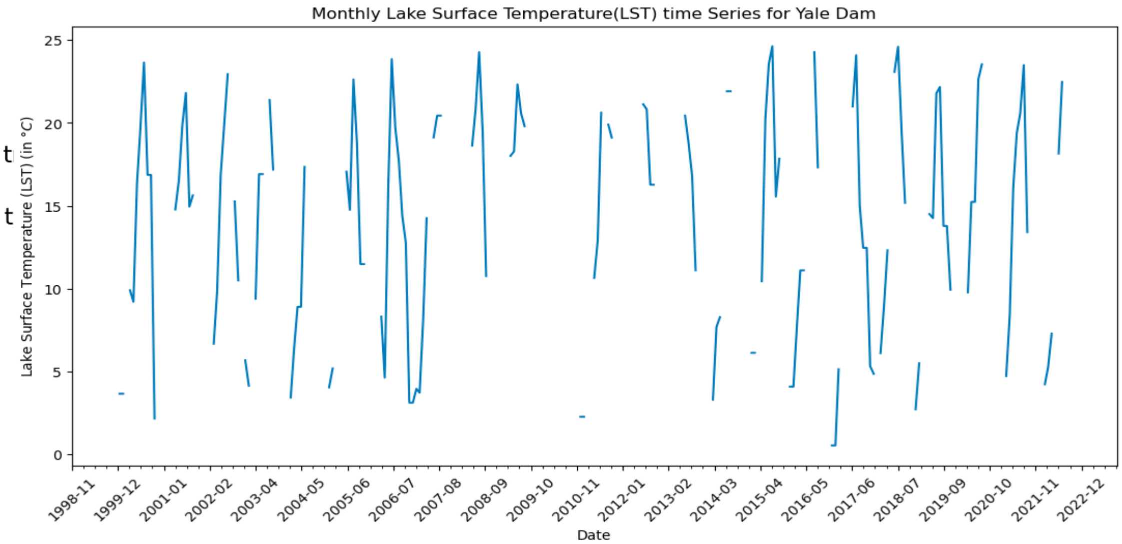


Figure 6: Correlation matrix showing Pearson correlation value between different morphological and meteorological variables calculated using all 115 reservoirs.

