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Trends in Water Temperature: A Case Study for New South Wales, Australia

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Abstract

River water temperature (T_w) plays an important role for balancing the ecosystem and biodiversity of the aquatic species. For this, it is very important to investigate the relationship between T_w and factors influencing it. This study used 24 years of data from five stations from different river basins within New South Wales (NSW) that were accessed from WaterNSW and Australian Bureau of Meteorology (BOM). This paper investigates the factors influencing T_w by the application of statistical methods like multiple linear regression (MLR) analysis and Man-Kendall (MK) test. MLR analysis was used to find the relationship between T_w and other independent variables like water level (WL), discharge (Q), electrical conductivity (EC) and air temperature (T_a), and MK test was used to find the trends of the variables over the time. It was found that for Stations 419003, 210055 and 410073, the group of predictors significantly explained the variability in T_w based on regression statistics. For annual minimum data series, none of the stations showed significance at the 0.10 level. Station 210055 showed highest co-efficient of determination (R^2) value indicating better explanatory power. The MK test results revealed that for both the annual maximum and minimum temperature series, Station 409061 had significant trend for most of the selected variables and Stations 418058, 210055 and 410073 had significant trend for one variable only. Further study is being conducted covering a greater number of stations across NSW.

Keywords: River temperature, trends, MK test, climate change, regression.

1. INTRODUCTION

Due to climate change, air temperature has been increasing at many locations globally. However, the impact of climate change on river water temperature is little understood. Climate change induced river water temperature has a direct impact on aquatic life such as specific adaption temperature and life cycle resulting an imbalance in the ecosystem (Johnson et al., 2024). Moulin et al. (2022) described that investigating long-term trends in river water temperature helps to know the triggering factors like thermal pollution or dam operations. Caissie (2006) stated that natural fluctuations and human activities have direct impact on river water temperature. Climate change, anthropogenic heat emission and water diversion play crucial role for altering river water temperature (Liu et al.,2020). Odjadjare and Okoh (2009) examined that comparison of the temperature of the river was higher at the final effluent and discharge point.

Croghan et al. (2018) used generalized additive models (GAMs) to describe the relationship between water temperature and precipitation intensity. Souaissi, Ouarda and St-Hilaire (2021) used various methodologies like local frequency analysis and goodness of fit criteria for analysis of river temperature data. Isaak et al. (2011) collected data from stream sites and computed stream temperature metrices. Statistical methods like Pearson correlations, multiple regression models, simple linear regression and standardized regression coefficients were used to examine the relationships between stream temperature, air temperature and discharge. Ouellet (2010) used a frequency analysis on time series data of air and water temperature, water level and solar radiation to investigate hydroclimatic conditions during a significant fish kill event in the St. Lawrence River in 2001. The analysis involved three hypotheses testing using the Wilcoxon test for homogeneity, the Kendall test for stationarity and the Wald-Wolfowitz test for randomness. Ptak (2019) examined air-water temperature correlations using MK, Sen's and Pettitt tests and used cluster analysis to identify the station's similarities. Chen (2016) investigated water temperature changes in the Yongan watershed, China (1980–2012) applying methodologies such as linear regression, standardized multiple regression and model evaluation.

There has been limited research on river water temperature in Australia. To fill this knowledge gap, this study aims to investigate the trends in river water temperature in NSW and impact of various factors that influences the river water temperature. The structure of this paper contains an introduction, study area and data, methodology, results and discussion, and conclusions.

2. STUDY AREA AND DATA

This study analysed long term air temperature data, which was accessed from Australian Bureau of Meteorology and water temperature data, water level data, discharge data and electrical conductivity were accessed from WaterNSW. Figure 1 shows the location of the selected five stations in NSW for both water temperature and air temperature data. For the river water temperature (T_w), the data series at all the stations covers 2000 to 2023 (24 years).

