Victorian Water Quality Analysis 2022

Technical Report

Energy, Environment and Climate Action

Authors

Danlu Guo, School of Engineering, College of Engineering, Computing & Cybernetics, Australian National University

Anna Lintern, Department of Civil Engineering, Monash University

Robert Sargent, Department of Civil Engineering, Monash University

Cami Plum, Department of Civil Engineering, Monash University

Leon Sun, Department of Civil Engineering, Monash University

Andrew W. Western, Department of Infrastructure Engineering, The University of Melbourne

Alysha Huxley, Scientell

Paul Holper, Scientell

Judy M. Hagan, Department of Energy, Environment and Climate Action

Paul Wilson, Department of Energy, Environment and Climate Action

We acknowledge and respect Victorian Traditional Owners as the original custodians of Victoria's land and waters, their unique ability to care for Country and deep spiritual connection to it.

We honour Elders past and present whose knowledge and wisdom has ensured the continuation of culture and traditional practices.

DEECA is committed to genuinely partnering with Victorian Traditional Owners and Victoria's Aboriginal community to progress their aspirations.

ISBN 978-1-76136-478-5 (pdf/online/MS word)

Accessibility

To receive this document in an alternative format, phone the Customer Service Centre on 136 186, email customer.service@delwp.vic.gov.au, or contact National Relay Service (www.relayservice.com.au) on 133 677. Available at DEECA website (www.deeca.vic.gov.au).

Contents

Abbreviations

BGA	blue-green algae
DEECA	Department of Energy, Environment and Climate Action, Victoria
DO	dissolved oxygen
EC	salinity/electrical conductivity
EPA	Environment Protection Authority
ERS	environment reference standard
FRP	filterable reactive phosphorus
NO_x	nitrate/nitrite
PCA	principal component analysis
SEPP	State Environment Protection Policy
TKN	total Kjeldahl nitrogen
TN	total nitrogen
TP	total phosphorus
TSS	total suspended solids
VicWaCI	Victorian Water and Climate Initiative

Executive summary

This is a report on the state's water quality status and trend in 2022, required under s.22 of the *Water Act (1989)*.

The Victorian Water Quality Analysis Report 2022 addresses seven questions about surface water quality in Victoria. The first four relate to water quality, of spatial and temporal variability, and seek to reveal how climate variation has, and may in the future, affect water quality.

These four questions are:

1. What is the overall status of water quality in Victoria?
2. How and why does water quality vary across Victoria?
3. How and why has water quality varied over recent decades?
4. How has, and how will, long-term climate variability and change impact water quality?

Questions five to seven address water quality issues of particular relevance to communities. These questions are:

5. How do bushfires affect water quality?
6. How are BGA blooms changing?
7. How can continuous water quality data be used to understand water quality events?

The analysis involves six key parameters regularly collected across the state, each of which has an objective under Victoria's Environment Reference Standard (previously the objectives of the State Environment Protection Policy (Waters). These six parameters are dissolved oxygen (DO), salinity/electrical conductivity (EC), pH, turbidity, total phosphorus (TP) and total nitrogen (TN). Additional parameters are analysed in questions five to seven to address specific interests.

Key findings of this report are:

On water quality temporal trends (Chapter 4):

- Surface water quality in Victoria has varied over the last 27 years.
  - Key factors affecting water quality are: streamflow for EC, pH, turbidity, TP and TN
  - water temperature for DO.
- Higher levels of DO, turbidity, TP and TN occur during wetter periods, and higher EC and pH during drier periods.
- Higher DO concentrations occurred during colder periods.
- Surface water quality has varied over time due to factors other than streamflow and temperature. We refer to these changes as underlying trends in this report.
- The majority of sites have increasing underlying trends in turbidity, pH and TP.
- Turbidity is increasing across almost all of Victoria (regardless of whether it is a mountainous forested area or lowland agricultural area) and this is not due to variations in streamflow.
- There are apparent regional patterns in the trends for EC, TN, TP:
  - EC: There are mostly decreasing underlying trends in more modified catchments, mostly not significant underlying trends in less modified catchments
  - TP: Theses are mostly increasing underlying trends in more modified catchments, mostly not significant in less modified catchments
  - TN: There are mostly significant underlying trends in Murray and Western Plains, and mostly not significant underlying trends in Central Foothills and Coastal Plains/Uplands.

On climate change impacts on water quality (Chapter 5):

- A drying climate under climate change will impact surface water quality.
- Climate change has had an impact on surface water quality, primarily due to the strong relationship between streamflow and water quality.
- Lower streamflow conditions in future are likely to lead to lower levels of DO, TN, TP and turbidity and higher pH and EC.
- The size of these impacts is likely to vary across the state. Larger effects are expected in the central and western parts of the state.
- In addition to water quality changes due to changing flow conditions, climate-related processes other than flow are likely impacting water quality.
- Land use, land management and biogeochemical processes will change under a changing climate and will impact water quality.

On bushfire impacts on water quality (Chapter 6):

- Climate change is also expected to result in an increasing frequency and intensity of bushfires, which is likely to affect water quality.
- Many sites saw the highest or second highest values on record in all parameters analysed (Turbidity, EC, TSS, NO_x, TKN, TP and FRP) following the 2019-20 bushfires. This impact was prolonged, with the impact of these fires experienced to March 2022 at some sites.

On water quality spatial variation (Chapter 3):

- In line with previous analyses, surface water quality varies spatially across Victoria.
- Higher levels of EC, turbidity, TP and TN, and lower concentrations of DO typically occur in lowland agricultural and urban regions of western Victoria, Murray plains, and Melbourne regions.
- Lower levels of EC, turbidity, TP and TN, and higher concentrations of DO typically occur in mountainous forested regions.

On blue-green algal blooms (Chapter 7):

- Focusing on 16 non-potable rural supply reservoirs with recreational BGA warning records since 2007, we see no overarching increase in frequency, duration or start date of BGA warnings.
- The annual average bio-volume levels for Waranga Basin, Lake Nillahcootie and Laanecoorie Reservoir all significantly increased over time, although likely due to statistical artefact due to scum events later in the records for the latter two sites.
- Significant change in the duration of each BGA event is seen in Lake Eppalock, where each event is approximately 16 days longer than the previous one (across a total of 10 events).
- BGA event start dates were significantly later over the data record at Laanecoorie Reservoir and Tullaroop Reservoir each year, with shifts of 1.2 days and 6.6 days later per year, respectively.
- Findings may be impacted by the relatively short period of record (longest records start in 2007) and the relative coarseness of the measure (only 1 or 2 events a year).

On high-frequency DO monitoring (Chapter 8):

- The continuous DO monitoring network has expanded greatly in priority regions in Victoria.
- These continuous data show that the frequency and duration of low and critical DO events are strongly associated with climate variation. Data between 1995 and 2021 showed an increase in low and critical DO events during the second half of the Millennium Drought, with a major peak during the 2010 floods and an uptick in 2021.
- It is noted that data from 2022 was not examined, and therefore the impacts of the 2022 floods was not analysed as part of this study.
- Continuous water quality monitoring can help identify diurnal and seasonal patterns in low DO events – in particular it revealed that hypoxia generally occurs in the early morning and during warmer months.

1. Introduction

1.1 Background

This report on surface water quality has been developed for the Victorian Department of Energy, Environment and Climate Action (DEECA). DEECA has a reporting role for the state's water quality status and trend every five years, required under s.22 of the *Water Act (1989)*.

DEECA's previous Water Quality Trend reports have been unable to adequately account for the drivers of water quality, with no clear trend evident in the data. This may be a result of the methodology used, which included run charts for all sites to summarise water quality change across periods with different hydrologic conditions, and further detailed investigation via regression models at only a limited number of sites. Consequently, this report trials a different approach for assessing water quality in Victoria.

- Rigorous investigation of spatial drivers affecting water quality across the state and within individual regions (using geographic segments of the Environment Reference Standard).
- Statistical modelling that separates long-term trends from other drivers of water quality (such as flow and seasonality), which enables understanding of the changes in water quality over time under various flow conditions and seasons. This contrasts with the previous approach of comparing 'current' and 'historic' values, which may be greatly influenced by significant changes in flow over time, such as drought.
- Using data to quantify spatial variation and temporal trends in water quality and understand their potential drivers, and providing scientifically sound answers to management questions rather than a general discussion of water quality status.

In light of these changes, this report:

- includes analysis of surface water quality data to understand and highlight spatial and temporal patterns in the data
- develops a clear narrative that answers questions relevant to communities, policymakers and stakeholders about the water quality in their waterways
- incorporates key messages and approaches from recent water quality analyses to enhance the water quality story
- Is delivered in four forms: a technical report, an informative policy report, a general public fact sheet and website content, to be included in the Water Management Information System, currently undergoing a major redevelopment.

The report focuses on six key parameters (DO, EC, pH, turbidity, TP, TN) to provide a comprehensive overview of the status of water quality in Victorian catchments and its spatial and temporal variation. In addition, the report also answers questions of management interest, such as the impact of climate change and bushfires on water quality.

1.2 Development of this report

Between July and November 2022, the project team (from the University of Melbourne, the Australian National University and Monash University) worked closely with the DEECA project team to develop components of this report including: defining the management questions to be answered, identifying statistical methods and approaches for answering the questions, and developing graphical concepts to communicate findings.

The work was developed using workshops with a steering committee consisting of staff from DEECA; the Environment Protection Authority (EPA) Victoria; Melbourne Water; and Goulburn-Murray Water as a representative of regional organisations.

1.3 Key management questions

The project team identified questions that would be important to communities, practitioners and policymakers. Initially, 15 questions were presented in the Request for Quote, and through workshopping, this list was reduced to three overarching questions to present water quality for the state, and four more targeted questions that would draw on available resources and link to other work underway.

The seven key questions covering DEECA interest in water quality management are listed below. They are complemented by sub-questions in Chapters 2-8 of this document.

1.3.1 Overarching questions

1. What is the overall status of water quality in Victoria?
2. How and why does water quality vary across Victoria?
3. How and why has water quality varied over recent decades?

1.3.2 Targeted questions

4. How has, and how will, long-term climate variability and change impact water quality?
5. How do bushfires affect water quality?
6. How are BGA blooms changing?
7. How can continuous water quality data be used to understand water quality events?

These questions were identified via a collaborative process between the project team, DEECA and key stakeholders (EPA Victoria, Goulburn-Murray Water). The project team answered the questions using a variety of data-oriented, analytical methods, drawing on water quality monitoring information from across Victoria. The subsequent sections provide more details on the analytical approaches and results, and the findings for each question.

1.4 Data and selection of study sites

Chapter 2 presents an overview of Victoria's water quality status based on the findings from statistical analyses in the subsequent chapters. The analyses of Chapters 3-4 focus on the spatial and temporal variation of water quality, and are based on spot-sampled data of six water quality parameters (turbidity, EC, TN, TP, pH and DO) at a common set of monitoring sites selected based on data availability. Chapter 5 uses a subset of the sites in Chapters 3-4 to explore the impacts of climate change. Chapter 6 is a literature review and thus involved no statistical data analysis. Chapters 7 and 8 are based on two separate datasets: BGA events in Victorian major storages, and continuously sampled DO and turbidity data.

For analyses in Chapters 3-4, we selected the monitoring sites with at least 27 years (1995–2021 inclusive) of spot-sampled data for each water quality parameter, with ≥80% complete data in each quarter of the 27-year period after excluding any cease-to-flow period. Multiple selection criteria combining different duration and data completeness were evaluated, and the final criteria led to the optimal balance between a larger number of selected sites and a long study period. The 27 years between 1995 to 2021 were used as the study period for each site and water quality parameter. This led to a total of 137 study sites selected across the six water quality parameters (turbidity: 103 sites; EC: 118 sites; TN: 103 sites; TP: 105 sites; pH:119 sites; DO: 116 sites), based on the data availability of individual parameters. The analysis in Chapter 4 (analysis of temporal trends) required full years of data, so a few sites with incomplete data in the first/last year or records were removed, resulting in 106 sites for DO, 109 sites for EC, 110 sites for pH, 94 sites for turbidity, 97 sites for TP and 86 sites for TN.

The six digit site IDs and location of these sites is provided in Figure 1, and the site names of all sites are provided in Table 1. The spatial distribution of these sites with respect to catchment conditions and Victorian Environmental Reference Standards (ERS) segmentation are shown in Figures 2-4. The maps of elevation, average temperature, annual average rainfall (Figure 2) and land use (Figure 3), reveal common large scale variations reflecting a gradient from the Victorian Alps in the east to lowland regions about the state with the mountains being colder and wetter and much more likely to have close to natural vegetation cover. The ERS segments broadly represent these trends.

The state is relatively well represented by the selection of study sites, except for the north-western part of the Murray and Western Plains ERS segment (Figure 4 a). That area has many small ephemeral endorheic (internally draining) basins due to its semi-arid climate, flatness and lack of upland high runoff catchments feeding into the region. There is also only one site selected within the Highlands segment, although several sampling sites just outside this region receive flow mainly from the highland region (Figure 4 b).

All abovementioned water quality data analysed in this study were supplied by DEECA. In addition, we acquired various spatial datasets for the analyses in individual chapters, specifically:

- Chapters 3: Spatial data of a comprehensive set of 48 catchment characteristics (including climate, land use, land cover, soil and geology, topography, and hydrology) were obtained to explain the spatial variation of water quality. The 48 characteristics were selected based on a literature review conducted previously to identify the factors affecting spatial variability in in-stream water-quality constituent concentrations (Lintern et al., 2018). These datasets were gathered from multiple sources: Geofabric (Bureau of Meteorology, 2012), Soil and Landscape Grid of Australia (Bureau of Meteorology, 2014; Malone & Searle, 2022; Viscarra Rossel et al., 2014a, 2014b) and DataVic (Department of Energy Environment and Climate Action, 2022a, 2022b), which were originally supplied as gridded spatial datasets, and were then aggregated to catchment-averaged values. The detailed definitions and data sources of individual characteristics are provided in Appendix B: Explanation of the catchment characteristics.
- Chapters 4: A subset of the spatial dataset obtained for Chapter 3 on land use and land cover has been used for identifying study catchments with minimal human disturbance to determine the effect of climate change.
- Chapters 5, 7 and 8: Gridded daily climate datasets (temperature and rainfall) were obtained from the Australian Water Availability Projects (Raupach et al., 2009, 2012) to help interpret the impact of climate change on water quality (Chapter 5), potential drivers of BGA (BGA) events (Chapter 7) and low DO and high turbidity events (Chapter 8). The original data were aggregated to catchment-averaged values and appropriate time scales for individual analyses.

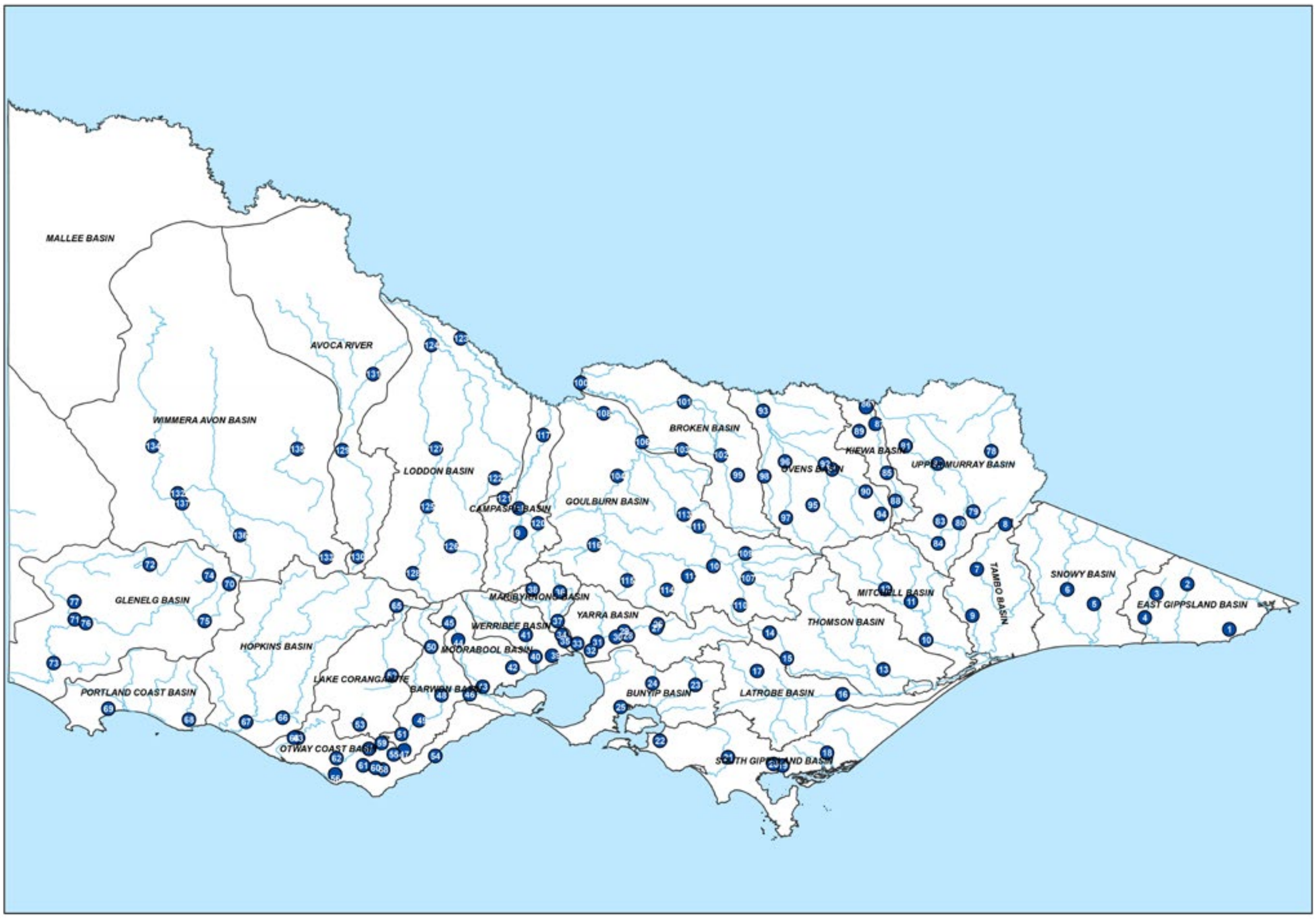


Figure 1: Location and 6-digit site IDs of 137 sites selected for the study. Full site names corresponding to 6-digit site IDs provided in Table 1. The numbers on the dots indicate the index of sites, which are detailed in Table 1.

Table 1: List of the 137 sites used in core analysis in this report, listed by basin, with rivers listed east to west, and upstream to downstream.

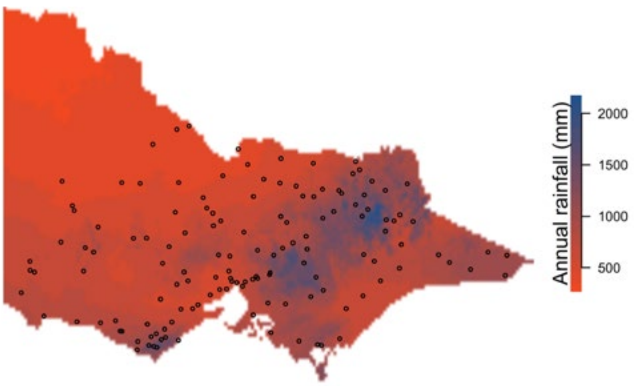
Basin	Index	Site ID	Site name
East Gippsland Basin	1	221208	Wingan River @ Wingan Inlet National Park
	2	221201	Cann River (west branch) @ Weeragua
	3	221211	Combienbar River @ Combienbar
	4	221212	Bemm River @ Princes Highway
Snowy Basin	5	222202	Brodribb River @ Sardine Creek
	6	222217	Rodger River @ Jacksons Crossing
Tambo Basin	7	223202	Tambo River @ Swifts Creek
	8	223214	Tambo River @ U/S Of Smith Creek
	9	223204	Nicholson River @ Deptford
Mitchell Basin	10	224203	Mitchell River @ Glenaladale
	11	224213	Dargo River @ Lower Dargo Road
	12	224206	Wonnangatta River @ Crooked River
Thomson Basin	13	225201	Avon River @ Stratford
	14	225114	Thomson River @ D/S Whitelaws Creek
	15	225210	Thomson River @ The Narrows
Latrobe Basin	16	226228	Latrobe River @ Rosedale (Main Stream)
	17	226226	Tanjil River @ Tanjil Junction
South Gippsland Basin	18	227200	Tarra River @ Yarram
	19	227211	Agnes River @ Toora
	20	227237	Franklin River @ Toora

Basin	Index	Site ID	Site name
	21	227202	Tarwin River @ Meeniyan
	22	227231	Bass River @ Mcgrath Road
Bunyip Basin	23	228248	Tarago River @ Labertouche (Morrisons Road)
	24	228217	Toomuc Creek @ Pakenham
	25	228250	Watsons Creek @ Somerville
Yarra Basin	26	229144	Watts River @ Healesville Racecourse
	27	229232	Yarra River @ Healesville (Maxwell Bridge)
	28	229252	Brushy Creek @ Lower Homestead Road Wonga Park
	29	229608	Watsons Creek @ Henley Road
	30	229250	Andersons Creek @ Warrandyte (Everard Drive)
	31	229229	Koonung Creek @ Bulleen
	32	229231	Gardiners Creek @ Glenferrie Road Hawthorn
	33	229643	Moonee Ponds Creek @ Racecourse Road, Flemington
Maribyrnong Basin	34	230105	Maribyrnong River @ Keilor (Brimbank Park Ford)
	35	230235	Maribyrnong River @ Avondale Heights (Canning St. Ford)
	36	230232	Deep Creek @ Bolinda
	37	230205	Deep Creek @ Bulla (D/S of Emu Creek Junction)
	38	230209	Barringo Creek @ Barringo (U/S Of Diversion)
Werribee Basin	39	231108	Skeleton Creek @ Point Cook Road Laverton
	40	231204	Werribee River @ Werribee (U/S Riversdale Rd. Weir)
	41	231231	Toolern Creek @ Melton South
Moorabool Basin	42	232200	Little River @ Little River (You Yangs Road)
	43	232202	Moorabool River @ Batesford
	44	232204	Moorabool River @ Morrisons
	45	232210	Moorabool River West Branch @ Lal Lal
Barwon Basin	46	233200	Barwon River @ Pollocksford
	47	233214	Barwon River East Branch @ Forrest
	48	233218	Barwon River @ Inverleigh
	49	233224	Barwon River @ Ricketts Marsh
	50	233215	Leigh River @ Mount Mercer
	51	233228	Boundary Creek @ Yeodene
Lake Corangamite	52	234201	Woady Yaloak River @ Cressy (Yarima)
	53	234203	Pirron Yallock Creek @ Pirron Yallock (Above H'wy Br.)
Otway Coast Basin	54	235216	Cumberland River @ Lorne
	55	235202	Gellibrand River @ Upper Gellibrand
	56	235224	Gellibrand River @ Burrupa
	57	235227	Gellibrand River @ Bunkers Hill
	58	235209	Aire River @ Beech Forest
	59	235234	Love Creek @ Gellibrand
	60	235204	Little Aire Creek @ Beech Forest
	61	235205	Arkins Creek West Branch @ Wyelangta
	62	235211	Kennedys Creek @ Kennedys Creek
	63	235237	Scotts Creek @ Curdie (Digneys Bridge)
	64	235203	Curdies River @ Curdie
Hopkins Basin	65	236215	Burrumbeet Creek @ Lake Burrumbeet
	66	236216	Mount Emu Creek @ Taroon (Ayrford Road Bridge)
	67	236209	Hopkins River @ Hopkins Falls
Portland Coast Basin	68	237200	Moyne River @ Toolong
	69	237207	Surry River @ Heathmere
Glenelg Basin	70	238208	Jimmy Creek @ Jimmy Creek

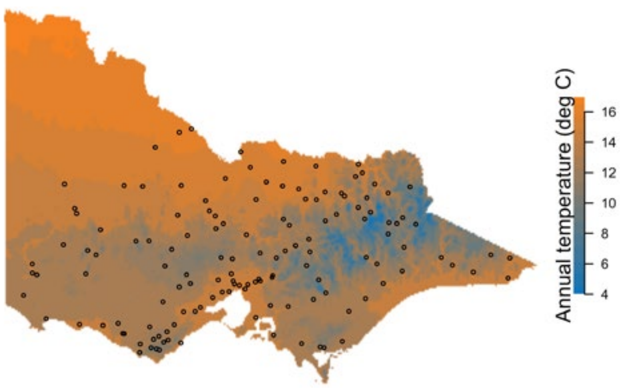
Basin	Index	Site ID	Site name
	71	238202	Glenelg River @ Sandford
	72	238205	Glenelg River @ Rocklands Reservoir
	73	238206	Glenelg River @ Dartmoor
	74	238231	Glenelg River @ Big Cord
	75	238204	Wannon River @ Dunkeld
	76	238228	Wannon River @ Henty
	77	238223	Wando River @ Wando Vale
Upper Murray Basin	78	401212	Nariel Creek @ Upper Nariel
	79	401215	Morass Creek @ Uplands
	80	401203	Mitta Mitta River @ Hinnomunjie
	81	401204	Mitta Mitta River @ Tallandoon
	82	401211	Mitta Mitta River @ Colemans
	83	401216	Big River @ Jokers Creek
	84	401226	Victoria River @ Victoria Falls
Kiewa Basin	85	402203	Kiewa River @ Mongans Bridge
	86	402205	Kiewa River @ Bandiana
	87	402222	Kiewa River @ Kiewa (Main Stream)
	88	402223	Kiewa River West Branch @ U/S Of Offtake
	89	402204	Yackandandah Creek @ Osbornes Flat
Ovens Basin	90	403205	Ovens Rivers @ Bright
	91	403210	Ovens River @ Myrtleford
	92	403230	Ovens River @ Rocky Point
	93	403241	Ovens River @ Peechelba
	94	403244	Ovens River @ Harrietville
	95	403217	Rose River @ Matong North
	96	403223	King River @ Docker Road Bridge
	97	403228	King River @ Lake William Hovell T.G.
	98	403213	Fifteen Mile Creek @ Greta South
Broken Basin	99	404207	Holland Creek @ Kelfeera
	100	404210	Broken Creek @ Rices Weir
	101	404214	Broken Creek @ Katamatite
	102	404216	Broken River @ Goorambat (Casey Weir H. Gauge)
	103	404224	Broken River @ Gowangardie
Goulburn Basin	104	405200	Goulburn River @ Murchison (Mcphee's Rest)
	105	405203	Goulburn River @ Eildon
	106	405204	Goulburn River @ Shepparton
	107	405219	Goulburn River @ Dohertys
	108	405232	Goulburn River @ Mccoys Bridge
	109	405214	Delatite River @ Tonga Bridge
	110	405264	Big River @ D/S Of Frenchman Creek Junction
	111	405251	Brankeet Creek @ Ancona
	112	405209	Acheron River @ Taggerty
	113	405234	Seven Creeks @ D/S Of Polly Mcquinn Weir
	114	405205	Murrindindi River @ Murrindindi Above Colwells
	115	405231	King Parrot Creek @ Flowerdale
	116	405212	Sunday Creek @ Tallarook
Campaspe Basin	117	406202	Campaspe River @ Rochester D/S Waranga Western Ch Syphn
	118	406207	Campaspe River @ Eppalock
	119	406213	Campaspe River @ Redesdale

Basin	Index	Site ID	Site name
	120	406235	Wild Duck Creek @ U/S Of Heathcote-Mia Mia Road
	121	406214	Axe Creek @ Longlea
Loddon Basin	122	407255	Bendigo Creek @ Huntly
	123	407209	Gunbower Creek @ Koondrook
	124	407202	Loddon River @ Kerang
	125	407203	Loddon River @ Laanecoorie
	126	407215	Loddon River @ Newstead
	127	407229	Loddon River @ Serpentine Weir
	128	407214	Creswick Creek @ Clunes
Avoca Basin	129	408200	Avoca River @ Coonooer
	130	408202	Avoca River @ Amphitheatre
	131	408203	Avoca River @ Quambatook
Wimmera Avon Basin	132	415200	Wimmera River @ Horsham
	133	415207	Wimmera River @ Eversley
	134	415246	Wimmera River @ Lochiel Railway Bridge
	135	415257	Richardson River @ Donald
	136	415203	Mount William Creek @ Lake Lonsdale (Tail Gauge)
	137	415251	Mackenzie River @ Mckenzie Creek

a) Annual rainfall



a) Annual temperature



c) Elevation

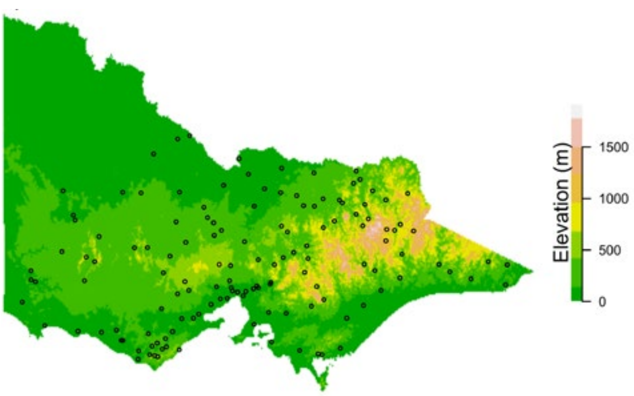


Figure 2: Maps of the full set of 137 selected study sites across six water quality parameters, showing a) annual mean rainfall (mm); b) annual mean temperature (deg C); c) elevation (m).

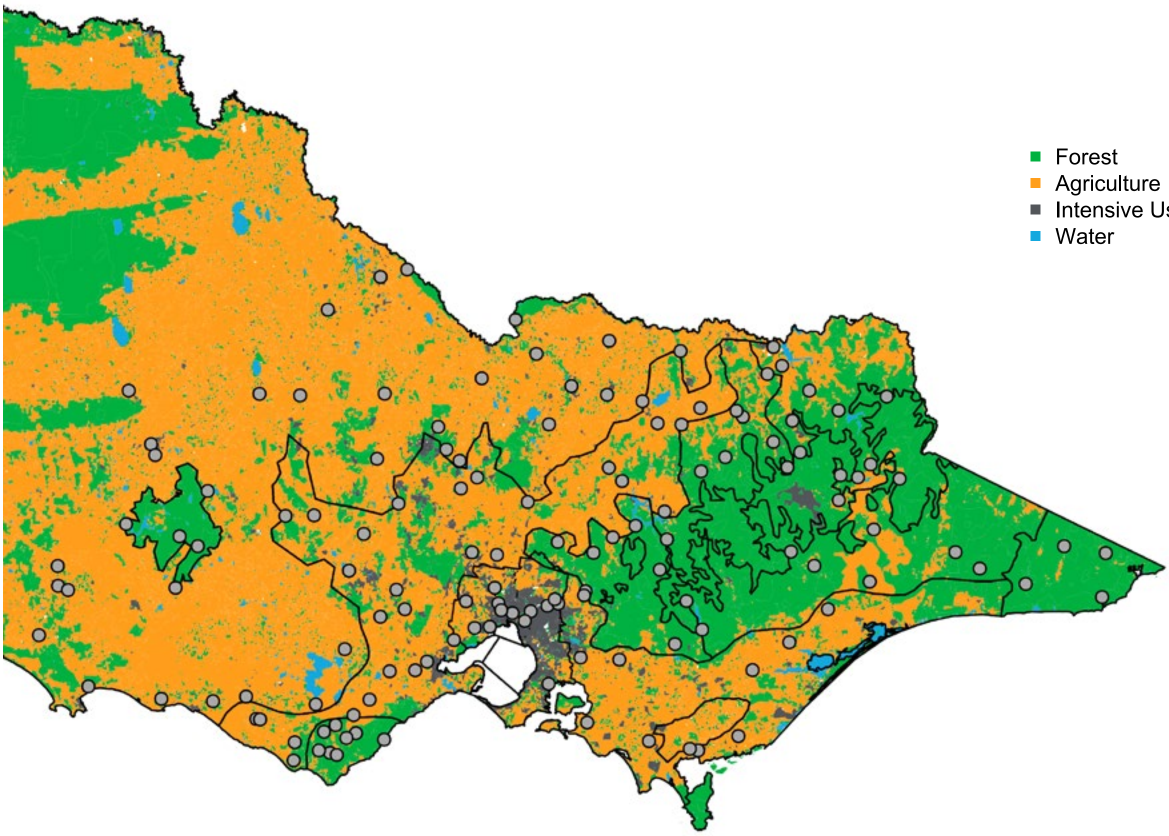


Figure 3: The full set of 137 selected study sites across six water quality parameters, showing key land use categories.

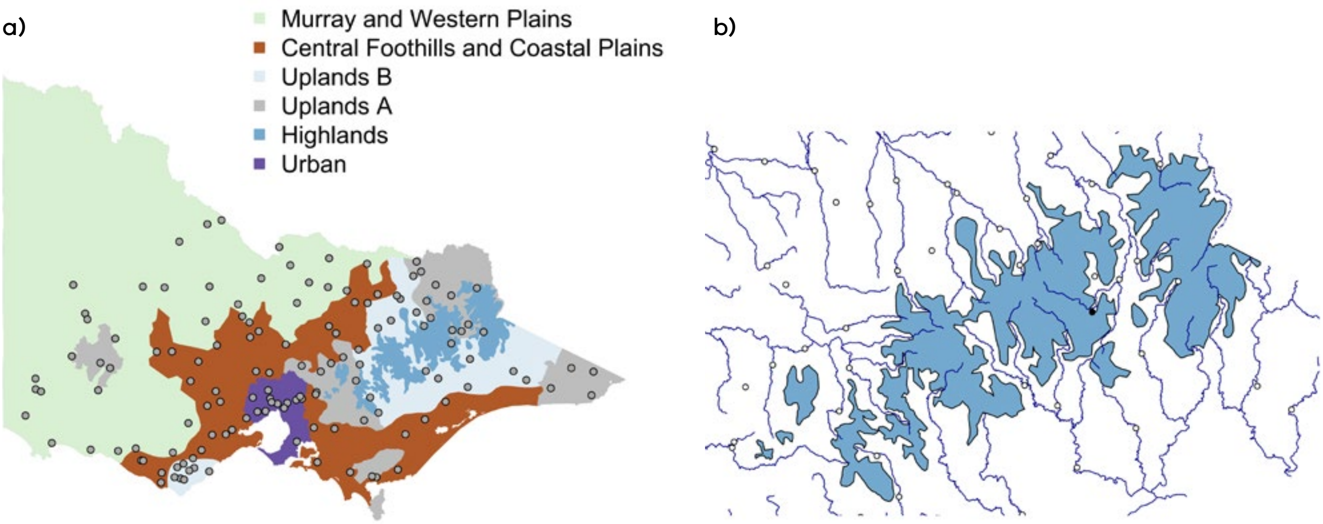


Figure 4: a) The full set of 137 selected study sites across six water quality parameters, showing ERS segments; b) selected monitoring sites surrounding and within the 'Highland' ERS segment and the major streams shown as reference, noting that only one site was selected within the segment (401226 for EC, TP, pH and DO, as highlighted with the solid dot).

1.5 Geographic regions for presenting analysis

A key element of the preliminary work was determining the appropriate geographic boundaries to define different regions to categorise monitoring sites. For example, we needed to consider how upper reaches of waterways may differ in their water quality responses to drivers from reaches in flatter floodplain areas. Basins were not appropriate as they incorporate full river systems from upstream to plains. We determined that the segments defined in the ERS (previously part of the State Environment Protection Policy (SEPP) (Waters)) provided the most suitable initial subdivision of monitoring sites, having already been shown to have distinct inherent water quality characteristics during development of water quality objectives under the SEPP.

For surface waters (Rivers and streams), ERS segments were identified based on their baseline conditions, sensitivities to pollution, and environmental values, specifically:

- characteristics of the water quality, such as pH, nutrients, salinity and DO
- physical characteristics, such as substrate and altitude
- ecological characteristics of the environment, such as biological communities and habitat types
- climatic influences, such as rainfall, temperature, and climate variability
- population pressure and surrounding land use.

The ERS surface water segments (Rivers and streams) were used as they are designed to represent regions of Victoria with different waterways. Different ERS segments often have contrasting land use, land management, topographic, geological and hydro-climatic features, which are likely to contribute to regional differences in water quality to varying degrees (EPA Victoria, 2021).

Six ERS surface water segments are considered as geographic units in this study (Figure 4), and the segmentation generally follows patterns of elevation. The six regions include:

- Highland – rivers and streams in alpine and sub-alpine environments above 1,000 metres
- Uplands A and Uplands B – rivers above 400 metres
- Central Foothills and Coastal Plains, Murray and Western Plains – lowland rivers and streams
- Urban – urban streams of the Melbourne Region.

Appendix A presents details of the six ERS segments and the expected water quality status for each segment.

2. What is the overall status of water quality?

2.1 Background

Water quality is an indicator of underlying catchment and stream condition, underpinning ecosystem health and biodiversity. The quality of water flowing in rivers and streams has a major influence on the water quality and ecological health of receiving water bodies such as lakes, bays and estuaries.

Good water quality is also critical from a social and economic perspective as it affects the suitability of water for a wide range of human uses from recreation to drinking water supplies. In particular, poor water quality imposes significant costs of treatment in water supply systems and can reduce agricultural productivity where used in irrigation or for stock water.

Examples of the impacts of poor water quality include excessive nutrient levels that can lead to eutrophication of water bodies and dangerous algal blooms. Excessive concentrations of sediments, once settled, can smother biota on the streambed. Low DO concentrations can cause stress and potentially death to aquatic biota. All these impacts have been observed in Victoria's waterways at various times.

Maintaining good water quality in Victoria's streams is important given all these potential impacts of poor water quality. Consequently, monitoring of water quality has been an important tool for understanding river health and suitability of water for different uses. Taking stock to examine this data holistically is an important step for understanding the status of water quality in Victoria's streams.

Water quality changes over time and between places for many different reasons. A key aim of this study is to understand how and why water quality varies between places in Victoria and how and why it has been changing over the last three decades. Understanding these differences and pinpointing the underlying causes are critical for designing policies and management strategies to improve water quality.

The study primarily analysed monthly water quality data collected under the Regional Water Monitoring Partnership and stored on the Water Measurement Information System at data.water.vic.gov.au and data supplied by Melbourne Water. Data from 137 sites was included and analysed in this report, including data over 27 years (1995-2021). In addition, other water quality data relevant to individual questions was analysed.

2.2 What is water quality and what influences it?

The term 'water quality' refers to many chemical, physical and biological characteristics of water – typically referred to as water quality parameters. Those focused on here are salinity, turbidity (a measure of water clarity), TN, TP, DO, pH and BGA. These are a suite of fundamental water quality parameters that are routinely measured and provide a basic characterisation of water quality. In addition, algal concentrations in water storages are examined.

Water quality parameters most often refer to a concentration of a substance in the water, for example salt, nitrogen or phosphorus. The specific measures of each of these used here are outlined in Table 2.

The importance of different water quality parameters varies depending on the considered use of water; whether that be sustaining the aquatic environment, irrigating crops, or water for drinking. There are many other parameters that can be important for specific uses, however, they are not considered here.

Every water sample taken will have a unique water signature that is influenced by many factors occurring in the catchment and streams. There is, however, a general framework to assess what might be causing changes in water quality either between places or over time (Lintern et al., 2018a).

The measured value of a water quality parameter is affected by:

- Source: the extent of the material, such as high levels of nutrients on agricultural lands, or saline soils
- Mobilisation: how easily it is mobilised or carried away from the source, such as if it can dissolve in rain water, or be changed by biological, chemical and physical processes
- Transportation: how efficiently it is delivered to the waterway, where it is ultimately measured (Figure 5).

The efficiency of transportation can be affected by biochemical changes such as nitrogen species (e.g. nitrate) being subject to denitrification, leading to some of the nitrogen in the water being lost to the atmosphere. A physical effect on the efficiency of transport is the settling of sediments from the water while it is flowing from the pollutant source to the waterway, thereby reducing the turbidity.

Table 2: General description of water quality parameters and their importance.

Characteristic	Parameter analysed	Importance
Salinity	EC (µS/cm)	Salinity affects suitability for human and animal consumption, irrigation and the habitat quality for various aquatic fauna and flora.
Suspended sediment and water clarity	Turbidity (NTU)	Turbidity affects light penetration into water bodies, is an indicator of fine sediment that can smother fauna and flora, and affects sight distances through water and treatment requirements. Suspended sediments often have attached nutrients.
Phosphorus	TP concentration (mg/L)	Phosphorus can influence the growth of plants and algae in a water body, the food web of the ecosystem. High concentrations can lead to algal blooms.
Nitrogen	TN concentration (mg/L)	Nitrogen can influence the growth of plants and algae, and can lead to algal blooms.
Oxygen content	DO concentration (mg/L)	Oxygen is required to sustain aquatic fauna such as fish, and can have a strong influence on biochemical processes, odours, etc.
Acidity	pH	pH affects a range of biogeochemical and ecological processes. pH close to neutral is desirable.
Blue-green algae	Cell concentration (cells/L), biomass and species	Algal blooms can be toxic, irritate skin and eyes, cause low oxygen content when they die and affect light transmission and aquatic organisms.

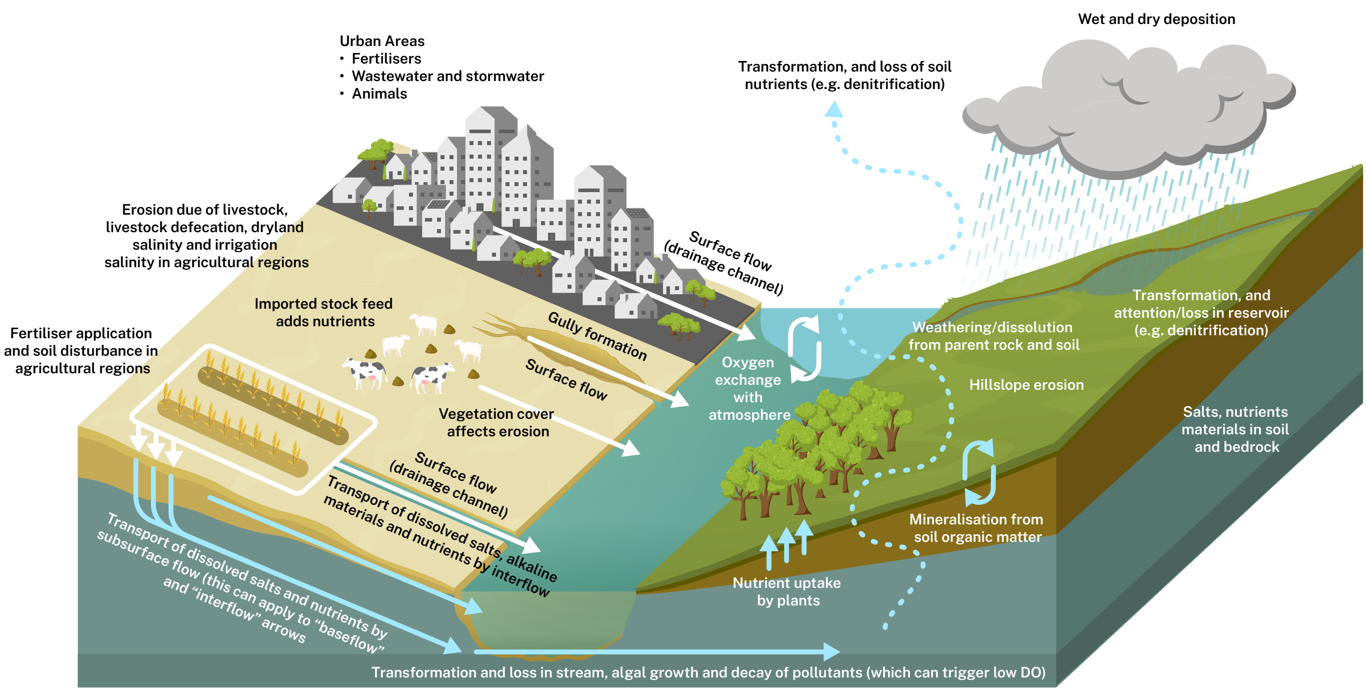


Figure 5: Conceptual diagram of drivers of water quality in catchments.

Substances affecting water quality can be transported to receiving waterways via surface flows across the land and by subsurface flows through the soil or groundwater aquifers, with different flow pathways affecting water quality in different ways. The complexities in these flow pathways can make it difficult to predict and understand the key processes driving water quality variability (over space and time).

The sources, mobilisation and delivery of materials from catchments varies over time and between places. Each water quality parameter is influenced by different environmental and management factors. The following section provides a brief introduction to the water quality parameters addressed in this report.

Salinity reflects the amount of salt in the water. The vast majority of salt in Victoria's waterways comes from natural sources. There are three main origins of salt in our catchments. Rainfall brings significant amounts of salt into out catchments that originate from ocean spray being carried on the wind – rainfall salinity tends to reduce with distance from the coast. Salts are also produced by the slow weathering of rocks. Finally, salts can be trapped in geological formations that were deposited under the sea, such as in larger areas of north-western Victoria that were covered by the sea at various times during the Tertiary geologic period (50 to 1.8 million years ago). Salts are stored for long periods (decades and centuries or longer) in the deeper parts of the soil profile and in groundwater systems. These are the main immediate sources of salt in our streams. Salts are primarily mobilised and delivered to streams by subsurface water flows, so groundwater is important.

The main influences of people on salinity are through changes in the way water moves through our catchments. The clearing of deep-rooted native vegetation leads to increased seepage of water from soils into groundwater aquifers, a process known as groundwater recharge. This results in water tables rising closer to the land surface, increased flows of groundwater towards streams and mobilisation and transport of previously stored salt into the streams. Likewise, irrigation increases groundwater recharge as large volumes of water are applied to irrigated fields. This also increases the mobilisation of salt to streams. Variations in stream salinity between low flow conditions and high flow conditions occur due to changes in the relative contribution of groundwater and surface flows, with groundwater being most important at low flows, resulting in higher salinity.

The brown colour associated with turbidity comes from light absorbed and reflected from material suspended in the water, mostly clays, silts, and organic material, including algae. Turbidity is a surrogate for the concentration of suspended material. Suspended clays have a strong influence on turbidity, and so the types of soils and sediments in a catchment and their susceptibility to mobilisation and transport are critical. Rivers and water bodies naturally carry these materials and they are essential to many ecological systems. However, in excessive amounts, or in the wrong proportions, these suspended materials are significant pollutants. Further, nutrients (especially phosphorus) are chemically bound to suspended sediments, so water turbidity also gives some indication of nutrient concentrations.

In most catchments, the main sources of suspended sediments are natural and dependent on the local soils, sediments and rocks. Sources of sediments include stream banks, erosion gullies, and the hillslopes making up the broader catchment surface. Factors that affect erosion within catchments are important for the mobilisation and delivery of sediments and for turbidity. These include the geomorphic stability of catchments; rainfall patterns; flows of water over the catchment surface, through gullies and streams and (where tunnel erosion occurs) through the subsurface; vegetation conditions and management actions such as cultivation. The clearing of landscapes has triggered episodes of gully and streambank erosion and gold mining has also had a lasting effect on catchments.

People influence turbidity in a variety of ways. Changes and removal of vegetation, particularly ground cover, alongside and within stream channels, and across catchments can affect erosion and thus turbidity. Activities that disturb soils and sediments make them more easily eroded. Actions that change the locations of water flows can lead to erosion and increase turbidity. In general, in south-eastern Australia, erosion of gullies and stream banks has been the major source of turbidity.

Phosphorus sources will be affected by the characteristics of the local rocks and soils and their rates of weathering, which are climate dependent, the addition of fertilisers which depends on land use and management, and the deposition of dung and urine from livestock, which also depends on land use and grazing intensity. Stock feed can be a substantial source of phosphorus. Phosphorus can be removed from a catchment through agricultural products as well as via streamflow, where it affects water quality. Land use is partly climate dependent as climate has an important effect on the suitability of land for agriculture. Mobilisation of phosphorus depends on both rainfall and flows of water, as well as the vegetation conditions, as phosphorus tends to be transported on soil particles and vegetation affects soil erosion. As phosphorus is mainly transported attached to soil particles, its delivery depends on rates of sedimentation, which is influenced by topographic slope, the water flows, the tendency of soils to form fine particles that settle slowly, and vegetation levels. For example, water flowing through heavily grassed areas tends to deposit more sediment along with its associated phosphorus.

Nitrogen cycles between different forms, both through biogeochemical processes within the soil and through plants and animals in catchments. Natural sources of nitrogen include small amounts of nitrate produced by lightning and deposited in rainfall and through biological 'fixation' by plants. Biological fixation converts nitrogen gas from the atmosphere to ammonia and related chemicals in the soil. Air pollution can increase nitrogen deposition, due to higher atmospheric concentrations of various nitrogen oxides. In agricultural landscapes, sources of nitrogen include organic and inorganic fertilisers, fixation by legumes in crops (e.g. chickpeas, lupins) and pastures (e.g. clover, lucerne) and stock feeds. Urban landscapes have similar anthropogenic sources of nitrogen.

Nitrogen in streams takes a variety of chemical forms including nitrate, ammonium, and various organic compounds. Nitrate is highly soluble in water and easily leached from soils into groundwater and streams by subsurface flows. Ammonium tends to be soil-attached and hence surface flows may be more important in its mobilisation, which is also the case for particulate organic forms of nitrogen. The delivery of nitrate and other forms of nitrogen can be affected by transformations in the nitrogen cycle. Organic nitrogen forms are broken down into ammonium through mineralisation and ammonium is nitrified into nitrate. Nitrate is taken up by plants and converted to organic forms. Nitrate is also subject to denitrification – conversion of nitrate to nitrous oxide (a potent greenhouse gas) and then to nitrogen gas which forms 78% of the atmosphere. Denitrification is strongly favoured by wet conditions where there is a lack of oxygen, and organic matter present. Hence denitrification occurs most in waterlogged conditions. Another important pathway for the removal of nitrogen from catchments is in agricultural produce. The largest management influences on nitrogen loss from catchments relate to the timing, amount, and chemical form of nitrogen additions to the landscape as fertiliser.

Water acidity is measured by pH, reflecting the concentration of hydrogen ions. A value of 7 represents neutral conditions, lower values indicate acidic conditions and higher pH shows basic or alkaline conditions. The pH of natural waters is usually in the range of about 6.5 to 8.5, varying depending on the amount of rainfall, and the soil and geological characteristics of a catchment. Alkaline rocks such as limestone and alkaline soils are an important influence on water pH, with environments with limestone having higher pH. High rainfall tends to increase acidity by leaching alkaline minerals from soils and reducing their acid neutralising capacity. There are many management influences on soil pH which affect the pH of stream water by leaching of various chemicals. Management influences include the acidifying effect of fertilisers, particularly nitrogen fertilisers, leaching of nitrate, and the removal of plant and animal products. The addition of soil ameliorants such as lime that increase soil acid neutralising capacity and soil pH is a common practice to maintain appropriate soil pH for agriculture and gardens.

The influences on DO concentration in water contrast strongly with the water quality parameters discussed above. Any water body is continually exchanging oxygen with the atmosphere; oxygen is being produced by any algae or aquatic plants growing in the water, and it is being consumed by the decay of any organic material in the water. The exchange of oxygen with the atmosphere depends on the relative concentrations of oxygen in the water and the atmosphere. There is an equilibrium or balance point where the net exchange is zero. This equilibrium point depends on water temperature and atmospheric pressure and the rate of exchange depends on how far away from the equilibrium point the water DO concentration is and on the rates of mixing, which are strongly influenced by streams flow velocities. Turbulent streams with lots of white water, as occurs in mountainous areas, have much more rapid transfer of oxygen than sluggish lowland streams. Very low DO concentrations are typically caused by a combination of low mixing and high amounts of organic matter decaying in the water. Low mixing can be exacerbated by density stratification due to warm water sitting above cooler water or saltier water below fresher water which can occur during low flow conditions. High organic matter concentrations can be due to a variety of causes such as floods washing organic matter into the stream, a cause of so-called black water events during flood conditions, or by polluted water entering a stream. Algal blooms can produce very high DO levels due to high photosynthesis but can also cause low levels when they die and algal biomass decays. Management can affect DO directly through river regulation affecting flow rates and mixing, and indirectly through actions that affect the amount of organic matter in streams, such a high nutrient levels that can lead to algal blooms. DO can vary across a 24-hour period due to changes in photosynthesis, with highest concentrations in the afternoon and lowest in the early morning.

The final water quality parameter in focus in this report is BGA, also known as cyanobacteria. Photosynthesis is the key energy source for any ecosystem and the many types of algae are important photosynthesisers. Where the growth of one or more species of algae greatly exceeds the combination of its consumption by organisms higher in the food chain and its death rate, algal blooms can form, resulting in accumulation of algae. Blue-green algal blooms are of particular concern as they can be toxic, as well having a range of other negative impacts. These algal blooms favour high nutrient levels, high light and still water. There are complex interactions between these factors making algal blooms difficult to predict. Density stratification can be important in producing still water conditions as vertical mixing is suppressed and BGA are slightly buoyant and can accumulate at the surface where there is much light.

The above descriptions show that there are a wide range of natural and anthropogenic factors that influence water quality. These factors vary between water quality parameters. There are also interactions between water quality parameters as demonstrated with DO and blue-green algal blooms. The factors influencing water quality change with the seasons and between dry and wet years. The factors also vary from place to place. Strong relationships exist between the natural characteristics of land and its suitability for various uses. The mountains tend to be forested, steep, have high rainfalls and be cooler. The lowlands tend to be used for agriculture, but the specific types of agriculture are strongly influenced by the climate and soil suitability. Most urban areas occur on the flatter lowlands. This interrelationship between natural and anthropogenic factors presents a challenge in teasing apart their specific influences, as will be seen in Chapter 3. This understanding of factors influencing water quality has informed our analysis and is expanded on in each chapter.

2.3 The status of water quality in Victoria

2.3.1 Variability over space and time

There is a marked difference in water quality spatially across Victoria. There is poorer water quality (higher EC, turbidity, TP and TN, lower DO) in lowland agricultural/cropping and urban regions, and better water quality in mountainous regions (See Chapter 3 for more details). This finding is in line with previous studies (Lintern et al., 2018a or 2018b; Sadayappan et al., 2022) where water quality parameters are higher (for EC, turbidity, TP and TN) and lower for DO in lowland regions that have high levels of human activity, compared to mountainous regions set aside for conservation.

Water quality also varies over time. The key factors affecting water quality in the short-term (within years) in Victoria are streamflow (for EC, pH, turbidity, TP and TN) and water temperature (for DO) (See Chapter 4). These findings accord with those from previous Water Quality Trend reporting in Victoria, with previous studies, and studies from other regions such as the United States (Guo et al., 2019; Zhi et al., 2023). We observe higher DO, turbidity, TP and TN during wetter periods, and higher EC and pH during drier periods. We have also observed higher DO concentrations during colder periods.

After accounting for the effects of flow and seasonality, more than half of sites in Victoria have increasing trends in turbidity, pH and TP. Almost all areas (regardless of whether they are a mountainous forested area or lowland agricultural area) are experiencing increasing trends in turbidity – above any effects of changes in streamflow. At least half of the lowland agricultural sites have experienced increasing TP trends, while the mountain areas have not. While pH shows increasing trends, these are small, and stream pH levels generally remain between 6.5-8.5, which is generally considered acceptable.

Nutrients in rivers are particularly of concern due to the blue-green algal blooms that can result when nutrient concentrations are high. An analysis of 16 major water bodies and reservoirs across Victoria found that since 2007, and subject to the sometimes significantly shorter records at each water body, there has been no statistically significant change in the frequency or duration of blue-green algal bloom events, as represented by the period of recreational warnings due to algal blooms (see Chapter 7). An important caveat on this analysis is that the recorded lengths for BGA are short and hence only large changes are statistically detectable.

Continuous water quality monitoring data show that low and critical DO events increased in frequency and duration from 2000 during the Millennium Drought, but since 2010, have declined to a near-steady level. The continuous water quality monitoring data identified the diurnal and seasonal patterns in low DO events. Hypoxia generally occurs in the early morning and during warmer months (see Chapter 8). This is in line with global research (Blaszczak et al., 2023).

2.3.2 How water quality will change with climate change and bushfires

The impact of climate change on water quality is poorly understood. It is expected that changes in water flow patterns, chemical reactions and human activities will all affect stream water quality under climate change (Whitworth et al., 2012; Winter et al., 2023). The analysis suggests that under climate change we may experience lower DO, TN, TP and turbidity due to the strong influence of streamflow on these constituents (Chapter 5). However, there is still significant uncertainty regarding the biogeochemical constituent processes under climate change; there may be unexpected shifts in water quality in future.

In addition, climate change is expected to result in an increased frequency and intensity of droughts. Previous studies have indicated that drought can result in a change in the water quality processes within catchments for both nitrogen (Winter et al., 2023) and salts (Lintern et al., 2023). We found that the Millennium Drought led to shifts in EC and TN concentrations that cannot be explained by the decline in streamflow alone. These shifts may be due to changes in flow paths, biogeochemical processes or human activities within the catchments.

Due to its effects on streamflow, it is more difficult to identify the impact of climate change on water quality parameters in streams and rivers.

Despite this uncertainty, we do have empirical evidence of the impact of bushfires on water quality. All water quality parameters were the highest or second highest concentrations on record at many sites affected by the 2019-20 bushfires. It appears that this impact was prolonged, with the impact of these fires occurring until at least March 2022 at some sites, likely due to the continual flushing of contaminants from the landscape during rainfall events and to the temporary storage and remobilisation by high flow events of materials in river systems. Under climate change, bushfires are likely to become more frequent, and rain events will likely become more intense, presenting a risk to water quality. International research indicates that bushfires pose a threat to water security (Robinne et al., 2021; Rust et al., 2018).

3. How and why does water quality vary across Victoria?

3.1 Summary

Water quality varies across Victoria, influenced by a variety of landscape features. Some of these features are natural and some are related to human activities. A wide range of landscape features were examined to determine their influence, including climate, hydrology, topography, soils and geology, land use and land management. The relative importance of natural and human factors varies between water quality parameters. It can be difficult to tease the impact of these natural and human factors apart based purely on data analysis. However, the combination of analysis results and our knowledge of the underlying processes influencing specific water quality parameters enables us to comment on the likely relative impacts of human and natural factors across the state.

A common spatial pattern to the multiple water quality parameters evaluated here is a marked difference in levels between cooler mountainous forested regions and warmer lowland agricultural/cropping and urban regions, where the latter generally have poorer water quality (higher EC, turbidity, TP, TN with lower DO).

These spatial patterns of water quality broadly align with ERS regions (see Chapter 1.5 *Geographic regions for presenting analysis*). Regions with more intense human activities (agriculture, cropping, grazing and urbanisation) and landscape modification generally have poorer water quality. Specifically, the Murray and Western Plains, the Central Foothills and Coastal Plains and the Urban ERS segments have the highest overall turbidity, EC, TN and TP concentrations, higher pH (slightly more alkaline), and the lowest overall DO concentrations. These segments also tend to have greater between-site variation of water quality. In contrast, the Uplands A and Uplands B segments have lower levels of recorded parameters with low between-site variations. While the Highlands segment is represented by only one site, several sites within Uplands A and B are immediately downstream of their boundary between the Highlands, suggesting equivalent water quality status for the Highlands.

We analysed a comprehensive set of 48 catchment characteristics including climate, hydrology, topography, soils and geology, land use and land management to further understand factors associated with the spatial variation of water quality. Appendix B contains the full list of the 48 catchment characteristics. There are strong relationships between many of these factors. For example, the Victorian Alpine regions are cooler all year, have high precipitation, have perennial streams with high runoff, are generally forested, steep and subject to relatively low human disturbance. In contrast, many lowland regions are warmer, have lower rainfall, more intermittent streams with lower runoff, are cleared, flatter, and are subject to intense human management. Most (>85%) of the spatial variations of the 48 catchment characteristics across Victoria can essentially be reduced to two underlying spatial patterns (or principal components), meaning that the catchment characteristics often follow similar spatial patterns, making it extremely difficult to attribute the water quality spatial variation to individual catchment characteristics.

Much of the systematic variation in water quality between catchments follows the dominant spatial patterns in catchment characteristics highlighted above. There is also significant local variation which is likely related to the local characteristics and processes of individual catchments. Nonetheless, the effects of the catchment characteristics can be considered as variation along a continuum between two extreme types of catchments with contrasting water quality:

(i) the warmer, drier, lowland catchments with greater proportions used for agriculture and intense usages, versus

(ii) the colder highland catchments with higher rainfall, greater proportions of natural and forested lands.

Water quality is poorer in the first type of catchment. There is higher turbidity, TN and TP, lower DO and greater salinity (higher EC).

3.2 Introduction

It is well known that water quality varies spatially. Catchments and streams in different regions have different characteristics such as land cover, land management and hydro-climatic conditions, which are all likely to influence water quality outcomes. This section addresses the question of *how and why water quality varies across Victoria*. This is divided into two sub-questions:

1. How does water quality vary spatially across Victoria, as well as within individual ERS segments?
2. What natural and anthropogenic influences are important in explaining the spatial differences in water quality observed in 1)?

This section focuses on typical conditions of water quality and catchment characteristics. There are many natural and anthropogenic catchment characteristics that influence water quality parameters and the focus of sub-question 2) is on trying to tease apart these different influences.

3.3 Summary of approach

Water quality at any site varies over time. To focus on the spatial variation, all analyses within this question focus on the overall water quality across the full study period (27-years from 1995 to 2021; see details in Chapter 1.4 *Data and selection of study sites*) with all water quality records available at individual sites. As such, the potential drivers of the spatial variation of water quality considered here are 'static' catchment characteristics (e.g. soil type, topography, average land use over time). Changes in water quality over time are examined later in Chapter 4.

The typical water quality at each site was represented with the 25th, 50th and 75th percentile[1] values for each water quality parameter. These percentiles were mapped across the state and were further summarised for each ERS segment (as detailed in Chapter 1.5 *Geographic regions for presenting analysis*).

The ERS surface water segments should represent similar waterway conditions. ERS segments were derived with consideration of:

- characteristics of the water quality, such as pH, nutrients, salinity and DO
- physical characteristics, such as substrate and altitude
- ecological characteristics of the environment, such as biological communities and habitat types
- climatic influences, such as rainfall, temperature, and climate variability
- population pressure and surrounding land use.

However, there are other physiographic characteristics that are also likely to influence water quality in both natural and disturbed catchments, and create variation within ERS segments. So, to examine the role of catchment characteristics in the spatial variation of water quality, we undertook a state-wide spatial analysis using a set of 48 catchment characteristics selected for being of most relevance to key water quality parameters based on existing knowledge (see detailed justification and relevant datasets in Chapter 1.4 *Data and selection of study sites*). We conducted multi-variate statistical modelling and a principal component analysis (PCA) to understand the individual and combined effects of the 48 predictors on water quality variation across the state.

There is overlap in the information embodied in the ERS segment mapping and the set of 48 characteristics used here; however, there are also important differences. The ERS surface water segments were identified based on the baseline conditions of Victorian waterways, their sensitivities to pollution and environmental values, which broadly reflect the land use, land management, topographic, geological and hydro-climatic features of the contributing catchments. The 48 catchment characteristics used here represent physiographic landscape characteristics with more detailed representation of anthropogenically-driven landscape disturbance.

Our analysis provides additional value by: i) including land use and management and a range of additional natural drivers; ii) understanding the individual and combined impacts of catchment characteristics on each water quality parameter; and iii) understanding the water quality differences within individual ERS segments.

The detailed analytical method used in this section is described in Appendix C. Appendix A includes the detailed descriptions of the six ERS surface water segments used as an initial basis of subdivision of site-specific results.

3.4 Results

This results section consists of two parts. The first assesses how each water quality parameter (EC, turbidity, TP, TN, pH, DO) varies between individual monitoring sites using the 25th, 50th and 75th percentile for each site and water quality parameter. These three percentiles are representative statistics for site-level water quality conditions. The spatial variabilities of each parameter are described from the perspective of the key natural and anthropogenic processes that drive them. The variation of each parameter is then summarised by ERS segment to assess water quality at the segment level.

The second part then relates the spatial patterns of each water quality parameter to the catchment characteristics and is presented in the sub-section titled Chapter 3.4.3 *Key factors related to water quality spatial variation*.

3.4.1 Spatial variation of water quality parameters across catchments

For each of the six water quality parameters evaluated, the 25th, 50th and 75th percentiles were extracted from individual monitoring sites and used to analyse their spatial variation (see details in Appendix C). The monitoring sites were selected based on availability of long-term records (see Chapter 1.4 *Data and selection of study sites*) so that they sufficiently represent the overall water quality condition of that location.

[1] A particular percentile is the value below which a given percentage of sample values are found. For example, one quarter (or 25%) of samples have a value less than the 25th percentile.

As will become apparent in the results below, a common overall spatial pattern to the six water quality parameters evaluated is a marked difference in concentrations/levels between cooler mountainous forested regions and warmer lowland agricultural/cropping regions, where the latter generally has poorer water quality (higher EC, turbidity, TP, TN with lower DO). The parameter-specific spatial patterns are detailed in turn below and the potential causes of these patterns are described. The spatial patterns of each water quality parameter are highly consistent across the different (25th, 50th and 75th) percentile levels over the period of record; thus, only the maps for the 50th percentiles are shown and discussed in the main report. Appendix D: Supplementary results for water quality spatial variation (Chapter 3) contains the detailed results for all three percentile levels.

EC

In Victoria, the spatial pattern of EC displays a distinct gradient from east to west, where the latter generally has higher EC levels (Figure 6). In addition, there is a marked difference of EC between colder mountainous forested regions (lower EC) and warmer lowland agricultural/cropping regions (higher EC). There is high variation between sites within the Central Foothills and Coastal Plains and the Murray and Western Plains ERS Segments.

EC (measured in µs/cm) is the indicator of salinity (i.e. concentration of salts) in rivers. The aridity of catchments is a key natural determinant of salinity levels as the high proportion of rainfall becoming evapotranspiration in drier catchments leads to high salt concentrations in the groundwater system and within soil profiles. In addition to the overall impact of climate, other natural causes of spatial variation in salinity relate to the geological history of the landscape. Western Victoria (such as the Mallee region) was once covered by an inland sea. When the sea retreated about 10 million years ago, the sediments it left behind contained large quantities of salt. Salt is typically transported via subsurface flows from groundwater into streams, highlighting a potential link between river salinity and groundwater salinity levels. This link can be illustrated by comparing the stream

EC 50th percentile

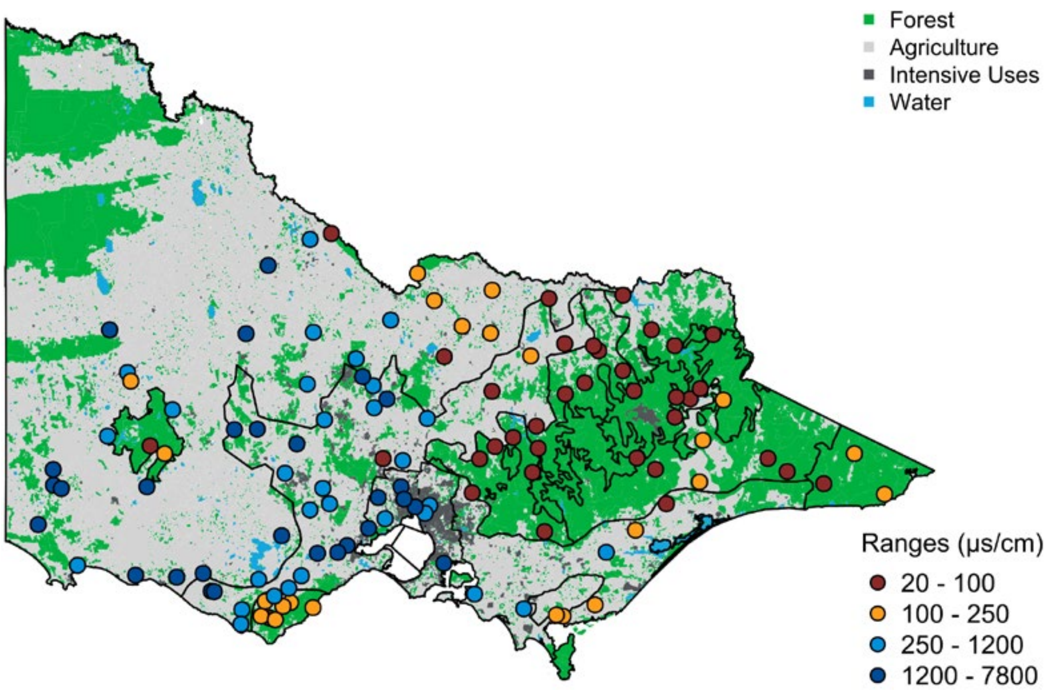


Figure 6: Maps of the 50th percentile of EC at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels across the state. The background colours indicate the land use types. The lines show the boundaries of the ERS segments (see 'Data and selection of study sites' for detailed definition).

salinity data across Victoria in Figure 6 (map site-level median EC) and with the water table aquifer or groundwater salinity in Figure 7 (map of groundwater salinity by Victoria Measurement Information System), although requiring validation from further study with consideration of basin information and detailed processes.

Anthropogenic activities mainly affect salinity through modification of the catchment water balance, specifically recharge to groundwater and subsequent impacts on groundwater flows to streams. In Victoria, there are two processes of salinisation: dryland salinity and irrigation salinity. While Victoria has naturally saline landscapes in some regions, secondary dryland salinity has been caused by clearing of deep-rooted native vegetation which resulted in increased recharge to groundwater, high water tables and mobilisation of previously stored salt (Peck, 1993). Likewise, irrigation salinity (at least historically) is also a result of clearing native vegetation combined with adding irrigation water to the catchment, which together increases recharge to groundwater and the mobilisation of salt to streams. These processes have been further modified by various salinity management activities being implemented in Victoria over the past 30 to 40 years. Locations with higher river salinity are mainly concentrated in the west, closely aligned with agricultural regions (Figure 6). Our understanding of stream salinity processes suggests that these land use patterns (and associated vegetation modification) strengthen a natural spatial pattern in stream salinity rather than being the fundamental cause.

Turbidity

Turbidity is a measure of the scattering of light by fine particles (mainly clay sediments) in water. Figure 8 shows the spatial pattern of 50th percentile (median) turbidity across Victoria over 27 years. In general, in Victoria, turbidity increases moving from the highlands to lowlands. There tends to be high turbidity on the riverine plains in northern Victoria, in particular where the alluvial valleys are dominated by fine sediments. There is high variation between sites within the Urban, Central Foothills and Coastal Plains and the Murray and Western Plains ERS Segments.