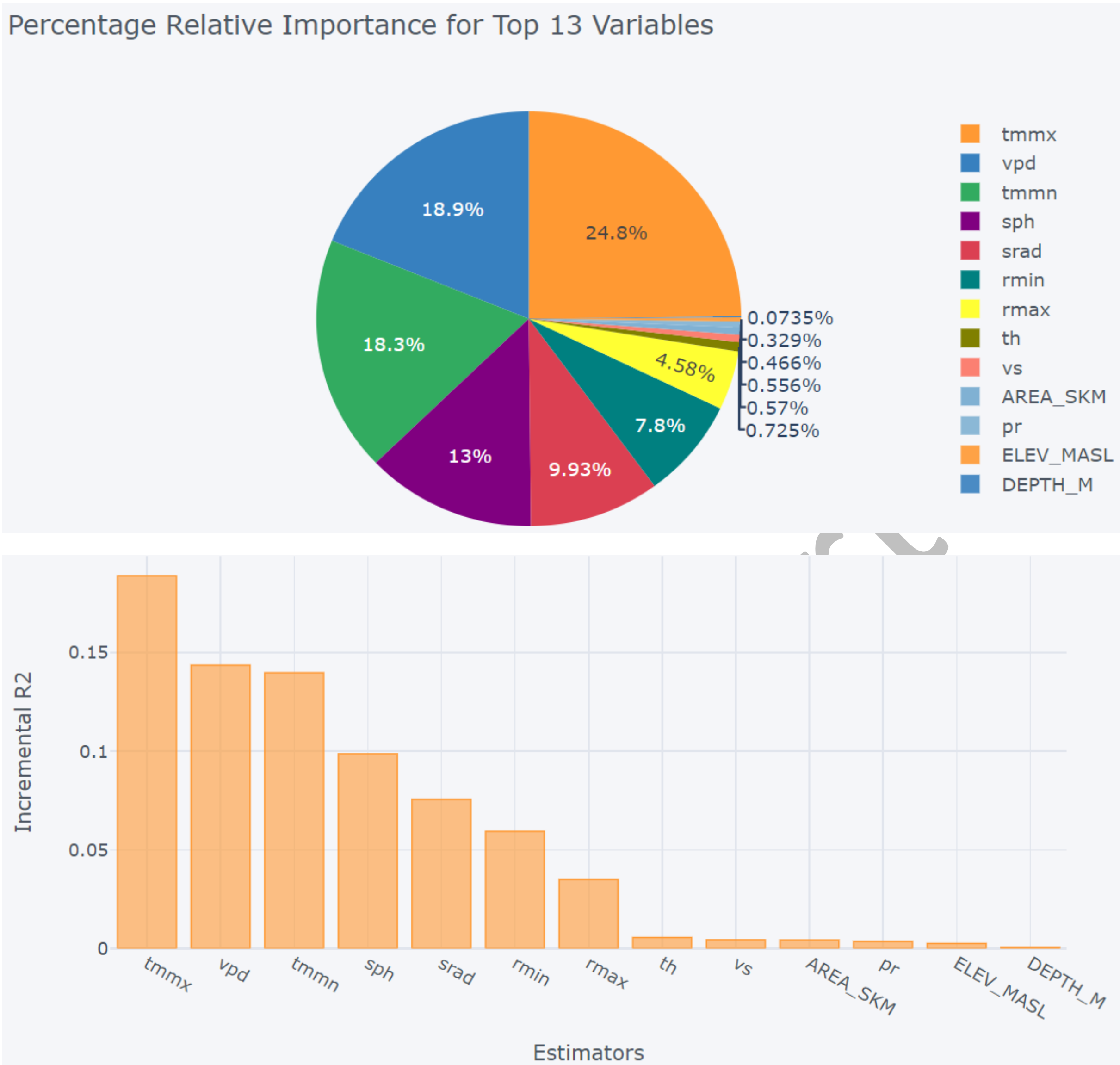


Figure 7 (a): Pie chart for percentage of relative importance of each meteorological and morphological variable in influencing LST; (b): Bar chart for Incremental R^2 for each of these predictors using contribution analysis method.

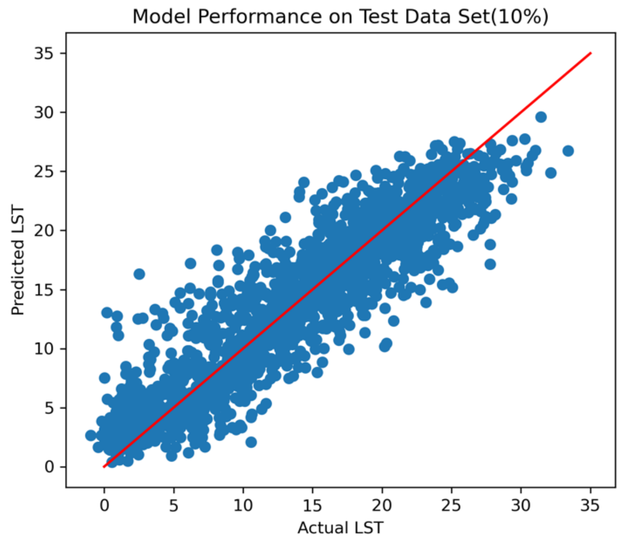


Figure 8: Scatter plot of Predicted monthly LST vs Actual Monthly LST for test data that 10% of the total non-missing dataset

