NSW NRC Forest Monitoring and Improvement Program Project 3 (Water) Extension

Final Report: State-wide Long-term Trends of Water Quality and Quantity for Forested Catchment

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Executive Summary

This report summarizes the methodologies, key findings and recommendations for the Extension of Project 3 ('the Extension Project' hereafter) of the Forest Monitoring and Improvement Program by the NSW Natural Resources Commission (NRC). The previous Project 3 was a collaboration between NRC and the University of Melbourne, which focused on identifying the key indicators of water quality and quantity within forests in NSW RFA regions, and establishing trends in these indicators. The current Extension Project is an upscaling of the previous Project 3 from the RFA regions to the entire extent of NSW. The intent is to establish trends for a broader region while extending the analytical approach to enable more comprehensive trend attribution.

The aims of the Extension Project are to:

1) Identifying long-term trends in key water quality/quantity indicators in forested catchment within NSW, outside of the RFA regions;
2) Attributing water quality and quantity trends to potential drivers including climate and catchment disturbances.

In addressing these aims, the Extension Project estimated temporal trends for each key water quality/quantity indicator at all catchments with suitable data availability. The project also summarized the spatial patterns of these established trends and explored potential drivers of trends with specific focus on forest disturbances from wildfire and changes in vegetation cover and climate.

Our key findings from analysing the trends in water quality/quantity for NSW forested catchments outside the RFA regions are:

1. Catchment flow displays large-scale declining trends throughout the study region. Out of the 90 catchments analysed, 42 catchments show statistically significant decreases at a 0.05 level.
2. For catchments with significant flow decreases, the magnitudes of decline are mostly 10-25% per decade relative to the mean annual flow of the individual catchments.
3. The water quality indicators (phosphorus, nitrogen, electrical conductivity, dissolved oxygen and turbidity) generally show mixed trends which vary between indicators. Within the study region, the number of long-term monitoring sites for each indicator is generally too limited to reveal large-scale trend patterns.

Our analyses on trend attribution, combining observations from forested catchments in the NSW RFA and non-RFA regions, suggest that:

1. Wetter catchments and catchments with a greater percentage of area used for grazing experienced greater percentage decline in flow.

2. With the currently available data, there is little evidence that the 2019/20 fire has a substantial impact on the quantity of streamflow at the catchment scale, compared with long-term historical conditions.

3. The impact on of the 2019/20 fire on water quality is highly case specific, which is also controlled by the hydrological condition, especially the timing of recent rainfall/flow events. The frequency and availability of water quality data is generally not adequate to clearly identify water quality impacts occur during runoff events.

4. Over the longer historical period (2001-2021 period), fire events have some influences on the quantity of streamflow, but the impacts are generally smaller than the effect of coincident changes in climatic drivers.

Our study suggested a large-scale decline in water quantity in the forest catchments within NSW outside of the RFA regions; this clear decline pattern across landscape is also observed in the preceding Project 3. Therefore, the two projects together strengthened the finding of declining water quantity over NSW, which is also consistent with existing literature. This has significant implication on the future water security for NSW. We also found that for the catchment scale, historical changes in flow are generally more heavily affected by hydro-climatic drivers than fire events. This emphasizes the importance for water resources management for forested catchments to consider potential responses to climate conditions, which is especially important under a changing climate.

1. Background

The NSW Natural Resources Commission (the Commission) is responsible for independently overseeing the design, implementation, review and improvement of a state-wide Forest Monitoring and Improvement Program. The Commission worked with the project team of University of Melbourne's Water, Agriculture and Environment Program (the UoM team) on Project 3 of this Program from July 2020 to June 2021. Project 3 delivered baselines and trends for environmental values related to water quality and quantity, for the NSW Forest Monitoring and Improvement Program and the Coastal IFOA Monitoring of Landscape-scale Trends. The previous Project 3 focused on delivering the baselines, drivers and trends in water quality and quantity within the NSW Regional Forest Agreement (RFA) regions, as highlighted in the map in Figure 1.

The Commission has been engaged with the UoM team on an extension of Project 3 from July 2021 to June 2022. The objectives of this extended project are to:

1) Upscale the existing Project 3 from the three RFA regions to the entire extent of NSW's forest cover (Figure 1);
2) Extend the analytical approach that has been used for trend attribution;
3) Improve understanding of which metrics most accurately reflect forest management inputs.

Objective 3 specifically aims to develop better understanding of the impacts of climate variability and forest disturbances (such as climate, wildfires, harvesting, mining, grazing, prescribed burning and post-harvest burning) on water quality/quantity. This has been identified as a key challenge in attributing the trends in water quality/quantity in Project 3, which will be further explored in the Extension Project.

Specific work in the Extension Project includes:

1) Collating representative datasets for water quality/quantity and climate over the whole of NSW's forest extent;
2) Estimating the trends in water quality/quantity;
3) Identifying the impacts of climate drivers and key catchment disturbances on water quality/quantity using multiple statistical approaches.