EC 50th percentile

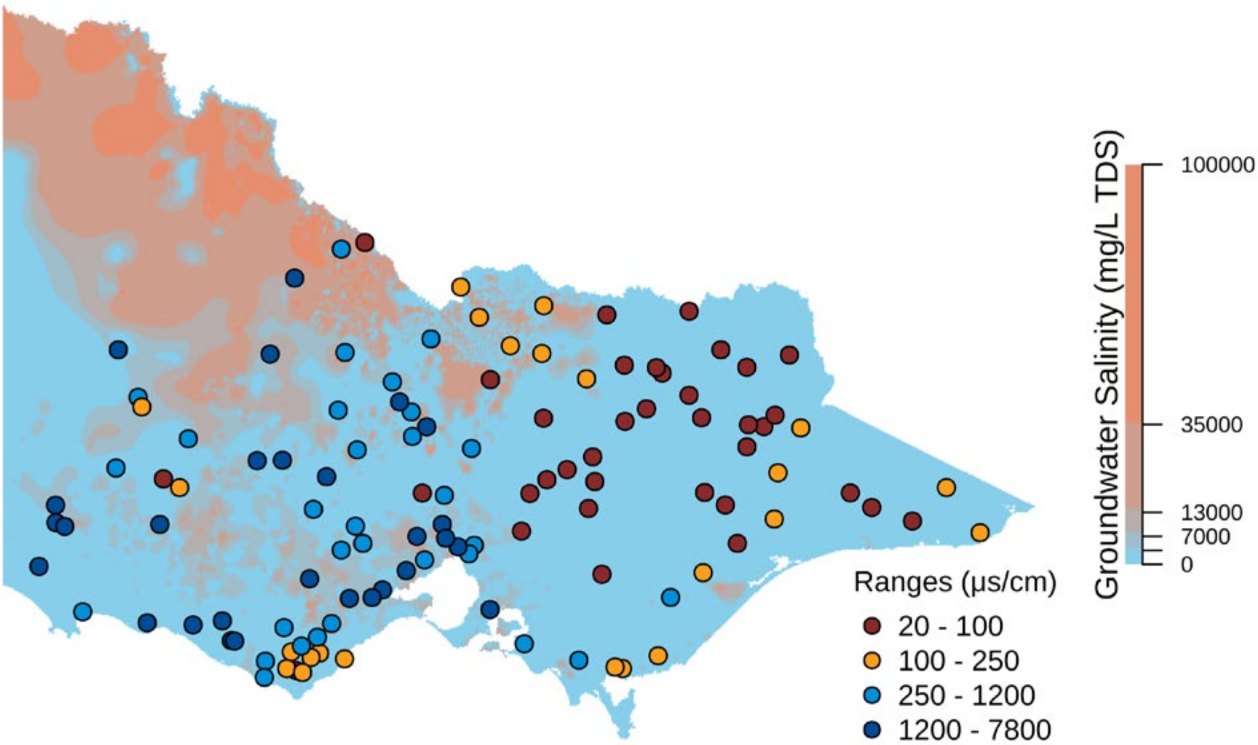


Figure 7: Maps of the 50th percentile of EC at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels. The background colour shows the groundwater salinity in Victoria (data sourced from Department of Environment Land Water & Planning (2018).

Turbidity 50th percentile

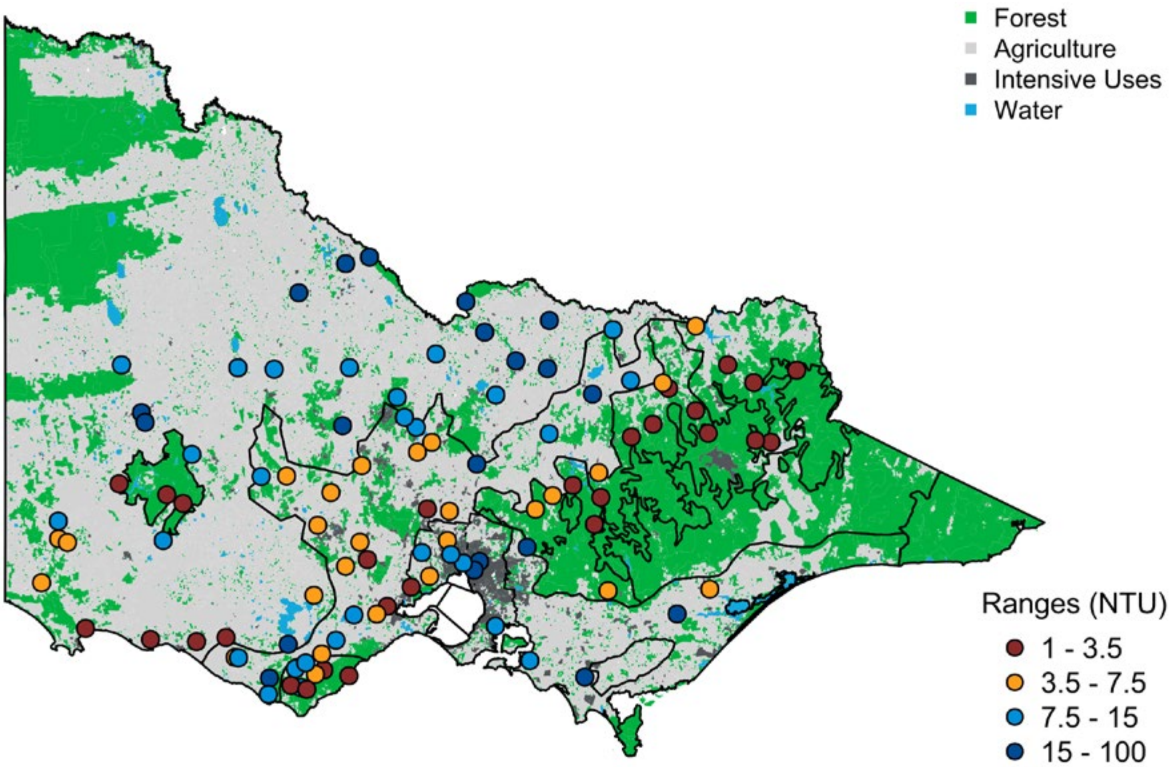


Figure 8: Maps of the 50th percentile of turbidity at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels. The background colours indicate the land use types. The lines show the boundaries of the ERS segments (see 'Data and selection of study sites' for detailed definition).

Across catchments, different geological materials provide sources of sediments via erosion from stream banks, erosion gullies or hillslopes and the erodibility of these materials varies substantially. Vegetation cover and vegetation type vary across catchments and influence erosion processes. Furthermore, catchments have different rainfall intensities and runoff rates, changing the potential for sediment erosion from the catchment surface, gullies and streams. Therefore, stream turbidity is expected to vary across space naturally due to these differences in geology and climate.

There is a complex history of catchment erosion and sedimentation that has occurred since Colonisation related to intense catchment disturbance and erosion early in the period, followed by stabilisation, reduced sediment delivery downstream of large dams following their construction and the impact of regulated flows in some systems (Rutherfurd et al., 2020). Most of this has occurred prior to the current study period but the geomorphic history remains important. While turbidity is a complex water quality parameter, there is significant evidence that landscape disturbance continues to have a major impact on it.

TP and TN

Within Victoria, TP and TN share similar spatial patterns (Figure 9 and Figure 10), with marked differences between colder mountainous forested regions (lower TP and TN) and warmer lowland agricultural/cropping regions (higher TP and TN). There appears to be more variability between neighbouring sites in the Murray and Western Plains, Foothills and Coastal Plains, and Urban segments than there is for EC and turbidity.

While there are natural sources of phosphorus and nitrogen in Victoria's catchments, the use of fertilisers has a major influence on the availability of these elements in agricultural systems (and urban gardens). In agriculture there are a range of mechanisms to

TP 50th percentile

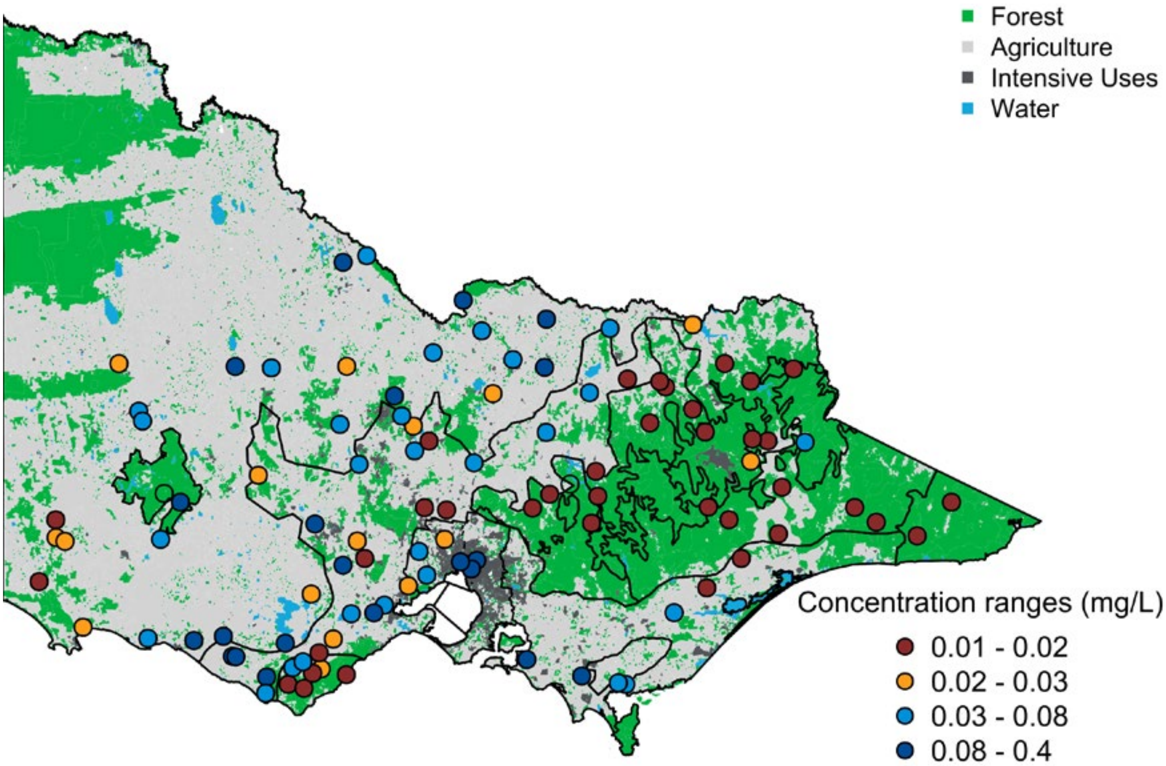


Figure 9: Maps of the 50th percentile of TP at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels. The background colours indicate the land use types. The lines show the boundaries of the ERS segments (see 'Data and selection of study sites' for detailed definition).

increase nutrient availability, such as import of stock feeds and fertilisers. There are mechanisms that reduce nutrients, such as denitrification in wet and oxygen-limiting environment, nitrogen fixation in crops/pastures (e.g. clover, lucerne) and removal of nutrients by harvesting and transport of agricultural produce. The timing and intensity of fertilisation and stocking activities within catchments influence the in-stream nutrient concentration.

However, the intensification of nutrient cycles and enhanced losses to streams associated with agricultural production is substantial globally (Gruber & Galloway, 2008) and it is very likely that this is also the underlying cause of the spatial differences in TN and TP in streams across Victoria (Gourley & Weaver, 2012; Smith et al., 2013).

pH

The pH of natural waters is about 6.5 to 8.5. The pH in Victorian waterways are mostly within this neutral range. There are only three sites examined with a 50th (median) below 6.5 and no site has median pH above 8.5 over the period of data (Figure 11 b). For the 25th percentile, there are 12 sites below 6.5 and no site above 8.5 (Figure 11 a); for the 75th percentile, there are two sites below 6.5 and two sites above 8.5 (Figure 11 c).

In-stream pH naturally varies across catchments with rainfall, soil and geological characteristics of the catchment. Higher alkaline content in soil and bedrock can make river flow more alkaline (having higher pH). Further, regions with higher average rainfalls tend to have lower pH soils and streamflow due to leaching.

TN 50th percentile

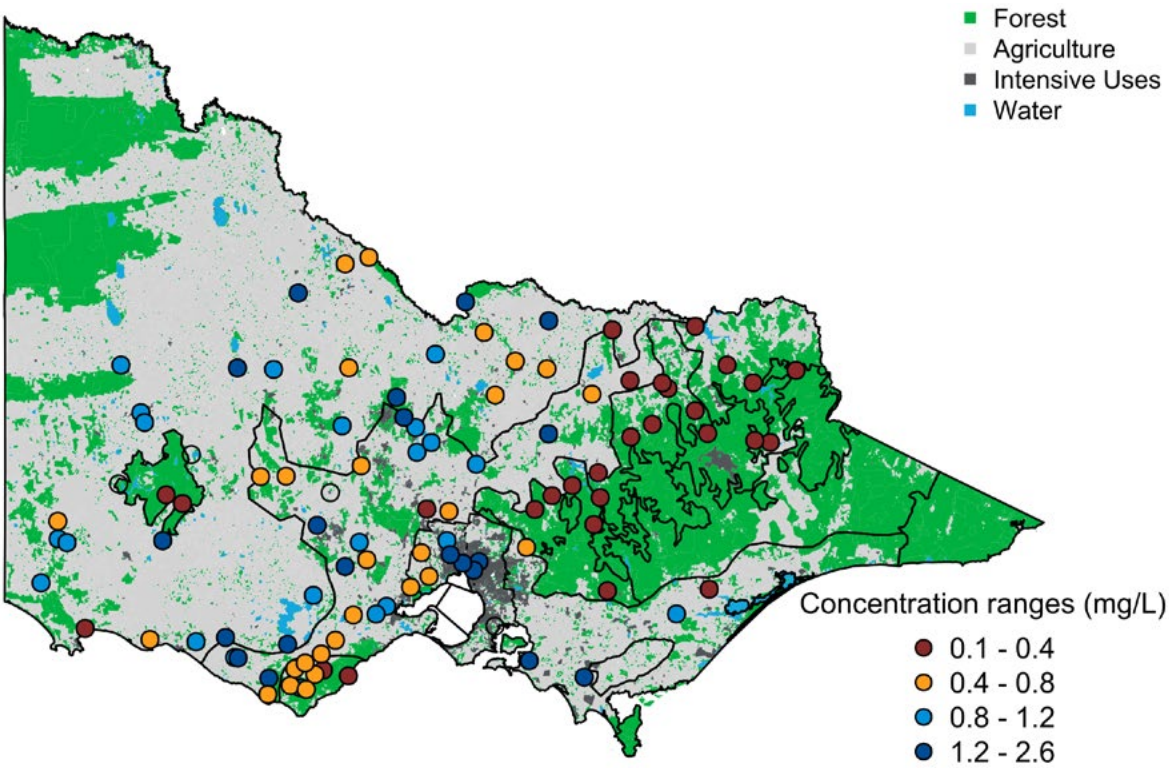
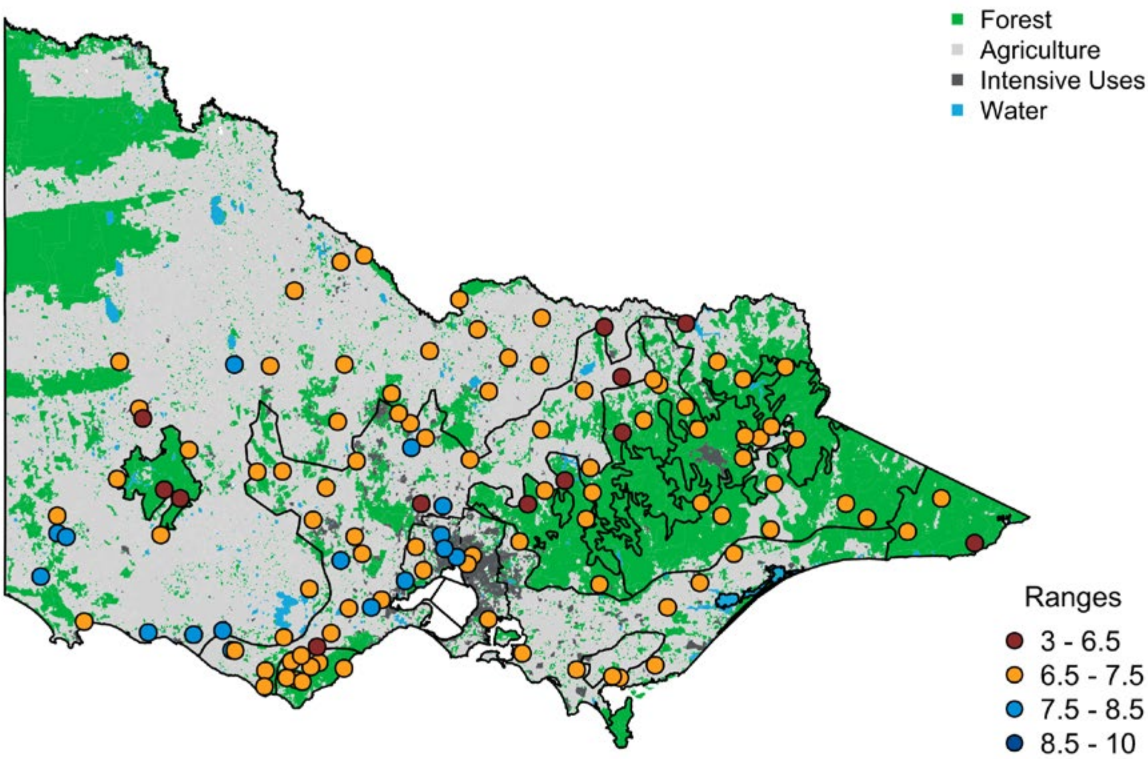


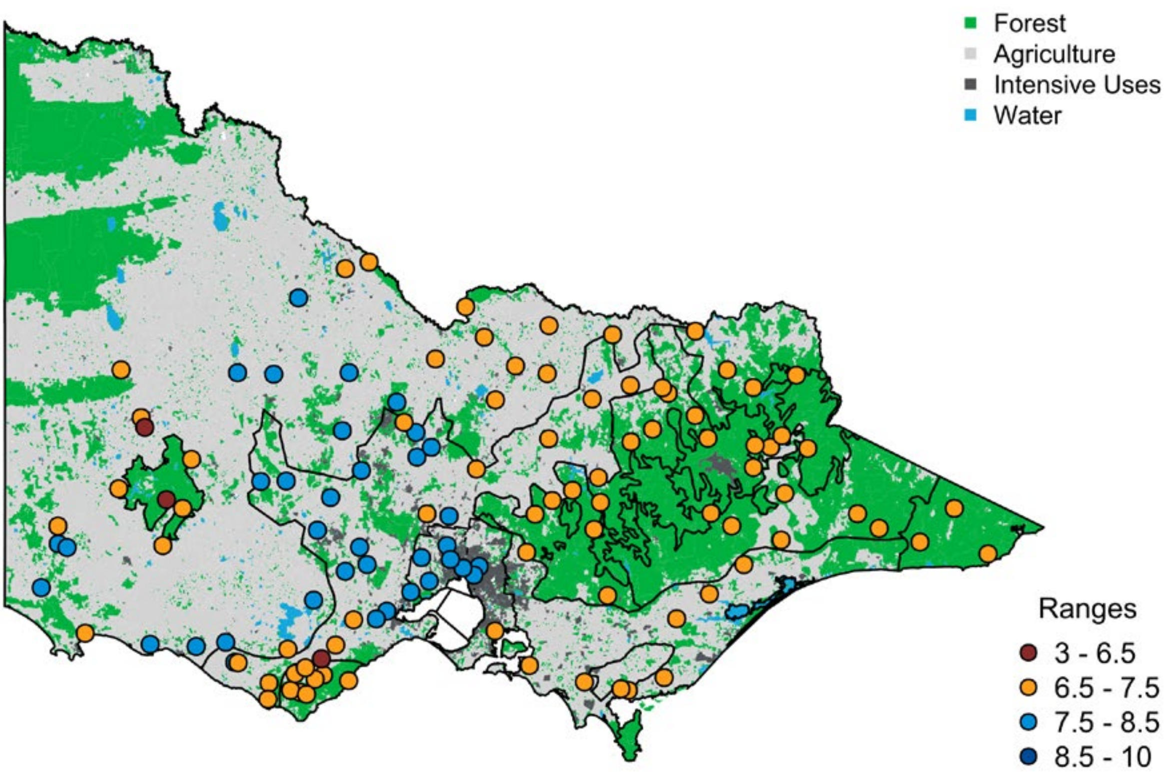
Figure 10: Maps of the 50th percentile of TN at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels. The background colours indicate the land use types. The lines show the boundaries of the ERS segments (see 'Data and selection of study sites' for detailed definition).

The human activities most likely to influence pH in Victorian streams are likely those associated with agriculture (given that we do not have the acid rain issues that occur in some other parts of the world). While soil pH varies naturally depending on climate and parent materials, soil pH is also affected by: 1) the acidifying effects of agriculture such as fertiliser application (in particular nitrogen); and 2) addition of ameliorants such as lime or other alkaline chemicals to soil, to increase soil pH and thereby maintain appropriate levels for agriculture. Agricultural managers have a strong incentive to maintain soil pH close to neutral to avoid productivity impacts associated, for example, with strongly acidic soils. The ability of soils and groundwater systems to buffer pH fluctuations is also likely to be significant, which would reduce in-stream pH responses. Although surface soil pH shows distinct spatial variation across Victoria (generally lower and acidic in the eastern and western Uplands, while being higher and alkaline in the north-west, Figure 12), the in-stream pH does not appear to display distinct variation by region or land use.

a) pH 25th percentile



b) pH 50th percentile



c) pH 75th percentile

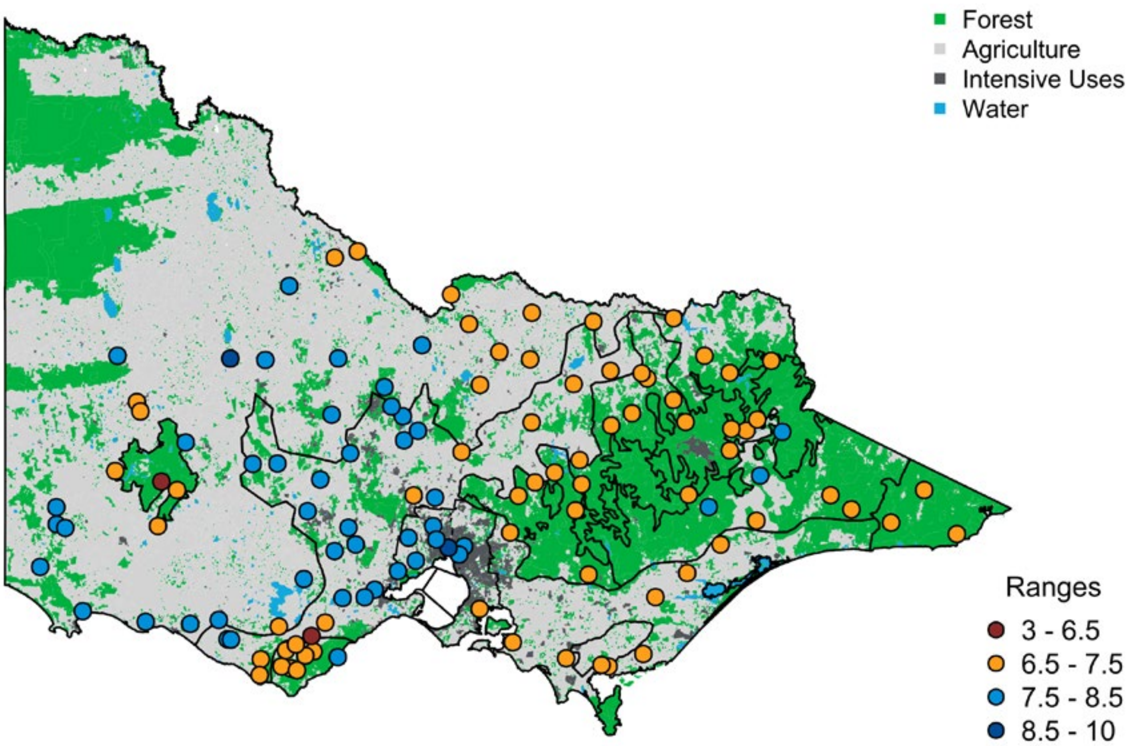


Figure 11: Maps of the a) 25th, b) 50th and c) 75th percentiles of pH at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels. The background colours indicate the land use types. The lines show the boundaries of the ERS segments (see 'Data and selection of study sites' for detailed definition).

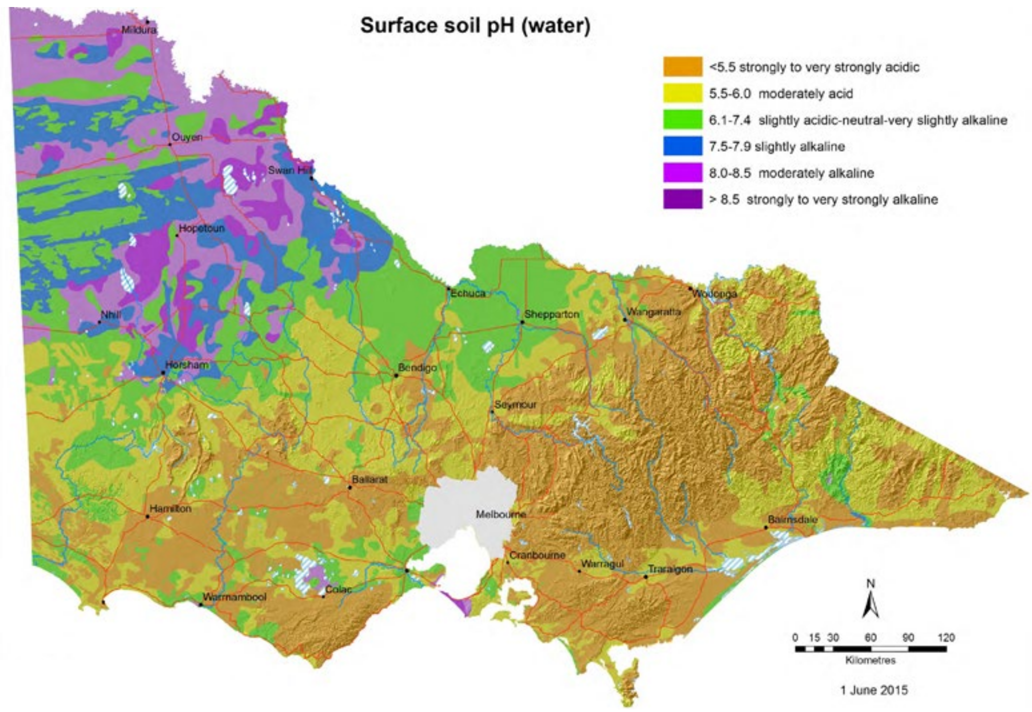


Figure 12: The soil pH for Victoria. Sourced from Victoria Resources Online (VRO) Soil pH Mapping.

DO

The spatial pattern of the spot-sampled DO data (approximately monthly) displays a distinct gradient from east to west, where the latter generally has lower DO levels (Figure 13). The colder mountainous forested regions generally have higher DO compared with the warmer lowland agricultural/cropping regions. Spatial patterns of DO are likely to be influenced by factors including water temperature, flow velocity and turbulence, as well as organic matter loads and photosynthesis within the water body. The higher DO concentrations in the uplands correspond with lower temperatures (and hence high DO saturation levels) and perennial streams with more rapid gas exchange. The DO concentrations are lower in the west, with the highly intermittent streamflow reducing gas exchange.

DO 50th percentile

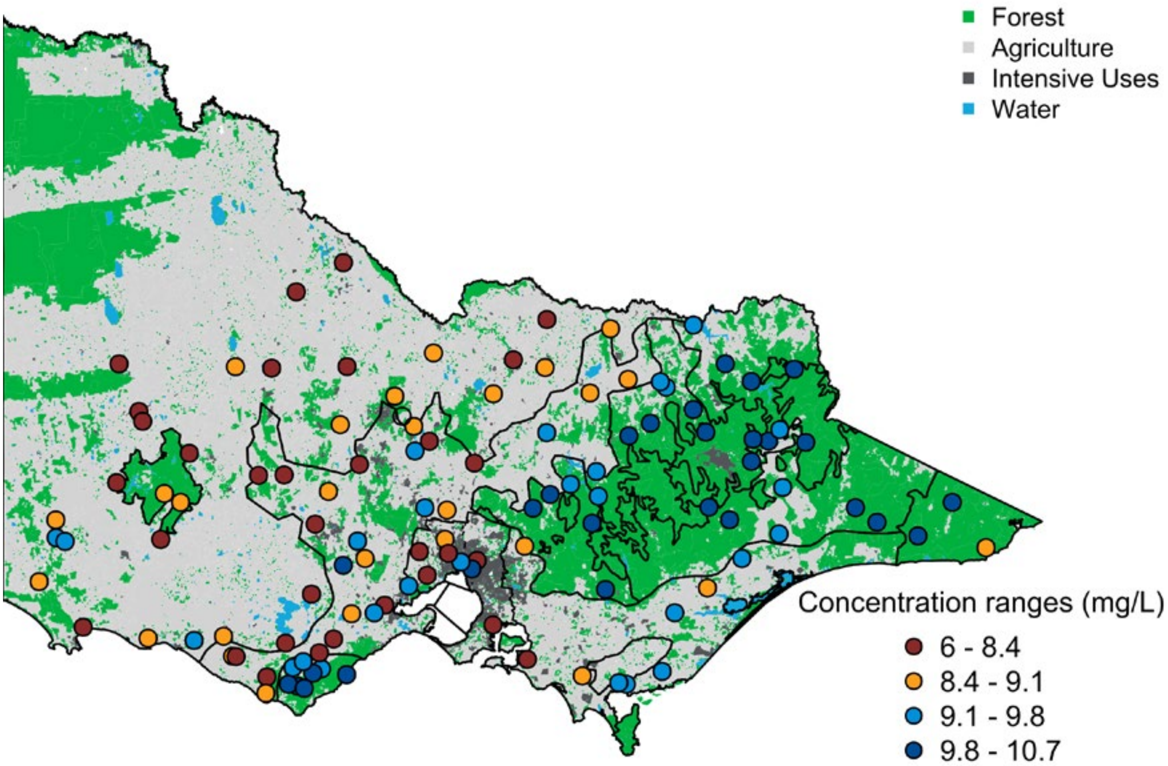


Figure 13: Maps of the 50th percentile of DO at individual monitoring sites calculated with the full historical data. The colours of the dots represent four ranges which are approximates of the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the site-level 50th percentile levels. The background colours indicate the land use types. The lines show the boundaries of the ERS segments (see 'Data and selection of study sites' for detailed definition).

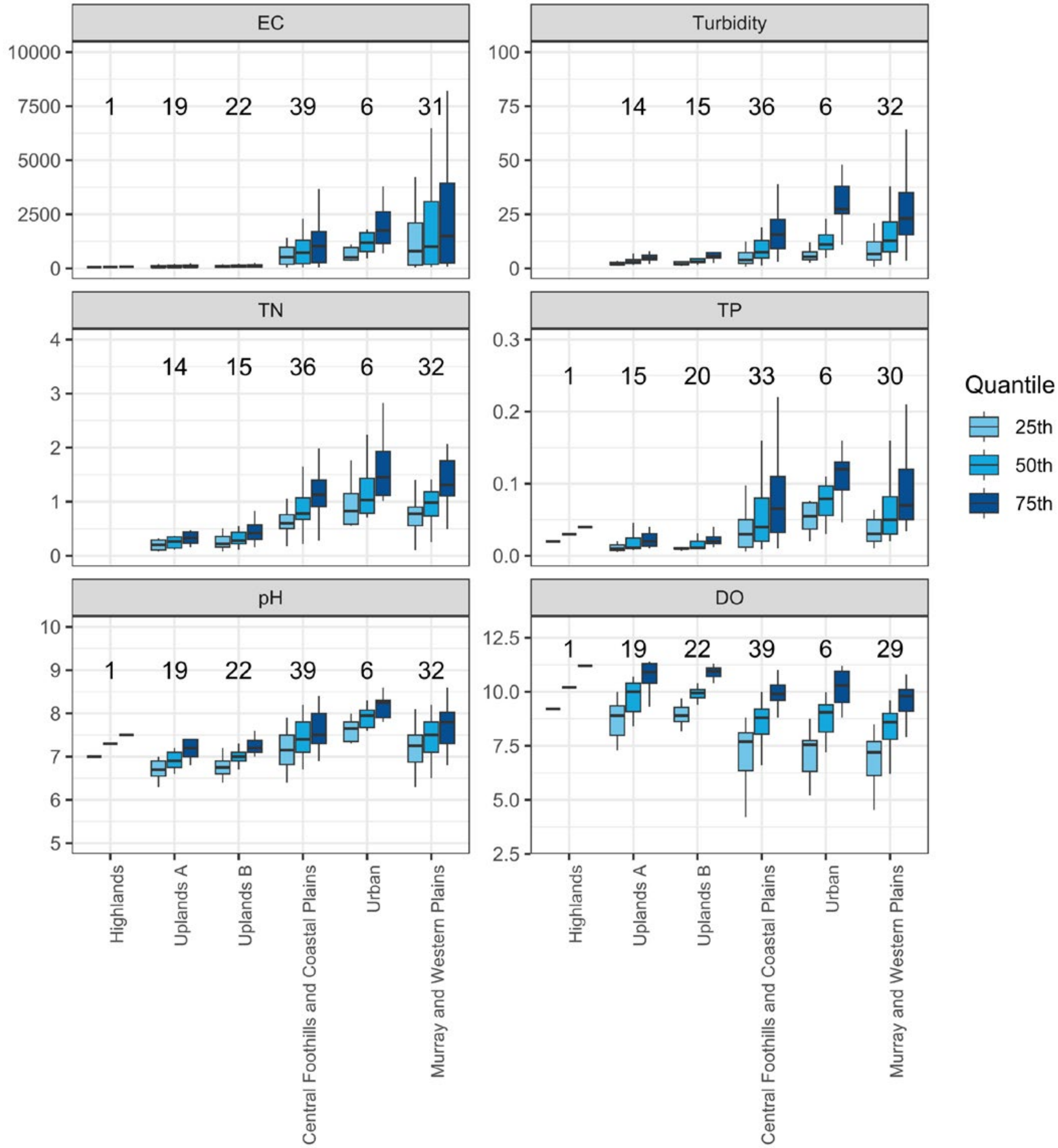


Figure 14: Distribution of the site-level quantile levels of each water quality parameter (in individual panels) within each ERS segment (x-axes). For each parameter-segment combination, the 25th, 50th and 75th quantiles are differentiated by three shades of blue. The bottom and top of each box represents the interquartile ranges (which 25% values and 75% values are lower than) for the specific parameter-segment combination, while the whiskers extend to 1.5 times the interquartile ranges. The numbers within each panel denote the number of long-term monitoring sites included in each box. The 'Highlands' ERS segment does not contain any sites for turbidity and TN.

3.4.2 Spatial variation of water quality parameters at the level of ERS segments

The site-level 25th, 50th and 75th percentile of the levels/concentrations of each water quality parameter are grouped by ERS segments and a comparison is presented in Figure 14.

The Murray and Western Plains, the Central Foothills and Coastal Plains and the Urban ERS segments have the highest overall turbidity, EC, TN and TP concentrations, pH, and the lowest overall concentrations of DO. These segments also tend to have greater variation of the site-level water quality, potentially due to the varying intensities of anthropogenic land use (e.g. agriculture, intensive uses). In contrast, the Uplands A and Uplands B segments have lower concentrations of pollutants and low variation in the site-level concentration of each parameter.

While the Highlands segment is represented by at most one site in Figure 1, there are a number of sites within Uplands A and B which are immediately downstream of the boundary between these two segments whose catchments are dominated by the Highlands segment, strongly suggesting that the Highlands segment also has equivalent water quality status. The water quality variation between ERS segments, and the factors driving spatial variations in water quality have already been described for each parameter in the sections above. Specifically, the Central Foothills and Coastal Plains and the Murray and Western Plains consist of warmer lowland catchments that are often intensively modified from natural conditions (e.g. used for agriculture and grazing), while the Urban segment is highly urbanised (Figure 3 and 4 a). The water quality variation between ERS segments emphasised the overall spatial patterns in the earlier results, in which the warmer lowland agricultural/cropping regions generally have poorer water quality (higher EC, turbidity, TP, TN with lower DO) than the cooler mountainous regions.

3.4.3 Key factors related to water quality spatial variation

A comprehensive set of 48 catchment characteristics were considered as potential explanatory variables for water quality spatial variation (see Appendix B for full explanation). We first assessed how these characteristics individually influence the spatial variation of water quality using a multi-variate modelling framework (see detail in Appendix C), which allowed identification of a set of catchment characteristics that are most strongly correlated with the spatial variation in each quantile of each water quality parameter.

In undertaking this analysis, it became clear that there are very strong relationships between the 48 catchment characteristics and that these relationships prevented the clear identification of key influences on water quality. We therefore undertook a separate analysis to identify the spatial patterns underlying the 48 catchment characteristics using a technique called principal component analysis (PCA) (see detail in Appendix C). PCA is able to identify underlying relationships in a dataset and re-express the data using principal components, each of which represents an independent[2] piece of information.

Using PCA, we found that most (>85%) of the spatial variations of all the 48 catchment characteristics can be essentially reduced to two dimensions (principal components 1 and 2, which are mapped in Figure 15; further details of the PCA results are presented in Appendix E). In other words, the catchment characteristics often vary in similar ways, making it difficult to attribute the spatial patterns in water quality to individual catchment characteristics.

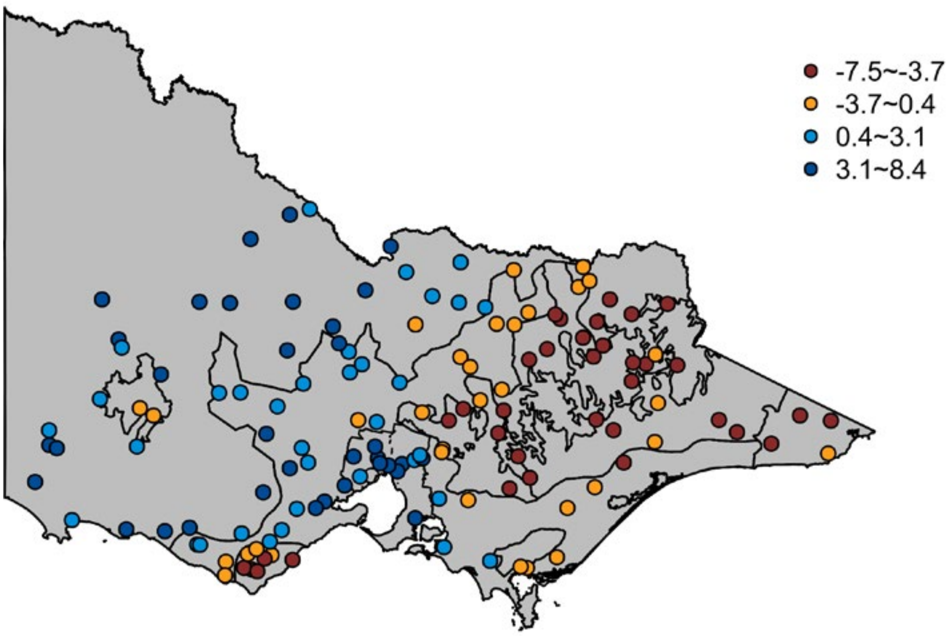
An example of the challenge is that warmer, lowland catchments are generally more intensely used for agricultural activities, and consequently are more likely to receive fertiliser and pesticide inputs. Considering this, we decided to focus on the results from the PCA to assess the combined effects of catchment characteristics on the spatial variation in water quality, instead of interpreting the effects of individual characteristics on the spatial variation of water quality based on the multi-variate models.

The first dimension of the catchment characteristics, PC1, explains around 76% of the spatial variation of all 48 characteristics. The spatial patterns of PC1 (Figure 15 a) are most closely related to those of climate, hydrology, land use, soil and topography, across Victoria. The second principal component, PC2 (Figure 15 b), which is predominantly defined by catchment land cover, land use, soil and topography, explains an additional 9% spatial difference of all catchment characteristics. A detailed list of the important catchment characteristics for each of PC1 and PC2 and their directions of influences on each PC is included in Figure 16 a) and b); a positive influence of any catchment characteristic on a PC means that an increase in the level of that catchment characteristic is correlated with an increase in the value of the PC. For example, higher PC1 values occur in catchments with lower annual rainfall, lower erosivity, lower catchment slope, higher percentage area of fertiliser application and higher average temperature (Figure 16 a). Such catchments occur more often in western Victoria, which broadly aligns with the Murray and Western Plains ERS segment (Figure 15 a).

[2] As opposed to the inter-related information in the original variables such as temperature, rainfall and altitude, where high altitude leads to cooler conditions and higher rainfall.

Higher values of PC2 occur in catchments with higher woodland and grassland cover, higher percentage area with metamorphic bedrock, higher average runoff, with lower proportion of area modified from natural conditions (Figure 15 b). These characteristics are strongest in the far north-east and around the Grampians/Gariwerd, but there is also a general north-south trend probably related to the greater presence of woodland (as opposed to forest) in the north (Figure 15 b).

a)



b)

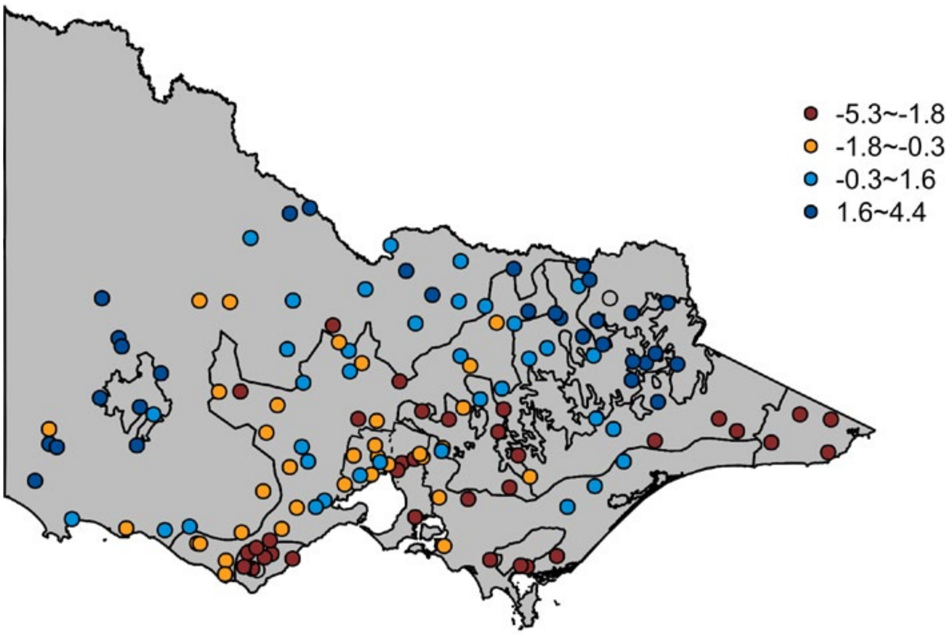


Figure 15: The maps of the values of: a) principal components 1 (PC1), which explains 76% spatial variation of all 48 catchment characteristics and b) principal component 2 (PC2), which explains 9% spatial variation of all 48 catchment characteristics. The colours of the dots represent the interquartile ranges (lowest to 25%, lowest 25-50%, lowest 50-75%, and highest 25%) of the values of each principal component. The values of the two PCs are linear combinations of multiple catchment characteristics and do not have physical meanings. The lines show the boundaries of the ERS segments.

a) b)

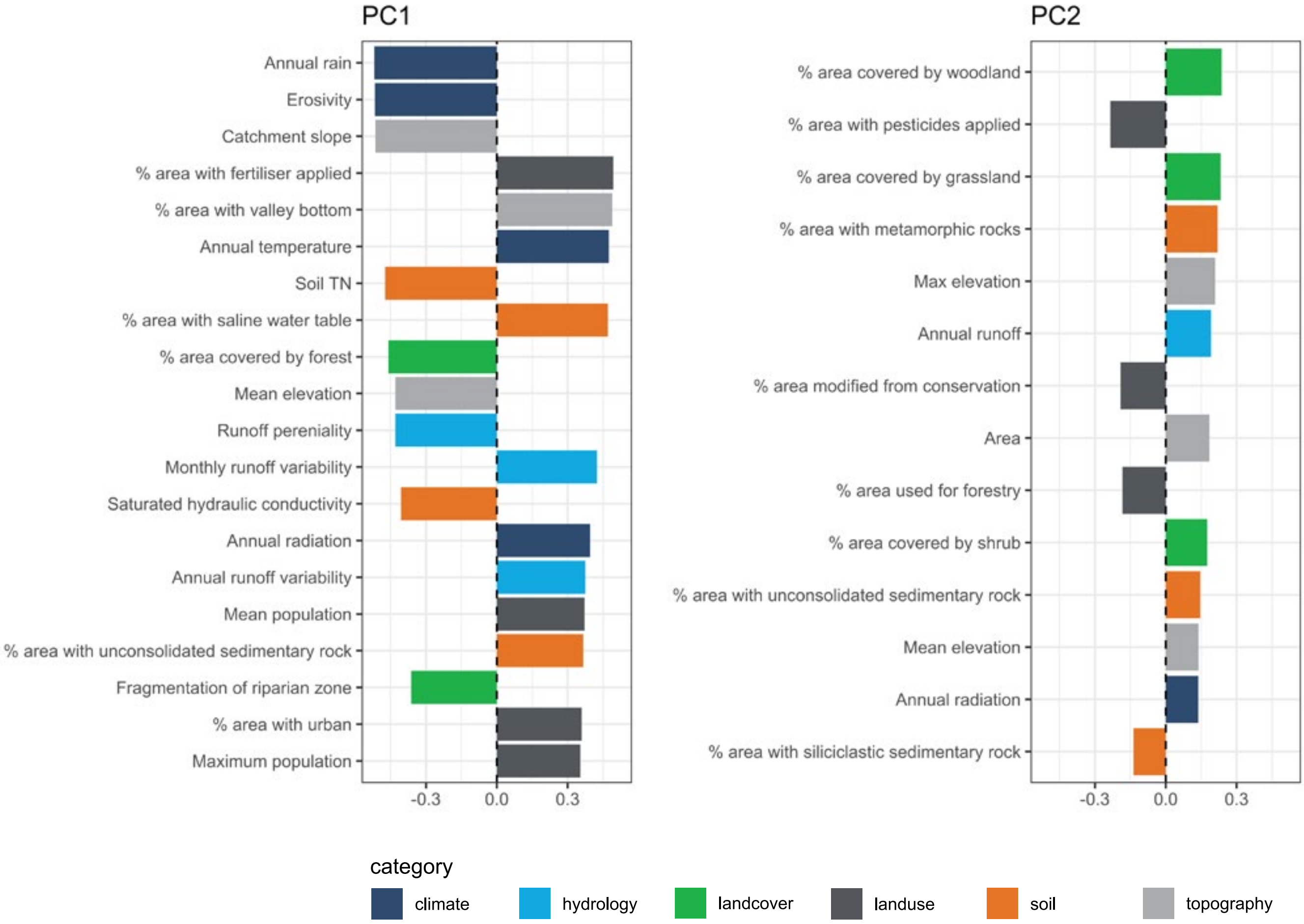


Figure 16: The correlations between individual catchment characteristics with: a) principal components 1 (PC1), which explains 76% spatial variation of all 48 catchment characteristics and b) principal component 2 (PC2), which explains 9% spatial variation of all 48 catchment characteristics. The length of each bar shows strength of the correlation, while the direction indicates a positive/negative correlation. Only the important variables for each of PC1 and PC2 identified from the principal component analysis are included in the corresponding plot. The colours indicate the categories of individual catchment characteristics, being one of climate, hydrology, land use, land cover, soil and topography. Details of catchment characteristics, their abbreviations and categorisation are included in Appendix B.

While the PCA results demonstrate the highly cross-correlated nature of the catchment characteristics and the two main dimensions of their spatial patterns, they focus on the catchment characteristics themselves and do not reveal how water quality varies across different types of catchments. Thus, we calculated the linear correlations between each principal component and the site-level 50th percentiles of each water quality parameter (Table 3). PC1 has statistically significant ($p<0.05$) correlations (with the absolute correlation coefficients ranging from 0.33 to 0.67) with all six water quality parameters, with positive correlations with all parameters except for DO. This means that the catchment characteristics that positively correlate with PC1 together have positive correlation with EC, turbidity, TP, TN and pH but a negative correlation with DO. There is no statistically significant correlation between any water quality parameter and PC2, and the strength of linear correlations are much lower, with absolute correlation coefficients ranging from 0.01 to 0.17.

Table 3: Correlation coefficient between the site-level 50th percentile values of each water quality parameter and the values of each principal component, PC1 and PC2. Bolded text highlights statistically significant correlations ($p<0.05$).

Parameter	Correlation with PC1 (explains 76% catchment differences)	Correlation with PC2 (explains 9% catchment differences)
EC	**0.33**	0.12
Turbidity	**0.59**	0.01
TN	**0.43**	-0.17
TP	**0.55**	-0.07
pH	**0.55**	-0.02
DO	**-0.67**	-0.07

Combining the results of Table 3 and Figure 16, Table 4 provides a list of catchment characteristics that are important to PC1, and their effects on each water quality parameter. Table 4 does not intend to summarise the individual effects of the catchment characteristics on water quality; instead, all characteristics listed for each water quality parameter should be considered together in defining the catchment type where higher levels/concentrations of the parameter are expected in Victoria.

The results suggest that the effects of the catchment characteristics represent a variation along a continuum, between two extreme types of catchments with contrasting water quality conditions:

(i) the warmer, drier, lowland catchments with greater proportions used for agriculture and intense usages, versus

(ii) the colder highland catchments with higher rainfall, greater proportions of natural and forested lands.

Water quality is generally poorer for the first type of catchment, with higher turbidity, TN and TP, lower DO and more saline (higher EC).

Table 4: Direction of correlations between the site-level 50th percentile of each water quality parameter and each catchment characteristic that is important to PC1: '+' indicates a positive correlation and '-' indicates a negative correlation. This table does not present the individual effects of the catchment characteristics on water quality; instead, all characteristics listed for each water quality parameter should be considered together in defining the catchment type where higher levels/concentrations of the parameter are expected in Victoria.

Catchment characteristics	EC, Turbidity, TN, TP, pH	DO
Annual rain	-	+
Erosivity	-	+
Catchment slope	-	+
% area with fertiliser applied	+	-
% area with valley bottom	+	-
Annual temperature	+	-
Soil TN	-	+
% area with saline water table	+	-
% area covered by forest	-	+
Mean elevation	-	+
Runoff pereniality	-	+
Monthly runoff variability	+	-
Soil saturated hydraulic conductivity	-	+
Annual radiation	+	-
Annual runoff variability	+	-
Mean population	+	-
% area with unconsolidated sedimentary rock	+	-
Fragmentation of riparian zone	-	+
% area with urban	+	-
Maximum population	+	-

4. How and why has water quality varied over recent decades?

4.1 Summary

Understanding how water quality responds to different drivers, and how water quality is trending is critical to preparing for and responding to water quality challenges in the short and long term.

Water quality at any site is expected to vary over time as hydro-climatic conditions vary. This chapter examines how water quality changes in response to streamflow and season. Statistical modelling indicates that streamflow is the most important driver of water quality for turbidity, TN, TP and EC. Temperature is the most important driver for DO. The underlying trend (i.e. a temporal factor that cannot be explained by streamflow or season) is most important for pH, although these trends are generally small.

It is also important to identify whether there has been an underlying trend in water quality over the study period that cannot be explained by changes in hydro-climatic conditions (streamflow and season/time of year), as these changes could be attributed to changes in human activities in the catchments. When investigating the underlying trends in water quality (i.e. the temporal variability that cannot be explained by streamflow or season):

- the biggest proportion of sites for EC (45.9%) have experienced a decreasing trend
- the biggest proportion of sites for TN (46.5%) and DO (48.1%) have not experienced a statistically significant trend
- the biggest proportion of sites for turbidity (79.8%), TP (40.2%) and pH (58.2%) have experienced an increasing trend (noting that 96% of sites stay within the neutral range of pH 6.5-8.5 during the period).

Investigating these underlying trends (that cannot be explained by streamflow and seasonality) regionally (by ERS segments), there are generally more sites with deteriorating water quality trends (that cannot be explained by streamflow or seasonality) in the two most modified segments (Central Foothills and Coastal Plains and Murray and Western Plains), compared to the more unmodified segments (Uplands A and B). The only exceptions to this are (i) turbidity, where all segments have the largest proportion of sites with an increasing underlying trend; and (ii) TN, where both modified and unmodified segments have the largest proportion of sites with no statistically significant underlying trend.

When relating these underlying trends that cannot be explained by streamflow and seasonality back to ERS attainment, the bigger the underlying trend, the more likely a site is to not attain the ERS. In addition, the potential risk of ERS non-attainment posed by DO, turbidity and TP conditions increased between 1995-2007 and 2009-21, while the potential non-attainment risk posed by EC and TN conditions remained stable. The potential risk to ERS non-attainment posed by pH declined overall.

4.2 Introduction

A fundamental question in water management is whether water quality is improving or declining. The answer to this question may inform whether management intervention is needed, or if management practices are working or need to change.

Water quality of rivers and streams varies naturally due to changing conditions. Rainfall and runoff will change conditions in waterways and likely cause changes to water quality parameters. Long periods of rainfall can lead to further changes, and extended dry periods can drive responses in water quality. Temperature and other factors also affect water quality. Understanding how water quality responds to different environmental conditions helps us understand long-term trends and prepare for and manage shorter-term impacts where necessary. To identify a long-term trend, it is necessary to understand the underlying long-term variation of water quality so as not to misinterpret a response to a temporary change in conditions (be it over a few hours or a few years) as an overall shift in water quality. Separating the impact of streamflow and seasonality is critical to understanding how land use, and land management have affected water quality. It also indicates whether water quality is improving or deteriorating, which can often be masked when the effects of streamflow and seasonality are not separated.

Answering this question is often fraught by having insufficient data and the inability to remove the influence of short-term variation from longer-term trends.

Water quality data over 27 years from 1995 until 2021 is significantly influenced by the dry years of the Millennium Drought and the flooding in 2010. These shifts in hydro-climatic conditions can potentially confound our understanding of water quality trends and their causes.

In this chapter, we first investigate the relationship between hydro-climatic variables (daily streamflow, season and water temperature – for DO only) and water quality. Understanding this relationship is important to determining what causes shifts in water quality, and how water quality might change in dry years compared to wet years.

We then investigate the underlying trend in water quality that cannot be explained by streamflow. It is critical to extract and investigate these underlying trends to understand whether water quality is improving or declining (regardless of future wet or dry shifts in climate).

Finally, we investigate the impact of these underlying trends on ERS attainment.

The study therefore undertook the following analyses:

1. Identification of drivers of temporal variability in water quality based on statistical modelling of each monitoring site and comparisons either at state or regional levels
2. Statistical analyses of underlying trends in water quality (after the effects of streamflow and seasonality are removed) for each of the six selected parameters at each site over the period of record and summarised across the state
3. Statistical analyses of underlying trend for each of the six selected parameters at each site and summarised for each ERS region to determine how trends varied in different systems
4. A more detailed analysis of sites with the strongest increasing and decreasing underlying trends to identify significantly improving and high-risk sites
5. An analysis of change in ERS attainment due to underlying trends in individual water quality parameters.

4.3 Approach

Multiple linear regression models were used to separate the temporal variability in water quality into components in order to identify the drivers and assess their influences on this temporal variability. The three components considered were:

1) the effect of flow on temporal variability in water quality
2) the effect of seasonality on temporal variability in water quality
3) the effect of an underlying trend on temporal variability in water quality.

For DO, the effect of water temperature was also considered.

Streamflow and seasonality (and water temperature for DO) affect water quality and thus can help explain part of the observed temporal variability (Figure 18). Day of the year is usually used as a proxy for seasonality, and represents the effects of temperature, rainfall and human activities in that particular season on water quality on that day of the year. Accounting for these influences also allows the effect of drought years and flood years to be separated from other potential impacts.

Analysis Undertaken	**Time series** Plots of each parameter at each site over the period of record (see Victorian Water Quality Analysis, Supplementary Analysis)	**Drivers of temporal variability** Understand drivers (streamflow, seasonality, water temperature, long-term trend) on parameters, their direction of influence and relative strength, overall and in ERS segments	**Long-term linear trends** Trends for each parameter removing influence of streamflow and seasonality – i.e. changes in water quality driven by other factors. At state, site and ERS segment scales	**Hot Spots in long-term linear trends** 8 sites with greatest increasing trend. 8 sites with greatest decreasing trend for each parameter.
Purpose of Analysis	See measured value of the parameter across time. Visually identify relationship with ERS objective	Identify how important streamflow, seasonality, water temperature is in driving temporal variability and fluctuations in water quality	Identify if water quality is trending despite flow or seasonality impacts. Eg. If change driven by anthropogenic causes such as land use change	Identify sites with greatest declining or improving water quality trends over the 27 year data period. Enable further investigation for areas of risk, or improvement

To drive understanding of how different parameters have changed, and may change in the future.

Figure 17: Conceptual diagram of aims and analysis in Chapter 4.

The underlying trend was assumed to be linear (in the log space) and is simply called the 'underlying trend' throughout the report. It represents the overall trend in water quality that cannot be explained by the commonly recognised drivers of water quality (i.e. streamflow and seasonality). Such trends might be due to long-term changes in land use, land management, and climate (other than the direct climate impact on flow). We assume a linear underlying trend in this chapter to enable summaries of the state-wide and regional patterns in trend directions and magnitudes for individual water quality parameters. This assumption was checked by examining model performance. A deeper investigation into the potential role of climate in driving some more complex non-linear behaviour in these long-term trends is presented in Chapter 5.

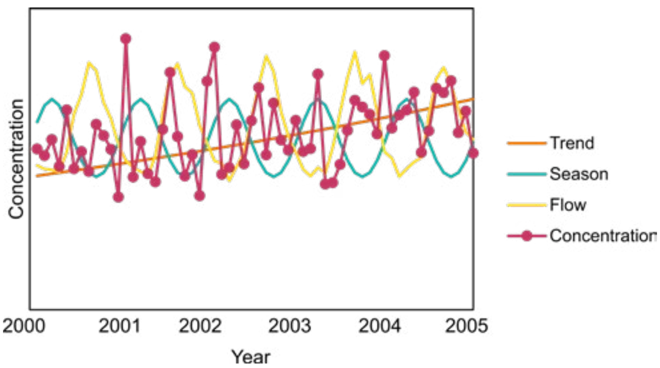


Figure 18: Representation of water quality temporal variability as made up of streamflow, seasonality and an underlying trend.

The detailed analytical method used in this section is described in Appendix F: Analytical approach used for Chapter 4. The performance of the models is described in Appendix F.

Victoria's ERS surface water quality segments were selected for undertaking regional analysis due to their appropriate scale and the fact that they capture the major variations in catchment types across the state.

4.4 Results

This section consists of three parts. The first describes the drivers of temporal variability in water quality by assessing the influence of streamflow and seasonality (and temperature for DO) on water quality.

The second section focuses on the 'underlying trend' or linear change in water quality over the whole 27-year study period that is not driven by streamflow and seasonality. The second section also describes the number of sites where there are increasing underlying trends, decreasing underlying trends, and where there is no underlying trend (average water quality does not change over the study period). This is done across all of Victoria and within the individual ERS segments.

The third section places these underlying trends in the context of attainment and investigates whether there is a relationship between attainment of ERS objectives and the identified underlying trend in water quality.

4.4.1 Key drivers of temporal variability in water quality

At state level

Drivers for water quality variability have been examined using the results obtained from the multiple linear regression. The regression coefficients from the multiple linear regression (Appendix F) have been used to assess the relative importance of streamflow, seasonality, water temperature (DO only) and the trend that cannot be explained by streamflow or seasonality in driving water quality. These regression coefficients have been standardised using the Z-score (Appendix F) to enable cross-comparison between regression coefficients to identify which coefficient has the greatest influence on the water quality parameters (Figure 19).

- Coefficients close to zero: that factor has little impact on variation in water quality
- Positive coefficients: the water quality parameter value increases when that driver increases
- Negative coefficients: the water quality parameter value decreases when that driver increases.

Across Victoria, streamflow, seasonality and water temperature (for DO only) are important influences on temporal variations in water quality (Figure 19). The magnitude of the regression coefficients from the multiple linear regression models indicate the importance of flow, seasonality, overall long-term trend, and water temperature (for DO only) on fluctuations in water quality over time. The regression coefficients from the multiple linear regression models for each site indicate that:

- EC: Most sites have negative relationships between streamflow and EC. Streamflow appears to explain the greatest amount of variability in EC. EC tends to decline as higher salinity groundwater is diluted by fresher overland and near-surface flows during runoff.
- Turbidity: Most sites have a positive relationship between streamflow and turbidity. Streamflow appears to explain the greatest amount of variability in turbidity. Higher streamflows lead to higher turbidity because the erosive and transport capacity of water flows is greater and erosion gullies and the broader catchment surface may be better connected to streams under higher flow conditions.

- TP: Most sites have a positive relationship between streamflow and TP. Streamflow appears to explain the greatest amount of variability in TP, with increased streamflows leading to higher concentrations. This is because phosphorus is often transported attached to fine particles and there is greater erosion and transport capacity at higher flows.
- TN: Most sites have a positive relationship between streamflow and TN. Streamflow appears to explain the greatest amount of variability in TN. There is a more diverse range of chemical forms in which nitrogen occurs in streams, compared with phosphorus. Some of these are organic and/or particulate, are transported from the surface of the catchment and are subject to broadly similar influences to phosphorus. Others such as nitrate are dissolved and result from leaching of soil water into streams which occurs under wet catchment conditions and hence also typically during higher flow conditions.
- pH: Most sites have a negative relationship between streamflow and pH. The long-term trend appears to explain the greatest amount of variability in pH. The slight tendency for streams to become more acidic during higher flows is likely due to acidic surface soils having more influence at higher flows. However, the pH buffer capacity of various sediments and water bodies likely also dampens this response.

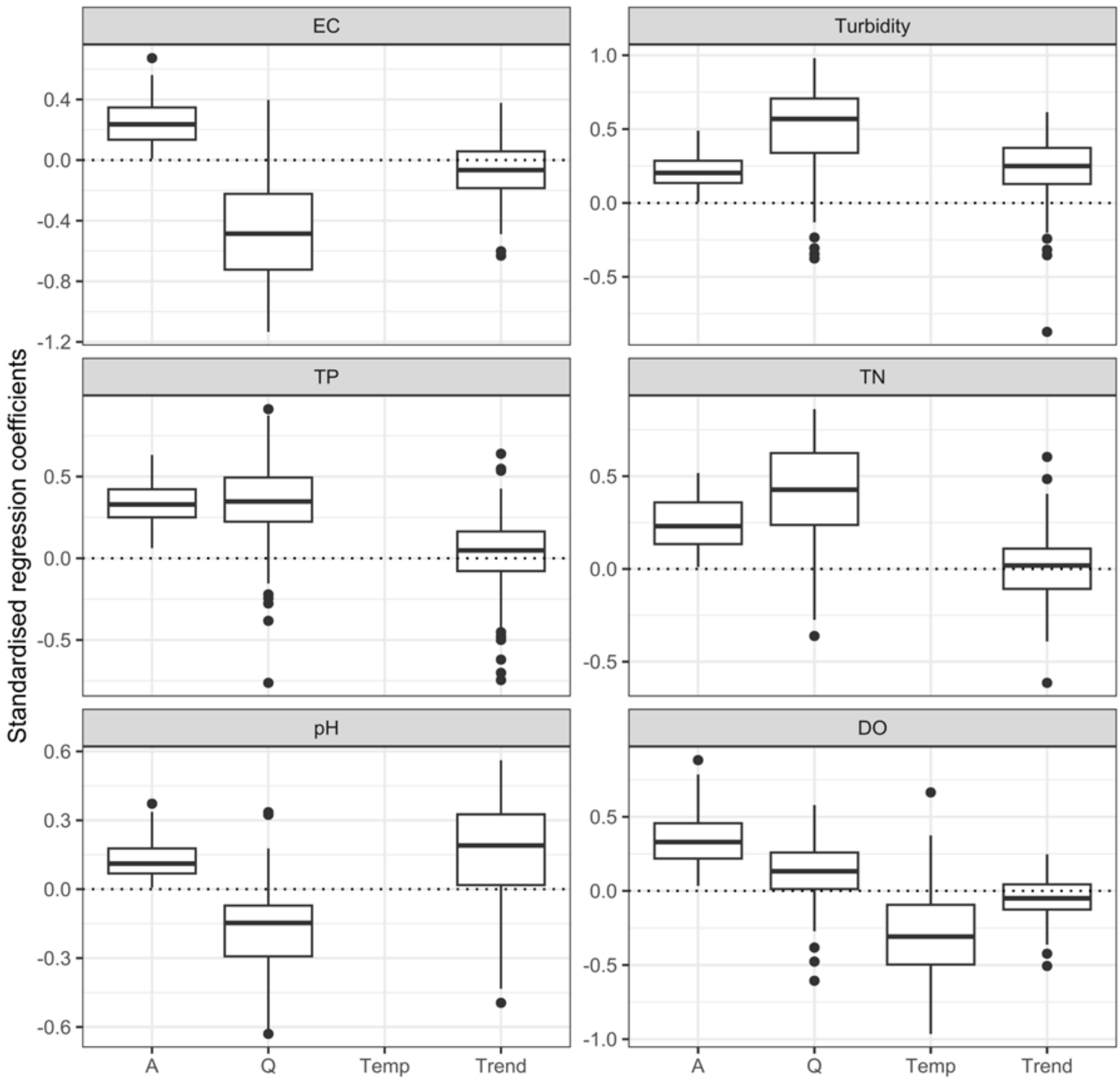


Figure 19: Distribution of regression coefficients between water quality parameter and drivers (amplitude of the seasonality effect, A; Flow, Q; Temperature, Temp; long-term trend, Time). Dots indicate outliers (1.5 times the inter-quartile range).

- DO: Most sites have negative relationships between water temperature and DO concentrations. Water temperature appears to explain the greatest amount of variability in DO. This is likely in part through the increase in saturation DO concentration that occurs as temperature reduces. The increase in DO with flow is likely due to better mixing and exchange with the atmosphere; however, on occasion high flows interacting with the floodplain can lead to catastrophically low DO due to the presence of a substantial amount of organic matter.

There are several outliers in Figure 19. These indicate sites where the regression coefficient between the water quality parameter and the driver of water quality (streamflow, seasonality, trend) is more than 1.5 times greater than the interquartile range of regression coefficients. In other words, the relationship between the water quality parameter and the water quality driver is unusual. These outlier sites are detailed in Appendix G: Supplementary results for temporal variability in water quality (Chapter 4). 90% of these sites are in the more modified Murray and Western Plains and Central Foothills segments, suggesting that these sites in the more human-impacted catchments may exhibit unusual relationships between water quality and drivers of water quality.

Regional trends across Victoria – using ERS segment boundaries

This analysis investigated specific drivers (seasonality, flow, temperature and year) of temporal change in water quality within each ERS segment. It appears from the regression coefficients that the relationship between parameter concentrations, seasonality, streamflow and temperature is largely consistent across ERS segments. This indicates that the broad process reasons for temporal changes in water quality are likely similar across the state (Figure 20). There is some discrepancy in the relationships between water quality parameter concentrations and the long-term trend (year), investigated more closely below.

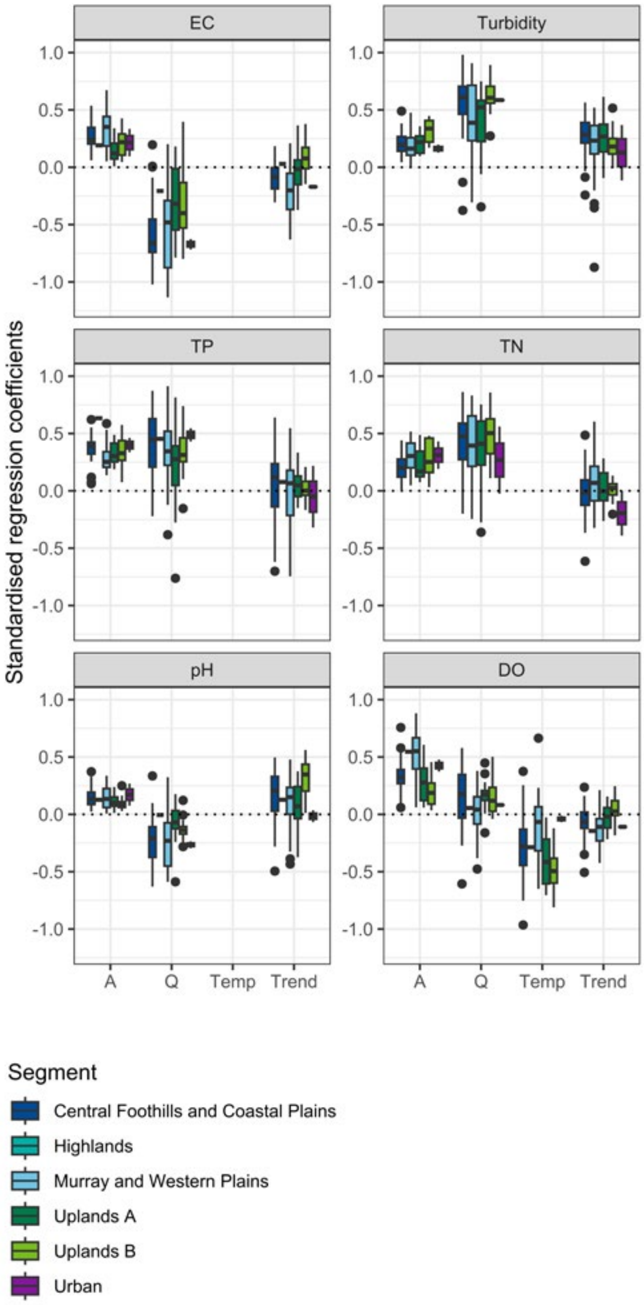


Figure 20: Distribution of regression coefficients between water quality parameter and drivers in each ERS segment (amplitude of the seasonality effect, A; Flow, Q; Temperature, Temp; long-term trend, Time). Dots indicate outliers (1.5 times the inter-quartile range).

4.4.2 Examination of underlying water quality trends between 1995 and 2021

Of particular interest is whether there have been systematic changes in water quality occurring across Victoria over the study period. This section examines the underlying trend component of the statistical models described above.

We report on the directions and magnitudes of the underlying trend in water quality that cannot be explained by streamflow (or water temperature). The underlying trend in water quality is represented by the regression coefficient of the trend component in the multiple linear regression model. These regression coefficients are not standardised by the z score, to enable easier identification of the percentage change in water quality parameters per year. Our confidence that the regression coefficient represents a statistically significant change (increase or decrease) in the water quality parameter was assessed using the statistical significance of the regression coefficient. All sites have either a statistically significantly increasing (when the regression coefficient is positive), decreasing (when the regression coefficient is negative), or not statistically significant (where the regression coefficient is not statistically significant) underlying trend.

