A detailed streamflow and groundwater salinity dataset for Muttama Creek Catchment, NSW, Australia

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Abstract. Dryland salinity remains a major global natural resource management concern, and which is amplified in Australia. However, limited detailed space-time data sets with observations of stream and groundwater salinity has constrained a deep understanding of the range of processes that can lead to dryland salinity problems in landscapes. The aim of this study is to report on the open dataset resulting from a 14-year data collection effort in a subcatchment of the Murrumbidgee catchment in New South Wales, Australia. Over a 14-year period a series of different sampling campaigns has resulted in a large dataset with hydrogeochemical data which includes both in-situ (field) data and post laboratory analysis of major anions and cations. This data is augmented with observed groundwater levels and publicly available streamflow and climate data. The data set covers 23 groundwater sample sites and 39 surface water sites. Because the data was collected by four distinct groups and over many years, we analyse to see if this has caused a bias in the dataset. In addition, we show the major spatial and temporal trends to provide an overview of the dataset. The dataset is made open access to encourage further research and the current paper shows the richness of the collected data and opportunities for further research.

1 Introduction

Dryland and irrigation salinity has long been a major natural resource management concern in Australia (Jolly et al., 2001; White et al., 2009; Scanlon et al., 2007; Walker et al., 2002; Finlayson et al., 2010). Globally, the success of management of salinity, while extensively documented, has remained patchy (Leblanc et al., 2012). As a result, in Australia, the volume of research and number of publications in this area has decreased significantly in recent years (Figure 1). This is partly due to the effect of the millenium drought on groundwater levels and the consequent reduction in the appearance of salinity effects in the landscape (McFarlane et al., 2016). However, the reduction in research is also because of the increased understanding that salinity processes are more complex than previously recognised. For example, salinity processes can vary substantially across the landscape (Conyers et al., 2008) and the processes of salt delivery to the stream also varies in the landscape (Summerell et al., 2006; Hughes et al., 2007) and is dependent on landscape characteristics (van Dijk et al., 2008; Dahlhaus et al., 2010). As a result, the investment required to improve the understanding and increase the effectiveness of management is considerable and this has resulted in a reduction of the number of studies after the large investment in the late 1990s and 2000s in Australia.
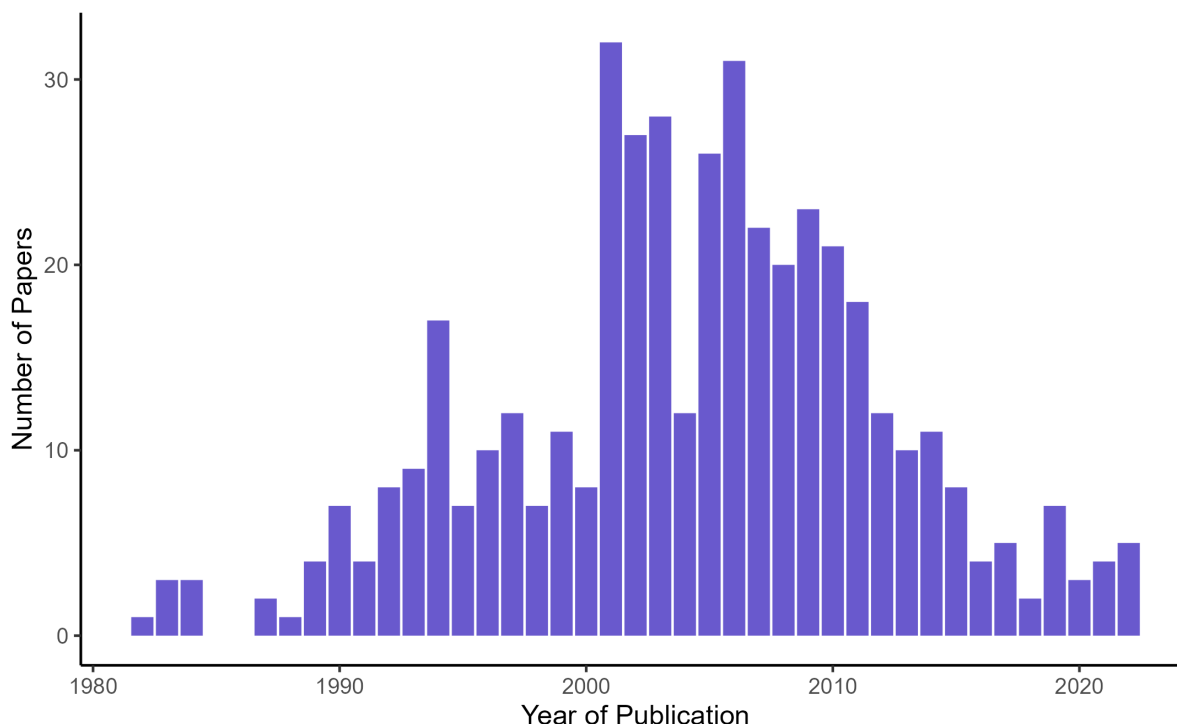
Figure 1. Number of papers on the Web of Science related to the search terms (Dryland Salinity) AND Australia, 1980 - 2022

The poor spatial and timescale distribution of water quality datasets has long been an obstacle to measuring trends in salinity. Studies such as Jolly et. al. (2001) and White et. al (2009) used large historical datasets to detect broadscale trends over large periods throughout the Murray Darling Basin (MDB). This work identified that southern and eastern dryland regions in the Murray Darling Basin have rising salinity trends that were worse in areas of low rainfall (White et al., 2009; Jolly et al., 2001). However, the ion composition varied greatly throughout the Murray Darling Basin (MDB) (White et al., 2009). More specifically, Conyers et al. (2008) tried to isolate which areas in the middle portion of the Murrumbidgee catchment acted as sources of salinity, as well as whether this was predominantly marine cyclic salts (NaCl) as previously assumed, or whether salts from mineral weathering were also involved (e.g. Ca, Mg, HCO_3). While both are captured in the bulk measurement of electrical conductivity (EC), a rise in marine cyclic salts can be a major source of osmotic stress, whereas mineral weathering salts are far less harmful and are more likely to precipitate at reasonably low concentrations (Conyers et al., 2008). The ratio of Cl:HCO_3 ions was identified as the best indicator of the source of salinity, with Cl^- acting as a measure of marine cyclic salts and HCO_3^- acting as a measure of mineral weathering salts. The Muttama catchment was specifically identified as a candidate for future research as ion concentrations appeared to result in a change from east to west, correlating with the underlying geology and their mineral composition.

It is clear from these examples that detailed spatial and temporal datasets are key to understanding different hydrogeochemical processes in the landscape (e.g. Cartwright et al., 2010; Dahlhaus et al., 2010), but overall publicly available datasets on dryland
40   salinity in Australia remain limited to detailed data from small experimental catchments (< 100 ha) (Summerell et al., 2006; Hughes et al., 2007) or sparse government datasets from official monitoring (i.e. WaterNSW WaterInsights platform) which tend to be limited in hydrogeochemical data. Part of this is related to the sensitivity of the data given the relationship with possible land values. However, as the understanding of salinity occurrence grows, this argument is less valid. Making data more widely available would increase the opportunities for research and increase our understanding of dryland salinity processes.

45   Without regular and expensive automated sampling, field campaigns to collect water quality data tend to be "snapshot" activities (Grayson et al., 1997; Breuer et al., 2015; Lyon et al., 2008; Cartwright et al., 2010; Lintern et al., 2018) which can be biased due to the over representation of low flow conditions (Lessels and Bishop, 2020). Even the analyses of substantial government databases (Lintern et al., 2018) are likely to be biased in this way. This means that overall there are limited streamflow and groundwater salinity data sets that combine multiple locations across a significant time period and that combine
50   a range of flow characteristics.

The aim of this paper is to present and describe the space time dimensions and basic relationships of a complex groundwater and surface water hydrogeochemistry dataset that was collected over a 14 year period in a 1000 km^2 agricultural catchment in New South Wales, Australia. The Muttama catchment, which is the focus of this paper, provides a microcosm of groundwater and surface water salinity variability in Australia. Focusing on a medium size catchment in greater detail creates opportunities
55   to test whether sources of salinity can be traced back to specific areas of land.