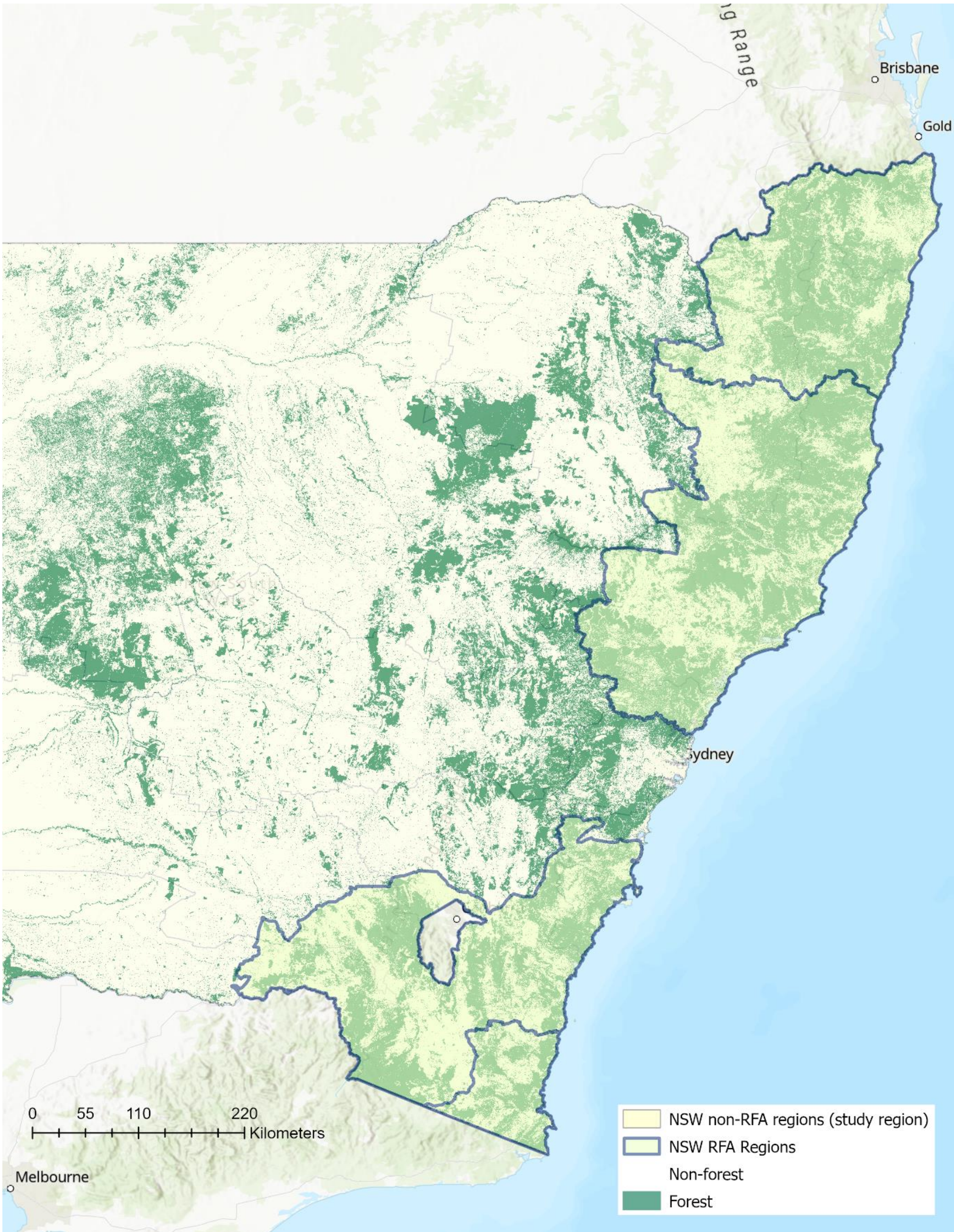


Figure 1. The RFA and non-RFA regions within NSW; the latter is the focused area of this study. Colours in the base map indicate forested and non-forested areas.

2. Methods

2.1 Review of key water quality and quantity indicators for trend analysis

The key indicators of water quality and quantity in the designated forest regions were identified through a comprehensive literature review as part of the previous Project 3. This review covered areas of sustainable forest management, key drivers of changes in water quality/quantity in forested catchments, and existing national and state-level water quality/quantity guidelines and objectives. Thus, some potential water quality/quantity indicators were identified, and the final set of key indicators (Table 1) was further selected using multiple criteria: sensitivity to forest management, suitability and availability of data for landscape-scale assessment, statistical power of data analyses, and effort required for future monitoring. The full details and justification for choosing these indicators are provided in the Section 3 of the final report of Project 3 Stage 1 (Guo et al., 2021a).

Table 1. Key water quality/quantity indicators recommended for trend analyses (identified in Project 3 Stage 1)

Water quality	• Concentration of nutrients (mg/L): total phosphorus (TP), total nitrogen (TN), nitrate-nitrite (NO_x)* • Dissolved oxygen (DO in mg/L) • pH • Electrical conductivity (EC in µg/cm) • Turbidity (in NTU) • Water temperature (WTemp in ˚C) • Macroinvertebrates population and composition: SIGNAL score, Ephemeroptera + Plecoptera + Trichoptera (EPT)
Water quantity	• Annual flow (mm) • Indicators of climate-streamflow relationship (rainfall-runoff residual) • Indicators of baseflow/drought/high flow (7-day low flow, cease to flow, annual 10^{th} and 90^{th} quantiles of flow, all in mm). Specifically, the 7-day low flow is an indication of catchment storage and cease to flow is an indication of groundwater disconnection. All water quantity indicators are annual summaries aggregated by hydrological years instead of calendar years (see Section 2.3.3 for details on data processing).

*Note: NO_x is the sum of nitrate (NO_3) and nitrite (NO_2) in mg/L Nitrogen.

This list of indicators was further revised considering data availability within the RFA regions. For water quality, macroinvertebrates population and composition (SIGNAL score and EPT) and NOx were excluded due to lack of data at a landscape scale. For water quantity, the final focus was signatures of daily flow data, the relationship between climate and flow, and indicators of baseflow, drought and high flow. The derivation of each signature indicator is detailed in Section 2.3.3.

2.2 Data acquisition

2.2.1 Water quality and quantity

To estimate trends in water quality and quantity (detailed in Section 2.3), we collated available monitoring datasets for indicators of water quality and quantity. Three large-scale long-term datasets (e.g., nation- or state-wide) were identified for water quality and quantity from a comprehensive review of data availability in these indicators in NSW:

- *WaterNSW continuous water monitoring network* (WaterNSW, 2022), which monitors the quantity and quality of surface water and groundwater throughout NSW. The monitoring program combines automatic digital sensors, logging devices and manual sampling. All monitoring data have been collated, quality checked and made publicly available via the WaterNSW's online portal (https://realtimedata.waternsw.com.au/).

- *Water Data Online by Australian Bureau of Meteorology* (BoM WDO) (Bureau of Meteorology, 2022a), including the surface water (quality and quantity) dataset from the abovementioned WaterNSW monitoring, as well as data owned by organizations such as Snowy Hydro Limited, Hunter Water, Sydney Water Corporation and the Department of Planning, Industry and Environment - Water. All data are available from BoM WDO's online portal (http://www.bom.gov.au/waterdata/).
- *Forestry Corporation of NSW* (FCNSW), which maintains monitoring programs for water quality and quantity in NSW state forests. Datasets are available upon request.

The numbers of selected monitoring sites as well as total numbers of sites assessed from different data sources are summarised in Table 2 for water quantity and Table 3 for water quality.

Table 2. Number of long-term monitoring sites selected (>35 year) / total number of sites assessed, from each source of flow data.

Data source	Flow
WaterNSW	90/472
FCNSW	0/6
WaterWatch	-
BoM Water Data Online (including various sources e.g., DPI NSW, Sydney Water and local councils)	0/45

For water quantity (Table 2), the availability of continuous flow data has been assessed, because all other water quantity indicators (such as annual flow, high/low flow) can be derived from this flow data. WaterNSW provides the majority of the data (472 sites). To establish reliable long-term trends, a data quality filter (flow record length >35 years with no major gaps) was applied for site selection, after which only qualified monitoring stations were retained. After applying the record length threshold, a total of 90 flow monitoring sites (all from WaterNSW) were kept for trend analysis.

Table 3. Number of long-term monitoring sites selected (>10 year) / total number of sites assessed, from each data source of each water quality variable. Red text indicates the number of long-term monitoring sites where flow data is unavailable, and thus not used for the trend analyses.

Data source	DO	EC	pH	Turbidity	Water temperature	TP	TN
WaterNSW	3/42	38/77	1/8	1/19	41/83	15/79	18/81
FCNSW	-	0/2	0/2	0/6	-	-	-
WaterWatch	2/361	2/361	2/361	2/361	2/361	-	-
BoM Water Data Online (including various sources, e.g., DPI NSW, Sydney Water and local councils)	-	-	0/180	3/218	4/150	-	-
Sydney Water/Sydney Catchment Authority	17/40	0/29	18/48	17/45	-	18/59	18/42
Old NSW Office of Water	0/157	0/172	0/151	0/41	-	0/80	0/57

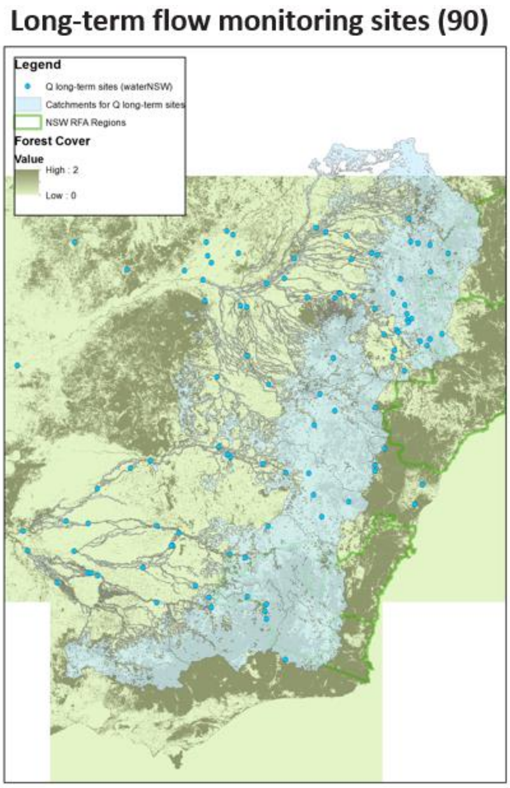
Note: data from Sydney Water/Sydney Catchment Authority do not have available matching flow records, thus not usable for the trend analysis model (see details in Section 2.3.2).