At the state level

Many sites have demonstrated statistically significant underlying trends in water quality, which cannot be explained by streamflow. These underlying trends are not driven by long-term flow changes; they may result from either other hydro-climatic and environmental processes, or from human-induced change.

These underlying trends have been quantified using the coefficient of the 'trend' component in the multiple linear regression models. A positive coefficient means that the water quality parameter is increasing over time (when controlling for seasonality and flow); a negative coefficient means the parameter is decreasing (when controlling for seasonality and flow). The coefficient value of 1 represents a change in 1 in the log (with base 10) scale of the water quality parameter concentration when there is a 1 log (base 10) change in streamflow.

Table 5 and Figure 21 provide the proportion of sites with (i) decreasing, (ii) not statistically significant, and (iii) increasing underlying trends. They indicate that the largest proportion of sites:

- for EC (45.9%) have experienced a decreasing underlying trend
- for TN (46.5%) and DO (48.1%) have not experienced a statistically significant underlying trend
- for turbidity (79.8%), TP (40.2%) and pH (58.2%) have experienced an increasing underlying trend.

Table 5: Percentage of sites with increasing, not significant and decreasing water quality underlying trends for each parameter. Green highlight indicates the category with the largest number of sites.

	Decreasing	Not significant	Increasing
EC	45.9%	38.5%	15.6%
Turbidity	7.4%	12.8%	79.8%
TN	23.7%	36.1%	40.2%
TP	27.9%	46.5%	25.6%
pH	12.7%	29.1%	58.2%
DO	34.9%	48.1%	17.0%

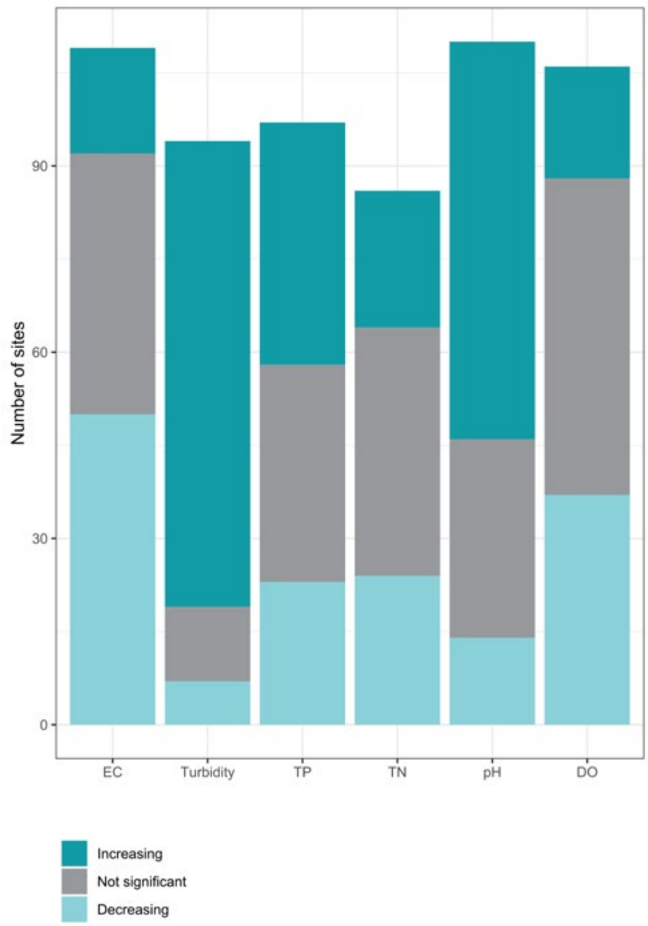


Figure 21: Number of sites with statistically significant increasing, statistically significant decreasing and not statistically significant underlying trends in water quality.

The spatial distribution of these underlying trends is provided in Figures 22-27, showing both the direction of the trend (increasing, not significant and decreasing) and the magnitude of the trend (coefficient of the trend component, where a value of 1 is a 1 log change (base 10) in concentration each year). A detailed view of the direction of the underlying trend in pH is provided in Figure 28, showing that despite the large proportion of sites with an increasing underlying trend in pH, the majority have remained within neutral pH (6.5-8.5) between 1995 and 2021. Broad and generalised patterns across the state are as follows:

- EC: underlying trends are not statistically significant largely in the south and in the east of the state. However, there are groups of sites with increasing underlying trends in the south-west (the Otways Coast region) and in the north-east (the Snowy Basin region)
- Turbidity: increasing underlying trends across the state. There are, however, some regions where turbidity has a decreasing underlying trend in the central north and in the Yarra catchment.
- TP and TN: no noticeable spatial pattern. Exceptions are groups of sites with increasing TN underlying trends in the Wimmera, and groups of sites with no statistically significant underlying trend in the Ovens basin.
- pH: most sites appear to be experiencing increasing underlying trends in pH. The sites with no significant underlying trend appear to be in the east of the state.
- DO: sites with increasing underlying trends in DO appear to be concentrated in the north-east of the state, while decreasing underlying trends seem to cluster in the west.

The above observations are general spatial patterns across the state and these broad generalised patterns are investigated in more detail in subsequent sections.

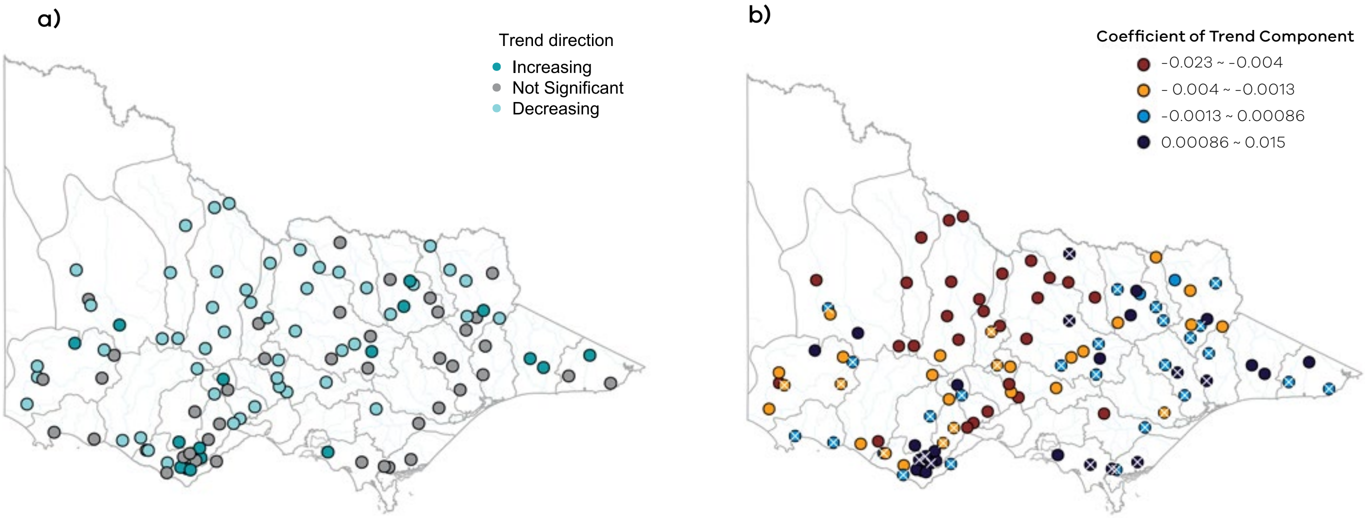


Figure 22: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for EC (a) with the magnitude of the coefficient of underlying trend component (b). A value of 1 indicates that there is a 1 log change (base 10) in concentration each year. Only statistically significant underlying trends shown. 'x' indicates not statistically significant underlying trend at that site.

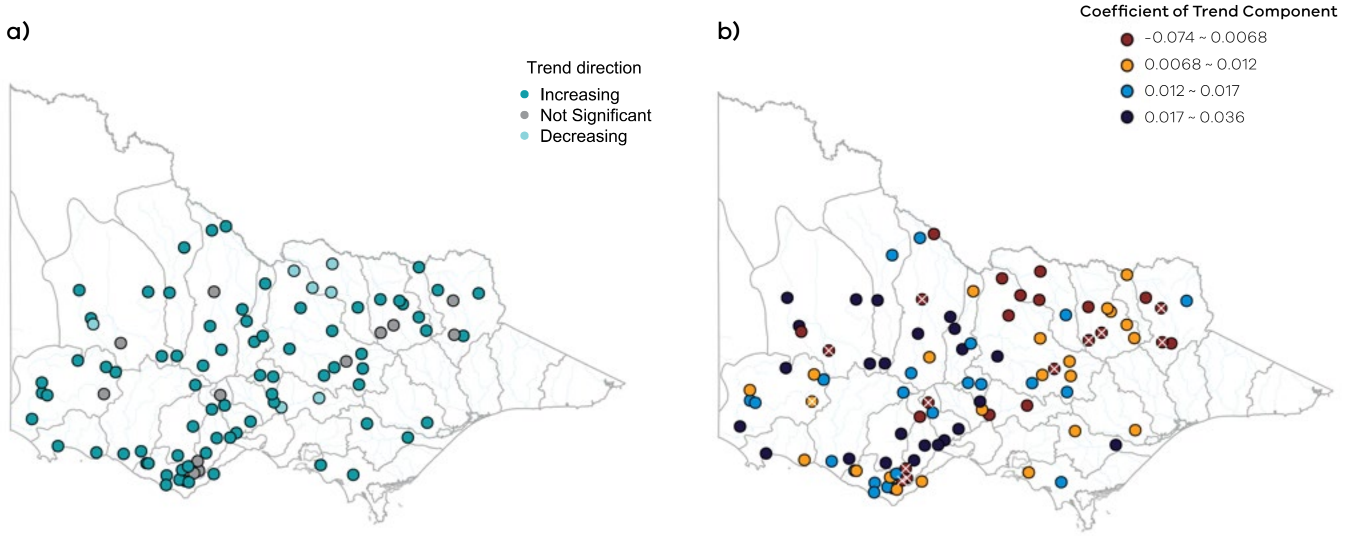


Figure 23: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for Turbidity (a), with the magnitude of the coefficient of underlying trend component (b). A value of 1 indicates that there is a 1 log change (base 10) in concentration each year. Only statistically significant underlying trends shown. 'x' indicates not statistically significant underlying trend at that site.

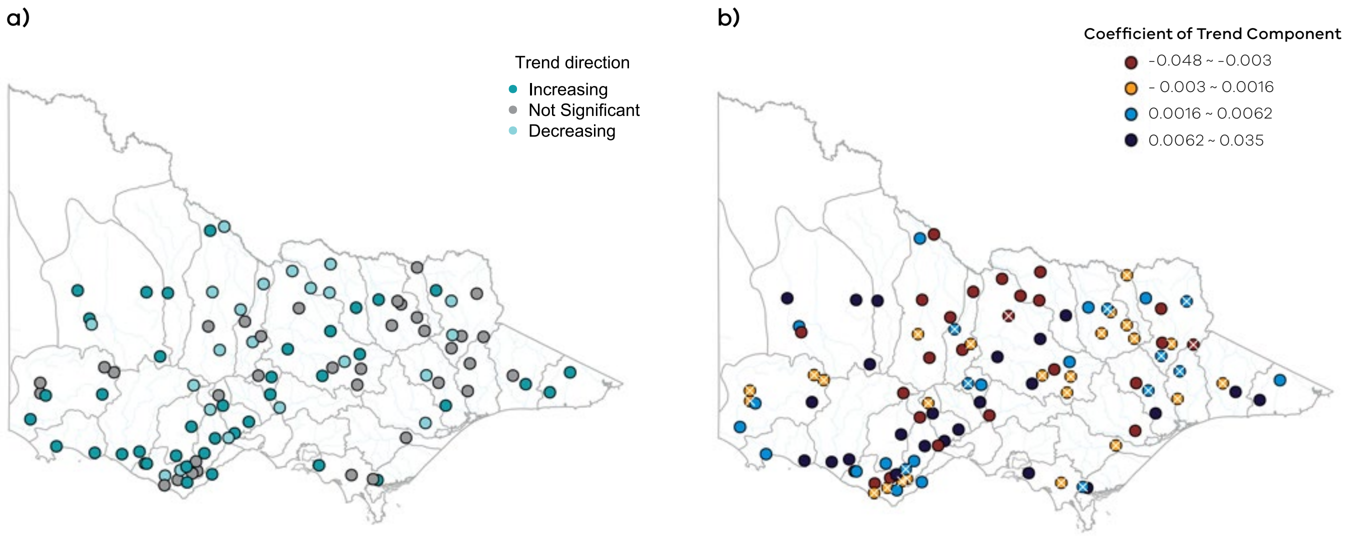


Figure 24: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for TP (a), with the magnitude of the coefficient of underlying trend component. A value of 1 indicates that there is a 1 log change (base 10) in concentration each year. Only statistically significant underlying trends shown. 'x' indicates not statistically significant underlying trend at that site (b).

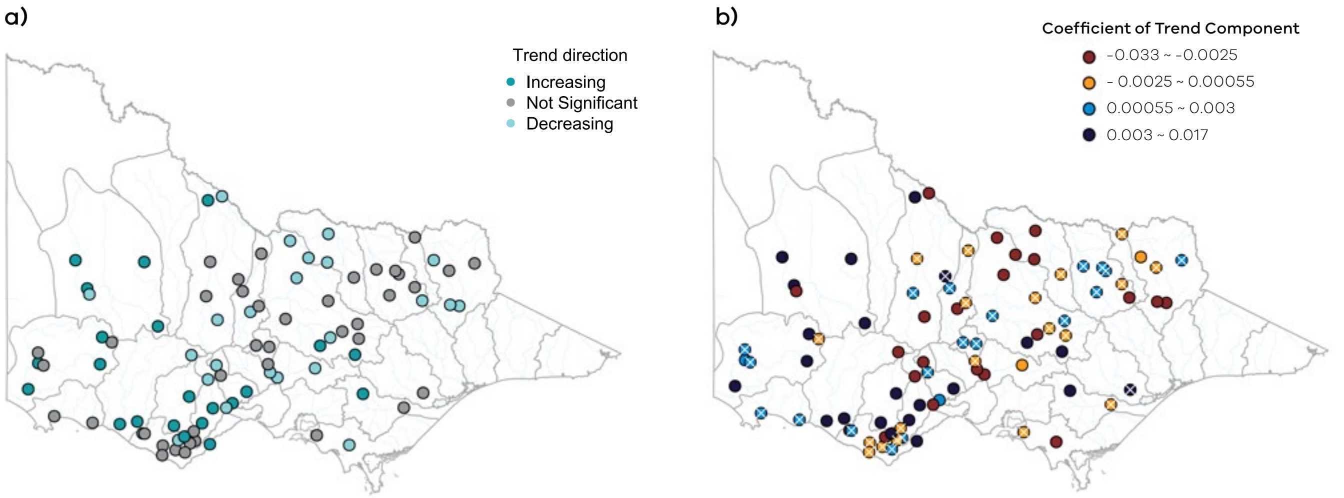


Figure 25: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for TN (a), with the magnitude of the coefficient of underlying trend component. A value of 1 indicates that there is a 1 log change (base 10) in concentration each year. Only statistically significant underlying trends shown. 'x' indicates not statistically significant underlying trend at that site (b).

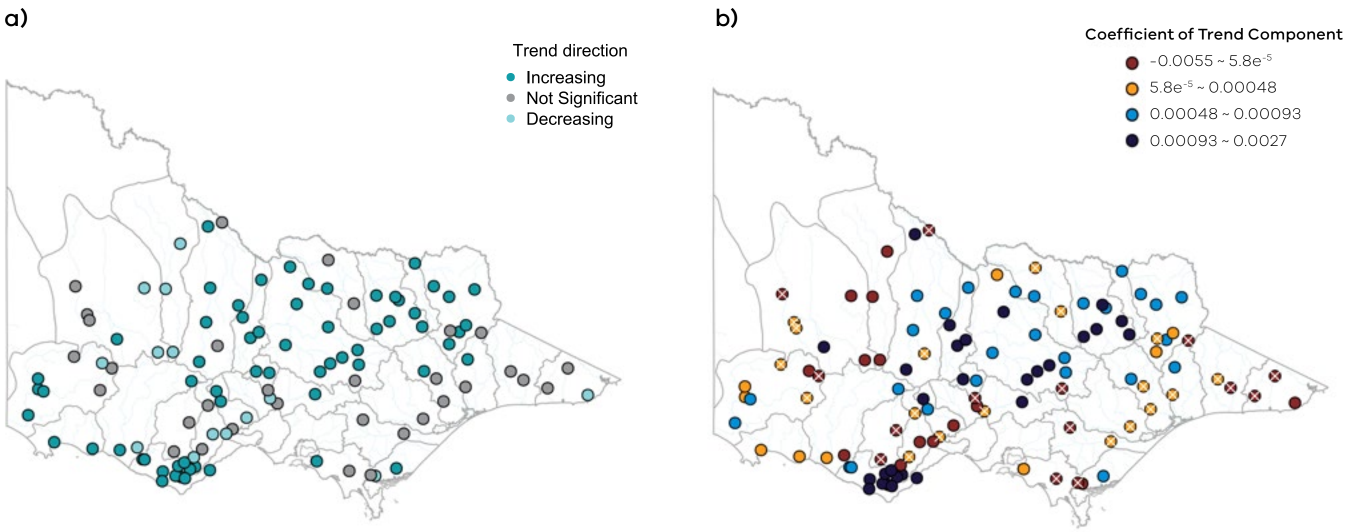


Figure 26: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for pH (a), with the magnitude of the coefficient of underlying trend component. A value of 1 indicates that there is a 1 log change (base 10) in concentration each year. Only statistically significant underlying trends shown. 'x' indicates not statistically significant underlying trend at that site (b).

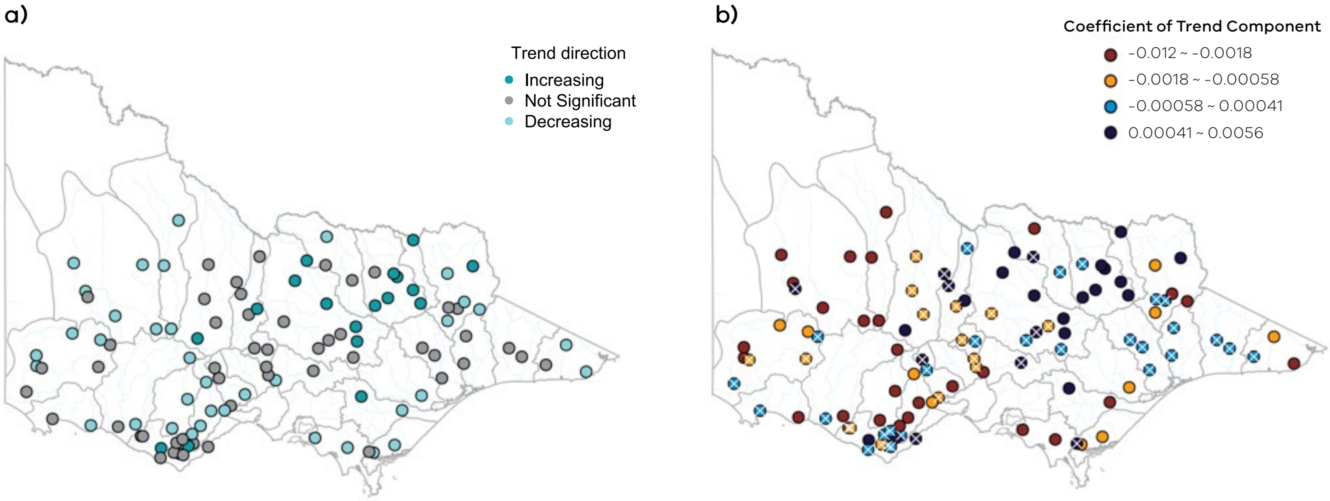


Figure 27: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for DO (a), with the magnitude of the coefficient of underlying trend component. A value of 1 indicates that there is a 1 log change (base 10) in concentration each year. Only statistically significant underlying trends shown. 'x' indicates not statistically significant underlying trend at that site (b).

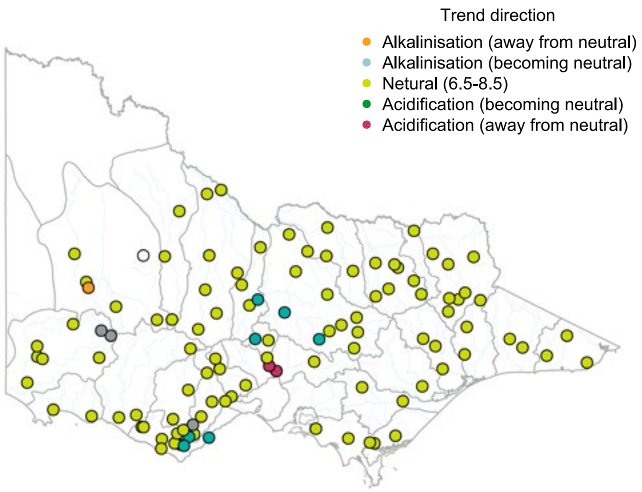


Figure 28: The direction of the coefficient of underlying trend component of the multiple linear regression model for each site for pH.

The previous water quality trends report (1991-2016) focused on 79 sites across Victoria. Most of the sites had a decrease in DO, an increase in pH, turbidity and TN and TP, and no consistent state-wide patterns in EC. There are some differences between the previous report findings and those in this report. In particular: (i) the previous report found that most sites had a decrease in DO, but we found that most sites have an increase or no statistically significant trend; (ii) the previous report found that there was no spatially consistent trend in EC; we found that the majority of sites have a decrease or no statistically significant trend; (iii) the previous report found increases in TP and TN across the state; we found that the majority of sites have a not statistically significant or a decreasing trend.

The differences in findings between the reports are likely due to the different method used to identify water quality trends. The previous report's trends were largely driven by changes in streamflow. This report describes trends in water quality that are not due to fluctuations in streamflow or due to seasonality.

Regional underlying trends across Victoria – using ERS segments

The occurrence of statistically significant underlying trends in water quality differ in some ways between ERS segments and the overall statewide analysis (Figure 29). The important differences are as follows. For all parameters, the results for the Urban and Highlands ERS segments should be treated with caution as very few sites within these ERS segments were examined.

- EC: The greatest proportion of sites in the most human-affected ERS segments, Central Foothills and Coastal Plains, Murray and Western Plains and Urban, are experiencing a decreasing underlying trend. In contrast, the greatest proportion of sites in the least modified ERS segments (Highlands, Uplands A and B) are experiencing no statistically significantly changing underlying trend. These underlying trends cannot be explained by changes in streamflow over time.
- Turbidity: Both state-wide and across all ERS segments, the majority of sites have increasing underlying trends in turbidity that cannot be explained by flow.
- TP: The greatest proportion of sites in the Central Foothills and Coastal Plains and the Murray and Western Plains segments, which are the most modified, have an increasing underlying trend. In the Urban segment, one site has experienced an increasing underlying trend, and the other a decreasing underlying trend. Conversely, the least modified ERS segments (Highlands, Uplands A and B) have the largest proportion of sites with no statistically significant underlying trend.
- TN: The greatest proportion of sites in the Central Foothills and Coastal Plains and Uplands B segments have no statistically significant underlying trend. For the Murray and Western Plains and the Uplands A segments, there are just as many sites with an increasing underlying trend as there are with no statistically significantly changing underlying trend. For the Urban segment, there is one site with a decreasing underlying trend and one site with no statistically significant underlying trend. It appears that there is not a clear distinction in underlying trends between human-affected segments (Central Foothills and Coastal Plains, Murray and Western Plains, Urban) and unaffected segments (Uplands A and B).
- pH: Both state-wide and across all ERS segments, the majority of sites remain at a neutral pH (6.5-8.5).
- DO: The greatest proportion of sites in all ERS segments do not have a statistically significantly changing underlying trend. There are two exceptions. In the Murray and Western Plains, the greatest proportion of sites have had a decreasing underlying trend, and in the Urban segment one site has had a decreasing underlying trend and one has not had a statistically significantly changing underlying trend.

Figure 31 provides the distributions of underlying trend coefficient magnitudes and identifies that there are outlier sites: those that have either markedly higher or more negative underlying trend coefficients than most. These outlier sites have been listed in Appendix G. Outliers are more common in the more developed and modified Central Foothills and Coastal Plains, and the Murray and Western Plains. Investigation of these sites would be necessary to fully understand the factors that have caused these anomalously large positive and negative underlying trends in water quality, for each ERS segment.

Our results provide an overall picture of changes in water quality both state-wide and in each ERS segment. To further explore changing water quality, the following sections focus on sites with the greatest improvements and the greatest deteriorations as identified by the magnitude of the underlying trend coefficients.

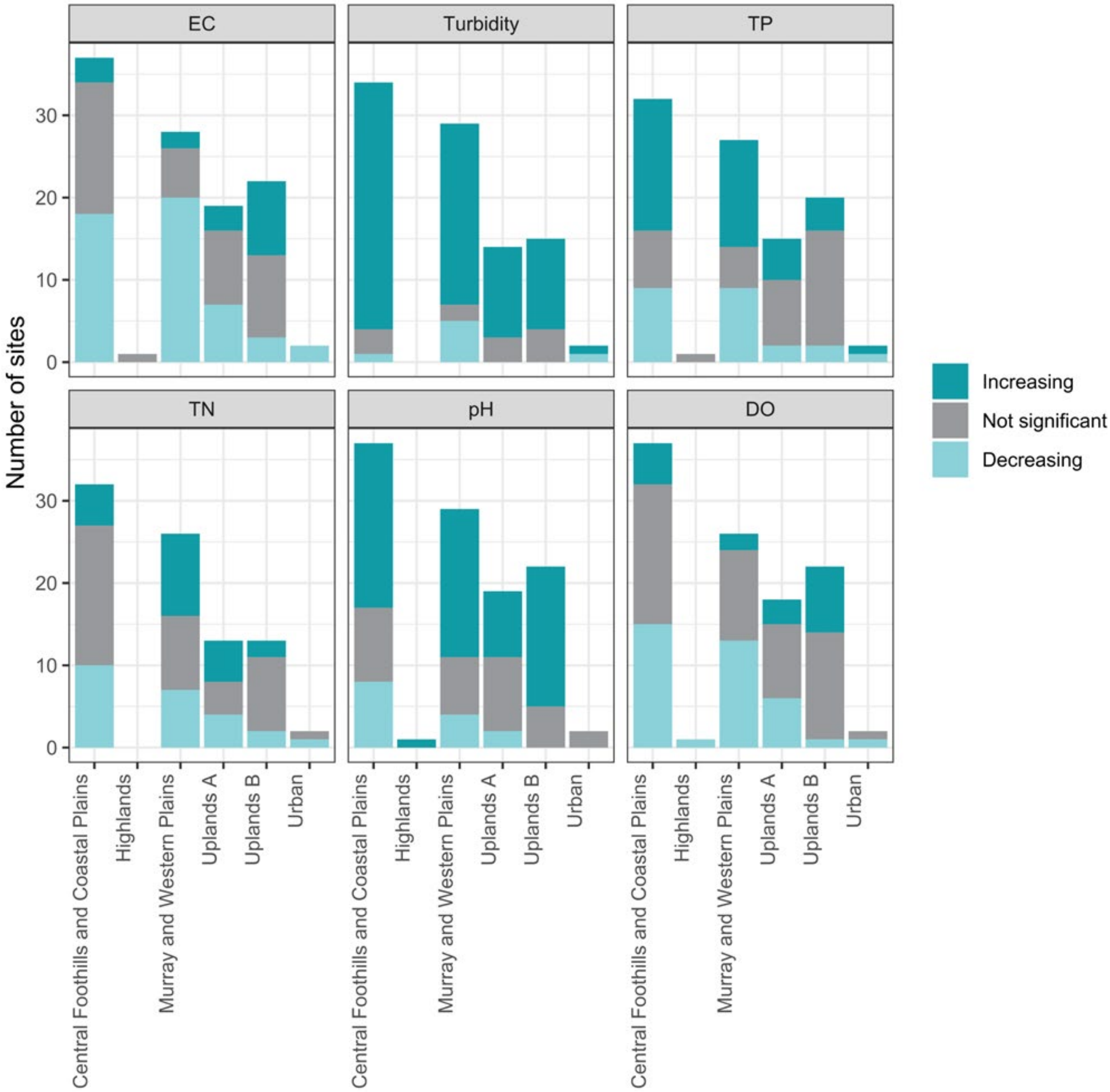


Figure 29: Number of sites with statistically significant increasing, statistically significant decreasing and not statistically significant ('Not significant') underlying trends in water quality.

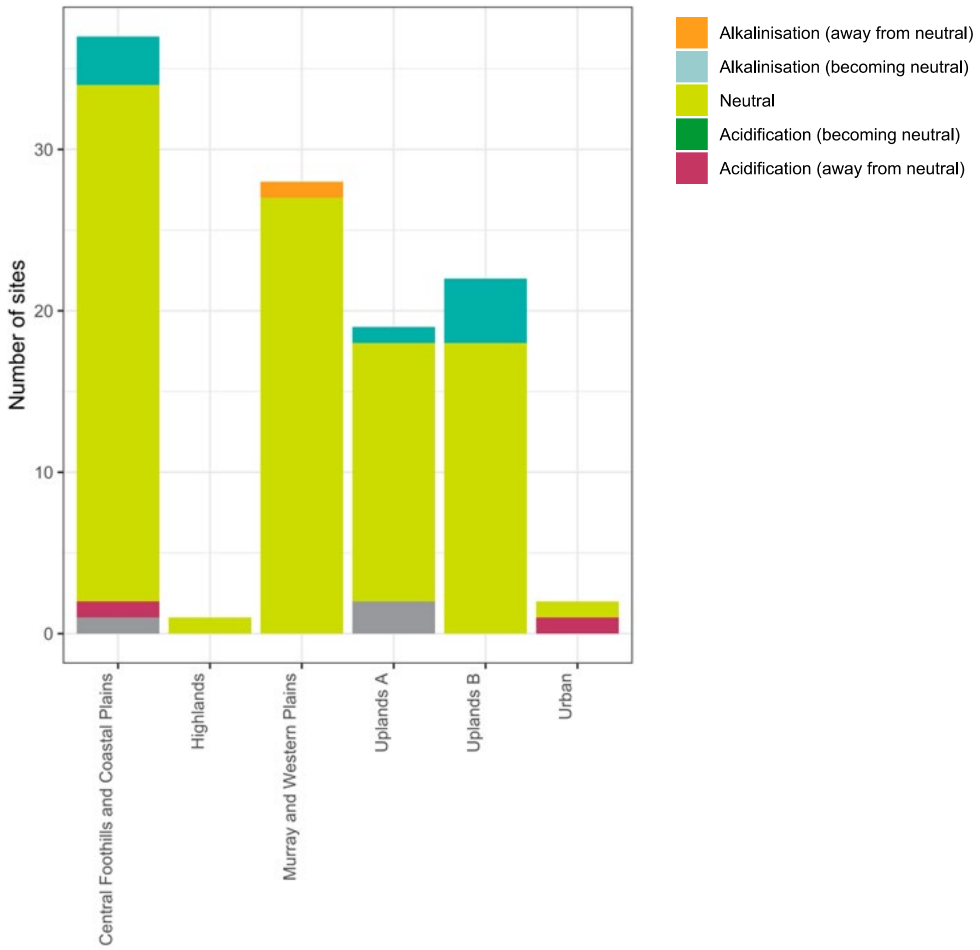


Figure 30: The number of sites in each segment with direction of underlying trend in pH.

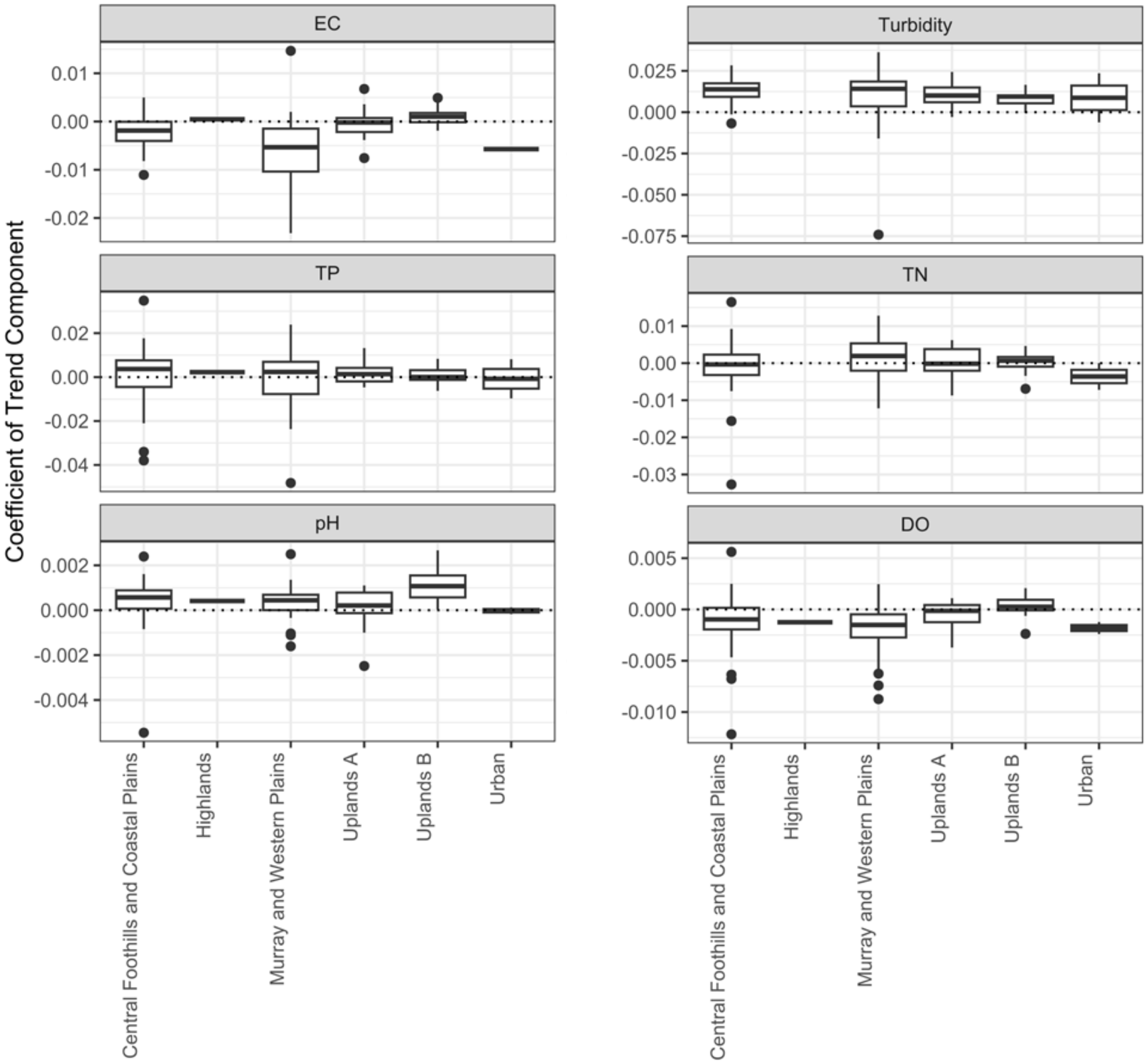


Figure 31: Distribution of the magnitude of the coefficient of underlying trend component of the multiple linear regression model within each ERS segment. Dots are outliers (1.5 times interquartile range). All outlier sites are listed in Appendix G.

Sites with improving underlying trends in water quality

We assessed the strength of trends at individual sites. The description below focuses on the 8 sites with the greatest underlying trends (increasing and decreasing). Appendix G provides more insight into the top 25 sites with the largest underlying trends in water quality.

Time-series plots for the 8 sites with the strongest improving underlying trends (decreasing EC, turbidity, TP, TN and increasing DO) are shown in Figure 32 to Figure 36.

These sites have three or more water quality parameters with strong improving underlying trends:

- Moonee Ponds Creek at Racecourse Road, Flemington (229643): for turbidity, TP and TN
- Goulburn River at Shepparton (405204): for DO, EC, turbidity, TP and TN
- Goulburn River at McCoys Bridge (405232): for EC, turbidity, TP and TN

Investigating the local conditions at these sites, and the relationships between the underlying trends in the water quality parameters, may reveal information on the drivers of the improvements.

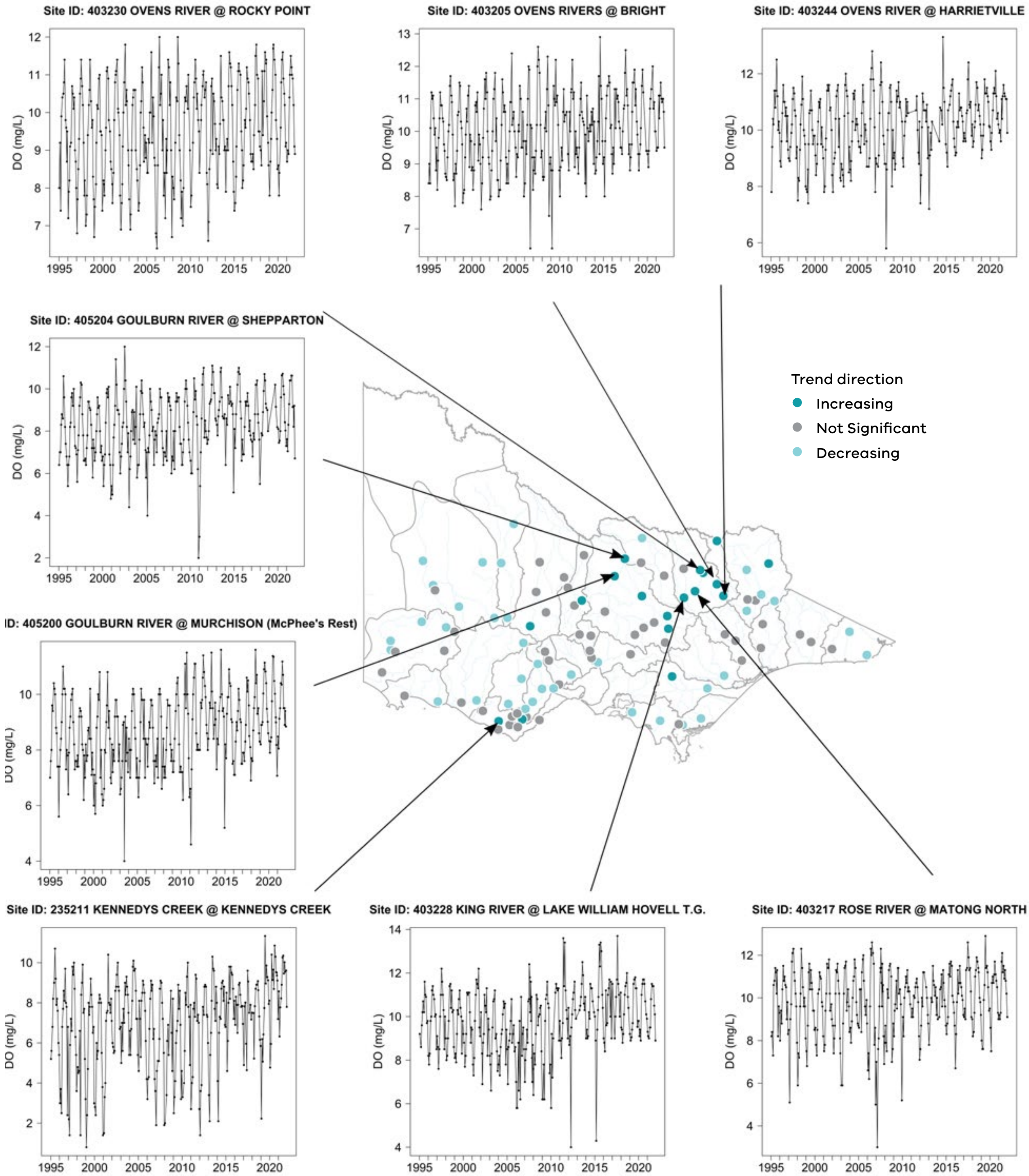


Figure 32: The 8 sites with the strongest increasing underlying trends in DO.

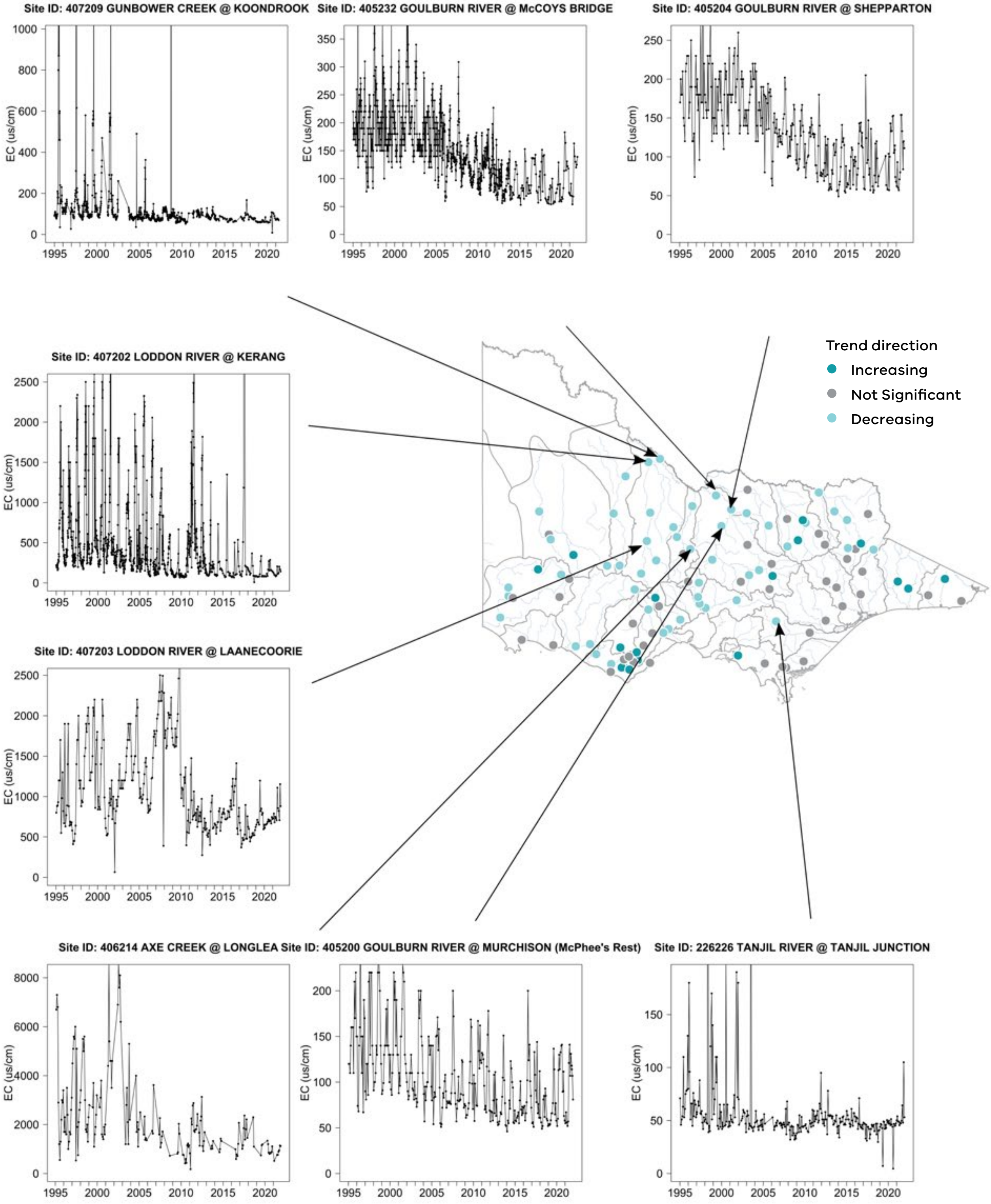


Figure 33: The 8 sites with the strongest decreasing underlying trends in EC.

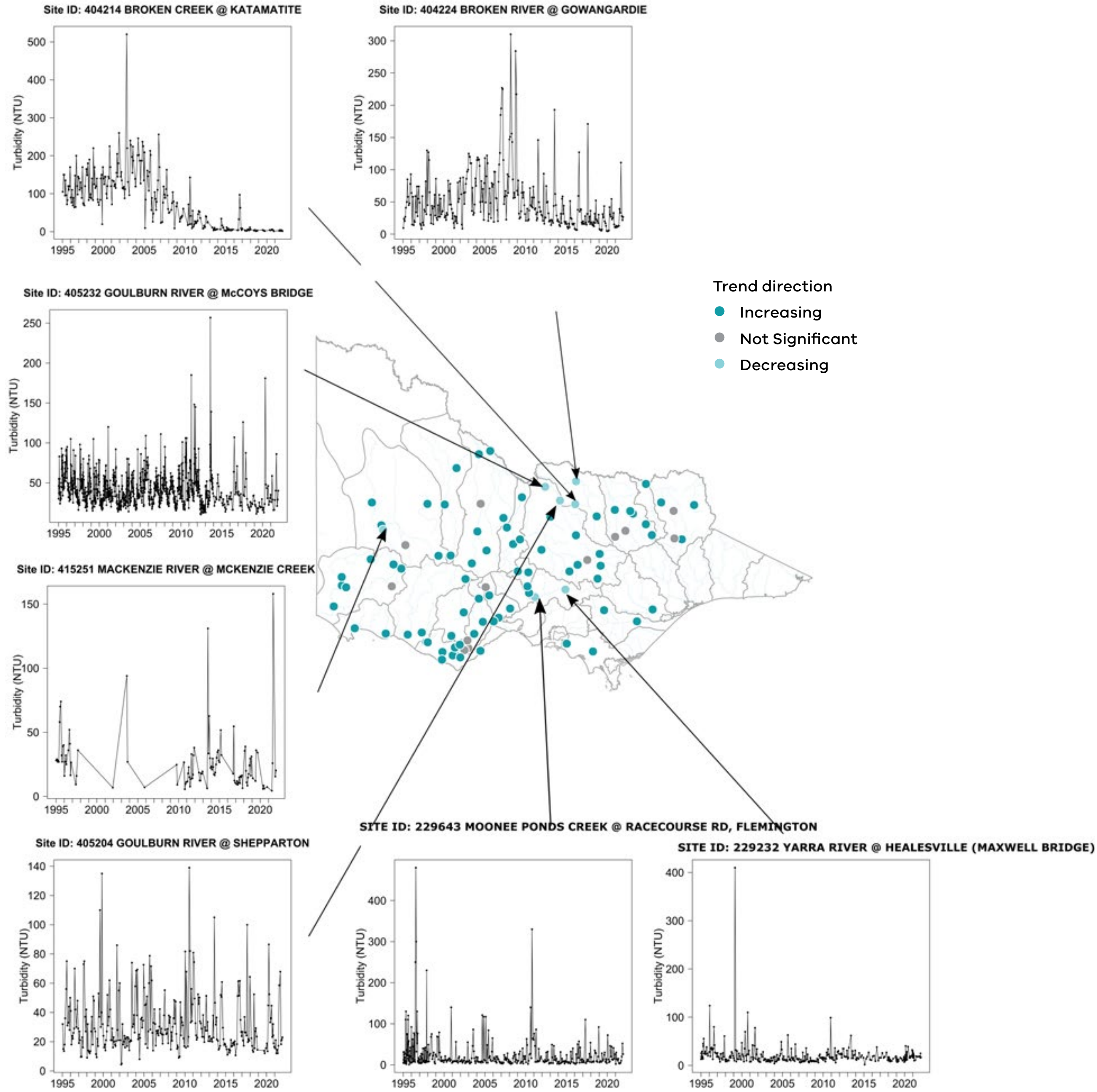


Figure 34: The 8 sites with the strongest decreasing underlying trends in turbidity.

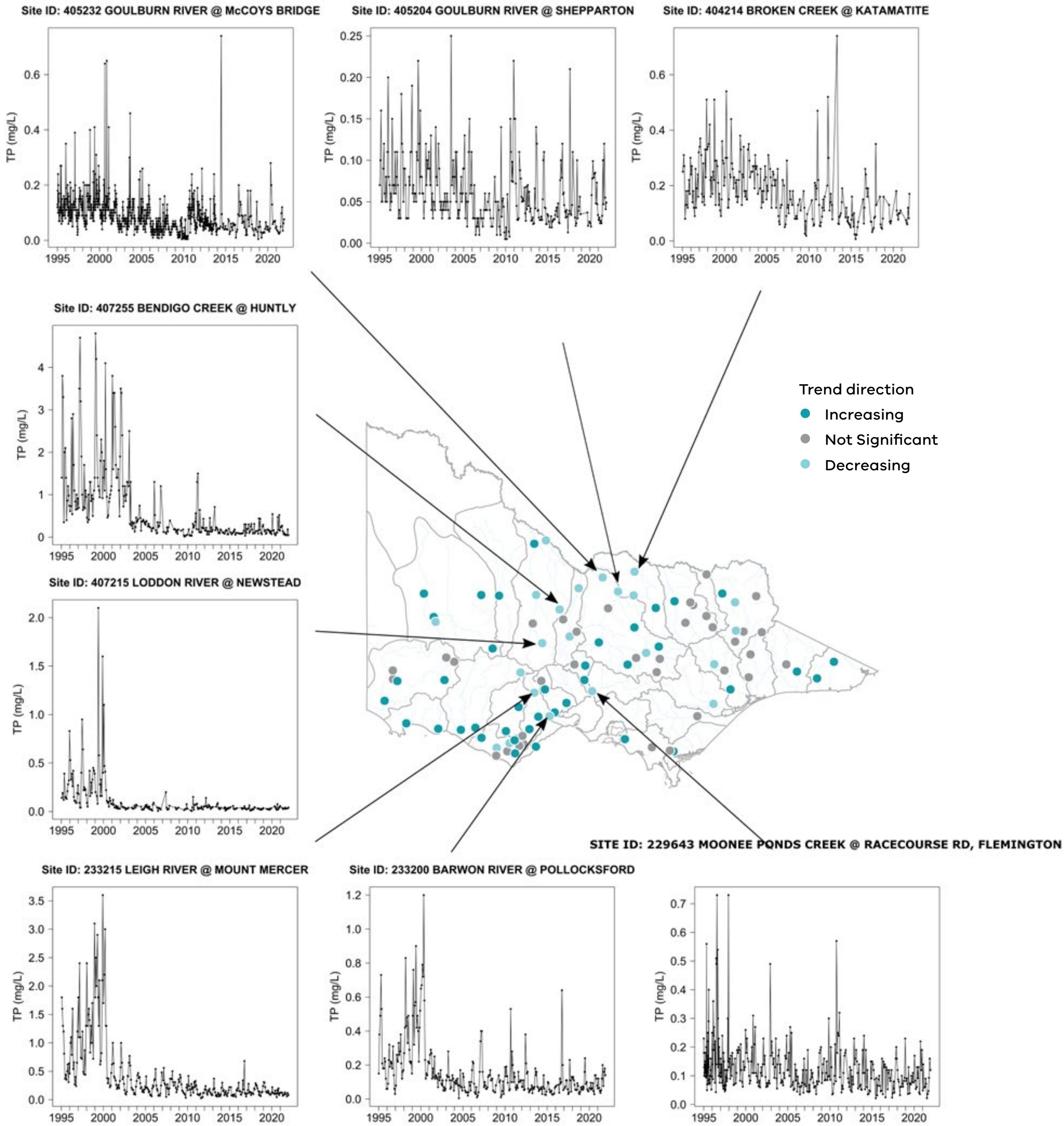


Figure 35: The 8 sites with the strongest decreasing underlying trends in TP.

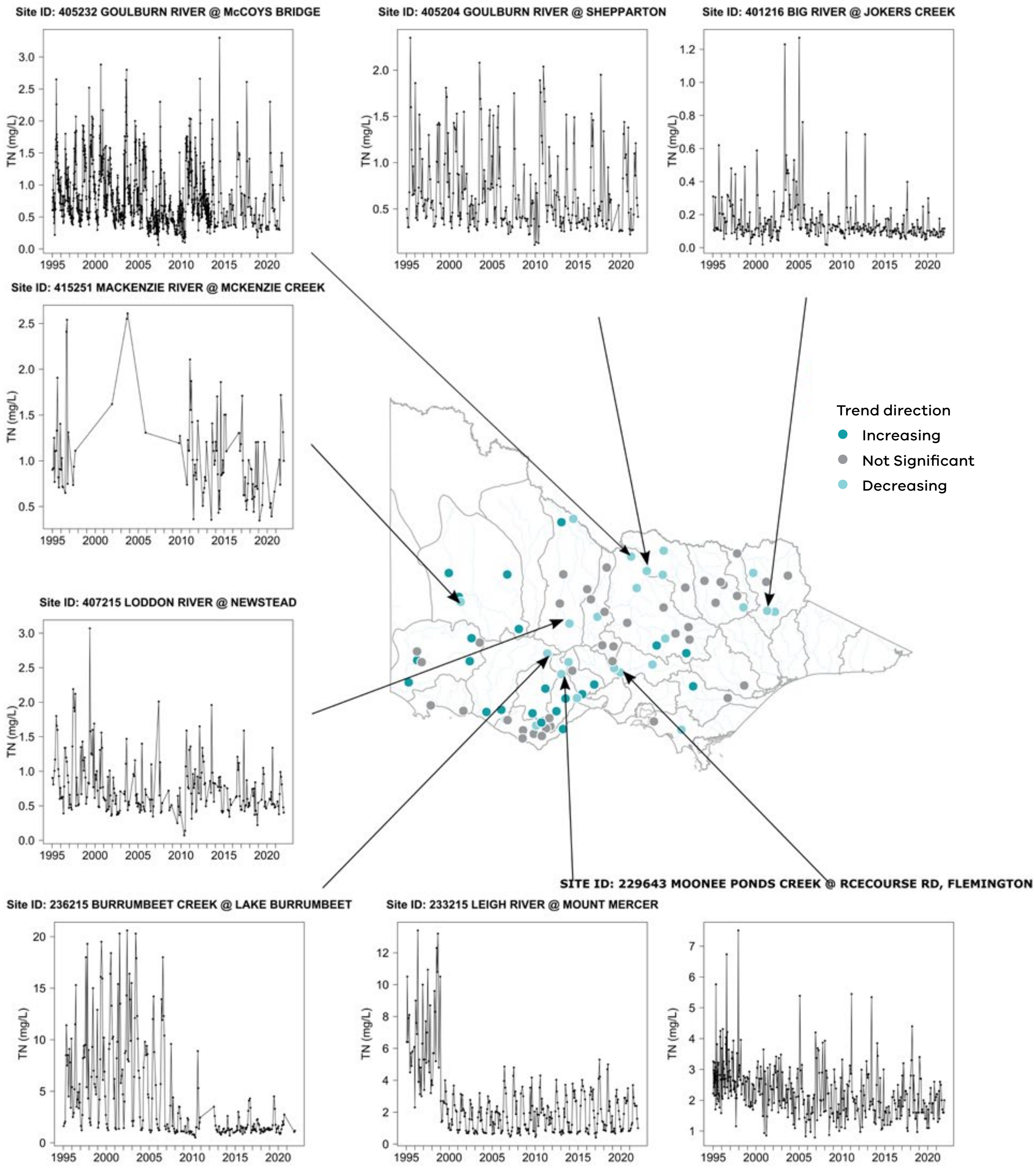


Figure 36: The 8 sites with the strongest decreasing underlying trends in TN.

Sites with deteriorating underlying trends in water quality

Time-series plots for the sites with the 8 strongest deteriorating underlying trends (decreasing EC, turbidity, TP, TN and increasing DO) are shown in Figure 37 to Figure 43.

There are sites where there are three or more water quality parameters with strong deteriorating underlying trends:

- Little River at Little River (232200): for pH (increasing acidity), TP and TN
- Avoca River at Coonooer (408200): for DO, pH (increasing in acidity), turbidity and TP
- Avoca River at Amphitheatre (408202): for DO, pH (increasing acidity), and turbidity
- Avoca River at Quambatook (408203): for DO and pH (increasing acidity)
- Wimmera River at Eversley (415207): for DO, turbidity, TP and TN
- Wimmera River at Lochiel Railway Bridge (415246): for turbidity, TP and TN
- Richardson River at Donald (415257): for DO, pH (increasing acidity), turbidity, TP and TN

By investigating further the local conditions at these sites, and the relationships between the underlying trends in the water quality parameters, we may be able to further identify the key drivers of these underlying trends.

Figure 38 indicates that there are increasing EC underlying trends in three locations: the north-east, the south-west and the west. At least half of the sites with the strongest increasing underlying EC trends are also experiencing the strongest increase in underlying pH trends. This could be due to increasing groundwater contributions to the streamflow, adding ions and salts to the streams. These increasing groundwater contributions could also be linked to the increase in alkalinity and pH.

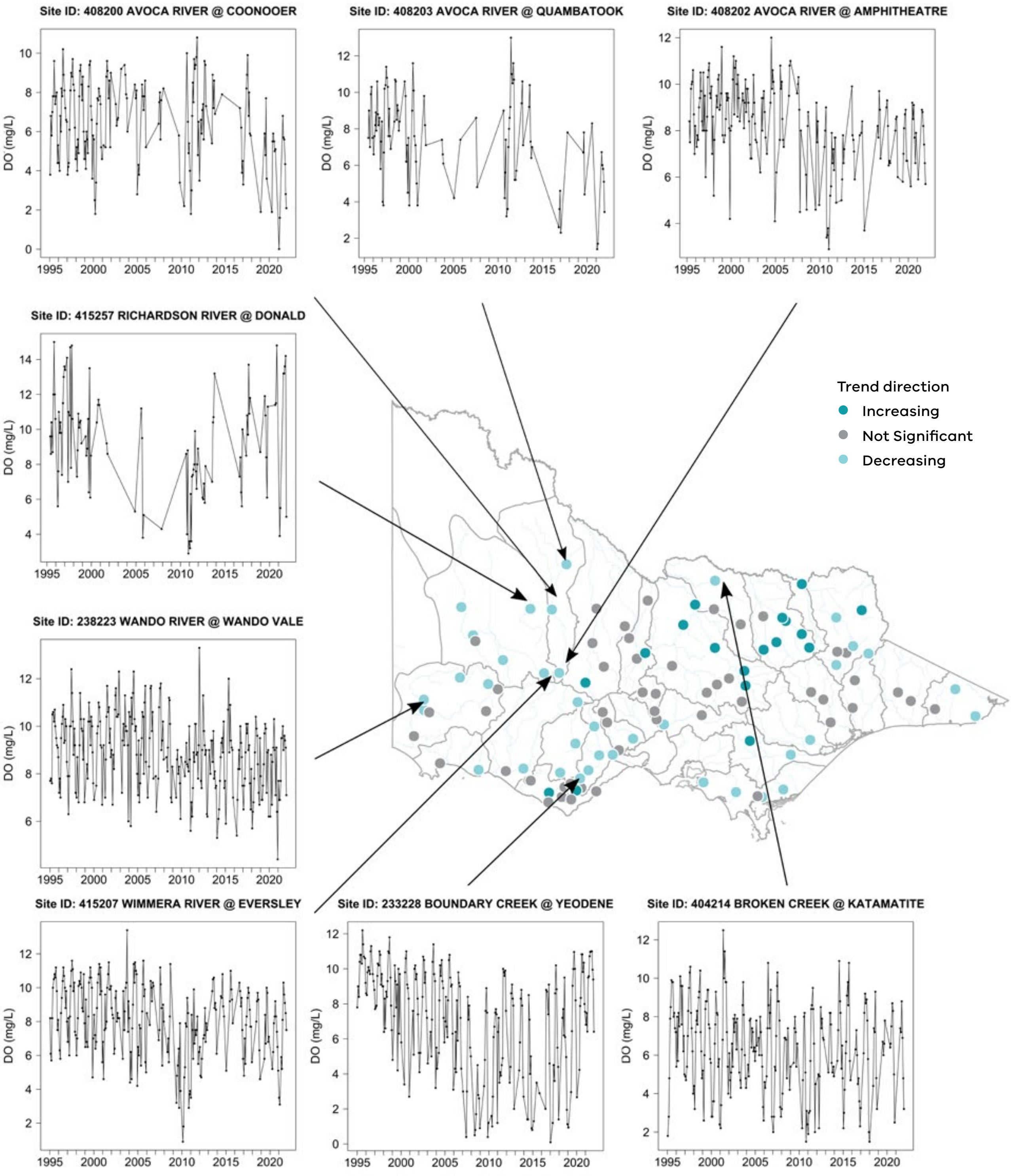


Figure 37: The 8 sites with the strongest decreasing underlying trends in DO.

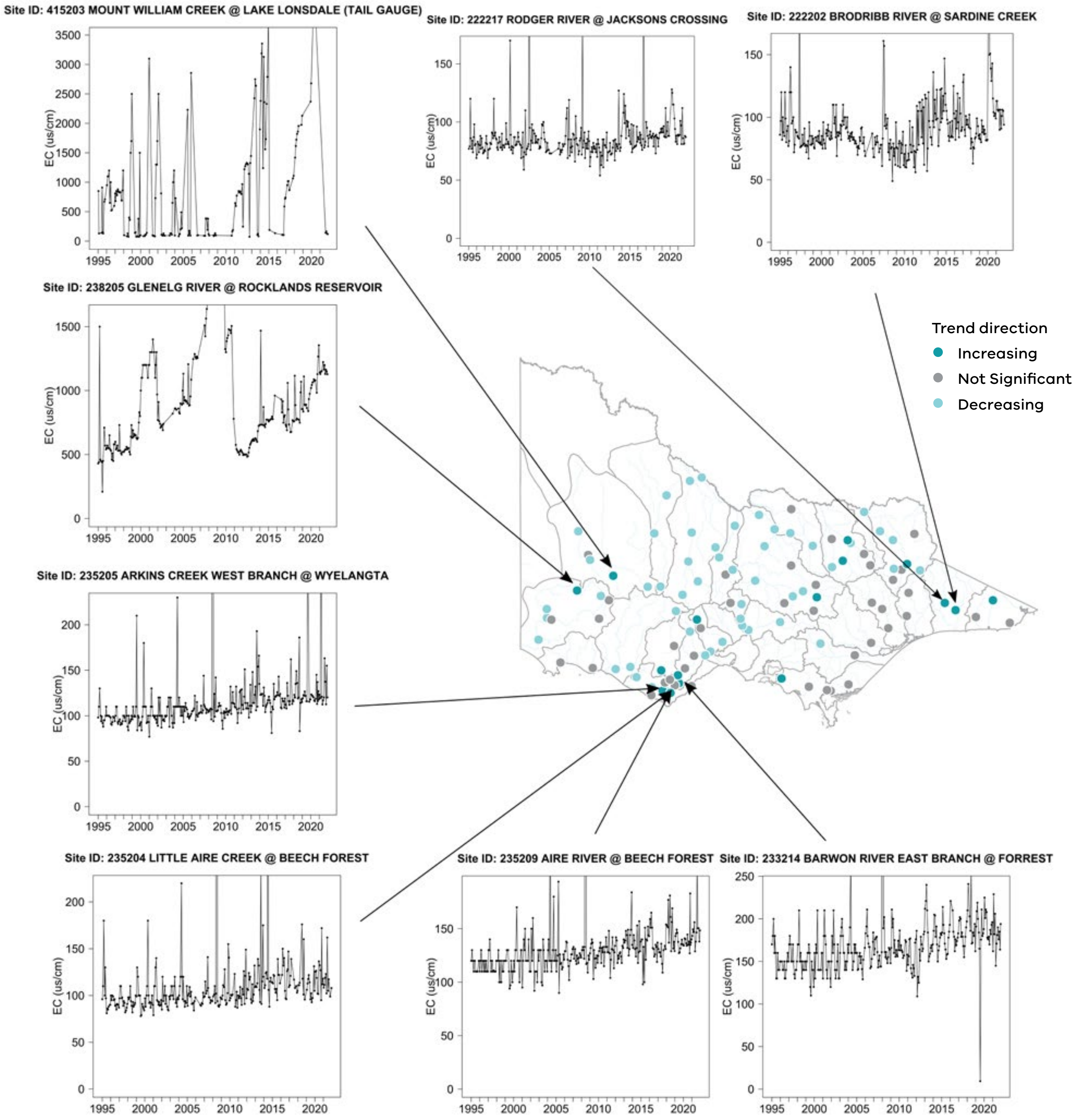


Figure 38: The 8 sites with the strongest increasing underlying trends in EC.

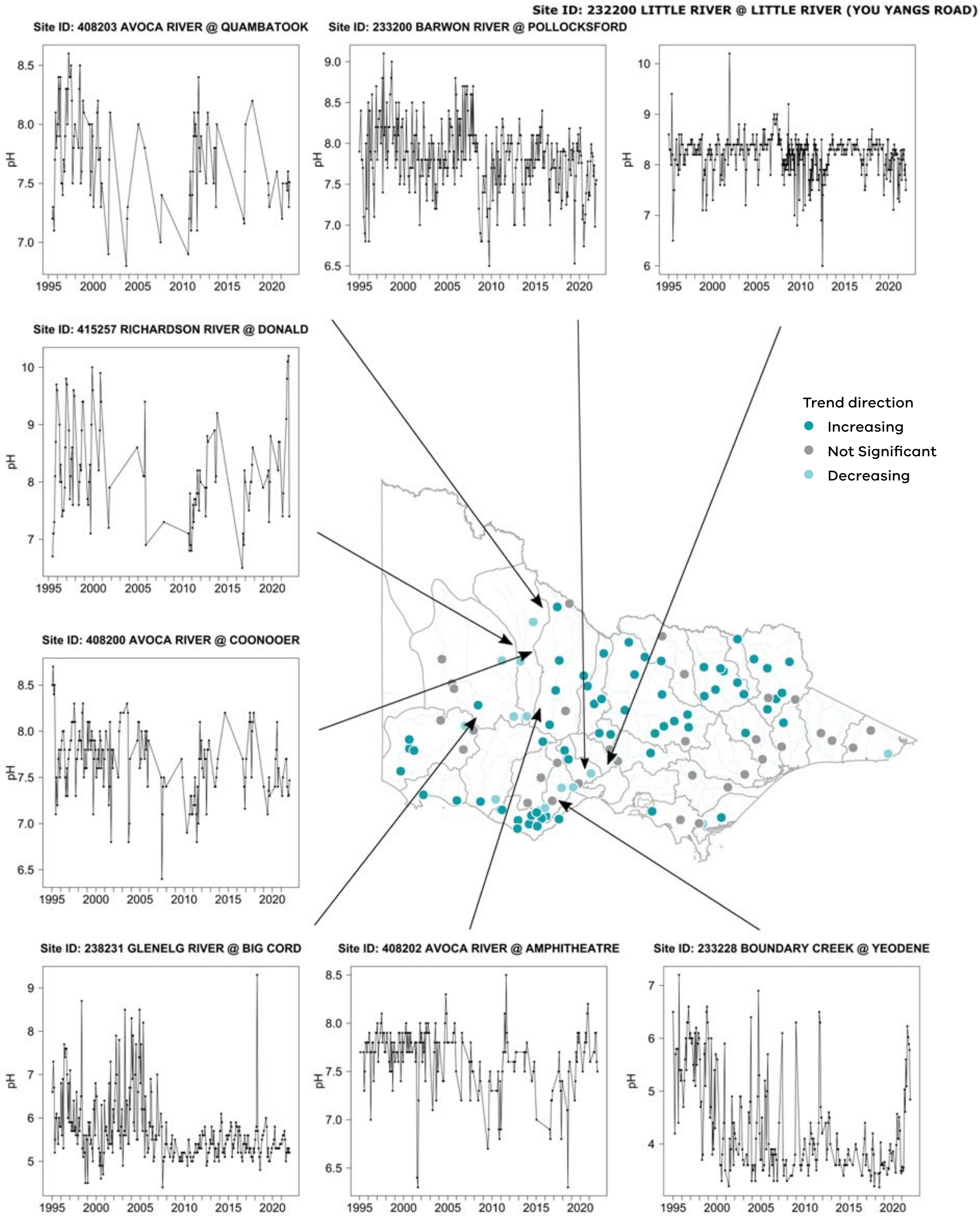


Figure 39: The 8 sites with the strongest decreasing underlying trends in pH (i.e. increasing acidity).

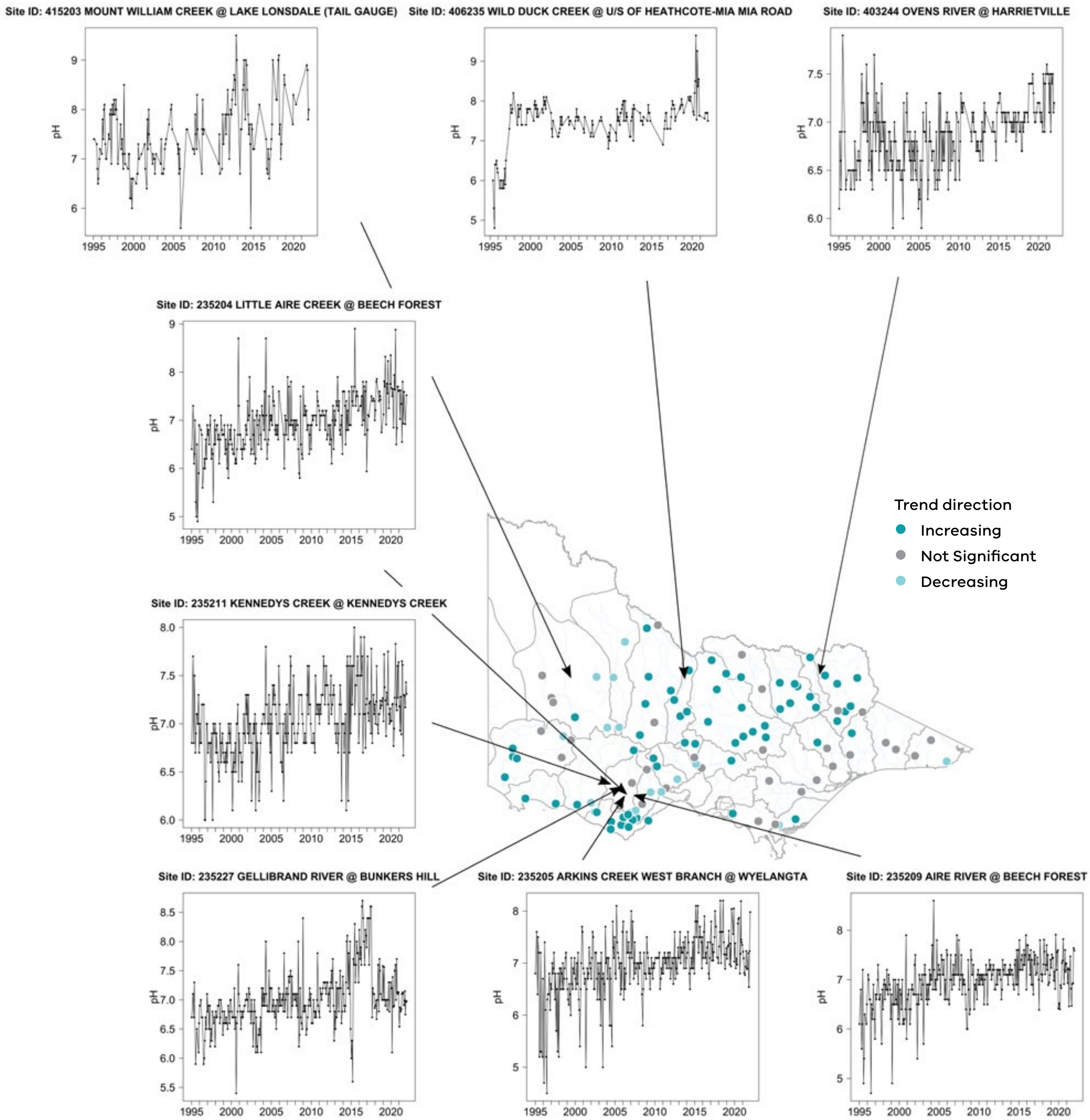


Figure 40: The 8 sites with the strongest increasing underlying trends in pH (i.e. increasing alkalinity).