This paper gives a description of the dataset to facilitate open access of the dataset, but does not analyse the physiochemical relationships in the data in detail. This will be analysed in follow-up papers and was partly analysed in an earlier thesis (Akter, 2018). The main aim of this paper is to make the data set accessible to other researchers to encourage further research in this catchment and in salinity in general.

60   # 2   Methods

2.1   Muttama catchment

The 1000 km^2 Muttama creek catchment (Figure 2) is located in the Mid-Murrumbidgee catchment area of NSW in south eastern Australia. The landscape is undulating with elevation variations ranging from 227 - 719 m. Muttama creek flows north-south through the length of the catchment towards the Murrumbidgee River near Gundagai. The main township, Cootamundra
65   is located in the upper half of the catchment. The dominant land use type of this catchment is about 93% agriculture, dominated by winter-spring cropping and pasture. Mean annual rainfall (1891-2024) in the catchment is 654 mm for the longest running Bureau of Meteorology Landgrove station (station 073022), while potential evapotranspiration far exceeds this total.

Streamflow is measured continuously by WaterNSW, the state agency responsible for water data collection, at three locations in the catchment: Coolac, station no. 410044, the main downstream point, and Berthong, station no. 41000207 and Jindalee,
70   station no. 410112 on two branches above the Cootamundra township. This data is available as open access via the WaterNSW
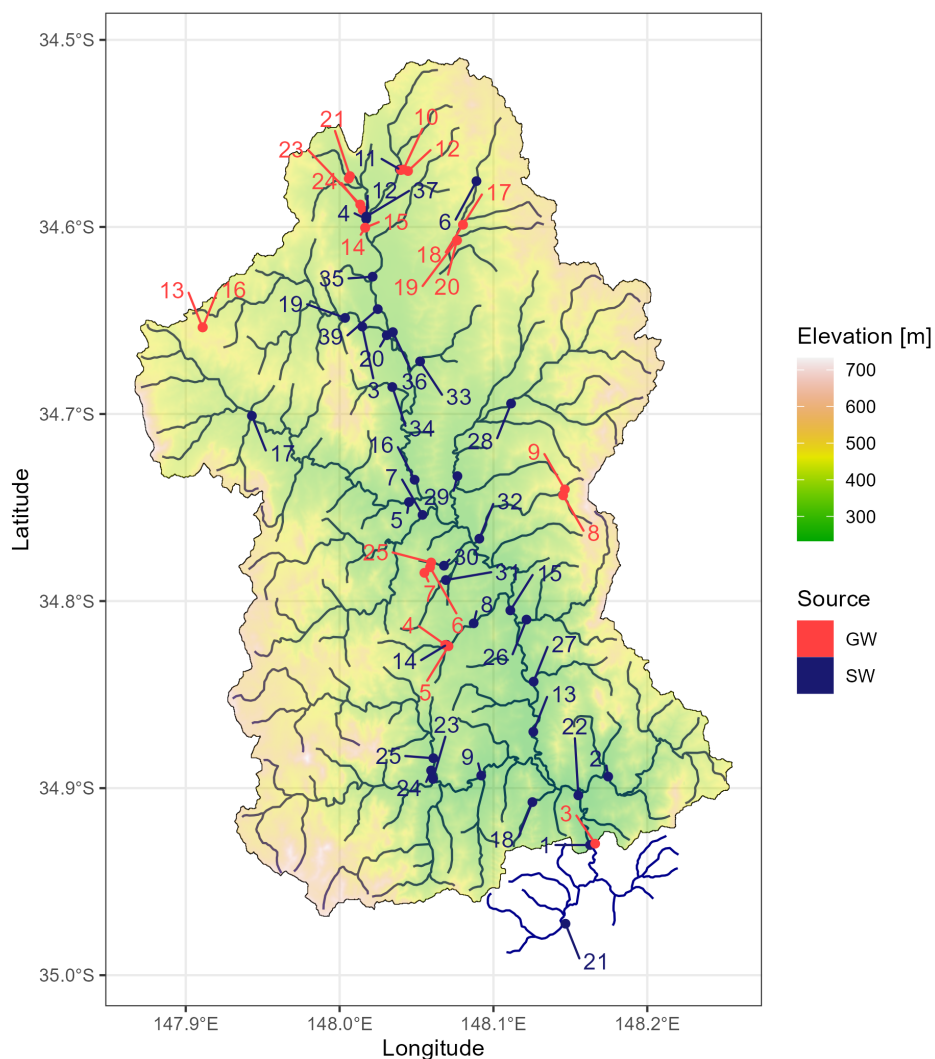
Figure 2. Muttama Catchment Sampling Locations with Elevation. Symbol colour indicates whether location was a groundwater or surface water source, with blue being surface water and brown/orange being groundwater. The numbers on the map represent the sample location number.

WaterInsights platform or through the Bureau of Meteorology. Here, we only use the data from the Coolac station as a comparison.

The depth to the nearest groundwater table varies across the Muttama catchment and it ranges from < 2 m to 20 m below ground level (Department of Environment and Climate Change NSW, 2009). Deep groundwater in the catchment occurs mostly in fractured rock aquifers common on the eastern, and western fringes of the catchment. In contrast, shallow groundwater is

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associated with unconfined alluvial, colluvial, and eluvial aquifers. Some aquifers in the northern part of this catchment show artesian behavior (Webb, 1999; Akter, 2018).

Saline areas of the catchment tend to be associated with geological heterogeneity, primarily the sedimentary materials in the west and rhyolite on the northwest side (Conyers et al., 2008). Overall, Muttama creek is a significant salt contributor to the downstream Murrumbidgee river with suggested contributions of around 58% from cyclic sources and 42% salts originating from mineral weathering (Conyers et al., 2008).

2.2 Data Collection

2.2.1 Data Sources

The water quality dataset contains data from 4 main sampling sources related to four distinct groups of "people" doing the sample collection. The term "people" is used loosely, as it mainly related to four different types of sampling campaigns, which potentially had differences in the rigour of the sampling campaign (quality control, types of samples taken, training of the people taking the samples). These groups are designated as:

- Source 1: Data from the PhD study by Akter (2018).

- Source 2: Data from the sampling campaign of two former students, the PhD from Lessels (2014) and unpublished data from another student, E. Milne.

- Source 3: A dataset collected by undergraduate and postgraduate students as part of field trips in different units of study at the University of Sydney is identified as "Student data". This data was sampled "ad-hoc" during the field trip period using standard sampling protocols as described for the data from Akter (2018).

- Source 4: Data from several autosamplers installed in the catchment during the PhD from Lessels (2014). Because these samples were not taken by a "person" and were taken on a flow weighted basis, we separated the data from the "grab" samples in the other methods. These samples are also missing field measurements, as these were only analysed in the laboratory.

Overall, 1160 water samples were collected from 62 sample locations over the 2010 - 2024 period. However, not all sites were sampled at all times and not all samples were fully analysed for all hydrogeochemical variables. Both surface water and groundwater samples were collected at 23 groundwater sample sites and 39 surface water sites. These are distributed across the catchment, depending on standing water availability and access.

In addition to the water quality dataset, data from 23 groundwater data loggers is provided from the same groundwater sample sites as in the hydrogeochemical dataset.

Table 1. Variables measured in the field and laboratory.

Field measurements	Lab repeat	Anions	Cations	Others
pH	pH	Cl^-	Na^+	Total Nitrogen
EC (Electrical conductivity)	EC	HCO_3^-	Mg^{2+}	Total Phosphorus
SPC (temperature corrected EC)	SPC	SO_4^{2-}	K^+	
Temperature			Ca^{2+}	
Alkalinity (HCO_3^-)				
Dissolved Oxygen (DO)				
Turbidity				

2.2.2 Hydrogeochemical Variables

105 The overall structure of the hydrogeochemical dataset consists of repeated measurements over time at multiple locations in Muttama catchment. For each location the name of the location and the spatial coordinates were recorded in decimal degrees (Longitude = x and Latitude = y) as well as whether the location was a groundwater or a surface water location. The names of the locations are fairly random and basic locality indicators, which cannot be interpreted exactly.

The data for each location consist of up to six variables which were measured in the field (Table 1). These were complemented

110 by laboratory analysis, which repeated some of the field measurements, and for additional major anion and cation variables (Ca, Mg, Na, K, Cl, SO4, HCO3), and total Nitrogen (N) and total Phosphorus (P) for part of the sample set. Some other variables were infrequently measured and are not included in the data set.

