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

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Abstract. Dryland salinity remains a major natural resource management concern, specfcially in Australia, but also globally. However, a lack of detailed space-time data sets with observations of stream and groundwater salinity has limited further 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 data available as a result of a 10-year data collection effort in a subcatchment of the Murrumbidgee catchment in New South Wales, Australia. Over a 10 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. The data set covers 23 groundwater sample sites and 37 surface water sites. Because the data was collected by four distinct groups and over many years we analyse 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 and analyse any posible biases. The dataset is made open access to encourage further research and the basic description already shows the richness of the collected data and opportunities for further research.

ACTIONS

- check data, include new data

- explain group 4 in EC pH figure

- CL/HCO3 = 1 line

- check number of anions/cations analysed

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). The success of management of salinity,

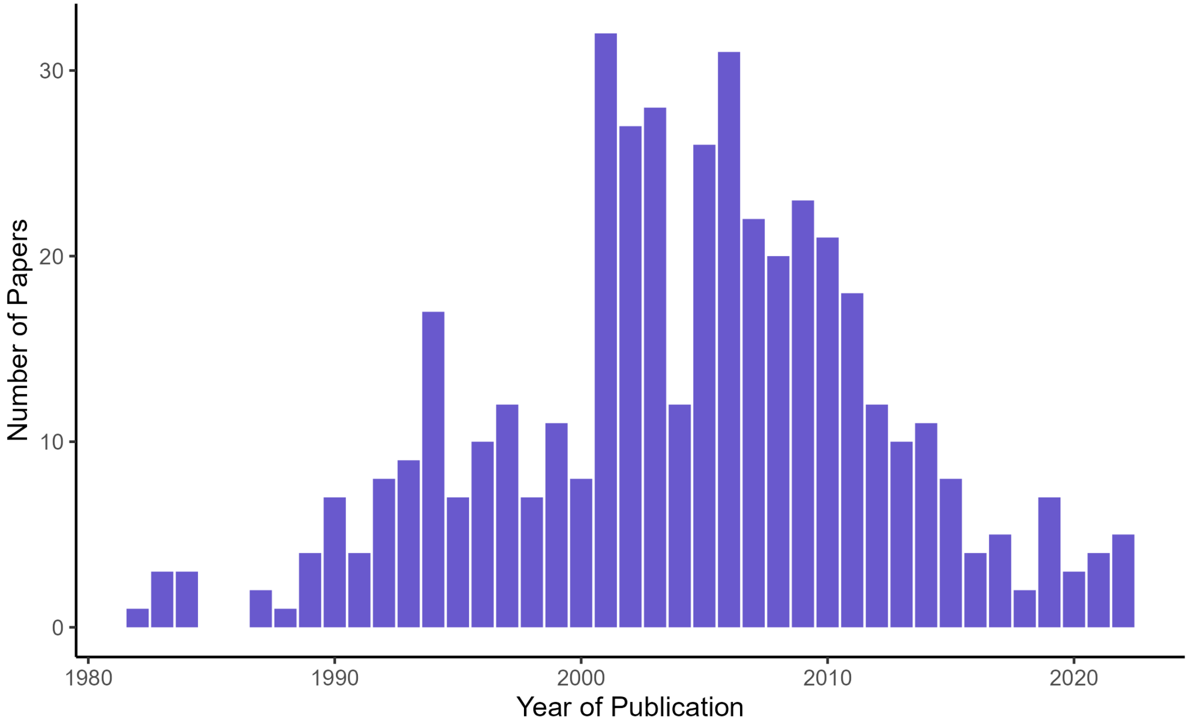

Figure 1. Number of papers on the Web of Science related to the search terms (Dryland Salinity) AND Australia 1980 - 2022

while extensively documented, has remained patchy (Leblanc et al., 2012). As a result, 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 consequently salinity (McFarlane et al., 2016), but this is also because of the increased understanding that salinity processes can vary substantially across the landscape (Conyers et al., 2008) and that 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).

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 region 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 MDB (White et al., 2009). More specifically, Conyers et al. (2008) tried to isolate which areas of land in 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 can be measured using conventional methods such as EC, a rise in marine cyclic salts can be a major source of osmotic stress, whereas mineral weathering salts are far less harmful and 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 change from east to west, correlating with the underlaying mineral types.

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 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. https://realtimedata.waternsw.com.au 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.

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 data bases (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 a range of flow characteristics.

The aim of this paper is to present and describe the space time dimensions and relationships of a complex groundwater and surface water hydrogeochemistry dataset that was collected over a 10 year period in a $1000km^2$ agricultural catchment in New South Wales, Australia. The Muttama catchment, which is the focus of this paper, provides a micro-cosm of groundwater and surface water salinity variability in Australia. Focusing on a smaller catchment in greater detail creates opportunities 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 physicochemical relationships in the data in detail. This will be analysed in follow-up papers. 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.

2 Methods

2.1 Muttama catchment

Muttama creek sub-catchment (Figure 2) is located in the Mid-Murrumbidgee catchment area of NSW in south eastern Australia. The landscape is undulating with only limited elevation variations (227 - 719 m). Muttama creek flows north-south through the length of the catchment towards the Murrumbidgee River near Gundagai. The main township, Cootamundra 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).

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, station no. 410112 on two branches above the Cootamundra township. This data is available as open access via the (WaterNSW WaterInsights platform)[https://waterinsights.waternsw.com.au/]. Here, we only use the data from the Coolac station as a comparison.