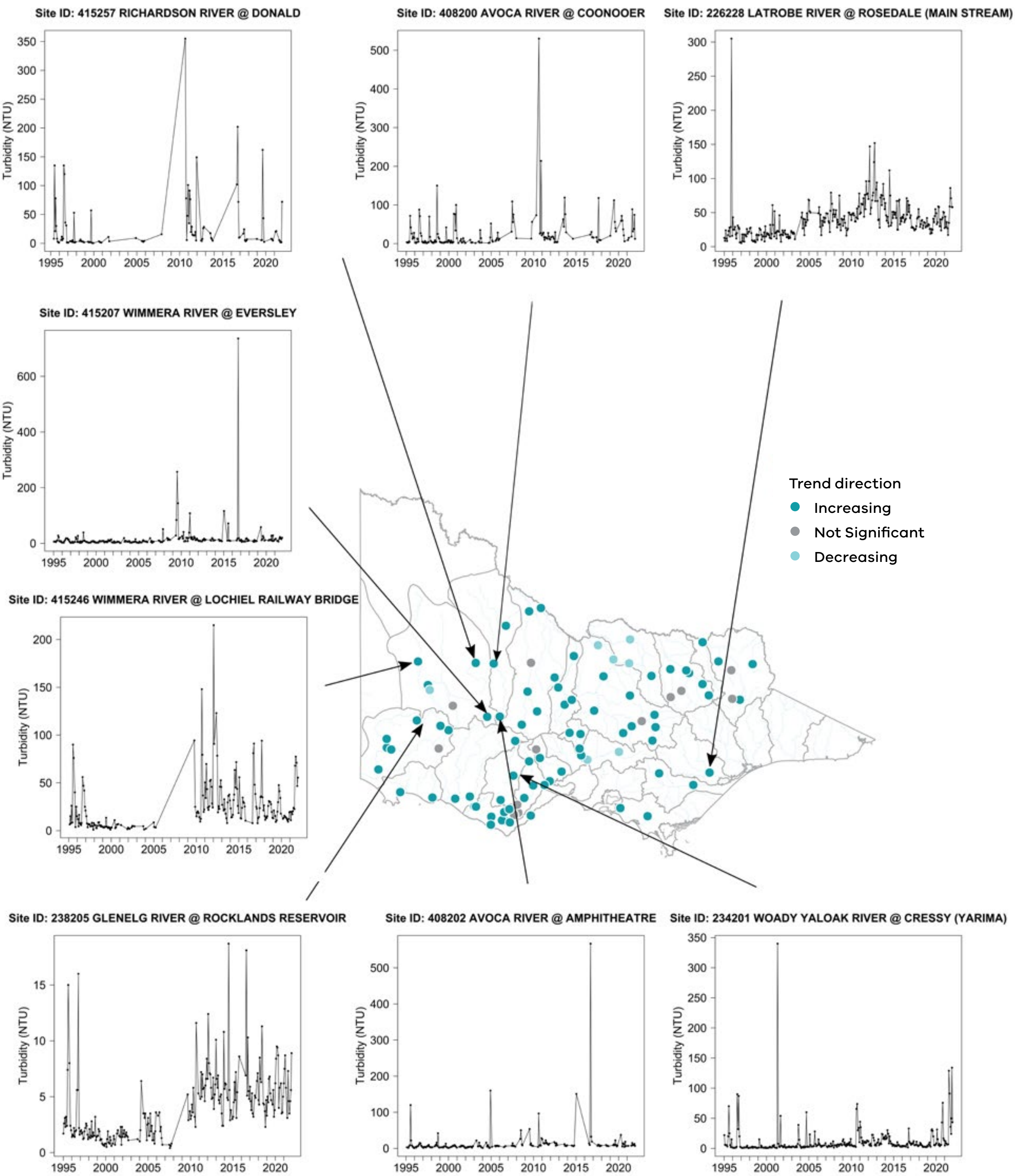


Figure 41: The 8 sites with the strongest increasing underlying trends in turbidity.

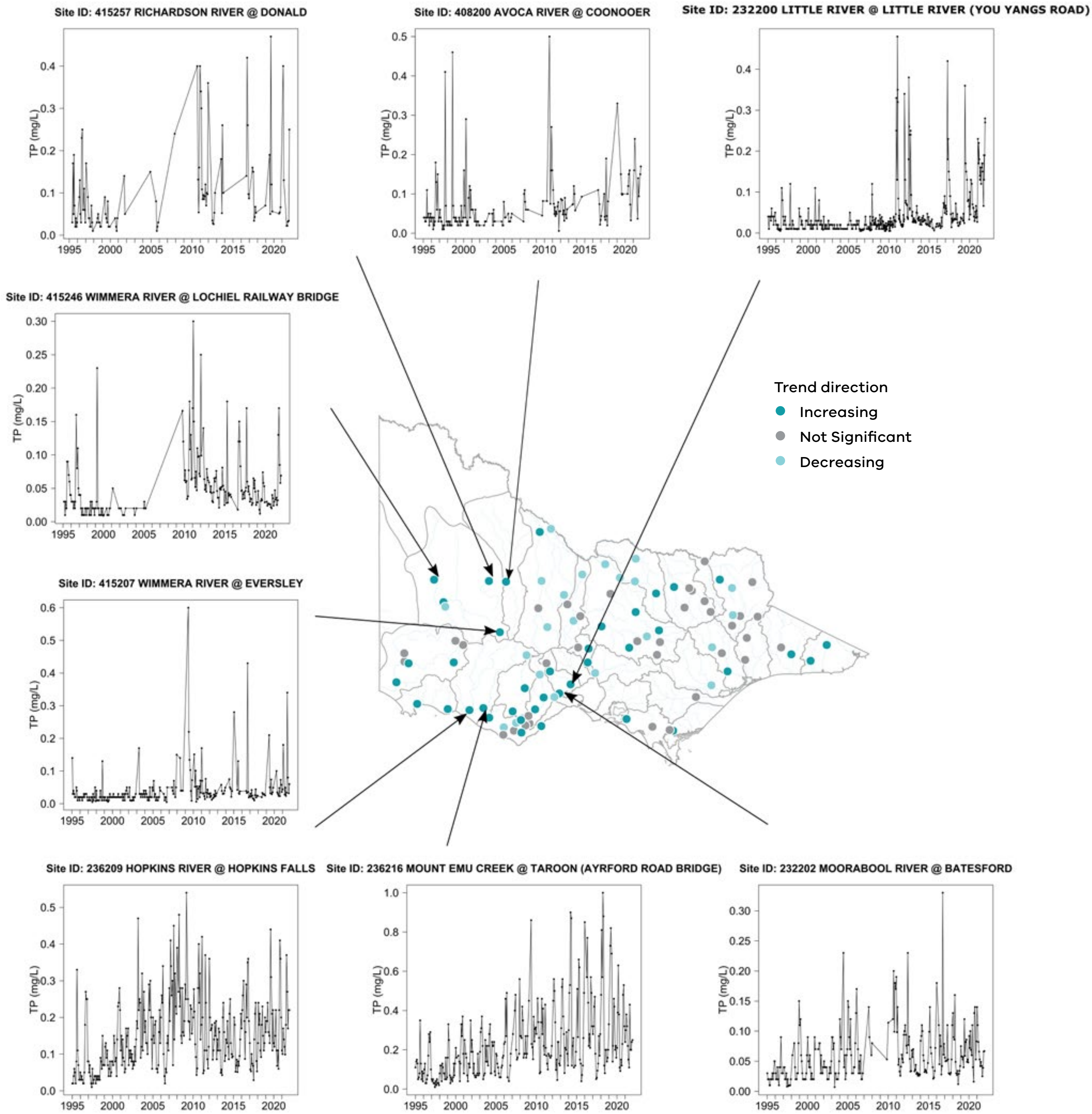


Figure 42: The 8 sites with the strongest increasing underlying trends in TP.

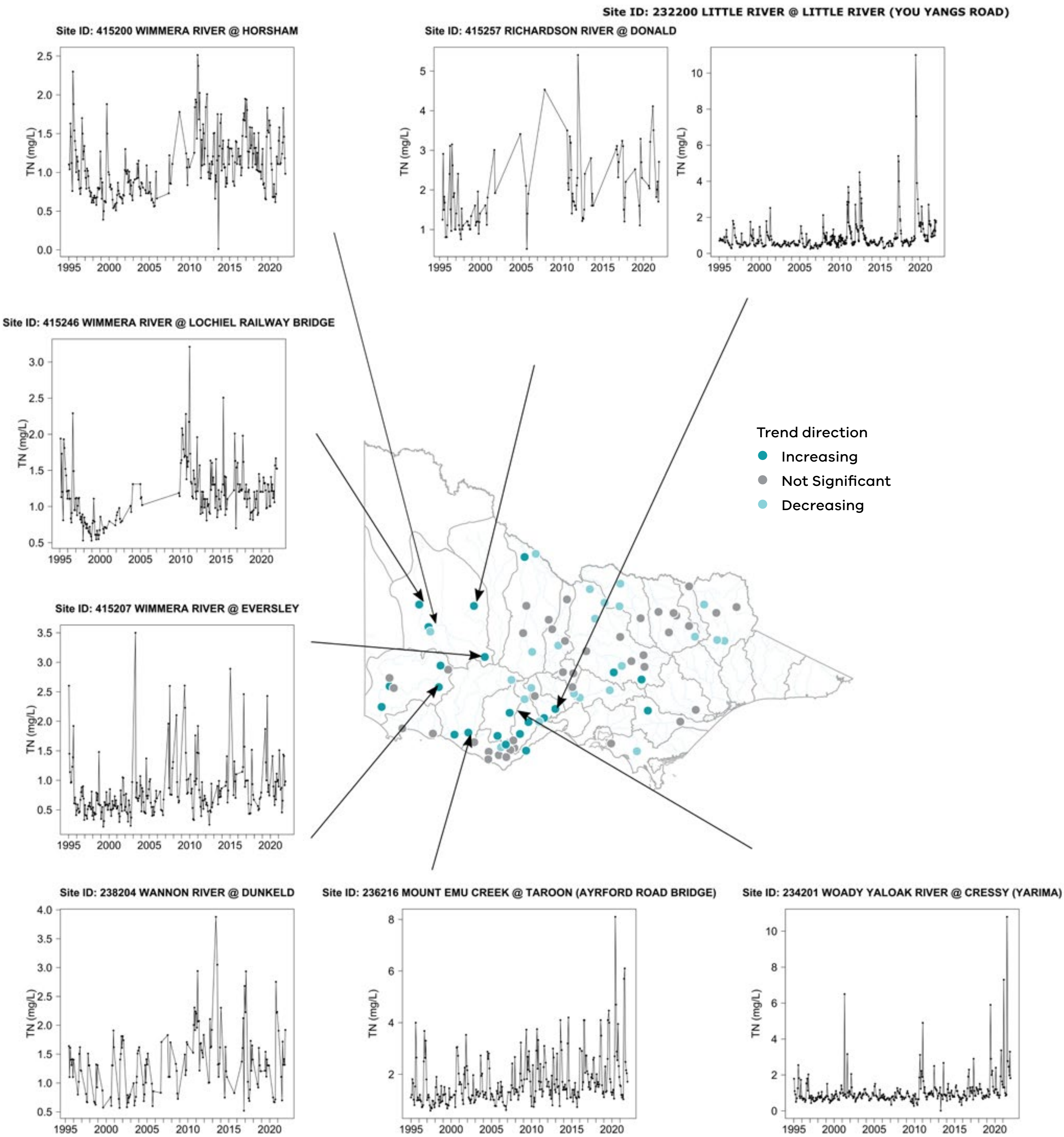


Figure 43: The 8 sites with the strongest increasing underlying trends in TN.

4.4.3 Changes in risk to ERS attainment between 1995 and 2021

Underlying trends in water quality imply change is occurring, but provide no information on implications for ecosystem health, or attainment of ERS objectives (referred to hereafter as ERS attainment), as the underlying trends may be insufficient to have an impact. The following section describes the links between the underlying trend and ERS attainment to set the underlying trends in the context of the available environmental water quality benchmarks.

The State Environmental Protection Policy sets Environmental Reference Standards for water quality for different regions. The regions are the ERS segments that we have used in regional analysis of water quality. The ERS objectives themselves are expressed as percentages of time that water quality should be meeting specific thresholds. For most parameters considered here (EC, turbidity, TP, TN), the parameter value should be below the ERS threshold 75% of the time. Given that samples are taken regularly, this implies that the 75th percentile value should be below the ERS threshold. For DO, low concentrations are problematic, so the ERS states that DO should not fall below the ERS threshold more than 25% of the time. Consequently, the 25th percentile value is key. pH should be maintained at near-neutral conditions. For pH, the ERS considers both the 25th and 75th percentiles and pH should not be below the lower ERS threshold more than 25% of the time and should not be above the upper ERS threshold more than 25% of the time, so the 25th and 75th percentiles are important. The thresholds for each water quality parameter vary between ERS segments.

In the following section, the ERS attainment is analysed on an annual basis using all the samples from a particular year. This is done by finding the relevant (usually 75th) percentile value from the samples for the year and then comparing that with ERS for the site segment. To estimate the change in ERS attainment over time, we calculated the percentage of years in which the ERS is attained for the first 13 years of the study period (1995-2007) and repeated the exercise for the last 13 years of the study period (2009-21), and determined the difference in attainment between these two periods. These periods were selected in order to maximise the use of data within the full 27-year period, while comparing periods of equal duration. The first assessment period largely occurs during the Millennium Drought, while the second period corresponds with post-drought conditions. Chapter 5 presents a detailed examination of the impact of climate variability on constituent behaviour.

Considering all sites in Victoria, there was a decline in ERS attainment between the periods 1995-2007 and 2009-21 for DO, turbidity and TP (i.e. more sites had a decline in the percentage of years attaining ERS objectives than had an improvement) (Table 6). For EC and TN conditions, attainment remained stable. ERS attainment improved for pH. Changes in attainment at each site for all constituents are detailed in Appendix G.

Underlying water quality trends are contributing to changes in ERS attainment, with increasing underlying trends in turbidity, TN, TP. Statistically significant correlations between underlying trends and changes in the attainment of water quality standards occurred for all parameters except pH (Figure 44). For pH, the relationship between the underlying trend and threat to ERS attainment is complicated by the presence of upper and lower bounds to the acceptable pH range. Overall pH demonstrates an improving trend in ERS attainment.

The changes in ERS attainment presented here are likely related to changes in various factors including land use and land use intensity, as well as broad climatic trends.

Table 6: The percentage of sites across Victoria where water quality increased, decreased, and displayed no change between the periods 1995-2007 and 2009-2021 is shown for each of the six constituents studied. Changes in water quality were defined by changes in the number of years within each time period where sites attained the ERS objectives (for EC, turbidity, TP, TN and pH) or a target minimum concentration of 3.5mg/L (for DO). The average change in attainment for each parameter, across all sites in the state is also shown. For example, if a site attained the ERS objective in 3 of the 13 years assessed in the period 1995-2007 (23% attainment), and 7 of the 13 years assessed in the period 2009-2021 (54% attainment), water quality is said to have improved, with an increase in ERS attainment of +31%. Negative values indicate a decrease in ERS attainment between the two periods.

Parameter	Sites where water quality improved	Sites where water quality declined	Sites with no change in water quality	Average change in attainment - all sites
EC	21%	15%	64%	+1%
Turbidity	16%	61%	23%	-14%
TP	16%	51%	33%	-8%
TN	28%	39%	33%	-3%
pH	51%	30%	19%	+6%
DO	11%	35%	54%	-5%

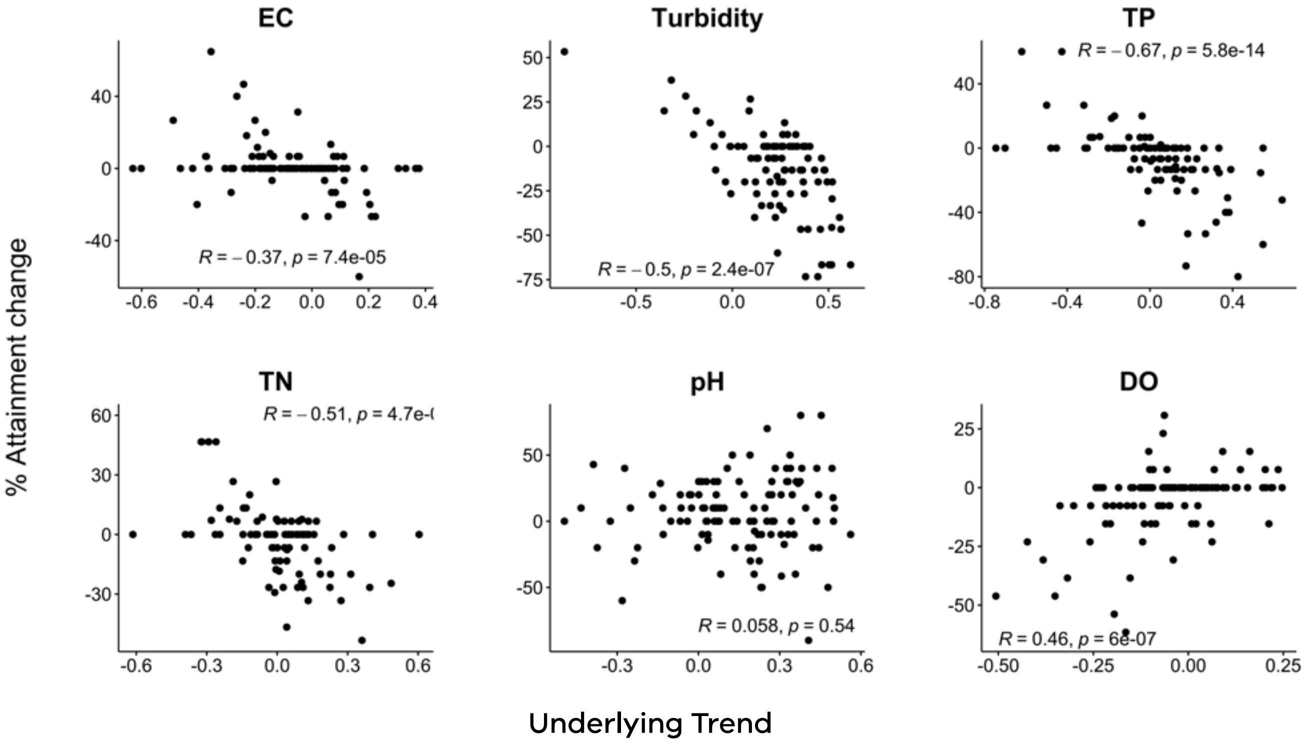


Figure 44: Scatterplots showing the relationship between underlying trend across the period 1995-2021, and percentage change in attainment between the periods 1995-2007 and 2009-21 for all parameters. The Spearman correlation coefficient rho (shown here as R) and the corresponding p-value are also shown for each parameter.

Considering all sites in Victoria, there was a decline in ERS attainment between the periods 1995-2007 and 2009-2021 for DO, turbidity and TP (i.e. more sites had a decline in the percentage of years attaining ERS standards than had an improvement). For EC and TN conditions, attainment remained stable. ERS attainment improved for pH.

5. How has, and how will, long-term climate variability and change impact water quality?

5.1 Summary

Climate change is expected to result in lower streamflow in Victoria. This will affect water quality. Due to the relationships between most water quality parameters and streamflow, we expect that the lower streamflow in Victoria will lead to increased EC, decreased turbidity, decreased TN, decreased TP, increased pH and decreased DO.

Focusing solely on 30 sites with negligible identifiable changes in land use, we identified strong non-monotonic trends in the water quality that could not be explained by streamflow or seasonality. That is, processes other than flow and seasonality are driving trends in water quality. At over half of the monitoring sites, the model residuals correlated moderately with hydro-climatic variables. It appears that water quality is driven by medium to long-term hydro-climatic variables (such as 5-10-year average temperature or rainfall) for DO, EC, pH and turbidity. This suggests that water quality is being affected by decadal scale fluctuations in climate, although further work is required to identify the specific processes that lead to these impacts. Consequently, further work is needed for prediction of the impact of climate change on water quality.

Climate change is expected to lead to lower overall streamflow and higher temperatures, and to higher frequency and intensity of extreme events such as drought. Using the Millennium Drought (1997-2009) as a case study, we investigated its impact on water quality. We examined both the impact of reduced streamflows, as well as changes in water quality that cannot be explained by changes in streamflow, seasonality (or water temperature, for DO only). Flow reductions led to reductions in TN, TP and turbidity, and increases in EC, which were most pronounced in the Murray and Western Plains ERS segment due to larger reductions in streamflow in this area. There were significant shifts in these residuals between the pre-drought, drought and post-drought periods. This suggests that there are additional effects on water quality that cannot be predicted from streamflow-water quality and seasonality-water quality (and water temperature-water quality) relationships alone. They may include changing relationships between streamflow, seasonality and water quality (e.g. due to changes in hydrological flow paths, due to a change in rainfall, altered biogeochemical processes due to changes in temperature and rainfall, and changing agricultural management and urban water management in response to changed climatic conditions) over time.

In addition to the processes mentioned above, an increase in the severity and frequency of bushfires with climate change is anticipated to lead to more frequent poor water quality events. This topic is addressed further in Chapter 6: *How do bushfires affect water quality?*.

There is still more research that needs to be done to fully understand the impact of climate change on water quality and the processes underlying these impacts. We recommend that future studies use more complex spatially distributed models to assess climate change impacts on water quality. In addition, multi-disciplinary investigations – which explore biogeochemical processes, hydrological processes, behavioural and governance changes and fire regime changes – are required to predict impacts of climate change on water quality.

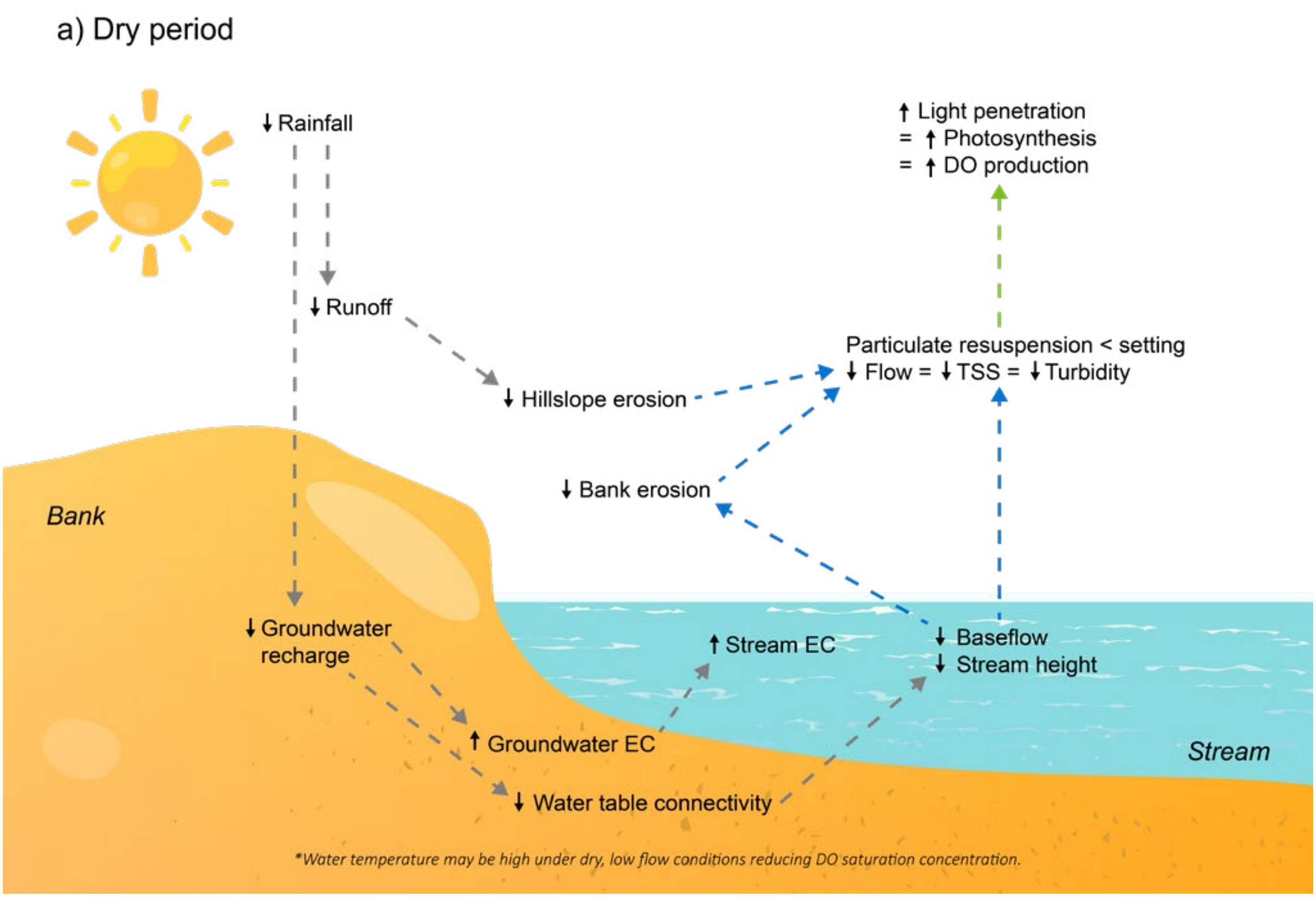
5.2 Introduction

Changes in weather and streamflow patterns brought about by climate change have potential to substantially alter water quality.

In Victoria, climate change is predicted to result in increased temperatures (Jakob et al., 2020), increased drying (Rauniyar & Power, 2020) and increased frequency of extreme weather events (Jakob et al., 2020) including drought (Delage & Power, 2020). An overall reduction in rainfall depth across Victoria is likely to translate into substantially reduced streamflow (Saft et al., 2015). The exact relationship between reduced rainfall and streamflow is complex, site specific, and relies on many factors. It is therefore somewhat uncertain. Climate change is expected to lead to lower overall streamflow and higher temperatures, and higher frequency and intensity of extreme events such as drought (Delage & Power, 2020). This will likely also affect events such as bushfires that have significant impacts on water quality (Department of Environment Land Water and Planning et al., 2020a).

Box 1 - Precipitation and hydrological variability under climate change: findings of the Victorian Water and Climate Initiative

The Victorian Water and Climate Initiative (VicWaCI) is examining the impacts of climate change and variability on water resources in Victoria. The research within VicWaCI has a focus on precipitation and catchment hydrology, and how these are changing over time. Climate change is expected to lead to less rainfall and streamflow over future decades, as well as more intense but less frequent rainfall events. Analysis through VicWaCI has shown a decline in rainfall during the cooler half of the year since 1997 (Department of Environment Land Water and Planning et al., 2020a). Southern and eastern Victoria are experiencing reduced rainfall due to fewer cold fronts and low pressure systems, particularly during the cooler months. Reduced rainfall, especially during the cooler months, affects water availability and streamflow. Runoff and streamflow in Victoria are likely to decrease over future decades due to declining cool-season rainfall and increased evapotranspiration. However, the changes in precipitation and catchment hydrology have not been uniform across the state, leading to variations in water quality in different catchments. Some areas have experienced increased warm-season rainfall, particularly due to thunderstorms, but trends are unclear. Despite the long-term trend towards drying, variability in climate characterised by wet and dry years is still expected and may increase. Linked to the VicWaCI research program are projections of future rainfall and streamflow, which can be applied to assess current and future water availability through Victorian guidance (Department of Environment Land Water and Planning, 2020b).



b) Extreme event following a dry period

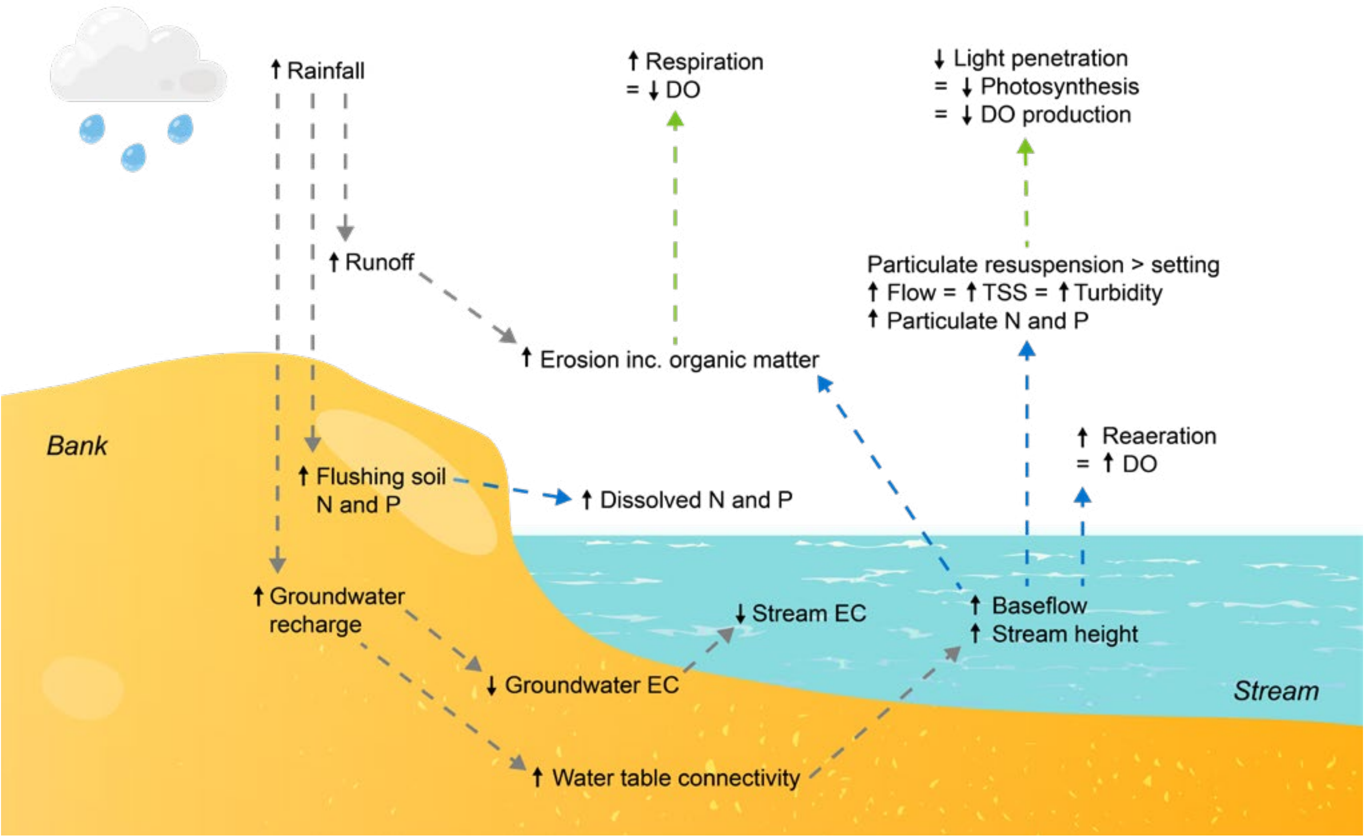


Figure 45: Conceptual diagram of catchment processes influencing water quality a) under drying conditions and b) after an extreme rainfall event following dry conditions.

Further, interrelated physical, biological and chemical processes can affect water quality. Changes in rainfall and temperature may alter the biogeochemical processes that affect nutrient cycling, evaporative processes that affect salinity, and erosive processes governed by flow. Climate-mediated changes to hydrological regimes may also affect water quality processes by changing water flow pathways, erosion, enrichment and dilution, mixing and biogeochemical processes.

Therefore, understanding the impacts of climate variability and change on water quality requires consideration of the behaviour of water quality under hydrological regimes predicted under climate change. However, this is unlikely to fully capture the long-term effects of land management adaptation to climate change, nor the impacts of changing fire regimes.

5.3 Summary of approach

To understand the potential impacts of climate change on water quality, we used:

1. The relationships between streamflow (and water temperature for DO) and water quality obtained from Chapter 4 to infer the impact of an incremental reduction in streamflow (and increased temperature for DO) on water quality.
2. The trend in multiple linear regression model residuals from 1995-2021 to explore the impact of climate change (as represented by hydro-climatic conditions) on water quality processes other than those caused by changes in streamflow and temperature.
3. Observed changes in streamflow and concentration-streamflow relationships, as well as trends in model residuals from 1995-96, 1997-2009 and 2010-21 to identify the impact of sustained fluctuations in climatic conditions (using the Millennium Drought as a case study) on possible changes in water quality.

5.3.1 The multiple linear regression model

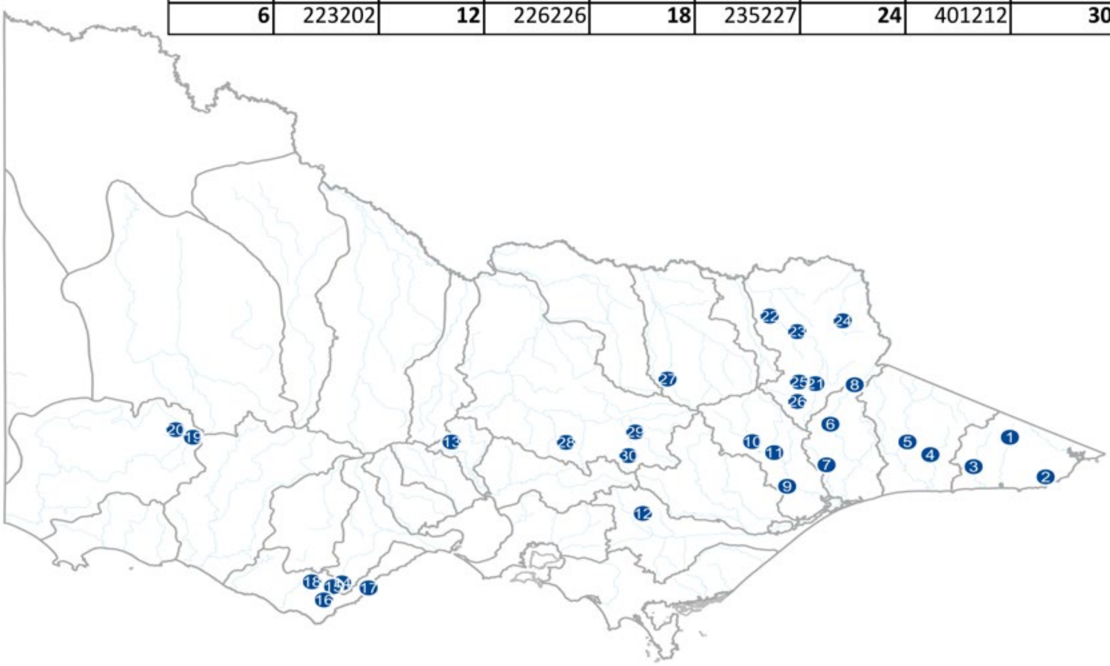
The potential impacts of climate change on water quality were investigated using the outputs of a multiple linear regression model, fitted to time-series data of each water quality parameter at each site. The model links the temporal variability of water quality with streamflow and seasonality (and water temperature for DO). The multiple linear regression model structure assumes that: (1) the temporal variability in water quality can be explained by streamflow and seasonality (and water temperature for DO), and (2) that the relationship between streamflow, seasonality and water quality is constant throughout the period 1995-2021. This model is similar to the statistical model that has been used in Chapter 4 for estimating long-term trends in water quality.

5.3.2 Analysis of model outputs

The water quality impact of anticipated changes in streamflow due to a drying climate was investigated. The proportional change in concentration expected as a result of an incremental change in streamflow (set at 1%) was calculated using the modelled beta coefficient for flow, using the equation displayed in Appendix H. This calculation allows a ready comparison of the direction and magnitude of relationships between flow and the six water quality constituents studied.

1. The model residuals (the difference between modelled and observed water quality parameter concentrations) are due to deviations from the two key model assumptions (that concentration can be explained by flow and seasonality, and that these relationships remain constant with time). If there are consistent excursions, or variations over periods of sustained fluctuation in the climate, such as the Millennium Drought, this is interpreted to mean that there are additional changes induced by these sustained climate fluctuations. This provides an indication of potential future responses to sustained climate changes. These residual fluctuations were further investigated through correlation analysis with a number of climate metrics, including antecedent rainfall and temperature, which were calculated for different antecedent timescales spanning from the same day as the residual observation, up to five years beforehand. Significant correlations with climate metrics suggested the possibility of a climate process that may be affecting concentration.
2. The impact of the Millennium Drought on water quality was investigated, both in terms of a) the impact of streamflow, and b) impacts unrelated to streamflow. Understanding the impact of the Millennium Drought will help understand the water quality impact of future drier climatic periods anticipated under climate change.
   a. The impact of reduced streamflows on water quality constituents during the drought was estimated by combining observed flow reductions with model coefficients for flow at each site, following the method used to calculate the impact of a 1% flow reduction described above. Reductions at each site were calculated using a dataset of long-term streamflow at 155 sites (Saft et al., 2023) by calculating the proportional difference in average streamflow between the period of the Millennium Drought (1997-2009 inclusive) and all other available observations. For this analysis, coefficients of flow were taken from all sites included in the Chapter 4 analysis, of which 53 sites had corresponding flow data available in the long-term streamflow dataset.
   b. Impacts of climate on water quality that are unrelated to streamflow and seasonality were investigated using an analysis of model residuals before (1995-96), during (1997-2009) and after (2010-21) the Millennium Drought. Boxplots and statistical testing (Kruskal-Wallis and Dunn's test, $\alpha = 0.05$) were used to compare pre-drought, drought and post-drought periods. A significant shift in residuals between pre-drought and drought periods followed by a shift back towards pre-drought behaviour during the post-drought period would be considered evidence of a climatic effect on water quality, unrelated to flow.

Thirty case study catchments were selected for analyses of model residuals (Figure 46). As the 30 sites selected for this study have negligible identifiable land use and land cover change, the trends in these residuals over time are most likely driven by climate fluctuations sustained over multiple years. There are few sites in western Victoria selected for this analysis due to the greater land use and land cover modification that have occurred here. We hypothesise that the trends in residuals represent the impact of climate change on changing relationships between streamflow, seasonality and water quality (e.g. due to changes in hydrological flow paths due to a change in rainfall, altered biogeochemical processes due to changes in temperature and rainfall, or changing agricultural management and urban water management in response to changed climatic conditions) over time.



1	221201	7	223204	13	230209	19	238208	25	401216
2	221208	8	223214	14	233214	20	238231	26	401226
3	221212	9	224203	15	235202	21	401203	27	403228
4	222202	10	224206	16	235209	22	401204	28	405205
5	222217	11	224213	17	235216	23	401211	29	405219
6	223202	12	226226	18	235227	24	401212	30	405264

Figure 46: Location of 30 sites used in analysis. Full site names corresponding to 6-digit site IDs provided in Table 7.

Table 7: Full site names corresponding 6-digit site IDs for sites used in Chapter 5.

Site ID	Site Name
221201	Cann River (West Branch) @ Weeragua
221208	Wingan River @ Wingan Inlet National Park
221212	Bemm River @ Princes Highway
222202	Brodribb River @ Sardine Creek
222217	Rodger River @ Jacksons Crossing
223202	Tambo River @ Swifts Creek
223204	Nicholson River @ Deptford
223214	Tambo River @ U/S Of Smith Creek
224203	Mitchell River @ Glenaladale
224206	Wonnangatta River @ Crooked River
224213	Dargo River @ Lower Dargo Road
226226	Tanjil River @ Tanjil Junction
230209	Barringo Creek @ Barringo (U/S Of Diversion)
233214	Barwon River East Branch @ Forrest
235209	Aire River @ Beech Forest

Site ID	Site Name
235216	Cumberland River @ Lorne
235227	Gellibrand River @ Bunkers Hill
238208	Jimmy Creek @ Jimmy Creek
238231	Glenelg River @ Big Cord
401203	Mitta Mitta River @ Hinnomunjie
401204	Mitta Mitta River @ Tallandoon
401211	Mitta Mitta River @ Colemans
401212	Nariel Creek @ Upper Nariel
401216	Big River @ Jokers Creek
401226	Victoria River @ Victoria Falls
403228	King River @ Lake William Hovell T.g.
405205	Murrindindi River @ Murrindindi Above Colwells
405219	Goulburn River @ Dohertys
405264	Big River @ D/S Of Frenchman Creek Junction

There may be undocumented changes in these catchments (e.g. changes in land management, fertiliser application rates, logging, bushfires) that may also influence the water quality trends. Such changes would likely be partly responses to weather conditions but also partly responses to the many other factors land managers need to account for in their decisions. We assume that any such changes are a direct response to the observed climate fluctuations; however, there will inevitably be other influences present in the data to an unknown extent.

5.4 Results

5.4.1 The impact of climate change-induced changes in streamflow and air temperature on water quality in Victoria

In the previous chapter, we identified that streamflow is a key driver of temporal variability for EC, turbidity, TN and TP. There were negative relationships with streamflow and EC and pH, and positive relationships with streamflow and DO, turbidity, TN and TP. As such, it is expected that the decreased streamflow predicted for Victoria will result in decreased DO, turbidity, TN and TP and increased EC and pH (Table 8). That is:

Decreasing streamflow leads to:	↓DO ↓Turbidity ↓TN ↓TP
	↑ EC ↑pH

Table 8: Expected percentage change in water quality parameter due to 1% decrease in streamflow. 25, 50 and 75th percentiles of expected change across all sites provided.

Water quality parameter	% change in water quality parameter with a 1% decrease in streamflow		
	25th percentile	50th percentile	75th percentile
DO (mg/L)	-0.039%	-0.018%	-0.0028%
EC (us/cm)	0.054%	0.11%	0.17%
pH	0.0018%	0.0052%	0.010%
Turbidity (NTU)	-0.42%	-0.28%	-0.17%
TP (mg/L)	-0.24%	-0.16%	-0.094%
TN (mg/L)	-0.21%	-0.14%	-0.068%

5.4.2 Changes in water quality that cannot be explained by the climate change induced changes in streamflow or air temperature

Figure 47 shows the residuals of the multiple linear regression models – that is the variation in water quality that is not explained by flow or seasonality (for all constituents) and air temperature (for DO). It provides the 25th percentile, median and 75th percentile residual at each time point across all 30 selected sites. When the residual is positive, it means that the model overestimated the observed water quality. When the residual is negative, the model underestimated observed water quality. When the absolute value of the residual is small, it means that the water quality variability can be mostly explained by streamflow and seasonality (and water temperature for DO). When the absolute value of the residual is large, it means that there is an unknown driver for temporal variability in water quality – and that this driver is having a large impact on temporal variability in water quality. If the residuals fluctuate rapidly between positive and negative values, it indicates there are short term random influences acting on the water quality. However, if residuals are mainly positive or mainly negative for several years, it means that there is a long-lasting influence changing the water quality response. When the distance between the 25th and 75th percentiles is smaller, the temporal drivers that influence water quality vary less between sites. When the distance between the 25th and 75th percentiles is larger, the temporal drivers that influence water quality vary more between sites.

When correlating the residuals with hydro-climatic variables for each water quality parameter, we found that there are correlations ($|\rho|>0.2$) between the residuals and medium to long-term (1, 3 or 5 years) climate drivers for EC, turbidity, pH and DO at more than half of the sites across Victoria (see Appendix I). The correlations between the residuals and these medium to long-term (on the scale of 1, 3 or 5 years) climatic variables such as antecedent temperature and precipitation suggest that the unexplained variance in the statistical models are potentially being driven to some extent by climate change, and that we may be able to expect the impact of climate change on water quality in future.

While the current analysis shows that climate change appears to be driving change in water quality (separate to the impact of decreased streamflow and increased temperature on water quality), the specific mechanism is still unclear. We hypothesise that it could be:

- Changing relationships between streamflow and water quality, and water temperature (for DO only) and water quality associated with long-term hydrological changes that are well documented to occur
- Changes to agricultural and urban water management due to climate change
- Changes in other biogeochemical processes as a result of changes to rainfall and temperature.
- While we cannot yet quantify the precise impact that climate change will have on water quality, we can infer that there is likely to be an impact.

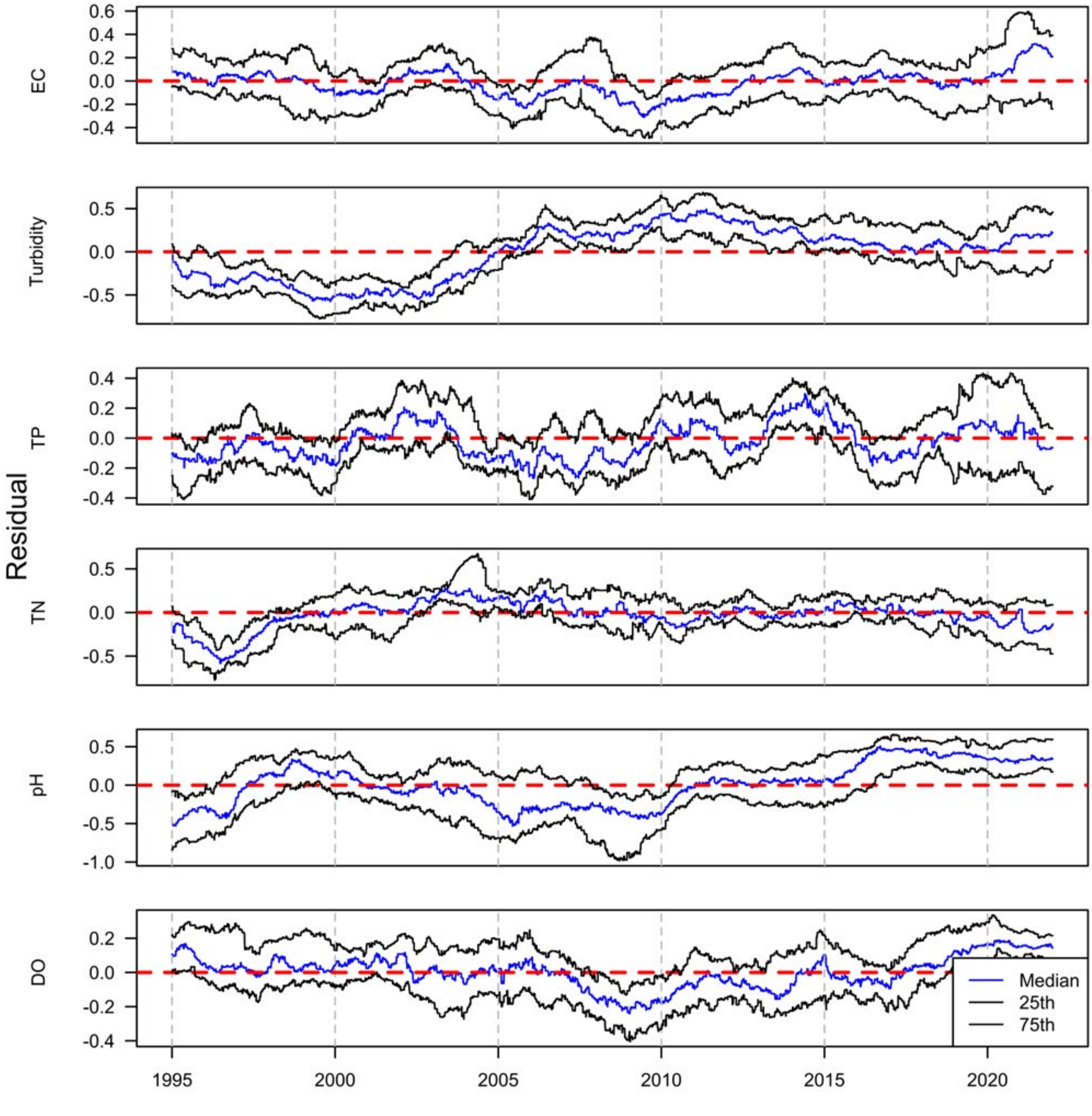


Figure 47: Across the selected sites over the period of record, the 2-year moving average of residuals is summarised by median, 25th and 75th percentiles at daily timesteps. Positive residuals indicate that observed concentrations were higher than modelled concentrations (i.e. the model underestimated concentrations). X-axis labels at 5-year intervals are positioned at January 1st. The number of sites used to construct the combined timeseries plots were: EC, 30 sites, turbidity, TP, 27 sites, TN, 17 sites, pH, 30 sites, and DO, 30 sites.

5.4.3 Changes in water quality due to extreme events caused by climate change: a case study of the Millennium Drought

Impact of reduced streamflow

The low streamflow conditions associated with the Millennium Drought can provide an insight into a possible future scenario of drier climatic conditions. The Millennium Drought caused substantial reductions in streamflow across Victoria (Saft et al., 2015) .

Reductions in streamflow during the drought varied between -22% and -87% at the sites assessed in this study, and were greatest in Central and Western Victoria (see Appendix I: Supplementary results for Chapter 5). There were corresponding changes in water quality, with the magnitude of change being greatest in the Murray and Western Plains (for EC, pH, TN and TP) and Central Foothills and Coastal Plains (for DO) ERS segments. Changes in streamflow broadly resulted in reduced turbidity, TN and TP concentrations (Figure 48). Reduced streamflows broadly increased both pH and EC concentrations, with the largest changes occurring in Western Victoria and the Central Foothills and Coastal Plains (Figure 48). Furthermore, in addition to changes in concentration, it is highly likely that reduced streamflows will lead to reduced loads (or the total amounts) of all contaminants reaching lake, reservoir and estuarine receiving waters state-wide. This is because the total volumes of water flowing in our streams are likely to change more than concentrations, so even where concentrations might increase, this would be more than offset by reductions in flow volumes. The larger response of flow than concentration is evidenced by both our regression analyses and observations from the Millennium Drought.

These results suggest that substantial changes in water quality could occur under future drier climates with reduced streamflow. However, concentration-discharge relationships are often not consistent with time, and many other factors influence constituent concentrations. Additonal drivers, including poorly understood physical and biogeochemical processes, may contribute to unforeseen water quality behaviour and emerging water quality issues under climate change.

Additionally, VicWaCI identified that rainfall-runoff relationships (used to identify the amount of runoff produced by rainfall in catchments) can shift during droughts (e.g. Saft et al. 2015), and that many catchments (particularly in the West and Central Victoria) did not recover their pre-drought rainfall-runoff relationships even after the drought. From this, we can infer that the change in water quality that occurs due to extended drought (expected change outlined in Table 8) may continue following the drought, with water quality failing to return to pre-drought levels.

Finally, the patterns of land use across Victoria are likely to change with climate change. This is particularly true in the agricultural areas where rainfall and temperature are important determinants of the suitability of land for different agricultural purposes. While this study has not considered subsectors within the agricultural industry in detail, different types of farming are associated with different water quality impacts due to factors such as different levels of fertiliser input between low intensity grazing, cropping, dairy and intensive horticulture, for example. Potential changes in agriculture have been studied in the Victorian Climate Change Adaptation Program (Morris & Eckard, 2010). These changes include in situ responses and movement of industries. An example of an in situ reponse might be reduced fertiliser inputs in cropping systems, assuming rainfall declines become a greater constraint on production as fertiliser input should match water availability in rainfed cropping for best financial outcomes to growers. An example of a relocation might be wine production moving to cooler regions to counter the current climate change-induced trend to earlier maturing of grapes (Webb et al., 2012). While such changes are likely and would be expected to impact water quality, the details are uncertain. Consequently it is not possible to make detailed predictions of such impacts.

Impact of climate variability other than streamflow

Significant differences in behaviour between time periods (pre-drought, drought, and post-drought) were observed for all water quality parameters except DO (Figure 49).

A temporary step-change in behaviour associated with the drought was only apparent for EC and TN (Figure 49). During the drought, observed EC values were lower than expected according to the model, displaying more negative residuals than during both pre-drought and post-drought periods (pre-drought vs. drought: Dunn's Z=-1.8, p=0.04, drought vs. post-drought: Dunn's Z=-3.4, 0=3.4E-4).

During the drought, observed TN values across the state were lower than expected before the drought, similar to expected during the drought, and lower than expected after the drought, though the difference between drought and post-drought periods was not statistically significant (pre-drought/ drought Dunn's Z=4.3, p=1.0E-5, drought/post-drought Dunn's Z=2.9, 0=8.3E-2).

Both pH and turbidity displayed a significant change towards higher than expected values between drought and post-drought periods, while TP displayed a consistent significant change towards values that were higher than expected between the pre-drought, drought and post-drought periods.

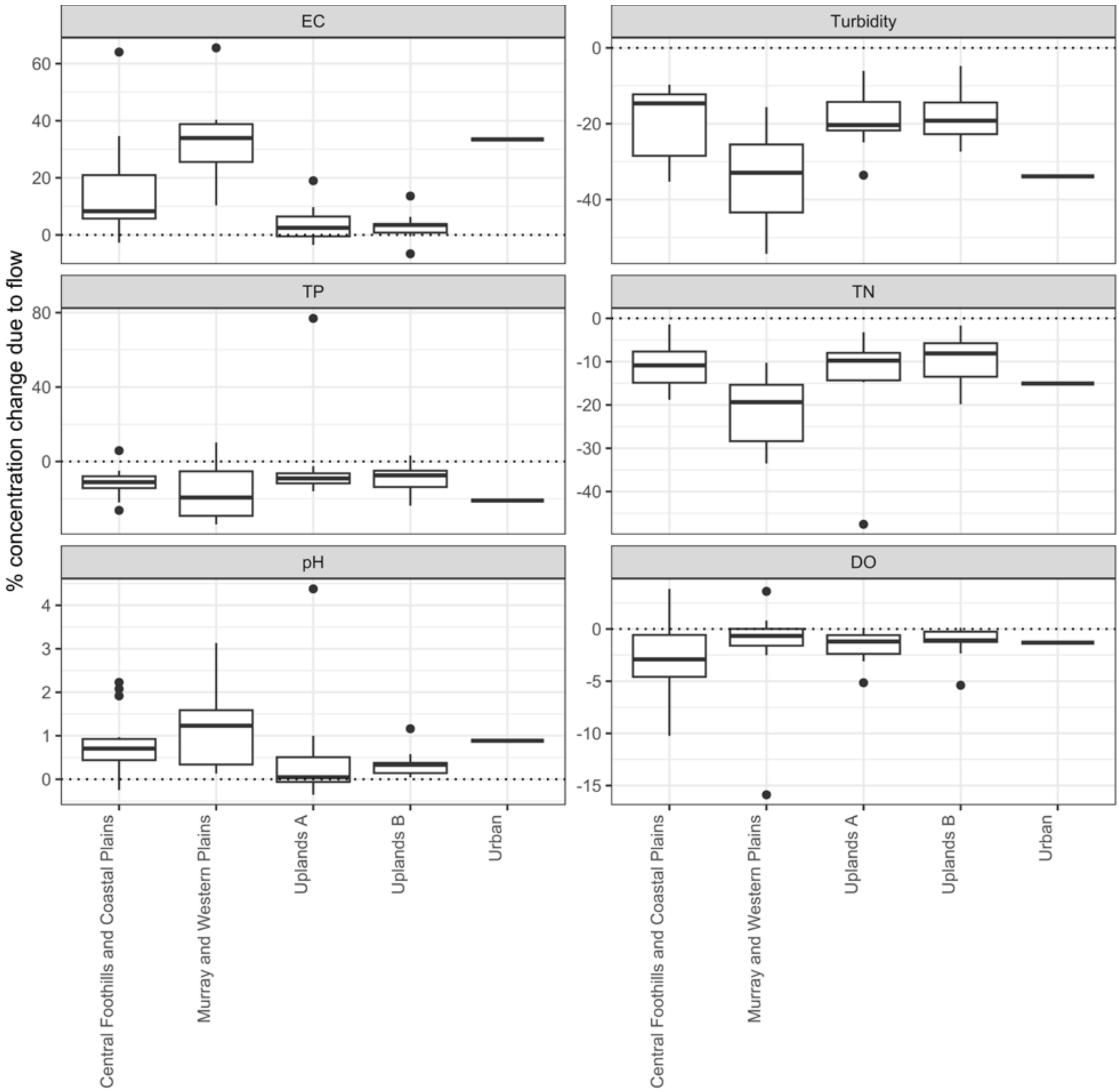


Figure 48: Changes in constituent concentrations due to changes in streamflow observed during the Millennium Drought. Compared with non-drought conditions, streamflow during the drought declined by 30-90%. More substantial streamflow declines occurred at sites in the west of Victoria.

No significant differences in DO behaviour were observed between pre-drought, drought and post-drought periods.

Complete results of statistical testing can be found in Appendix I.

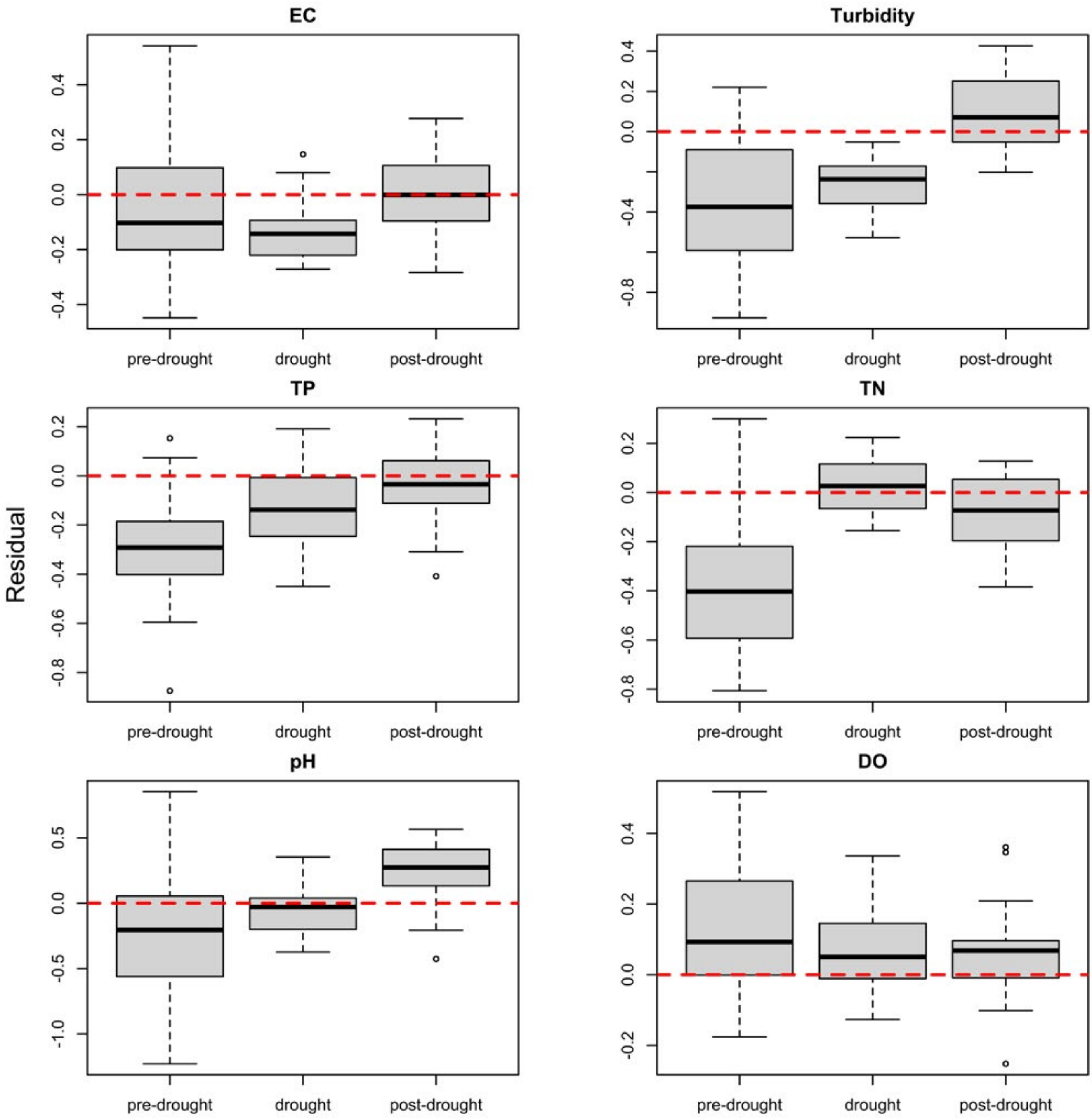


Figure 49: Distribution of median residuals for all selected sites during pre-drought (1995-1996), drought (1997-2009) and post-drought (2010-2021) periods. Residuals of greater than zero indicate that observed values are higher than expected, residuals less than zero indicate that observed values are lower than expected, and residuals of zero indicate that observed values are the same as those expected according to the model.

This indicates that the central tendency and variability in the residuals shifted between the pre-drought, drought and post-drought periods. These shifts are not directly linked to changes in streamflow or temperature, since the residuals are the component of the model where water quality has not been explained by streamflow, temperature (for DO) or seasonality. We hypothesise that these shifts in the residuals could be due to: (i) changes in the relationship between concentration and streamflow between the three time periods (Peterson et al., 2021; Saft et al., 2015), (ii) changes in biogeochemical processing during droughts and after droughts (Gómez-Gener et al., 2020); (iii) changes to agricultural and urban water management (Grant et al., 2013); or (iv) increased frequency of bushfires during and after droughts (Johnston & Maher, 2022).

As we cannot yet untangle the key processes driving the change in water quality caused by drought, it is difficult to quantify the impact of future droughts on water quality in Victoria. However, it is clear from the analysis that it is likely that drought will lead to a change in water quality due to the decrease in streamflow and increase in temperature, and may change catchment hydrology and water quality processes, exacerbating the change in water quality. In addition, in Chapter 6, we address the impact of bushfires on water quality, noting that increased frequency and severity of bushfires is likely under climate change.

5.5 Recommendations for future work to understand the impact of climate change on water quality

To further understand the impact of climate change on water quality in a range of different landscapes, the following should be investigated:

- More complex models that incorporate the impact of land use/land cover and land use intensity change, and climate impacts. This will require more complex process-based models, and sufficient data to support this complexity. The data required are: (i) information on changes in land use intensity, and (ii) water quality and streamflow monitoring data. For (i), this could be obtained using more data on fertiliser use in catchments, animal density, best management practice installation and urban and farm infrastructure changes. For (ii), this could be identified through higher frequency monitoring at locations experiencing significant changes in land use (and land use intensity), and no changes in land use (and land use intensity).
- A detailed multi-disciplinary investigation that uses a systems approach into the impact of climate change on (i) biogeochemical processing in the catchment; (ii) hydrological processes; (iii) behavioural changes (from the perspective of the change in agricultural and urban water management due to climate change); and (iv) the impact of changing fire regimes.
- Additional water quality and flow monitoring sites within appropriate reference catchments could be installed for long-term monitoring. This will enable us to successfully untangle the influence of land use change and human activities from the impacts of climate change on water quality.

6. How do bushfires affect water quality?

6.1 Summary

All basins affected by the 2019-20 bushfires experienced changes to water quality. All water quality constituents studied (Turbidity, EC, TSS, NO_x, TKN, TP and FRP) were the highest or second highest concentration on record at many sites following the fires. 27 sites (across all basins except Keiwa) experienced impact on three or more water quality parameters.

The bushfires led to an increase in TSS, nitrate, phosphorus and trace metals from legacy contamination as well as a decrease in DO in north-east Victoria and Gippsland. The impact of the bushfires of 2019-20 occurred until March 2022 at some sites, with some experiencing recurring impacts from 'flushing' rainfall events.

Bushfire intensity and frequency are expected to increase as a result of climate change. In addition, climate change is expected to result in more frequent and intense rain events which are likely to further increase sediment deposition into fire-impacted rivers. Hence, the impacts of the 2019-20 fire on water quality have important implications for our future under a changing climate.

6.2 Introduction

Bushfires can have a large impact on the hydrological and biogeochemical processes within catchments. We hypothesise that stream water quality will change in response to bushfires. Bushfires can generate ash, changing the properties of soil, and increasing erosion (Ebel et al., 2022). These processes can contribute to a decrease in water quality following bushfires.

This section addresses how bushfires affect water quality. We focus on the impacts of the 2019-20 Black Summer fires on water quality in Gippsland and north-east Victoria (Figure 50).

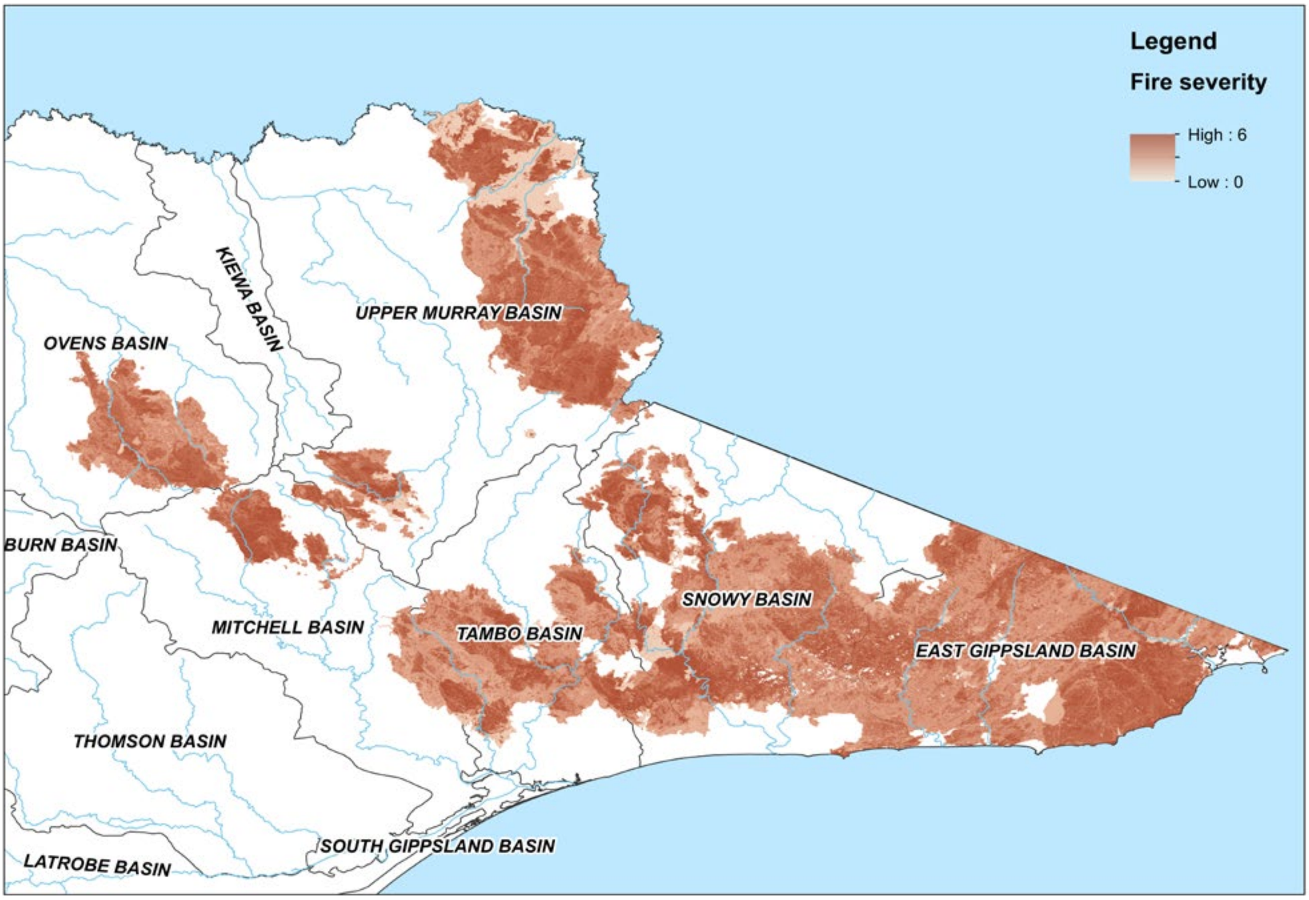


Figure 50: Extent of the Black Summer bushfires in north-east Victoria and Gippsland. The colours represent fire severity, with a darker colour representing more severe burning. Data obtained from DEECA.

6.3 The approach

A previous bushfire report commissioned by DEECA on the impact of the 2019-20 Black Summer bushfires on water quality in Gippsland and north-east Victoria (Baldwin, 2022) was reviewed. We summarised the results from this report to describe the impact of bushfires on water quality parameters and make statements about the impacts across eight basins.

We quantified the number of sites experiencing different degrees of impact for each water quality parameter. In order to achieve this, we summarised Tables 2-8 from the Baldwin report. Data that were classified 'very strong increase' were relabelled 'highest on record'. Data that had been classified as a 'definite increase' or 'strong increase' were pooled to create the group 'impact evident'. Four groups that had been classified as no discernible increase or decrease based on different types of data collection methods and/or statistical comparison were pooled to create the group 'no change'. Blank cells were compiled into a group named 'not measured'. All other groups were pooled to form the category 'inadequate data'. For the purpose of clear and simplified graphics, the groups 'not measured' and 'inadequate data' were joined into one category for display on the maps but numbers are presented individually in the text.

In addition to the DEECA's bushfire report, we examined some additional data in order to make statements. We accessed DO data for Snowy River at Orbost from https://data.water.vic.gov.au/. The daily average DO was calculated from 20 January 2020 in order to make a statement about water quality following a rainfall/flushing event.

We drew on other sections of this report as well as scientific literature to highlight potential feedback loops with climate change, given the expected impact of climate change on the frequency and intensity of bushfires.

6.4 Results

6.4.1 Overall impacts

Data to March 2022 were collected from 59 sites within seven basins across Gippsland, north-east Victoria and southern New South Wales in order to assess the impact of the fires on water quality.