The variables pH, EC, SPC (specific conductance: field temperature corrected EC), Temperature, and in some cases DO and Turbidity were measured using a range of field probes. All field probes measured pH, EC, Temperature and calculated SPC.

115 Early measurements (samples up to November 2014) used a YSI probe that included a turbidity and DO probe (YSI 6600 and YSI 600 for surface and groundwater, respectively). Later groundwater samples (After November 2014) used a different YSI probe (YSI ProPlus multi-parameter) that only included a DO probe. Finally, (after mid 2019) surface water and groundwater sampling used a Xylem Exo probe with DO, pH, EC, Temperature and SPC. Some of the variability in the field measurements might be due to this variation in the field instrumentation, because the exact instrument information was not recorded with the

120 data.

Anions in most of the samples were analysed using high-performance liquid chromatography method (Dionex P680 HPLC) and cations were measured on acidified samples using an Inductively Coupled Plasma Optical Emission Spectrometer (ICP-OES, Varian 720-ES) at the University of Sydney (Akter, 2018). Duplicate samples in the analysis had a reported relative percentage difference (RPD) lower than 5% in part of the sample dataset (Akter, 2018). Some of the later samples and the

125 student sample set (Source 3) were analysed by a commercial laboratory (ALS Environmental, Smithfield, NSW). Alkalinity

concentrations were generally measured in the field within 24h of collection using a HACH digital titrator (model 16900) (Akter, 2018) up to 2017 and by the commercial laboratory after this.

The hydrogeochemical data is stored on the University of Sydney escholarship repository: doi.org/10.25910/m0wp-8890

2.3 Continuous variables

130 The logger data, which collected groundwater pressure levels at 15 min and later at 2 hour intervals, were adjusted for the length of the cable and the height of the standpipe above the ground level. They were subsequently summarised to raw daily values using an R script (`SummariseDailyData.R`), which is stored with the raw data in the Open Science Foundation (OSF) repository associated with this paper https://doi.org/10.17605/OSF.IO/BEUWK.

The loggers in the field were uncalibrated. Due to logger failures, gaps occur in the daily data, followed by replacement of 135 the faulty loggers. In some cases the cable length was adjusted and this was recorded in the field notes. Overall, this resulted in data with gaps and sometimes shifts in the recorded logger data.

Manual water level measurements were taken at each manual sampling date to allow calibration of the logger data. To correct the groundwater logger data, the daily data was matched to the observed data using linear regression, if more than 3 manual observed data were available and slope and intercept of the regression had a p-value < 0.1. If there were less than 3 140 manual observed data points for the specific logger an adjustment to the data was based on the difference between the average observed data and the average recorded water levels. Otherwise no adjustment was made. This is slightly tricky: After the manual observations are made, the well is purged and the logger is temporarily removed from the well. This data (during the temporarily removal of the logger during the purging and subsequent recovery of the groundwater level) is removed from the logger data series. As a result, there is no direct time match between the logger data series and the manual observations. 145 However, the data showed that, in most cases, the groundwater level recovered within 24 hrs. To explain this more clearly the pseudocode below describes the process.

The code used to match the manually observed data with the logger data is in the script `Match_obs_logger_data.R`, which is stored with the raw data in the Open Science Foundation (OSF) repository associated with this paper https://doi.org/10.17605/OSF.IO/BEUWK.

150 After the automated process, two of the groundwater level data series still had substantial discrepancies in some sections of the data. This was most likely due to the a lack of observed data for the specific logger. A final manual correction was applied. As this process is based on judgement of the data by the authors of this paper, we documented this in detail in the supplementary material.

The final corrected data that is published with this paper on https://doi.org/10.17605/OSF.IO/BEUWK includes a column 155 which describes whether the data is based on the automatic correction or a further manual correction.

Algorithm 1 Pseudo code cleaning groundwater level data

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if sufficient points $\geq$ 3 **then**

    run a regression between interpolated depth and observed depth

    check the p-values of the slope and intercept

    if the slope is not significant (using p $\geq$ 0.10) **then**

        use only the intercept to correct the logger data

    else

        if the intercept is not significant, but the slope is **then**

            use only the slope to correct the logger data

        else

            use both slope and intercept of the regression to correct the logger data

        end if

    end if

else

    There are not enough values for a regression, use mean difference between logged and observed value to correct the logger data

end if
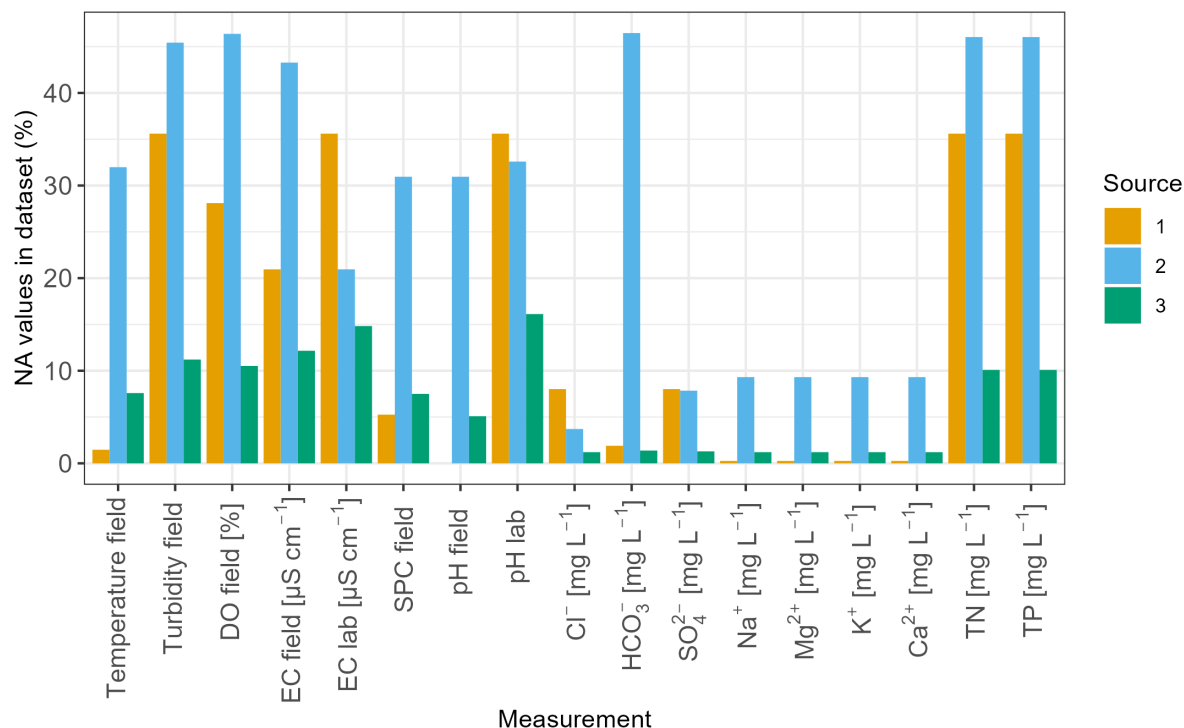
Figure 3. Distribution of missing values for the different data sources and measurement types. Most of these missing values were because not all the variables were analysed for all the samples, see the explanation in the article text

2.4 Boxplots and maps

Using the most complete data, boxplots and spatial maps were generated to highlight the spatial and temporal variation in the data set. The boxplots visually highlight empirical differences in the data.

The mean concentration and interquartile range (25th - 75th percentile) of the concentration data distributions were calculated to give an indication of variation of the data in the spatial maps.

All graphs and maps were produced using R version 4.3.1 (R Core Team, 2023). All code can be found in the associated github repository, as part of the markdown document for this paper.