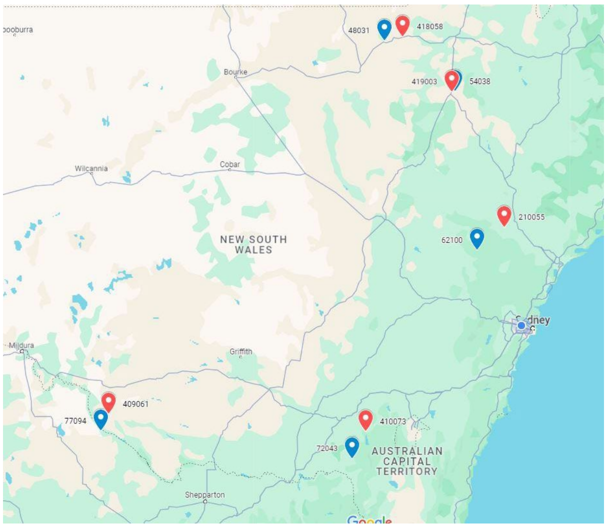

Figure 1. Locations of the selected five stations in NSW (blue colour indicates land station and red colour indicates river station)

3. METHODOLOGY

3.1. Preliminary data analysis

A boxplot is statistical tool for graphical representation of data which shows the spread, distribution and skewness of a dataset with the help of quartiles. Basically, boxplot interpret the distribution on its five points: the minimum value, first quartile (Q1 or 25th percentile), median (Q2 or 50th percentile), third quartile (Q3 or 75th percentile) and maximum.

3.2. Multiple Linear Regression Analysis

Multiple linear regression analysis is used for forecasting, predicting and understanding the relationship between variables across many fields like engineering, economics and social sciences (Etemadi and Khashei, 2021). Equation 1 shows the general form of MLR analysis:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \tag{1}$$

where,
Y = Dependent variable
$X_1, X_2, \ldots, X_n$ = Independent variables
β_0 = Intercept
$\beta_1, \beta_2, \ldots, \beta_n$ = Regression coefficients
ε = Error term

3.3. MK test

The Mann-Kendall (MK) test is non-parametric test which does not require data to be normally distributed. This test is used for evaluating trend in the time series data. Data which are reported as non-detects are included by assigning them a common value that is smaller than the smallest measured value in the data set (Rauf et al., 2016). Two hypotheses are considered for this test:
- Null hypothesis (H_0): there is no trend in the dataset.
- Alternative hypothesis (H_1): there is trend in dataset.

MK test is based on the test statistic S defined as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \tag{2}$$

where x_j are the sequential data values, *n* is the length of data set, and

$$sign(x_j - x_i) = \begin{cases} 1 & if\ x_j - x_i > 0 \\ 0 & if\ x_j - x_i = 0 \\ -1 & if\ x_j - x_i < 0 \end{cases} \tag{3}$$

Mann (1945) and Kendall (1975) have documented that when *n* ≥, the statistic *S* is approximately normally distributed with mean and variance as follows:

$$E(S) = 0 \tag{4}$$

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{n} t_i i(i-1)(2i+5)}{18} \tag{5}$$

where t_i is the number of ties of extent *i*. The standardized test statistic is computed by:

$$z_{Mk} = \begin{cases} \dfrac{s-1}{\sqrt{Var(S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{s+1}{\sqrt{Var(S)}} & if\ S < 0 \end{cases} \tag{6}$$

The standardized MK statistic Z follows the standard normal distribution with mean of zero and variance of one.

4. RESULTS AND DISCUSSION

4.1. Preliminary data analysis

Preliminary data analysis was done for examining the variability of the data series. Tables 1, 2 and 3 show the summary of the annual maximum and minimum data series of selected variables. For Stations 409061 and 410073, electrical conductivity (EC) showed highest and least variability respectively for both annual maximum and minimum data series for Station 409061. For Station 419003, discharge (Q) showed the highest variability for both data series. Station 418058 showed the least variability for parameter Q and air temperature (T_a). Stations 409061 and 410073 showed highest variability for parameter river water temperature (T_w).