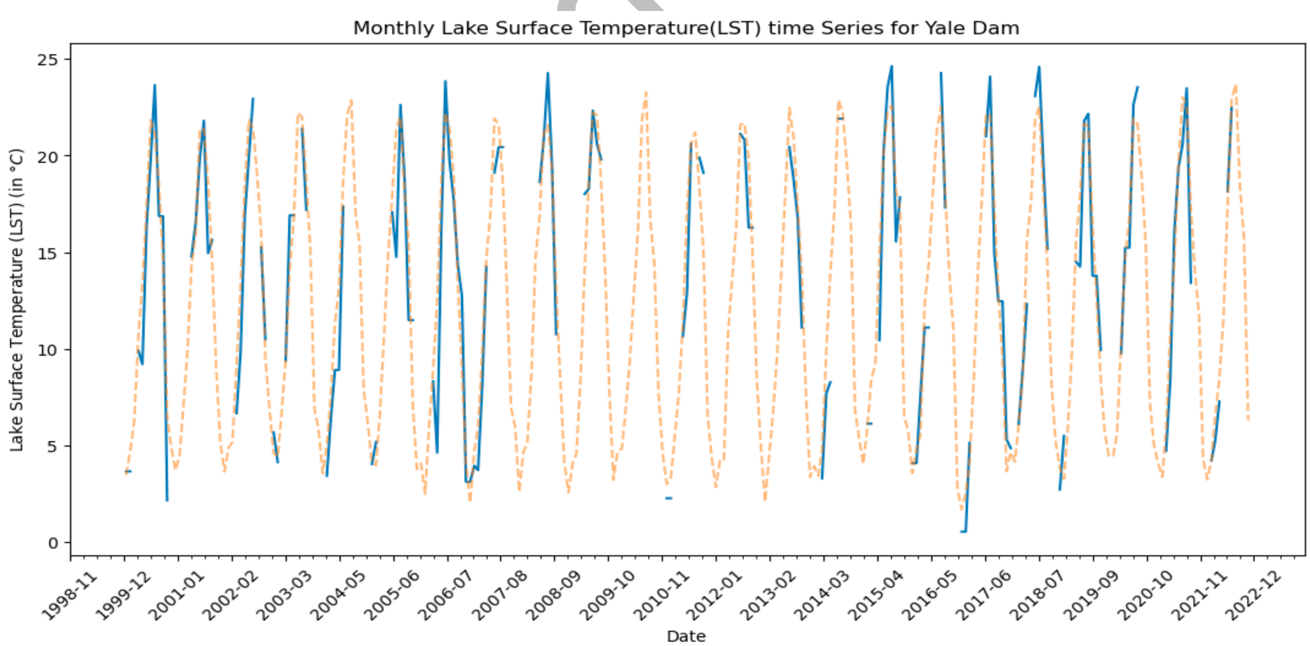


Figure 9: ML model based monthly LST predictions (dotted curve) with comparison to the actual monthly LST values (blue curve) for Yale Lake.