- 27 sites (across all basins except Keiwa) experienced impact on three or more water quality parameters.
- Upper Murray basin sites that are located in NSW were considered. Data from eight of these sites (401012, 401549, 401017, 401016, 401009, 401008, 401024 and 401013) were included in the assessment of bushfire impact on water quality.
- Due to variation in monitoring regimes, sites were divided into five categories as per Figure 51.
- Comparison to pre-2019 data allowed assessment of change in water quality. This was not possible at some sites (e.g. Cann River) as a lack of pre-fire data prevented capturing the extent of fire impact.
- Ten sites had insufficient data to determine ongoing impact, including four from group one and four from group two. These sites were all located in the Snowy, Ovens and Tambo basins (Table 9).
- As data availability varied across sites, it was difficult to assign change in water quality over time; however, a consistent approach was applied to all data.
- Bushfires affected water quality in 6 of the 7 basins that were investigated. Kiewa basin (only 1 monitored site) did not experience burning.
- It appears that water quality has returned to pre-fire levels at three upland river sites. Baldwin (2022). determined the water quality of 6 sites had returned to pre-fire in March 2022. Three of these sites (401406, 401009 and 401008) are in NSW and only EC data were available on which to make this judgement.
- Of the sites with adequate data, there was no evidence of bushfire effect on water quality at 13 sites. These were predominantly upper catchment sites in the Ovens and Upper Murray basins as well as one site in the Mitchell basin.

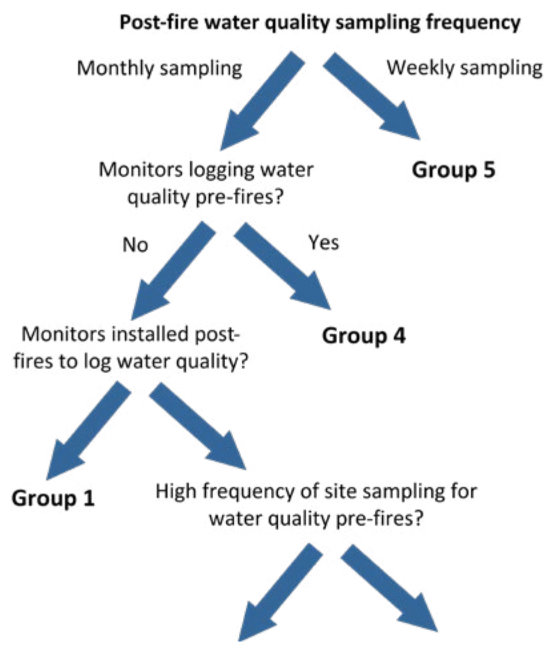


Figure 51: Schema showing data availability and how division of sampling sites was determined. Adapted from Baldwin (2022).

Data distribution across the basins

The 2019-20 fires were widespread and intense; however, each basin was affected differently (Figure 50). The Snowy and Gippsland basins experienced extreme fire, with most of the basin experiencing burning. Part of the Tambo basin was unburnt, while less than half of the Ovens, Upper Murray and Mitchell basins burnt. Kiewa did not receive any burning.

Sampling sites across the Snowy and Gippsland basins experienced fire nearby, but not all sites had loggers installed prior to the fires. The Ovens and Murray basins had monitoring sites within areas affected by fire, so they were able to capture bushfire impacts. The Tambo and Mitchell basins did not experience fire near some of the monitoring sites; however, downstream sampling sites captured effects on water quality.

Table 9. Distribution of the various data analysis groups across the relevant basins in Gippsland and north-east Victoria. EC is the only constituent reported at those sites in brackets and asterisk (*). Sites with unknown impact are in brackets with a dagger (†).

	Basin (number of sites)							
Group	East Gippsland	Snowy	Tambo	Mitchell	Ovens	Kiewa	Upper Murray	TOTAL
Group 5 Weekly pre-fire sampling							2	**2**
Group 4 Loggers pre-fire & monthly sampling	1		2	2	2 (1*)	1	10 (3*) (1†)	**18**
Group 3 Loggers post-fire & many spot samples pre fire	2 (1†)	1			2		1	**6**
Group 2 Loggers post-fire & few spot samples pre-fire	2	1			5 (3†)		3	**11**
Group 1 No loggers post-fire	2	6 (3†)	3 (1†)	3	5		3	**22**
TOTAL	**8**	**8**	**5**	**5**	**14**	**1**	**19**	**59**

Approximately 60% of sites with data in north-east Victoria and Gippsland experienced poor water quality following the Black Summer fires.

- The number of sites varied for each measured water quality parameter (turbidity n= 48, TSS n=46, EC n=56 & 23 logged, NO_x n=47, TKN n=47, TP n=47, FRP n=47, DO n=20).
- Following the fires, all constituents were the highest or second highest concentration on record for water quality at multiple sites and occurred across all basins (turbidity n=12, TSS n=12, EC n=6, NO_x n=10, TKN n=8, TP n=11, FRP n=4).
- This was particularly evident for the Murray River at Jingellic where all measured water quality parameters at this site were highest on record following the fires.
- Of the 59 sites investigated, 8 sites across the Tambo, Mitchell, Ovens and Upper Murray basins had ongoing impacts on water quality. There was impact at 20 sites (ranging from likely to probably, some improving), 21 sites received no impact or had inadequate data and no conclusion could be drawn for 10 sites.

There are many potential causes and drivers of bushfire impact on water quality, including:

- Lack of protection due to loss of surface cover
- Increase transport, e.g. dissolved/total nutrients
- Hydrophobicity increasing runoff
- Macro level increase e.g. debris flows

Debris flows

Debris flows are fast moving slurries of sediment and water that continue downslope in steep channels (Pánek, 2020). The slurries can contain sand, silt, clay, gravel and boulders. This erosion process can mobilise large quantities of sediment and associated nutrients (Beavis et al., 2023).

An increase in runoff can lead to debris flows (Nyman et al., 2011). This phenomenon occurs in fire-affected areas. Following the 2009 Black Saturday fires in Victoria, 315 debris flows were recorded (Nyman et al., 2015).

During the 2019-20 fires, debris flows prevented sensors from accurately measuring water quality data at five sites across four rivers, being Buckland River (Harris Lane - Site 403233), Bemm River (Princess Highway - Site 221212), Buffalo River (D/S Rose River Junction - Site 403254) and Ovens River (Eurobin – Site 403250 and Rocky Point – Site 403230).

6.4.2 Region-specific impacts

The bushfires of 2019-20 led to an increase in movement of legacy contaminants (particularly arsenic, copper, lead and nickel), from mining activities in north-east Victoria and Gippsland.

TSS was measured at 46 sites. 12 had the highest measurement on record, 11 exhibited impact, 12 exhibited no change and 11 had inadequate data on which to draw any conclusion.

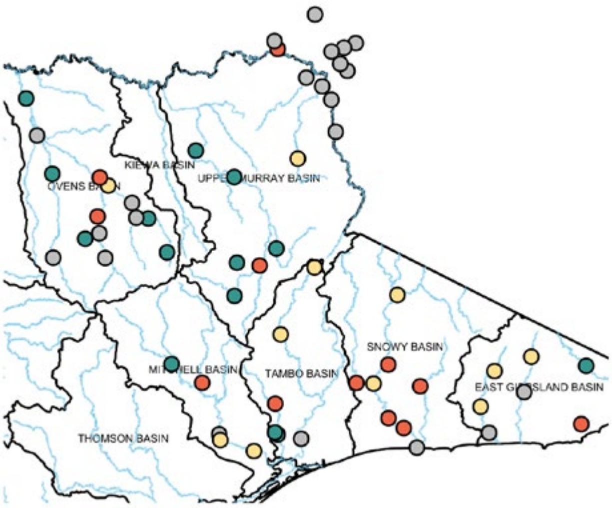
- Sediment loads into the Murray River were routinely high following the fires and even similar to those observed immediately post-fires.
- All of the Gippsland sites that had adequate data exhibited impact via high TSS loads
- The bushfires led to an increase in turbidity at many sites, including the Tambo River and the Gippsland river valleys (Figure 53a).
- Turbidity was measured at 50 sites, including spot-sampled measurements at 48 sites. Continuous loggers measured turbidity at 23 sites, but only 12 returned reliable data.
- Of the 48 spot measured sites, 12 exhibited the highest measurement on records, 11 sites had evident impact, 14 sites had no change and 11 sites had inadequate data.
- Data from three loggers show consistent patterns with spot measurements, which show the highest measurement on records. 5 loggers exceed spot measurements where two loggers show highest measurement when spot shows clear increase, and three loggers show highest measurement when spot classified no change in turbidity at the site. This highlights spot samples are not always collected in time to assess the impact of bushfires.
- All sites except one (which did not have inadequate data) in the Snowy basin experienced the highest measurements on record and/or demonstrated impact.

Case study

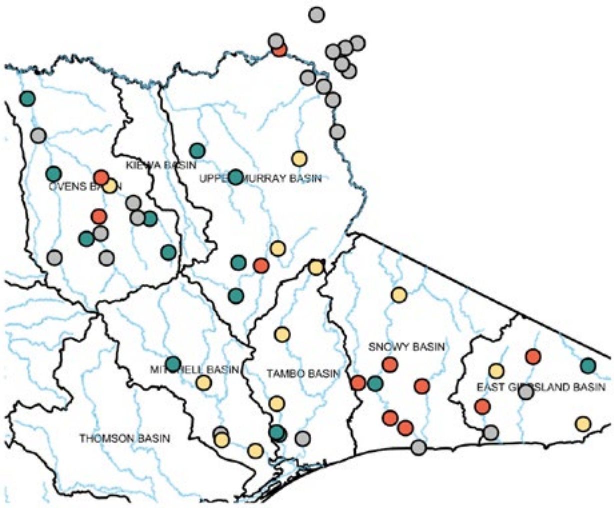
Lake Buffalo protected downstream sites. This site functioned as a sediment pond by collecting or diluting sediment from inflowing water containing high loads of TSS. The physical process of settling naturally occurred in the lake, which effectively prevented transport of sediment to downstream sites in the Ovens River Valley (Figure 52).

Figure 52: Schematic outlining how a sediment pond works with (1) water entering the pond, (2) water slowing and coarse sediment settling in the pond due to gravity. The water without TSS is on top and, finally, (3) flows out of the pond.

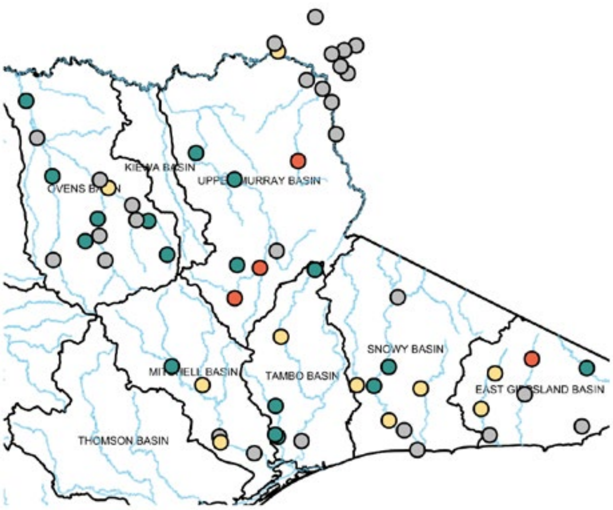
a)



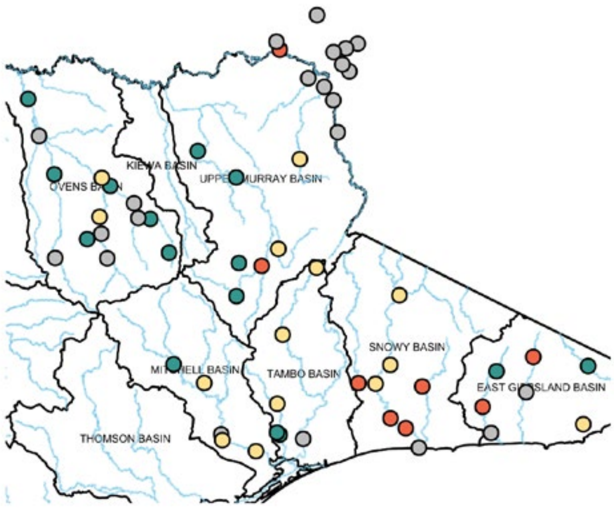
b)



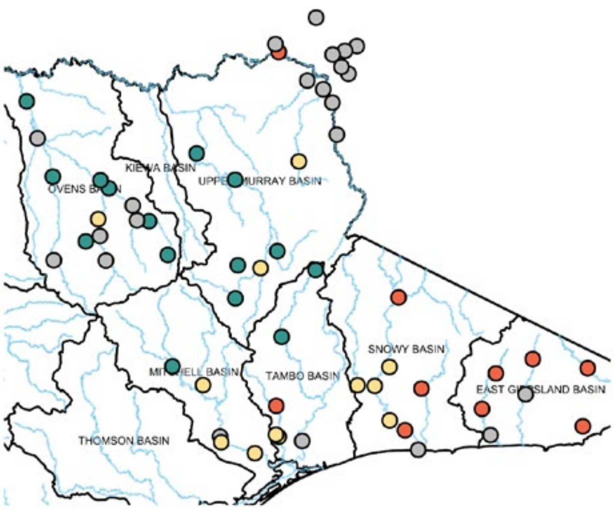
c)



d)



e)



- Highest level measured following the fires
- Marked increase following the fires
- No change was evident following the fires
- Inadequate data

Figure 53: Overview of spot-sampling measurements for a) turbidity, b) TP, c) FRP, d) TKN and e) NO_x across north-east Victoria and the Gippsland region following the fires. Red circles represent sites where the highest levels on record were measured post-fires; yellow circles represent sites where there was a distinct increase in levels after the fires (in some cases, being the second or third highest on record); green circles represent sites where no change was evident following the fires and white circles indicate sites where there was inadequate data to determine fire impact. Adapted from Baldwin (2022).

For 13 sites, bushfires led to the highest or near highest phosphorus concentrations on record.

- TP was measured at 47 sites (Figure 53b) with 11 sites experiencing the highest measurement on record, 12 sites exhibited impact, 14 exhibited no change and 10 had inadequate data.
- FRP was measured at 46 sites (Figure 53c). Four sites experienced the highest measurement on record, 10 exhibited impact, 17 exhibited no change and 15 had inadequate data on which to draw any conclusion.

Bushfires led to high nitrate and nitrogen concentrations for all catchments except the Ovens Basin and Kiewa (Figure 53 d & e).

- NO_x and TKN were both measured at a total of 47 sites.
- Ten sites had the highest measurement of NO_x on record, 12 exhibited impact, 15 exhibited no change and 10 had inadequate data.
- For TKN, eight sites had the highest measurement on record, 14 exhibited impact, 15 exhibited no change and 10 had inadequate data.
- Some of the highest nitrate concentrations were measured in the months following the fires, particularly across East Gippsland.
- All of the Gippsland sites that had adequate data experienced high nitrate (but not TKN).

EC was measured at 57 sites total, including spot measurements at 56 sites and logged at 23 sites.

- For the spot measurements, 6 sites had the highest measurement on record, 11 exhibited impact, 26 exhibited no change and 13 had inadequate data.
- Three sites where spot data determined no change in EC returned logged data showing worst on record.
- No sites sampled in the Mitchell basin appeared to experience changes to EC.

DO at several sites in East Gippsland and north-east Victoria dropped to very low levels (i.e. unable to sustain aquatic life) following the fires.

- Not all sites experienced low DO as a result of the 2019-20 fires.
- The duration of low DO varied across impacted sites and varied from hours (e.g. Ovens River @ Myrtleford) to days (e.g. Tambo River at Battens Landing).
- DO drops may have been recurring at some sites due to rainfall events having a 'flushing' effect.
- For the Snowy River at Orbost, DO dropped to 2 mg/L in response to the first flush (occurring 20 Jan 2020). DO remained below 5 mg/L for <1 day (21 Jan 2020). The DO fluctuated with a general increase; however, instances of DO <6 mg/L were recorded until 26 January. The daily mean DO remained below 7 mg/L until 28 January (inclusive).

All basins (except Kiewa) have sites with impact experienced to at least March 2022.

- The Ovens River sites at Myrtleford and Rocky Point experienced elevated turbidity, TSS and TP. Besides Lake Buffalo, no other sites in the Ovens Basin had water quality impact due to the fires.
- All sites in the Snowy Basin (that had adequate data) exhibited elevation in turbidity, TSS, NO_x and TKN.
- Three sites in the Upper Murray Basin (Murray River at Jingellic, Mitta Mitta R. at Hinnomunjie and Nariel Creek at Upper Nariel) were severely affected, showing a change in turbidity, TSS, NO_x, TN, TP and FRP.

Not all basins showed a change in water quality via all parameters

- All sites with adequate data in the Mitchell Basin experienced no change in EC.
- All sites with adequate data in the East Gippsland, Mitchell and Ovens basins did not demonstrate any change in DO.
- All other basins exhibited some impact across sites for all other water quality parameters.

6.4.3 Climate change

Climate change is expected to result in more frequent and intense bushfires, and the academic literature indicates that bushfires pose a threat to water security (Robinne et al., 2021; Rust et al., 2018).

Climate change is expected to affect the forest ecosystems (Jasechko, 2018; Keenan et al., 2013). It is predicted that forest water use efficiency will change (Iverson et al., 2008), as well as distribution and composition of forest communities (Sun et al., 2011; Vose & Klepzig, 2013). These changes will all increase the frequency and intensity of fires.

Rainfall events following the fires in Victoria have harmed water quality by sediment deposition from burnt areas into rivers and streams, but also resuspension of sediment previously deposited into waterways. The conversion of rainfall to runoff is complex and dependant on the antecedent wetness of catchment. Increased intensity of rain events due to climate change may lead to increased runoff and is likely to further increase sediment deposition into fire-affected drivers in north-east Victoria and Gippsland.

Nutrient contribution (particularly phosphorus) into waterways as a result of runoff from the fires may lead to blue-green algal blooms, particularly around the Gippsland Lakes area. This may be exacerbated by increased temperatures due to climate change.

7. How are blue-green algal blooms changing?

7.1 Summary

This chapter explores how BGA blooms change over time. It is based on records of recreational BGA warnings for major Victorian water bodies issued by Goulburn-Murray Water, Grampians Wimmera Mallee Water and Southern Rural Water.

The total number of BGA warnings issued by each of the three organisations has not changed significantly over time. For each water body, the total duration of BGA events each year has not experienced significant change. The duration of each BGA event in each water body has not changed significantly expect in Lake Eppalock, where each BGA event is approximately 16 days longer than the previous one (within a total of 10 events). The starting date of BGA events in each year has not changed significantly except for Laanecoorie Reservoir and Tullaroop Reservoir, where it shifted significantly by 1.2 days and 6.6 days later per year, respectively.

The general pattern of no or little significant trends identified is likely because of the low number of warning events in the available record.

The BGA event duration does not display significant correlation with any of short-term air temperature, water level, inflow TP and turbidity, suggesting the need for further site-specific investigation on potential explanatory variables.

7.2 Background

This question addresses:

1. What are the trends and patterns (frequency, duration and time of occurrence) in blue green algal bloom events?
2. What are the possible drivers of these patterns?

BGA are bacteria known as cyanobacteria. Blooms are problematic due to: (i) change in water colour during blue green algal blooms, (ii) the toxins that are released, which can affect mammals (including people) through skin contact and ingestion, and (iii) reduction in DO causing fish deaths when the algae decompose (Elliott, 2012). Risk of blooms in water bodies increases with: (i) high temperatures, (ii) high nutrient loads, (iii) stratification in the water body (Elliott 2012). These factors also affect how long the algal blooms last in water bodies.

The response to BGA blooms in Victoria is managed through the coordination framework outlined within the Victorian BGA Circular. Algal blooms require a prompt response through monitoring and communication to minimise harm to humans, animals, birds, livestock and crops. Based on collected water samples and visual observations from major water bodies and storages, local water managers issue warnings of BGA events to the public when these water bodies are not considered suitable for recreational use.

We obtained records on the periods of BGA warnings issued by three local water managers: Goulburn-Murray Water (records since 2003), Grampians Wimmera Mallee Water (GWM Water, records since 2013) and Southern Rural Water (records since 2017). Goulburn-Murray Water and GWM Water also provided data on BGA species counts, bio-volumes and scum observations. Based on preliminary consultation with DEECA and the three local water managers, we analysed trends in the following characteristics of BGA events in each water body to understand how they have changed over time:

- Event frequency – the number of annual warnings due to BGA events
- Event duration – the total number of days in warning period annually

For water bodies which experienced more frequent BGA events, defined as having five or more warning events on record, we further assessed the temporal trends in

- Event duration – the duration of each warning
- Event timing – the starting days of warnings in each year

We looked for trends in each variable from the start of the corresponding record. Preliminary consultation with Goulburn-Murray Water identified a major management change in 2007 when the Department of Sustainability and Environment introduced a bio-volume approach and triggers for issuing a BGA warning based on the recreational water guidelines by the National Health and Medical Research Council (NHMRC). For water bodies managed by Goulburn-Murray Water, we analysed only the BGA warning trends since 2007 to obtain unbiased estimates of the changes in BGA warning.

As a complementary analysis, we assessed the temporal trend in the spot samples of total bio-volume (only available for water bodies monitored by Goulburn-Murray Water and GWM Water) from each water body. The trends in the annual average value and the average of each season were analysed.

A detailed description of the analytical approach is included in Appendix J: Analytical approach used for Chapter 7.

7.3 Results

7.3.1 Trends and patterns in BGA events over time

Figure 54 is a summary of all BGA warnings issued across Goulburn-Murray Water, GWM Water and Southern Rural Water. There are 16 water bodies where warnings were issued: 9 by Goulburn-Murray Water (since 2007), 5 by GWM Water (since 2013) and 2 by Southern Rural Water (since 2017).

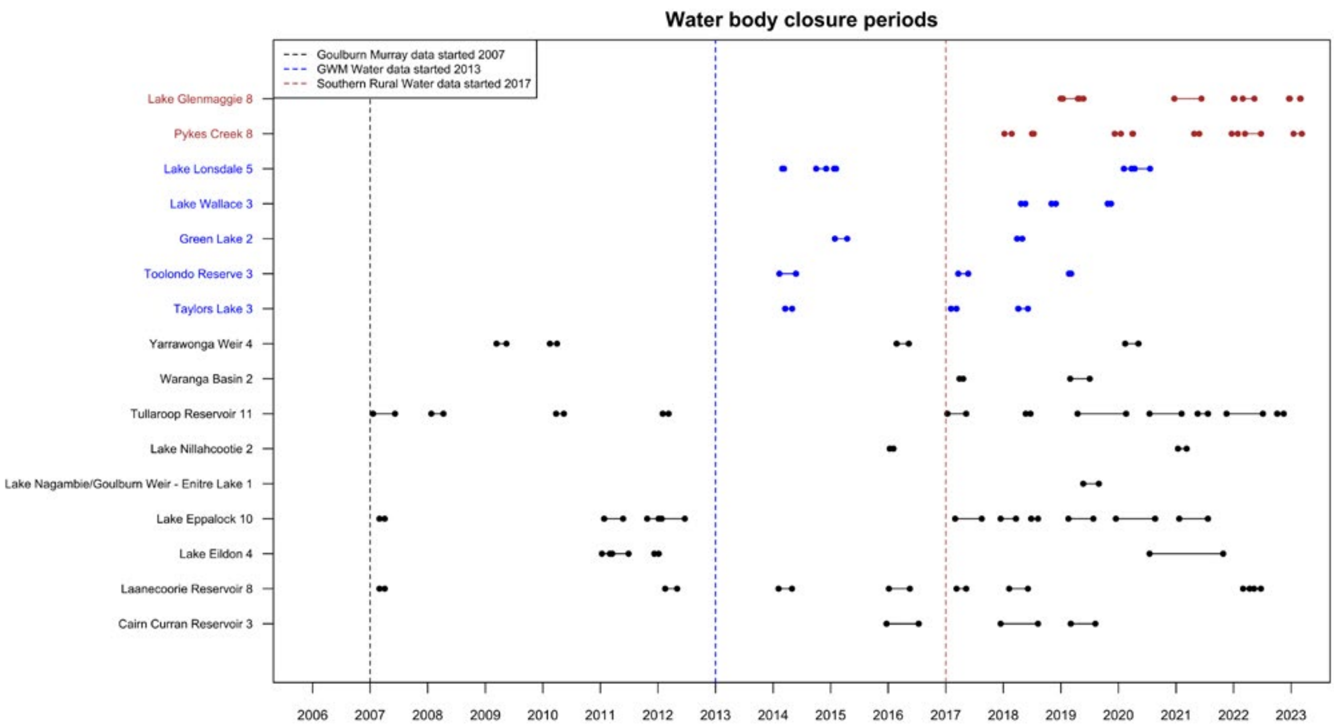


Figure 54: Summary of the periods of all BGA warnings issued across storages managed by Goulburn-Murray Water, GWM Water and Southern Rural Water. After the names of the water bodies is the total number of BGA warnings. The colours indicate the local water managers that issue warnings for each water body: Goulburn-Murray Water, GWM Water, and Southern Rural Water.

The number of BGA warnings that each local water manager (Goulburn-Murray Water, GWM Water and Southern Rural Water) issued each year has not changed significantly (Figure 55).

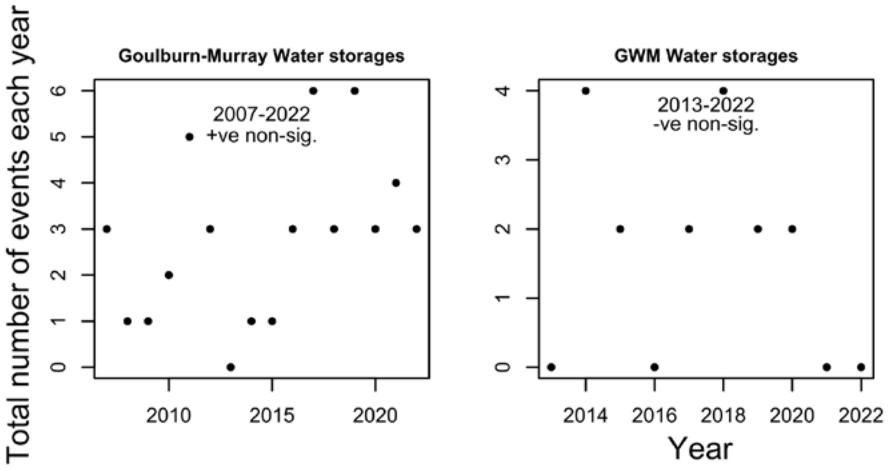


Figure 55: The number of annual BGA warnings issued by each local water manager. The total number of warnings and the start of warning records issued by each manager are: Goulburn-Murray Water, 45 events since 2007; GWM Water, 16 events since 2013; and Southern Rural Water, 16 events since 2017. Each panel summarises all warnings issued by each local water manager annually, denoted by the period over which trend analysis was performed, the resultant direction and significance of trend in annual warning event frequency.

The trend in annual event number was also assessed for each water body separately, which also shows no significant change in events over time. There is no year with more than three warnings being issued for a single water body. The data resolution for events over the limited record period may limit the ability to detect any significant trend. Details of event trends for individual water bodies are presented in Appendix K: Detailed results on BGA event trends (Chapter 7)

The total duration of BGA warnings for each water body each year has not changed significantly; non-significant increases occur in 11 out of 16 water bodies, with the others experiencing non-significant decreases (Figure 56).

In addition to understanding the total duration of annual BGA warnings, further analyses were conducted on the trends in the duration and starting days of individual warnings. These analyses focused on water bodies with five or more BGA warnings over the data period. The duration of each BGA warning has generally not experienced significant changes (Figure 57). Within the six water bodies analysed, non-significant increases occurred in three water bodies. Lake Eppalock experienced a statistically significant increase in the duration of BGA warnings within 10 warnings recorded; each event is on average 16 days longer than the previous one.

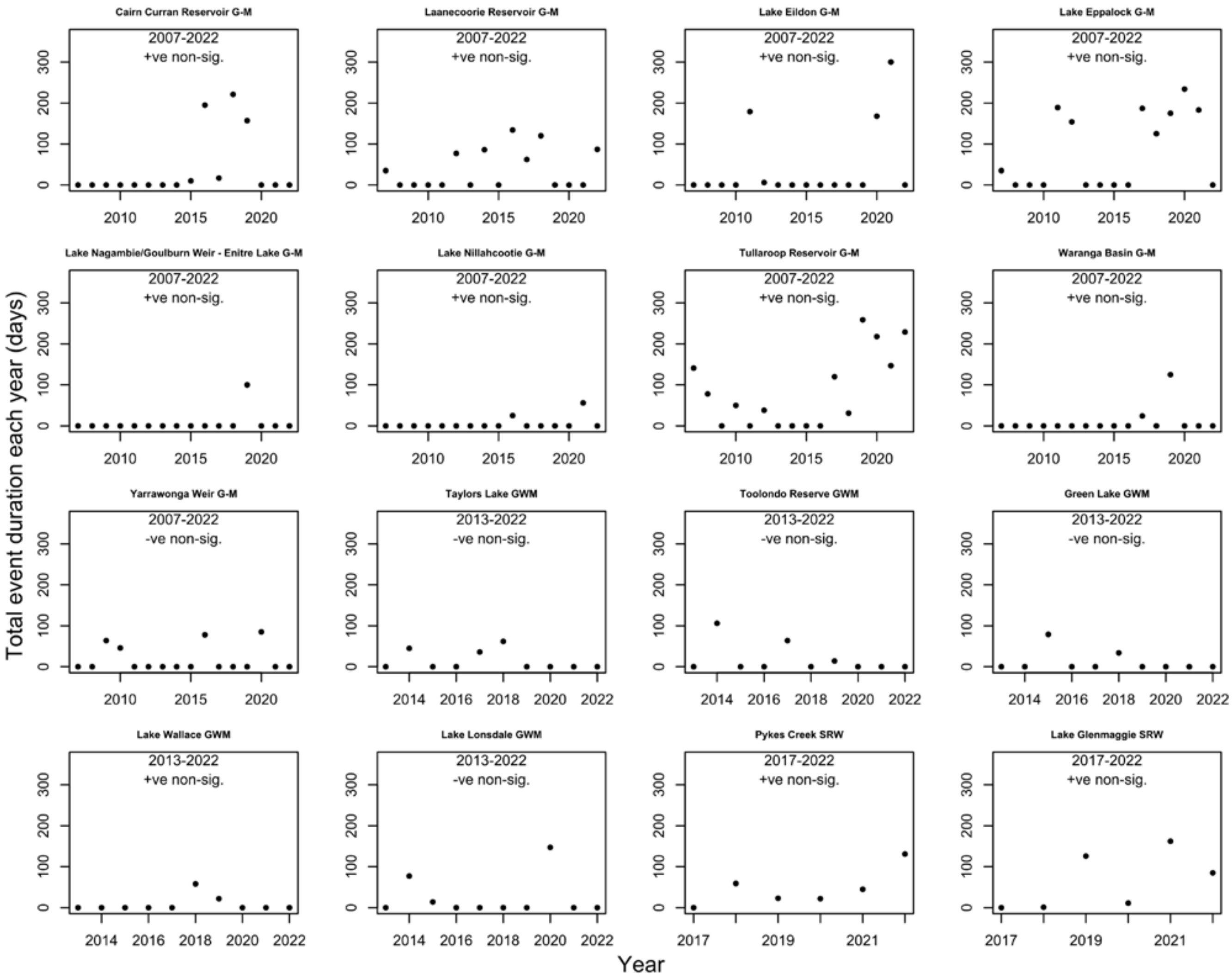


Figure 56: Total duration (days) of BGA warnings each year for each water body. Each panel summarises all warnings issued annually for each water body, denoted by the period over which trend analysis was performed, the resultant direction and significance of trend in the warning duration each year.

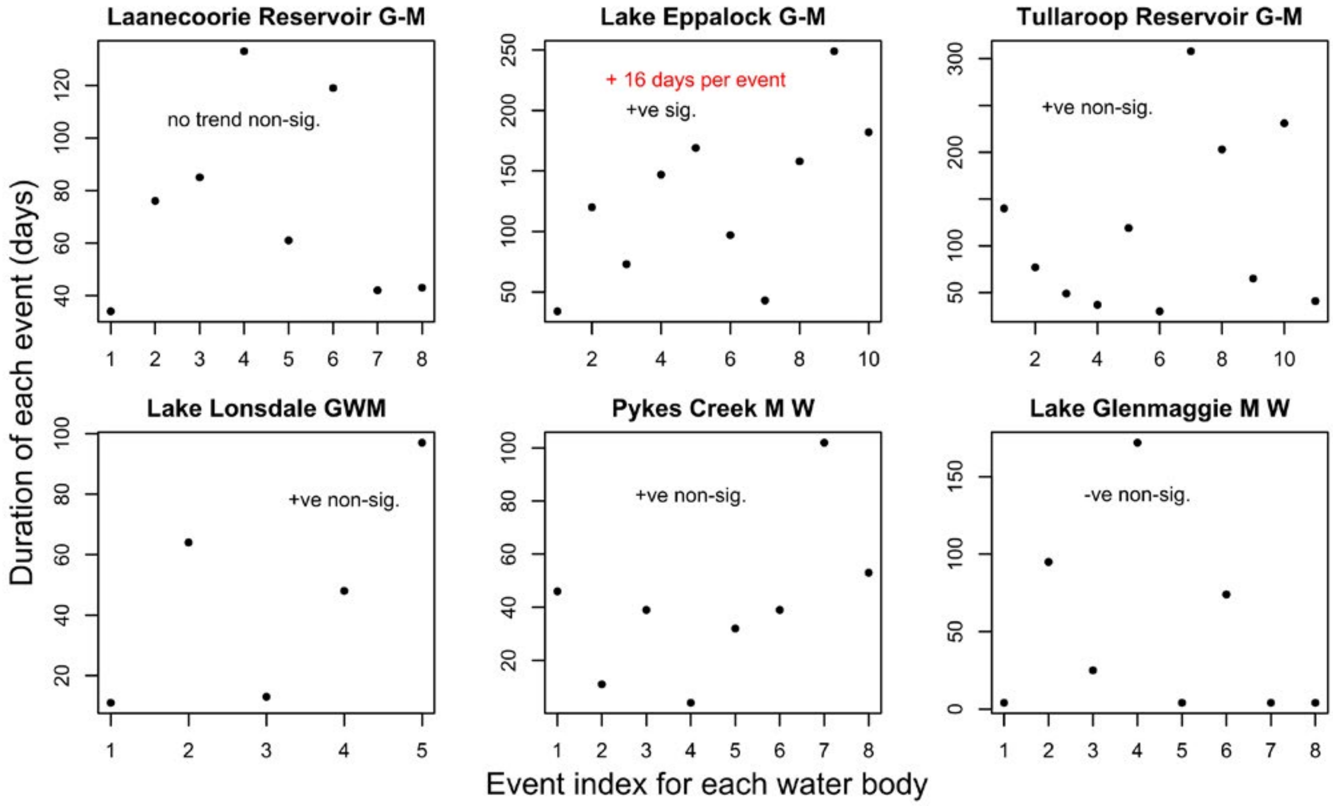


Figure 57: The duration (days) of individual BGA warnings plotted against the index of warnings (i.e. the 1st , 2nd, 3rd… event of each water body), for water bodies where five or more warnings were issued. Each panel summarises a water body, denoted by the resultant direction and significance of trend in the duration of each warning.

There are statistically significant shifts in the starting time of BGA event warnings for the Laanecoorie Reservoir and the Tullaroop Reservoir, which have positive trends of 1.2 and 6.6 days per year, respectively.

Initial warnings issued at Tullaroop Reservoir (on Tullaroop Creek, a tributary of Loddon River, west of Castlemaine) moved from mid- to late-summer, to later in winter into spring. At Laanecoorie Reservoir (on Loddon River, west of Bendigo) initial warnings were in mid- to late-summer, with the final two being in early- and late-autumn. Due to the circular nature of the data (see detailed discussion on the data and the corresponding trend analyses in Appendix J), a positive trend here represents a tendency of later start of warning events (Figure 58).

As a complementary analysis, we assessed the temporal trends over the data record in the total bio-volume of BGA (mm^3/L) sampled from each water body (available only for water bodies monitored by Goulburn-Murray Water and GWM Water).

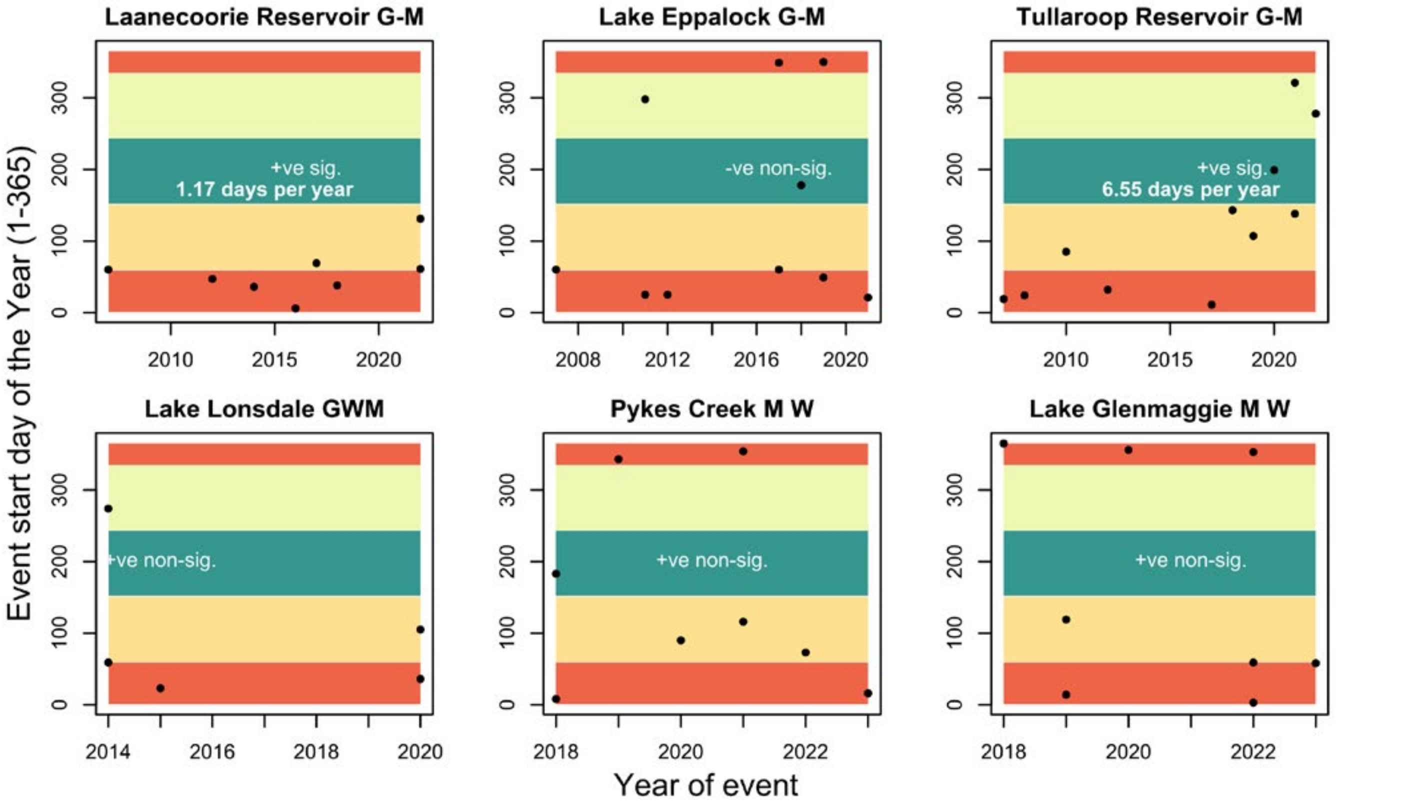


Figure 58: The starting day of individual BGA warnings plotted against the year of warning, for water bodies where five or more warnings were issued. Each panel summarises a water body denoted by the resultant direction and significance of trend in the starting day of the warnings. A positive trend represents a tendency for later start of warning events – from start toward the end of the year, or from the end of year toward the start of next year. Day 1 is 1 January of a given year. The four background colours highlight the seasons corresponding to the day of year, with red being summer, peach being autumn, dark green being winter, light green being spring.

The bio-volume sampling by Goulburn-Murray Water was performed at locations away from scums if present, while any scum observation is recorded on a separate dataset as either 'isolated scum observed' or 'widespread scum observed'. This means that the bio-volumes sampled from the Goulburn-Murray Water water bodies are likely underestimated due to the sampling practice. To address this limitation, we have manually added 250 and 500 mm^3/L to the observed bio-volumes on dates where isolated and widespread scums occurred, respectively. The adjusted bio-volume samples (Figure K2 in Appendix K: Detailed results on BGA event trends (Chapter 7)) were further averaged for each year and each season, for which the temporal trends were analysed (see analytical method in Appendix J).

Consistent with the abovementioned trends on the frequency and duration of BGA warnings, there were no significant changes in the bio-volume levels at many sites. The annual average bio-volume levels for Waranga Basin, Lake Nillahcootie and Laanecoorie Reservoir all significantly increased over time (Figure 59); however, for Waranga Basin and Lake Nillahcootie, the increasing trends are likely a statistical artefact in response to the scum events occurring later in the records (after 2020 for Waranga Bain and around 2015 for Lake Nillahcootie, respectively, Figure J2).

There are several occasions where significant trends occur in the seasonal average bio-volume levels (Figure K3), and the most common patterns are increasing trends for the summer and autumn levels. The significant trends observed in individual water bodies are:

- Yarrawonga Weir – significant increases in winter levels
- Waranga Basin – significant increases in summer and autumn levels
- Lake Nillahcootie – significant increase in autumn levels
- Laanecoorie – significant increases in summer and autumn levels

- Lake Wallace – significant increases in autumn levels
- Toolondo reservoir – significant increases in spring levels.

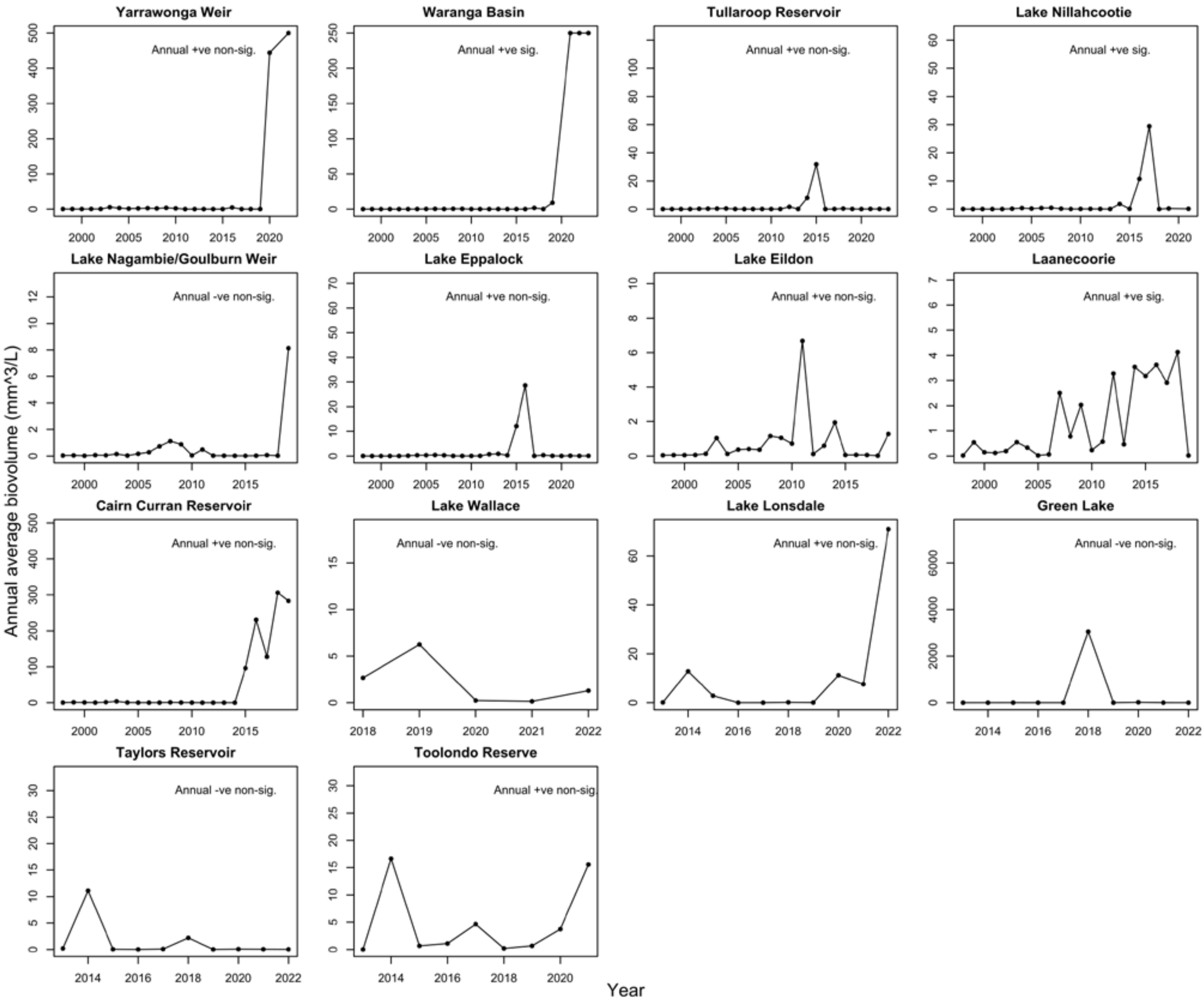


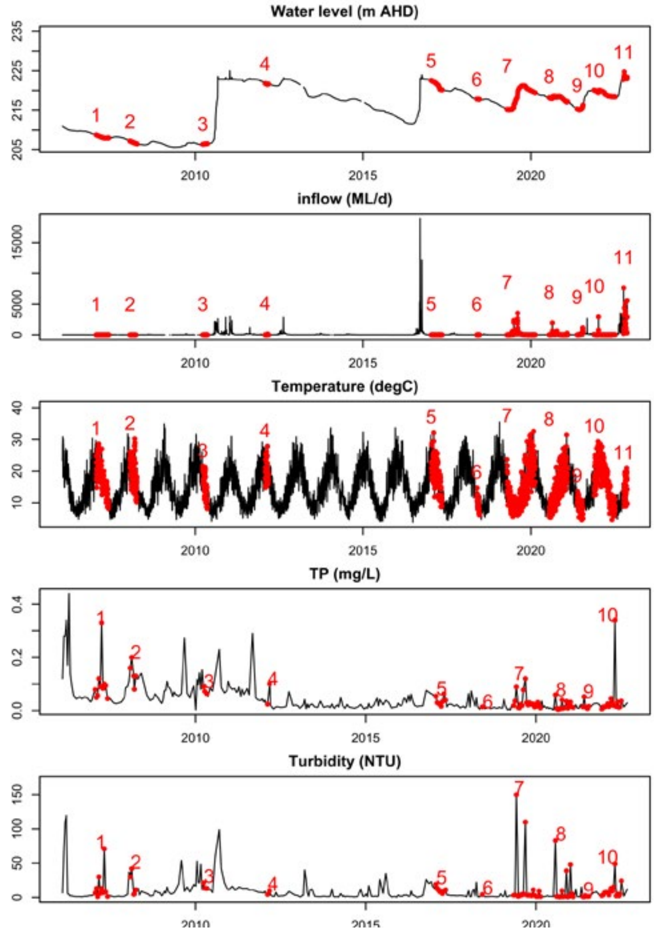
Figure 59: The annual average bio-volume sampled from each water body (available for 14 water bodies monitored by Goulburn-Murray Water and GWM Water only). The text denotes the direction and significance of trends in annual average bio-volumes. The raw bio-volume data used to derive these averages, and the trend in seasonal bio-volume data are in Figures K2 and K3, respectively.

7.3.2 Potential explanatory factors for BGA event patterns

To identify potential variables related to the patterns in BGA events, we explored the correlations between the duration of warning events in each water body with its five potential explanatory variables: air temperature, water level, inflow, turbidity and TP (the latter two are only available for the water bodies monitored by Goulburn-Murray Water). The detailed methodology for this analysis is described in Appendix J: Analytical approach used for Chapter 7.

Comparing various temporal scales for summarising the four potential explanatory variables, the conditions 1 month prior to the start of the warning events generally have strongest correlation with the event duration, but there is no statistically significant correlation. The lack of correlation might be because of the low number of warning events and thus data points available for this analysis. The scatterplots between the event duration and its four potential explanatory variables are shown in Appendix L: Detailed results on the analysis of explanatory variables (Chapter 7) with the corresponding values and significances of their correlations.

To further demonstrate the dynamics between BGA events and their potential explanatory variables, Figure 60 and Figure 61 show the time-series of air temperature, water level, inflow, turbidity and TP along with the periods of BGA events for each of Lake Eildon and Tullaroop Reservoir, which are the two water bodies that experienced the highest numbers of BGA events. The only visible pattern is that most BGA events tend to start when air temperature peaks, which is likely due to weather conditions that are favourable to algae growth (higher temperature and solar radiation), and/or higher potential of stratification during warm conditions. The conditions of water level, inflow, TP and turbidity vary substantially between individual events, which suggests potential local-scale drivers for individual events which requires further site-specific investigation.



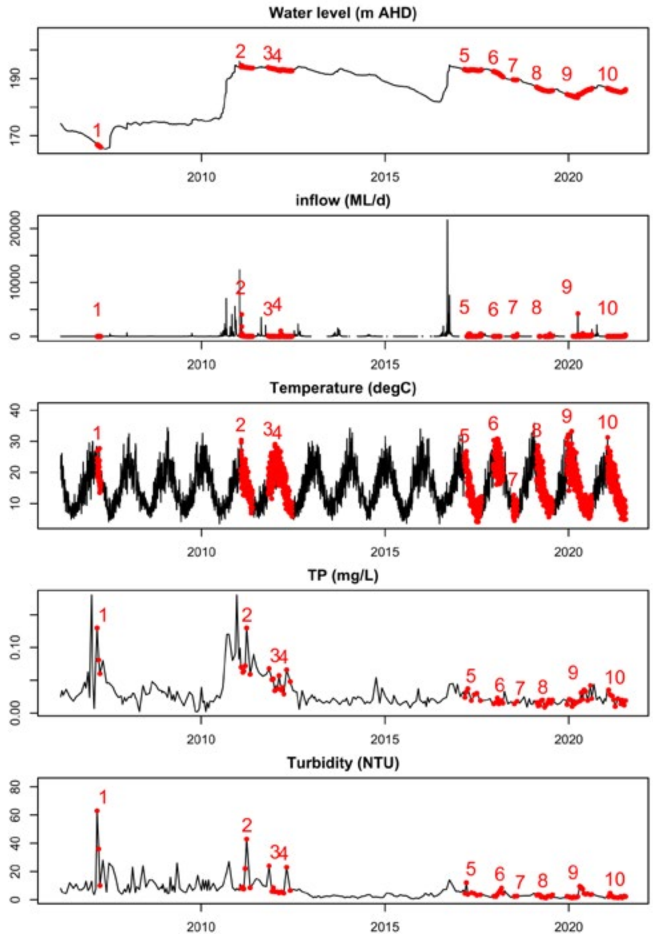


Figure 60: Time-series plots of water level, inflow, air temperature, TP and turbidity at the Tullaroop Reservoir. Red dots highlights data points that occur during a BGA event.

Figure 61: Time-series plots of water level, inflow, air temperature, TP and turbidity at Lake Eppalock. Red dots highlights data points that occur during a BGA event.

8. How can continuous water quality data be used to understand water quality events?

8.1 Summary

Continuous monitoring of water quality has become possible since the 1990s when the first EC probes were installed in Victoria. Since then continuous monitoring has expanded to include turbidity, DO, temperature and chlorophyll a and has become an increasingly important part of water quality management.

For the first time, this report has examined continuous water quality data to provide important information on water quality events and to highlight opportunities for future work.

There is no clear increasing or decreasing trend for low and critical DO events; rather their frequency and duration are strongly associated with known climate periods. Data between 1991 and 2022 showed an increase in low and critical DO events during the second half of the Millennium Drought, with a major peak in events during the 2010 floods. 2010-20 saw steady levels, with an increase in 2021.

The two types of hypoxic events, the critical DO event and the low DO event, were defined via expert consultation. Rather than being a 'blip' or short occurrence of low DO, 'low' and 'critical' events were at a level and longevity that managers of waterways would start to track and potentially expect to see stress in ecosystems.

The typical duration of critical and low DO events was days to weeks: with approximately 67% of critical and 59% of low DO events lasting less than a week; 94% of critical and 92% of low DO events lasted for less than a month.

Amplified and supressed diurnal patterns in DO occurred during critical and low DO events, reflecting the different drivers of these events. Hypoxia occurs most often in the early morning and increases significantly in frequency during warmer months.

Continuous turbidity data at six study catchments was studied to identify links between high turbidity events and potential hydro-climatic drivers. A basic machine learning model for predicting high turbidity events was used, which identified discharge and rainfall as the most important drivers for high turbidity events. This example demonstrates how continuous water quality sampling can be used to inform process understanding at higher temporal resolution.

8.2 Introduction

Continuous water quality data have been collected in Victoria since the 1990s, starting with EC. The coverage has increased greatly in the last 10 years to include turbidity, DO, temperature and chlorophyll a and has become increasingly important part of operational water quality management as in-situ probes became more reliable and affordable. Continuous water quality monitoring provides far higher temporal resolutions than traditional spot sampling taken manually onsite. Water managers can identify events as they develop, and respond or track as appropriate.

The approach is likely to enable a greater understanding of poor water quality events, especially for short events that are unlikely to be captured using weekly to monthly spot sampling.

This chapter demonstrates a range of insights that continuous DO data can provide on hypoxic water events. These insights are broken into:

- Quantitative characteristics – the frequency, duration, and spatial distribution of events
- Qualitative characteristics – the patterns and behaviour of events and their underlying drivers.

We also demonstrate a potential way to interpret continuous turbidity data.

We conclude with examples of the added value that continuous data can bring in comparison to spot sampling data, including:

- Identification of nocturnal DO troughs to highlight continuous water quality as a tool for understanding sub-monthly behaviour.
- A predictive model for high turbidity events to demonstrate continuous water quality as a rich dataset for model building and machine learning.

8.2.1 Understanding hypoxic events

Defining hypoxic events

Prior to analysing the characteristics of hypoxic events, a key step is to develop a fit-for-purpose definition. This section summarises the iterative approach taken to develop a relevant definition from an ecological, management and operational perspective.

The duration and frequency of low DO events are intrinsically linked to the definition of an 'event'. For example, using a hypoxic event definition proposed by Blaszczak et al. (2023), the first iteration of a critical DO event is defined as:

An event occurs whenever DO levels drop below 2 mg/L.

We refer to this definition as *hypoxic occurrence*. Using this definition, hypoxic occurrences at 237207A Surry River at Heathmere were analysed for its period of record (Figure 62).

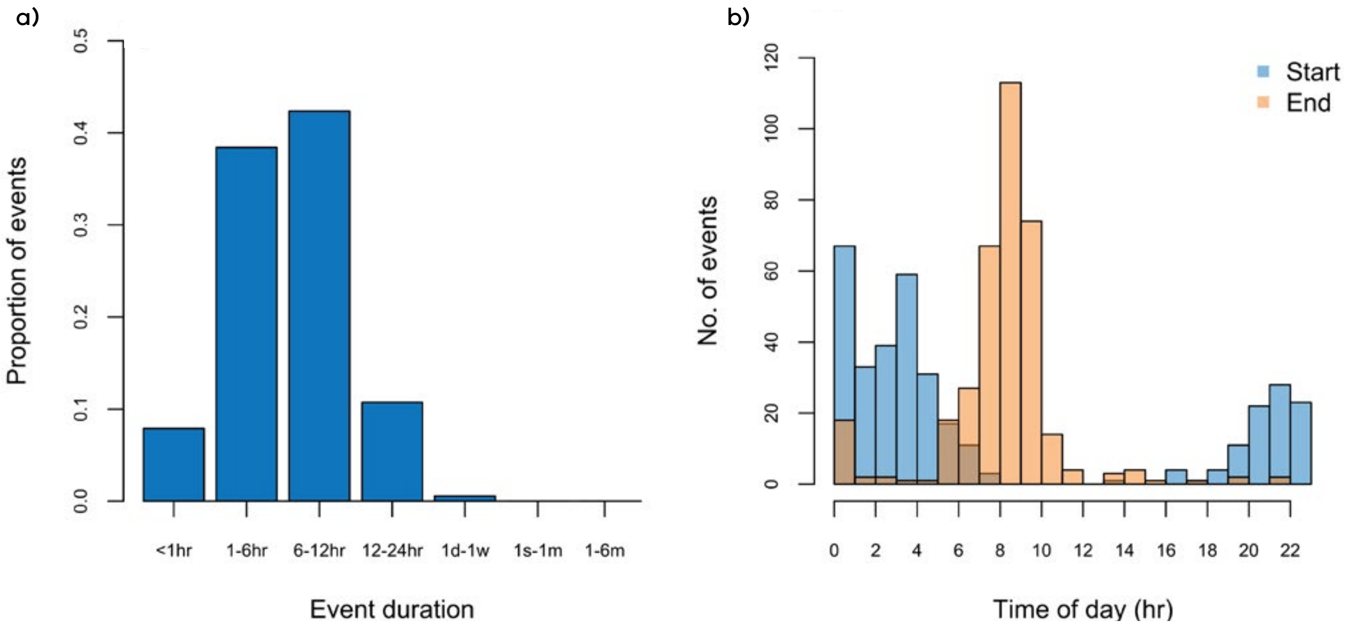


Figure 62: a) Period of hypoxic occurrence and b) Start and end times of hypoxic occurrences at 237207A Surry River @ Heathmere, using the first iteration DO definition (i.e. a hypoxic occurrence is whenever DO drops below 2 mg/L).

Most occurrences of hypoxic DO are nocturnal and have a median duration of 6-12 hours. The relevance of these occurrences was measured with respect to three major aspects:

- Ecological – Do these events pose a serious threat to biota?
- Management – Do these occurrences inform management practices?
- Operational – Were these occurrences actionable in hindsight?

From an ecological perspective, nocturnal drops in DO levels may be a stressor, but unlikely to pose a serious threat to riverine biota compared to chronically low DO (i.e. over the span of days or weeks) which can be associated with fish deaths.

From an operational point of view, it is unrealistic to investigate every single nocturnal hypoxic occurrence. However, an investigation may be warranted if these nocturnal occurrences persist for an extended period. Similarly, a series of consecutive nocturnal occurrences may be symptomatic of a single driver (e.g. elevated primary production in a stream). The ability to distinguish events by common drivers can provide additional insight for management purposes.

Based on these initial findings, a new set of hypoxic event definitions were developed and used in the following analysis sections. The general structure of the definition is explained in Table 10.

Table 10 General structure of low and critical DO events.

Structure	Justification
To trigger an event, we analyse a succeeding moving 24-hour window. The event begins when all the following criteria are satisfied:	DO follows a diurnal pattern which is accounted for by using a moving window.
90% of the readings must be below the threshold	There are instances where DO can hover or 'blip' above the threshold, thus breaking continuity of the event if a simple greater than X value threshold definition was used.
No reading can be more than 2 mg/L above the threshold	The trigger for an event is intended to search for periods of continuously low DO.
An event ends during the first instance when in the following 24-hour window, all DO readings are above the threshold.	The event end time window spans 24 hour to ensure that there are no further nocturnal drops in DO below the threshold.

Threshold values of 2 mg/L and 4 mg/L were used for critical and low DO events, respectively, following consultation with relevant experts. Their full definitions are:

Critical DO event

1. An event begins when in the following 24-hour window:
   a. more than 90% of the DO readings are less than 2 mg/L,
   b. the maximum DO level does not exceed 4 mg/L, and
2. An event ends when within the following 24-hour window, all DO readings are above 2 mg/L.

Low DO event

1. An event begins when in the following 24-hour window:
   a. more than 90% of the DO readings are less than 4 mg/L,
   b. the maximum DO level does not exceed 6 mg/L, and
2. An event ends when within the following 24-hour window, all DO readings are above 4 mg/L.

A limitation of using a single hypoxic event definition for all sites across the state is that the impact and outcome of an event will vary by location. The occurrence of a critical DO event does not guarantee an outcome (e.g. fish death event), rather, it should be interpreted as an environmental stressor with its actual impacts being dependent on the sensitivity of the local ecosystem, the location of the probe in the waterway, and the waterway structure. For example, hypoxic conditions occur frequently in billabongs along the Ovens River during dry summers. Fish communities in these water bodies tolerate periodic hypoxia (McNeil & Closs, 2007). The same hypoxic conditions in an undisturbed upland stream may result in very different impacts and outcomes.

However, this limitation also highlights the breadth of investigations that could be conducted using the continuous water quality dataset. For example, events can be defined with specific ecological endpoints in mind (e.g. species mortality or taxa abundance), thus allowing researchers to understand historical local-scale impacts.

Study sites

An exhaustive search of sites across the state identified those with continuous DO data. We used 131 sites for the subsequent analysis in the following section. The distribution of sites is presented in Figure 63; a detailed site list is presented in Table 11.

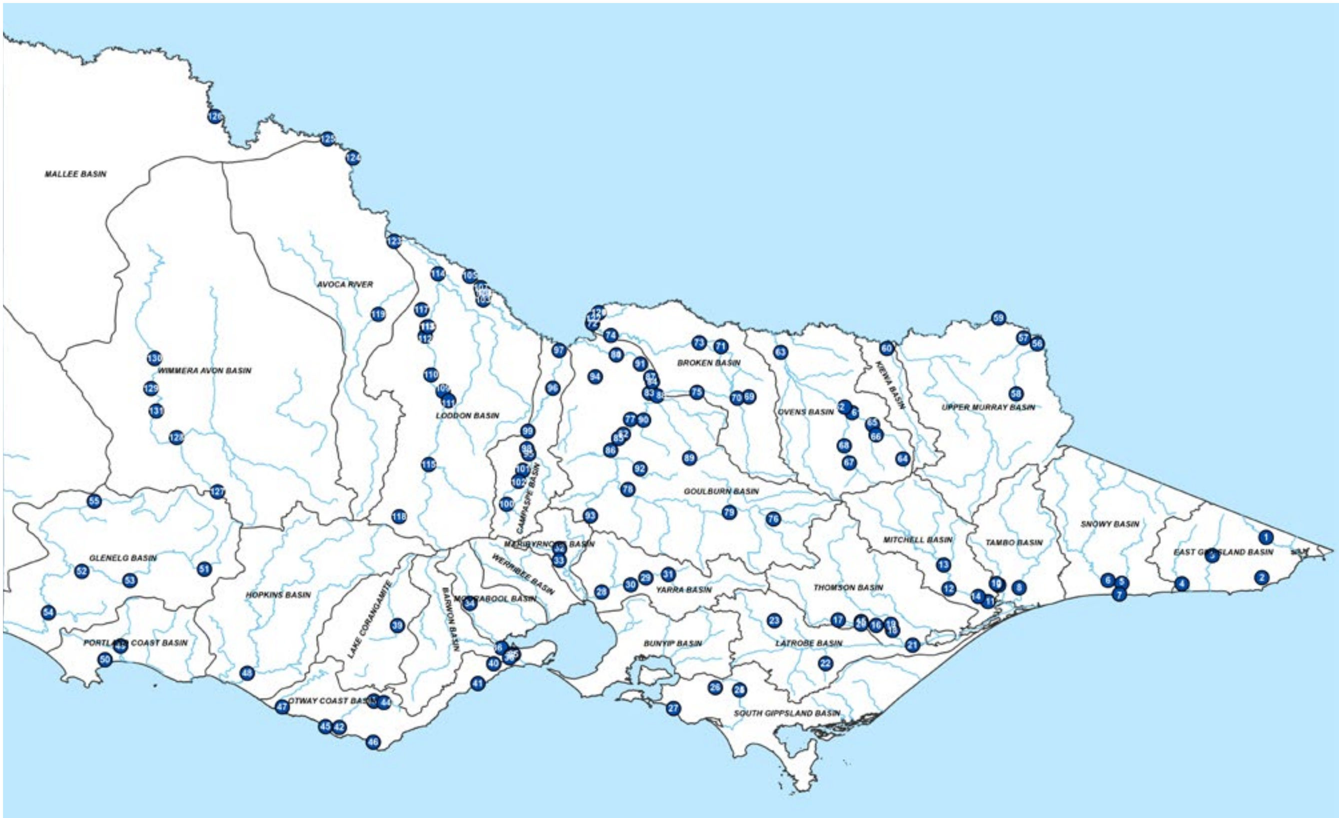


Figure 63: The distribution of the 131 sites with continuous DO data used in the analysis. The numbers on the dots indicate the index of sites, which are detailed in Table 11.

Table 11. List of the 131 sites used in the analysis in this chapter, along with the site names, basin, and the start and end years of records ('ACTIVE' indicates a site is still running). The sites are listed by basin, with rivers listed east to west, and upstream to downstream.

Basin	Index	Site ID	Site name	Start	End
East Gippsland Basin	1	221210A	Genoa River @ The Gorge	2020	ACTIVE
	2	221208A	Wingan River @ Wingan Inlet National Park	2020	ACTIVE
	3	221224A	Cann River U/S Cann River Offtake	2020	ACTIVE
	4	221225A	Bemm River U/S Of Pumphouse	2020	ACTIVE
Snowy Basin	5	222223A	Brodribb River @ U/S Lake Curlip	2020	ACTIVE
	6	222201B	Snowy River @ Orbost	2019	ACTIVE
	7	222203A	Snowy River @ Marlo Jetty	2020	ACTIVE
Tambo Basin	8	223209A	Tambo River @ Battens Landing	2016	ACTIVE
	9	223210A	Nicholson River @ Sarsfield	2016	2019
	10	223218A	Nicholson River @ Granite Rock	2020	ACTIVE
Mitchell Basin	11	224602A	Macleod Morass - Site 1 Regulator	2021	ACTIVE
	12	224203B	Mitchell River @ Glenaladale	2007	2008
	13	224215A	Mitchell River @ Angusvale (Tabberabbera)	2007	2007
	14	224217B	Mitchell River @ Rosehill	2016	ACTIVE
Thomson Basin	15	225200A	Thomson River @ Heyfield	2010	2011
	16	225212A	Thomson River @ Wandocka	2006	2008
	17	225231A	Thomson River @ U/S Of Cowwarr Weir	2008	2012
	18	225232A	Thomson River @ Bundalaguah	2008	2008
	19	225256A	Macalister R D/S Maffra (Smiths Br.)	2005	2014
	20	225236A	Rainbow Creek @ Heyfield	2010	2011
Latrobe Basin	21	226027B	La Trobe River @ Swing Bridge	2019	ACTIVE
	22	226415B	Traralgon Creek @ Traralgon South (Jones Rd)	2009	2011
	23	226226A	Tanjil River @ Tanjil Junction	1995	1996
South Gippsland Basin	24	227264A	Coalition Creek @ Leongatha (Spencers Road Bridge)	2006	2008
	25	227264B	Coalition Creek @ Leongatha (Spencers Road Bridge)	2008	2014
	26	227270A	Foster Creek @ Korumburra	2011	ACTIVE
	27	227273A	Powlett River @ Mouth of Powlett Road	2016	2017
Yarra Basin	28	229143A	Yarra River @ Chandler Highway Kew	1998	2004
	29	229147A	Yarra River @ Yering Gorge	2003	2004
	30	229200B	Yarra River @ Warrandyte	1998	2000
	31	229653A	Yarra River @ Yarra Grange	1998	2000
Maribyrnong Basin	32	230220B	Jackson Creek @ Clarkfield	2004	ACTIVE
	33	230240A	Jackson Creek @ Salesian College Sunbury	2004	ACTIVE
Moorabool Basin	34	232242A	Moorabool R @ Coopers Crossing Meredith	2007	ACTIVE
Barwon Basin	35	233603A	Reedy Lake @ Connewarre	2016	ACTIVE
	36	233217D	Barwon River @ Geelong	2010	ACTIVE
	37	233269A	Barwon River U/S Lower Barrage Of Geelong Wetlands	2019	ACTIVE
	38	233604A	Hospital Swamp @ Connewarre	2016	ACTIVE
Lake Corangamite	39	234201B	Woady Yaloak River @ Cressy (Yarima)	2019	ACTIVE
Otway Coast Basin	40	235255A	Thompson Creek @ Ghazeepore	2011	2015
	41	235278A	Anglesea River @ Great Ocean Road Bridge	2011	ACTIVE

Basin	Index	Site ID	Site name	Start	End
	42	235224A	Gellibrand River @ Burrupa	2020	ACTIVE
	43	235227A	Gellibrand River @ Bunkers Hill	2008	2009
	44	235228A	Gellibrand River @ Gellibrand	2008	2009
	45	235269A	Gellibrand River @ Princetown	2008	ACTIVE
	46	235283A	Aire River @ Horden Vale	2021	ACTIVE
	47	235268A	Curdies River @ Peterborough	2008	ACTIVE
Hopkins Basin	48	236209A	Hopkins River @ Hopkins Falls	2019	ACTIVE
Portland Coast Basin	49	237205A	Darlot Creek @ Homerton Bridge	2019	ACTIVE
	50	237207A	Surry River @ Heathmere	2005	ACTIVE
Glenelg Basin	51	238204C	Wannon River @ Dunkeld	2004	2015
	52	238228A	Wannon River @ Henty	2003	ACTIVE
	53	238219C	Grange Burn @ Morgiana	2003	2019
	54	238206C	Glenelg River @ Dartmoor	2004	ACTIVE
	55	238210D	Glenelg River @ Harrow	2009	2017
Upper Murray Basin	56	401230A	Corryong Creek @ Towong	2020	ACTIVE
	57	401229A	Cudgewa Creek @ Cudgewa North	2020	ACTIVE
	58	401212A	Nariel Creek @ Upper Nariel	2020	ACTIVE
	59	401201A	Murray River @ Jingellic	2020	ACTIVE
Kiewa Basin	60	402205A	Kiewa River @ Bandiana	2019	ACTIVE
Ovens Basin	61	403210B	Ovens River @ Myrtleford	2019	ACTIVE
	62	403230A	Ovens River @ Rocky Point	2020	ACTIVE
	63	403241A	Ovens River @ Peechelba	2020	ACTIVE
	64	403244B	Ovens River @ Harrietville	2019	ACTIVE
	65	403250A	Ovens River @ Eurobin	2019	ACTIVE
	66	403233A	Buckland River @ Harris Lane	2020	ACTIVE
	67	403222A	Buffalo River @ Abbeyard	2020	ACTIVE
	68	403254A	Buffalo River D/S Rose River Junction	2020	ACTIVE
Broken Basin	69	404219A	Lake Mokoan @ Head Gauge	1998	2000
	70	404216A	Broken River @ Goorambat (Casey Weir H. Gauge)	2019	ACTIVE
	71	404204B	Boosey Creek @ Tungamah	2007	2017
	72	404210A	Broken Creek @ Rices Weir	2008	2020
	73	404214A	Broken Creek @ Katamatite	2007	2017
	74	404244A	Broken Creek @ Harding's Weir	2009	2012
	75	404224B	Broken River @ Gowangardie	2019	ACTIVE
Goulburn Basin	76	405218B	Jamieson River @ Gerrang Bridge	2020	ACTIVE
	77	405200A	Goulburn River @ Murchison (Mcphee's Rest)	2019	ACTIVE
	78	405201B	Goulburn River @ Trawool	2021	ACTIVE
	79	405203C	Goulburn River @ Eildon	2003	ACTIVE
	80	405232C	Goulburn River @ Mccoys Bridge	2013	ACTIVE
	81	405232D	Goulburn River @ Mccoys Bridge	2009	2012
	82	405259A	Goulburn River @ Goulburn Weir (H.G.)	2005	ACTIVE
	83	405270A	Goulburn River @ Arcadia Downs	2019	ACTIVE
	84	405271B	Goulburn River @ Shepparton Golf Club	2013	ACTIVE
	85	405282B	Goulburn River @ Kirwan's Bridge	2008	ACTIVE
	86	405323A	Goulburn River @ Tahbilk Winery	2008	ACTIVE
	87	405324A	Goulburn River U/S Shepparton Treatment Plant	2009	2012

Basin	Index	Site ID	Site name	Start	End
	88	405269A	Seven Creeks @ Kialla West	2018	ACTIVE
	89	405307A	Seven Creeks @ Galls Gap Road	2016	ACTIVE
	90	405226B	Pranjip Creek @ Moorilim	2019	ACTIVE
	91	405276A	Goulburn River @ Loch Garry	2019	ACTIVE
	92	405228A	Hughes Creek @ Tarcombe Road	2016	ACTIVE
	93	405335A	Kilmore Creek U/S Waste Water Treatment Plant	2020	ACTIVE
Campaspe Basin	94	406756A	Mosquito Creek Depression @ Curr Road	1999	1999
	95	406219A	Campaspe River @ Lake Eppalock (Head Gauge)	2005	2011
	96	406275A	Campaspe River @ Burnewang-Bonn Road	2007	2014
	97	406276A	Campaspe River @ Fehrings Lane	2007	ACTIVE
	98	406277A	Campaspe River @ Doaks Reserve	2007	2014
	99	406278A	Campaspe River @ Backhaus Road	2007	2019
	100	406200C	Coliban River @ Malmsbury Rail Bridge	2007	2014
	101	406215B	Coliban River @ Lyal	2007	2014
	102	406279A	Coliban River U/S Summerhill	2007	2014
Loddon Basin	103	407330A	Gunbower Creek @ Cohuna Weir Pool	2012	2013
	104	407331A	Gunbower Creek @ Yarran Offtake	2012	2014
	105	407332A	Gunbower Creek @ Condidorios Bridge	2012	ACTIVE
	106	407368A	Gunbower Creek 5km Downstream Yarran Regulator	2014	ACTIVE
	107	407384A	Gunbower Creek @ Reedy Lagoon	2018	ACTIVE
	108	407373A	Yarran Creek 100m D/S Yarran Regulator	2015	ACTIVE
	109	407229C	Loddon River @ Serpentine Weir	2007	2014
	110	407320A	Loddon River D/S Loddon Weir	2007	2014
	111	407321A	Loddon River @ Turners Crossing	2007	2013
	112	407323A	Loddon River @ Yando Road	2007	ACTIVE
	113	407379A	Loddon River @ Canary Island	2017	2017
	114	407382A	Loddon River @ Donaghues Road Bridge	2017	2019
	115	407322A	Tullaroop Creek @ Mullins Road	2007	2015
	116	407380A	Twelve Mile Creek @ Canary Island	2017	2017
	117	407608C	Lake Meran @ Wq Monitoring Buoy	2019	ACTIVE
	118	407333A	Mccallum's Creek @ Evansford Res. H.G.	2015	ACTIVE
Avoca Basin	119	408203B	Avoca River @ Quambatook	2019	ACTIVE
Murray Basin	120	409397A	Little Budgee Creek @ Forcing Yard Track	2019	ACTIVE
	121	409396A	Budgee Creek @ Sand Ridge Track	2019	ACTIVE
	122	409398A	Budgee Creek @ War Plain	2015	ACTIVE
	123	409399A	Little Murray River @ Little Murray Weir	2009	2010
Mallee Basin	124	414200A	Murray River @ Below Wakool	2016	ACTIVE
	125	414201B	Murray River @ Boundary Bend	2016	ACTIVE
	126	414207A	Murray River @ Colignan	2018	ACTIVE
Wimmera Avon Basin	127	415202D	Mackenzie River @ Wartook Reservoir	1998	2000
	128	415200D	Wimmera River @ Horsham	2009	ACTIVE
	129	415246A	Wimmera River @ Lochiel Railway Bridge	2009	ACTIVE
	130	415247B	Wimmera River @ Tarranyurk	2009	ACTIVE
	131	415256A	Wimmera River @ U/S Of Dimboola	2009	ACTIVE

8.2.2 Identifying the drivers of high turbidity events

In addition to understanding the frequency, duration, and distribution of hypoxic events, we present a further example of how continuous water quality data can be used to understand the predictors of poor water quality events. High turbidity events were selected to be modelled in preference to hypoxic events. This is because DO levels are overwhelmingly influenced by stream temperature through gas solubility. Obtaining more nuanced and insightful predictors besides temperature was assumed to be difficult and may have yielded statistically insignificant results. Turbidity is influenced by various factors, including:

- The mobilisation of particles, influenced by soil moisture, rainfall, and slope.
- The transport and suspension of particles, influenced by stream velocity and discharge.