3 Results

3.1 Distribution of missing Values
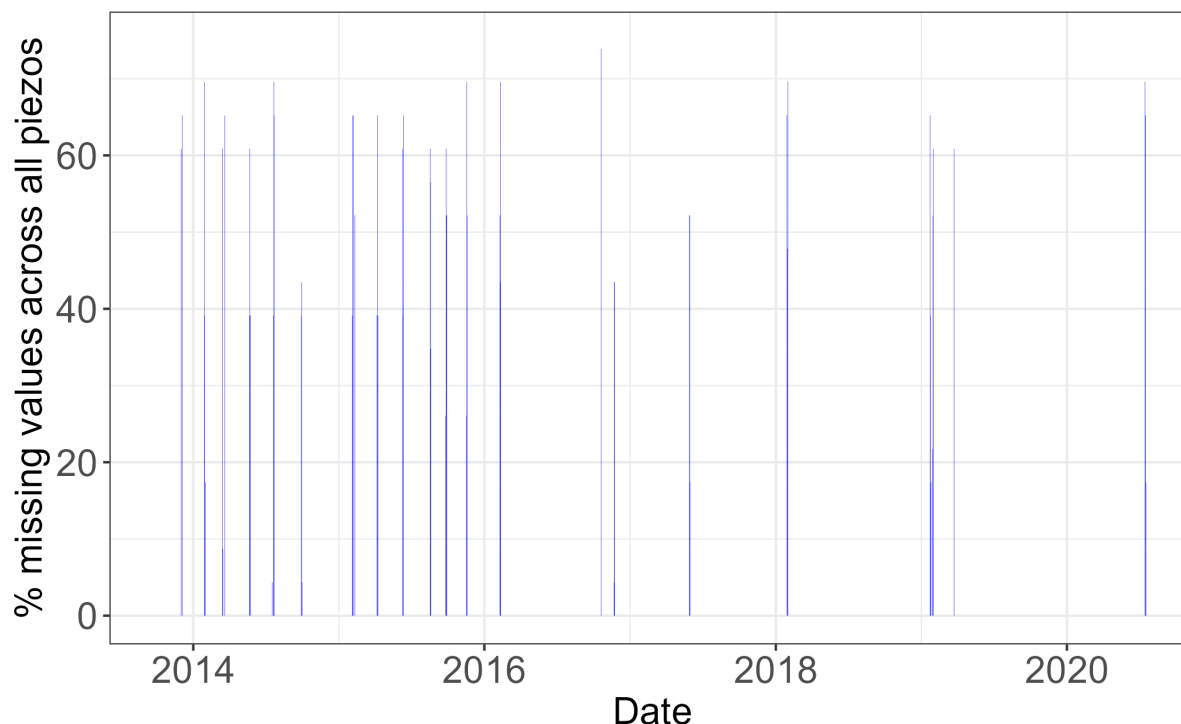
Figure 4. Percent missing values for the groundwater data across all piezometers. Thicker blue lines mean a group of missing values on closely related dates

165   In the hydrogeochemistry data, data source 3 was the most complete in terms of variables analysed, because in this set more variables were analysed in the commercial lab (Fig 3). Some of the variables analysed in the commercial lab were not analysed with the equipment at the University of Sydney. However, source 3 had the smallest number of overall samples. Source 2 has the most incomplete data points. Source 4 has a very consistent number of missing values, possibly because not all samples were analysed in the set. For source 2, the missing data suggests that for many of the samples only a few of the variables were

170   measured and analysed as highlighted above. In the data from source 2, almost 50% of samples are incomplete in terms of the measurement of all the variables in Table 2. Similarly, source 1 had more incomplete data, because some of the minor elements were not analysed. The field recorded variables pH, EC, SPC and Temperature were the most complete as they were generally measured directly in the field. Thus the distribution of the NA values in the overall data set is mostly a reflection of the time period of sampling and the change in methodology over the 14 years of sampling.

175   In the groundwater level time series, the missing data relate mostly to logger failures and the different times that wells were instrumented. Rather than giving a full breakdown by well location, the overall level of completeness of the series is displayed (Fig 4).

3.2 Temporal Distribution of Data
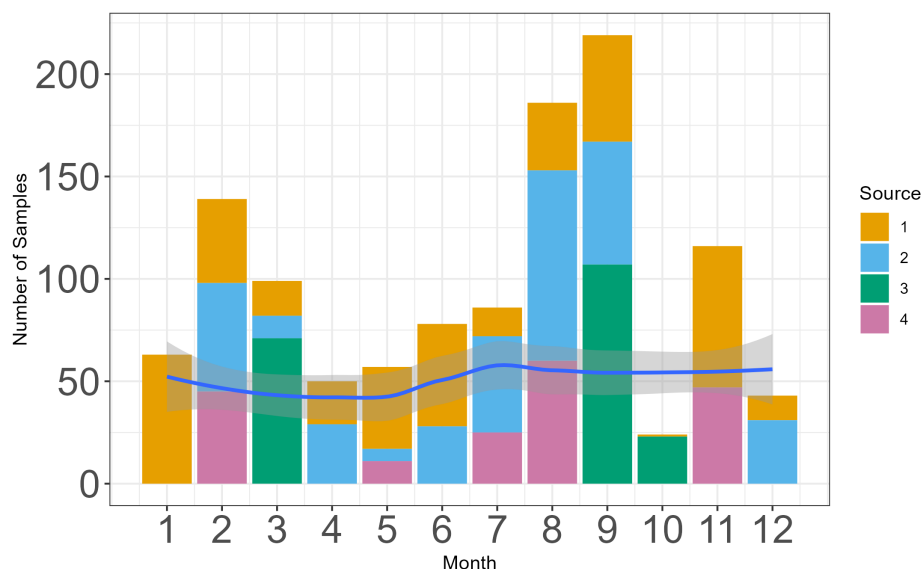
Figure 5. Distribution of samples throughout the year (total number of samples collected during each month) with the blue line representing the average monthly rainfall during the study period.

Overall the water quality sampling appears to have a reasonable distribution across all months (Fig 5), therefore seasonal
180 trends should be identifiable in the data. Average rainfall data (1995 - 2022) does not indicate any major seasonal trends, although there is a slight dominance of rainfall in the early Austral Spring (months 9 and 10, September and October). This also explains the higher number of samples because, more sampling trips were organised in this period, and spatially more channels could be sampled for surface water. The timing of source 3 (the student data) is the result of the yearly field trips, which tended to occur at approximately the same time of the year in early March and late September or early October, coinciding with the
185 University semester breaks.

The number of samples collected in each year relative to the different sources changes throughout the years reflecting the duration of the different studies and funding cycles (Fig 6); however the data is still well-distributed enough that overall trends should be clear. In addition, some of the sample volumes can be related to the occurrence of rainfall, as in drier years several of the channels would be dry and no sampling of surface water could occur.
190 Consistent groundwater sampling commenced later in the project, which means that there are very few groundwater samples before 2013. In contrast, the autosamplers were installed early in the project and there are no samples from this source after 2013.

Surface water samples were reasonably well distributed across the flow distribution, measured at the Coolac station (410044), with only a possible bias towards periods of medium flow. This is most likely since many of the upstream surface water
195 sampling points are often completely dry during periods of low flow at Coolac, and therefore cannot be sampled. Conversely,
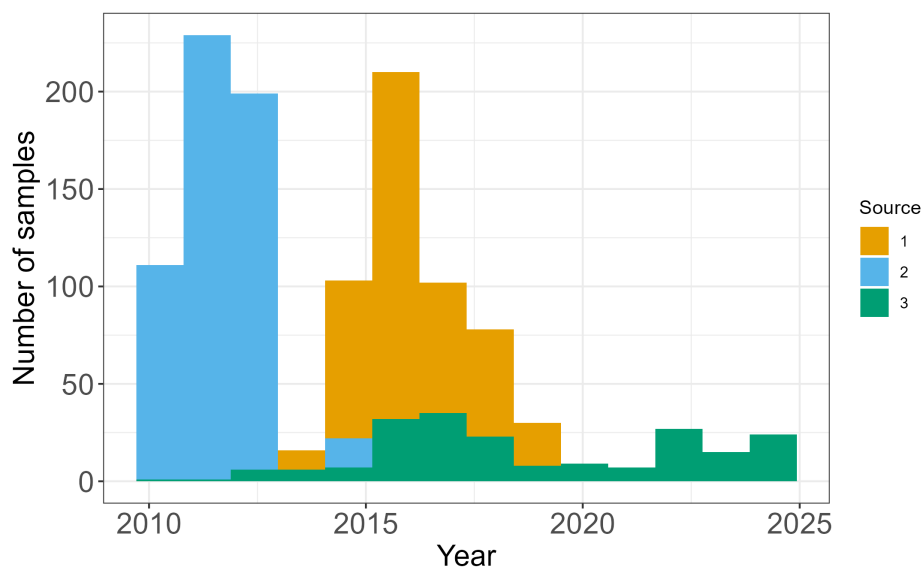
Figure 6. Distribution of samples over the study period (total number of samples collected during each year).

there are no manual samples during high or very high flow as during flood situations sampling was dangerous and restricted by work health and safety considerations. The samples at high flow are all from our automated sampling.