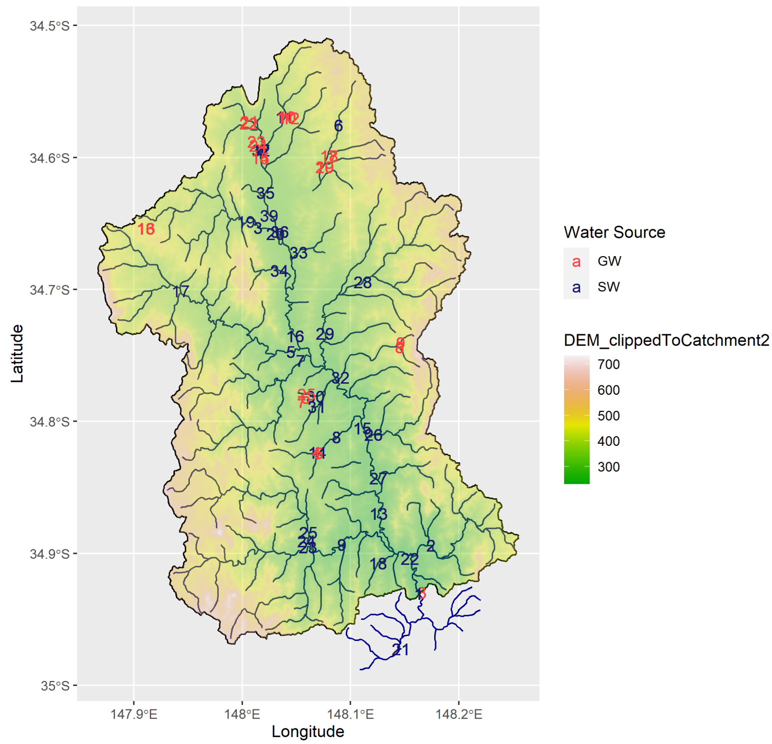

Figure 2. Muttama Catchment Sampling Locations with Elevation. Symbol colour indicates whether location was a groundwater or surface water source, with blue being surface water and brown/orange being groundwater. The numbers on the map represent the sample location number.

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

Overall, 1087 water samples were collected from 62 sample locations over the 2010 - 2020 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 (23 groundwater sample sites and 39 surface water sites) 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.

2.2.2 Hydrogeochemical Variables

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 by laboratory analysis, which repeated some of the field measurements, and for an additional 15 anion and cation variables.

Table 1. Variables measured in the field and laboratory

Field measurements	Lab repeat	Anions	Cations
pH	pH	NO3	Na
EC (Electrical conductivity)	EC	NH4	Ca
SPC (temperature corrected EC)	SPC	NH3	Mg
Temperature		Br	K
Alkalinity (HCO3)		PO4	S
Dissolved Oxygen (DO)		SO4	P
Turbidity			Al
			Fe
			Si

The variables pH, EC, SPC (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. 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. Later (After mid 2019) surface water and groundwater sampling used a Xylem EXO probe which also included DO and turbidity. Some of the variability in the field measurements might be due to this variation in the field instrumentation, because the exact instruments information was not recorded with the 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 samples in the undergraduate student sample set (Source 3) were analysed by a commercial laboratory (ALS Environmental, Smithfield, NSW). Alkalinity concentrations were measured in the field within 24h of collection using a HACH digital titrator (model 16900) (Akter, 2018).

Using the cation and anion data, ion balances were calculated from samples which had a complete set of anion and cation measurements.

2.3 Continuous variables

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 on the github repository.

The loggers in the field were uncalibrated. Due to logger failures, gaps occur in the daily data, followed by replacement of 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 odd shifts in the recorded data.

Manual water level measurements were taken at each manual sampling date to provide detailed hydrogeochemical 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 manual observed data point 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.

To explain this more clearly the following pseudo code describes the process:

Algorithm 1 Pseudo code cleaning groundwater level data

```
if sufficient points   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   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
```

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://osf.io/beuwk/.

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 Appendix 1.

The final corrected data that is published with this paper includes a column which describes whether the data is based on the automatic correction or a further manual correction.

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. We have chosen to use boxplots to visually highlight statistical differences between data variables rather than doing a full statistical analysis.

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

All graphs and maps were produced using R (R Core Team, 2023). All code can be found in the associated (github repository)[https://github.com/WillemVervoort/MuttamaDataPaper], as part of the markdown document for this paper.