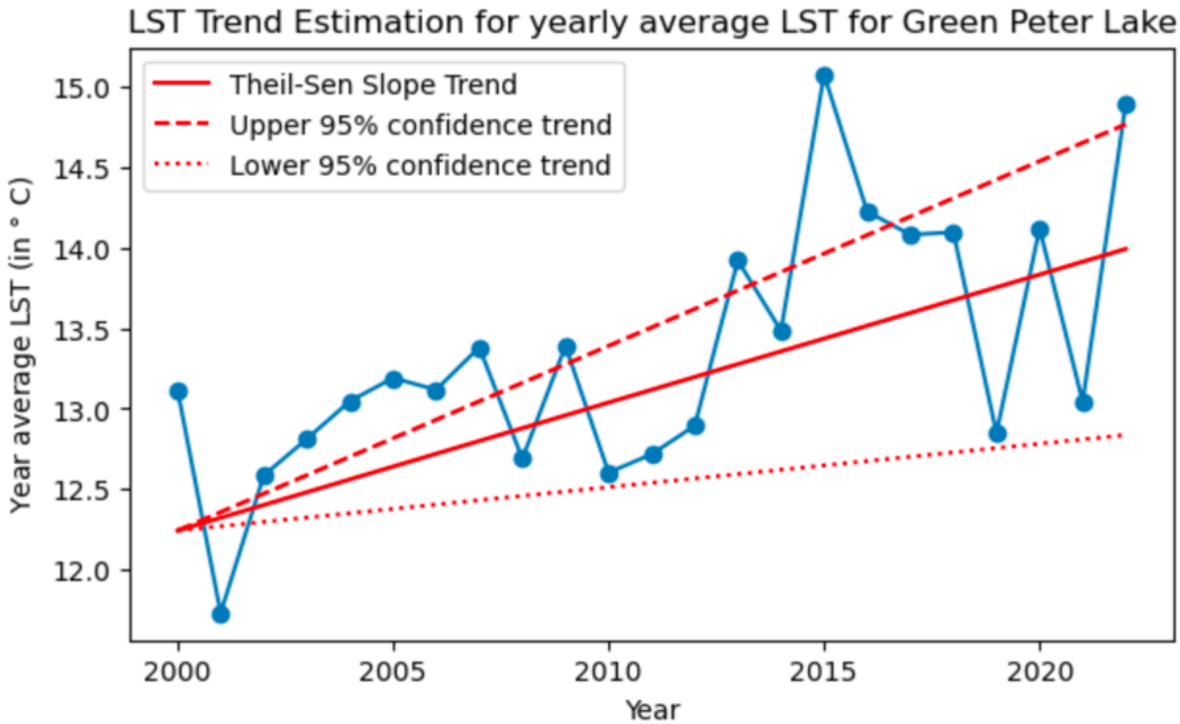


Figure 10: Theil-Sen slope estimation with 95% confidence interval for yearly average LST for Green Peter Lake