WaterNSW is also the largest provider for the water quality data selected for trend analysis (Table 3). Similar to the flow data, a quality filter (record length >10 years, at a minimum of seasonal frequency) was applied for selecting the suitable monitoring sites to be used for trend analysis. After filtering, there were a total of 59 sites retained for analysing trends in the water quality indicators. It is worth noting that WaterWatch maintains water quality dataset with an excellent spatial coverage with samples collected at nearly 400 locations, but most sites only have short records, which limited the number of eligible sites retained. Another key data source, Sydney Water/Sydney Catchment Authority, maintained only the water quality data but not the corresponding flow records as required by of the statistical model used for trend analysis (see Section 2.3.2 for further details on the model), therefore, no data from Sydney Water/Sydney Catchment Authority was suitable to be used for the further trend analysis.

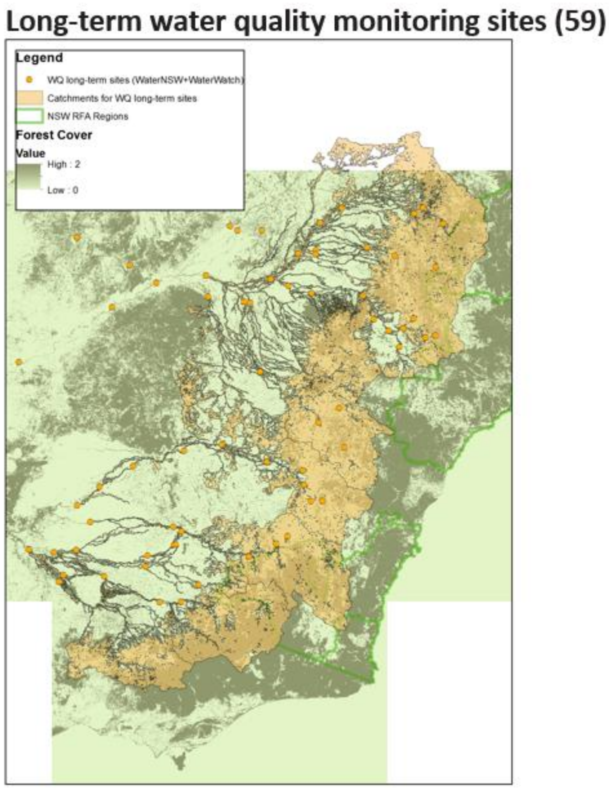
All data for water quantity and quality were extracted up to Sep 2021, when data analysis of the project commenced. A detailed list of site ID, coordinates and variables recorded for each of water quantity and quality is included in Tables A1 and A2 in the Appendix.

2.2.2 Catchment boundaries

Catchment boundaries is a fundamental base map for preliminary assessment of the condition of catchment corresponding to each monitoring station. Further, these catchment boundaries are critical to the attribution of trends in water quality and quantity, as they enable extraction of the disturbance history and the representative land use and land cover for areas that are most influential to the water quality and quantity at individual monitoring stations. Catchment boundaries were delineated using ArcMap based on the locations of the monitoring sites obtained along with the water quality and quantity datasets. The Bureau of Meteorology (BoM) Geofabric dataset was used to identify upstream contributing areas, thus delineating catchment boundaries. The delineated catchment areas were then compared against an alternative source of catchment area information (only available for WaterNSW monitoring sites) to confirm that errors were no larger than 10%. The maps in Figure 2 show the locations of long-term monitoring sites outside of RFA that we identified for water quantity and water quality, respectively, with their contributing catchments delineated shown in lighter shades. In the Northwest part of the maps, there are several sites which have a large contributing area with majority of the area being in Queensland. These sites were dropped off as they were out of our interest on NSW forests. The extent of forest coverage in NSW is shown in the base maps.



a)



b)

Figure 2. Maps of all the a) long-term flow monitoring sites (90 in total); and b) long-term water quality monitoring sites (59 in total), for NSW regions outside of RFA.

2.2.3 Spatial data on catchment condition and modification

Spatial data were obtained for preliminary assessment of land cover, land use and the extent of hydrologic modification of each catchment. This enabled us to identify catchments that are predominately covered by forest and have little modification from natural conditions. The relevant datasets obtained are:

- NSW woody area extent representative of the period 2007-2017 (internal data supplied by NRC)
- NSW land tenure 2019 (internal data supplied by NRC)
- NSE land use 2017 v1.2 (internal data supplied by NRC)
- Australian dams and water storages (Geosciences Australia, 2009; publicly available at: https://koordinates.com/layer/739-australian-dams-and-water-storages/data/)
- Australian digital elevation data (Geosciences Australia, 2015; publicly available at: https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search#/metadata/89644)

We assessed catchment modification by estimating the percentages of area covered by forest, the percentages of area for major land use and land tenure types for catchments corresponding to the water quality/quantity monitoring sites (Figures A1-A3, Appendix). Another major consideration for catchment modification is the presence of major anthropogenic water storages and extraction. However, it was difficult to obtain detailed water extraction and licencing data as well as farm dam locations at the matching spatial scale of our analyses, as well as information on the active periods of these modifications (e.g., period of water extraction, construction and decommission dates of farm dams). Thus, we relied on the presence of large dams within each catchment to assess whether the catchment hydrology has been substantially modified. Following the Australian National Committee on Large Dams Incorporated (ANCOLD), a large dam is defined as one that is either more than 15m in height, on one that is more than 10m in height, with the crest length over 500m and the capacity over 1 million m^3 (ANCOLD, 2012).

Across the 90 (59) selected catchments to analyse trends in water quantity (quality), the forest cover is generally fair and centred around 40%. The catchments selected are heavily occupied by private tenure (with median private percentage of around 80%), and heavily used for grazing (with median grazing percentage of around 60%). 9 water quantity catchments and 12 water quality catchments have large dams within their catchment boundaries. Considering the general limitation in the number of monitoring sites (Tables 2 and 3) identified to be suitable for trend analysis, when estimating the trends, we did not exclude any selected monitoring site/catchment due to low forest cover, undesirable (i.e., modified) land use and tenure or presence of large dams. Nevertheless, this assessment of catchment modification will inform the selection of catchments to only focus on unmodified forested catchments when explaining the trends (as detailed in Section 2.4).

2.2.4 Historical climate and forest disturbance data

Catchment climatic conditions are considered as important drivers of changes in water quality and quantity and thus used in multiple analyses in the later analyses of trend attribution (see details in Section 2.4.2 and 2.4.3). To represent catchment-average climate, we first extracted the nation-wide daily gridded climate data for rainfall and potential evapotranspiration (PET). The rainfall and PET data were both available at 5km x 5km gridded scale, with the former dataset was provided by the BoM Australian Water Availability Project (AWAP) (Raupach et al., 2009) and the latter provided by The Queensland Government SILO (Scientific Information for Land Owners) database (Queensland Government, 2022). We then used the delineated catchment boundaries to clip the gridded data to obtain individual catchment-averaged daily time-series for rainfall and PET. These historical climate data were extracted up to Sep 2021 to align with the analysis period of the water quality and quantity data.