3 Results

3.1 Distribution of missing Values

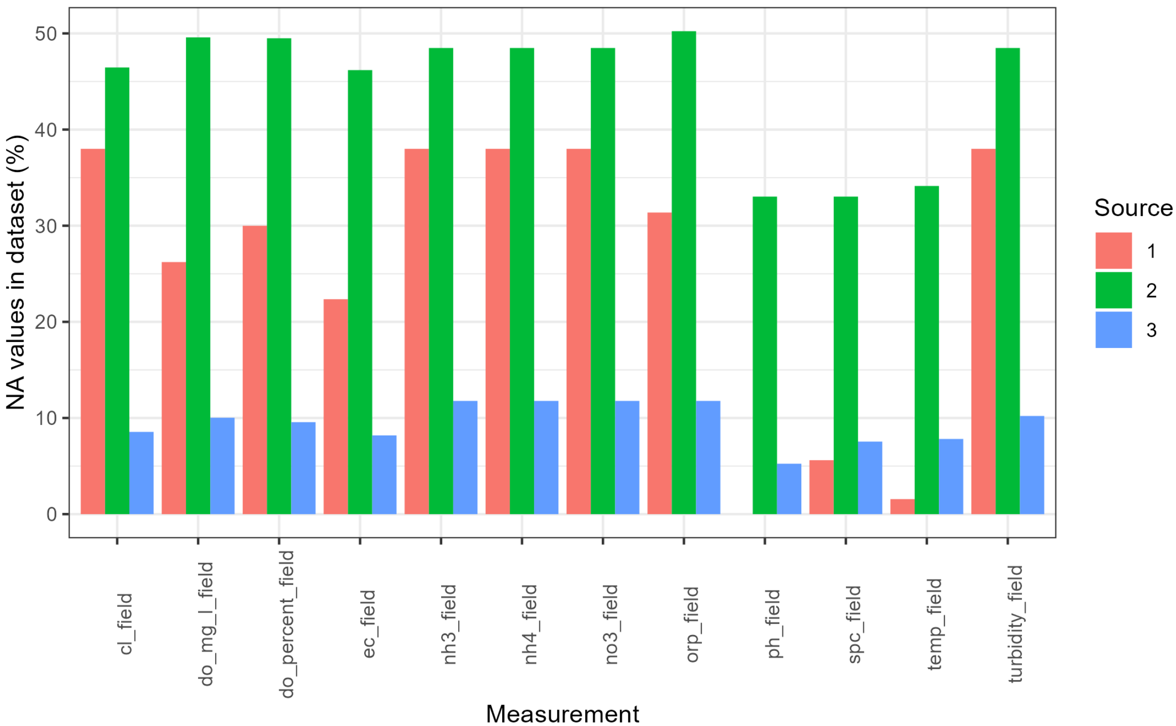

Figure 3. Distribution of missing values for the different data sources and measurement types.

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 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. Analysis of bicarbonate in the field only started around 2014. 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 ten years of sampling.

In the groundwater level time series, the missing data relate mostly to the 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).

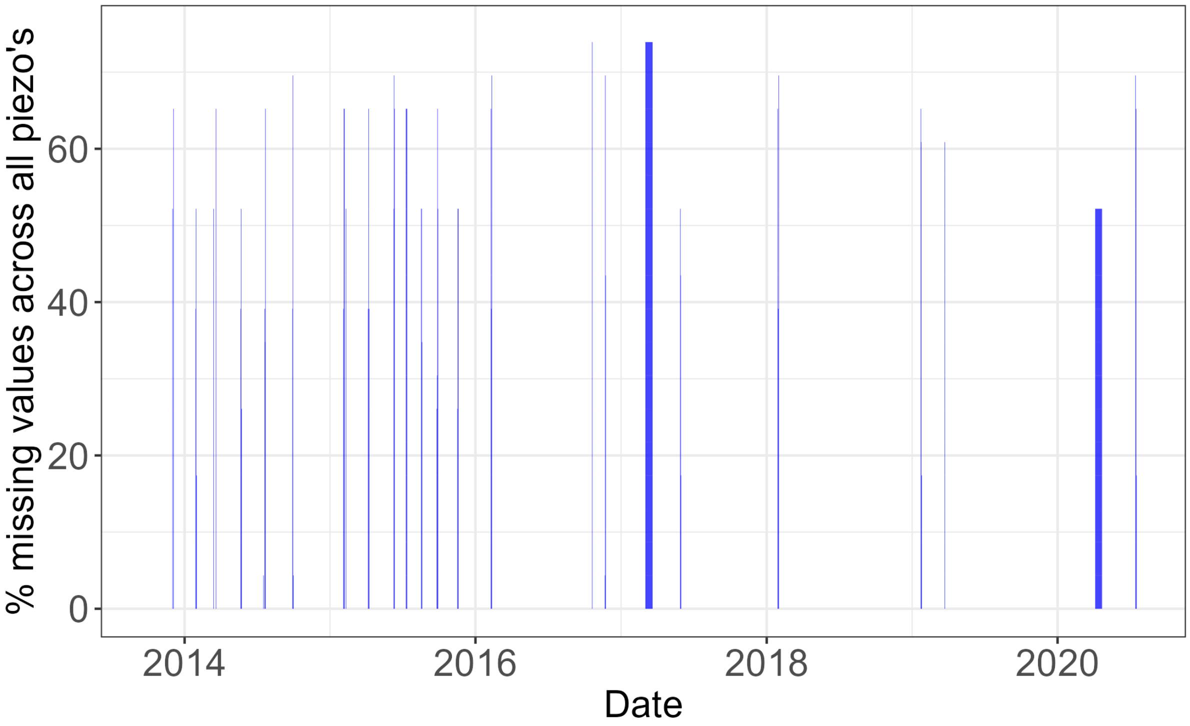

Figure 4. Percent missing values for the groundwater data across all piezometers.

3.1.1 Comparisons of Groundwater samples with Surface water samples

Table 2. Summary statistics for elements measured in the field

	GW			SW		
Element	Mean	Min	Max	Mean	Min	Max
temp_field	17.4	11.4	30.8	15.1	4.1	32.9
do_percent_field	19.9	-3.2	70.7	88.4	29.8	184.0
do_mg_l_field	1.9	0.0	6.7	7.7	2.2	18.3
spc_field	4633.9	347.4	16481.0	1054.1	61.0	4354.0
ec_field	4006.5	457.0	14385.0	1369.9	117.0	4163.0
ph_field	7.3	6.0	8.8	8.0	6.7	10.0
orp_field	73.2	-328.1	242.0	78.2	-126.5	211.1
turbidity_field		Inf	-Inf	14.0	0.5	44.0
cl_field	320.0	320.0	320.0	602.8	30.0	3830.0
no3_field		Inf	-Inf	3.7	1.5	6.5
nh4_field		Inf	-Inf	1.3	0.1	7.5
nh3_field		Inf	-Inf	0.0	0.0	0.5

Groundwater samples have quite a distinctive signature compared to the surface water samples (Fig 5). For example, groundwater samples tend to be higher in EC and lower in pH compared to surface water samples. Since ‘Source 1’ collected most of the groundwater samples, this results in differences between data collection sources. Field SPC measurements were used to represent EC since these samples had the best coverage.

