Estuarine & Marine Water Quality Trend Analysis

FINAL REPORT

September 2022

EP Consulting

alluvium

EcoFutures

EcoFutures recognises and acknowledges the unique relationship and deep connection to Country shared by Aboriginal and Torres Strait Islander people, as First Peoples and Traditional Owners of Australia. We pay our respects to their Cultures, Country and Elders past and present.

Artwork by Vicki Golding. This piece was commissioned by Alluvium Group and has told our story of water across Country, from catchment to coast, with people from all cultures learning, understanding, sharing stories, walking to and talking at the meeting places as one nation.

This report has been prepared by EcoFutures Consulting Pty Ltd and EP Consulting for Southeast Queensland Healthy Land and Water.

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Version:	*Final*
Date issued:	*September 2022*
Issued to:	*Emily Saeck, Healthy Land and Water*
Citation:	EcoFutures, 2022, Draft; Estuarine & Marine Water Quality Trend Analysis, report prepared by EcoFutures Consulting and EP Consulting for Healthy Land and Water
Cover image:	abstract river image, Shutterstock

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1 Introduction

The south east Queensland Healthy Land and Water (HLW), Marine and Estuarine Ecosystem Health Monitoring Program (EHMP) is a long running program focusing on tidally influenced waters in Moreton Bay. Data collected as part of this program are used to help inform the annual HLW Catchment and Waterway Report Card, which grades the overall health of catchments and coastal waterways. Water quality data forms a significant component of the program with nitrogen, phosphorus, turbidity, dissolved oxygen, chlorophyll a, salinity, temperature, and pH all collected on a regular (predominantly monthly) basis over the last 21 years at sites across estuarine and marine environments (Figure 1). The longevity of this dataset provides an opportunity to better understand the spatial patterns in regional water quality and assess the long- and short-term trends.

The aim of this study was to develop a robust and repeatable method to assess water quality trends and their significance in SEQ bays and estuaries. More specifically, we were asked to

1. Develop an analysis protocol that can be applied by HLW on a regular basis;
2. Complete a long-term (15-20 year) and short-term (five year) trend assessment, for nine water quality variables, at individual EHMP sites;
3. Create a user manual and R code to implement the methods; and
4. Provide recommendations for next steps, where further analyses may be required.

This report provides a description of the methodology adopted to provide a robust statistical analysis of water quality trends across all EHMP monitoring sites (Figure 1) and guidance on interpreting outcomes of the analyses presented. Additionally, recommendations are provided for further, more detailed analyses with a goal of identifying drivers of water quality and waterway health.

Figure 1. *Location of Healthy Land and Water marine and estuarine EHMP monitoring sites (white dots) within the different EHMP reporting regions (black boundaries).*

2 Dataset

In total there were 182 sites considered in this analysis across 26 different reporting regions. Of this, 18 reporting regions and 129 sites are located within estuarine environments, while 8 reporting regions and 53 sites are in marine environments. Water quality data from these sites were available between January 2001 through to March 2022, though some sites consisted of fewer samples than others. From 2003 to 2014, sampling was conducted monthly, after which the sampling frequency was reduced to eight times annually, by excluding sampling in January, April, June and July. The water quality constituents assessed as part of this analysis included temperature (°C), salinity (g/L), turbidity (NTU), dissolved oxygen saturation (DOSat, %), chlorophyll a (Chl a, µ/L), total nitrogen (TN, mg/L), dissolved inorganic nitrogen (DIN, mg/L), total phosphorus (TP, mg/L), and filterable reactive phosphorus (FRP, mg/L).

3 Analysis Protocol

The analysis protocol was broken into four iterative steps (Figure 2), which we describe in more detail in the sections below. We have attempted to explain each step with an example from the Logan estuary.