Catchment-averaged time-series of forest disturbance, specifically for wildfire extent and vegetation cover were compiled to identify any links between fire and temporal changes in water quality and quantity, for both the 2019/20 major fire event and the longer historical period (see details in Sections 2.4.2 and 2.4.3, respectively). Wildfire was selected amongst other types of disturbance (e.g., harvest, prescribed fire and forest age change) considering the consensus in literature that it is the most important forest disturbance that can affect water quality and quantity, as discussed in the final report of Project 3 Stage 1 (Guo et al., 2021a). To represent wildfire during the 2019/20 major event, we relied on a map of fire intensity for the 2019/20 fire event across NSW (internal data supplied by NRC), which shows the spatial difference in fire intensity with six different classes, where 'extreme' indicates the most severe burning. To capture historical fire events, we used long-term historical maps of wildfire over NSW (internal data supplied by NRC) which consist of spatial layers of the extent of individual fire events, which extends back to 1900. However, this dataset is unable to represent the intensity of individual fire events. To complement this, we further obtained the monthly nation-wide vegetation cover maps derived from MODIS satellite to extract the vegetation cover before and after each fire event as a proxy of fire intensity. This vegetation cover dataset is available from historical period since 2001 and made publicly available by the Terrestrial Ecosystem Research Network (TERN) (Guerschman, 2019). The further processing of these climate and forest disturbance datasets for the trend attribution analysis is detailed in Section 2.4.3.

2.3 Trend analyses for water quantity and quality

The previous project (Project 3) identified statistical approaches for analysing trends in the key water quality and quantity indicators within the RFA regions (Guo et al., 2021b). During this Extension Project, we built on our previous model approaches with further consideration of feedback from NRC on the last project to finalise the choice of trend estimation approaches.

The water quality indicators directly correspond to the time-series of monitored data (e.g., TP, DO, EC). Thus, we applied a temporal regression model for the full time-series of data for each indicator, observed at each site. This model assumes the presence of a linear trend over the full data period after accounting for the effects of flow and seasonality, and also any serial correlation in data when it consists of high-frequency monitoring (e.g., EC and turbidity, for which samples were collected at daily or even higher frequencies). With these components, the model structure is sufficiently sophisticated to describe non-linearity in data. The validity of the key model assumption of having a linear trend over the full data period is checked with the residuals of the calibrated trend model, as detailed in Section 2.3.2.

The water quantity indicators are based on signatures and indices derived from the monitored time-series of streamflow (e.g., annual flow). Thus, we applied non-parametric approach including Mann-Kendall (MK) (Kendall, 1955; Mann, 1945) and Sen's Slope (Sen, 1968; Theil, 1992) to analyse trends for these less temporally explicit data, which are both commonly used approaches for revealing regional long-term trends in streamflow (Gudmundsson et al., 2019; Petrone et al., 2010; Zhang et al., 2016). Although there is high variability/seasonality in the flow data, focusing on trends at an annual scale is sufficient because we do consider multiple water quantity indicators that together capture sub-annual variability in flow, including high/low flow and flow intermittency. Both the MK and the Sen's Slope models are capable to identify only monotonic trends in data. However, we have performed a comprehensive literature review which suggested that, although there are alternative approaches that are better suited to non-monotonic trends (e.g., using the spline multi-variate non-linear regressions e.g., Stojković et al., 2014, fitting time-varying parameters in a trend model such as with the WRTDS approach e.g., Hirsch et al., 2010), these approaches are mainly only applicable to local scales to limited number of catchments (e.g., Smith et al., 2013; Stojković et al., 2014; Liu et al., 2020). In contrast, when summarizing trends across a large number of catchments in regional studies, non-monotonic trends are typically very difficult to report; as a result, the trend statistics reported are often only able to summarize monotonic linear trends (Stahl et al., 2010; Zhang et al., 2016; Duan et al., 2018), even when a sophisticated non-monotonic trend model has been used to generate these trend statistics (e.g., Oelsner et al., 2017). Considering the scale of our study, we decided to keep these monotonic modelling approach for estimating trends in water quantity.

For each water quality and quantity indicator analysed, we run the abovementioned trend models over two analysis periods – long and short periods. The long period considered the full historical record period of individual monitoring sites, and thus maximizing the available data used for trend analysis, even though this can result in different data periods across sites. This is complimented with consideration of the short period as well, which is a common period across all monitoring sites when available records exist; therefore, the benefit of considering the short period is ensuring that trends are estimated over a consistent period for all sites. The short analysis period used for water quantity and quality indicators were 1984-current and 1990-current, respectively, based on the overall data availability of individual indicators.

2.3.1 Data processing

The water quantity indicators were largely based on signatures and indices derived from the monitoring time-series data of streamflow. Therefore, the raw daily flow data were first quality controlled based on the quality codes embedded with the raw data. Linear interpolation was performed to infill days with missing data or low-quality data. The daily flow data were then aggregated to derive annual time-series of the following water quantity indicators:

1) Annual flow i.e., the sum of all daily values within each year;
2) Annual rainfall-runoff residual. This was obtained by fitting a linear regression between annual flow and annual rainfall for each catchment and then extracting the residual of this regression. The flow data were Box-Cox transformed which leads to a better fit to the linear regression. The residuals for each catchment represent the deviations of annual flow from expectation with given rainfall. Therefore, assessing trends in the residuals can help explain whether trends in flow are due to changes in rainfall or other disturbances.
3) Annual 10^{th} and 90^{th} quantiles of daily flow;
4) Annual 7-day low flow, which is the average daily flow during the seven consecutive days with the lowest flow within each year; this is an indication of catchment storage and
5) Annual cease-to-flow (CTF), which is the number of days with zero flow in each year; this is an indication of groundwater disconnection.

It is worth noting that the above annual summaries were aggregated by hydrological years instead of calendar years. The starting month of hydrological years was identified for each catchment as the month with the lowest monthly average flow over the full data period. This approach minimized the chance of significant carry-over flow across years, which can make it more challenging to identify long-term trends.

The annual time-series of each indicator was further processed for the trend analyses (MK test and Sen's Slope). Since both analyses are non-parametric, they do not require the distribution of data to satisfy any model assumptions; however, both methods require input data to be temporally independent i.e., with no serial correlation. Our preliminary analysis found that the annual flow time-series generally have high correlations. To resolve this, we applied a statistical processing approach, pre-whitening (von Storch, 1995), to the annual time-series of all water quantity indicators across all catchments to remove serial correlation on the data.

The raw data for each water quality indicator were processed to satisfy the data required for the temporal regression. The linear model requires model residuals to be normally distributed. Therefore, we first applied log-10 transformation to the data for all water quality indicators, and then removed outliers that were greater than 3 standard deviations away from the median level of each catchment (Hampel, 1974). Further, some indicators were sampled at high frequencies i.e., roughly daily (EC, water temperature, DO, pH and turbidity). When there was more than one sample recorded in a day, we aggregated these samples to daily averages. Note that the temporal regression model did not require continuous data, so the presence of missing data or gaps had no impact on the water quality model.

2.3.2 Statistical analyses to estimate trends

As highlighted in the overview of Section 2.3, for each water quality variable, trends are estimated with input data that are directly corresponding to the time-series of monitored data, a temporal regression model was used for the full time-series data of each indicator, observed at each site. This model structure is informed by our understanding of the key factors driving temporal in river water quality in Victoria (Guo et al., 2019). This model explicitly accounts for a linear trend applied across each time step *t* over the whole record, together with effects of flow *f(Q)* and seasonality *f(seasonality)*:

$$\log(C_t) = t \times \beta_{tC} + f(\log(Q_t)) \times \beta_Q + f(seasonality) \times \beta_{seasonality} + f(\varepsilon_C) \qquad (1)$$

Note that both water quality and flow data were log-transformed due to data non-normality (see details in Section 2.3.3). $f(\varepsilon_c)$ is the error term, which was a first-order autoregressive (AR1) residual model for water quality indicators sampled at high frequencies (i.e., EC, water temperature, DO, pH and turbidity were sampled roughly at daily frequencies) to account for the potentially high serial autocorrelation. The low-frequency variables (TP and TN) are generally sampled at monthly steps, which are assumed to be sufficiently sparse so that serial autocorrelation is negligible – this was confirmed by checking all model residuals.