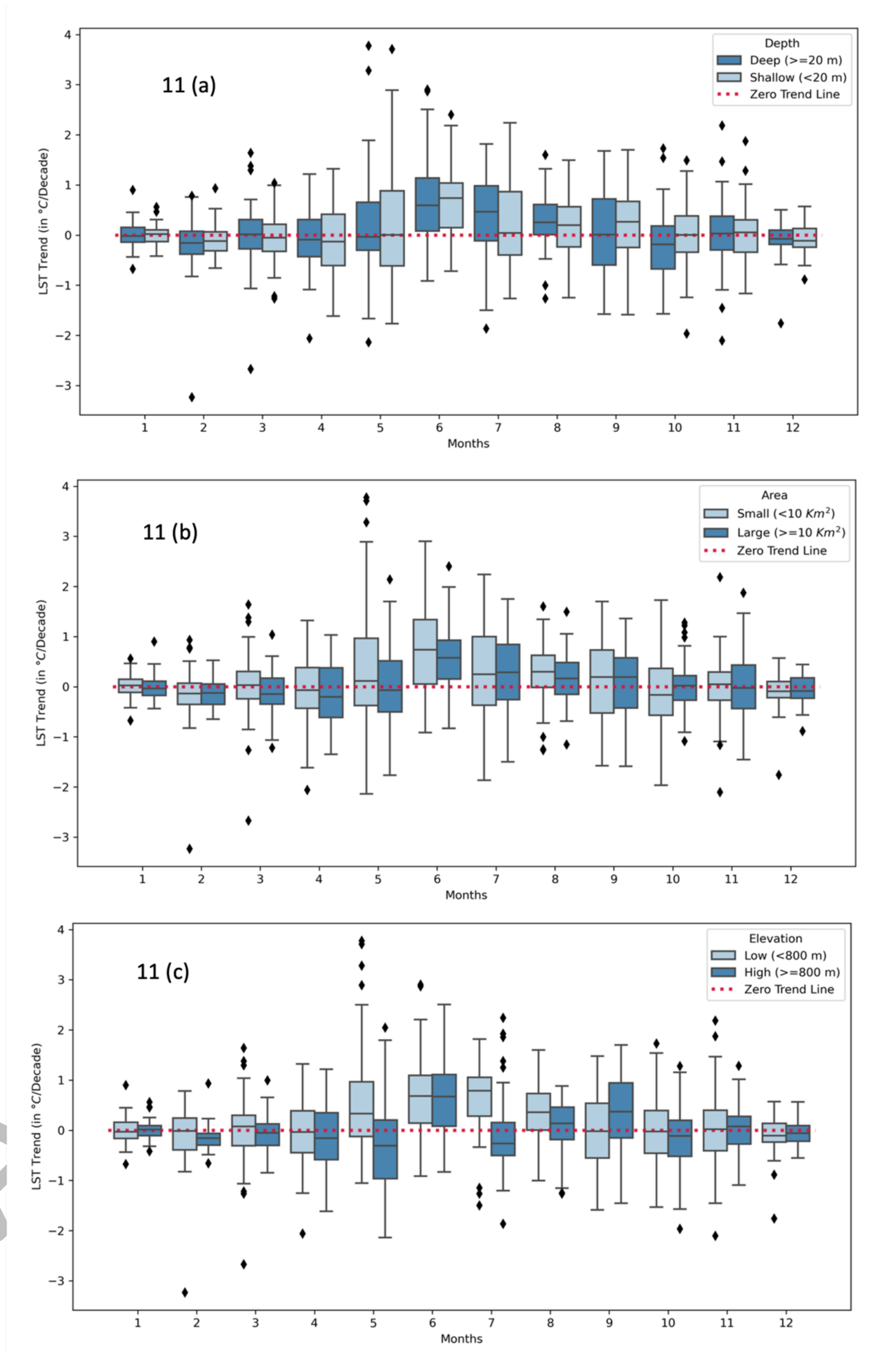


Figure 11(a, b and c): Monthly LST trend for different months of the year and for deep/shallow, small/large and low/high reservoirs respectively.