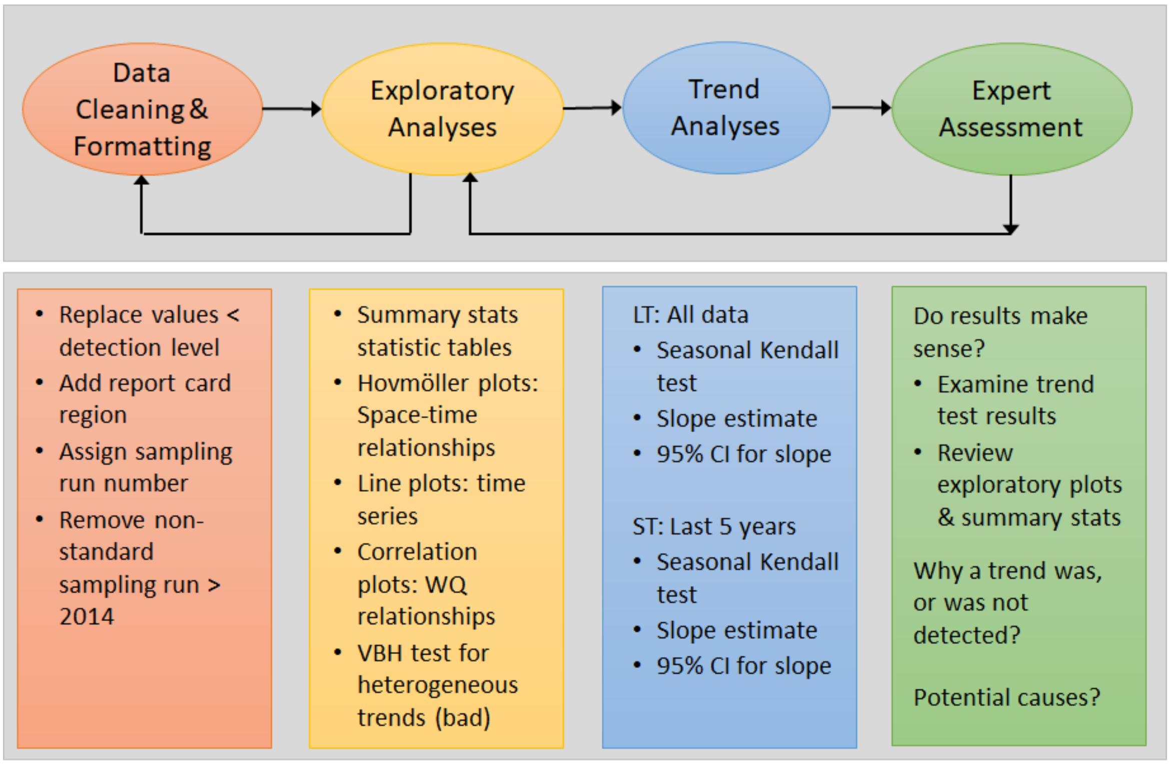


Figure 2. *The analysis protocol has been broken into four iterative steps.*

3.1 Data Cleaning and Formatting

Prior to conducting any exploratory or trend analyses, it was first necessary to clean and format the data. HLW removed values below the detection limit, which were instead replaced with values equal to one half of that detection limit. The raw input data was also formatted so that it contained information relating to EHMP site code, reporting region, adopted middle thread distance (AMTD) from the river mouth, and the date of sampling. From 2001 to 2014, water quality was measured at EHMP sites at monthly intervals. In 2015, the sampling frequency was reduced to eight times per year and samples were not collected in January, April, June and July. The monthly sampling intervals are approximate; meaning that a sample might be collected a few days earlier or later due to weather or tide events, causing it to fall outside the correct “month”. Therefore, we assigned a sampling run number (1-12) to intra-annual measurements to designate which monthly sampling campaign they belonged to. There were a small number of extra samples collected in non-standard sampling runs after 2014 (e.g. Runs 1, 4, 6, 7), which were removed prior to the seasonal trend analyses.

3.2 Exploratory analysis

A range of exploratory plots and tables were developed as a means to quickly interrogate the data. The exploratory analyses were undertaken using R Statistical Software (R Core Team 2022). The full set of tables and plots described in this section have been provided as separate files (see Section 5, Additional Materials for details).

This included summary statistics tables for each water quality variable by bay, estuary, region and site, which can be used to quickly identify errors in the data. An example summary table for several reporting regions is presented in Table 1.

Table 1. Example summary statistics for Turbidity (NTU) for several reporting regions

Group	Min	1st Qu	Med	Mean	3rd Qu	Max	Std Dev	N	Missing
Albert	2	16.8	29	50.6	57	792	72.4	1521	7
Logan	0.9	11	25	60.7	74.8	996	90.8	2669	18
Lower Brisbane	0	11	27	44.6	55	740	60.6	3348	37
Nerang	0	2.5	4	7.1	6.1	343	16.5	2230	0

Hövmoller plots were generated to explore the spatial and temporal trends of water quality in bays, estuaries, and reporting regions. As an example, Figure 3 shows the temporal change in dissolved inorganic nitrogen (DIN) along the length of the Logan Estuary from the river mouth to the upper estuary. A peak in concentrations can be seen to occur in the mid estuary (E00205 and E00206), which roughly corresponds to the location of the Loganholme wastewater treatment plant (WWTP). A decrease in concentrations can be seen in along the temporal axis following 2010, corresponding to improvements in the WWTP and wetter conditions which help flush nutrients from the system. These plots can be used to identify relative hotspots within the space-time record in a given region, where further analyses may be warranted to determine and confirm the drivers of water quality change.

Line plots were created for all water quality variables, by bay, estuary, reporting region and EHMP monitoring sites. These plots are useful for visual assessments of temporal patterns in water quality because they provide a detailed representation of the magnitude of change over time. Figure 4 presents the line plot for DIN for sites in the Logan estuary. This plot suggests that a decrease in the magnitude of DIN concentrations occurred at most sites following 2010, as was observed in the Hövmoller plot.

Lastly, Spearman rank correlation plots were generated to explore the relationship between pairs of water quality variables across all sites in bays, estuaries and different reporting regions. Figure 5 shows the strength of correlation between the variables for the Logan estuary sites. There is a high correlation between the different forms of nutrients and between turbidity and total nitrogen and total phosphorus. By contrast, there is strong inverse correlation between turbidity and salinity, which suggests that increases in turbidity are likely associated with freshwater flow events. Dissolved oxygen concentrations also have moderate inverse correlation to all forms of nutrients, but not chlorophyll a. Interestingly, chlorophyll a does not show a correlation with nutrients within the Logan estuary sites, which may suggest conditions are not ideal for algal growth. In combination this seems to suggest that elevated nutrient concentrations may be leading to increased macrophytes and not algae, which is reducing dissolved oxygen concentrations. This presumption would require further analysis to confirm. However, it provides a useful example of how these plots can be utilised to help develop a better understanding of the causal links between different variables.