The model was calibrated to water quality data at the catchment level, and the values of the calibrated model parameter β_{tC} were extracted to inform the direction, magnitude and significance of temporal trends. We do acknowledge the strong assumption of a linear trend over the full data period; the validity of this assumption is carefully checked by assessing the residuals of the calibrated trend models to ensure the residuals are trend-free, meaning that all trends have been picked up by our trend model.

To identify trends in the water quantity indicators, we applied the non-parametric approaches of Mann-Kendall (MK) and Sen's Slope. Both methods are rank-based and do not require model calibration. The outputs from MK inform the direction and significance of temporal trends. The outputs from Sen's Slope inform the magnitude of the temporal trends.

2.4 Trend attribution for water quantity and quality

Trend attribution consists of three key analyses: 1) linking spatial differences in trends to catchment characteristics; 2) assessing the impact of the 2019/2020 fire event on water quantity/quality; and 3) linking historical temporal changes in water quantity/quality to catchment disturbances including climate and wildfire.

For the purpose of these analyses, we selected only a subset of all long-term catchments that we used for trend analysis (Section 2.3) to minimize the impact of catchment modification (e.g., having major catchment storage) on the trend attribution results. To explain the spatial differences in trends in analysis 1), we excluded any catchment with substantial hydrological modification as identified by having large dams within the catchment boundary (Section 2.2.3) but did not exclude catchments with lower forest cover, in order to maintain a relatively large number of catchments for the statistical analysis on the spatial differences in trends. For analyses 2) and 3), we focused only on catchments with primarily forest coverage and low modification, specifically, any catchment with >50% area covered by forest and no large dams within the catchment boundary.

2.4.1 Linking spatial differences in trends to catchment characteristics

This analysis intends to explain the spatial difference in the estimated trends for catchments outside the RFA region (as detailed in Section 2.3). To assess how the estimated temporal trends in vary across catchments, we firstly considered a number of catchment characteristics that represent catchment climate/hydrology, topography, land use, land cover and fire disturbance history. The current NSW land tenure map was available to be used for this analysis, but was not considered due to the lack of clear definitions of land tenure types, and potential overlap of information with the land use dataset (e.g., a preliminary analysis suggested that 'State Forest' in the land tenure dataset is highly correlated with 'Plantation Forest' in the land use dataset).

Table 4 presents a full list of catchment characteristics considered as potential explanatory variables for spatial differences in flow trends; the corresponding values of these characteristics for individual catchments analysed and their cross-correlations are summarized in Figure A4 in the Appendix. We used a multi-variate analysis to link these catchment characteristics to the corresponding trend magnitudes at individual catchments, to identify the most important drivers for the spatial differences in the trends. It is worth mentioning that several similar or highly-correlated catchment characteristics were included (e.g., % forest and annual rainfall has a significant strong correlation exceeding 0.7). This is to ensure the inclusion of a comprehensive set of potential factors influencing the flow trends drawn from multiple datasets (e.g., data for % forest and % plantation forest were extracted from two individual datasets of land cover and land use), from which the most influential factors can be identified via our multi-variate analysis. Further, this analysis could potentially incorporate more detailed information on vegetation class and formation (e.g., sclerophyll forests, woodlands, rainforests); however, this is limited by the availability of existing spatial data, which are only available for the Eastern NSW region which rarely intersects with the non-RFA region of interest for this analysis (NSW Department of Planning, Industry and Environment, 2020; available at: https://datasets.seed.nsw.gov.au/dataset/nsw-state-vegetation-type-map).

Table 4. Catchment characteristics considered to explain spatial differences in flow trends and their corresponding data sources.

Catchment characteristics and category		**Data Source**
Climate	Mean annual flow (mm)	Long-term daily flow monitoring data at individual sites (see Section 2.2.1)
	Mean annual rainfall (mm)	Long-term daily rainfall data extracted from AWAP (see Section 2.2.4)
Topography	Catchment average elevation (m)	Australian digital elevation data (see Section 2.2.3)
Land Cover	% catchment area covered by Forest *Forest extent was identified from a three-class mapping system in this dataset, which includes: non-woody, sparse woody vegetation and woody vegetation – the latter defines the forest extent*	NSW woody area extent representative of the period 2007-2017 (internal data supplied by NRC, see Section 2.2.3)
Land Use	% catchment area as Natural Land *The extent of multiple combined land use types under ALUM classification v8 that are representative of natural land. The specific ALUM classes included are:* • *Nature conservation* • *1.2.0 Managed resource protection* • *1.3.0 Other minimal use* • *2.1.0 Grazing native vegetation* • *2.2.0 Production native forestry*	NSE land use 2017 v1.2 (internal data supplied by NRC, see Section 2.2.3)

	% catchment area as Plantation Forest *The extent of multiple combined land use types under ALUM classification v8 that are representative of plantation forest. The specific ALUM classes included are:* • *3.1.0 Plantation forests (dryland)* • *4.1.0 Irrigated plantation forest*	
	% catchment area as Cropping Land *The extent of multiple combined land use types under ALUM classification v8 that are representative of cropping land. The specific ALUM classes included are:* • *Cropping (dryland)* • *3.4.0 Perennial horticulture (dryland)* • *3.5.0 Seasonal horticulture (dryland)* • *4.3.0 Irrigated cropping* • *4.4.0 Irrigated perennial horticulture* • *4.5.0 Irrigated seasonal horticulture*	
	% catchment area as Grazing Land *The extent of multiple combined land use types under ALUM classification v8 that are representative of cropping land. The specific ALUM classes included are:* • *3.2.0 Grazing modified pastures* • *4.2.0 Grazing irrigated modified pastures*	
Fire	% total catchment area burnt over the flow record period	Long-term fire extent maps over NSW (internal data supplied by NRC, see Section 2.2.4)

With the estimated magnitudes of trends at each site, we ran a brute-force search for the best predictors (within the catchment characteristics considered) which can explain the spatial difference in annual flow trends via a linear regression model. The brute-force approach searched through every possible linear combination of these catchment characteristics (as a statistical model) to explain the difference in trends across catchments. The ability of these models to explain the difference was evaluated with the Akaike Information Criteria (AIC; Akaike, 1974) – a balanced performance metric that maximizes model performance while minimizes complexity. This process identified a best model, and thus a best set of catchment characteristics to explain the spatial differences in trends.

2.4.2 Assessing the impact of 2019/2020 fire on water quantity/quality

A preliminary assessment of the extent of the 2019/20 fire suggested that this event primarily affected the RFA region, therefore, we focused only on catchments within the RFA region for this analysis. To focus this analysis on the most severely burnt catchments in this event, we further narrowed the catchment selection to catchments that are predominantly forest (with >50% area covered by forest) with over 10% catchment area recognized as being 'extremely burnt', while maintaining long-term records. This led to nine catchments selected to analyse the impact on water quantity – a map of these catchments is shown in Figure A5 in the Appendix.