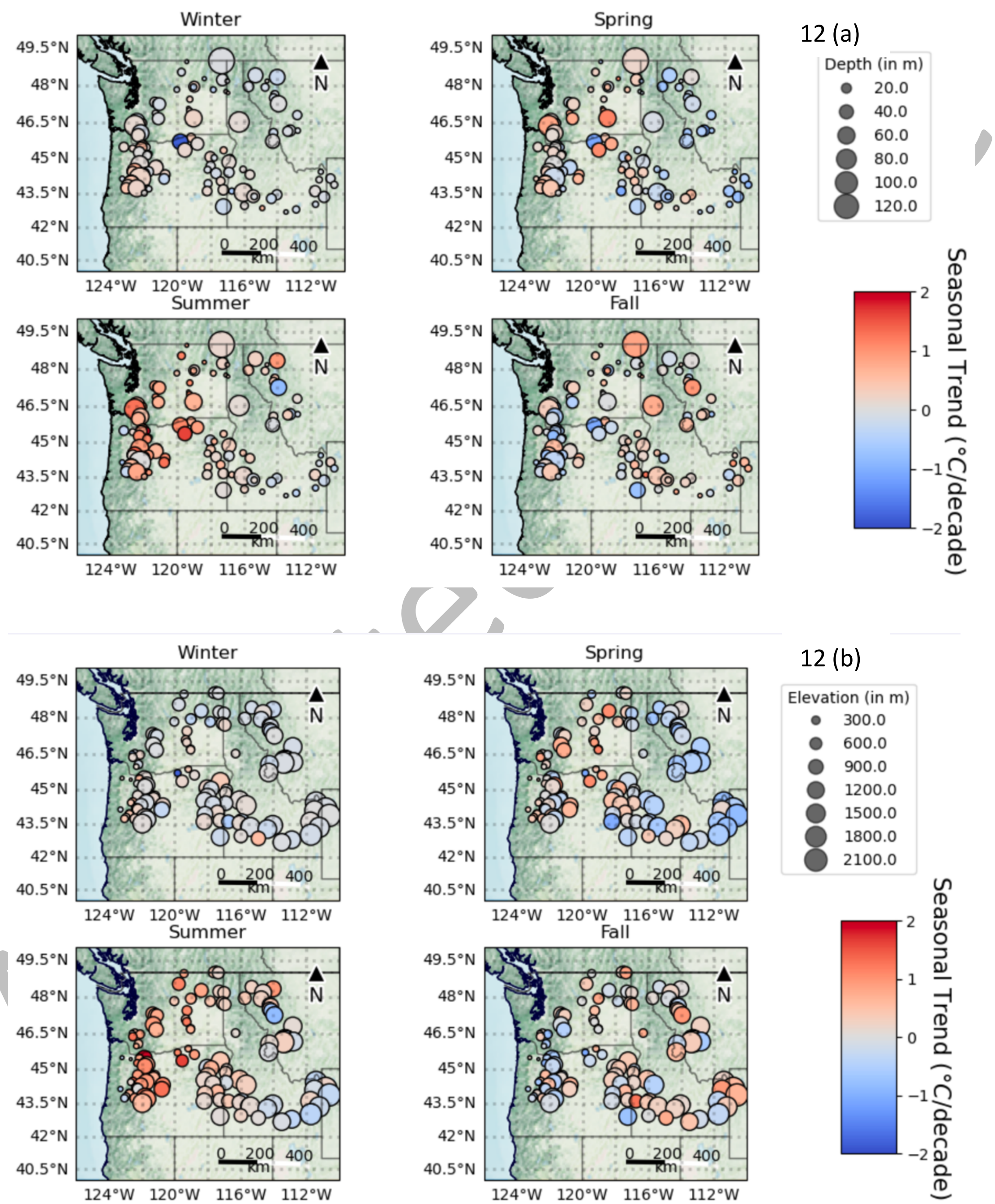


Figure 12(a and b): Seasonal LST trend for deep/shallow and low/high reservoirs respectively. The marker size represents the actual depth or elevation of the reservoir.

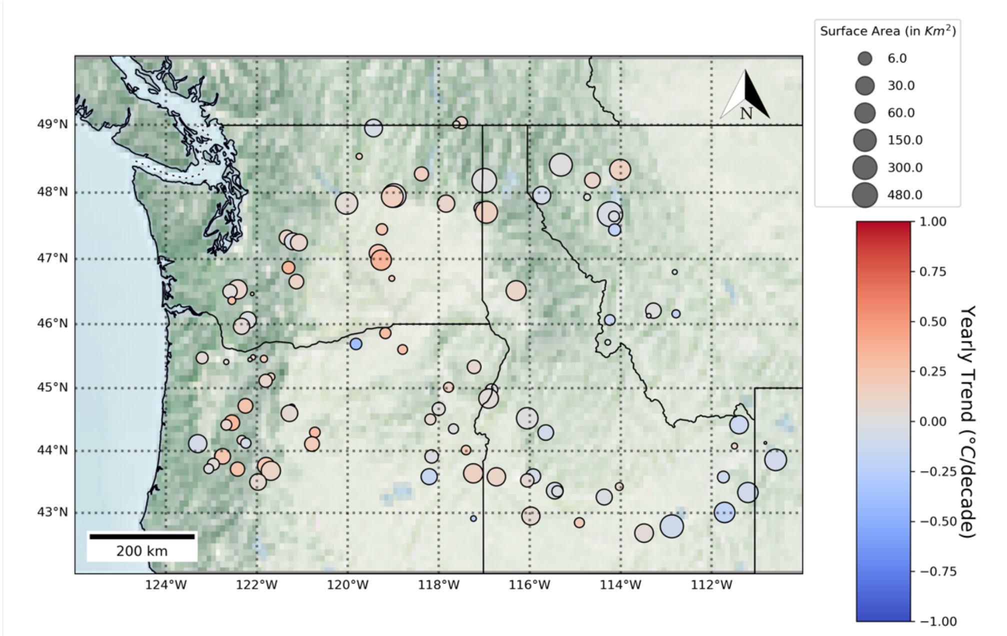


Figure 13: Yearly LST trend for reservoirs with marker size representing the surface area of the reservoir. Larger the marker, larger is the surface area of the reservoir.