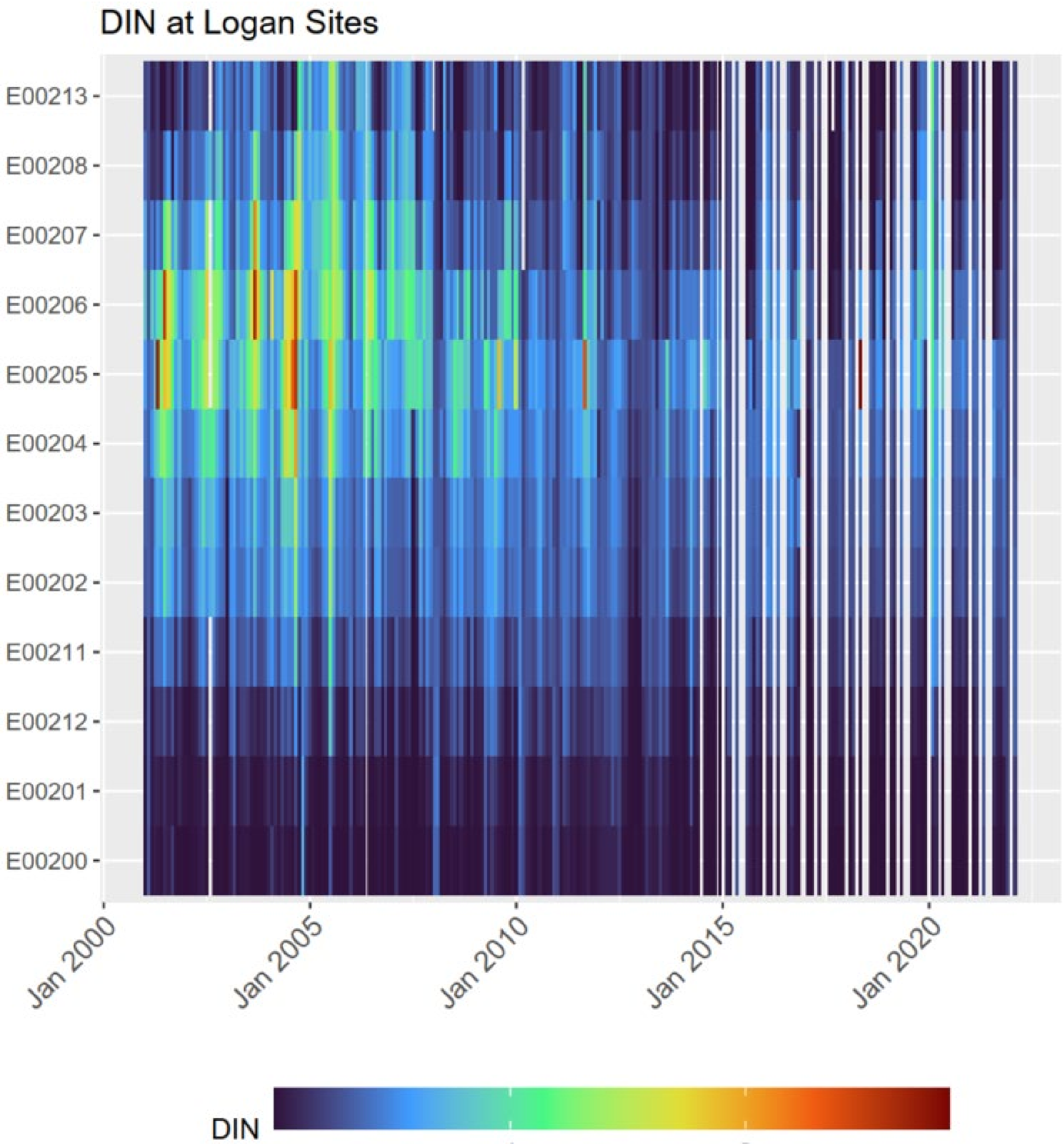


Figure 3. *Hövmoller plot of dissolved inorganic nitrogen in mg/L at the EHMP sites in the Logan estuary over time. Sites (y-axis) are arranged by distance from the river mouth (bottom) to the upper estuary (top) over the whole reporting period (2001-2022). Space-time combinations without colour represent missing data.*

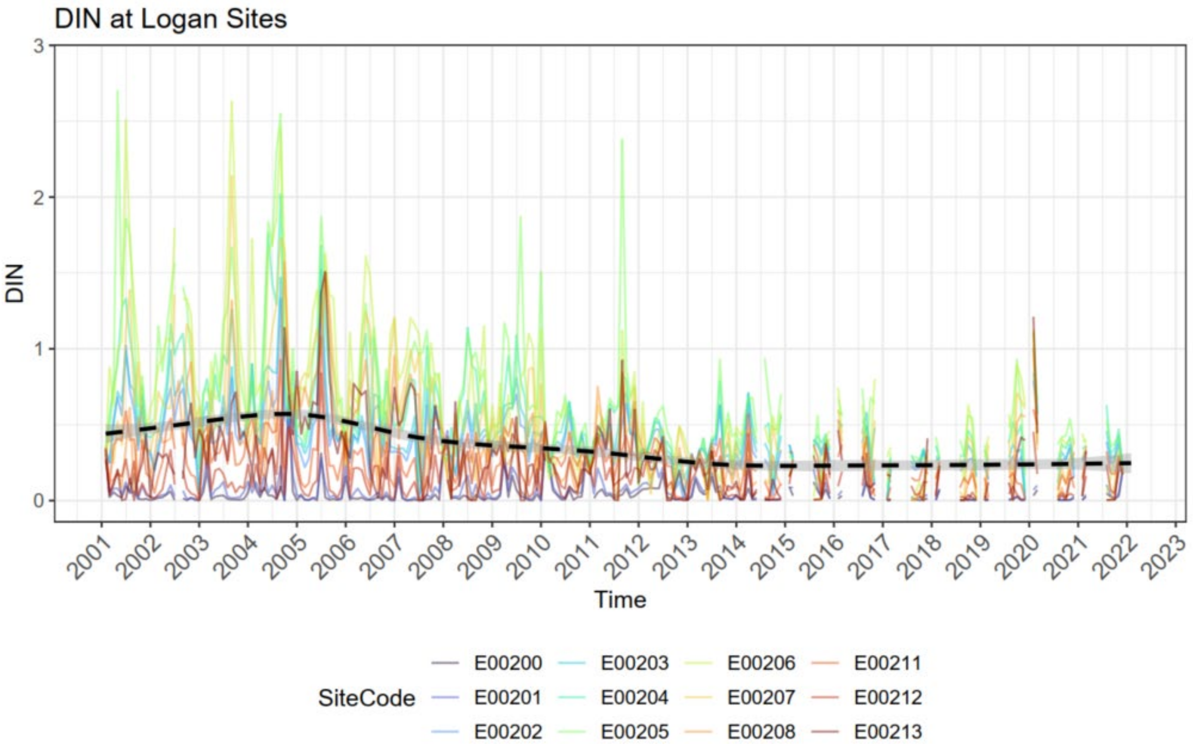


Figure 4. *Line plot of dissolved inorganic nitrogen concentrations (mg/L) over time at all EHMP sites in the Logan estuary. The smooth black-dashed line is fit to all of the DIN data to help highlight the pattern across all sites.*

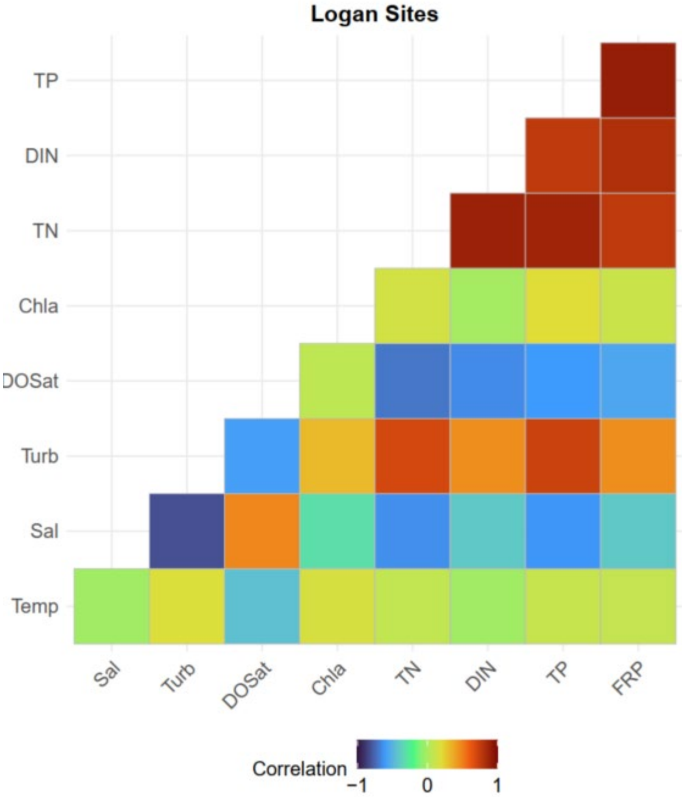


Figure 5. *Spearman rank correlation plot between water quality variables collected at Logan estuary sites.*