For assessing the impact of 2019/2020 fire on water quantity, we used both direct data-interpretation and a model-based approach to identify changes in rainfall-runoff relationship across pre/post fire periods. We started with comparing the relationship of rainfall and runoff before and after the fire, by plotting the monthly anomalies of flow (% difference of monthly flow to the long-term average) against the monthly anomalies of rainfall (% difference of monthly rainfall to the long-term average). As such, any significant change of the rainfall-runoff relationship can be attributed to the impact of fire. A model-based approach was pursued in parallel, in which we assumed that the flow signals in each catchment are influenced by climatic conditions as well as the fire. A conceptual monthly rainfall-runoff model (Wang et al., 2011), was calibrated to simulate the expected flow when only the climatic effects are considered. Then we compared the modelled flow and actual flow to identify any significant difference since the fire occurred, which was attributed to the impact of fire. Results from both the direct data interpretation and the model-based approaches were synthesized to draw the final conclusion on the impact of the 2019/20 fire event on water quantity. It is worth mentioning that to ensure the rainfall-runoff relationship before fire is accurately represented, in both the abovementioned approaches, we excluded any rainfall and runoff data prior to the 2019/20 fire but fall on another year during which the catchment experienced severe burning, which is defined as years with >5% catchment area burnt (based on the long-term historical wildfire maps supplied by NRC).

Regarding water quality, there are only five catchments with over 10% catchment area recognized as being 'extremely burnt', while also maintained long-term water quality records (see Figure A6 in the Appendix for a map of these catchments). Thus, separate investigation on water quality changes before/after the fire was performed for individual catchments.

2.4.3 Linking temporal changes to catchment disturbances

For analysing the temporal changes in water quantity (flow), we evaluated all catchments with long-term flow data across both the RFA and non-RFA regions, and selected twelve catchments that are primarily forested, having no or little hydrological modification and have experienced large fire events in history. Specifically, the criteria applied for catchment selection are: a) >50% catchment areas as forest and with no large dams (see definition in Section 2.2.3) in the catchment; b) >10% catchment area burnt in any single fire event in the record period; and c) maintained long-term (>35 years of) flow records. A map of these catchments is shown in Figure A7 in the Appendix. For water quality, there was no suitable catchment satisfying these three criteria.

To explain changes in historical flow, we considered 9 potential drivers for changes in flow, focusing on climate and wildfire. We used the annual rainfall-runoff residuals (residuals in annual flow from the expected rainfall-runoff relationship, as detailed in Section 2.3.1) as the response variable to enable the analysis to focus on any unexpected change in runoff after excluding the effects of rainfall. For the potential climatic drivers of flow, we considered the potential evapotranspiration (PET) of the current year, the average flow over the 7 days with lowest flow in the previous year, along with a number of attributes that capture the seasonality and variability of rainfall within the current year. All potential predictors and their data sources are explained in detail in Table 5. Note that annual rainfall was not included as a potential predictor; this is because of our focus of this analysis on the rainfall-runoff residuals (as explained above), which thus inherently assumed that any influence of annual rainfall has already been considered and should not be repeated.

Table 5. Potential drivers considered to explain temporal changes in flow, and their corresponding data sources and available record period. The 'full period' means that the dataset covered the full historical period when flow data was available.

Potential driver and acronym used			**Data source and available record period**	**Definition and derivation**
Climate	Annual PET	*AnnPET*	Queensland Government SILO database (Queensland Government, 2022) Full period	Annual PET of the current year
	7d low flow (previous year)	*low7dPrev*	WaterNSW flow data (same as used for water quantity trend analysis) Full period	The average flow over the 7 days with lowest flow in the previous year. This is an indication of catchment storage.

	Rainfall seasonality	*Seasonality*	BoM AWAP dataset (Raupach et al., 2009) Full period	The seasonal incidence of rainfall, determined from the ratio of median rainfall for two periods 1) May to October and 2) November to April, within each water year (Bureau of Meteorology, 2016; Gaffney, 1971).
	Annual maximum dry spell length	*maxDry*		The annual (within each water year) maximum number of consecutive days with daily precipitation < 1 mm (Bureau of Meteorology, 2019).
	Annual medium dry spell length	*medDry*		The annual (within each water year) medium number of consecutive days with daily precipitation < 1 mm (Bureau of Meteorology, 2019).
	Extreme rainfall frequency	*extremeFreq*		The annual number of days with rainfall exceeding the long-term 95th percentile of all daily rainfall (Haylock and Neville, 2000).
	Extreme rainfall intensity	*extremeInt*		The annual average daily rainfall for days with rainfall exceeding the long-term 95th percentile of all daily rainfall (Haylock and Neville, 2000).
	Extreme rainfall proportion	*extremeProp*		The extreme intensity divided by the year's total rainfall (Haylock and Neville, 2000).
Wildfire	Fire extent	*burnt_perc*	long-term historical maps of wildfire over NSW (internal data supplied by NRC) Full period	Total percentage catchment area burnt each year
	Fire intensity inferred by vegetation cover difference	*vegDiff*	MODIS monthly nation-wide fractional vegetation cover maps (Guerschman, 2019) 2001-2021	Total relative difference in fractional vegetation cover before/after fire events each year.

In addition to climate, two further potential drivers were considered to represent the extent and intensity of wildfire. For the former, we estimated the percentage of catchment area affected by individual fire events using ArcMap spatial analyst. This was done for each catchment, by overlaying the burnt extent dataset (Section 2.2.3) with the corresponding catchment boundary and then calculating the percentage area burnt. This yields a time-series of historical percentage area burnt for each catchment. The time-series of each catchment was aggregated to annual scale by summing the percentage area burnt within each hydrologic year.

The MODIS satellite-derived vegetation cover data (Section 2.2.3) (Guerschman, 2019) was further processed and used as an indicator of the intensity of individual fire events. Since the fire events often only affected a small proportion of the catchment, we focused on the vegetation cover change before and after each fire event only within the burnt region of the catchment as a proxy of fire intensity, which ensures that only the most relevant vegetation responses to fire were captured. Further, vegetation cover can potentially change even without fire, due to seasonality, climate and catchment wetness etc. Considering this, the change in vegetation cover within the unburnt region of the catchment was also considered to represent the 'background change'. Thus, we extracted two time-series for each catchment to capture the difference of vegetation cover after/before fire for a) within the burnt area of individual fire events; and b) within the unburnt area of individual fire events. Each time-series was generated by clipping the monthly nation-wide vegetation cover maps to the corresponding burnt/unburnt regions resulted from individual fire events in the catchment. We then used the difference of the two time-series to obtain a time-series of the 'relative change in vegetation cover' in the catchment, which represent the vegetation cover change in response to fire, after excluding any background noise due to other catchment changes such as seasonality, climate and catchment wetness (Figure 3). This time-series of the relative vegetation cover change was then aggregated to annual scale by a weighted sum within each hydrologic year; the weights were assigned based on the area of individual burning events, so that a fire event with large extent was weighted higher in the summation. The vegetation cover dataset was only available from 2001, which limited the period of this analysis of explaining temporal changes in flow to post 2001.

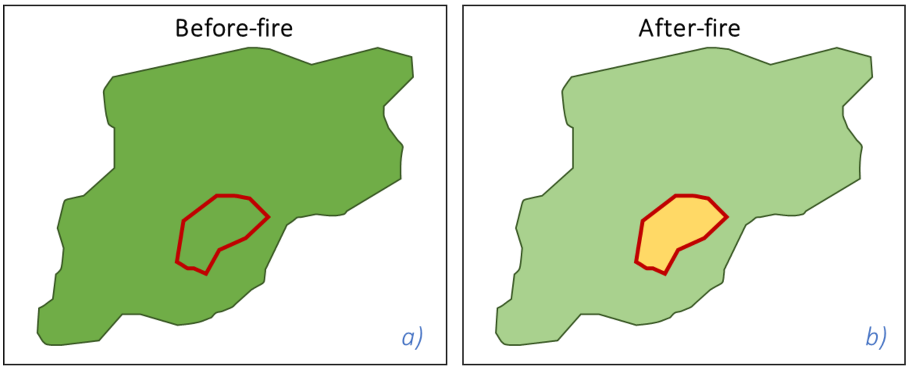


Figure 3. An illustrative map of a catchment (bounded by green border), and the area affected by a single fire event (bunded by red border) for a) before fire and b) after fire. Vegetation cover is illustrated with shaded colours for individual areas. The relative change in vegetation cover that we extracted is the difference between the burnt area and the unburnt area.in the vegetation cover change before/after fire, which intends to capture the vegetation cover change in response to fire, after excluding any background noise due to other catchment changes such as seasonality, climate and catchment wetness.