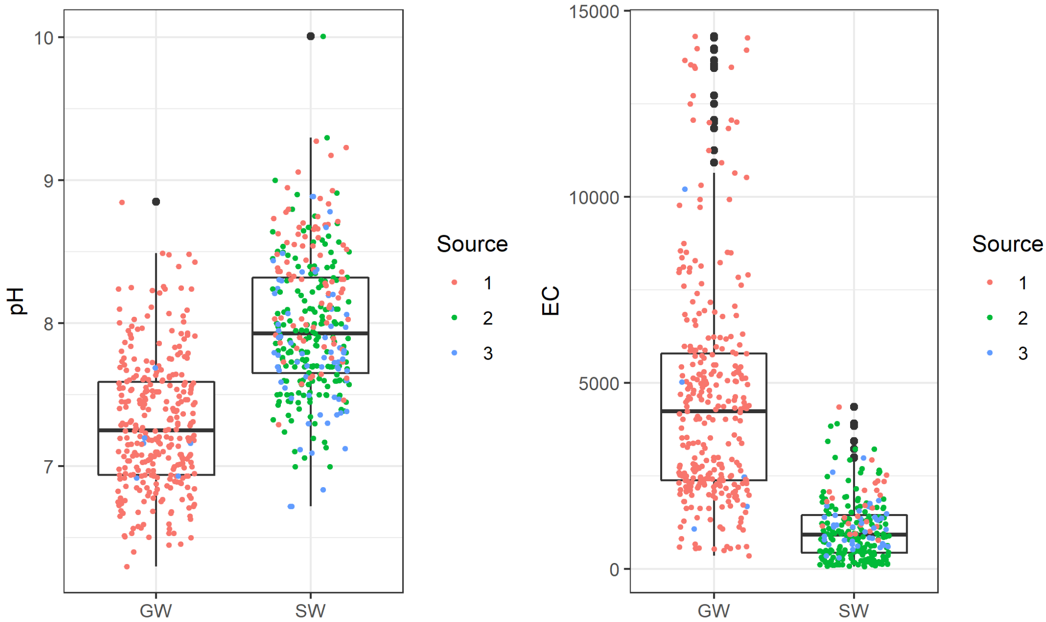

Figure 5. Difference in pH and EC for groundwater and surface water samples. The source of the data (the samping group) is indicated with colour

3.2 Temporal Distribution of Data

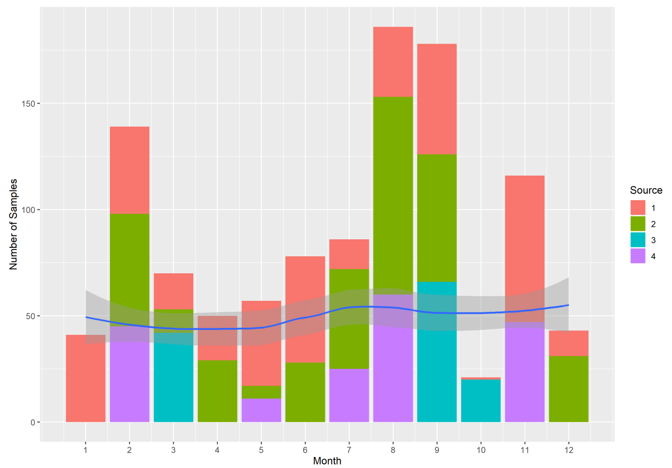

Figure 6. Distribution of samples throughout the year (total number of samples collected during each month) against average monthly rainfall during the study period.

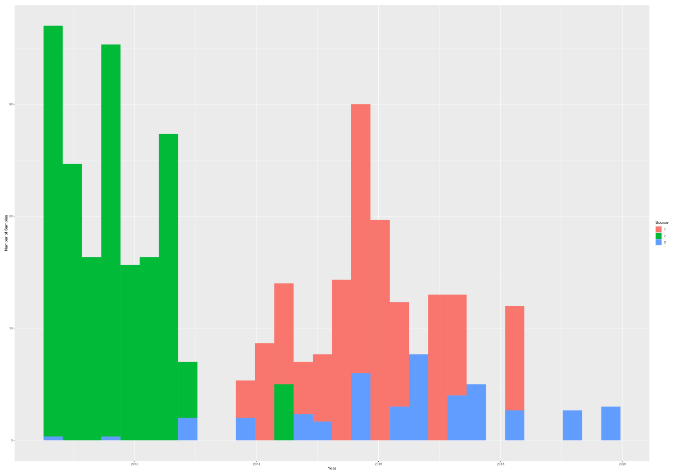

Figure 7. Distribution of samples over the study period (total number of samples collected during each year) against average monthly rainfall during the study period.

Overall the water quality sampling appears to have a reasonable distribution across all months (Fig 6), so seasonal 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 early Austral Spring (months 9 and 10, September and October). This also explains the higher number of samples because, we would organise more sampling trips in this period, and spatially more channels could be sampled for surface water. The timing of Source 3, (the student data) is a clear effect of yearly field trips, which tended to occur at approximately the same time of the year in late September/early October.