The relative effects of these factors are quantified with a logistic model (see details in Appendix N: Further details on the analytical approach for understanding the drivers of high turbidity events (Chapter 8)). The purpose is not to accurately predict high turbidity events; rather it serves as a demonstration of how large continuous datasets can be used in predictive models. Interest in machine learning has accelerated in the past decade and there has been growing interest in predictive surface water quality models. Examples include:

- The coupling of continuous and spot data to predict continuous values of difficult-to-monitor constituents (e.g. predicting Ca^{2+} and Al^{3+}, which are typically only measured in spot measurements, using continuous datasets of nitrate, DO, turbidity) (Green et al., 2021).
- Using machine learning tools to predict hypoxic events, algal blooms and imputing missing values (Zhu et al., 2022).

For this analysis, we adopted a relatively simple definition of high turbidity events due to the lack of widely applicable thresholds (which exist for DO). Turbidity readings that exceed the 95th and 99th percentile limits were determined to be events. Percentiles were used, as opposed to absolute thresholds, to account for the differences in baseline turbidity for each site.

Six sites were selected (Figure 64) based on data availability covering different bioregions in Victoria. These sites have long continuous turbidity records (10-20 years), relatively natural flow control methods, and a variety of land uses across the state (e.g., including both heavily forested upland catchments and agricultural ones).

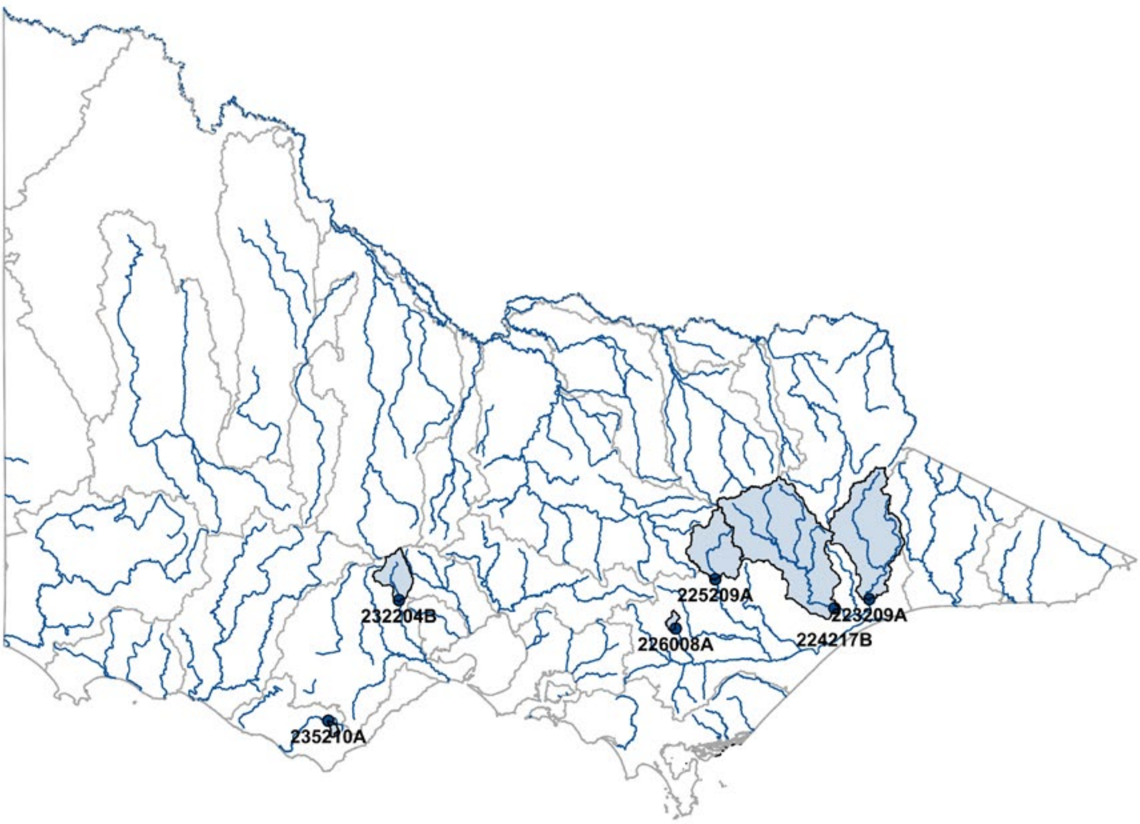


Figure 64: Modelled sites for turbidity events.

8.3 Results

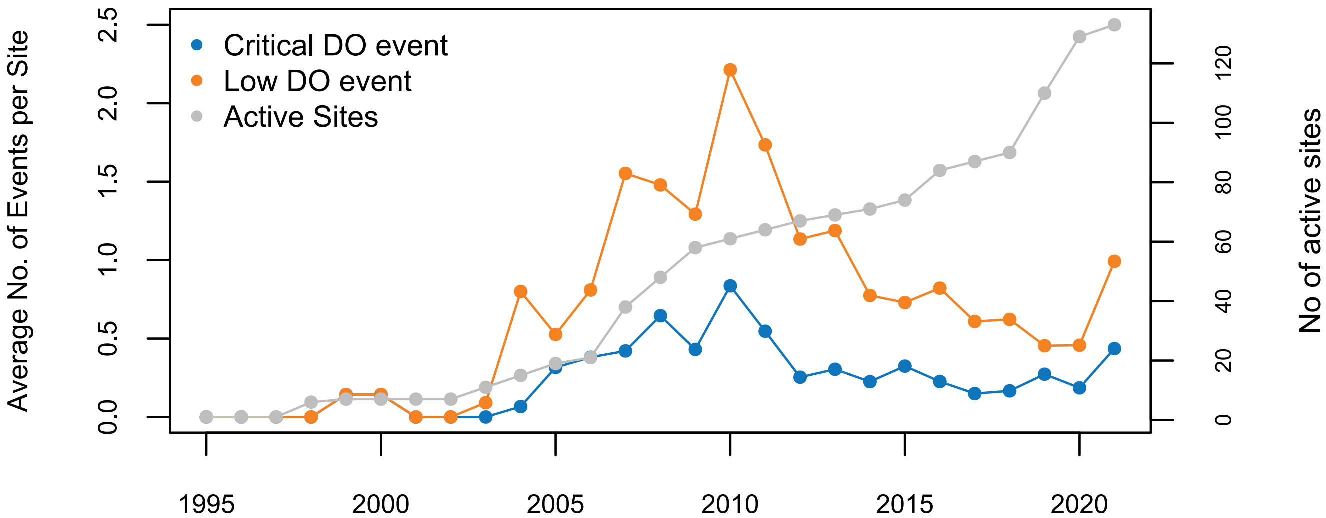
8.3.1 Understanding low DO events

Event frequency

The frequency of hypoxic events was quantified using the number of hypoxic events per year across the state. As data availability increased significantly across the period of record from installation of the first continuous DO probes, a normalised value is provided in addition to an absolute number of events to account for the increases in the number of active monitoring sites with time.

Figure 65 shows an increase in the normalised number of events per site starting around 2004 through the latter half of the Millenium Drought, with peak events and duration occurring in the flooding year of 2010. This is consistent with reports of mass blackwater events in the southern Murray-Darling basin during the flooding that broke the drought in 2010-11 (Whitworth et al., 2012). Post 2010 numbers of events declined to a near steady level, with an uptick in 2021.

a)



b)

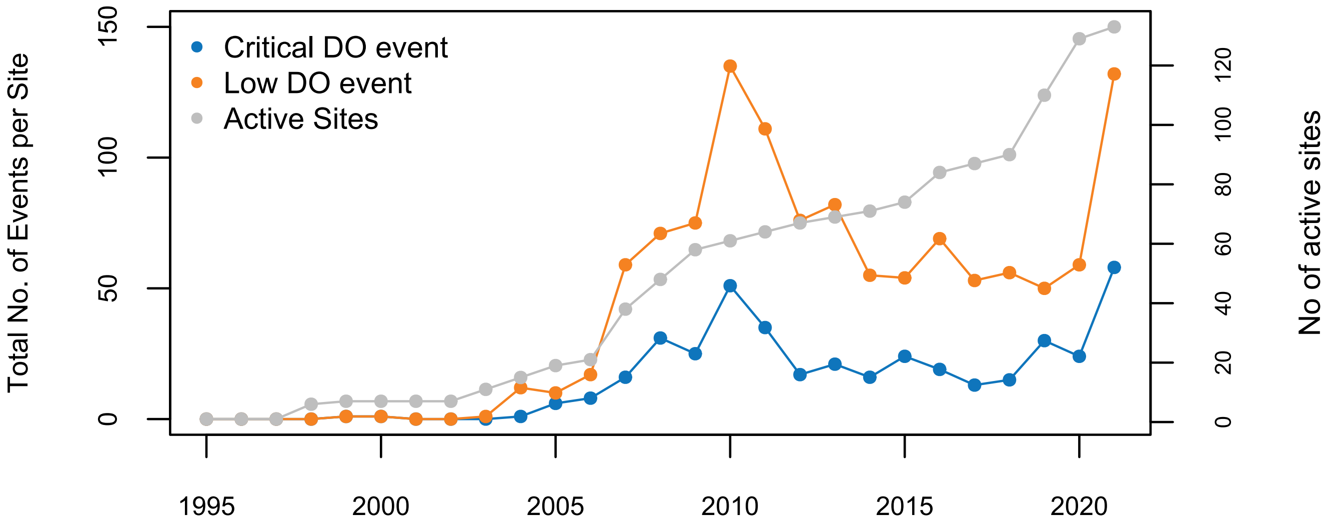


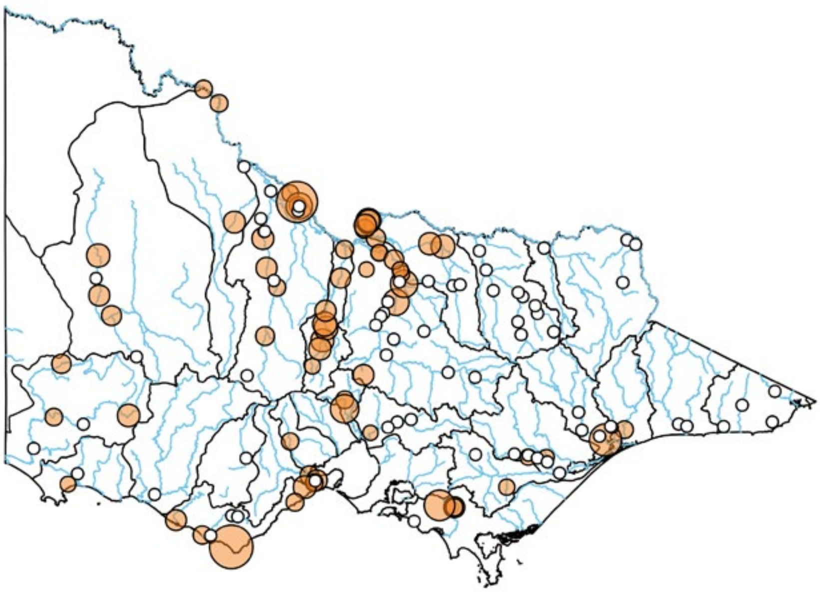
Figure 65: a) The average number of events per year per site. This plot accounts for the increase in sites with data from 1995 to 2021, as the monitoring network increased and b) the total number of events per year across the state. The entire record for each continuous DO site was analysed. The number of active sites, denoted by grey dots, can be interpreted as a proxy for statistical power.

Relative to the state average critical event frequency of 0.4 events per year, notable hotspots include:

- Aire River at Horden Vale near Cape Otway, with a critical event frequency of 12 per year. However, the site has a short record and came online during 2021.
- Gunbower Creek at Reedy Lagoon, a wetland site along the Murray River with a critical event frequency of 9 per year and 2 years of records.

Events along the lower Goulburn and Campaspe (downstream of Eppalock Reservoir) typically occur at higher than average frequencies, with 1-2 critical events per year and 3-4 low events per year.

a)



b)

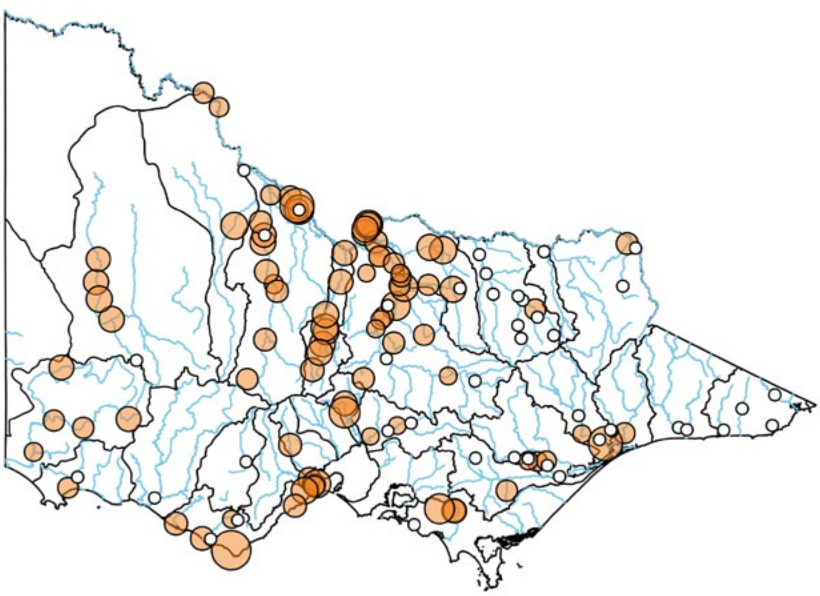


Figure 66: Distribution of event frequencies for a) critical and b) low DO events, where dot size is proportional to the event frequency in cumulative hours of hypoxia per year. White dots indicate sites with no event. Data details are included in Appendix O: Detailed statistics of low and critical DO events across Victorian sites.

Duration of events

Hypoxic events usually last from days to weeks, with low DO events lasting longer than critical DO events (Figure 67). Approximately 67% of critical and 59% of low DO events lasted less than a week; 94% of critical and 92% of low DO events lasted for less than a month.

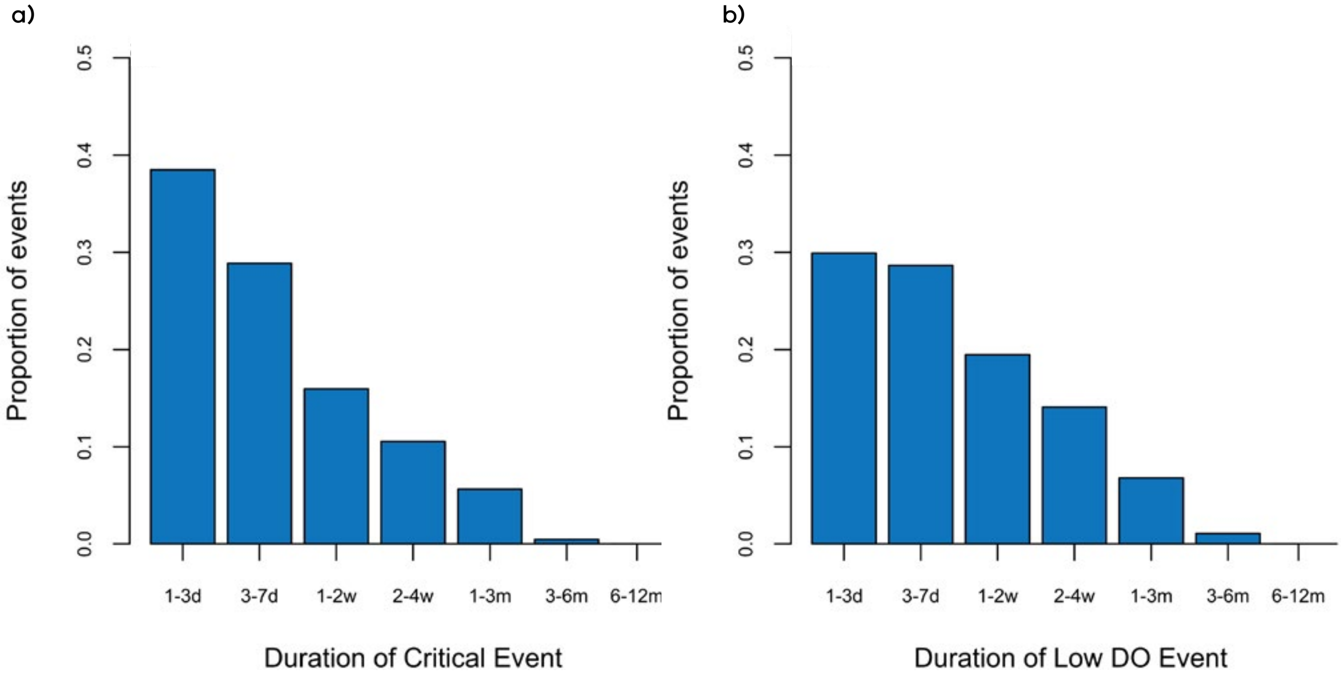


Figure 67: Duration of a) critical DO events and b) low DO events.

The duration of events followed a similar trend to the frequency of events. There was an increase in the longevity of hypoxic events during the Millennium Drought (Figure 68).

When interpreting Figure 65 and Figure 68, it should be noted that the deployment of in-situ probes, and consequently the spatial distribution of sites is not random but rather related to management interest.

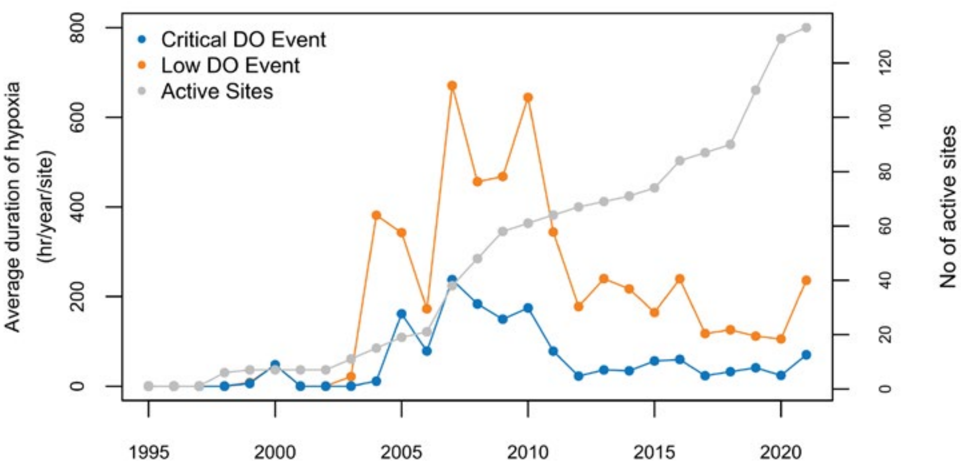


Figure 68: The cumulative duration of hypoxic events per year, normalised with respect to the number of active monitoring sites.

For example, some of the sites with the earliest period of record are in protected national parks as well as regulated river systems including the Yarra River and Goulburn River at Lake Eildon. Consequently, the average duration and number of events shown are not representative of all river systems and locations, but may potentially be skewed to sites at higher risk of low DO, or where there is higher anticipated impact from low DO, such as upstream from treatment plants or sensitive ecosystems. Potential skewing is especially relevant during the early 2000s where the sample size (i.e. number of sites) was small (<10 until 2003).

The spatial distribution of event duration is comparable to that of event frequency (Figure 69).

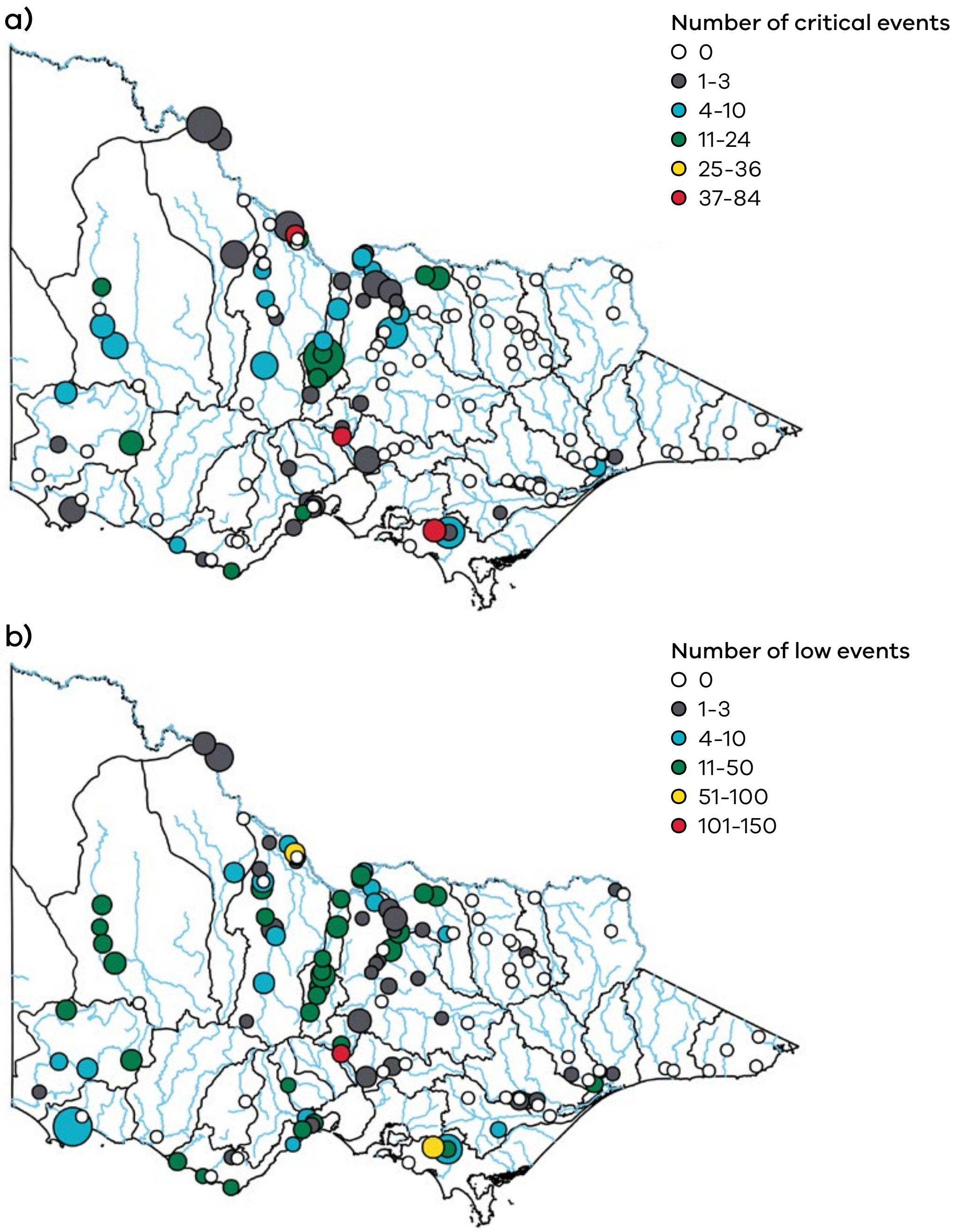


Figure 69: The spatial distribution of event durations in hours, where dot size is proportional to the average event duration for a) the critical DO events and b) the low DO events at each site for its period of record and colour denotes the number of events. White dots indicate sites with no events and thus the average event duration is 0. Data details are included in Appendix O: Detailed statistics of low and critical DO events across Victorian sites.

Behaviour and features of events

During the data discovery stage of analysis, two opposing DO patterns were observed.

Ecosystems with elevated primary productivity can result in amplified diurnal DO patterns (Figure 70). This is due to high rates of photosynthesis during the day, and high rates of respiration at night. This results in an amplified diurnal pattern, with both extremely low and extremely high levels of DO.

Supressed diurnal patterns can be observed for other types of events often associated with a constant depletion of oxygen (e.g. blackwater events) (Figure 71). In the case below, a diurnal pattern can still be seen. From an ecological perspective, this kind of behaviour poses a far greater threat to biota due to the possibility of continuous and chronic hypoxia in streams, relative to amplified diurnal patterns.

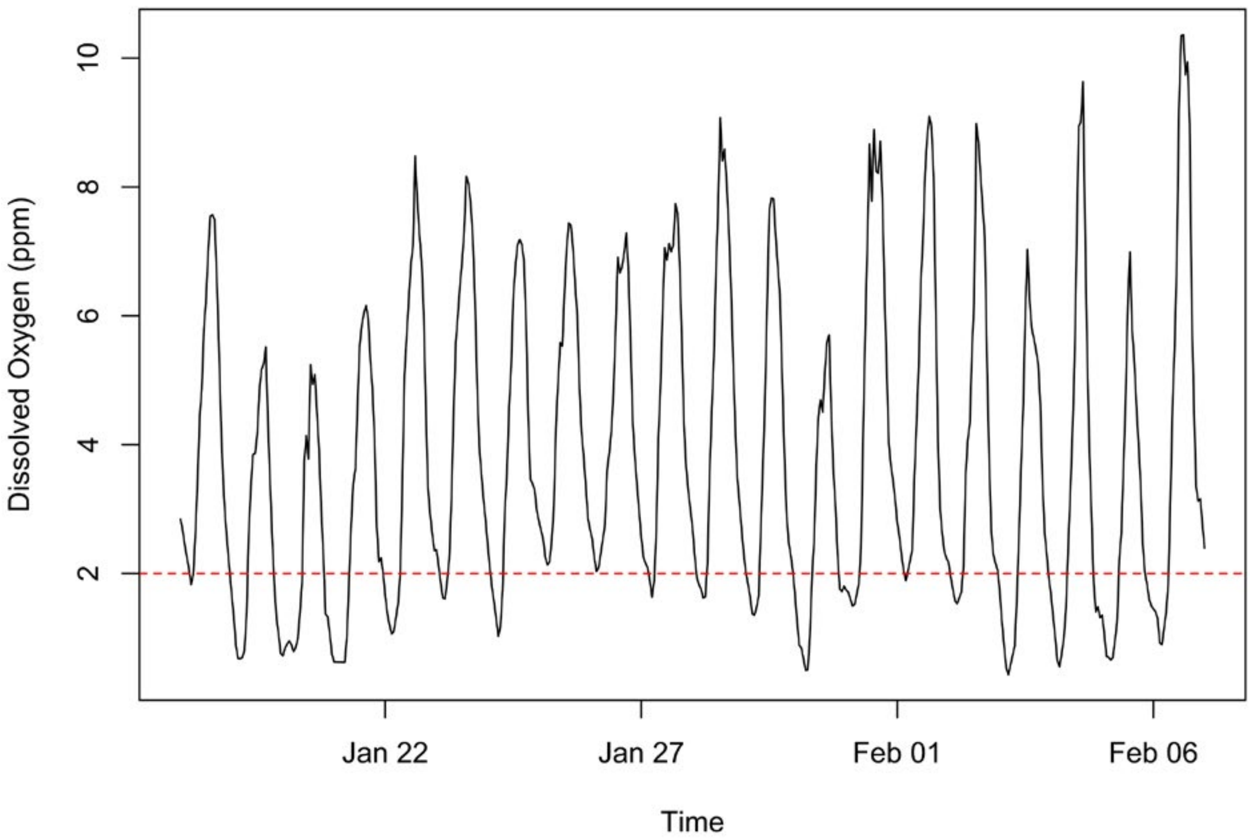


Figure 70: DO levels at site 237207 Surry River @ Heathmere from 18 January to 7 February 2007 during a low DO event.

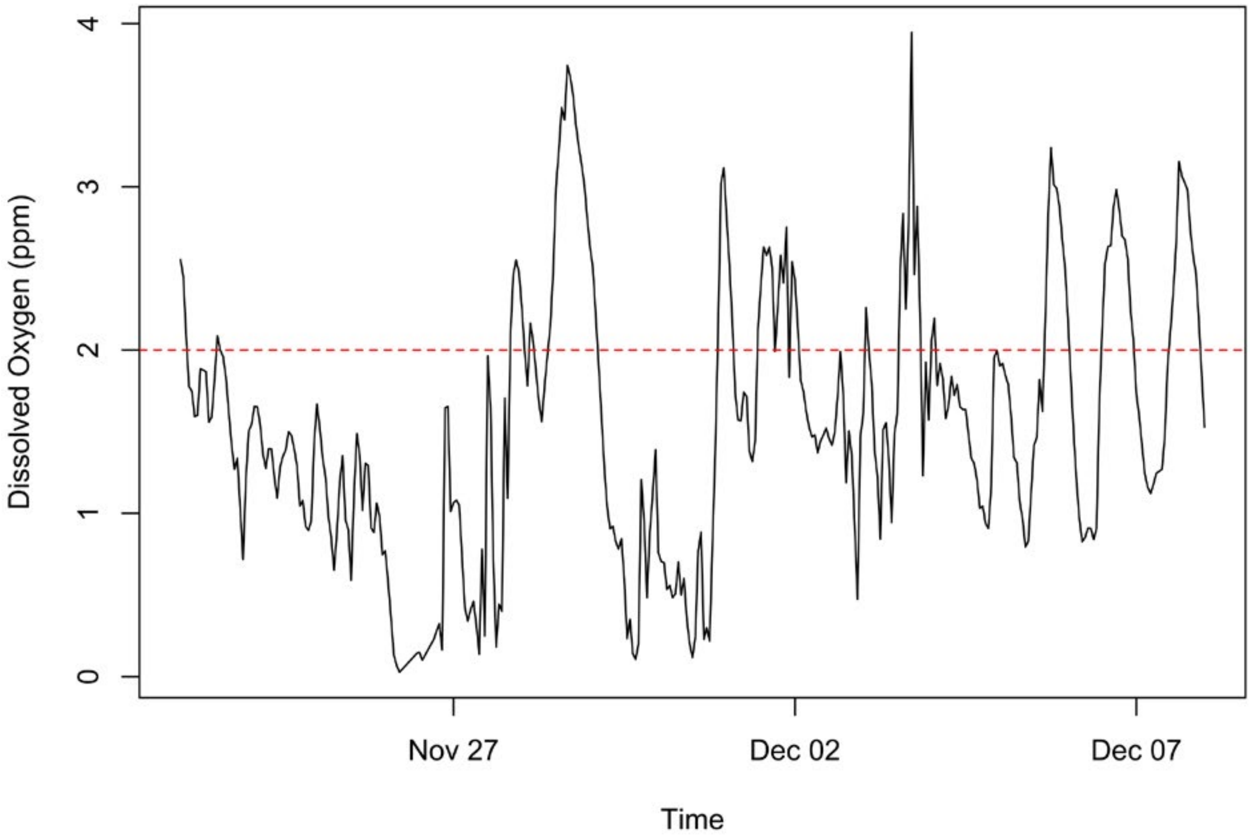


Figure 71: DO levels at site 404214 Broken Creek @ Katamatite from 23 November to 8 December 2010 during a critical DO event.

Nocturnal DO patterns

Hypoxic occurrence was investigated to understand the extent of nocturnal hypoxia, which is defined here as:

whenever DO levels drop below the critical threshold of 2 mg/L.

Hypoxic occurrence should not be confused with a hypoxic event. A hypoxic event was defined to be associated with potential negative ecological outcomes. Hypoxic occurrence is simply a state of low oxygen.

Analysis of hypoxic occurrences enabled an examination of trends in the period of hypoxic occurrences, relative frequency of occurrences by day of the year, and patterns in start and end time of day of hypoxic occurrences.

Figure 72 presents the findings. Hypoxic occurrences most often last from 1-6 hours, with 77% lasting for less than 24 hours. Hypoxic occurrences are far more likely in the warmer months, with less than 8% occurring between 1 June and 31 August (winter). They mostly occur nocturnally during the early morning.

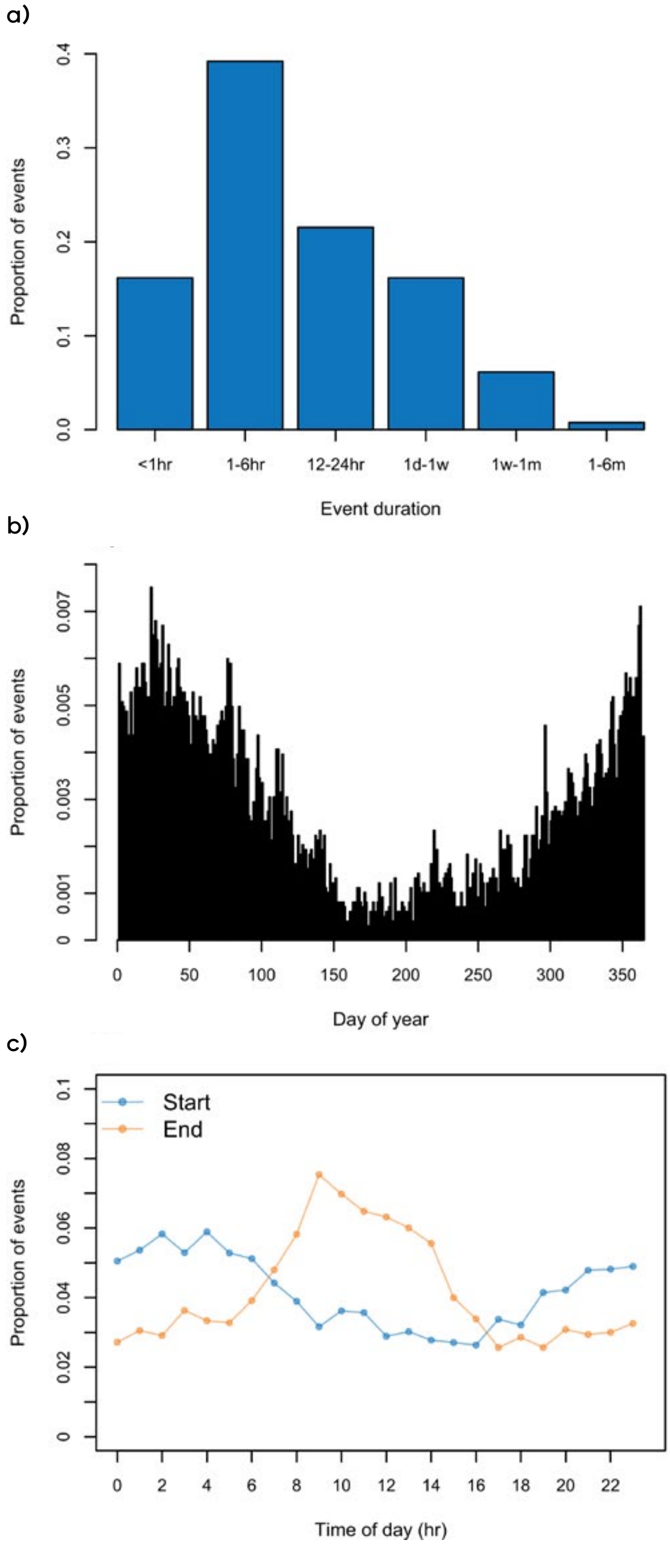


Figure 72: Hypoxic occurrences broken down into: a) duration or longevity of occurrences; b) seasonal patterns; and, c) diurnal patterns in the form of start and end times of hypoxic occurrences. This analysis was performed on all sites for their entire record.

These findings are consistent with a study conducted by Blaszczak et al. (2023) using high frequency DO data across continental United States. In the absence of human factors, DO is expected to follow two main patterns:

- A diurnal pattern associated with photosynthesis during daylight and respiration at night (Blaszczak et al., 2023; Butcher et al., 1927). The effect of temperature on gas solubility is expected to be antagonistic, but its effects appear to be far weaker than photosynthesis/respiration.
- A seasonal pattern associated with temperature changes and stream discharge. For example, during warmer months, oxygen solubility decreases, stream discharge is lower and is coupled with more oxygen-starved groundwater baseflow contribution (Brunke & Gonser, 1997). Warmer nights also promote increased rates of respiration. Cumulatively, these effects result in lower DO.

Our analyses of DO events highlight the value of continuous sampling of DO, which enabled us to identify diurnal and seasonal DO patterns that cannot be quantified from spot sampling data.

8.3.2 Potential drivers for high turbidity events

The detailed analytical approach to analyse high turbidity events is presented in Appendix N. In short, a logistic model was chosen due to its ability to predict binary events (i.e. whether an event is occurring) using continuous inputs (the predictors). The following predictors were used:

- Daily rainfall – a proxy for sediment mobilisation
- Weekly rainfall – a proxy for cumulative run-off events
- River discharge – a proxy for sediment transport and suspension
- Air temperature – a weak proxy for vegetation coverage through evapotranspiration
- Year – proxy for long term trends
- Autoregression (AR) – how much does yesterday's turbidity affect today's chance of a high turbidity event?

Results of the logistic model are consistent with our understanding of turbidity (Figure 73). In line with our understanding of sediment mobilisation and transport, daily rainfall and discharge were the strongest predictors and are associated with the mobilisation and transport of sediments. A strong autoregression term (AR) indicates that turbidity of the previous timestep is strong predictor of the current timestep. All predictors were weaker for 99th percentile events than for 95th percentile events, suggesting that more extreme events are less influenced by hydro-climatic conditions.

Figure 73: The strength of a predictor (quantified using the average marginal effect) for different predictors and sites, across a) the 95th and b) the 99th percentile limits. Faded bars indicate statistically insignificant relationship between turbidity events and the predictor at the 95% confidence level. AR is the autoregressive term, which represents the extent which a turbidity event on a day affects the next day's chance of having a high turbidity event.

Our analyses of high turbidity events demonstrate how continuous samples of turbidity can enable modelling that cannot be done with spot sampled data, providing information on the drivers of high turbidity events.

Appendices

Appendix A:
ERS surface water segments (Rivers and streams)

i. **Highlands** segment comprising the mountain river and stream reaches in the Upper Murray, Mitta Mitta, Kiewa, Ovens, Goulburn, Yarra, Latrobe, Thomson, Macalister, Mitchell, Tambo and Snowy basins, being the mountain river and stream reaches in the generally alpine and sub-alpine environments above 1,000 metres in altitude

ii. **Uplands A** segment comprising the river and stream reaches of the following (which are generally above 400 metres in altitude but also including some coastal areas)
   a) Wilsons Promontory, Strzelecki Ranges, and uplands of the East Gippsland basin; uplands of the Upper Murray and Kiewa basins
   b) the Grampians
   c) uplands of the Upper Thomson, Latrobe, South Gippsland, Bunyip and Yarra basins
   d) uplands of the Upper Goulburn (part) and Broken basins.

iii. **Uplands B** segment comprising the river and stream reaches of the following (which are generally above 400 metres in altitude)
   a) Otway Ranges
   b) uplands of southern draining basins - East Gippsland, Snowy, Tambo and Mitchell; 22 S 245 26 May 2021 Victoria Government Gazette
   c) uplands of northern draining basins – Ovens, Broken and Goulburn (part).

iv. **Central Foothills and Coastal Plains** segment comprising the river and stream reaches of the following (the central foothills are generally above 200 metres in altitude and the coastal plains are below 200 metres in altitude, but do not include the river and stream reaches in the Urban segment)
   a) lowlands of the Barwon, Moorabool, Werribee and Maribyrnong basins and the Curdies and Gellibrand Rivers
   b) lowlands of the Yarra, South Gippsland, Bunyip, Latrobe, Thomson, Mitchell, Tambo and Snowy basins
   c) uplands of the Moorabool, Werribee, Maribyrnong, Campaspe, Loddon Avoca, Wimmera and Hopkins basins
   d) foothills of the Ovens, Broken and Goulburn basins.

v. **Urban** segment comprising the areas within the urban growth boundary for Metropolitan Melbourne (as shown on the metropolitan fringe planning schemes set out in section 46AA of the Planning and Environment Act 1987), including Dandenong Creek, the tributaries of the Yarra, Maribyrnong and Werribee Rivers, and the current developed areas in the Mornington Peninsula and Western Port catchments, but not including
   a) the Yarra, Maribyrnong and Werribee Rivers which are included in the Central Foothills and Coastal Plains segment; or
   b) the undeveloped urban land in the Urban Growth Zones and Low Density Urban Residential Zone in the metropolitan fringe planning schemes, as set out in the Victoria Planning Provisions which are included in the Central Foothills and Coastal Plains segment.

vi. **Murray and Western Plains** segment comprising the river and stream reaches of the following (which are generally below 200 metres in altitude)
   a) lowlands of the Kiewa, Ovens, and Goulburn basins
   b) lowlands of the Campaspe, Loddon, Avoca, Wimmera and Mallee basins
   c) lowlands of the Glenelg, Hopkins, Portland and Corangamite and Millicent Coast basins.

Table A1: Water quality objectives for rivers and streams within the ERS are shown in bold. For comparison, the SEPP (Waters of Victoria) – known as SEPP (WoV) - water quality objectives are included in brackets. The objectives of SEPP (WoV) were updated for the final SEPP (Waters) released in 2018 and these objectives were carried over to the ERS.

Segment	Indicator							
	TP (µg/L)	TN(µg/L)	DO % saturation		Turbidity (NTU)	EC (µS/cm) @ 25 degrees C)	pH (pH units)	
	75th percentile	75th percentile	25th percentile	max.	75th percentile	75th percentile	25th percentile	75th percentile
Highlands (largely unmodified)								
Streams above 1000 m altitude	**≤20**	**≤150**	**≥85**	**130**	**≤3**	**≤30**	**≥5.9**	**≤6.9**
	(≤20)	(≤150)	(≥95)	(110)	(≤5)	(≤100)	(≥6.4)	(≤7.7)
Uplands A (largely unmodified)								
Wilsons Promontory, Strzelecki Ranges & East Gippsland basin	**≤20**	**≤520**	**≥90**	**130**	**≤10**	**≤200**	**≥6.6**	**≤7.6**
	(≤25)	(≤500)	(≥90)	(110)	(≤5)	(≤500)	(≥6.4)	(≤7.7)
Upper Murray and Kiewa basins	**≤230**	**≤470**	**≤90**	**130**	**≤10**	**≤10**	**≥6.5**	**≤7.5**
	(≤25)	(≤350)	(≥90)	(110)	(≤5)	(≤5)	(≥6.4)	(≤7.7)
The Grampians	**≤35**	**≤370**	**≥80**	**130**	**≤5**	**≤200**	**≥5.4**	**≤7.0**
	(≤25)	(≤350)	(≥90)	(110)	(≤5)	(≤500)	(≥6.4)	(≤7.7)
Upper Thomson, Latrobe, South Gippsland, Bunyip and Yarra basins	**≤35**	**≤900**	**≥80**	**130**	**≤15**	**≤100**	**≥6.4**	**≤7.6**
	(≤25)	(≤500)	(≥90)	(110)	(≤5)	≤100	(≥6.4)	(≤7.7)
Upper Goulburn (part) and Broken basins	**≤25**	**≤550**	**≥90**	**130**	**≤10**	**≤100**	**≥6.4**	**≤7.4**
	(≤25)	(≤500)	(≥90)	(110)	(≤5)	≤100	(≥6.4)	(≤7.7)
Uplands B (largely unmodified)								
Otway Ranges	**≤25**	**≤650**	**≥80**	**130**	**≤10**	**≤200**	**≥6.5**	**≤7.5**
	(≤25)	(≤350)	(≥90)	(110)	(≤5)	(≤500)	(≥6.4)	(≤7.7)
Uplands of southern draining basins – East Gippsland, Snowy, Tambo and Mitchell	**≤25**	**≤350**	**≥90**	**130**	**≥10**	**≥6.7**	**≥6.7**	**≥7.7**
	(≤25)	(≤350)	≥90	(110)	(≤5)	(≤500)	(≥6.4)	(≤7.7)
Uplands of northern draining basins – Ovens, Broken and Goulburn (part)	**≤25**	**≤400**	**≤85**	**130**	**≤10**	**≤50**	**≥6.4**	**≥7.4**
	(≤25)	(≤350)	≥90	(110)	(≤5)	(≤100)	(≥6.4)	(≤7.7)
Foothills and Coastal Plains (slightly to moderately modified)								
Lowlands of Barwon, Moorabool, Werribee, Maribyrnong basins and the Curdies & Gellibrand rivers	**≤60**	**≤1,100**	**≥75**	**130**	**≤25**	**≤2,000**	**≥6.8**	**≤8.0**
	(≤45)	(≤600)	(≥85)	(110)	(≤10)	(≤500)	(≥6.5)	(≤8.3)
Lowlands of Yarra, South Gippsland, Bunyip, Latrobe, Mitchell, Tambo, Snowy and Thomson basins	**≤55**	**≤1,100**	**≥75**	**130**	**≤25**	**≤250**	**≥6.7**	**≥7.7**
	(≤45)	(≤600)	(≥85)	(110)	(≤10)	(≤500)	(≥6.4)	(≤7.7)

Segment	Indicator							
	TP (µg/L)	TN (µg/L)	DO % saturation		Turbidity (NTU)	EC (µS/cm) @ 25 degrees C)	pH (pH units)	
	75th percentile	75th percentile	25th percentile	max.	75th percentile	75th percentile	25th percentile	75th percentile
Foothills and Coastal Plains (slightly to moderately modified)								
Uplands of Moorabool, Werribee, Maribyrnong, Campaspe, Loddon, Avoca, Wimmera and Hopkins basins	**≤55**	**≤1,050**	**≤70**	**130**	**≤15**	**≤2,000**	**≥6.8**	**≥8.0**
	(≤25)	(≤600)	≥85	(110)	(≤10)	(≤500)	(≥6.5)	(≤8.3)
Foothills of Ovens, Goulburn and Broken basins	**≤50**	**≤1,050**	**≤75**	**130**	**≤20**	**≤250**	**≥6.8**	**≥7.4**
	(≤25)	(≤600)	≥85	(110)	(≤10)	(≤500)	(≥6.4)	(≤7.7)
Urban (highly modified)^								
Tributaries of Werribee and Maribyrnong Rivers	**≤110**	**≤1,200**	**≥60**	**130**	**≤30**	**≤3,000**	**≥6.5**	**≥8.2**
	(≤45)	(600)	(≥85)	(110)	(≤10)	(≤1500)	(≥6.5)	(≤8.3)
Lowlands of Dandenong Creek, Mornington Peninsula, Westernport catchment and tributaries of the Yarra River	**≤110**	**≤1,300**	**≥70**	**130**	**≤35**	**≤500**	**≥6.4**	**≥7.9**
	(≤45)	≤^{3}600)	(≥85)	(110)	(≤10)	(≤500)	(≥6.4)	(≤7.7)
Murray and Western Plains (Slightly to moderately modified)								
Lowlands of Kiewa, Ovens and Goulburn basins	**≤55**	**≤800**	**≤70**	**130**	**≤15**	**≤2,000**	**≥6.4**	**≥7.5**
	(≤45)	(≤900)	≥85	(110)	(≤10)	(≤500)	(≥6.4)	(≤7.7)
Lowlands of Campaspe#, Loddon #, Avoca #, Wimmera* and Mallee* basins	**≤50**	**≤900**	**≤75**	**130**	**≤20**	**≤250**	**≥6.8**	**≥7.8**
	(≤45# or ≤40*)	(≤900)	≥85	(110)	(≤10)	(≤500)	(≥6.5)	(≤8.3)
Lowlands of Glenelg, Hopkins, Portland and Corangamite and Millicent Coast basins	**≤55**	**≤1,000**	**≥65**	**130**	**≤20**	**≤2,000**	**≥7.0**	**≥8.0**
	(≤40)	(≤900)	(≥85)	(110)	(≤10)	(≤1500)	(≥6.5)	(≤8.3)

^ A separate segment for sites within the Urban Growth Boundary was introduced under the ERS. In previous SoE reporting, these sites were assessed against the SEPP (WoV) objectives for the Cleared Hills and Coastal segment, which corresponds with the Central Foothills and Coastal plains segment under the ERS.

* The ERS subsegment 'Lowlands of the Loddon, Avoca, Wimmera and Mallee Basins' was previous defined as two separate subsegments under the SEPP (WoV): Lowlands of the Campaspe, Loddon and Avoca catchments, and lowlands of the Wimmera and Mallee Basins.

Appendix B:
Explanation of the catchment characteristics

Table B1. abbreviation, explanation, category, units and the corresponding data source of the 48 catchment characteristics used as potential explanatory variables for water quality spatial variation.

Catchment characteristics	Category	Explanation	Units	Source
Annual radiation	Climate	Annual Average Radiation	MJ/m2/day	National Stream Attributes
Annual temperature		Annual Average Temperature	°C	National Stream Attributes
Annual rain		Annual Average Rainfall	mm	National Stream Attributes
Erosivity		Catchment Erosivity	(MJ mm)/(ha hr yr)	National Stream Attributes
Maximum population	Land use	Maximum Population Density	no/km^4	National Stream Attributes
Mean population		Mean Population Density	no/km^4	National Stream Attributes
% area modified from conservation		Proportion of catchment modified (not used for conservation)	%	National Stream Attributes
% area irrigated		Proportion of catchment irrigated	%	National Stream Attributes
% area used for intensive animal production		Proportion of catchment used for intensive animal production	%	National Stream Attributes
% area used for intensive plant production		Proportion of catchment used for intensive plant production	%	National Stream Attributes
% area with pesticides applied		Proportion of catchment where pesticides are likely to be used	%	National Stream Attributes
% area with fertiliser applied		Proportion of catchment were fertilisers are likely to be used	%	National Stream Attributes
% area used for forestry		Proportion of catchment used for forestry	%	National Stream Attributes
% area used for mining		Proportion of catchment used for mining	%	National Stream Attributes

Catchment characteristics	Category	Explanation	Units	Source
% area with urban		Proportion of catchment urbanised	%	National Stream Attributes
% area used for irrigation supply/ drainage		Proportion of catchment used for irrigation supply/ drainage	%	National Stream Attributes
% area with artificial impoundment		Proportion of catchment that is artificial impoundment	%	National Stream Attributes
% area with road		Proportion of catchment used for road	%	National Stream Attributes
% area with farm dam		Percentage of catchment covered by farm dam	%	https://discover.data.vic.gov.au/dataset/farm-dam-boundaries1
Fragmentation of riparian zone		Average fragmentation of riparian zone in catchment (higher number means less fragmentation)	Unique scale of 1 to 5	https://discover.data.vic.gov.au/dataset/2010-index-of-stream-condition-full-set-of-isc2010-data-sets1
Stream density	Hydrology	Stream Density	km/km^2	National Stream Attributes
Annual runoff		Annual mean runoff	ML	National Stream Attributes
Runoff pereniality		Runoff Perenniality	%	National Stream Attributes
Monthly runoff variability		Coefficient of variation of monthly runoff		National Stream Attributes
Annual runoff variability		Coefficient of variation of annual runoff		National Stream Attributes
% area with unconsolidated sedimentary rock	Soil	Proportion of catchment with unconsolidated rock	%	National Stream Attributes
% area with igneous rock		Proportion of catchment with igneous rock	%	National Stream Attributes
% area with siliciclastic sedimentary rock		Proportion of catchment with siliciclastic/ undifferentiated sedimentary rock	%	National Stream Attributes

Catchment characteristics	Category	Explanation	Units	Source
% area with carbonate sedimentary rock		Proportion of catchment with carbonate sedimentary rocks	%	National Stream Attributes
% area with other sedimentary rock		Proportion of catchment with other sedimentary rock	%	National Stream Attributes
% area with metamorphic rocks		Proportion of catchment with metamorphic rocks	%	National Stream Attributes
% area with mixed sedimentary and igneous rocks		Proportion of catchment with mixed sedimentary and igneous rocks	%	National Stream Attributes
% area with old bedrock		Proportion of catchment with old bedrock	%	National Stream Attributes
Saturated hydraulic conductivity		Average saturated hydraulic conductivity	mm/h	National Stream Attributes
Soil TN		Mean soil TN (0-5 cm)	%	Soil and Landscape Grid National Soil Attribute Maps
Soil TP		Mean soil TP (0-5 cm)	%	Soil and Landscape Grid National Soil Attribute Maps
Soil clay		Mean soil clay proportion (0-5 cm)	%	Soil and Landscape Grid National Soil Attribute Maps
% area with saline water table		Percentage of area with saline (>3000 mg/L) water table	%	http://www.bom.gov.au/metadata/catalogue/19115/ANZCW0503900106
Max elevation	Topography	Maximum elevation	m	National Stream Attributes
Mean elevation		Mean elevation	m	National Stream Attributes
Area		Catchment Area	km^2	National Stream Attributes
% area with valley bottom		Area of catchment made up of valley bottoms (%)	%	National Stream Attributes
Catchment slope		Catchment slope	degrees	National Stream Attributes
% area covered by grassland	Land cover	Current proportion of catchment grass	%	National Stream Attributes

Catchment characteristics	Category	Explanation	Units	Source
% area covered by forest		Current proportion of catchment forest	%	National Stream Attributes
% area covered by shrub		Current proportion of catchment with shrubs	%	National Stream Attributes
% area covered by woodland		Current proportion of catchment with woodland	%	National Stream Attributes
% area with bare soil		Current proportion of catchment bare	%	National Stream Attributes

Appendix C:
Analytical approach used for Chapter 3

To determine which drivers are important to the spatial differences in water quality, two statistical analyses on water quality concentration data of six key parameters (DO, EC, pH, turbidity, TP, TN) were undertaken. We first developed a statistical multi-variate model to explain the spatial difference in each water quality parameter across catchments with a comprehensive set of hydro-climatic and landscape characteristics (see detailed definitions and data sources of these characteristics in Appendix B). We then performed a principal component analysis to understand the similarities and differences in the spatial patterns among the hydro-climatic and landscape characteristics of individual catchments.

Statistical multi-variate modelling

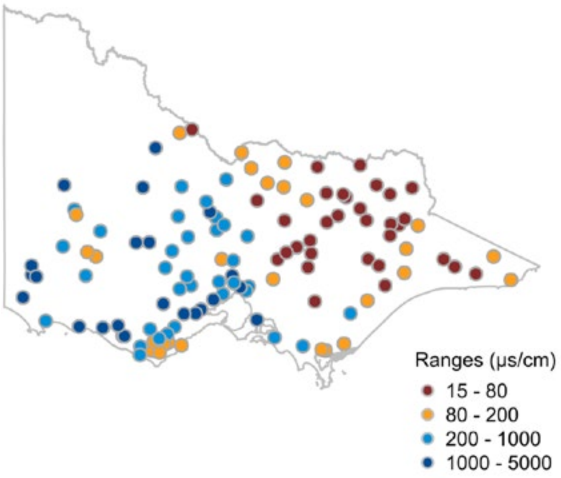
- The input data in the statistical models are the concentration of the six key parameters using all samples collected at all of DEECA's water quality monitoring sites.
- For each water quality parameter, we developed many statistical models to predict the concentration quantiles (25^{th}, 50^{th}, 75^{th}).
- In these models, we expressed the concentration quantile as a function of catchment characteristics (e.g. land use, climate, geology) or catchment characteristic principal components (depending on the strengths of relationships found).
- We selected the best performing statistical models for each water quality parameter using a weight of evidence approach and Bayesian Variable selection approach.
- The catchment characteristics included in this 'best performing model' were drivers that explain spatial differences in water quality across Victoria. For example, the selected model may identify temperature and percentage catchment area used for agricultural land as the most important drivers related to the spatial difference in TP.
- This approach has been applied in Linkage Project LP140100495 (Lintern et al., 2018b) and follow-up work (Guo et al., 2019) to explain spatial variations in water quality across 102 catchments in Victoria. Our proposed analysis expanded the understanding in literature by including a larger number of catchments (in particular, with inclusion of urban catchments) as well as more recent water quality data.

Principal component analysis

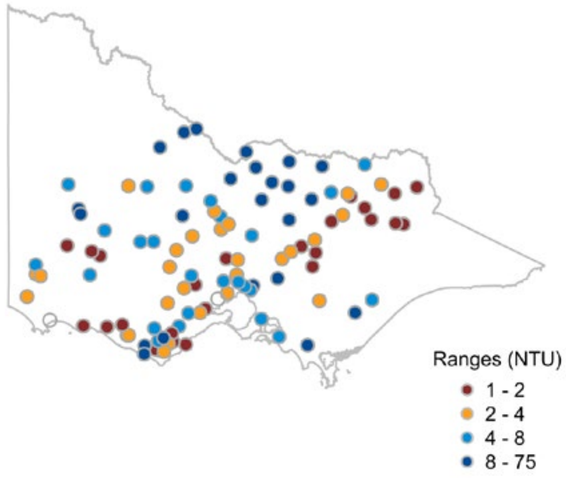
- Independent of the statistical modelling, we performed a principal component analysis to understand the relationships between catchment characteristics. The interpretation of each principal component was described in terms of the collective catchment characteristics that they represent. For example, a principal component might represent a relationship between topography and climate. This analysis was used to assist the interpretation of the results obtained from the statistical multi-variate models to understand the relationships between individual catchment characteristics, and how their individual effects on water quality can be separated.
- The principal component analysis of the catchment characteristics was used to identify: (I) linear correlations between the principal components and individual catchment characteristics; and (ii) linear correlations between the principal components and the 50^{th} percentile of each water quality parameter.

Appendix D:
Supplementary results for water quality spatial variation (Chapter 3)

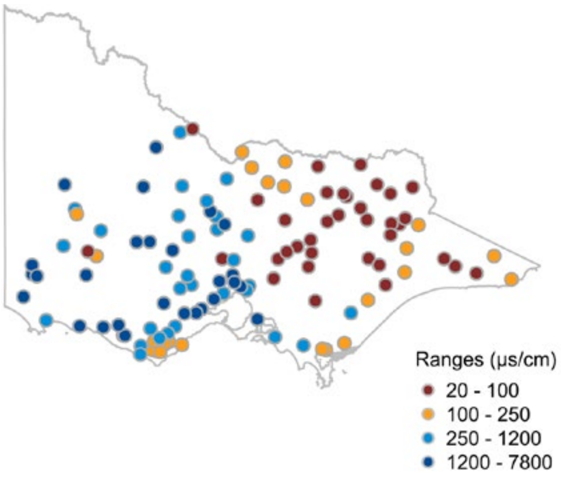
EC 25th percentile



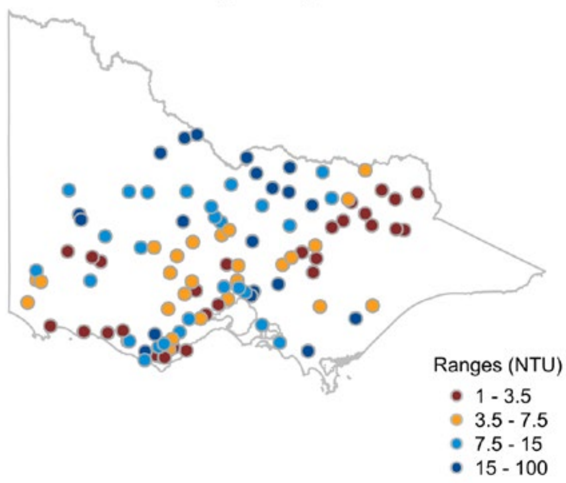
Turbidity 25th percentile



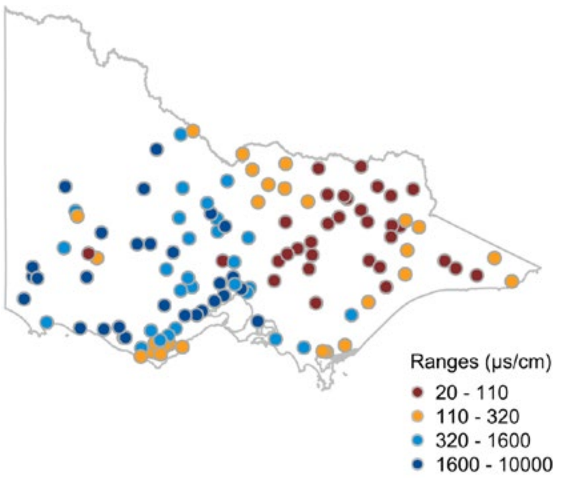
EC 50th percentile



Turbidity 50th percentile



EC 75th percentile



Turbidity 75th percentile

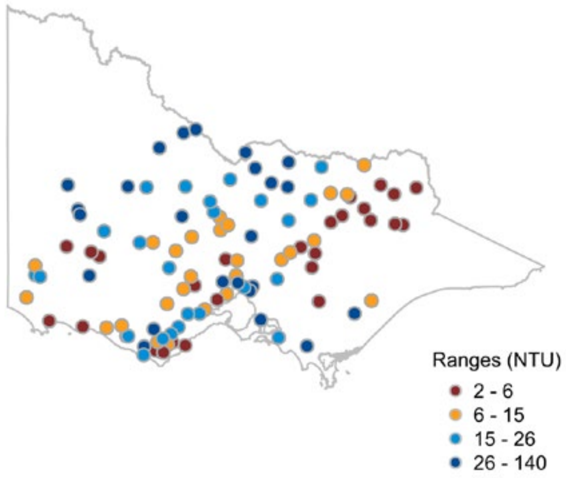
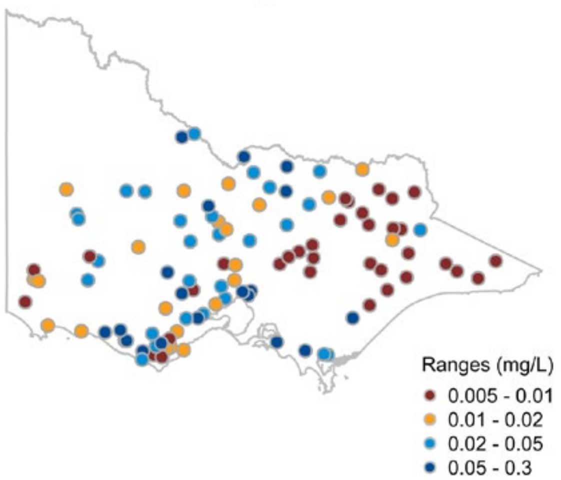
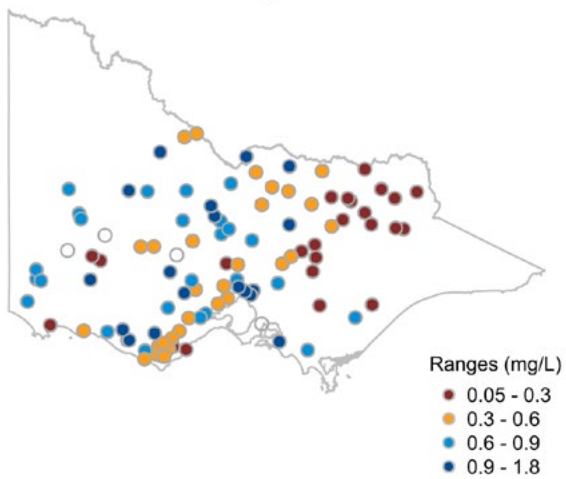


Figure D1: Maps of 25th (top) ,50th (middle) and 75th (bottom) percentile of EC (left) and turbidity (right) at monitoring sites in Victoria calculated with the full historical data. The colours of the dots represent the interquartile ranges (lowest to 25th percentile, 25th-50th percentile, 50th-75th percentile, 75th percentile to highest) across the state.