Combining the above potential drivers of flow on climate and wildfire, we assessed importance and impact of individual drivers using a Random Forest model. This model is a widely used machine-learning model (Breiman, 2001) which evaluates a large number of different combinations of potential predictors to explain changes in the response variable, with different model structures including non-linearity and lagged effects. The best combination of predictors and model structure was selected, from which the importance of individual predictors can be established to identify the most important predictors.

3. Results

3.1 Estimated trends in water quantity and quality indicators

Annual flow (Figures 4-6)*:* There is a wide-spread decreasing trend in annual flow throughout the catchments outside the RFA regions, for both the long and short analysis periods. Out of the 90 catchments, 42 have significantly decreasing trends at a 0.05 level, while 48 have non-significant trends or no trend, both in long and short terms (Figure 4). For catchments where annual flows are significantly decreasing, the long-term magnitudes of decline are mostly 10-20% per decade with the greatest decline of -30% per decade, relative to the mean annual flow of individual catchments over their full records. The short-term magnitudes of declining trends – estimated with data since 1985 only – are mostly 15-25% per decade, with the greatest decline of -34% per decade relative to the mean annual flow since 1985 of individual catchments (Figures 6 and 7). Less extreme declining trends are seen when focusing only on the predominantly-forested catchments and unmodified catchments (having no large dams with forest covering >50% of the corresponding catchment areas); however, most trend magnitudes are still in similar ranges compared to those across all catchments. In general, the magnitude of significant flow declines we see throughout the non-RFA regions highlights large declines of the state's water resources – we further compare our results to existing literature and discuss these implications in Section 4.1.

Figure 8 a) presents the trend difference in annual flow due to analysis periods. The difference in these two trends can be due to record length, where the greatest differences occur at sites with longer records. We also expect that for sites with longer records, the estimated long trends may be more influenced by potential changes in climate and land management. The distribution of annual flows at individual catchments in Figure 8 b) highlight two major periods of flow decline, for 1900-1940 and 1980 onwards, respectively.

Annual rainfall-runoff residual (Figures 4 and 9)*:* For annual rainfall-runoff residuals over the long analysis period, there is 1 site with significant increase, 36 sites with significant decreases, and 53 sites with non-significant trends / no trend. For the short analysis period, 26 sites have significant decreases, and 64 sites have non-significant trends / no trend. This commonly occurring declining trends in rainfall-runoff residuals, together with the previously observed large-scale decline in annual flow, suggest that the flow declines are generally greater than expected with given changes in rainfall i.e., the flow declines cannot be attributed solely to changes in rainfall. Considering the large spatial scale of the declining flow, potential drivers other than rainfall are likely large-scale factors such as climate. These will be further investigated in the trend attribution analysis in Section 3.2.3. We also provide a more detailed discussion on the potential drivers of the large-scale declining flow in Section 4.2.

High (90^{th} percentile) (Figure 10) *and low (10^{th} percentile) flows* (Figure 11): Similar to the annual flow, the high and low flows both display large-scale decreasing trends throughout catchments outside the RFA regions. The spatial distribution of significantly decreasing trends in high flows has a similar spatial pattern to that of the annual flow. This is likely due to the high skewness that is often seen in daily flow data i.e., mean flow is closer to the higher flow percentiles, which causes annual flow to be largely dominated by high flows. In the northeast of NSW outside the RFA regions, the significantly decreasing trends in low flows also demonstrate such a similar pattern to the annual flows. In contrast, in the remainder of NSW outside the RFA regions, the catchments where low flow has decreased are different to those that have had significant decreases in annual flow. It should be noted that there are around 10 sites with significant increases in low flows for both the short and long analysis periods.

Cease-to-flow (CTF, Figure 12Figure 12*):* While the above trends highlight a large-scale decline in water quantity throughout the catchments outside the RFA region, cease-to-flow (the number of days with flow each year) generally display a significant increasing trend in about a third of the 90 catchments. Since the trends in CTF summarizes the change in no-flow conditions in individual catchments, the generally increasing trend in CTF seen here is consistent with the overall drying trend as suggested by the above-mentioned water quantity indicators.

7-day low flow (Figure 13)*:* 7-day low flow generally decreases throughout catchments outside the RFA regions, and the spatial distribution of catchments that have significant decreases is very similar to that of low flow. A declining trend in 7-day minimum flow indicates a likely decline in catchment-wide groundwater levels (Brutsaert, 2008; Zhang, 2014).

Total phosphorus (TP, Figure 14*):* There are non-significant trends / no trend in TP within about half the catchments, and significant increases in more than 10 sites. In the long term, 13 catchments experienced significant decreases.

Total nitrogen (TN, Figure 15*):* Most sites demonstrate significant increases in TN, especially in the long term.

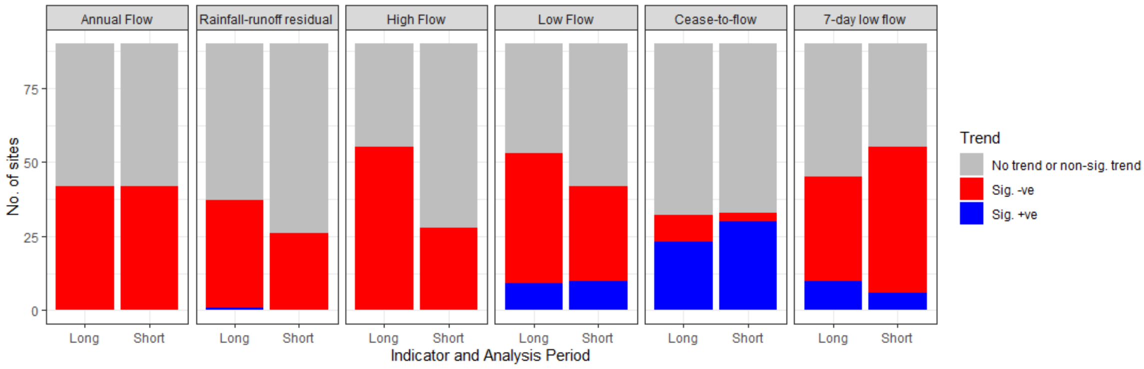
Electrical conductivity (EC, Figure 16*)* and *water temperature* (Figure 17) generally show non-significant trends / no trend in catchments outside RFA, with several sites having significant increases. For both variables, there is no clear pattern in the spatial distribution of trend directions.

The generally limited number of monitoring stations for the water quality variables make it difficult to inform large-scale conclusions on water quality trends with existing data. Note that the statistical model used to estimate water quality trends included flow among the predictors, and the model residuals confirmed that these models have effectively accounted for any impacts from flow change. Thus, any significant trend identified are not due to changes in flow.

Table 6 presents a summary of trend directions for individual water quality/quantity indicators, with the corresponding proportion of catchments with each type of trend further summarised in Figure 4. The detailed maps of trends for individual catchments for each indicator are shown in Figures 5-17.

Table 6. Summary of trends for individual water quantity/quality indicators. The 'Long' and 'Short' indicate whether the analysis period used was the full record periods of individual sites, or since 1984 for all sites, respectively. All trend significance values were evaluated at a 0.05 level.