3.2.1 Comparisons of Groundwater samples with Surface water samples

The summary of the samples (Table 2) highlights the range of the data for the different variables. Obviously, surface water will
200 record higher DO values, while groundwater recorded higher EC and SPC values. The rest of the variables have fairly similar ranges for both groundwater and surface water. Both total P and total N are low across the catchment samples, with only a few outliers related to specific locations and dates.

Groundwater samples have quite a distinctive hydrogeochemical signature compared to the surface water samples (Fig 8). Since 'Source 1' collected most of the groundwater samples, this results in differences between data collection sources. Field
205 SPC measurements were used to represent EC since these samples had the fewest missing data. There also appears to be a slight bias towards lower EC values for sampling group 2, but this is likely because these samples were collected during two very wet years in 2010 and 2011 (Fig 6) and are mostly associated with high flow values (Fig 7).

3.2.2 Groundwater level data

The overall corrected groundwater timeseries shows the shorter time that loggers were installed in the wells (Fig 9), associated
210 with the PhD thesis from Akter (2018). It also indicates that the manual data can not always be fully matched with the logger data, but further corrections are likely to be speculation.
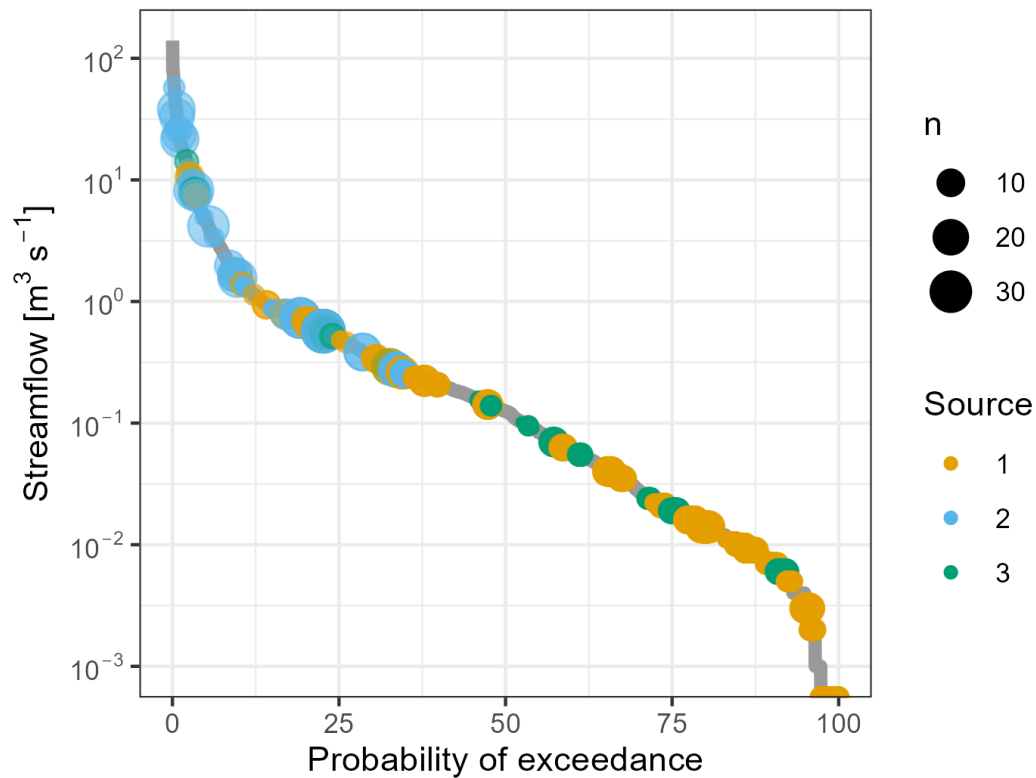
Figure 7. Sample distribution on flow duration curve derived from flow data at the Coolac NSW government station.

In general, shallow groundwater occurs between 1 and 5 meters below the surface and is responsive to dry and wet periods. Some of the wells have positive pressures, resulting in occasional groundwater levels above the ground surface, such as at GW10, GW12, GW13 and GW21 (Fig 9).