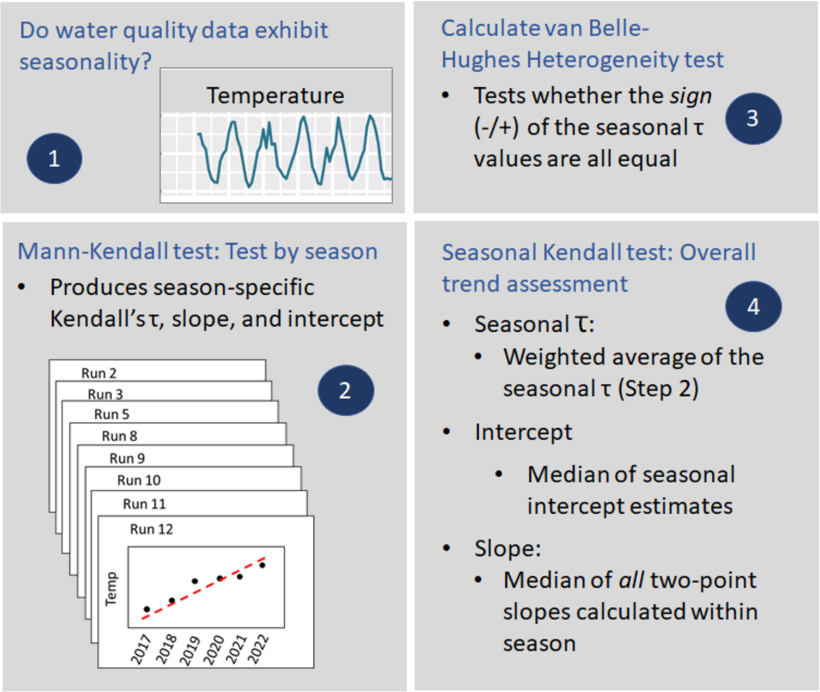
4 Trend analyses

4.1 Description

Many methods can be used for trend assessment (Morton and Henderson 2008; Meals et al. 2011; Beck et al. 2022), but we chose to use the seasonal Kendall trend (SKT) test (Hirsch and Slack 1982) to assess long-term (15-20 years) and short-term (5 years) monotonic trends (i.e. constant linear increase or decrease) for a number of reasons. The SKT test is a non-parametric (does not assume the data follows a particular distribution) extension to the Mann-Kendall test (Mann 1945) that can accommodate the strong seasonal variability present in many water quality samples. The test handles missing data without the need for interpolation or imputation and is relatively simple to implement as there is no need for model selection, making it suitable for running large numbers of trend tests. Thus, it is not surprising that the SKT test has been widely adopted to assess monotonic trends in time series of environmental and streamflow data (Li et al. 2018).

The analysis protocol for the SKT test actually involves a series of tests to assess trends within seasons, test the assumption of monotonic trends, and estimate the overall trend across seasons (Figure 6). It works by grouping data into ”seasons” (e.g. sampling runs). A non-seasonal Mann-Kendall test is applied to each season independently from other seasons, resulting in season-specific estimates of Kendall's τ (i.e. Kendall rank correlation coefficient), a slope parameter estimate, and intercept (Figure 6, Step 2).. The SKT test is only appropriate if the sign (-/+) of all the non-zero season-specific trends in Step 2 (Figure 6) are in the same direction and the van Belle Hughes test for heterogeneous trends (van Belle and Hughes 1984) is used to test this assumption (Figure 6, Step 3). If the data show evidence of heterogeneous trends (e.g. increase and decreases in trend), the SKT test is inappropriate, and another trend assessment method must be used (see Section 6 Next Steps for details). Otherwise, the SKT test is used to combine the season-specific τ, intercept, and slope estimates to obtain information about the overall trend (Figure 6, Step 4).

Please see van Belle Hughes (1984) and Hirsch and Slack (1982) for a more detailed description of the van Belle Hughes and SKT tests, respectively. The trend analyses were implemented in R Statistical Software (R Core Team 2022) and a detailed description of the Mann-Kendall test, van Belle Hughes test, and SKT test as implemented in the EnvStats package can be found in Millard (2013).



- Tests whether the *sign* (-/+) of the seasonal τ values are all equal

- Produces season-specific Kendall’s τ, slope, and intercept

- Seasonal τ:
  - Weighted average of the seasonal τ (Step 2)
- Intercept
  - Median of seasonal intercept estimates
- Slope:
  - Median of *all* two-point slopes calculated within season

Figure 6. *Seasonal Kendall trend test analysis steps. Note that Kendall's* $\boldsymbol{\tau}$ *represents the seasonal Kendall rank correlation coefficient.*

4.2 Results interpretation

The results from the SKT included four key pieces of information: 1) van Belle Hughes test and associated p-value; 2) SKT test statistic (i.e. seasonal Kendall τ) and associated p-value; 3) slope parameter estimate and the associated two-sided 95% confidence intervals for the slope. These outputs were used to assess long-term and short-term water quality trends at all EHMP (Table 2 and Table 3). The SKT test was deemed appropriate if the p-value for the van Belle Hughes test was greater than 0.1 ($\alpha > 0.1$). Otherwise, there is evidence of a non-monotonic trend and the SKT test is inappropriate. If this condition was met, the trend was deemed significant for a given variable at a site if the 95% confidence intervals for the slope estimate did not include 0. In other words, the upper and lower confidence limits were both negative or both positive. If the confidence intervals for the slope include 0, then there is no evidence of a trend. Appendix A provides tables of long- and short-term trends for the water quality variables in all reporting regions.

The results of the trend analyses can be used to spatially assess trends across SEQ for each water quality constituent (Figure 7 and Figure 8). Over the long-term, significant improvements in DIN concentrations can be seen along the Brisbane and Logan estuaries in particular, which correspond to the locations of WWTP upgrades. However, when assessing these trends over the short-term, there was no evidence of a trend at these locations. When used in combination with the exploratory plots, these analyses provide an insightful initial assessment of the spatial and temporal patterns of change but cannot be readily used to determine the drivers of this change.