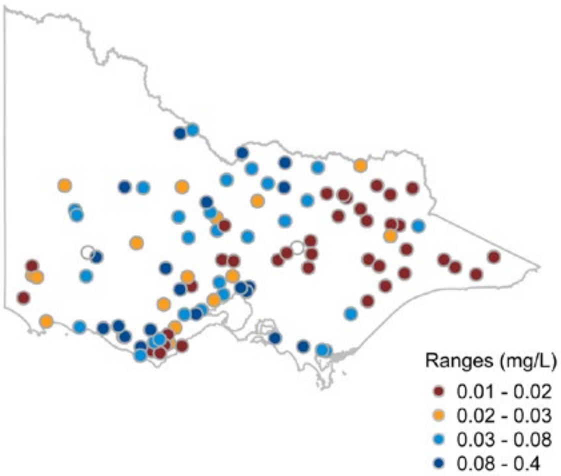
TP 25th percentile



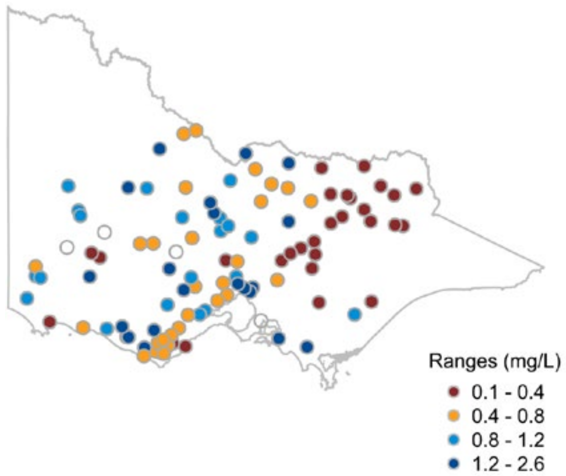
TN 25th percentile



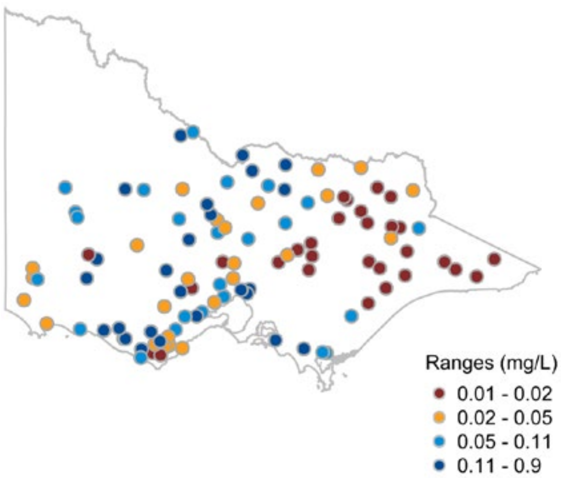
TP 50th percentile



TN 50th percentile



TP 75th percentile



TN 75th percentile

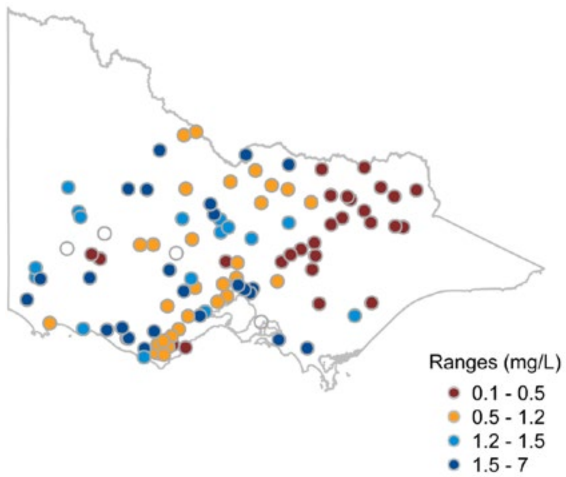
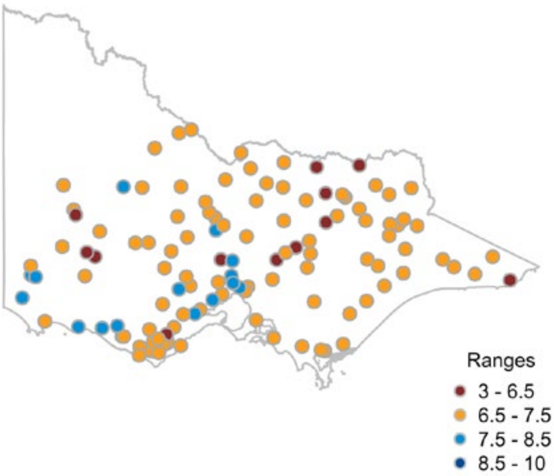
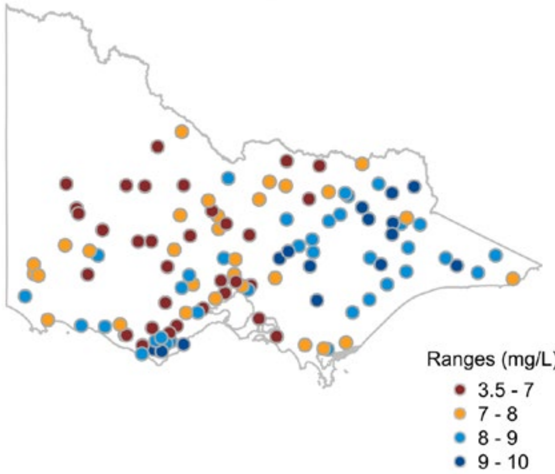


Figure D2: Maps of 25th (top) ,50th (middle) and 75th (bottom) percentile of TP (left) and TN (right) at monitoring sites in Victoria calculated with the full historical data. The colours of the dots represent the interquartile ranges (lowest to 25th percentile, 25th-50th percentile, 50th-75th percentile, 75th percentile to highest) across the state.

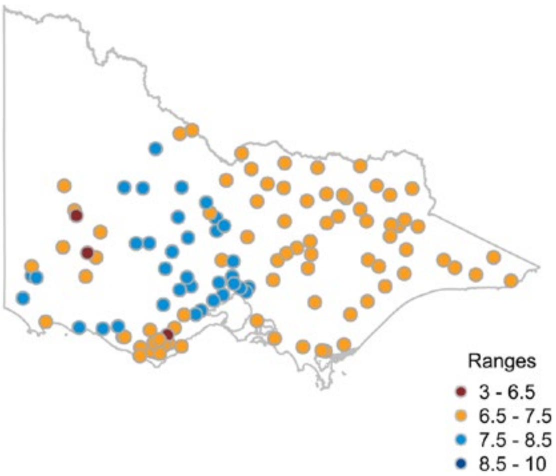
pH 25th percentile



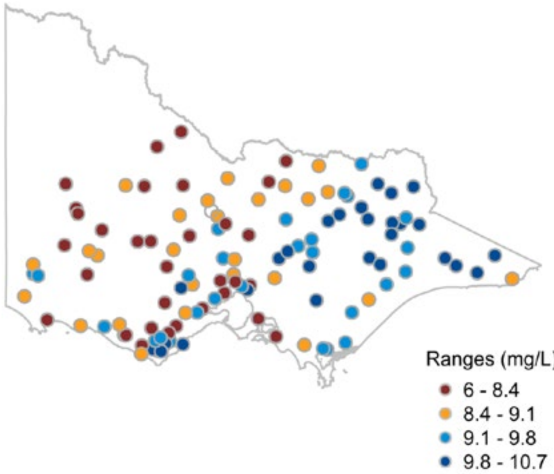
DO 25th percentile



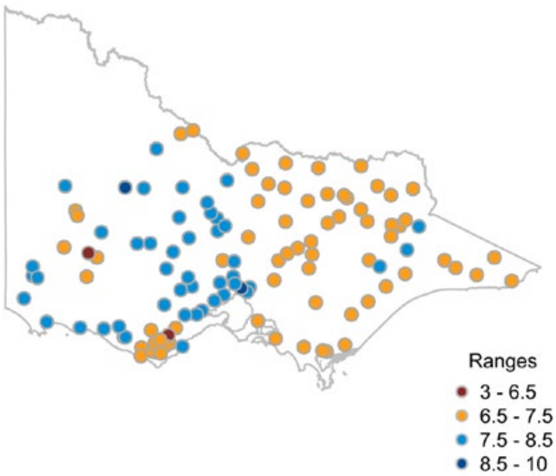
pH 50th percentile



DO 50th percentile



pH 75th percentile



DO 75th percentile

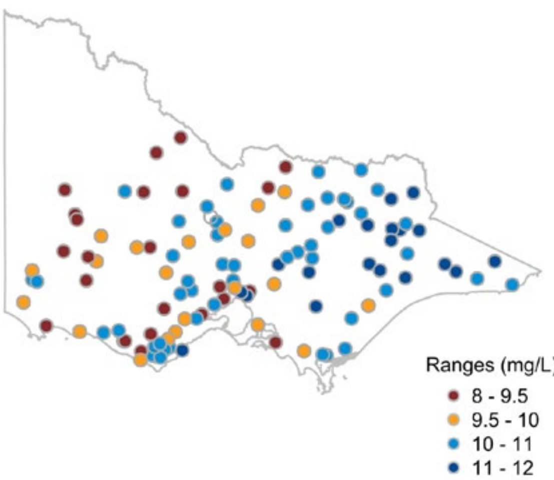


Figure D3: Maps of 25th (top) ,50th (middle) and 75th (bottom) percentile of pH (left) and DO (right) at monitoring sites in Victoria calculated with the full historical data. The colours of the dots represent the interquartile ranges (lowest to 25th percentile, 25th-50th percentile, 50th-75th percentile, 75th percentile to highest) across the state.

Appendix E:
Supplementary results for the principal component analysis (Chapter 3)

The principal component analysis (PCA) was used to understand how different landscape features that may influence water quality variability relate to one another, and the extent to which different groups or 'classes' of variables explain the total variability across a landscape.

The results of PCA for the catchment characteristics that can potentially affect water quality are summarised in Figures E1 and E2. Figure E1 shows the scree plots for catchment characteristics, indicating the percentage of spatial variation in all these characteristics that is explained by each principal component (PC1-PC10). Figure E2 shows the correlations of the catchment characteristics with each of the first four principal components (PC1-PC4), which can be summarised as:

- PC1 (76.7% spatial variation explained): mainly correlated with predictors on climate and hydrology, as well as some land use and some soil predictors
- PC2 (9.2% spatial variation explained): mainly correlated with predictors on land cover, as well as some land use predictors
- PC3 (4.3% spatial variation explained): mainly correlated with land use predictors, as well as some predictors on soil and hydrology
- PC4 (3% spatial variation explained): mainly correlated with topography predictors, as well as some land use predictors.

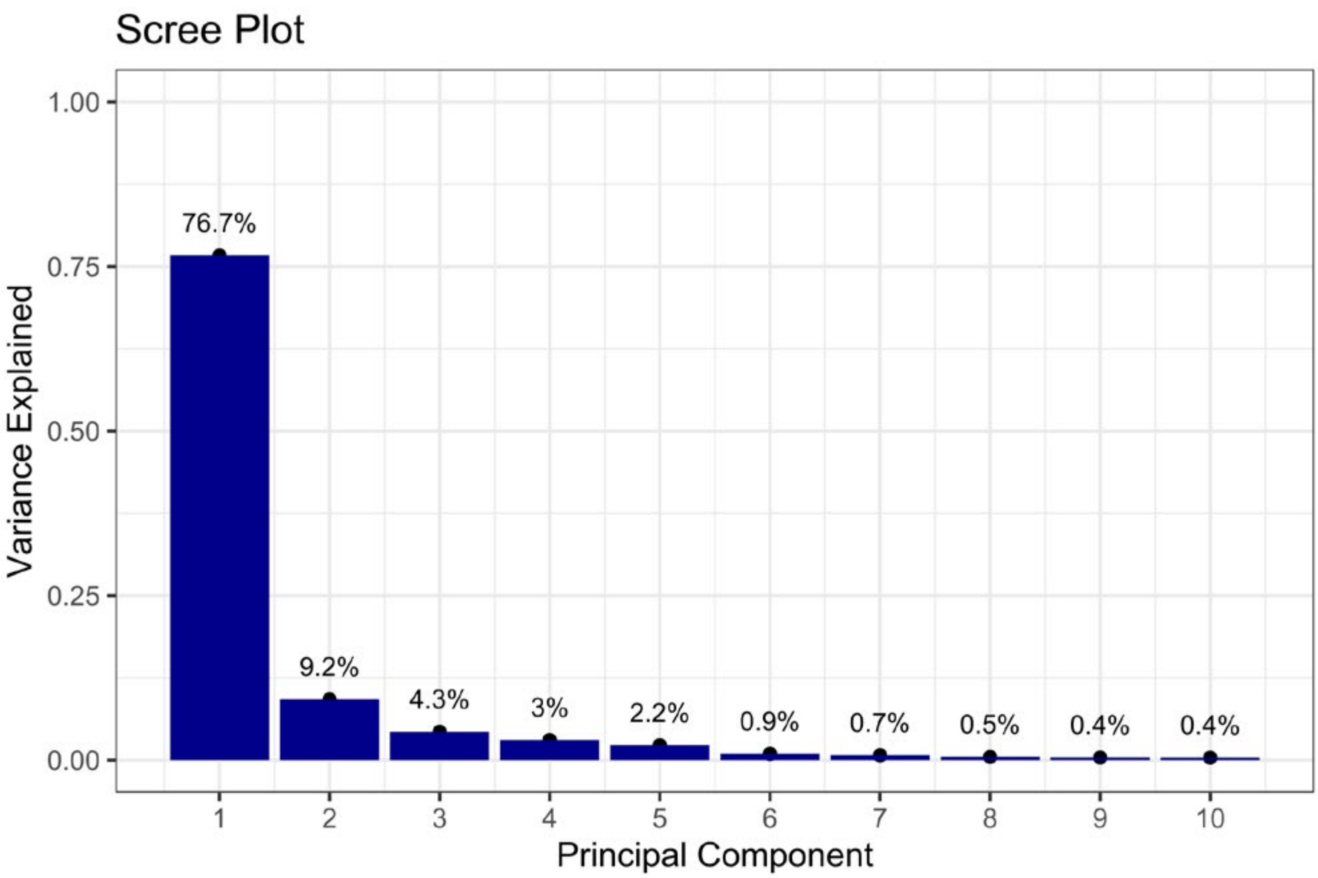


Figure E1: Scree plot of catchment characteristics (potential predictors for water quality). Proportion of spatial variation in all spatial characteristics across Victoria explained by different principal components.

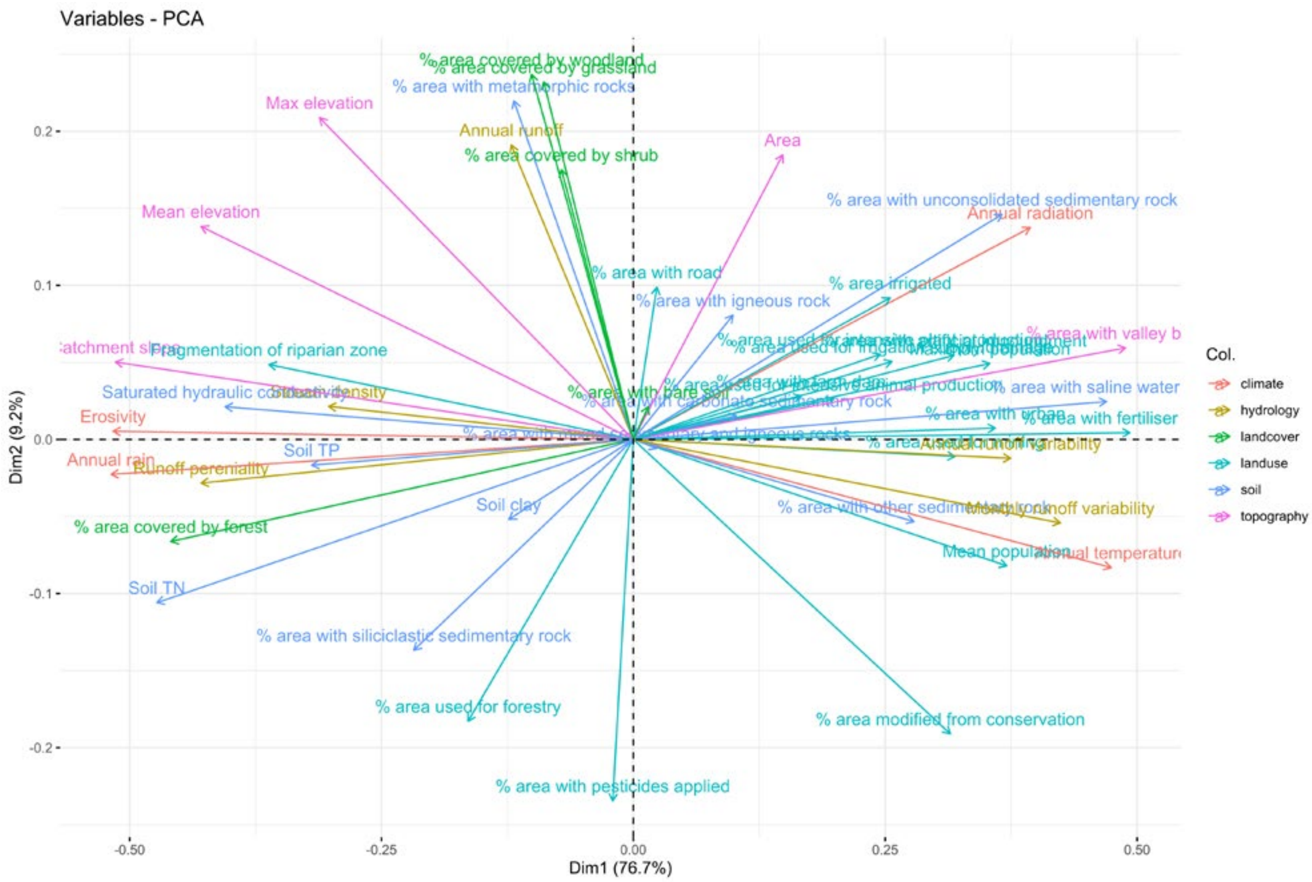


Figure E2: Bi-plots of the catchment characteristics contributing to: principal components 1 and 2 (85.9% total spatial variation explained). The arrow of each catchment characteristic highlights the principal component(s) that specific characteristic correlates with, while the length of the arrow shows the strength of the correlation. The colours indicate the categories of individual catchment characteristics. The detail of catchment characteristics, their abbreviations and categorisation are included in Appendix B.

Appendix F:
Analytical approach used for Chapter 4

Model description and analysis of model results

The analysis of temporal variability (1995-2021) in Victoria's water quality focused on the concentration of six key parameters. The monitoring sites used for this analysis are described in the Chapter 1.4 *Data and selection of study sites*. Only sites for which there were water quality monitoring data between 1995 and 2021 (inclusive) were used for the analysis. This led to 106 sites for DO, 109 sites for EC, 110 sites for pH, 94 sites for turbidity, 92 sites for TP and 86 sites for TN. All samples collected between 1995 and 2021 were used for the analysis. All water quality data were log transformed (base 10) to facilitate subsequent analyses of these data, which assume linear relationships between water quality and its potential driving variables.

1. Key drivers of temporal variability in water quality

Key drivers of temporal variability in water quality were assessed with a statistical multiple linear regression model that incorporates a linear underlying trend (in log space of water quality concentration) while also considering the effect of flow and seasonality (and water temperature for DO), which have been identified as important drivers of temporal variation in water quality across Victoria (e.g. Guo et al., 2019). Seasonality is represented by the day of the year, and is a representation of the expected temperature, rainfall and human activities expected then. Only 'dynamic' variables that change over time (e.g. streamflow) were used in this modelling. All streamflow (daily streamflow) and water temperature data used in these models were collected by DEECA. All streamflow and water temperature data were log transformed (base 10) prior to modelling. When assessing the drivers of temporal variability in water quality, the variables (water quality parameter concentration, streamflow, seasonality and underlying trend) were standardised by transforming into z scores (as per Guo et al., 2019).

Water quality value (transformed to ensure normality) at time t is expressed as a linear underlying trend applied over the whole record, together with functions of flow (and water temperature, for DO) and seasonality.

$$Ct = t \times \beta_{tC} + f((Q_t)) \times B_Q + f\,(seasonality) \times \beta_{seasonality}\ f(\mathcal{E}c)$$

The statistical trend model assumes a linear underlying trend in log space of water quality concentration, which is appropriate for this study because we do not expect large-scale patterns of step change or non-linear underlying trend across Victoria.

The model parameters were fitted using maximum likelihood. Model performance was assessed using the Nash-Sutcliffe Efficiency. The values of the standardised regression coefficients $\beta_{tC}, \beta_{q}, \beta_{seasonality}$ were used inform the direction, magnitude and significance of the three potential drivers (underlying trend, streamflow and seasonality) at a specific site (catchment).

The seasonality is modelled as a function of the sine and cosine of the day of the year (J), where a and b are coefficients.

$$a \sin\left(\frac{2\pi J}{365}\right) + b \cos\left(\frac{2\pi J}{365}\right)$$

The seasonality can then be presented as a sinusoidal function, where A is the amplitude of seasonal variation and P is the phase shift.

$$A \sin\left(\frac{2\pi J + P}{365}\right)$$

In using this model, we assume a linear underlying trend over the full data period. The validity of this assumption was checked by assessing the residuals of the calibrated model; the residuals should be trend-free, meaning that all trends have been picked up by our model.

2. Determining underlying trends in water quality that cannot be explained by streamflow

Underlying trends in water quality that cannot be explained by fluctuations in streamflow or water temperature were identified using the multiple linear regression models introduced above. However, for determining the underlying trends in water quality (that cannot be explained by streamflow or seasonality), the variables were not standardised prior to the regression analysis. The regression coefficients of the underlying trend component (β_{tC}) represent the direction and magnitude of the underlying trend in water quality. Positive values indicate that the water quality parameter underlying trends are increasing, negative values indicate that they are decreasing. The value itself represents the change in concentration (log transformed – base 10) in a year at a particular monitoring site. Statistical significance was assessed using the Field Significance (Wilks, 2006).

3. Relating the underlying trends in water quality to ERS attainment

The potential impact of underlying trends on ERS attainment during 1995-2021 was assessed. The ERS is a tool used to evaluate water quality in Victoria, whereby attainment of the ERS indicates satisfactory water quality.

We compared underlying trends with either changes in attainment of the ERSs (for EC, turbidity, TN, TP and pH) or changes in the attainment of an annual minimum threshold value of 3.5 mg/L (for DO). Changes in attainment were calculated by dividing the total period of record (1995-2021) into two 13-year periods (1995-2007 inclusive, and 2009-21 inclusive). The difference in attainment between the two periods was calculated using the following equation:

$$\%\ Attainment\ change = 100 \times \left(\frac{\#years\ attained\ 2009\text{-}2021}{\#years\ assessed\ 2009\text{-}2021}\right) - \left(\frac{\#years\ attained\ 1995\text{-}2007}{\#years\ assessed\ 1995\text{-}2007}\right)$$

In this equation, '*#years attained*' refers to the number of calendar years that attained the standard within each period, and '*#years assessed* 'the number of years for which data were available. Consequently, negative values indicate a reduction in the proportion of years that attain the standard with time. Wilcoxon signed-rank tests were used to determine whether the attainment of standards for each parameter increased or decreased significantly between the two time periods.

Relationships between underlying trends and changes in attainment were assessed using Spearman rank correlation, where significant relationships indicated that temporal trends may be contributing to changed potential or ERS attainment due to the long-term linear trend in water quality.

Model performance

The performance of the multiple linear statistical model was assessed at each site using the Nash-Sutcliffe Efficiency (NSE), which represents the proportion of temporal variability that the model explains. A value of one represents a perfect model; zero or a negative value is a very poor model. This approach was used to assess the performance of the model that can be used to understand key drivers of temporal variability in water quality (i.e. understand the relative importance of streamflow, seasonality, temperature – for DO only, and underlying trend that cannot be explained by the previous three hydro-climatic parameters).

As indicated by Figure F1, the DO model performed the best of all parameters. The median NSE across the state was higher than 0.2 for all parameters except pH and TP. However, performance ranges from 0 (very poor model performance) to close to 1 (almost perfect fit between measured and observed data).

For ERS segments (Figure F2) Urban catchments were most difficult to predict for DO, pH, TP and TN. This suggests that there are factors other than daily streamflow, seasonality and trend that dominate the temporal variation of water quality in many of these catchments. Uplands catchments also had the worst performing models for turbidity, TP and TN, suggesting that there could be additional important drivers of water quality (e.g. vegetation cover or soil moisture).

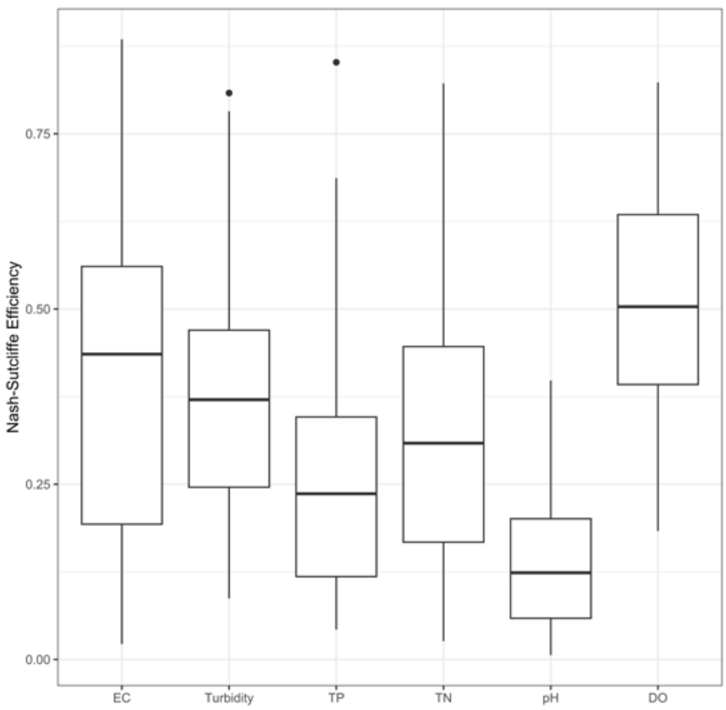


Figure F1: Distribution of Nash-Sutcliffe Efficiency calculated at each site for each parameter across Victoria.

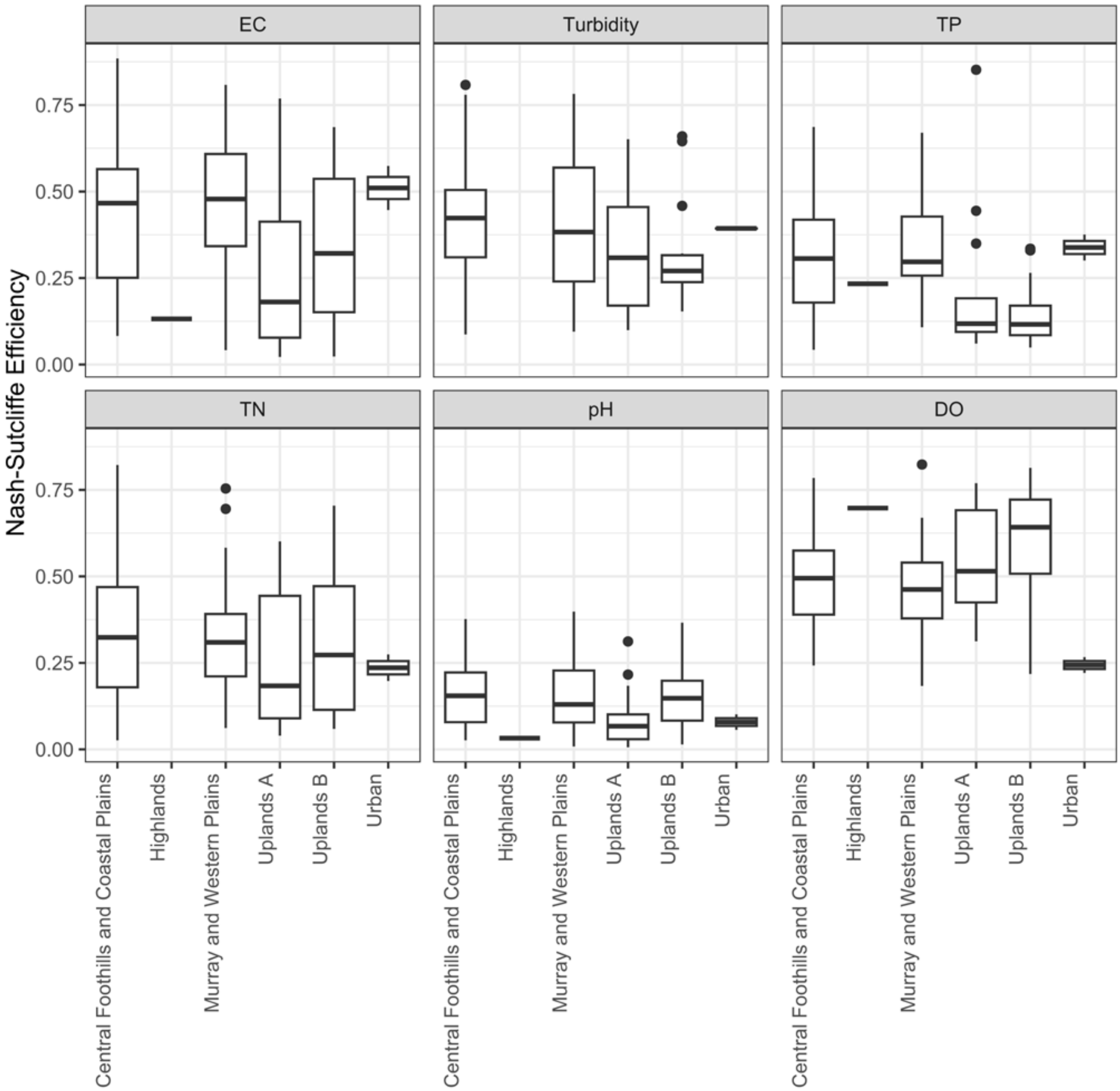


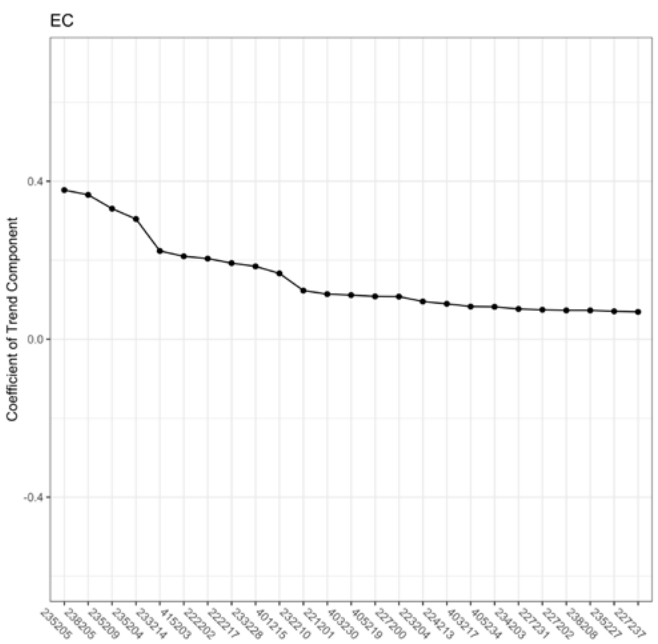
Figure F2: Distribution of Nash-Sutcliffe Efficiency calculated at each site for each segment. Boxplots indicate the distribution of NSEs for each parameter and ERS segment across Victoria. Dots indicate outliers (1.5 times the inter-quartile range).

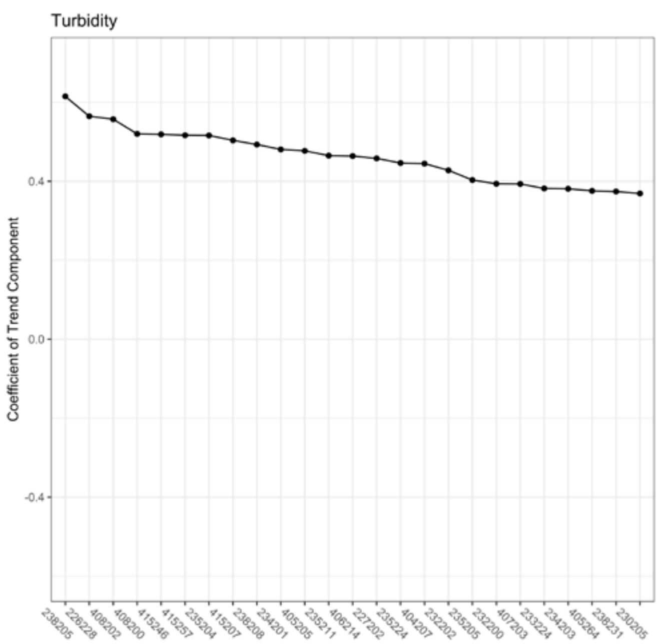
The Nash Sutcliffe Efficiency is an indicator of model fit and the ability of the model to predict water quality. However, it is not an indication of whether the regression coefficients extracted from the model are an accurate representation of the relationships between specific drivers and water quality.

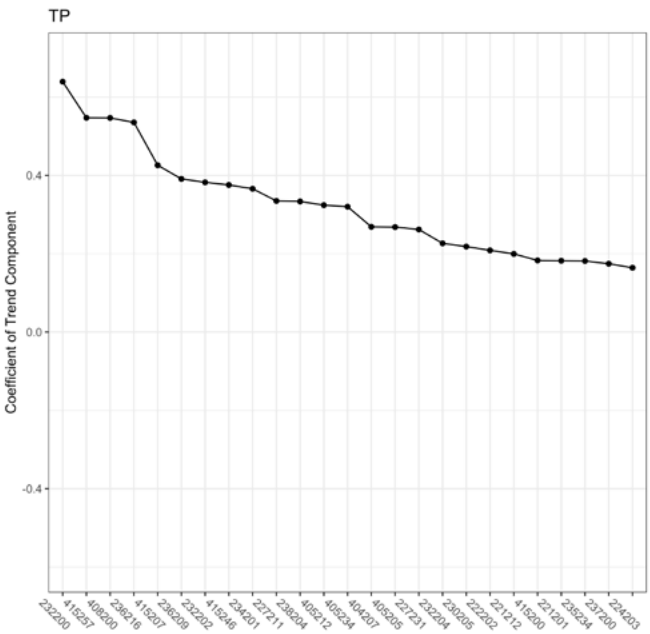
Appendix G:
Supplementary results for temporal variability in water quality (Chapter 4)

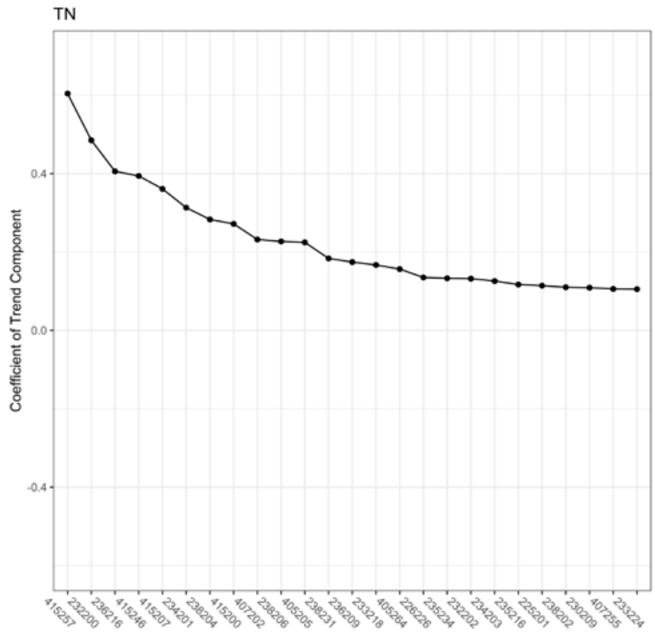
Table G1: Table of outlier sites from Figure 19. Check marks indicates that site was an outlier for a particular driver. Orange denotes a positive relationship between the driver and constituent, blue a negative relationship.

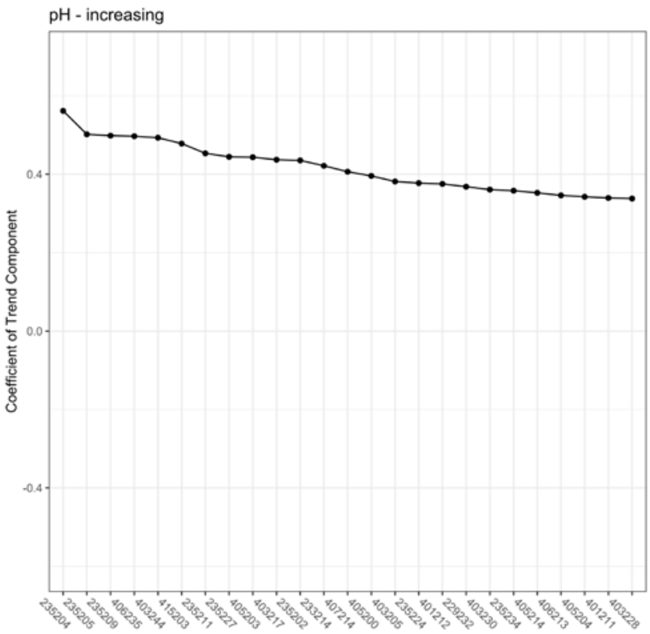
	EC			Turbidity			TP			TN			pH			DO			
Site	A	Q	Trend	A	Q	Trend	A	Q	Trend	A	Q	Trend	A	Q	Trend	A	Q	Temp	Trend
232200									✓			✓							
233215								✓											
233218														✓					
233228														✓	✓				
235203																	✓		
236215												✓							
236216										✓								✓	
238206	✓							✓									✓		
238208								✓											
299232						✓													
401204								✓											
401211					✓			✓											
404214						✓			✓										
404244						✓													
405203					✓														
405204			✓																
405232			✓						✓										
406213													✓						
407202					✓														
407215									✓										
407255									✓										
408200									✓										
408202																			✓
408203																			✓
410204											✓								
415203														✓					
415213					✓														
415246																✓			
415251						✓		✓											
415257									✓			✓					✓		

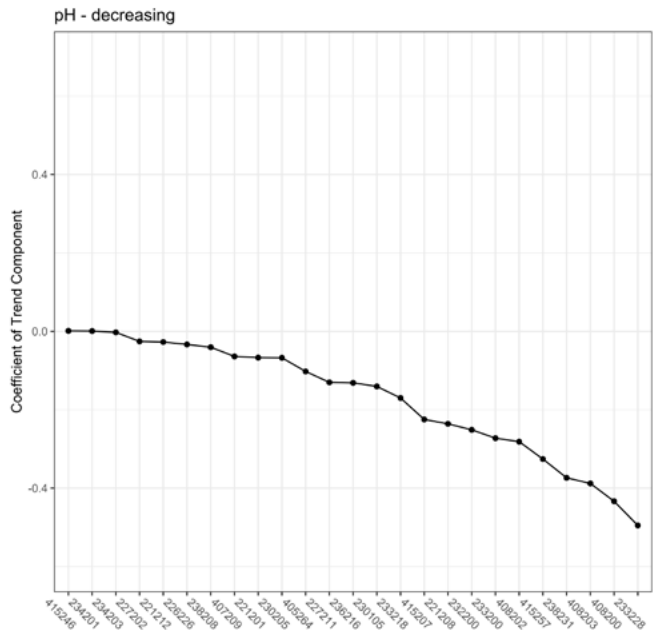












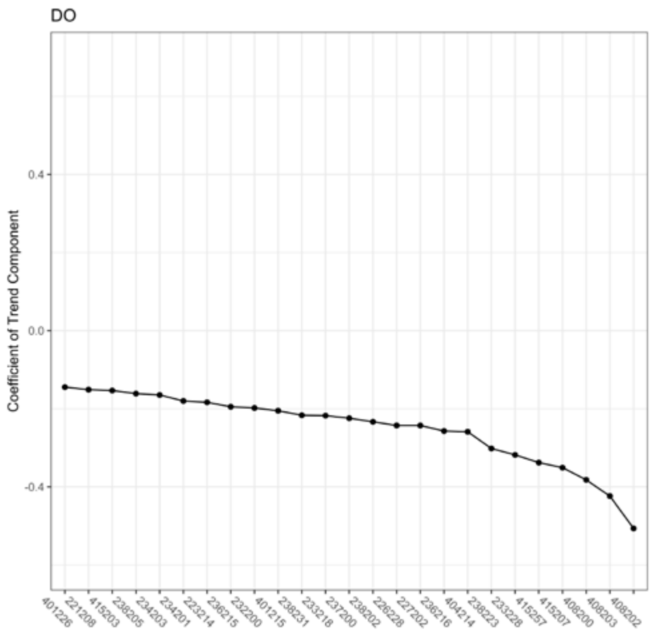
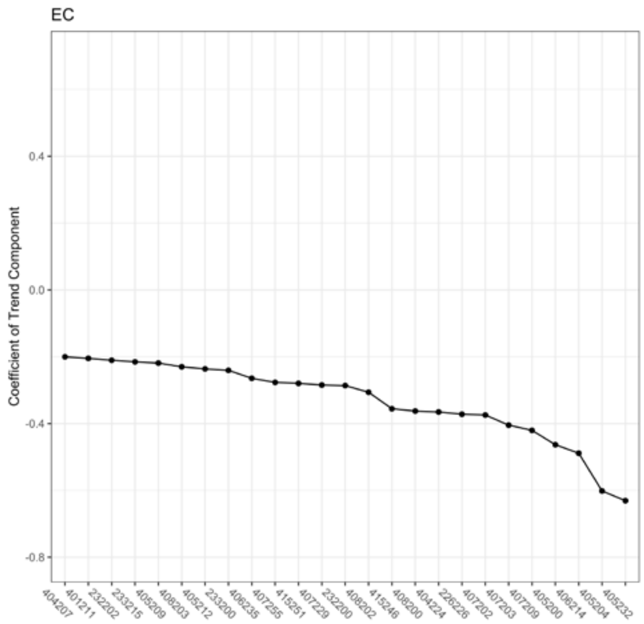
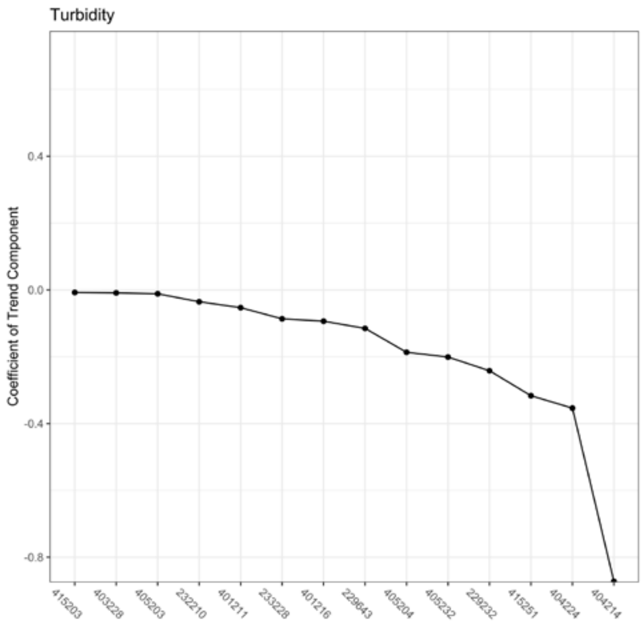
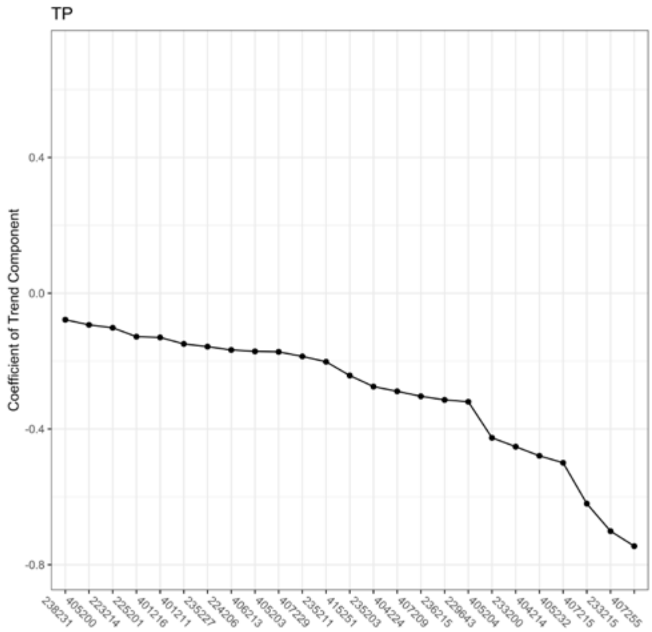
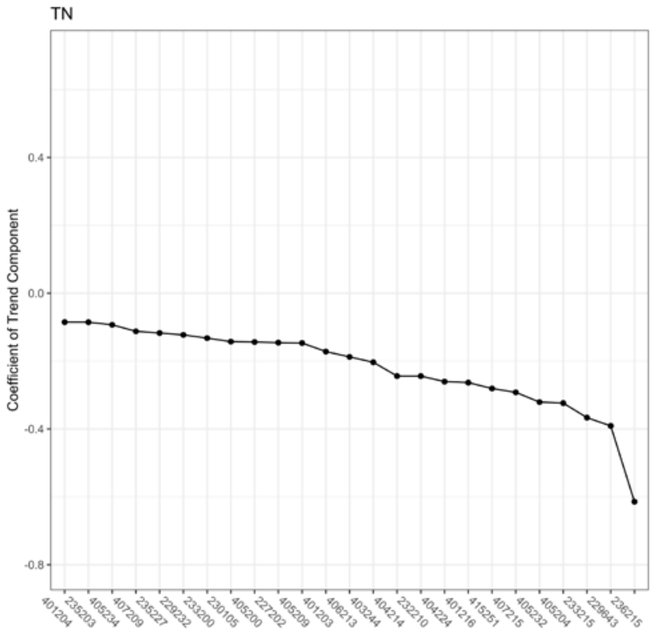


Figure G1: Regression coefficient of underlying component for 25 sites with the largest deteriorating underlying trend for DO, EC, pH, turbidity, TP and TN. For pH, 25 sites with both the greatest rate of increasing and decreasing pH are included.









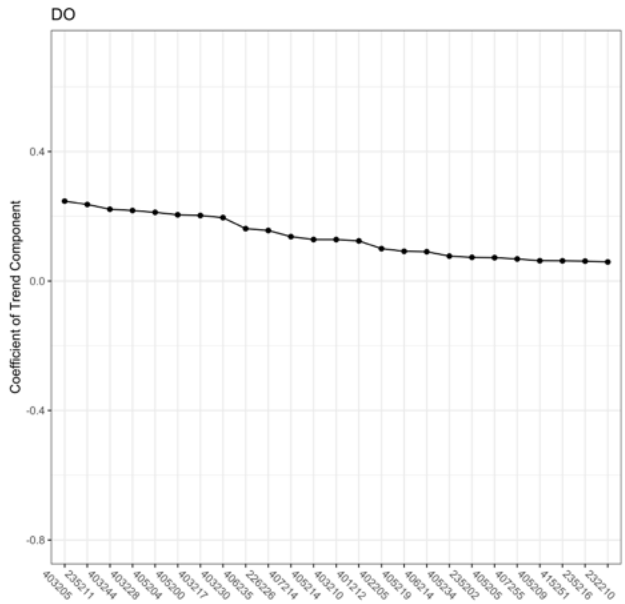


Figure G2: Regression coefficient of underlying trend component for 25 sites with the largest improving underlying trend for DO, EC, turbidity, TP and TN. Turbidity has only 7 sites with an improving underlying trend.

Table G2: The relative change in attainment (expressed as a percentage of the initial attainment) of ERS objectives (for EC, pH, TN, TP and turbidity) and a target minimum concentration of 3.5mg/L (for DO) between the two assessment periods (periods 1995-2007 inclusive, and 2009 to 2021 inclusive), at each site in Victoria. Negative values indicate a decrease in ERS attainment between the two periods. Positive values indicate an increase. NA indicates sufficient data were not available at that site.

Site ID	Site name	ERS segment	% Attainment change (1995-2007 to 2009-2021)					
			EC	Turbidity	TP	TN	pH	DO
221201	Cann River (West Branch) @ Weeragua	Uplands A	-7	NA	-7	NA	20	8
221208	Wingan River @ Wingan Inlet National Park	Uplands A	-27	NA	NA	NA	-30	0
221211	Combienbar River @ Combienbar	Uplands A	NA	NA	NA	NA	NA	NA
221212	Bemm River @ Princes Highway	Uplands A	0	NA	-13	NA	20	0
222202	Brodribb River @ Sardine Creek	Uplands B	-20	NA	-13	NA	30	0
222217	Rodger River @ Jacksons Crossing	Uplands B	-13	NA	-7	NA	20	0
223202	Tambo River @ Swifts Creek	Uplands B	0	NA	-7	NA	-20	0
223204	Nicholson River @ Deptford	Uplands B	-20	NA	0	NA	10	0
223214	Tambo River @ U/S Of Smith Creek	Uplands B	0	NA	7	NA	10	0
224203	Mitchell River @ Glenaladale	Central Foothills and Coastal Plains	0	NA	-13	NA	30	0
224206	Wonnangatta River @ Crooked River	Uplands B	0	NA	0	NA	10	0
224213	Dargo River @ Lower Dargo Road	Uplands B	7	NA	-7	NA	10	0
225114	Thomson River @ D/S Whitelaws Creek	Uplands B	NA	NA	NA	NA	NA	NA
225201	Avon River @ Stratford	Central Foothills and Coastal Plains	31	0	0	0	0	0
226226	Tanjil River @ Tanjil Junction	Uplands A	7	7	NA	0	20	0
226228	Latrobe River @ Rosedale (Main Stream)	Central Foothills and Coastal Plains	0	-47	0	-7	30	0
227200	Tarra River @ Yarram	Central Foothills and Coastal Plains	-20	NA	NA	NA	40	0
227202	Tarwin River @ Meeniyan	Central Foothills and Coastal Plains	0	-47	0	0	10	0
227211	Agnes River @ Toora	Central Foothills and Coastal Plains	7	NA	-15	NA	-10	0
227231	Bass River @ Mcgrath Road	Central Foothills and Coastal Plains	0	-27	0	0	40	-8
227237	Franklin River @ Toora	Uplands A	-13	NA	0	NA	-10	0
229232	Yarra River @ Healesville (Maxwell Bridge)	Central Foothills and Coastal Plains	0	28	NA	-7	29	0

Site ID	Site name	ERS segment	% Attainment change (1995-2007 to 2009-2021)					
			EC	Turbidity	TP	TN	pH	DO
229643	Moonee Ponds Creek @ Racecourse Road, Flemington	Urban	0	13	27	0	-14	-15
230105	Maribyrnong River @ Keilor (Brimbank Park Ford)	Central Foothills and Coastal Plains	12	-13	NA	13	29	23
230205	Deep Creek @ Bulla (D/S Of Emu Creek Junct.)	Urban	20	-20	-27	-7	0	8
230209	Barringo Creek @ Barringo (U/S Of Diversion)	Central Foothills and Coastal Plains	0	0	0	0	70	-8
230232	Deep Creek @ Bolinda	Central Foothills and Coastal Plains	8	-20	-27	0	-41	-8
232200	Little River @ Little River (You Yangs Road)	Central Foothills and Coastal Plains	0	-7	-32	-25	10	-8
232202	Moorabool River @ Batesford	Central Foothills and Coastal Plains	7	-13	-40	-33	10	-8
232204	Moorabool River @ Morrisons	Central Foothills and Coastal Plains	-27	-13	-7	7	0	-8
232210	Moorabool River West Branch @ Lal Lal	Central Foothills and Coastal Plains	0	-20	-47	13	-10	-15
233200	Barwon River @ Pollocksford	Central Foothills and Coastal Plains	47	0	0	13	40	0
233214	Barwon River East Branch @ Forrest	Uplands B	-27	20	0	0	-20	-15
233215	Leigh River @ Mount Mercer	Central Foothills and Coastal Plains	0	27	0	0	0	0
233218	Barwon River @ Inverleigh	Central Foothills and Coastal Plains	0	7	-20	7	20	-15
233224	Barwon River @ Ricketts Marsh	Central Foothills and Coastal Plains	0	0	-11	8	0	0

Site ID	Site name	ERS segment	% Attainment change (1995-2007 to 2009-2021)					
			EC	Turbidity	TP	TN	pH	DO
233228	Boundary Creek @ Yeodene	Central Foothills and Coastal Plains	0	-13	2	-29	0	-38
234201	Woady Yaloak River @ Cressy (Yarima)	Murray and Western Plains	0	-13	-40	-20	30	-8
234203	Pirron Yallock Creek @ Pirron Yallock (Above H'wy Br.)	Murray and Western Plains	7	-73	0	0	-20	-62
235202	Gellibrand River @ Upper Gellibrand	Uplands B	0	-7	7	-27	0	0
235203	Curdies River @ Curdie	Central Foothills and Coastal Plains	0	0	7	7	-50	0
235204	Little Aire Creek @ Beech Forest	Uplands B	0	-67	NA	NA	-10	0
235205	Arkins Creek West Branch @ Wyelangta	Uplands B	0	0	-7	9	10	0
235209	Aire River @ Beech Forest	Uplands B	0	-7	-19	-13	0	0
235211	Kennedys Creek @ Kennedys Creek	Central Foothills and Coastal Plains	0	-67	0	0	80	8
235216	Cumberland River @ Lorne	Uplands B	13	7	-13	-7	-10	0
235224	Gellibrand River @ Burrupa	Central Foothills and Coastal Plains	0	-20	-7	-7	80	0
235227	Gellibrand River @ Bunkers Hill	Uplands B	0	-33	0	20	-20	0
235234	Love Creek @ Gellibrand	Uplands B	0	0	0	7	-40	0
235237	Scotts Creek @ Curdie (Digneys Bridge)	Central Foothills and Coastal Plains	7	-33	0	0	10	0
236209	Hopkins River @ Hopkins Falls	Murray and Western Plains	0	0	-13	-13	0	0
236215	Burrumbeet Creek @ Lake Burrumbeet	Central Foothills and Coastal Plains	0	0	0	0	-40	-54
236216	Mount Emu Creek @ Taroon (Ayrford Road Bridge)	Murray and Western Plains	0	7	-15	0	10	-8

Site ID	Site name	ERS segment	% Attainment change (1995-2007 to 2009-2021)					
			EC	Turbidity	TP	TN	pH	DO
237200	Moyne River @ Toolong	Murray and Western Plains	0	0	-73	-47	-10	0
237207	Surry River @ Heathmere	Murray and Western Plains	0	0	-13	0	0	0
238202	Glenelg River @ Sandford	Murray and Western Plains	0	0	20	-27	50	0
238204	Wannon River @ Dunkeld	Uplands A	0	0	0	0	0	31
238205	Glenelg River @ Rocklands Reservoir	Uplands A	0	-67	NA	NA	0	-8
238206	Glenelg River @ Dartmoor	Murray and Western Plains	7	-13	-13	-20	0	0
238208	Jimmy Creek @ Jimmy Creek	Uplands A	0	-20	0	8	0	0
238223	Wando River @ Wando Vale	Murray and Western Plains	0	-20	-27	-27	30	-8
238228	Wannon River @ Henty	Murray and Western Plains	0	-13	-13	-20	-30	-15
238231	Glenelg River @ Big Cord	Uplands A	0	-27	0	-20	-20	-8
401203	Mitta Mitta River @ Hinnomunjie	Uplands A	0	-7	7	7	-10	0
401204	Mitta Mitta River @ Tallandoon	Uplands A	0	0	-13	7	20	NA
401211	Mitta Mitta River @ Colemans	Uplands A	0	7	0	0	40	0
401212	Nariel Creek @ Upper Nariel	Uplands A	0	-13	-20	0	30	0
401215	Morass Creek @ Uplands	Uplands A	-60	NA	NA	NA	20	-15
401216	Big River @ Jokers Creek	Uplands A	0	0	0	0	10	0
401226	Victoria River @ Victoria Falls	Highlands	0	NA	0	NA	0	0
402205	Kiewa River @ Bandiana	Uplands A	0	-40	-20	27	50	0
403205	Ovens Rivers @ Bright	Uplands B	0	-7	0	7	40	0
403210	Ovens River @ Myrtleford	Uplands B	0	-7	7	7	30	0
403217	Rose River @ Matong North	Uplands B	-13	-20	-7	-27	40	8
403223	King River @ Docker Road Bridge	Central Foothills and Coastal Plains	0	-7	-7	0	20	0
403228	King River @ Lake William Hovell T.g.	Uplands B	0	0	NA	NA	50	0
403230	Ovens River @ Rocky Point	Uplands B	7	-33	-13	7	30	0
403244	Ovens River @ Harrietville	Uplands B	0	0	1	8	40	0
404207	Holland Creek @ Kelfeera	Central Foothills and Coastal Plains	27	-73	-53	0	30	-15
404214	Broken Creek @ Katamatite	Murray and Western Plains	-7	53	0	0	10	-23

Site ID	Site name	ERS segment	% Attainment change (1995-2007 to 2009-2021)					
			EC	Turbidity	TP	TN	pH	DO
404224	Broken River @ Gowangardie	Murray and Western Plains	0	20	7	47	-18	0
405200	Goulburn River @ Murchison (Mcphee's Rest)	Murray and Western Plains	0	-20	-13	13	10	0
405203	Goulburn River @ Eildon	Central Foothills and Coastal Plains	0	0	0	0	20	-8
405204	Goulburn River @ Shepparton	Murray and Western Plains	0	20	60	47	0	-15
405205	Murrindindi River @ Murrindindi Above Colwells	Uplands A	0	-13	-13	-27	0	0
405209	Acheron River @ Taggerty	Uplands A	0	-20	-13	-13	-10	0
405212	Sunday Creek @ Tallarook	Central Foothills and Coastal Plains	0	0	-13	-24	30	-31
405214	Delatite River @ Tonga Bridge	Central Foothills and Coastal Plains	0	-7	0	-7	-10	0
405219	Goulburn River @ Dohertys	Uplands B	0	-33	-7	-13	40	0
405232	Goulburn River @ Mccoys Bridge	Murray and Western Plains	0	7	27	47	-40	NA
405234	Seven Creeks @ D/S Of Polly Mcquinn Weir	Central Foothills and Coastal Plains	0	-60	-46	0	-8	0
405264	Big River @ D/S Of Frenchman Creek Junction	Uplands A	0	0	0	0	0	0
406202	Campaspe River @ Rochester D/S Waranga Western Ch Syphn	Murray and Western Plains	-7	-27	-7	-13	-20	-8
406213	Campaspe River @ Redesdale	Central Foothills and Coastal Plains	0	-13	20	27	20	8
406214	Axe Creek @ Longlea	Murray and Western Plains	27	-7	0	-8	20	15
406235	Wild Duck Creek @ U/S Of Heathcote-Mia Mia Road	Central Foothills and Coastal Plains	40	-36	-8	-18	18	15
407202	Loddon River @ Kerang	Murray and Western Plains	7	0	0	-7	30	NA

Site ID	Site name	ERS segment	% Attainment change (1995-2007 to 2009-2021)					
			EC	Turbidity	TP	TN	pH	DO
407203	Loddon River @ Laanecoorie	Murray and Western Plains	-20	-47	-13	-7	-50	-8
407209	Gunbower Creek @ Koondrook	Murray and Western Plains	0	-40	0	0	10	NA
407214	Creswick Creek @ Clunes	Central Foothills and Coastal Plains	7	13	NA	NA	-90	8
407215	Loddon River @ Newstead	Central Foothills and Coastal Plains	7	0	60	47	0	15
407229	Loddon River @ Serpentine Weir	Murray and Western Plains	-13	0	18	-18	-30	-15
407255	Bendigo Creek @ Huntly	Murray and Western Plains	0	-27	0	0	-20	8
408200	Avoca River @ Coonooer	Murray and Western Plains	0	-20	-60	NA	10	-31
408202	Avoca River @ Amphitheatre	Central Foothills and Coastal Plains	0	-40	NA	NA	-60	-46
408203	Avoca River @ Quambatook	Murray and Western Plains	18	-17	NA	NA	43	-23
415200	Wimmera River @ Horsham	Murray and Western Plains	7	-47	-53	-33	-10	-23
415203	Mount William Creek @ Lake Lonsdale (Tail Gauge)	Murray and Western Plains	-27	-27	NA	NA	-50	-38
415207	Wimmera River @ Eversley	Central Foothills and Coastal Plains	0	-67	-80	-53	-20	-46
415246	Wimmera River @ Lochiel Railway Bridge	Murray and Western Plains	65	-30	-31	-27	20	-8
415251	Mackenzie River @ Mckenzie Creek	Murray and Western Plains	0	37	7	7	10	-23
415257	Richardson River @ Donald	Murray and Western Plains	NA	-46	0	0	0	-8

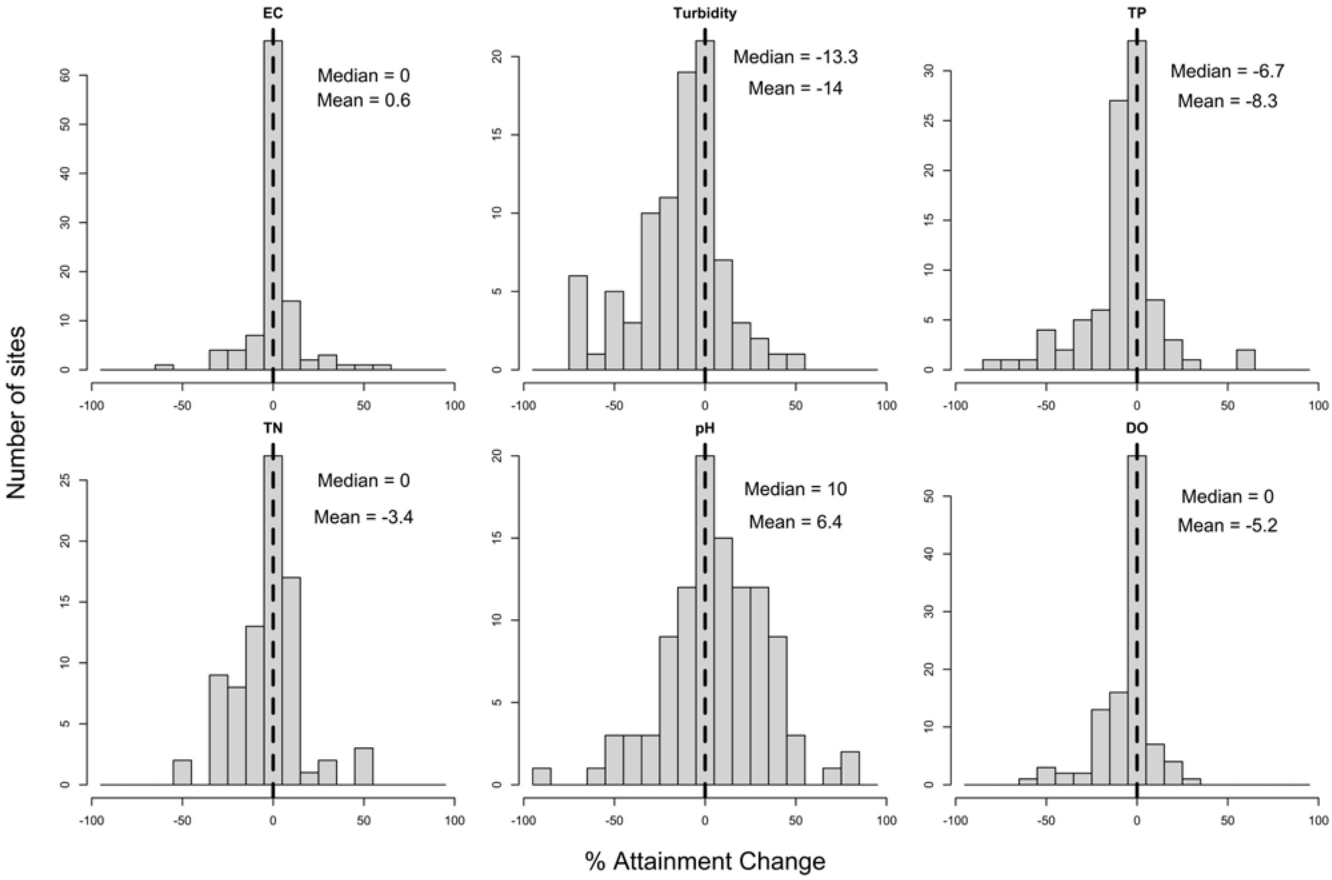


Figure G3: The relative change in attainment (expressed as a percentage of the initial attainment) of ERS objectives (for EC, pH, TN, TP and turbidity) and a target minimum concentration of 3.5mg/L (for DO) between the two assessment periods (periods 1995-2007, and 2009 to 2021, for all sites in Victoria). Negative values indicate a decrease in ERS attainment between the two periods; positive values an increase.

Appendix H:
Analytical approach used for Chapter 5

Catchment selection

The same catchments used in Chapter 5 were used to identify the relationship between streamflow and water quality, and the impact that climate change may have on this relationship.

To assess the impact of climate change on water quality, a set of case study catchments was selected. The selection process was designed to minimise the potential for factors other than climatic variability to influence water quality variability.

Catchments had to meet the data requirements described in the Introduction (at least 27 years of data record with 80% completeness of sampling when flow occurred, across four periods of equal duration). Catchments were also screened using criteria relating to land cover, based on Victoria's multi-temporal land cover dataset (White et al., 2020). Land cover within the 137 study catchments identified in (Section 1.4) was collated for 1990-95 and 2015-18. Catchments were included in the climate change analysis if:

- less than 0.1% of the total catchment area (in 2015-19) was occupied by urban or residential development. This was done to exclude the potential for changes in urban land use intensity to influence water quality, and
- no category of land use/land cover changed in extent by more than 1% of the total catchment area between 1990-95 and 2015-19. This mitigated the potential impact of changing land use on water quality.

Catchment screening identified 30 catchments minimally impacted by changing land cover, though we acknowledge that changes in land use intensity and practices may influence temporal changes in water quality.

The landcover in these catchments is summarised in Table H1.

Most catchments are dominated by forest or other native vegetation cover (including some catchments containing areas of plantation forestry). Introduced crops and pastures cover 0-13% of the selected catchments.

Many of these catchments have also been affected by one or more bushfires, which likely contribute to some observed trends in water quality.

Understanding the effect of changing streamflow on water quality

To better understand the impact of climate variability on water quality within the selected catchments, we developed a linear model with flow, seasonality, and water temperature (for DO only) as predictor variables. This model is the same one used for Chapter 4, but without the linear trend component. The variables were log transformed (base 10) and standardised using a z-score (refer to Chapter 4) prior to the regression.

The regression coefficients for streamflow were extracted from the model and used to identify the expected percentage change in water quality as a result of a 1% decrease in streamflow. The following equation was used for this calculation:

$$100 \times \left(\frac{y_{new} - y}{y}\right) = 100 \times (0.99^{\beta_1} - 1)$$

where y_{new} is the new water quality parameter concentration when there is a 1% decrease in streamflow, y is the old water quality parameter concentration (without the decrease in streamflow) and β is the regression coefficient for streamflow.

This was done for all catchments that were analysed in Chapter 4.

We then undertook a closer investigation of the model residuals (log transformed – base 10 and standardised using z score), to understand the impact of climate drivers on water quality. This research was conducted for the 30 case study catchments with negligible identifiable land use change. These residuals were compared with climatic and flow metrics, to better understand what processes might be driving changes in residuals. Climatic variables were separated into three temporal classes, to understand the influence of different scales of climatic phenomena:

1. **Event-based climatic variables** (Same-day to 14-day antecedent period) describing conditions of individual rainfall events that may have short-term impacts on water quality. Future shifts in frequency, intensity and duration of rainfall events may have corresponding influences on water quality.
2. **Seasonal climatic variables** (30 days to 180 days antecedent period, and antecedent quarter) describing climatic conditions associated with antecedent seasons.
3. **Medium-term climatic variables** (1 year to 5 years antecedent period) changes in climatic conditions associated with climatic cycles, e.g. El Niño and La Niña periods.

Table H1: Landcover in selected catchments (% of catchment area).

Site ID	Site name	Introduced Crop and Pasture	Native Vegetation (Inc. grassland)	Urban and built-up	Disturbed Ground	Exotic and plantation treet
221201	Cann River (West Branch) @ Weeragua	1	99	0	0	0
221208	Wingan River @ Wingan Inlet National Park	1	99	0	0	0
221212	Bemm River @ Princes Highway	2	97	0	0	1
222202	Brodribb River @ Sardine Creek	0	99	0	0	0
222217	Rodger River @ Jacksons Crossing	0	100	0	0	0
223202	Tambo River @ Swifts Creek	10	90	0	0	0
223204	Nicholson River @ Deptford	0	100	0	0	0
223214	Tambo River @ U/S Of Smith Creek	3	97	0	0	0
224203	Mitchell River @ Glenaladale	2	98	0	0	0
224206	Wonnangatta River @ Crooked River	0	100	0	0	0
224213	Dargo River @ Lower Dargo Road	4	96	0	0	0
226226	Tanjil River @ Tanjil Junction	4	96	0	0	1
230209	Barringo Creek @ Barringo (U/S Of Diversion)	0	95	0	0	5
233214	Barwon River East Branch @ Forrest	0	100	0	0	0
235202	Gellibrand River @ Upper Gellibrand	1	91	0	0	7
235209	Aire River @ Beech Forest	0	58	0	0	42
235216	Cumberland River @ Lorne	0	100	0	0	0
235227	Gellibrand River @ Bunkers Hill	12	75	0	0	13
238208	Jimmy Creek @ Jimmy Creek	0	100	0	0	0
238231	Glenelg River @ Big Cord	0	100	0	0	0
401203	Mitta Mitta River @ Hinnomunjie	12	87	0	0	0
401204	Mitta Mitta River @ Tallandoon	10	88	0	0	0
401211	Mitta Mitta River @ Colemans	11	88	0	0	0
401212	Nariel Creek @ Upper Nariel	0	100	0	0	0
401216	Big River @ Jokers Creek	1	99	0	0	0
401226	Victoria River @ Victoria Falls	13	87	0	0	0
403228	King River @ Lake William Hovell T.G.	0	100	0	0	0
405205	Murrindindi River @ Murrindindi Above Colwells	0	100	0	0	0
405219	Goulburn River @ Dohertys	0	100	0	0	0
405264	Big River @ D/S Of Frenchman Creek Junction	0	100	0	0	0
Average		**3**	**95**	**0**	**0**	**2**

Model residuals were then compared with climatic variables using Spearman correlation. For each site, the 10 strongest correlations were extracted and reviewed. Where both event-scale and medium-term antecedent metrics displayed strong correlations, these metrics were checked for cross-correlation to determine whether they had independent effects.

Each parameter was summarised in terms of the metric-type with the strongest correlation, where the strongest correlation returned significant value (Bonferroni-corrected for multiple comparisons).

The climatic metrics compared are summarised in Table H2.

Table H2: Parameters used in correlation analysis with model residuals. All metrics were calculated from daily rainfall, temperature and flow data.

Parameter	Class	Period	Relevance
Antecedent mean (daily minimum and maximum) temperature	Climatic	Same day, 3 days, 7 days, 14 days, 30 days, 90 days, 180 days, 1, 3 and 5 year	Potential driver of catchment wetness (via ET), biogeochemical processes, e.g. denitrification
Antecedent total rainfall volume	Climatic	Same day, 3 days, 7 days, 14 days, 30 days, 90 days, 180 days, 1, 3 and 5 years	Catchment wetness, infiltration and groundwater recharge processes
Average antecedent rainfall depth on wet days (> 2, 5mm)	Climatic	Same day, 3 days, 7 days, 14 days, 30 days, 90 days, 180 days, 1, 3 and 5 years	Catchment wetness, infiltration and groundwater recharge processes
Days since rainfall event of > depth X occurring in a 7-day period (X = 5, 10, 20, 30, 50 mm)	Climatic	Whole record	Catchment wetness, infiltration and groundwater recharge processes
Depth of last rainfall event > depth (X = 5, 10, 20, 30, 50mm)		Whole record	
Rainfall volume in preceding wettest and driest quarters	Climatic		Infiltration and groundwater recharge/discharge processes
Antecedent discharge	Flow	3 days, 7 days, 14 days, 30 days, 90 days, 180 days, 1, 3 and 5 years	Changes in underlying hydrological processes (e.g. groundwater reserves, mixing and dilution)

Understanding the effect of drought

The proportional change in streamflow during the Millennium Drought, when compared with non-drought conditions, was calculated using streamflow data from 155 sites collated by Saft et al. (2023) using the following equation:

$$\Delta Q = \frac{\overline{Q_{drought\ obs}} - \overline{Q_{non\text{-}drought\ obs}}}{\overline{Q_{non\text{-}drought\ obs}}}$$

where ΔQ is the proportional change in streamflow due to the drought, Qdrought obs are all flow observations from during the Millennium Drought (1997-2009 inclusive), and $Q_{non\text{-}drought\ obs}$ are all other flow observations from the dataset.

We used the site-specific change in streamflow described above, and the regression coefficients for streamflow from the linear model, to estimate the impact of flow changes on water quality during the Millennium Drought via the following equation:

$$100 \times \left(\frac{y_{new} - y}{y}\right) = 100 \times \left((1 + \Delta Q)^{\beta_1} - 1\right)$$

where y_{new} is the new water quality parameter concentration when there is a proportional change in streamflow of ΔQ, y is the old water quality parameter concentration (without the decrease in streamflow) and β is the regression coefficient for streamflow.