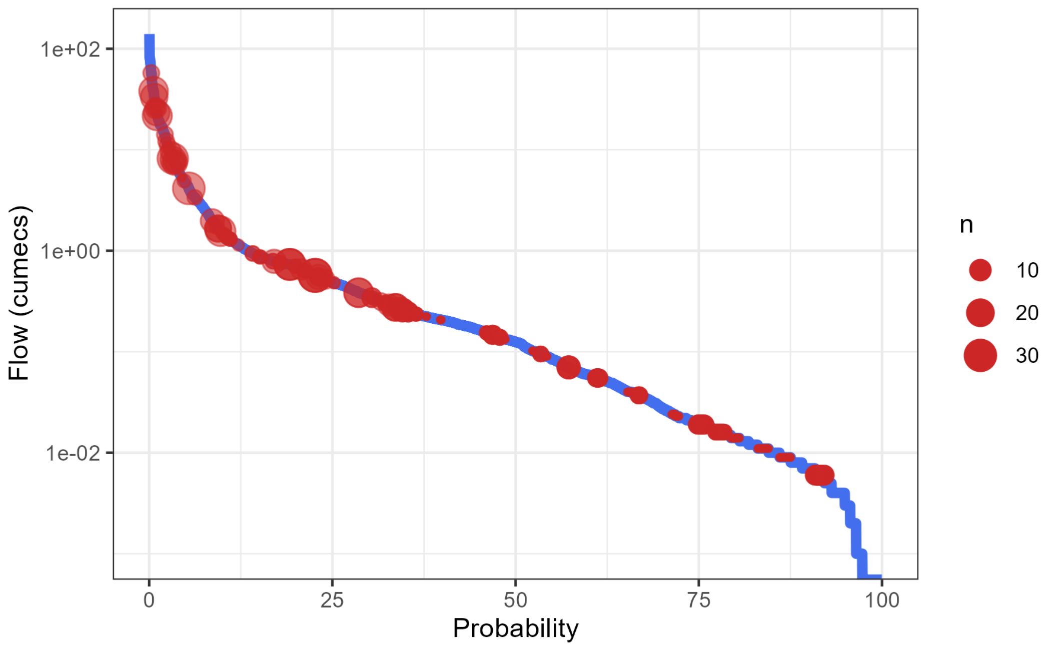

Figure 8. Sample distribution on flow duration curve derived from flow data from Coolac autosampler.

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 7); 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.

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 duration curve, measured at the Coolac station (410044), with only a possible bias towards periods of medium flow. This is most likely since many of the surface water sampling points are often completely dry during periods of low flow, and therefore cannot be sampled. Conversely, 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.

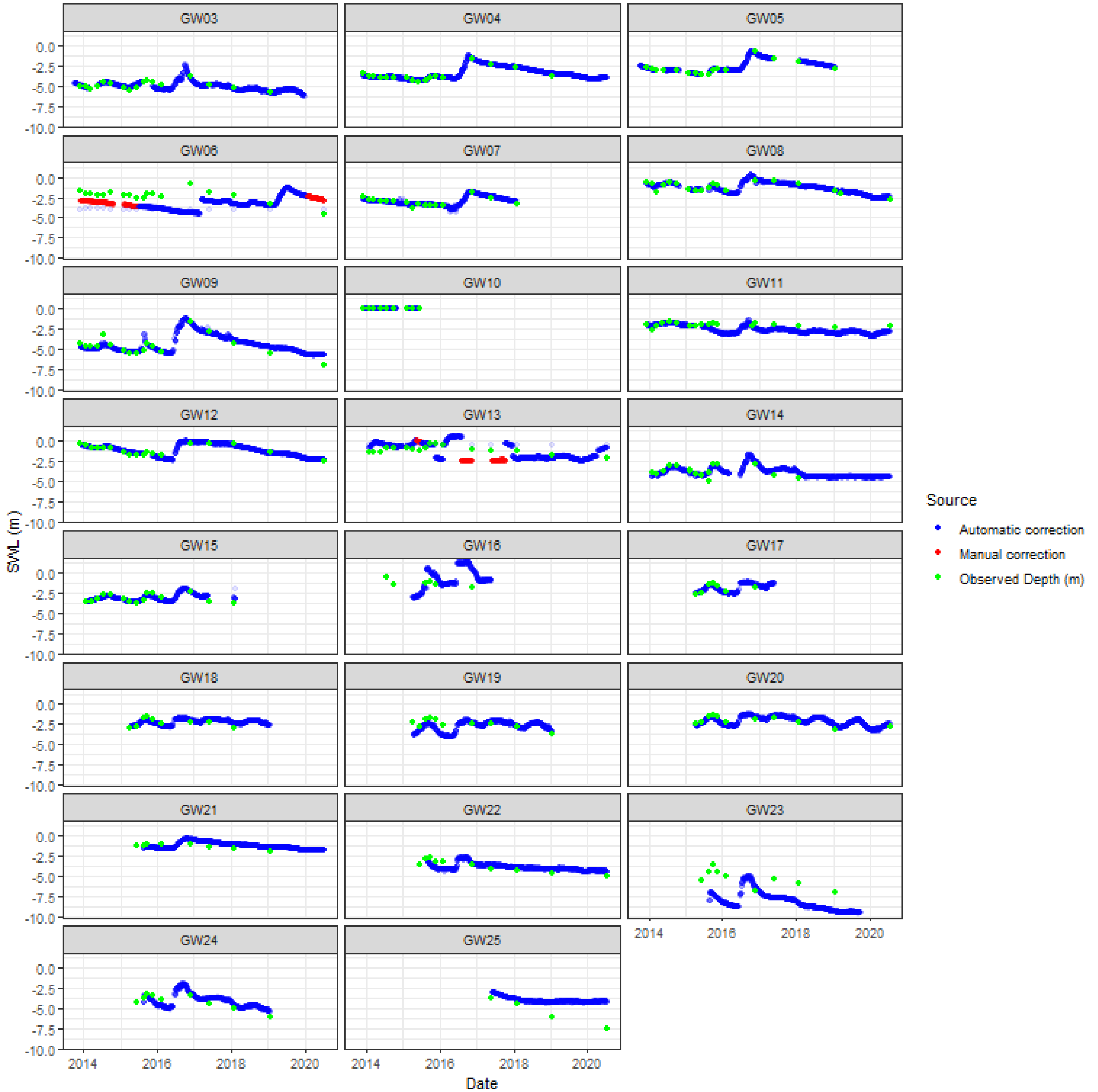

Figure 9. Overview of the corrected groundwater time series for all the wells

The overall corrected groundwater timeseries shows the shorter time that loggers were installed in the wells (9). It also indicates that the manual data is not always fully matched with the logger data, but further corrections are likely to be speculation.