Table 2. Results of the short-term (2017-2022) trend assessment for EHMP sites in the Logan estuary. Bold values indicate that there was a significant linear trend. Red cells represent a degrading trend and green an improving trend. Underlined values show failure of the van Belle Hughes test, meaning that the seasonal Kendall test is inappropriate.

Site Code	AMTD	Chla (mg/L/yr)	DIN (mg/L/yr)	DOSat (%/yr)	FRP (mg/L/yr)	Sal (g/L/yr)	Temp (°C/yr)	TN (mg/L/yr)	TP (mg/L/yr)	Turb (NTU/yr)
E00200	0	0	**0.0033**	-0.1167	**0.0023**	-0.4167	-0.1167	0.0150	0.0043	-0.0500
E00201	2	-0.1000	0.0053	-0.3500	0.0025	-0.3583	-0.0500	0.0113	0.0046	-0.3125
E00212	4.8	-0.0250	0.0100	-0.0250	0.0025	-0.6167	-0.0833	0.0250	0.0040	-0.2875
E00211	7.8	-0.3167	0.0116	-1.0000	0.0033	-0.5500	-0.0500	0.0417	0.0033	-0.1792
E00202	11.1	-0.0667	**0.0153**	-0.8167	0.0007	-0.8500	0	**0.0400**	0.0029	0.3000
E00203	13.3	0.1000	**0.0140**	-0.1250	0	-1.0125	0.0250	**0.0300**	0.0013	-0.7125
E00204	15.6	0.2375	0.0044	-0.5750	-0.0050	-0.7375	0	0.0213	0	-1.6333
E00205	17.4	**0.7500**	0.0125	-0.3667	-0.0081	-0.5667	-0.0750	**0.0550**	0.0013	-1.0750
E00206	23	-0.0667	0.0215	**-2.0917**	-0.0042	-0.2000	-0.1000	0.0300	0	1.4500
E00207	26.3	-0.5000	0.0293	-2.1750	-0.0020	-0.0750	-0.1000	**0.0438**	0.0017	3.5125
E00208	29.3	-0.7500	0.0033	-2.7083	0.0028	-0.0500	-0.0125	0.0458	0.0060	3.3667
E00213	33	0.4833	0.0012	-1.3583	0.0015	-0.0417	-0.0458	0.0317	0.0058	1.4375

Table 3. Results of the long-term (full dataset) trend assessment for EHMP sites in the Logan estuary. Bold values indicate that there was a significant linear trend. Red cells represent a degrading trend and green an improving trend. Underlined values show failure of the van Belle Hughes test, meaning that the seasonal Kendall test is inappropriate.

Site Code	AMTD	Chla (mg/L/yr)	DIN (mg/L/yr)	DOSat (%/yr)	FRP (mg/L/yr)	Sal (g/L/yr)	Temp (°C/yr)	TN (mg/L/yr)	TP (mg/L/yr)	Turb (NTU/yr)
E00200	0	-0.0133	0	**-0.1323**	-0.0008	-0.0200	0.0172	0.0017	-0.0002	-0.1000
E00201	2	-0.0250	-0.0006	-0.1000	-0.0010	-0.0268	0.0111	0.0008	-0.0005	0
E00212	4.8	-0.0500	**-0.0021**	-0.1355	-0.0008	-0.0886	0.0111	-0.0009	-0.0009	-0.0200
E00211	7.8	-0.0500	**-0.0079**	-0.1075	-0.0019	**-0.1912**	0.0100	-0.0075	-0.0029	-0.0393
E00202	11.1	-0.0458	**-0.0129**	0.0433	**-0.0046**	**-0.2000**	0.0091	-0.0150	-0.0059	-0.2500
E00203	13.3	-0.0250	**-0.0135**	0.0437	**-0.0050**	**-0.2148**	0.0125	-0.0160	-0.0064	**-0.3333**
E00204	15.6	-0.0188	**-0.0228**	0.1292	**-0.0100**	**-0.1871**	0	-0.0241	**-0.0117**	-0.3472
E00205	17.4	0.0433	**-0.0309**	**0.2406**	**-0.0150**	**-0.2073**	0	**-0.0333**	**-0.0161**	-0.4799
E00206	23	**0.1323**	**-0.0396**	**0.5971**	**-0.0175**	**-0.0342**	0	**-0.0500**	**-0.0260**	**-4.2816**
E00207	26.3	0.0800	**-0.0245**	**0.4800**	**-0.0108**	-0.0167	0	**-0.0319**	**-0.0183**	**-3.0000**
E00208	29.3	0.0154	**-0.0150**	**0.4160**	**-0.0067**	0	0	**-0.0209**	**-0.0140**	**-3.4000**
E00213	33	-0.0906	**-0.0087**	**0.3750**	**-0.0050**	0	0	**-0.0160**	**-0.0106**	**-3.7375**