3.3 Spatial variation

Table 2. Summary statistics for elements measured in the field

Element	GW			SW		
	Mean	Min	Max	Mean	Min	Max
Temperature field	17.4	11.4	30.8	15.9	4.1	32.9
Turbidity field	30.2	0.1	90.0	13.1	0.5	51.6
DO field [%]	20.1	-3.2	70.7	86.8	10.4	220.2
EC field [µS cm^{-1}]	4006	457	14385	1411	117	4163
EC lab [µS cm^{-1}]	NA	NA	NA	1292	1	5230
SPC field	4667	347	17799	1246	61	6046
pH field	7.3	6.0	8.8	8.0	6.7	10.0
pH lab	NA	NA	NA	7.6	6.8	8.5
Cl^- [mg L^{-1}]	1218.3	73.0	4960.7	294.2	8.9	4577.1
HCO_3^- [mg L^{-1}]	599.5	68.0	1115.0	333.9	25.6	782.0
SO_4^{2-} [mg L^{-1}]	261.1	0.0	1319.2	48.4	0.0	987.6
Na^+ [mg L^{-1}]	492.1	17.8	2283.7	122.1	7.1	866.2
Mg^{2+} [mg L^{-1}]	167.6	6.4	654.6	66.7	1.4	276.9
K^+ [mg L^{-1}]	4.4	0.0	30.8	7.6	1.0	43.8
Ca^{2+} [mg L^{-1}]	256.4	16.3	1354.2	61.6	2.3	682.1
TN [mg L^{-1}]	3.7	0.6	10.3	1.2	0.0	4.9
TP [mg L^{-1}]	0.3	0.0	1.0	0.5	0.0	5.5
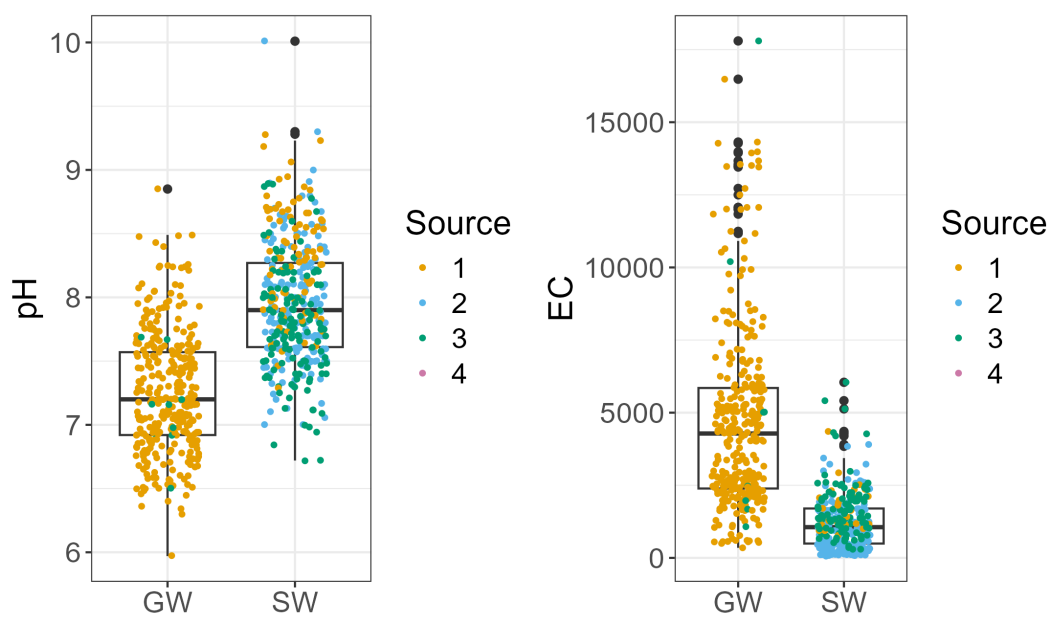
Figure 8. Difference in pH and EC for groundwater and surface water samples. The source of the data (the sampling group) is indicated with colour.
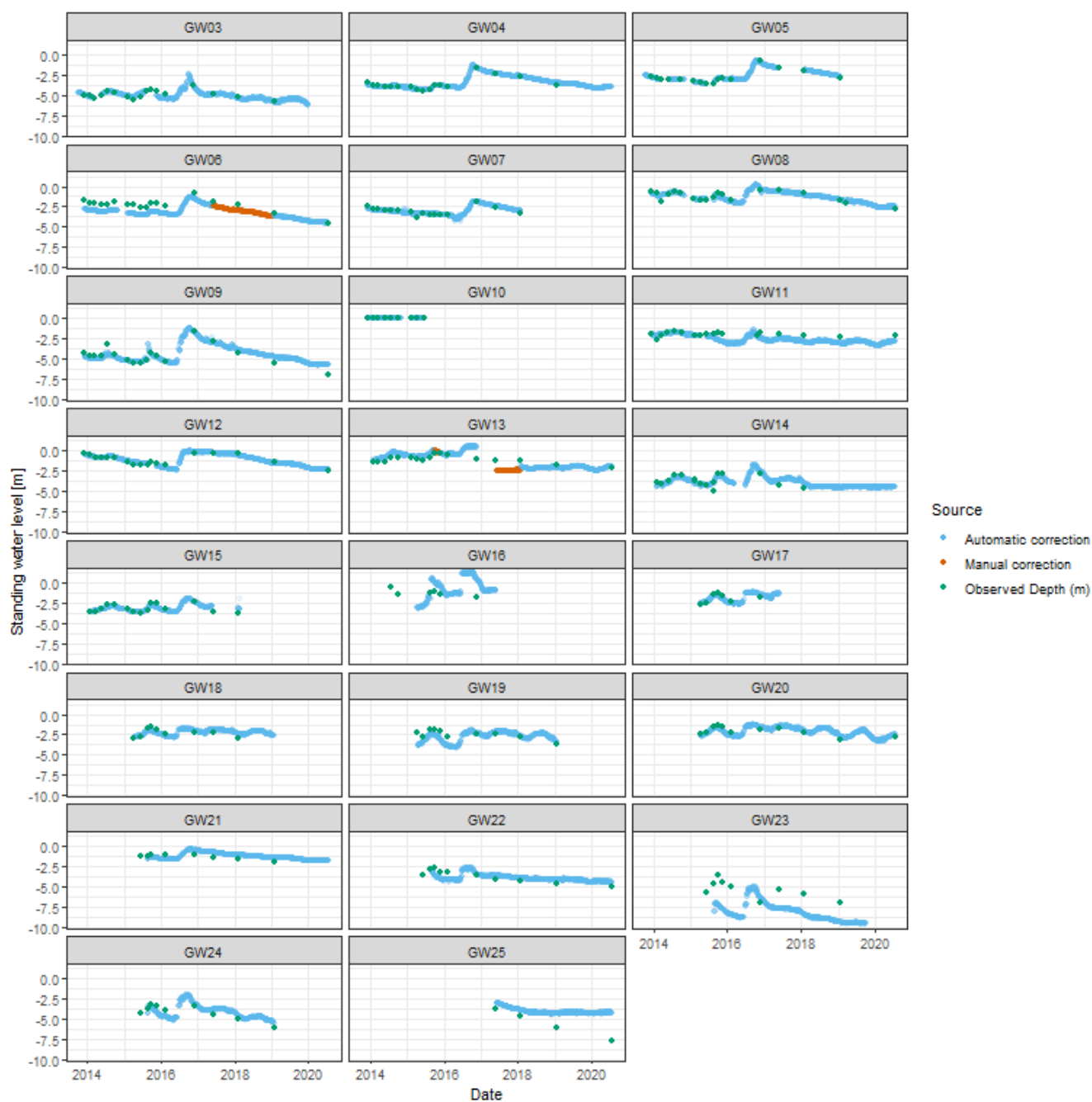
Figure 9. Overview of the corrected groundwater time series for all the wells. Different panels relate to the different locations highlighted in Figure 2.
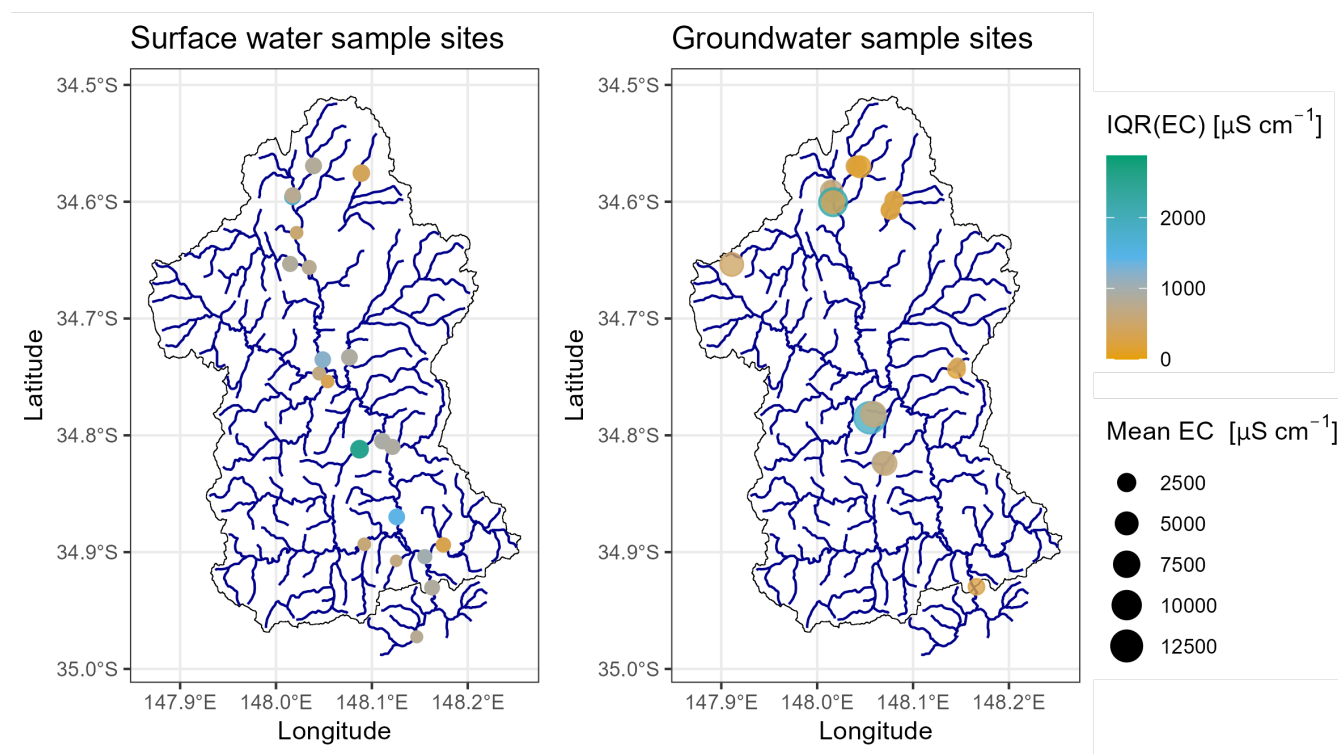
Figure 10. Spatial Variation of EC throughout the catchment, using Mean EC in $\mu S\ cm^{-1}$ and interquartile range (IQR) for each sampling location. Only locations with more than 10 observations over the 14 years are included. Surface water sample sites are on the left panel, while groundwater sample sites are on the right panel.
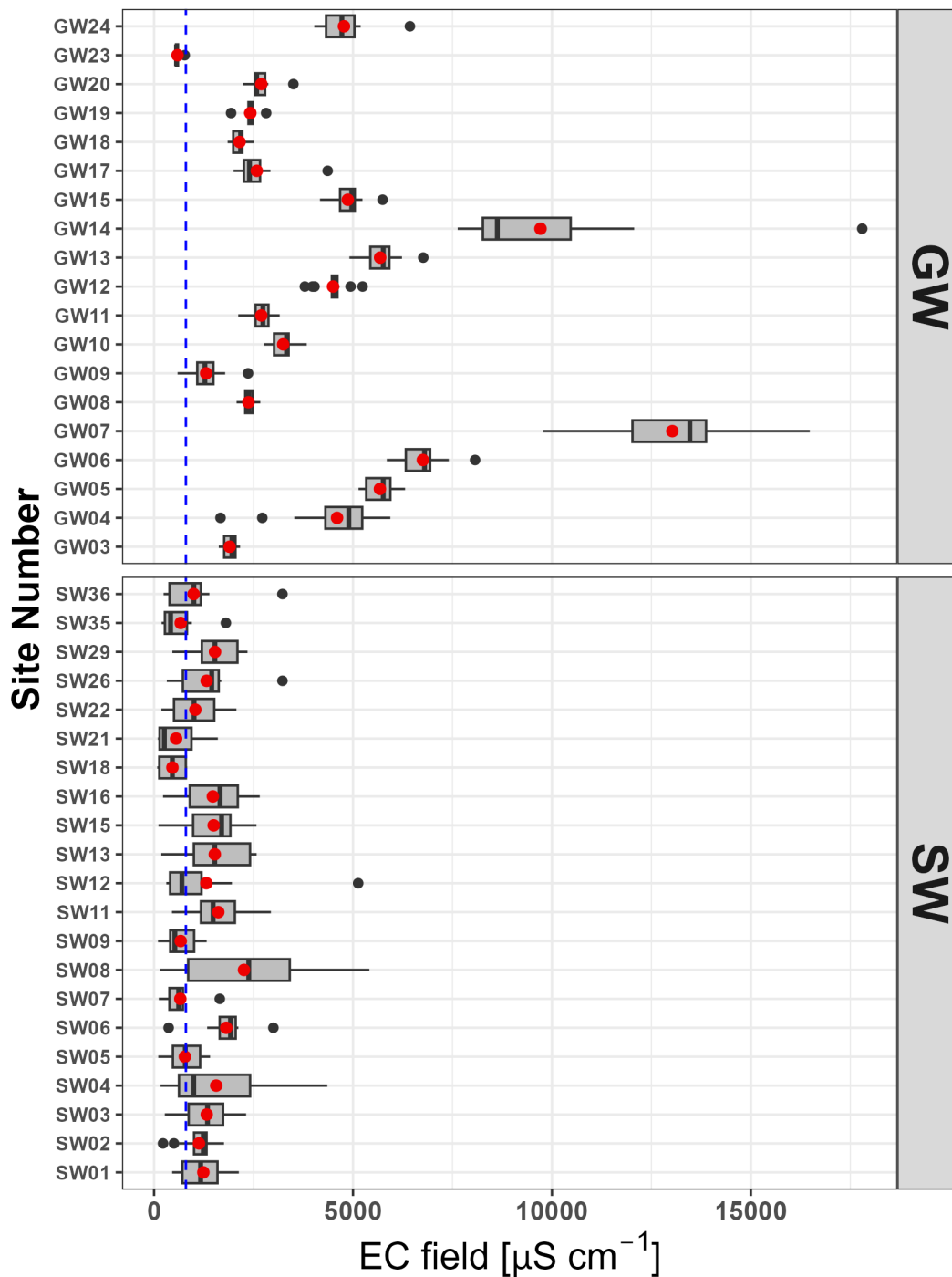
Figure 11. Variation in EC throughout the catchment across time by sample location presented as boxplots. Only locations with more than 10 observations over the 14 years are included. The blue dashed line is the drinking water limit of 800 μS cm^{-1}.
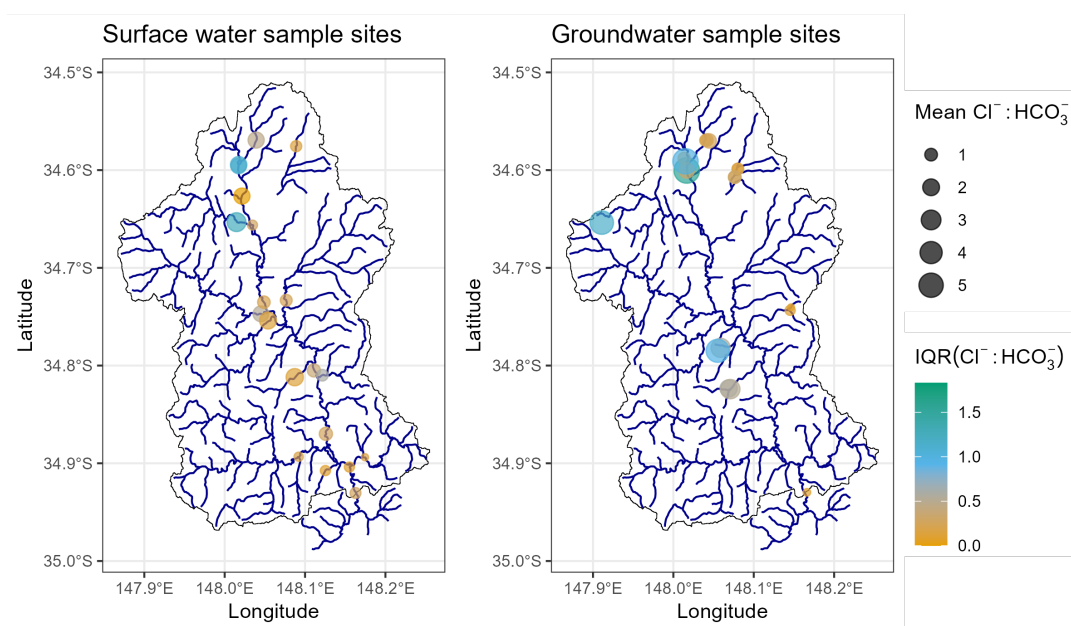
Figure 12. Spatial Variation of $Cl^- : HCO_3^-$ ratio throughout the catchment, highlighting mean and interquartile range (IQR) for each sampling location. Only locations with more than 10 observations over the 14 years are included. Surface water sample sites are on the left panel, while groundwater sample sites are on the right panel.
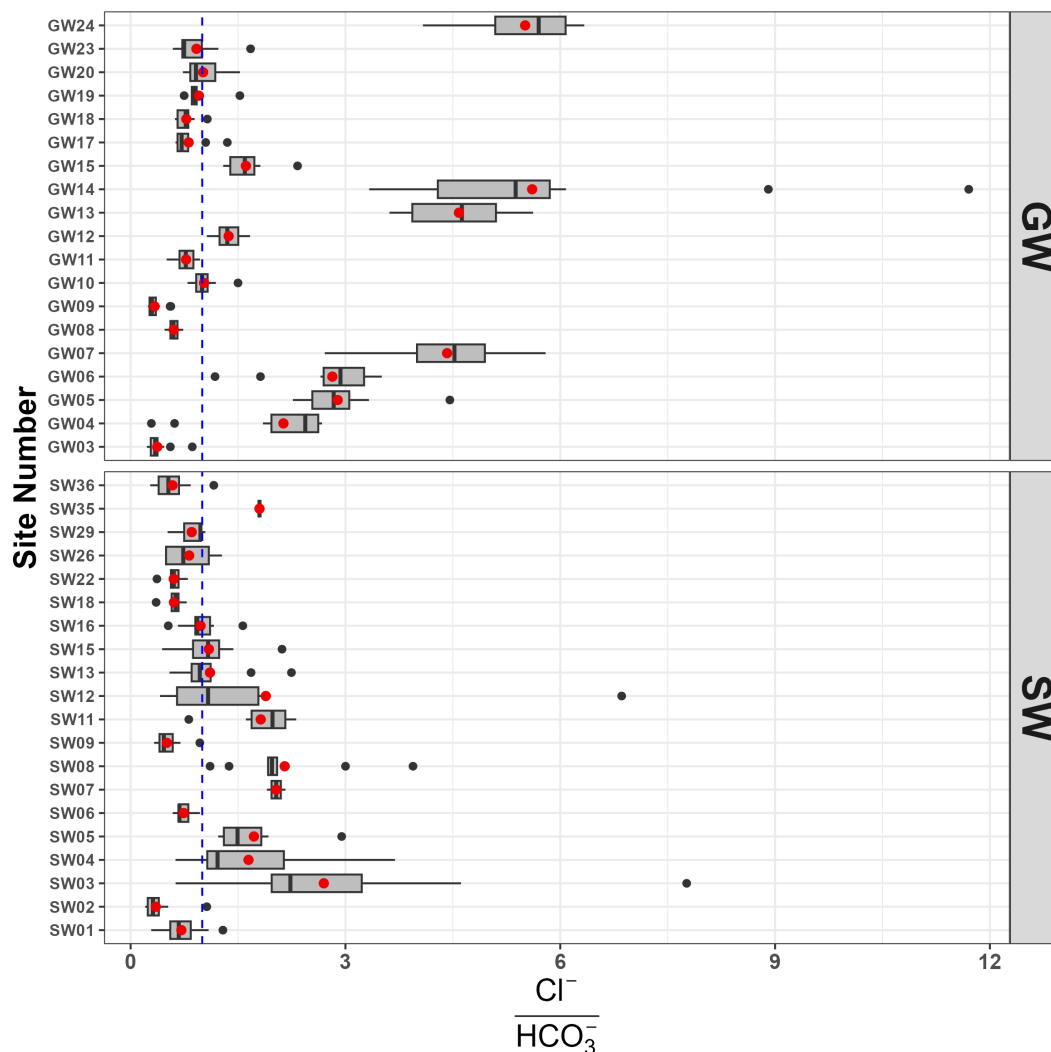
Figure 13. Variation across time of the Cl : HCO₃ ratio by sampling location represented as a boxplot. Only locations with more than 10 observations over the 14 years are included. The blue dashed line indicate a Cl : HCO₃ ratio of 1