Table 1 Summary of annual maximum data series

Station		WL	Q	EC	T_w	T_a
409061	Mean	0.92827	951.42	1506.3	15.284	33.832
	Variance	0.80494	3838600	14215000	65.296	2.6385
	Std. Deviation	0.89718	1959.2	3990.2	8.0806	1.6243
	Minimum	-0.234	9.717	63.6	8.3	31.1
	Q1	0.37	60.338	170.08	9.475	32.675
	Median	0.6675	265.32	407.4	9.75	34.05
	Q3	1.0997	870.43	1293.1	25.775	35.05
	Maximum	3.906	8926.1	18026	27.9	37.7
419003	Mean	0.50033	1353.8	407.31	27.586	35.505
	Variance	0.36589	1655400	23728	1.3763	2.6935
	Std. Deviation	0.60488	1286.6	154.04	1.1732	1.6412
	Minimum	-0.594	0	0	25.5	31.8
	Q1	0.001	194.86	326.05	26.8	34.55
	Median	0.527	1036.3	389.7	27.5	35.4
	Q3	0.948	2428.3	502.35	28	36.75
	Maximum	1.554	4287.3	689.7	30.5	38.8
418058	Mean	1.2459	404.24	331.88	22.942	37.063
	Variance	0.81018	1217800	24080	56.066	3.1391
	Std. Deviation	0.9001	1103.5	155.18	7.4877	1.7718
	Minimum	0.093	12.192	5.3	9.4	35.1
	Q1	0.707	21.201	239.3	18.45	36
	Median	1.108	59.982	273.3	26.4	36.9
	Q3	1.325	89.987	395.7	27.5	37.7
	Maximum	4.255	4454.1	623.5	30.9	43.3
210055	Mean	0.87014	503.54	573.25	24.952	25.168

	Variance	0.20135	5330600	15639	15.474	3.5518
	Std. Deviation	0.44872	730.11	125.06	3.9337	1.8846
	Minimum	0.27	53.569	419.9	9.9	21.6
	Q1	0.4255	149.86	475.32	25	23.725
	Median	0.941	249.59	530.44	25.9	25.05
	Q3	1.21	558.89	665.48	26.65	26.85
	Maximum	1.665	3250.5	872.4	28.8	28.4
410073	Mean	2.0565	7758	41.679	17.137	30.413
	Variance	0.04123	2613400	96.137	6.1598	2.4742
	Std. Deviation	0.20305	1616.6	9.805	2.4819	1.573
	Minimum	1.482	3474.5	30.9	12.8	27.8
	Q1	1.9628	7052.1	35.575	15.25	29.225
	Median	2.087	8049.8	39.05	17.45	30.6
	Q3	2.188	8767.5	43.55	18.85	31.4
	Maximum	2.378	10908	68.1	22	34.7

Table 2 Summary of annual minimum data series

Station		WL	Q	EC	T_w	T_a
409061	Mean	0.8043	658.31	1074.6	10.55	-2.5909
	Variance	0.58482	2419600	2387600	0.35595	1.5809
	Std. Deviation	0.76473	1555.5	1545.2	0.59662	1.2573
	Minimum	0.103	13.596	92.4	10	-5.2
	Q1	0.41725	58.165	248.35	10.1	-3.7
	Median	0.577	205.13	539.35	10.35	-2.3
	Q3	0.8415	507.79	1246.6	10.9	-1.65
	Maximum	3.75	7285.7	6614.5	12.5	-1
419003	Mean	0.26238	875.08	465.27	11.657	-2.8762
	Variance	0.2708	2093000	39423	0.41757	1.1549
	Std. Deviation	0.52038	1446.7	198.55	0.6462	1.0747
	Minimum	-0.594	0	0	10.8	-4.6
	Q1	-0.05	54.457	359.75	11.1	-3.6
	Median	0.056	273.24	440.8	11.7	-2.8
	Q3	0.5665	1053.3	544.5	12.05	-2.25
	Maximum	1.686	5225.7	983.8	13.1	-0.3
418058	Mean	1.0382	119.5	480.57	22.942	-2.6789
	Variance	0.23688	60096	48898	56.066	1.5806
	Std. Deviation	0.4867	245.14	221.13	7.4877	1.2572
	Minimum	0.587	0.077	228	9.4	-4.6
	Q1	0.671	5.427	287	18.45	-3.7
	Median	0.773	17.97	478.8	26.4	-2.7
	Q3	1.275	29.003	596.9	27.5	-2
	Maximum	2.355	910.54	1026.5	30.9	0
210055	Mean	0.8805	464.61	633.53	11.382	-2.6364
	Variance	0.19936	105060	15048	0.69965	0.40242
	Std. Deviation	0.4465	324.13	122.67	0.83645	0.63437
	Minimum	0.305	68.854	434.8	10.1	-4.1
	Q1	0.49975	165.56	539.21	10.875	-3.1