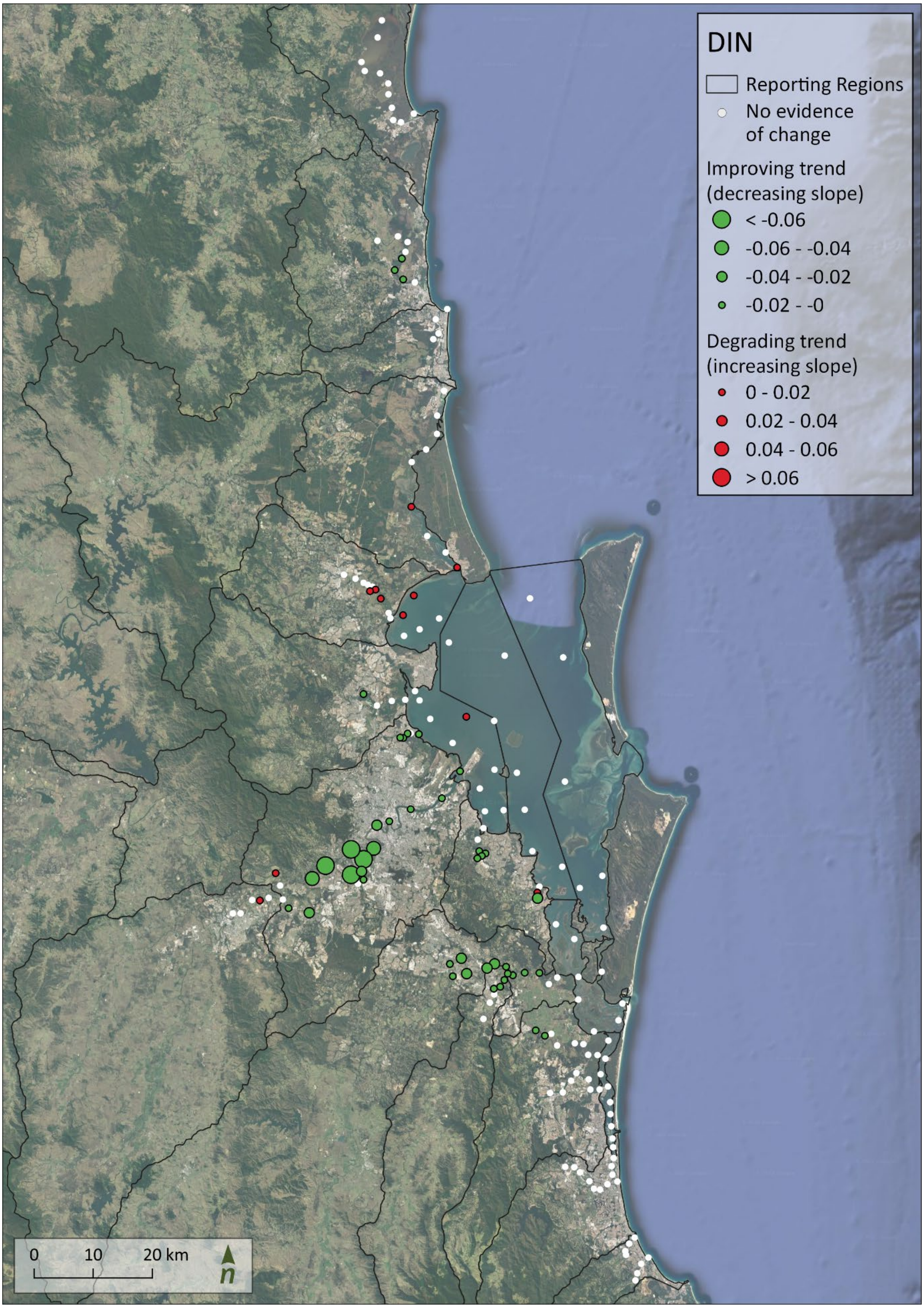


Figure 7. *Spatial distribution of long-term trends in dissolved inorganic nitrogen (mg/L) across EHMP marine and estuarine monitoring sites between 2001-2022.*

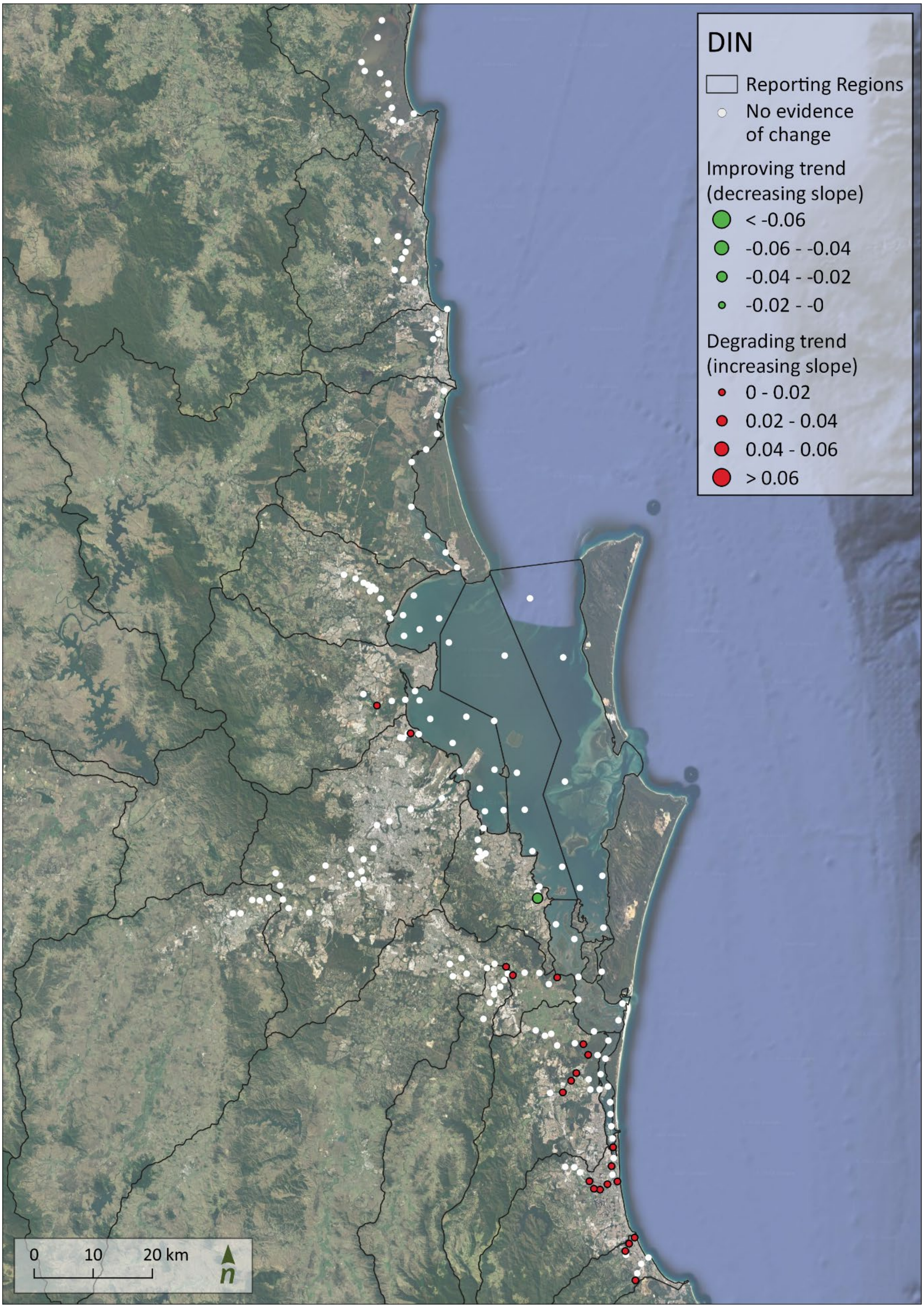


Figure 8. *Spatial distribution of short-term trends in dissolved inorganic nitrogen (mg/L) across EHMP marine and estuarine monitoring sites between 2017-2022.*

5 Additional materials

The R Statistical Software version 4.2.1 (R Core Team 2022) used to implement analysis protocol steps 2-4 (Figure 2), with the exception of the results summary tables (Appendix A) and maps of trends (Appendix B). The full set of summary statistics tables, plots, and SKT test results is provided as supplementary data. An R tutorial has also been developed so that the analyses described in this report can be easily reproduced when more up-to-date data are gathered.