All residual (log-transformed, standardised using z score) time series from the 30 minimally impacted case study sites were smoothed (using a 2-year window moving average), combined, and visualised in order to identify temporal patterns shared across the sites, considering that shared temporal patterns may reflect a common climatic driver.

- Residuals were checked for obvious trends or patterns associated with the Millennium Drought by subdividing the 27-year record into the following periods:
  - Pre-drought (1995-96 inclusive)
  - Drought (1997-2009 inclusive)
  - Post-drought (2010-21 inclusive)

The distribution of residuals in each of these periods was visualised using boxplots, and the direction and significance of residual trends during the drought and post-drought were investigated.

Appendix I:
Supplementary results for Chapter 5

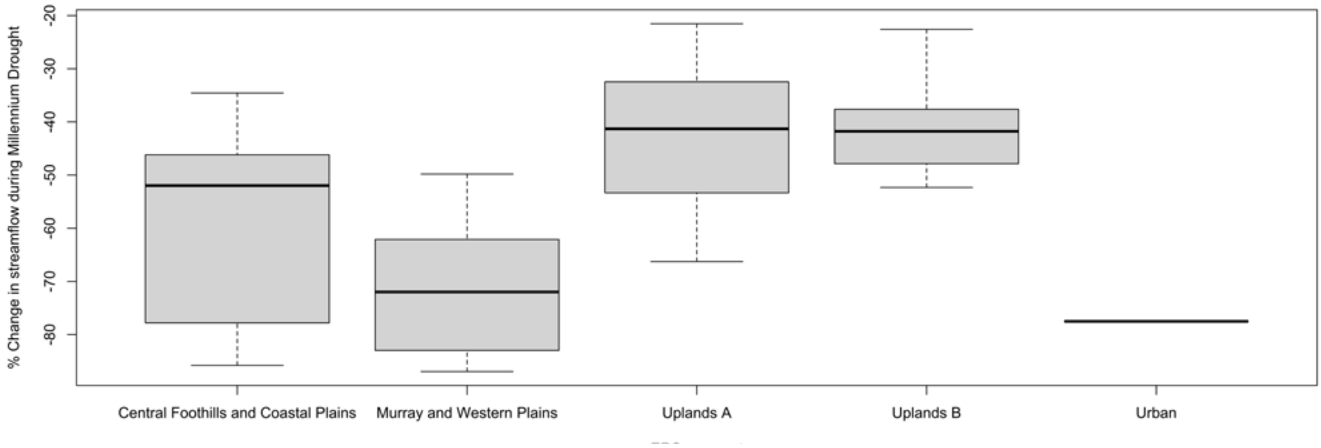


Figure I1: Percentage streamflow declines during the Millennium Drought at sites where water quality changes were calculated, for different ERS segments.

Table I1: Results of Kruskal-Wallis and Dunn's post-hoc tests comparing model residuals prior to, during and after the Millennium Drought (1997-2009 inclusive) at 95% confidence level. The columns headed kw_chi2 and kw_p are the Kruskal-Wallis test statistic (Chi2) and p values respectively. d_post-d_Z, D_pre-d_Z, and pre-d_post-d_Z are the Dunn's test statistics, and d_post-d_p, D_pre-d_p, and pre-d_post-d_p are the p values for the drought vs post-drought, drought vs re-drought, and pre-drought vs post-drought comparisons, respectively.

Constituent	kw_chi2	kw_p	d_post-d_Z	d_pre-d_Z	pre-d_post-d_Z	d_post-d_p	d_pre-d_p	pred_post-d_p
DO	2.3E+00	3.2E-01	3.5E-02	-1.3E+00	-1.3E+00	4.9E-01	9.8E-02	9.2E-02
EC	1.2E+01	3.1E-03	-3.4E+00	-1.7E+00	1.6E+00	3.4E-04	4.0E-02	5.0E-02
pH	2.9E+01	5.2E-07	-3.7E+00	1.5E+00	5.2E+00	1.0E-04	6.5E-02	8.6E-08
Turbidity	2.5E+01	3.1E-06	-4.2E+00	3.2E-01	4.5E+00	1.4E-05	3.8E-01	3.2E-06
TP	1.9E+01	7.8E-05	-1.8E+00	2.5E+00	4.3E+00	3.4E-02	6.1E-03	7.4E-06
TN	1.9E+01	8.0E-05	1.4E+00	4.3E+00	2.9E+00	8.3E-02	1.0E-05	2.0E-03

When correlating the residuals with hydro-climatic variables for each water quality parameter, we found:

- For EC: 25/30 sites exhibited medium correlations |ρ|>0.2 between residuals and hydro-climatic parameters. Of these, the majority of sites (17 sites) exhibited medium correlations between residuals and 'medium or long term' climate parameters (1, 3 or 5 year temperature or rainfall depth).
- For turbidity: 17/18 sites exhibited medium correlations |ρ|>0.2 between residuals and hydro-climatic parameters. Of these, the majority of sites (11 sites) exhibited medium correlations between residuals and 'medium or long term' climate parameters (1, 3 or 5 year temperature or rainfall depth).
- For TP & TN: 24/27 (TP) and 16/17 (TN) sites exhibited medium correlations |ρ|>0.2 between residuals and hydro-climatic parameters. The majority of sites (16 for TP and 12 sites for TN) exhibited medium correlations between residuals and 'short term' climatic parameters (3 day, 7 day or 14 day temperature or rainfall depth).
- For pH: 26/30 sites exhibited medium correlations |ρ|>0.2 between residuals and hydro-climatic parameters. Of these, the majority of sites (22 sites) exhibited medium correlations between residuals and 'medium or long term' climate parameters (1, 3 or 5 year temperature or rainfall depth).
- For DO: 17/30 sites exhibited medium correlations |ρ|>0.2 between residuals and hydro-climatic parameters. Of these, the majority of sites (10 sites) exhibited medium correlations between residuals and 'medium or long term' climate parameters (1, 3 or 5 year temperature or rainfall depth).

Appendix J:
Analytical approach used for Chapter 7

This question 'How are BGA blooms changing?' was answered by running two statistical analyses on data from the BGA events at 16 major Victorian water bodies and the corresponding data of two potential explanatory variables: air temperature and water level.

Trends in BGA events

To understand how the BGA events have changed over time, we assessed the temporal trends in the following characteristics of the recreational warning for each water body due to BGA events:

- Event frequency – the number of warnings due to BGA events each year
- Event duration each year – the total number of days as part of the warning period each year

For water bodies which experienced more frequent BGA events, defined as having five or more warning events in the record, we further assessed the temporal trends in

- Event duration – the duration of each warning
- Event timing – the starting days of warnings in each year

As a complementary analysis, we also assessed the temporal trend in the spot samples of total bio-volume (only available for water bodies monitored by Goulburn-Murray Water and GWM Water) from each water body. The trends in the annual average value and the average of each season were analysed.

Most of the abovementioned BGA event characteristics are summarised at an annual scale due to the low number of warnings in this record. Thus, we applied non-parametric trend analyses, namely Mann-Kendall (MK) (Kendall, 1957; Mann, 1945) and Sen's Slope (Sen, 1968; Theil, 1992), which are common approaches for revealing long-term trends in annual water quantity and quantity across multiple locations (Gudmundsson et al., 2019; Zhang et al., 2016). The MK model was first used to identify the direction and significance of temporal trends, and the Sen's Slope was then applied on any site with a significant trend to estimate the magnitude of the temporal trend. The MK and Sen's Slope models are both able to identify only monotonic trends (i.e. single direction) in data, however, are suitable for this report for understanding the overall change in BGA events. The non-parametric nature of both models also means that the results are comparable across multiple locations for the ease of interpreting and summarising trends over multiple water bodies.

The analysis of the temporal changes in the timing of BGA event focuses on the starting days of BGA events. Considering the circular nature of the data (e.g. day 1 in a year is close to day 365), a different trend approach – the circular regression (Lund, 1999) – was used for this specific analysis. Similar to the MK and Sen's Slope models, the circular regression also reveals the direction, magnitude and significance of temporal trends; the difference is that it specifically deals with circular data.

Potential explanatory variables for BGA event patterns

For the water bodies that experienced five or more warning events in the record, we further looked at how the duration of individual warning events in each water body are related to four potential explanatory variables: air temperature, water level, turbidity and TP (the latter two are only available for the water bodies monitored by Goulburn-Murray Water).

The water level is continuously monitored at each water body. The water quality parameters (TP and turbidity) are spot-sampled at each water body, while daily air temperature data are available at each water body via the gridded climate data obtained from the Australian Water Availability Project (AWAP, Raupach et al., 2009). The high resolution of these data relative to the data on BGA events allows exploration of multiple temporal scales of potential impacts. We specifically assessed the correlations between the duration of each warning event and the four explanatory variables averaged:

- during the warning period
- within 1 month prior to the starting day of the warning
- within 3 months prior to the starting day of the warning
- within 6 months prior to the starting day of the warning
- within 1 year prior to the starting day of the warning.

These correlations were interpreted for their strengths and significances and their links with physical processes driving the BGA events.

Appendix K:
Detailed results on BGA event trends (Chapter 7)

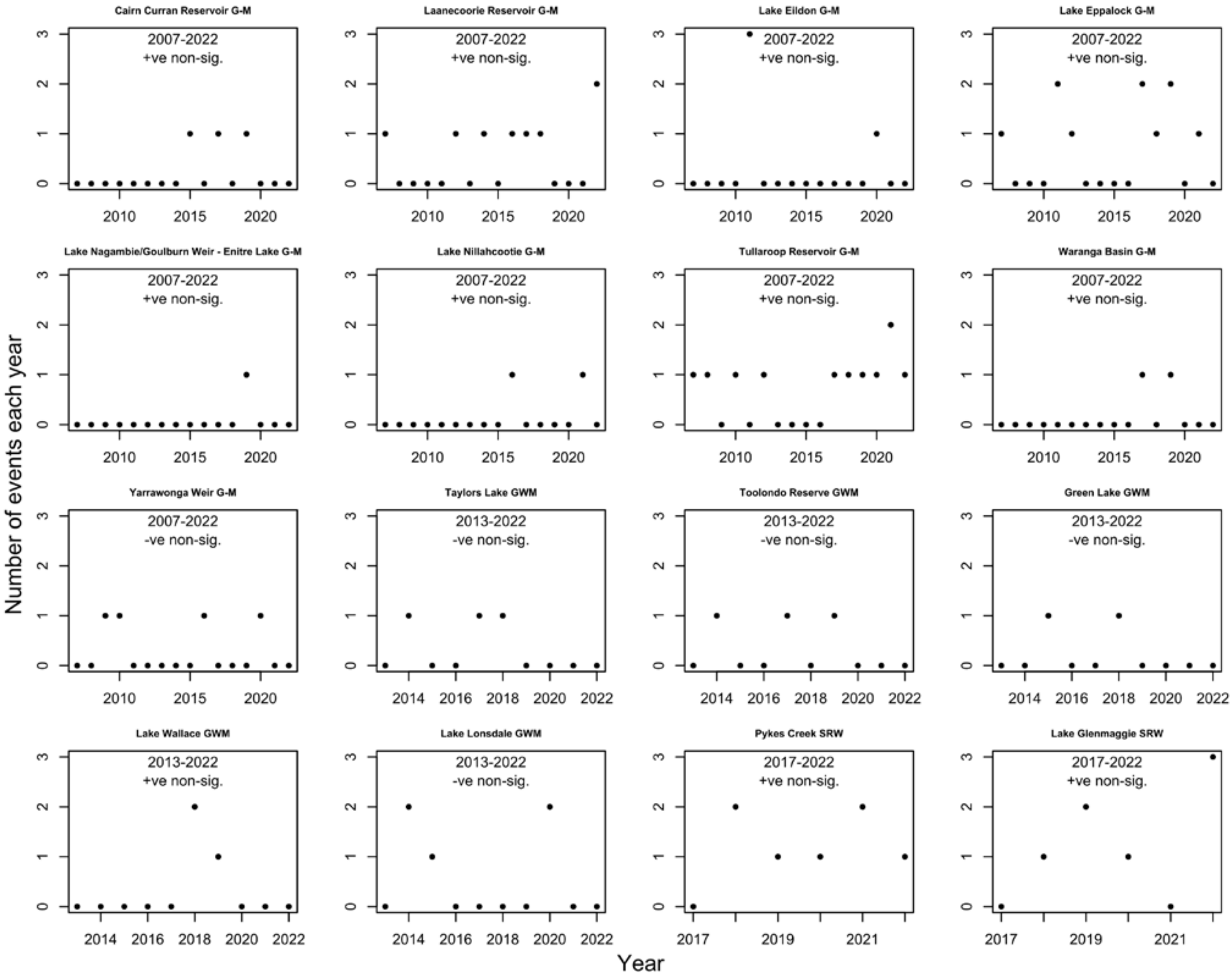


Figure K1: Total number of BGA warnings each year for each water body. Each panel summarises all warnings issued for each water body each year, denoted by the period over which trend analysis was performed, the resultant direction and significance of trend in the warning frequency each year.

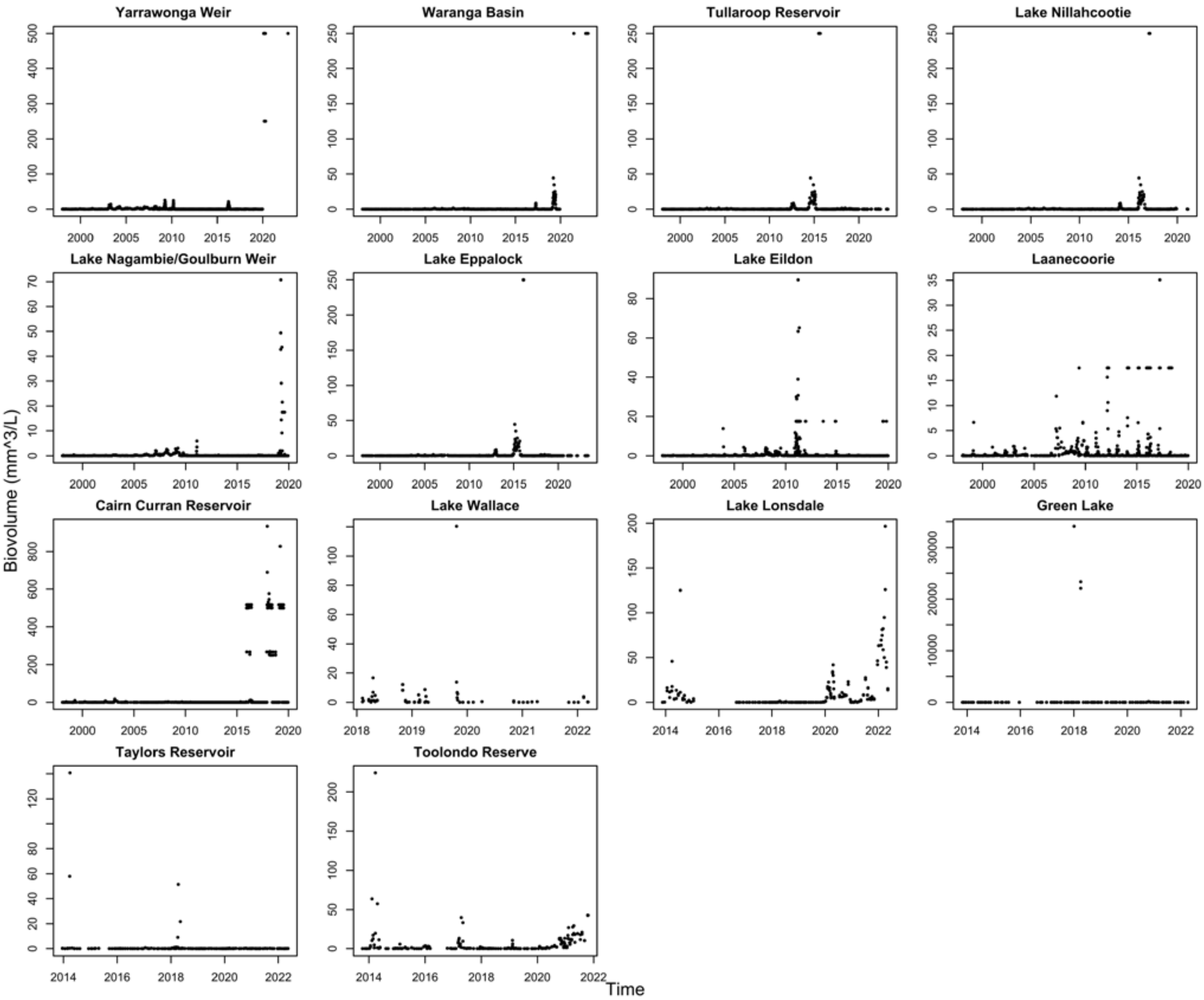


Figure K2: Raw bio-volume sampled from each water body (available for 14 water bodies monitored by Goulburn-Murray Water and GWM Water only). Each panel summarises a water body, denoted by the resultant direction and significance of trends in annual average, summer average, autumn average, winter average and spring average bio-volumes.

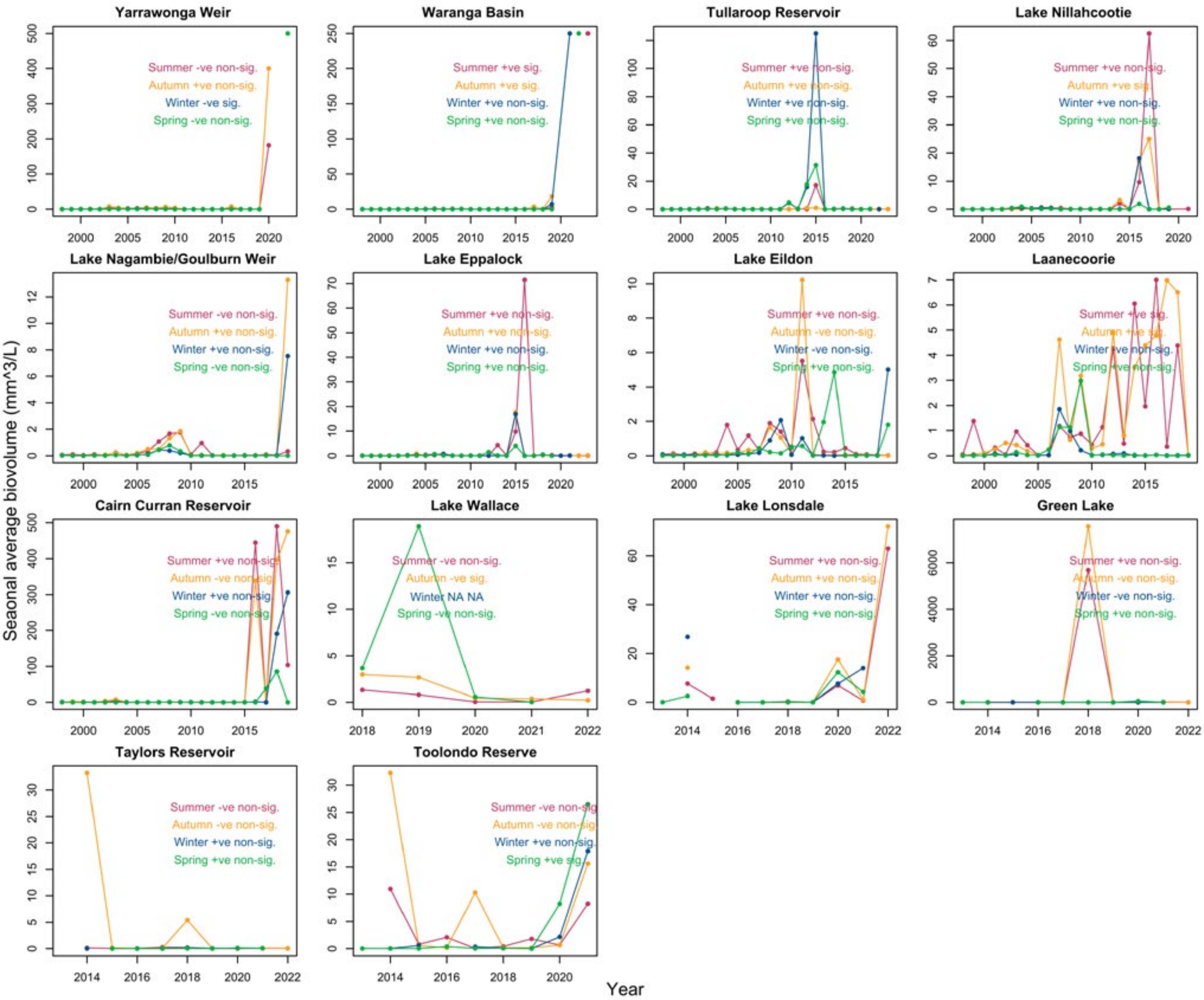


Figure K3: The seasonal average bio-volume sampled from each water body (available for 14 water bodies monitored by Goulburn-Murray Water and GWM Water only). The colours represent different averaging methods for the raw bio-volume samples for trend analyses: black – annual; pink – summer; orange – autumn; blue – winter; green – spring. Each panel summarises a water body, denoted by the resultant direction and significance of trends in annual average, summer average, autumn average, winter average and spring average bio-volumes. Lake Wallace has no winter sample so a trend cannot be estimated (shown as NA).

Appendix L:
Detailed results on the analysis of explanatory variables (Chapter 7)

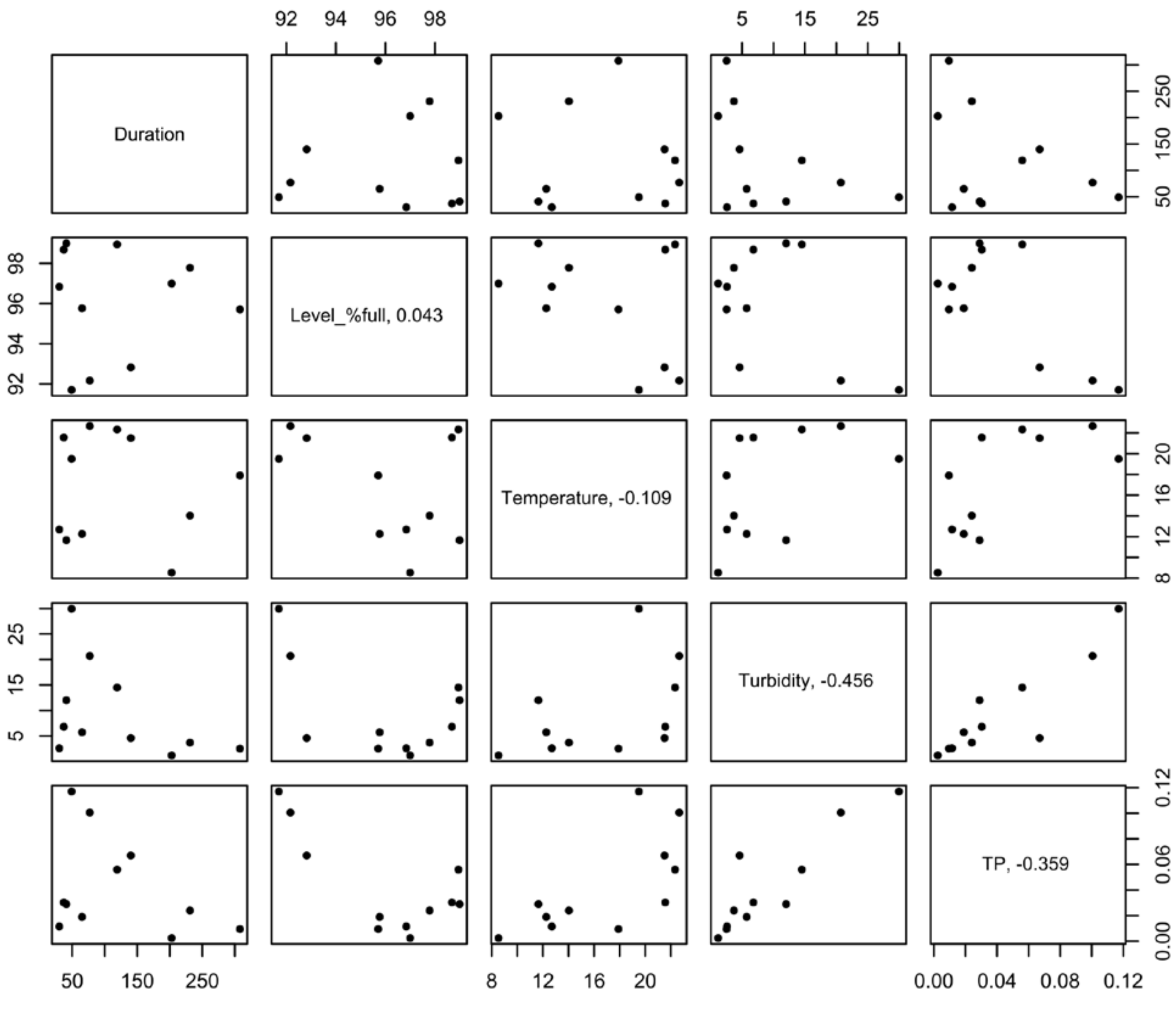


Figure L1: Scatter plots (first row) and linear correlations (diagonal) between BGA warning duration (days) and each of its four potential explanatory variables at the Tullaroop Reservoir: water level (as % of the full level), air temperature (deg C), turbidity (NTU) and TP (mg/L). For each warning event, all potential explanatory variables are summarised as the average of all values one month prior to the start of the event. Any appearance of ** denotes a statistically significant correlation between event duration and any potential explanatory variable at 0.05 level.

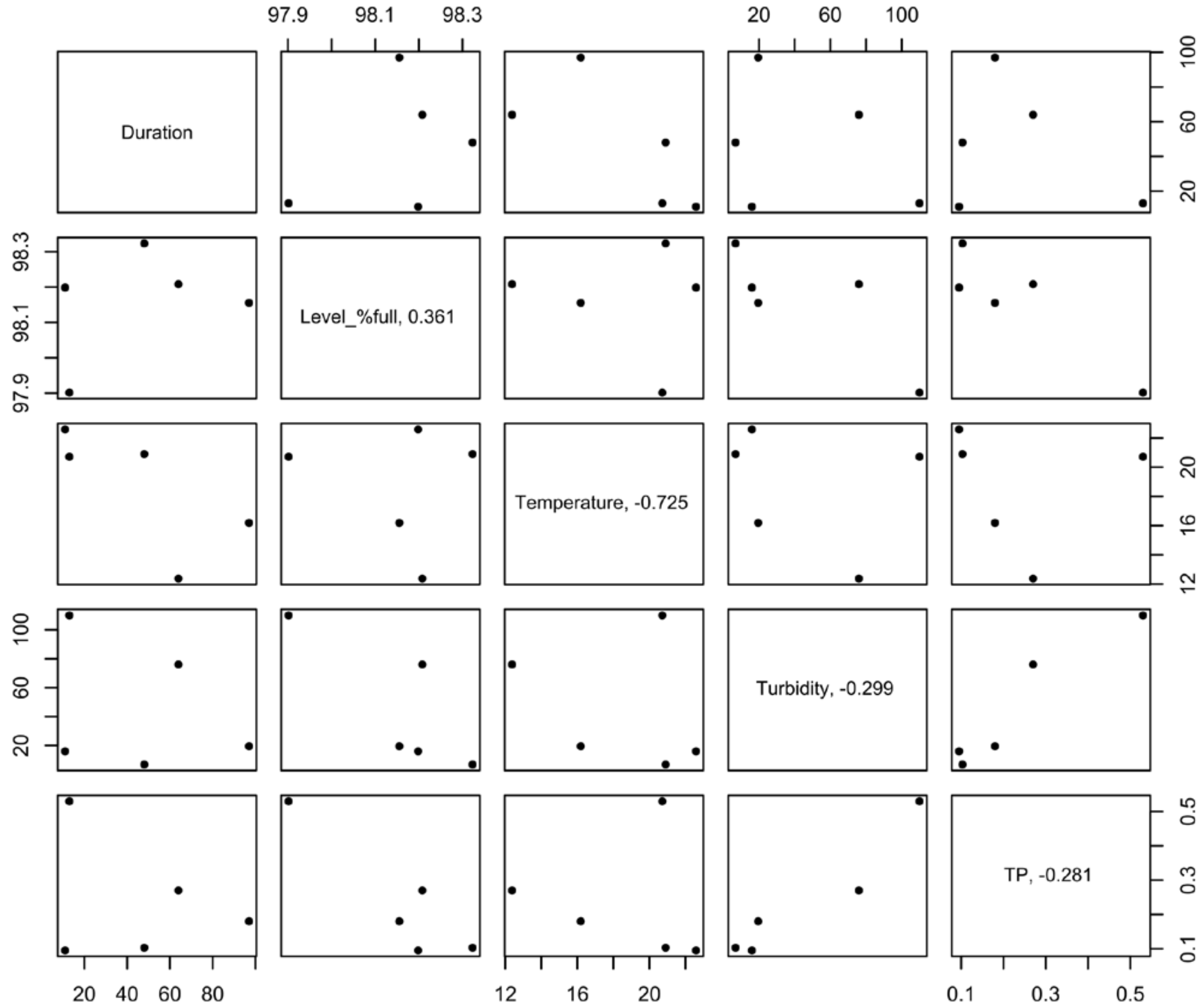


Figure L2: Scatter plots (first row) and linear correlations (diagonal) between BGA warning duration (days) and each of its four potential explanatory variables at Lake Lonsdale: water level (as % of the full level), air temperature (deg C), turbidity (NTU) and TP (mg/L). For each warning event, all potential explanatory variables are summarised as the average of all values one month prior to the start of the event. Any appearance of ** denotes a statistically significant correlation between event duration and any potential explanatory variable at 0.05 level.

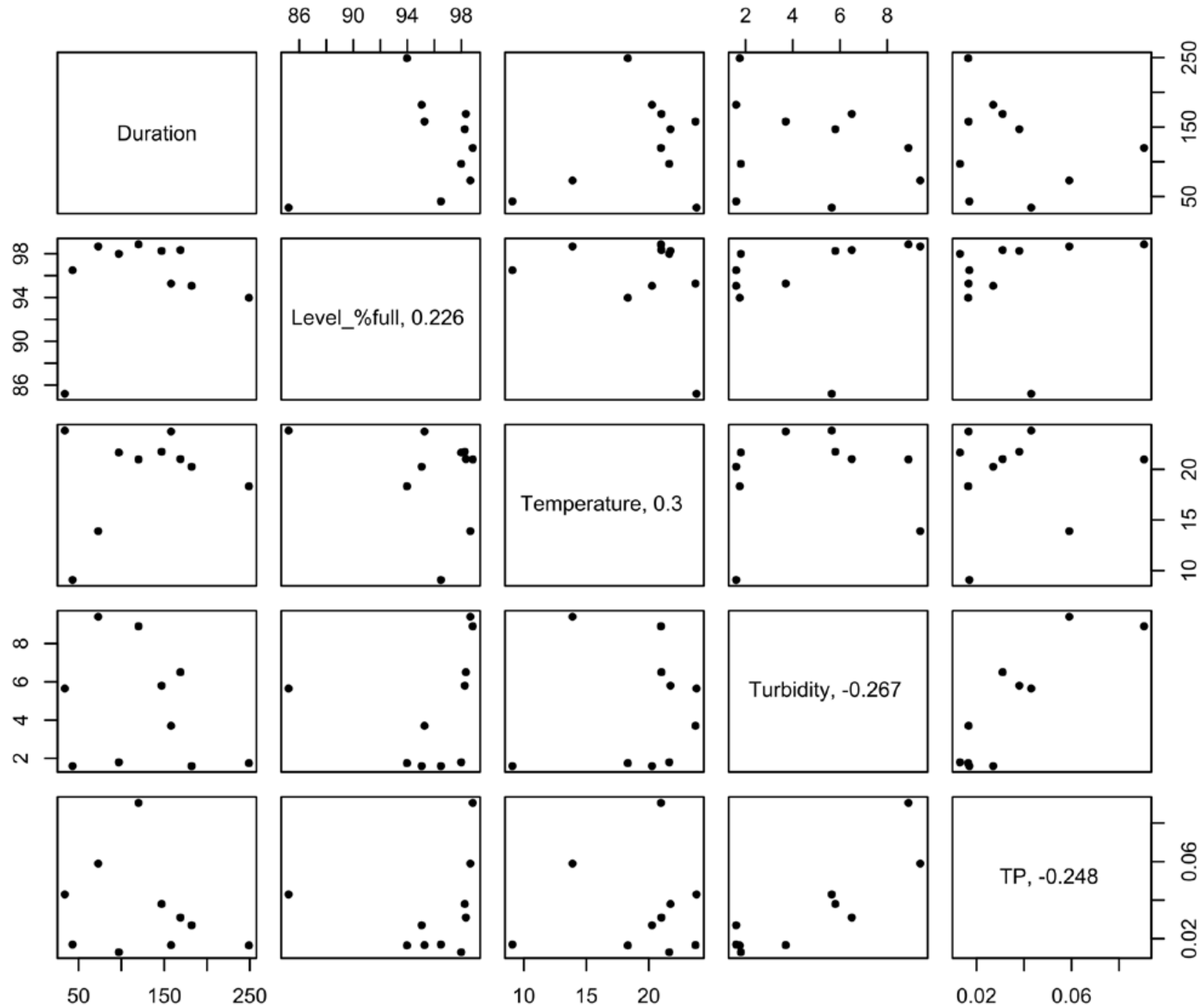


Figure L3: Scatter plots (first row) and linear correlations (diagonal) between BGA warning duration (days) and each of its four potential explanatory variables at Lake Eppalock: water level (as % of the full level), air temperature (deg C), turbidity (NTU) and TP (mg/L). For each warning event, all potential explanatory variables are summarised as the average of all values one month prior to the start of the event. Any appearance of ** denotes a statistically significant correlation between event duration and any potential explanatory variable at 0.05 level.

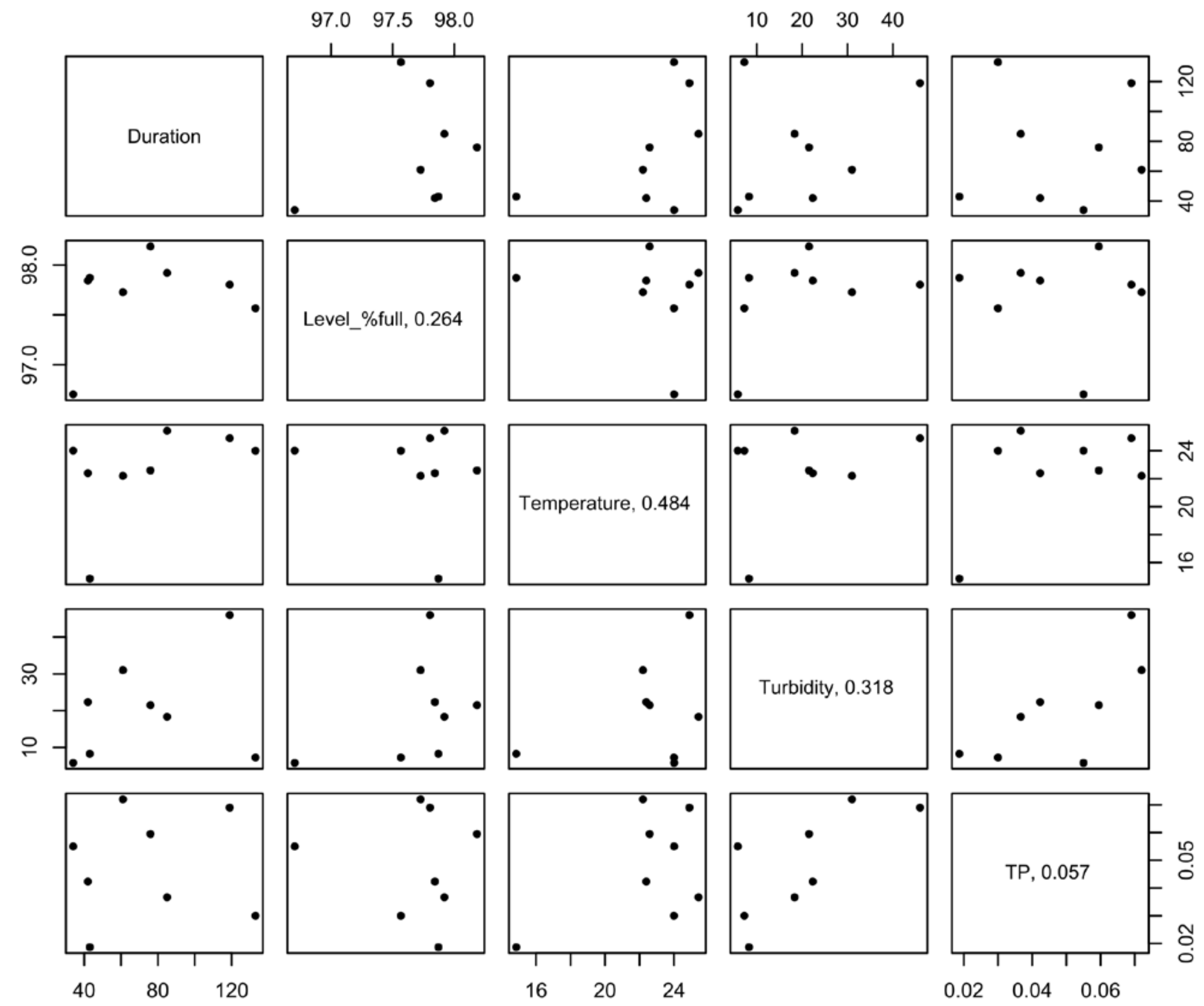


Figure L4: Scatter plots (first row) and linear correlations (diagonal) between BGA warning duration (days) and each of its four potential explanatory variables at the Laanecoori Reservoir: water level (as % of the full level), air temperature (deg C), turbidity (NTU) and TP (mg/L). For each warning event, all potential explanatory variables are summarised as the average of all values one month prior to the start of the event. Any appearance of ** denotes a statistically significant correlation between event duration and any potential explanatory variable at 0.05 level.

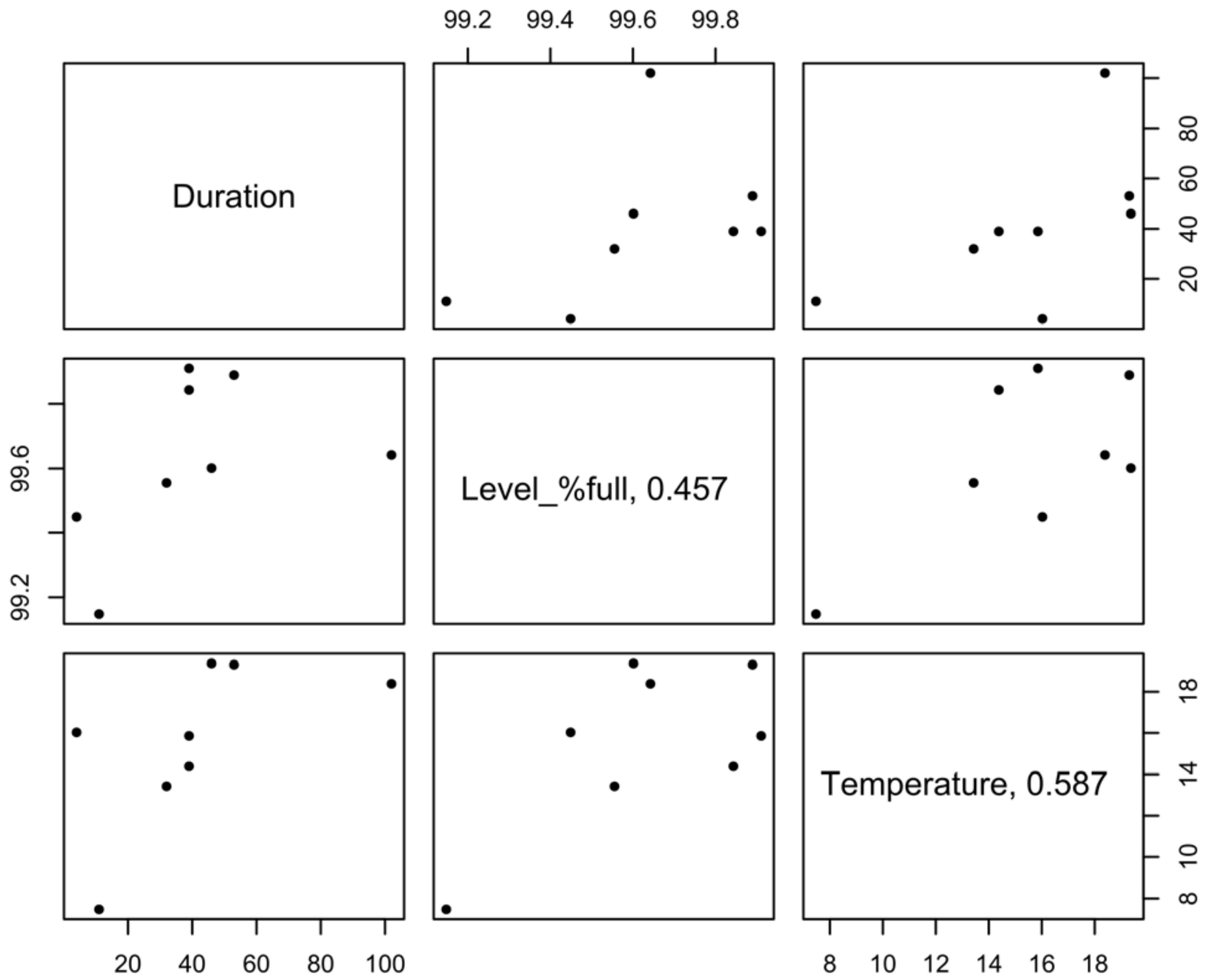


Figure L5: Scatter plots (first row) and linear correlations (diagonal) between BGA warning duration (days) and each of its four potential explanatory variables at Pykes Creek: water level (as % of the full level), air temperature (deg C). For each warning event, all potential explanatory variables are summarised as the average of all values one month prior to the start of the event. Turbidity and TP data are not available for this water body. Any appearance of ** denotes a statistically significant correlation between event duration and any potential explanatory variable at 0.05 level.

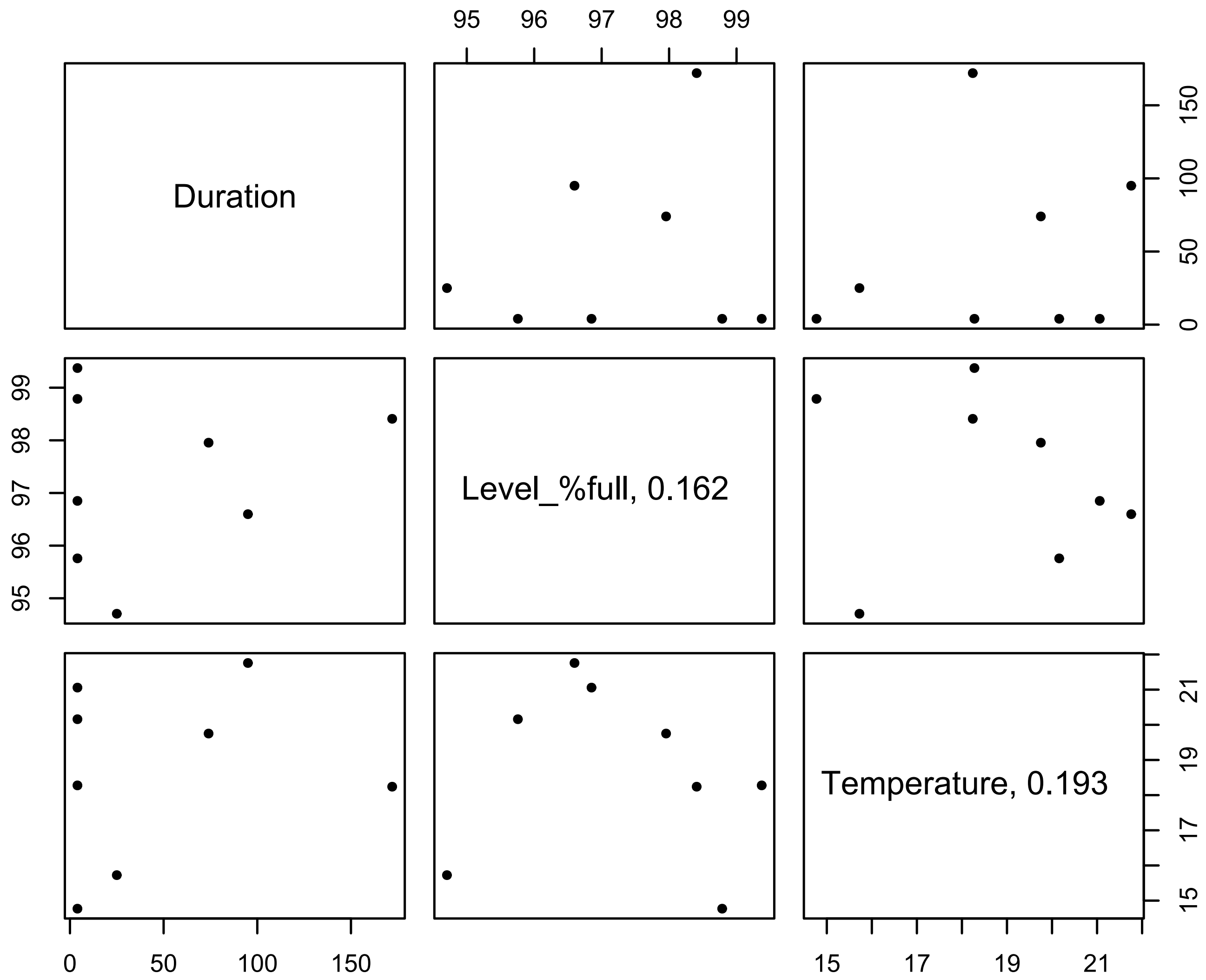


Figure L6: Scatter plots (first row) and linear correlations (diagonal) between BGA warning duration (days) and each of its four potential explanatory variables at Lake Glenmaggie: water level (as % of the full level), air temperature (deg C). For each warning event, all potential explanatory variables are summarised as the average of all values one month prior to the start of the event. Turbidity and TP data are not available for this water body. Any appearance of ** denotes a statistically significant correlation between event duration and any potential explanatory variable at 0.05 level.

Appendix M:
Further details on the analytical approach for quantifying DO event frequency, duration, and spatial distribution (Chapter 8)

An exhaustive search of continuous DO data were conducted on an extract of continuous water quality across the state from up to the end of 2021.

For each site with at least one high frequency DO reading:

- A mask was applied based on the selected hypoxic event definition to highlight periods where events were occurring. This included conditional testing of DO values with moving time windows per definition.
- Frequency was quantified by first identifying event start and end times. The number of event start times in a given year, at a site, was its frequency.
- The duration was quantified via the number of measurements between the start and end time of an event. Since the data were resampled to hourly, the duration is given in hours.
- For state-wide analyses, the durations and frequency of events at each site were compiled and analysed. For spatial distributions, they were plotted on bubble maps.

Appendix N:
Further details on the analytical approach for understanding the drivers of high turbidity events (Chapter 8)

- Turbidity data were resampled to the daily scale to be consistent with rainfall data. 80% of the data were used for training and 20% were used for validation.
- An event mask was created such that for all instances when the event threshold was exceeded, the value of the mask would be 1, and 0 for event non-occurrence.
- A first-order autoregression coefficient was used based on the previous time step's turbidity (i.e. yesterday's turbidity to predict today's occurrence of an event).
- The event mask was used to train a logistic regression model for each site. Since high turbidity events were rare (i.e. non-occurrence is very much greater than event occurrence), our training dataset suffered from imbalanced classes. A fitting method proposed by Firth (1993) addressed this issue. This is consistent with the output results. Confusion matrices measuring the true positive rates suggest that the model is overwhelmingly accurate at predicting event non-occurrence but performs less accurately for prediction occurrence.
- The average marginal effects, derived from the coefficients of the logistic model, were used as a proxy for the strength of a predictor. This allows for comparison across sites and predictor variables (Mood, 2009).
- The false negative rates, or how likely a true positive will be missed, are listed in Table N1. A lower value means more accurate predict of event occurrence.

Table N1: False negative rates associated with analysis of turbidity data.

Site	Threshold	False negative rate
224217B	0.95	0.19
223209A	0.95	0.26
225209A	0.95	0.38
226008A	0.95	0.74
232204B	0.95	0.47
235210A	0.95	0.41
223209A	0.99	0.69
224217B	0.99	0.17
225209A	0.99	0.90
226008A	0.99	0.57
232204B	0.99	0.67
235210A	0.99	0.82

Appendix O:
Detailed statistics of low and critical DO events across Victorian sites

Table O1: Duration and frequency of low and critical DO events.

		Critical DO event			Low DO event	
Site		Frequency (number per year)	Number	Average duration (hrs)	Frequency (number per year)	Number
221208A	0	0	0	0	0	0
221210A	0	0	0	0	0	0
221224A	0	0	0	0	0	0
221225A	0	0	0	0	0	0
222201B	0	0	0	0	0	0
222223A	0	0	0	0	0	0
223209A	56	0	1	59	0	2
223210A	0	0	0	0	0	0
223218A	0	0	0	0	0	0
224203B	0	0	0	86	0	1
224215A	0	0	0	0	0	0
224217B	0	0	0	0	0	0
224602A	166	4	5	200	13	13
225200A	0	0	0	0	0	0
225212A	0	0	0	89	0	3
225231A	0	0	0	0	0	0
225232A	0	0	0	0	0	0
225236A	38	0	1	260	0	1
225256A	32	0	1	154	0	3
226027B	0	0	0	0	0	0
226226A	0	0	0	0	0	0
226415B	24	0	1	136	0	5
227264A	459	1	8	689	1	10
227264B	89	0	2	169	1	18
227270A	243	3	37	383	6	61
227273A	0	0	0	0	0	0
229143A	337	0	1	337	0	1
229147A	0	0	0	235	0	1
229200B	0	0	0	0	0	0
229653A	0	0	0	0	0	0
230220B	43	0	3	189	1	29
230240A	151	2	47	213	7	136
232242A	72	0	2	101	1	13

		Critical DO event			Low DO event	
Site		Frequency (number per year)	Number	Average duration (hrs)	Frequency (number per year)	Number
233217D	114	0	3	264	1	8
233269A	0	0	0	79	0	1
233603A	189	1	3	211	4	21
233604A	144	0	1	127	0	2
234201B	0	0	0	0	0	0
235224A	0	0	0	0	0	0
235227A	0	0	0	89	0	1
235228A	0	0	0	0	0	0
235255A	81	1	11	212	3	28
235268A	93	1	7	220	1	11
235269A	43	0	3	91	1	14
235278A	91	0	2	95	1	9
235283A	84	12	12	132	30	31
236209A	0	0	0	0	0	0
237205A	0	0	0	0	0	0
237207A	325	0	1	1057	0	5
238204C	273	1	14	346	2	27
238206C	0	0	0	58	0	2
238210D	233	0	5	307	2	20
238219C	0	0	0	327	0	7
238228A	91	0	3	196	0	7
401212A	0	0	0	0	0	0
401229A	0	0	0	35	1	1
401230A	0	0	0	0	0	0
402205A	0	0	0	0	0	0
403210B	0	0	0	0	0	0
403222A	0	0	0	0	0	0
403223A	0	0	0	0	0	0
403230A	0	0	0	0	0	0
403233A	0	0	0	0	0	0
403241A	0	0	0	0	0	0
403244B	0	0	0	0	0	0
403250A	0	0	0	44	0	1
403254A	0	0	0	0	0	0

		Critical DO event			Low DO event	
Site		Frequency (number per year)	Number	Average duration (hrs)	Frequency (number per year)	Number
403601A	0	0	0	0	0	0
404204B	256	1	15	300	3	45
404210A	123	0	4	205	2	25
404214A	158	1	11	264	2	31
404216A	0	0	0	150	2	6
404219A	0	0	0	0	0	0
404224B	0	0	0	85	0	1
404244A	116	0	4	190	1	9
405200A	0	0	0	0	0	0
405201B	0	0	0	0	0	0
405203C	0	0	0	39	0	1
405218B	0	0	0	0	0	0
405226B	448	2	5	383	4	13
405228A	0	0	0	150	1	3
405232C	40	0	1	94	0	3
405232D	348	0	1	232	0	4
405259A	0	0	0	50	0	3
405269A	152	2	8	352	3	13
405270A	0	0	0	69	0	1
405271B	48	0	1	62	0	2
405276A	260	0	1	317	0	1
405282B	0	0	0	72	0	2
405307A	0	0	0	68	0	2
405323A	0	0	0	40	0	1
405324A	24	0	1	465	0	1
405335A	83	1	1	448	1	1
406200C	107	0	1	247	1	14
406215B	364	1	13	305	2	28
406219A	682	1	17	487	2	32
406275A	218	0	6	366	1	22
406276A	108	0	3	203	2	23
406277A	141	1	17	203	3	45
406278A	151	1	8	171	2	37
406279A	150	1	12	223	2	30
406756A	43	0	1	56	0	1

	Critical DO event			Low DO event		
Site		Frequency (number per year)	Number	Average duration (hrs)	Frequency (number per year)	Number
407229C	0	0	0	391	0	2
407320A	120	1	8	201	1	18
407321A	40	0	2	271	1	9
407322A	354	0	4	345	1	10
407323A	108	1	10	348	2	32
407330A	0	0	0	40	0	1
407331A	0	0	0	0	0	0
407332A	416	0	1	226	1	6
407333A	0	0	0	49	0	3
407368A	45	0	1	128	0	3
407373A	207	2	12	185	5	34
407379A	0	0	0	361	1	6
407380A	0	0	0	0	0	0
407382A	0	0	0	62	0	1
407384A	167	10	44	311	13	52
407608C	0	0	0	106	1	2
408203B	359	1	2	313	3	8
409396A	99	1	4	187	4	12
409397A	70	1	2	155	1	4
409398A	173	1	5	297	2	15
409399A	0	0	0	0	0	0
414200A	259	0	1	627	0	1
414201B	550	0	1	408	0	2
415200D	329	0	5	376	2	24
415202D	0	0	0	0	0	0
415246A	0	0	0	154	2	21
415247B	124	1	12	276	1	17
415256A	284	1	7	243	2	31

References

- Baldwin, D. S. (2022). *Impacts of the 2019/2020 Black Summer Bushfires on Water Quality in North-East Victoria and Gippsland (unpublished).*
- Beavis, S. G., Wong, V. N., Mosley, L. M., Baldwin, D. S., Latimer, J. O., Lane, P., & Lal, A. (2023). Water quality risks in the Murray-Darling basin. *Australasian Journal of Water Resources,* 27(1), 85-102.
- Blaszczak, J. R., Koenig, L. E., Mejia, F. H., Gómez-Gener, L., Dutton, C. L., Carter, A. M., Grimm, N. B., Harvey, J. W., Helton, A. M., & Cohen, M. J. (2023). Extent, patterns, and drivers of hypoxia in the world's streams and rivers. *Limnology and Oceanography Letters,* 8(3), 453-463. https://doi.org/10.1002/lol2.10297
- Brunke, M., & Gonser, T. (1997). The ecological significance of exchange processes between rivers and groundwater. *Freshwater Biology*, 37(1), 1-33. https://doi.org/10.1046/j.1365-2427.1997.00143.x
- Bureau of Meteorology. (2012). *Geofabric V2*. ftp://ftp.bom.gov.au/anon/home/geofabric/
- Bureau of Meteorology. (2014). *Geofabric Groundwater Cartography V2.1.1*. http://www.bom.gov.au/metadata/catalogue/19115/ANZCW0503900106#dataset-constraints
- Butcher, R. W., Pentelow, F. T. K., & Woodley, J. W. A. (1927). The Diurnal Variation of the Gaseous Constituents of River Waters. *Biochemical Journal*, 21(4), 945-957. https://doi.org/10.1042/bj0210945
- Delage, F. P. D., & Power, S. B. (2020). The impact of global warming and the El Niño-Southern Oscillation on seasonal precipitation extremes in Australia. *Climate Dynamics*, 54(9), 4367-4377. https://doi.org/10.1007/s00382-020-05235-0
- Department of Energy Environment and Climate Action. (2022a). *Farm Dam Boundaries*. https://discover.data.vic.gov.au/dataset/farm-dam-boundaries1
- Department of Energy Environment and Climate Action. (2022b). *Index of Stream Condition*. https://discover.data.vic.gov.au/dataset/index-of-stream-condition1
- Department of Environment Land Water & Planning. (2018). *Groundwater Salinity (DELWP)*. https://data2.cerdi.edu.au/dataset/vvg_vaf_watertable_salinity_tds100_20170508_raw_3857
- Department of Environment Land Water and Planning, Bureau of Meteorology, Commonwealth Scientific and Industrial Research Organisation, & The University of Melbourne. (2020a). *Victoria's Water in a Changing Climate*.
- Department of Environment Land Water and Planning (2020b). *Guidelines for Assessing the Impact of Climate Change on Water Availability in Victoria*.
- Ebel, B. A., Moody, J. A., & Martin, D. A. (2022). Post-fire temporal trends in soil-physical and -hydraulic properties and simulated runoff generation: Insights from different burn severities in the 2013 Black Forest Fire, CO, USA. *Science of The Total Environment,* 802, 149847. https://doi.org/10.1016/j.scitotenv.2021.149847
- Elliott, J. A. (2012). Is the future blue-green? A review of the current model predictions of how climate change could affect pelagic freshwater cyanobacteria. *Water Research*, 46(5), 1364-1371. https://doi.org/10.1016/j.watres.2011.12.018
- EPA Victoria. (2021). 1992: *Guide to the Environment Reference Standard*. https://www.epa.vic.gov.au/about-epa/publications/1992
- Firth, D. (1993). Bias reduction of maximum likelihood estimates. *Biometrika*, 80(1), 27-38. https://doi.org/10.1093/biomet/80.1.27
- Gómez-Gener, L., Lupon, A., Laudon, H., & Sponseller, R. A. (2020). Drought alters the biogeochemistry of boreal stream networks. *Nature Communications*, 11(1), 1795. https://doi.org/10.1038/s41467-020-15496-2
- Gourley, C. J. P., & Weaver, D. M. (2012). Nutrient surpluses in Australian grazing systems: management practices, policy approaches, and difficult choices to improve water quality. *Crop and Pasture Science*, 63(9), 805-818. https://doi.org/10.1071/CP12154
- Grant, S. B., Fletcher, T. D., Feldman, D., Saphores, J.-D., Cook, P. L. M., Stewardson, M., Low, K., Burry, K., & Hamilton, A. J. (2013). Adapting Urban Water Systems to a Changing Climate: Lessons from the Millennium Drought in Southeast Australia. *Environmental Science & Technology*, 47(19), 10727-10734. https://doi.org/10.1021/es400618z
- Green, M. B., Pardo, L. H., Bailey, S. W., Campbell, J. L., McDowell, W. H., Bernhardt, E. S., & Rosi, E. J. (2021). Predicting high-frequency variation in stream solute concentrations with water quality sensors and machine learning. *Hydrological Processes*, 35(1), e14000. https://doi.org/10.1002/hyp.14000
- Gruber, N., & Galloway, J. N. (2008). An Earth-system perspective of the global nitrogen cycle. Nature, 451(7176), 293-296. https://doi.org/10.1038/nature06592
- Gudmundsson, L., Leonard, M., Do, H. X., Westra, S., & Seneviratne, S. I. (2019). Observed Trends in Global Indicators of Mean and Extreme Streamflow. *Geophysical Research Letters*, 46(2), 756-766. https://doi.org/10.1029/2018GL079725
- Guo, D., Lintern, A., Webb, J. A., Ryu, D., Liu, S., Bende - Michl, U., Leahy, P., Wilson, P., & Western, A. (2019). Key factors affecting temporal variability in stream water quality. *Water Resources Research*, 55(1), 112-129.

- Iverson, L. R., Prasad, A. M., Matthews, S. N., & Peters, M. (2008). Estimating potential habitat for 134 eastern US tree species under six climate scenarios. *Forest Ecology and Management*, 254(3), 390-406. https://doi.org/10.1016/j.foreco.2007.07.023
- Jakob D., Osburn L., Hope, P., & Smith L. (2020). *Short duration, heavy rainfall is intensifying, but not everywhere, and not all the time – A literature review.* http://www.bom.gov.au/research/publications/researchreports/BRR-049.pdf
- Jasechko, S. (2018). Plants turn on the tap. *Nature Climate Change*, 8(7), 562-563. https://doi.org/10.1038/s41558-018-0212-z
- Johnston, S. G., & Maher, D. T. (2022). Drought, megafires and flood - climate extreme impacts on catchment-scale river water quality on Australia's east coast. *Water Research*, 218, 118510. https://doi.org/10.1016/j.watres.2022.118510
- Keenan, T. F., Hollinger, D. Y., Bohrer, G., Dragoni, D., Munger, J. W., Schmid, H. P., & Richardson, A. D. (2013). Increase in forest water-use efficiency as atmospheric carbon dioxide concentrations rise. *Nature*, 499(7458), 324-327. https://doi.org/10.1038/nature12291
- Kendall, M.G. (1957). "Rank Correlation Methods." Biometrika 44 (1/2): 298. doi:10.2307/2333282.
- Lintern, A., Kho, N., Peterson, T., & Guo, D. (2023). Shifts in stream salt loads during and after prolonged droughts. *Hydrological Processes*, 37(6), e14901. https://doi.org/10.1002/hyp.14901
- Lintern, A., Webb, J. A., Ryu, D., Liu, S., Bende-Michl, U., Waters, D., Leahy, P., Wilson, P., & Western, A. W. (2018a). Key factors influencing differences in stream water quality across space. *WIREs Water, 5*(1), e1260. https://doi.org/10.1002/wat2.1260
- Lintern, A., Webb, J. A., Ryu, D., Liu, S., Waters, D., Leahy, P., Bende-Michl, U., & Western, A. W. (2018b). What Are the Key Catchment Characteristics Affecting Spatial Differences in Riverine Water Quality? *Water Resources Research*, 54(10), 7252-7272. https://doi.org/https://doi.org/10.1029/2017WR022172
- Lund, U. (1999). Least circular distance regression for directional data. *Journal of Applied Statistics*, 26(6), 723-733.
- Malone, B., & Searle, R. (2022). *Soil and Landscape Grid National Soil Attribute Maps - Clay (3" resolution) - Release 2. v4.* CSIRO. Data Collection. . https://doi.org/10.25919/hc4s-3130
- Mann, H.B. (1945). "Nonparametric Tests against Trend." Econometrica 13 (3): 245–259. doi:10.2307/1907187.
- McNeil, D. G., & Closs, G. P. (2007). Behavioural responses of a south-east Australian floodplain fish community to gradual hypoxia. *Freshwater Biology*, 52(3), 412-420. https://doi.org/https://doi.org/10.1111/j.1365-2427.2006.01705.x
- Mood, C. (2009). Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It. *European Sociological Review*, 26(1), 67-82. https://doi.org/10.1093/esr/jcp006
- Morris, M., & Eckard, R. (2010). *Victorian Climate Change Adaptation Program (VCCAP) Final Project Report*.
- Nyman, P., Sheridan, G. J., Smith, H. G., & Lane, P. N. J. (2011). Evidence of debris flow occurrence after wildfire in upland catchments of south-east Australia. *Geomorphology*, 125(3), 383-401. https://doi.org/10.1016/j.geomorph.2010.10.016
- Nyman, P., Smith, H. G., Sherwin, C. B., Langhans, C., Lane, P. N. J., & Sheridan, G. J. (2015). Predicting sediment delivery from debris flows after wildfire. *Geomorphology*, 250, 173-186. https://doi.org/10.1016/j.geomorph.2015.08.023
- Pánek, T. (2020). Landslides and related sediments. In Alderton, D., Elias, S. A. (Eds) Encyclopedia of Geology, 2nd edn (pp. 708-728). Academic Press.
- Peck, A. J. (1993). Salinity. In McTainsh, G. H., Boughton, W.C. (Eds) Land Degradation Processes in Australia (pp. 243-270). Longman Cheshire.
- Peterson, T. J., Saft, M., Peel, M. C., & John, A. (2021). Watersheds may not recover from drought. Science, 372(6543), 745-749. https://doi.org/doi:10.1126/science.abd5085
- Rauniyar, S. P., & Power, S. B. (2020). The Impact of Anthropogenic Forcing and Natural Processes on Past, Present, and Future Rainfall over Victoria, Australia. *Journal of Climate*, 33(18), 8087-8106. https://doi.org/10.1175/JCLI-D-19-0759.1
- Raupach, M., Briggs, P., Haverd, V., King, E., Paget, M., & Trudinger, C. (2009). A*ustralian Water Availability Project (AWAP): CSIRO marine and atmospheric research component: final report for phase 3*.
- Raupach, M., Briggs, P., Haverd, V., King, E., Paget, M., & Trudinger, C. (2012). Australian Water Availability Project. Canberra, Australia: CSIRO Marine and Atmospheric Research. http://www.csiro.au/awap
- Robinne, F.-N., Hallema, D. W., Bladon, K. D., Flannigan, M. D., Boisramé, G., Bréthaut, C. M., Doerr, S. H., Di Baldassarre, G., Gallagher, L. A., Hohner, A. K., Khan, S. J., Kinoshita, A. M., Mordecai, R., Nunes, J. P., Nyman, P., Santín, C., Sheridan, G., Stoof, C. R., Thompson, M. P., Waddington, J. M., & Wei, Y. (2021). Scientists' warning on extreme wildfire risks to water supply. *Hydrological Processes*, 35(5), e14086. https://doi.org/10.1002/hyp.14086
- Rust, A. J., Hogue, T. S., Saxe, S., & McCray, J. (2018). Post-fire water-quality response in the western United States. *International Journal of Wildland Fire*, 27(3), 203-216. https://doi.org/10.1071/WF17115

- Rutherfurd, I. D., Kenyon, C., Thoms, M., Grove, J., Turnbull, J., Davies, P., & Lawrence, S. (2020). Human impacts on suspended sediment and turbidity in the River Murray, South Eastern Australia: Multiple lines of evidence. *River Research and Applications*, 36(4), 522-541. https://doi.org/10.1002/rra.3566
- Sadayappan, K., Kerins, D., Shen, C., & Li, L. (2022). Nitrate concentrations predominantly driven by human, climate, and soil properties in US rivers. *Water Research*, 226, 119295. https://doi.org/10.1016/j.watres.2022.119295
- Saft, M., Gardiya, H., Weligamage, G., Peel, M., Peterson, T., Brown, R., Jordan, P., Morden, R., & Fowler, K., 2023,. (2023). *Victorian Water and Climate dataset: long-term streamflow, climate, and vegetation observation records and catchment attributes*. https://doi.org/10.5281/zenodo.7527565
- Saft, M., Western, A. W., Zhang, L., Peel, M. C., & Potter, N. J. (2015). The influence of multiyear drought on the annual rainfall-runoff relationship: An Australian perspective. *Water Resources Research*, 51(4), 2444-2463. https://doi.org/10.1002/2014WR015348
- Smith, A. P., Western, A. W., & Hannah, M. C. (2013). Linking water quality trends with land use intensification in dairy farming catchments. *Journal of Hydrology*, 476, 1-12. https://doi.org/10.1016/j.jhydrol.2012.08.057
- Sun, F., Roderick, M. L., Lim, W. H., & Farquhar, G. D. (2011). Hydro-climatic projections for the Murray-Darling Basin based on an ensemble derived from Intergovernmental Panel on Climate Change AR4 climate models. *Water Resources Research*, 47(12). https://doi.org/10.1029/2010WR009829
- Viscarra Rossel, R., Chen, C., Grundy, M., Searle, R., Clifford, D., Odgers, N., Holmes, K., Griffin, T., Liddicoat, C., & Kidd, D. (2014a). *Soil and Landscape Grid National Soil Attribute Maps - Total Nitrogen (3" resolution) - Release 1. v5.* CSIRO. Data Collection. https://doi.org/10.4225/08/546F617719CAF
- Viscarra Rossel, R., Chen, C., Grundy, M., Searle, R., Clifford, D., Odgers, N., Holmes, K., Griffin, T., Liddicoat, C., & Kidd, D. (2014b). *Soil and Landscape Grid National Soil Attribute Maps - Total Phosphorus (3" resolution)* - Release 1. v5. CSIRO. Data Collection. https://doi.org/10.4225/08/546F617719CAF
- Vose, J. M., & Klepzig, K. D. (2013). *Climate change adaptation and mitigation management options: A guide for natural resource managers in southern forest ecosystems*. CRC Press.
- Webb, L. B., Whetton, P. H., Bhend, J., Darbyshire, R., Briggs, P. R., & Barlow, E. W. R. (2012). Earlier wine-grape ripening driven by climatic warming and drying and management practices. *Nature Climate Change*, 2(4), 259-264. https://doi.org/10.1038/nclimate1417
- White, M., Griffioen, P., & Newell, G. (2020). *Multi-temporal native vegetation extent for Victoria.* Arthur Rylah Institute for Environmental Research Technical Report Series, Issue.
- Whitworth, K. L., Baldwin, D. S., & Kerr, J. L. (2012). Drought, floods and water quality: Drivers of a severe hypoxic blackwater event in a major river system (the southern Murray–Darling Basin, Australia). *Journal of Hydrology, 450-451*, 190-198. https://doi.org/10.1016/j.jhydrol.2012.04.057
- Wilks, D. S. (2006). On "Field Significance" and the False Discovery Rate. *Journal of Applied Meteorology and Climatology*, 45(9), 1181-1189. https://doi.org/10.1175/JAM2404.1
- Winter, C., Nguyen, T. V., Musolff, A., Lutz, S. R., Rode, M., Kumar, R., & Fleckenstein, J. H. (2023). Droughts can reduce the nitrogen retention capacity of catchments. Hydrology and Earth System Sciences, 27(1), 303-318. https://doi.org/10.5194/hess-27-303-2023
- Zhang, X. S., Amirthanathan, G. E., Bari, M. A., Laugesen, R. M., Shin, D., Kent, D. M., MacDonald, A. M., Turner, M. E., & Tuteja, N. K. (2016). How streamflow has changed across Australia since the 1950s: evidence from the network of hydrologic reference stations. *Hydrology and Earth System Sciences*, 20(9), 3947-3965.
- Zhi, W., Ouyang, W., Shen, C., & Li, L. (2023). Temperature outweighs light and flow as the predominant driver of dissolved oxygen in US rivers. *Nature Water*, 1(3), 249-260. https://doi.org/10.1038/s44221-023-00038-z
- Zhu, M., Wang, J., Yang, X., Zhang, Y., Zhang, L., Ren, H., Wu, B., & Ye, L. (2022). A review of the application of machine learning in water quality evaluation. *Eco-Environment & Health*, 1(2), 107-116. https://doi.org/10.1016/j.eehl.2022.06.001

deeca.vic.gov.au