There is clear spatial variation in water parameters throughout the catchment, including between groundwater and surface water sampling sites (Figures 10 and 12). As examples, the spatial distributions for EC and Cl:HCO₃ are shown for sample sites with more than 10 observations over the sampling period. Similar maps can be easily generated for other parameters using the code in the markdown document. In the map, the concentration is indicated by the size of the symbol, while the colour shading indicates the variability. This suggests surface water samples had lower variability and lower salt concentrations. In addition, samples on the North western side of the catchment had higher salt concentrations and higher Cl:HCO₃ ratios, which is also associated with higher variance in the samples.
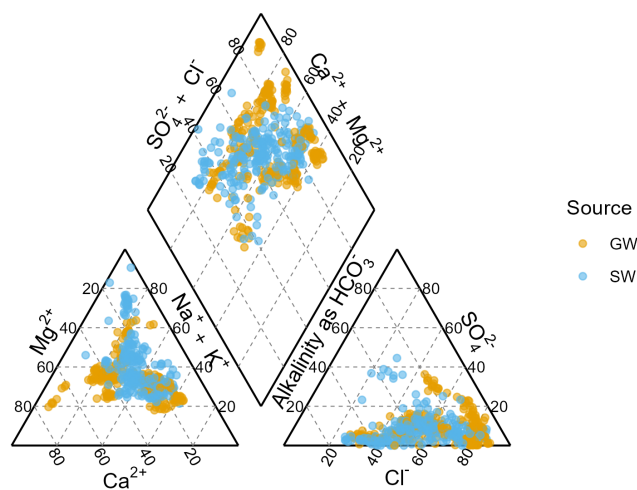
Figure 14. Piper-plot of all groundwater and surface water data collected over the period with complete major anion data