	Median	0.666	408.75	598.63	11.25	-2.55
	Q3	1.3262	720.15	746.5	11.725	-2.275
	Maximum	1.609	1254.9	875.4	13.5	-1.6
410073	Mean	0.84742	596.07	29.162	10.058	-5.8083
	Variance	0.0157	136120	14.339	0.43471	0.44949
	Std. Deviation	0.12529	368.95	3.7867	0.65933	0.67044
	Minimum	0.614	112.9	22.7	8.8	-7.6
	Q1	0.83425	488.35	26.475	9.525	-6
	Median	0.8585	542.15	28.9	10.1	-5.8
	Q3	0.89175	585.18	31.675	10.575	-5.35
	Maximum	1.145	1700.2	36.2	11.1	-4.7

Table 3. Summary of preliminary data analysis for annual maximum and minimum data series

Parameter	Annual maximum data series	Annual minimum data series
Water Level (WL)	• Highest variability for station 210055. • Higher median values for station 410073 and different from other stations.	• Least variability for station 410073. • Highest variability for station 210055.
Discharge (Q)	• Highest variability for station 419003. • Least variability for station 418058.	• Highest variability for station 419003. • Least variability for station 418058.
Electrical Conductivity (EC)	• Highest variability for station 409061. • Least variability for station 410073.	• Highest variability for station 409061. • Least variability for station 410073.
Water Temperature (T_w)	• Highest variability for station 409061. • Least variability for station 419003.	• Highest variability for station 410073. • Moderate variability for station 409061, 419003, 418058 and 210055.
Air Temperature (T_a)	• Highest variability for station 210055. • Least variability for station 418058.	• Highest variability for station 409061. • Least variability for station 410073.

4.2. Multiple linear regression (MLR) analysis

A multiple linear regression (MLR) analysis was done to find the relationship among the variables T_w as dependent variable and WL, Q, EC and T_a as independent variables. Table 2 shows the summary of the MLR analysis results for annual maximum series at 0.10 significance level. For Station 409061, none of the predictors were significant, for Station 419003, WL and Q were found to be significant, for Station 418058, EC was found to significant, for Station 210055 Q was significant and for Station 410073, WL and Q were significant. Since coefficient of determination (R^2) value for Station 210055 was 0.919 showing strong linear relationship and R^2 for Station 409061 was 0.1385 showing a weak linear relationship.

Table 3 shows the summary of the MLR analysis for annual minimum series. T_a was found to be significant for Station 409061, EC was found to be significant for Station 419003, WL and Q were found to be significant for station 210055 and T_a was found to be marginally significant for stations 419003 and 410073 at 0.10 significance level. Among all the five stations, Station 210055 had the highest R^2 value of 0.4698 indicating the best explanatory power and Station 418058 had the lowest R^2 value of 0.1613 indicating a poor explanatory power.