3.3 Spatial variation

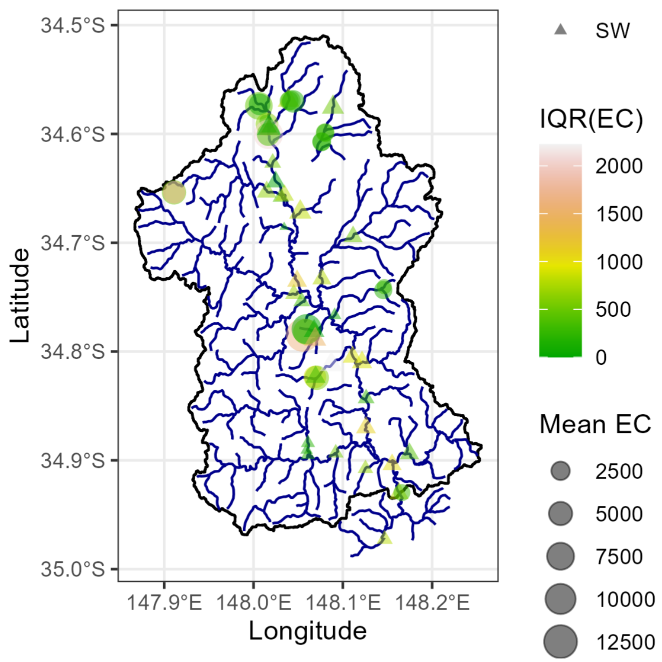

Figure 10. Spatial Variation of EC throughout the catchment, using Mean EC for each sampling location

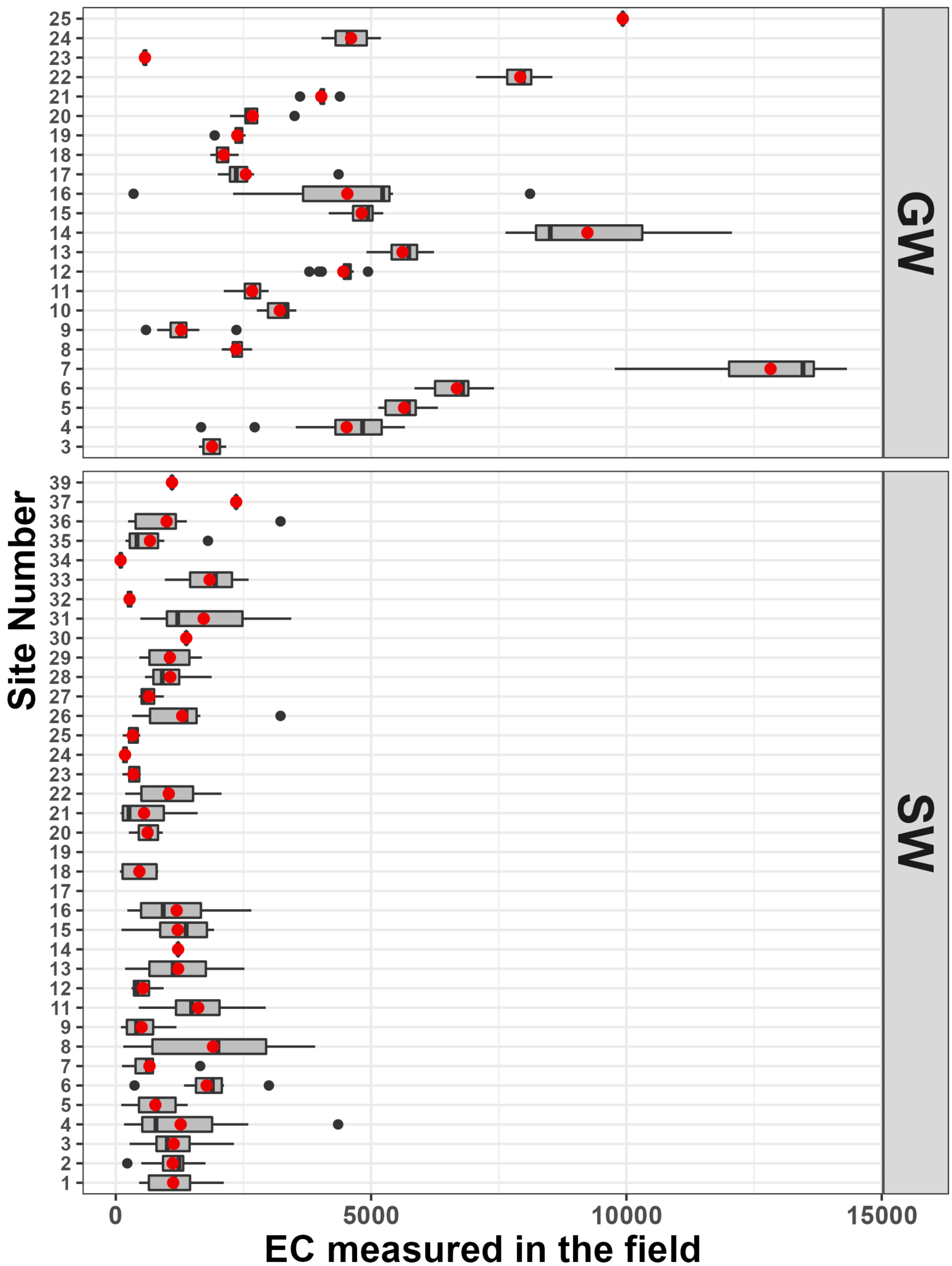

Figure 11. Variation in EC throughout the catchment and in time by sample location