Below the maps, boxplots (Figures 11 and 13) highlight the difference in the distributions between the surface water sample sites and the groundwater sample sites. For sites that have more than 10 observations, this highlights the difference between sample sites, reflected spatially on the maps. For example, it highlights that high EC sites also tended to have high Cl:HCO$_3$ values, and conversely that low salinity groundwater tended to be associated with low Cl:HCO$_3$ values. It also points out the single well (GW23) that has a very low EC. Previous studies have suggested there may be a difference in Cl:HCO$_3$ ratio in surface water between the eastern and western parts of the Muttama catchment (Conyers et al., 2008), and Figure 12 suggest a similar pattern, with samples in the North and West being higher in EC and high in Cl:HCO$_3$ values, while the Eastern and Southern areas have lower variability in the surface water samples and lower Cl:HCO$_3$ values.

3.4 Piper plot

The piper plot contains the data for all the samples with complete major anion and cation data, which are 500 samples. Of these, 229 are surface water samples and the rest groundwater samples. The piper plot of the data (Figure 14) does not provide much clarity as the samples cover a large area across the ternary space. There is a slight shift towards the HCO$_3$ and Ca/Mg type waters for the groundwater samples compared to the surface water samples, which are more Na dominated. There is also a small cluster of surface water samples that are more SO$_4$ dominated, potentially indicating different geological origins as mentioned earlier in the paper. However, some of the groundwater samples are very high in Cl, explaining the high EC values observed for these samples.

4 Discussion

240   The dataset in this paper is unique in Australia. There are substantial datasets from experimental small catchments (i.e. Hughes et al., 2007; Summerell et al., 2006), but not many of these are publicly or easily accessible. In contrast, there are data from very large state and national datasets (i.e. Jolly et al., 2001), but there are limited publicly available data sets that cover substantial space and time scales.

The dataset presented here covers multiple sites, multiple time periods and multiple sampling campaigns. This is a strength,
245   but also has limitations. As the groundwater data clearly shows, the actual number of possible sample sites is limited by the existing and accessible groundwater wells. Over the 14 years of research, several groundwater wells were accidentally destroyed during farm operations, further reducing the sample opportunities. The number of surface water sampling sites in the catchment is limited by the ephemeral nature of the stream network, with some creeks not flowing for long periods. Given the travel distance from the University of Sydney, this also meant that overall sampling is limited in scope, as is clearly shown
250   in the spatial maps (Figures 10 and 12).

The development of the dataset over many years regrettably does not allow a full uncertainty analysis. There is reasonable quality assessment of the laboratory analysis of the samples taken by Akter (2018) (see the appendices in Akter (2018)), there is less reporting of this for the other samples. An exception to this is the samples analysed by the commercial laboratory, where a strict quality protocol was followed. Some uncertainty can be gleaned from the mass balance closure of the major cations for
255   the laboratory analysis. None of this provides an understanding of the uncertainty associated with the field measurements and the potential manual handling errors. Despite these potential sources of uncertainty, the analysis in this paper highlights the spatial and temporal consistency of the data, thus providing evidence of manageable uncertainty in overall dataset. Therefore, the are valuable in the general space time information that it provides.

The dataset suggests implications for management of salinity in the Muttama catchment. The samples clearly indicate that
260   the main source of high Cl salinity originates from the sediments and rocks on the northwestern side of the catchment. This is further complicated by the artesian nature of some of the wells in this area. However, as the water level data and Akter (2018) has highlighted, the shallow groundwater levels only partly respond to rainfall recharge. Investment and incentives to reduce recharge should focus on these areas, particularly to limit the movement of saline discharge into the creek (Akter, 2018).

5 Conclusions

265   Detailed datasets for medium to large scale catchments are underrepresented in salinity research in Australia and worldwide. This paper reports on a long term (14 year) hydrogeochemistry dataset from a single medium scale catchment (> 1000 km^2) in NSW, Australia. This dataset includes a total of 1160 water samples from 62 locations within the catchment and includes groundwater and surface water sites. While the dataset was collected by different groups of people at different times and locations, it still provides a valuable long term and spatially diverse data set. The complete sample set covers a wide range of
270   flow and wetness conditions. Clear differences were observed in pH, electroconductivity, and in ion ratios between groundwater and surface water samples. Spatial differences in water chemistry are also apparent, with our data reinforcing prior chemical

gradients observed in the catchment. Though in this paper we only provide a limited analysis of the data, we anticipate the dataset can be used for research to gain better insight into the spatio-temporal evolution of hydrogeochemical processes from larger catchments and improve the understanding of catchment salinity.

275 **Competing interests**

The authors declare no competing interests.

Availability code & data

- The majority of the code and associated data, including the Rmarkdown for this paper, is stored on Github https://github.com/WillemVervoort/MuttamaDataPaper.

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- The hydrogeochemistry data is located on the University of Sydney escholarship repository Vervoort et al. (2025).

- However, due to the volume of raw data, the groundwater logger data is stored in a separate Open Science Foundation project: https://doi.org/10.17605/OSF.IO/BEUWK Vervoort and Akter (2024).

285 **Author contributions**

TB initiated the sampling campaign. TB, FvO, FD and RWV conceptualised the overall study, and managed the project. RWV and MT wrote the draft paper and analysed results. FA and JL collected and analysed the majority of the samples. MT, AB, JM, FA analysed and managed the data. All authors participated in sampling, laboratory analysis and review of the paper.

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