Table 4. Summary of MLR analysis for annual maximum series

Station	Parameters	Estimate	p-value	Residual standard error	R^2 value	F-statistic value	p-value
409061	Intercept	4.903	0.903	8.336	0.1385	0.6834	0.6131
	WL	0.6318	0.938				
	Q	0.0009568	0.785				
	EC	0.00060604	0.334				
	T_a	0.2332	0.842				
419003	Intercept	19.9736	0.000531	0.8794	0.5505	4.899	0.00907
	WL	-2.5848	0.014525				
	Q	0.0008242	0.077083				
	EC	0.0009217	0.556925				
	T_a	0.2099244	0.123643				
418058	Intercept	31.344167	0.4025	7.261	0.2686	1.285	0.3225
	WL	5.811983	0.3043				
	Q	-0.003728	0.4151				
	EC	-0.021253	0.0795				
	T_a	-0.191095	0.8514				
210055	Intercept	26.8224	5.06e-05	1.244	0.919	48.21	4.653e-09
	WL	0.7848924	0.219				
	Q	-0.0052571	5.32e-10				
	EC	-0.0037001	0.155				
	T_a	0.0878642	0.601				
410073	Intercept	83.0474	0.000313	1.997	0.4654	4.135	0.01414
	WL	-54.693392	0.001952				
	Q	0.006319	0.003836				
	EC	0.016608	0.702143				
	T_a	-0.103430	0.713108				

Table 5. Summary of MLR analysis for annual minimum data series

Station	Parameters	Estimate	p-value	Residual standard error	R^2 value	F-statistic value	p-value
409061	Intercept	1.022	1.17e-11	0.6019	0.176	0.9076	0.4816
	WL	-0.3327	0.754				
	Q	0.0001422	0.774				
	EC	0.00001894	0.883				
	T_a	-0.1877	0.105				
419003	Intercept	11.9392	1.36e-12	0.6221	0.2586	1.396	0.28
	WL	-0.5166994	0.589				
	Q	0.0000204	0.947				
	EC	0.0013952	0.104				
	T_a	0.2828	0.146				
	Intercept	10.6959	4.68e-09				
	WL	0.1065	0.880				

418058	Q	0.000886	0.517	0.6689	0.1613	0.6731	0.6215
	EC	0.0001812	0.813				
	T_a	-0.0512826	0.715				
210055	Intercept	11.00569	1.48e-10	0.6769	0.4698	3.766	0.02271
	WL	-0.7310759	0.0456				
	Q	0.0012535	0.0175				
	EC	0.0007164	0.5878				
	T_a	-0.3214190	0.2275				
410073	Intercept	10.3106	0.00407	0.6035	0.3079	2.113	0.119
	WL	-4.717300	0.17914				
	Q	0.001620	0.15797				
	EC	0.032921	0.42386				
	T_a	-0.313265	0.11623				

4.3. Mann-Kendall (MK) test

Table 4 shows the summary of the MK-test for all the stations for annual maximum data series. Station 409061 showed significant positive trends for WL and Q but showed a significant negative trend for EC. Station 419003 showed no statistically significant trends over the given period of time. Stations 418058 and 210055 showed significant positive trend for WL, and Station 410073 showed significant negative trend for T_w. Overall, Station 409061 showed most significant trend across multiple parameters. The results from the study conducted by Van Vliet et al. (2013) showed that mean water temperature would change by +1.3°C in Murray-Darling basin. The analysis carried out by Graf & Wrzesinski (2020) in order to detect water temperature patters in rivers in Poland revealed diversified positive and negative trends.

Table 5 shows the summary of the MK-test for all the stations for annual minimum data series. Station 409061 showed significant positive trends for WL, Q and T_w but showed significant negative trend for EC. Station 419003 showed no statistically significant trends over the study period. Station 418058 and 210055 showed significant positive trend for WL. And Station 410073 showed significant positive trend for T_w. Overall, Station 409061 showed most significant trend across multiple parameters.