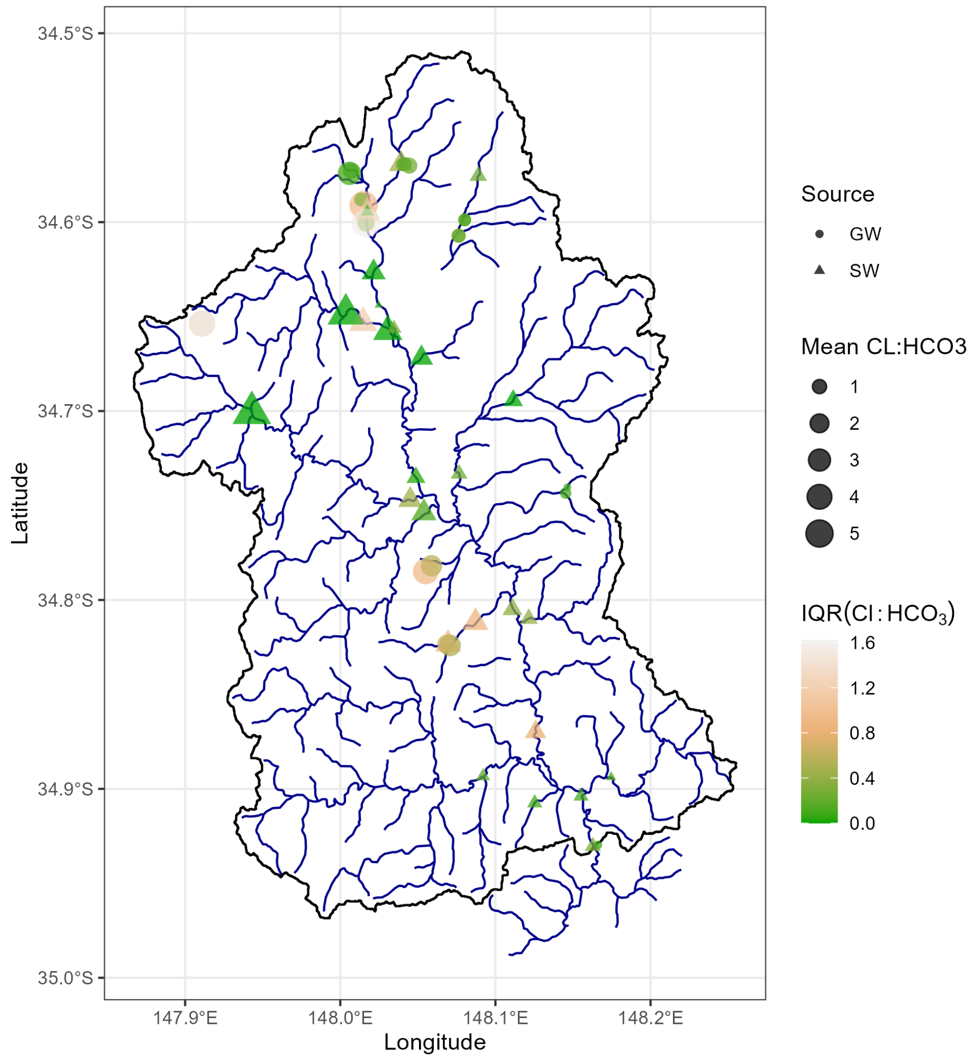

Figure 12. Spatial Variation of Cl:HCO3 ratio throughout the catchment, using Mean for each sampling location.

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:HCO_3 are shown, as well as the space time boxplots for the variables. Similar maps can be easily generated for other parameters. 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 concentrations.

Below the maps, a boxplot (Figures 11 and 13) highlights the difference in the distributions from the surface water sample sites and the groundwater sample sites, and also indicates the difference between sample sites.