6 Next steps

The advantage of the SKT is that it is easily replicable and suitable for use over many sites for many variables, with relatively little effort. Although the SKT test produced valid trend assessment results for many variables, there were many cases where non-monotonic trends were detected and as such, the test was inappropriate. This is highlighted with failures of the van Belle Hughes test, which occurred much more frequently with the long-term trend assessment and for total phosphorus, filterable reactive phosphorus, and turbidity (Figure 9). It would be worthwhile exploring alternative trend analyses for variables and sites that displayed a greater proportion of non-monotonic trend behaviour.

The percentage of times the van Belle Hughes test failed generally ranged between 0 and 10% for the short-term analysis and between 5 and 30% for the long-term analysis (Figure 10). Spatially, there was no clear pattern between in estuarine or marine environments or any single reporting region, except for Maroochy, which reported the highest failure percentage of any reporting region for both short- and long-term analyses (~30%). Table 4 shows the percentage of time the van Belle Hughes test failed according to water quality constituents for each reporting region. This suggests there is evidence of non-monotonic trends in TP in the Sunshine Coast waterways of Pumicestone Passage, Maroochy, Mooloolah, and Noosa at a much higher rate than other catchments.

This is not surprising because the user-assigned season (i.e. run number) is a relatively crude way to describe seasonality in water quality. Water quality within estuarine and marine environments is influenced by the prevailing climatic conditions as well as anthropogenic factors. Disentangling the climate signal from the water quality data can go some way in providing an indication if water quality improvements are the result of anthropogenic changes or just the climate signal. In estuarine environments the most influential factor relates to streamflow, while in marine environments wind is usually the most important factor. In addition, the SKT test cannot determine if significant trends are the result of changes to management actions (e.g. WWTP improvements or land use change). Future analyses should extend the work presented in this report by developing trend analyses based on detrended data using expected drivers like flow, rainfall and wind (for bay sites).

Generalised additive models (GAMs) are one such technique that can be adopted to remove the climate signal from data in order to better assess trends. In contrast to the SKT, GAMs can be used to model both non-linear and non-monotonic trends. However, this technique requires significantly more diagnostic testing, making it more time consuming to implement across all sites and variables. Alternate approaches involve applying the SKT test to linear model residuals of a function of concentrations against some function of flow (e.g. detrended WQ data). This however, requires stationarity in the streamflow distribution, which may not always be true and so additional predictors may be needed for detrending the data.

Raw flow data from the nearest upstream gauge could be used for the purpose of detrending estuarine sites, while modelled or measured wind data could be used for marine sites. Many of the estuaries monitored are situated in small ungauged catchments, and as such salinity or rainfall could be used as a surrogate. Salinity is measured as part of the EHMP monitoring program across all sites and is therefore likely to be a suitable consistent surrogate for flow. It would be worthwhile investigating which variables are best suited for detrending the data prior to conducting any analyses. In instances where a step change is evident, methods like the Before After Control Impact (BACI) design may be appropriate to determine if the change was the result of a particular anthropogenic change.

The exploratory and preliminary trend analysis conducted in this report provides a good basis in which to select a subset of sites and water quality variables of most interest for an extended more in-depth analysis of trends and the underlying drivers of change. This could involve selecting sites where a step change appears to have occurred, or significant changes in land use have been observed within the catchment. It would be worthwhile focussing on water quality variables that are strongly influenced by the flow regime, such as turbidity and nutrients for future detrending. In many instances there are strong correlations between water quality variables themselves (e.g. total phosphorus and filterable reactive phosphorus) and as such it may not be necessary to conduct a trend assessment on both. In this manner the number of sites and water quality variables to consider can be reduced to allow for a more in-depth analyses.

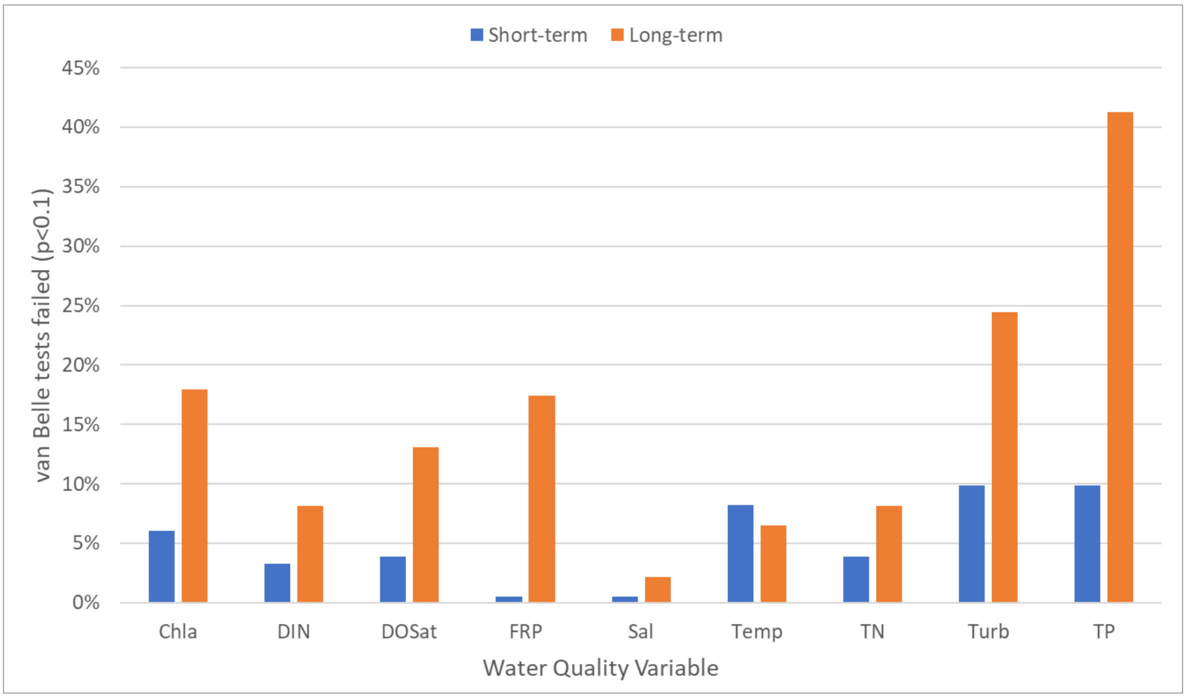


Figure 9. *Percentage of time the van Belle test failed by water quality variable.*