Table 6. Summary of MK test for annual maximum series

Station	Parameters	z-score	p-value	S statistic	varS	tau
409061	WL	2.1994	0.02785	79	1257.6667	0.3419
	Q	2.4814	0.01309	89	1257.6667	0.3852
	EC	-2.5378	0.01115	-91	1257.6667	-0.3939
	T_w	1.0465	0.2953	38	1250	0.1670
	T_a	0.6488	0.5165	24	1256.6667	0.1041
419003	WL	-0.2717	0.7858	-10	1096.6667	-0.04761
	Q	-0.2717	0.7858	-10	1096.6667	-0.04761
	EC	-0.3321	0.7398	-12	1096.6667	-0.05714
	T_w	0.4543	0.6496	16	1090	0.07730
	T_a	0.9676	0.3332	33	1093.6667	0.1582
418058	WL	2.449	0.01433	71	817	0.4152
	Q	1.3295	0.1837	39	817	0.2280
	EC	-1.6793	0.9309	-49	817	-0.2865
	T_w	0.0350	0.9721	2	816	0.0117
	T_a	0.4898	0.6243	15	817	0.0877
210055	WL	3.7785	0.0001578	135	1257.6667	0.5844
	Q	-0.5075	0.6118	-19	1257.6667	-0.0822
	EC	0.4795	0.6315	18	1256.6667	0.078

	T_w	0.5364	0.5917	20	1254.6667	0.08714
	T_a	0.1974	0.8435	8	1256.6667	0.0347
410073	WL	0.6451	0.5189	27	1624.3333	0.098
	Q	0.1736	0.8622	80	1625.3333	0.0289
	EC	-0.99248	0.321	-41	1624.3333	-0.1488
	T_w	-3.4031	0.000663	-138	1620.6667	-0.5036
	T_a	0.34808	0.7278	15	1617.667	0.0550

Table 7. Summary of MK test for annual minimum series

Station	Parameters	z-score	p-value	S statistic	varS	tau
409061	WL	2.9326	0.003362	105	1257.6667	0.4545
	Q	3.3274	0.0008787	119	1257.6667	0.5151
	EC	-3.1018	0.001924	-111	1257.6667	-0.4805
	T_w	2.0152	0.04389	72	1241.3333	0.3208
	T_a	-0.11318	0.9099	-5	1249	-0.022
419003	WL	1.571	0.1162	53	1095.6667	0.2529
	Q	1.6004	0.1095	54	1096.6667	0.2571
	EC	-0.8757	0.3812	-30	1096.6667	-0.1428
	T_w	-0.1818	0.8557	-7	1089	-0.0339
	T_a	0.1818	0.8557	7	1089	0.0339
418058	WL	2.1691	0.03007	63	817	0.3684
	Q	-0.7696	0.4415	-23	817	-0.1345
	EC	-0.9096	0.363	-27	817	-0.1578
	T_w	-1.1223	0.2617	-33	813	-0.1952
	T_a	1.5798	0.1141	46	811.3333	0.2730
210055	WL	3.7785	0.00015	135	1257.6667	0.5844
	Q	-0.2255	0.8215	-9	1257.6667	-0.0389
	EC	1.2407	0.2147	45	1257.6667	0.1948
	T_w	-0.8761	0.381	-32	1252	-0.1400
	T_a	-0.1415	0.8874	-6	1247.3333	-0.0264
410073	WL	0.3723	0.7097	16	1623.3333	0.05818
	Q	0.372	0.7098	1.6	1625.3333	0.05797
	EC	0.1240	0.9013	6	1625.3333	0.02173
	T_w	3.1805	0.00147	129	1619.6667	0.4716
	T_a	-1.4744	0.1404	-60	1601.3333	-0.2248

5. CONCLUSIONS

This study was conducted to identify the current state of knowledge on river water temperature research. It has been found that there has been limited research on river water temperature in Australia as opposed to other countries like Canada. In this study, a data base is compiled on T_w and relevant parameters from five different river stations across NSW. Here, the relationship between T_w and WL, Q, EC and T_a are investigated. Data analysis using boxplots, MLR and the MK-tests were carried out. Results emphasized that the relationships between dependent and independent variables in NSW rivers were complex and mainly site dependent. Some of the predictors like WL and Q showed significance in explaining T_w variability. Further study is being carried out by taking more stations from NSW and carrying out goodness-of-fit test to select the best-fit probability distributions to specify T_w and cluster analysis to explore homogeneous regions in relation to T_w.

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