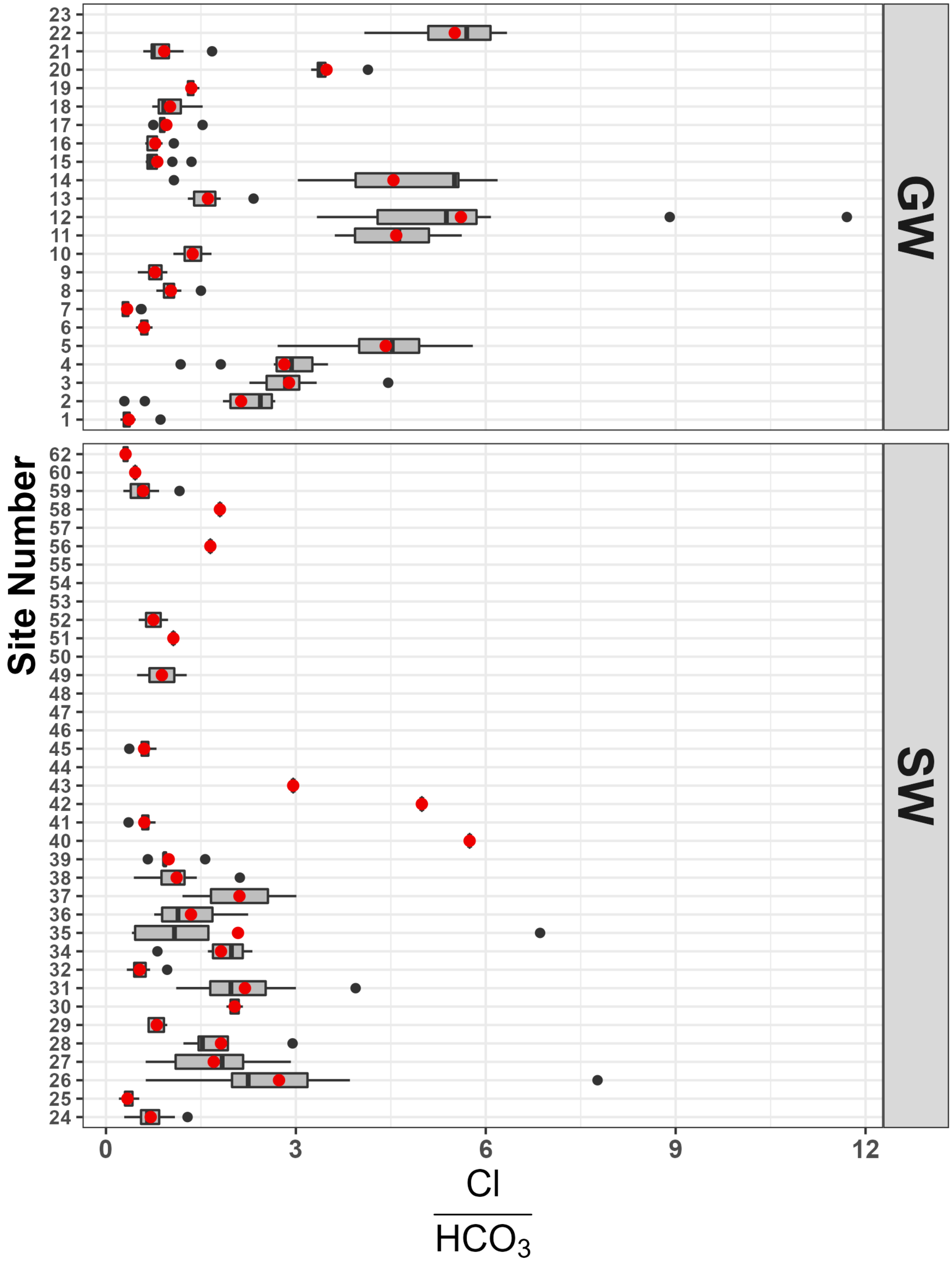

Figure 13. Space and time Variation of Cl:HCO3 ratio by sampling location.

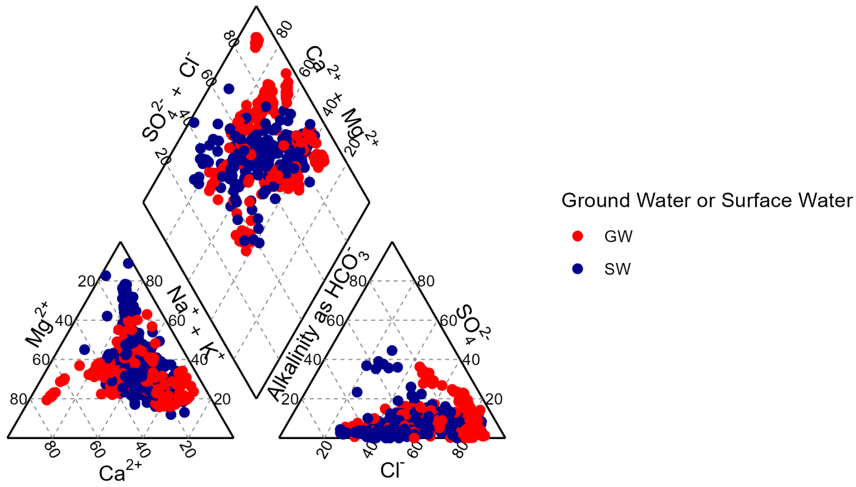

Figure 14. Piper-plot of all groundwater and surface water data collected over the period

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), however it is difficult to see whether this pattern occurs based on the spatial maps. This partly has to do with the limitations in the spatial sampling, which relied on existing groundwater tube wells and accessible stream points.

3.4 Piper plot

The piper plot of the data (14) also does not provide much further information. There is a slight shift towards the HCO_3 and Ca/Mg type waters for the groundwater samples compared to the surface water samples. 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.

4 Conclusions

This paper reports on a long term (12 year) hydrogeochemistry dataset from a single catchment in NSW, Australia. This dataset includes both groundwater and surface water samples for 60 locations within the catchment. 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 which can be used for research into the space and time variation of dryland and groundwater salinity.

. The majority of the code and data including the Rmarkdown for this paper is stored on Github https://github.com/WillemVervoort/MuttamaDataPaper However, due to the volume of raw data, the groundwater logger data is stored in a separate Open Science Foundation project: https://osf.io/beuwk/

Appendix A: Figures and tables in appendices

. T. Bishop initiated the sampling campaign. T. Bishop, F. van Ogtrop and R.W. Vervoort conceptualised the overall study. R.W. Vervoort and M. Tambrchi wrote the paper and analysed results. F.Akter and J. Lessels collected and analysed the majority of the samples. M. Tambrchi, A. Buzacott, J. Moloney, F. Akter analysed and managed the data. All authors participated in sampling, laboratory analysis and review of the paper.

. The authors declare no competing interests.

. This dataset would not have been possible without the generous assistance and access to properties from the following land owners in the Muttama Creek area: R. Last, the Tozer family, M. Sullivan, P. McClintock, P. McGuire, S. Sharman, A. Hollihan, the managers at Brawlin Springs as part of the Romani Pastoral Company, and the managers and owners of Wavehill, in particular J. Litchfield. We would like to thank several generations of students in the units LWSC2002, ENVX3003 and ENSY5708, as well a multiple interns from French Institutions and University and Wageningen University for assisting with the sample collection.

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