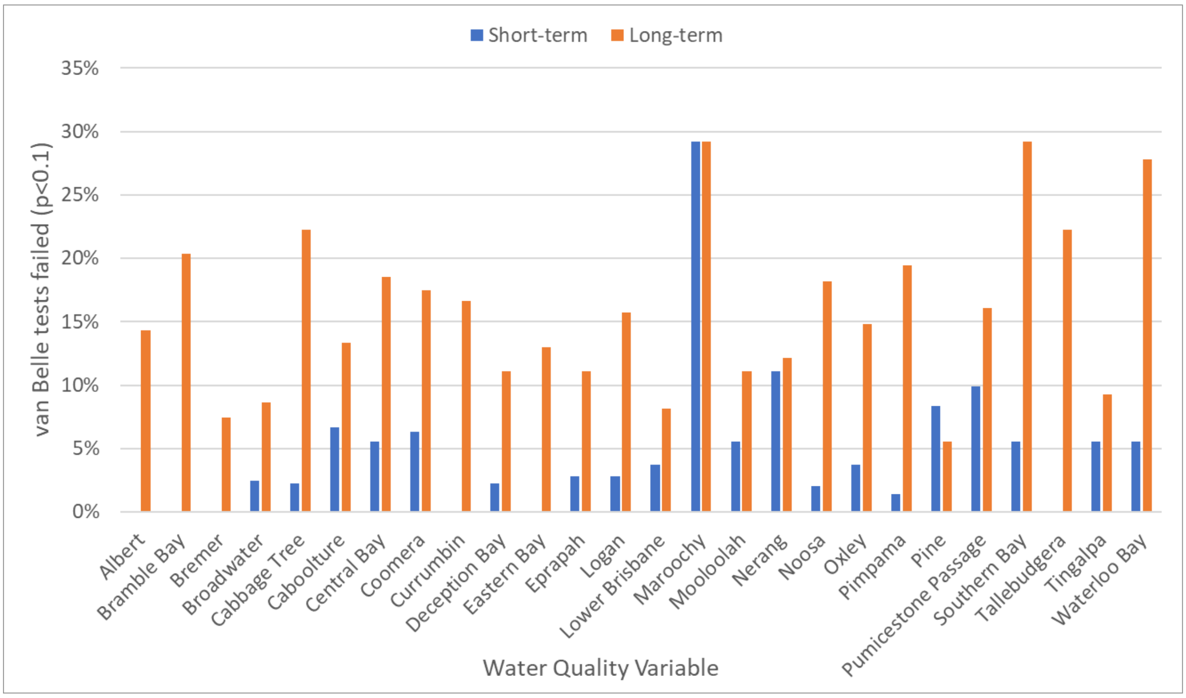


Figure 10. *Percentage of time the van Belle test failed by reporting region.*

Table 4. Percentage of time the van Belle Hughes test failed for the long-term (full dataset) trend assessment by combinations of reporting region and water quality variable

Reporting Region	Chla	DIN	DOSat	FRP	Sal	Temp	TN	Turb	TP
Albert	28.57%	0.00%	42.86%	0.00%	0.00%	0.00%	0.00%	42.86%	14.29%
Bramble Bay	16.67%	0.00%	33.33%	50.00%	0.00%	50.00%	0.00%	16.67%	16.67%
Bremer	0.00%	33.33%	0.00%	0.00%	0.00%	33.33%	0.00%	0.00%	0.00%
Broadwater	0.00%	0.00%	11.11%	0.00%	0.00%	11.11%	11.11%	0.00%	44.44%
Cabbage Tree	40.00%	20.00%	20.00%	20.00%	20.00%	0.00%	20.00%	40.00%	20.00%
Caboolture	0.00%	10.00%	20.00%	20.00%	0.00%	0.00%	10.00%	50.00%	10.00%
Central Bay	0.00%	0.00%	33.33%	50.00%	0.00%	0.00%	33.33%	0.00%	50.00%
Coomera	42.86%	0.00%	14.29%	42.86%	0.00%	0.00%	0.00%	14.29%	42.86%
Currumbin	75.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	25.00%	50.00%
Deception Bay	0.00%	0.00%	40.00%	20.00%	0.00%	0.00%	0.00%	0.00%	40.00%
Eastern Bay	0.00%	0.00%	33.33%	0.00%	0.00%	0.00%	0.00%	16.67%	66.67%
Eprapah	25.00%	0.00%	25.00%	0.00%	0.00%	0.00%	25.00%	25.00%	0.00%
Logan	16.67%	0.00%	0.00%	33.33%	0.00%	0.00%	33.33%	25.00%	33.33%
Lower Brisbane	33.33%	0.00%	6.67%	0.00%	0.00%	26.67%	0.00%	6.67%	0.00%
Maroochy	12.50%	12.50%	0.00%	50.00%	0.00%	0.00%	12.50%	87.50%	87.50%
Mooloolah	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	25.00%	75.00%
Nerang	54.55%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	18.18%	36.36%
Noosa	0.00%	0.00%	9.09%	0.00%	0.00%	0.00%	9.09%	54.55%	90.91%
Oxley	0.00%	33.33%	33.33%	0.00%	33.33%	0.00%	0.00%	33.33%	0.00%
Pimpama	12.50%	37.50%	0.00%	25.00%	0.00%	0.00%	0.00%	37.50%	62.50%
Pine	0.00%	50.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Pumicestone Passage	11.11%	33.33%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
Southern Bay	37.50%	0.00%	12.50%	62.50%	0.00%	25.00%	12.50%	25.00%	87.50%
Tallebudgera	0.00%	0.00%	25.00%	25.00%	50.00%	0.00%	0.00%	50.00%	50.00%
Tingalpa	16.67%	16.67%	0.00%	0.00%	0.00%	0.00%	0.00%	33.33%	16.67%
Waterloo Bay	25.00%	0.00%	50.00%	75.00%	0.00%	0.00%	50.00%	0.00%	50.00%

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