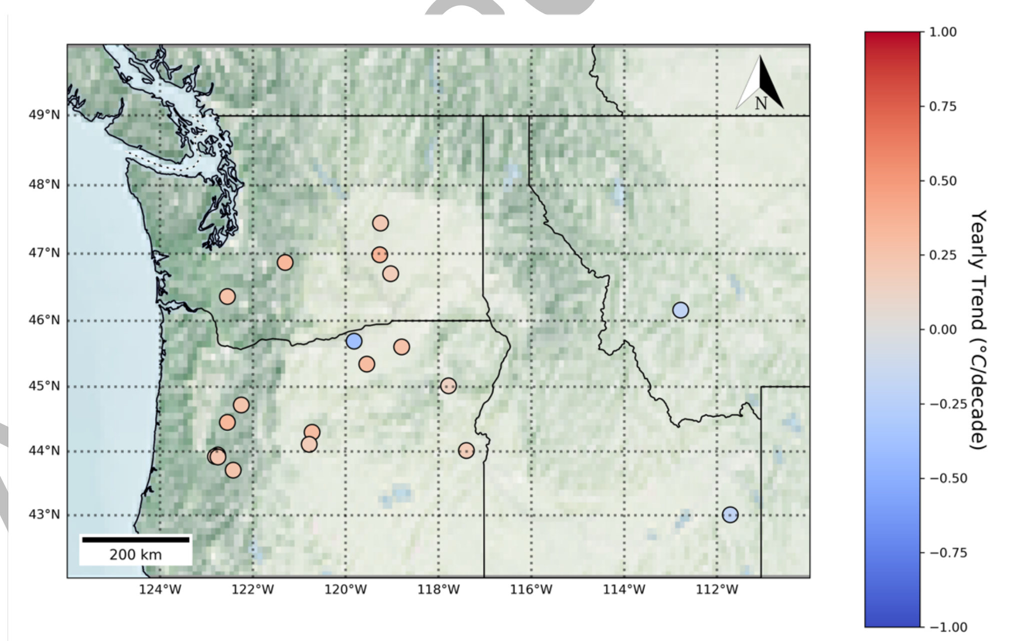


Figure 14: Yearly LST trend for reservoirs that exhibits statistically significant trend with 90% confidence using Mann-Kendall test. 20 reservoirs out of 115 reservoirs had a statistically significant yearly trend in LST with a mean value of 0.34℃*/decade.*

Data Type	Database	Data Variable	Abbreviation	Time Duration
Reservoir Morphological Data	GRanD Database (version-1.3)	Latitude	lat	NA
		Longitude	lon	NA
		Surface Area	area / AREA_SKM	NA
		Elevation	ELEV_MASL	NA
		Depth	DEPTH_M	NA
Reservoir Surface Temperature Data	Satellite Remote Sensing	Lake Surface Temperature	LST	Mar 2000 - July 2022
Meteorological Data	GRIDMET Database	Near-Surface Specific Humidity	sph	Jan 2000 - Nov 2022
		Mean Vapor Pressure Deficit	vpd	Jan 2000 - Nov 2022
		Precipitation	pr	Jan 2000 - Nov 2022
		Minimum Relative Humidity	rmin	Jan 2000 - Nov 2022
		Maximum Relative Humidity	rmax	Jan 2000 - Nov 2022
		Minimum Air Temperature	tmmn	Jan 2000 - Nov 2022
		Maximum Air Temperature	tmmx	Jan 2000 - Nov 2022
		Surface Downwelling Solar Radiation	srad	Jan 2000 - Nov 2022
		Wind Speed at 10 m	vs	Jan 2000 - Nov 2022
		Wind direction at 10 m	th	Jan 2000 - Nov 2022

Table 1: Description of various datasets and their variables used along with their sources and the time duration, if applicable.

	Depth	Area	Elevation
P value for LST before transformation	0.740	1.365×10^{-7}	5.810×10^{-4}
P value for LST after transformation	0.562	5.742×10^{-9}	2.949×10^{-3}

Table 2: Results of ANOVA test for Depth, Area and Elevation with dependent variable as LST and transformed LST.