Water quantity or quality indicator	**Number of catchments analysed**	**Number of catchments with significant increases**	**Number of catchments with significant decreases**	**Number of catchments with non-significant trends / no trend**
Annual flow Long	90	0	42	48
Annual flow Short	90	0	42	48
High flow Long	90	0	55	35
High flow Short	90	0	28	62
Low flow Long	90	9	44	37
Low flow Short	90	10	32	48
Rainfall-runoff residual Long	90	1	36	53
Rainfall-runoff residual Short	90	0	26	64
Cease-to-flow Long	90	23	9	58
Cease-to-flow Short	90	30	3	57
7day low flow Long	90	10	35	45
7day long flow Short	90	6	49	35
Total Phosphorus (TP) Long	45	11	13	21
Total Phosphorus (TP) Short	43	12	5	26
Total Nitrogen (TN) Long	44	28	2	14
Total Nitrogen (TN) Short	41	20	2	19
Electrical Conductivity (EC) Long	34	1	8	25
Electrical Conductivity (EC) Short	33	2	9	22
Water Temperature (Wtemp) Long	37	10	1	26
Water Temperature (Wtemp) Short	37	3	3	31



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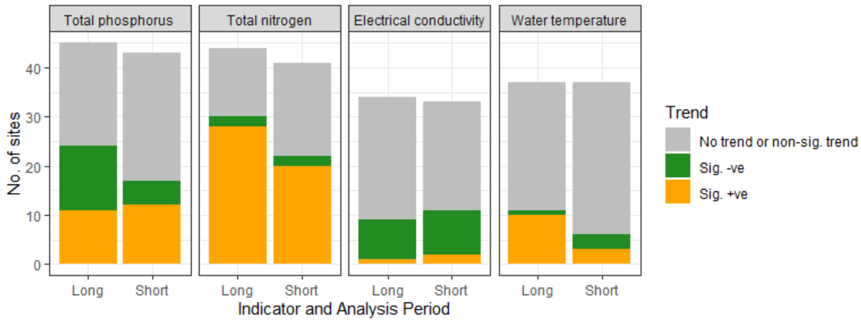
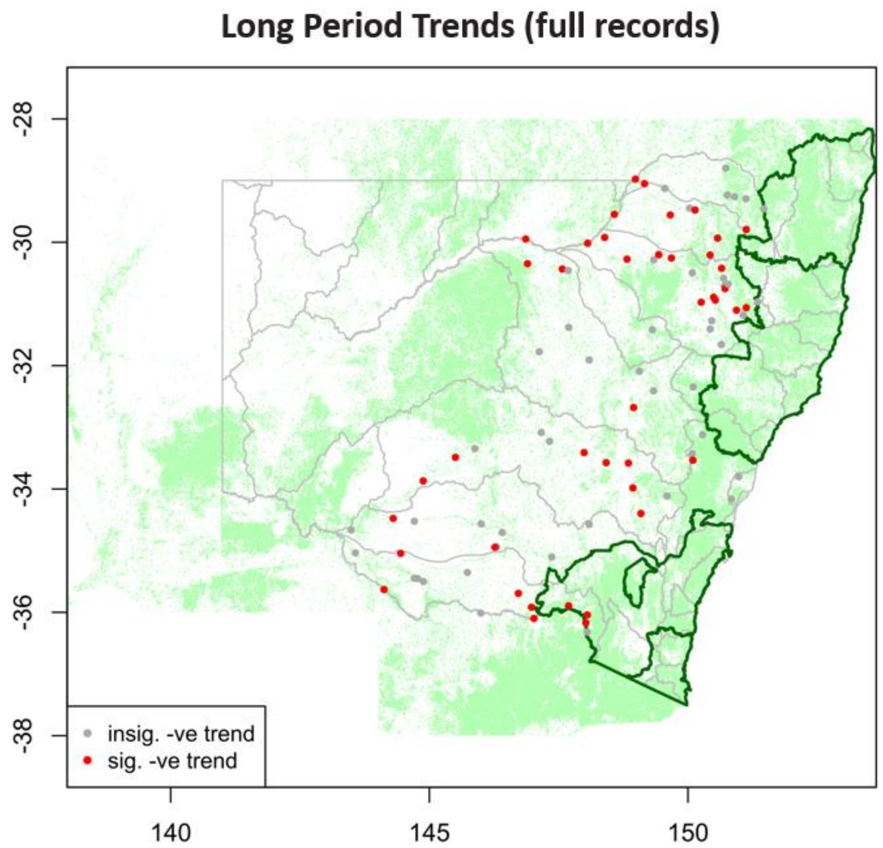


b)

Figure 4. Proportion of catchments analysed that has shown each type of long-term and short-term trends (significant increase, significant decrease, no trend or non-significant trend) for a) water quantity indicators; b) water quality indicators. Abbreviations for water quality variables are: WTemp = water temperature, EC = electrical conductivity, TP = total phosphorus, TN = total nitrogen, Turb = turbidity, DO = dissolved oxygen. Note that the availability of water quality data is generally limited to conclude large-scale trend patterns. All corresponding locations of the catchments analysed for each indicator are shown in Figure 5.



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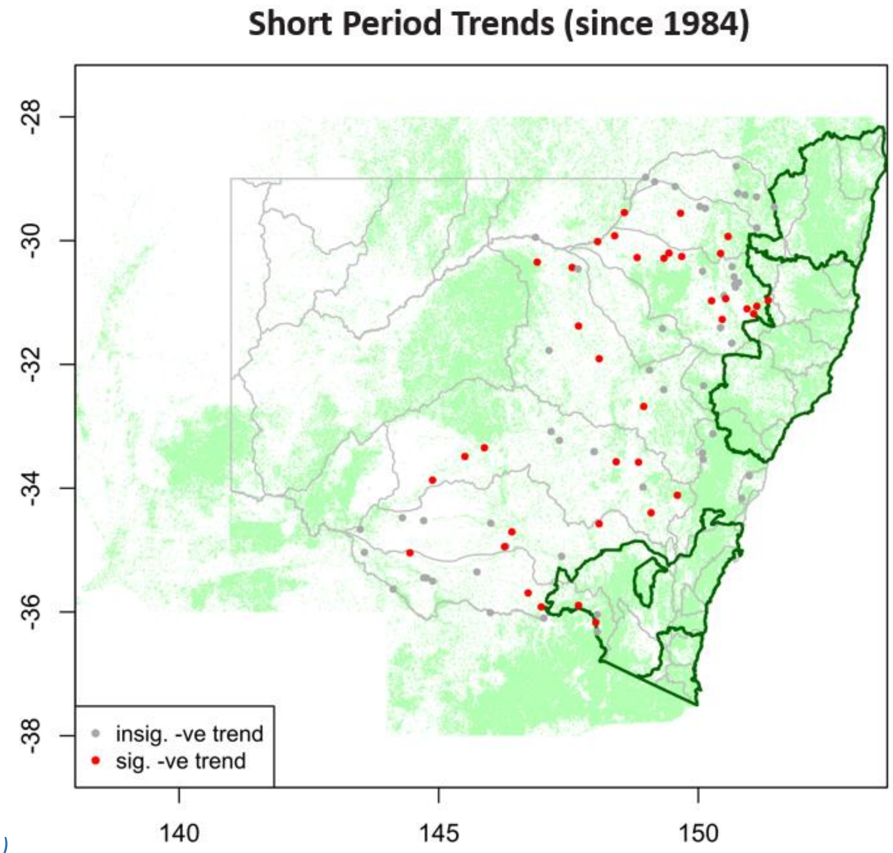

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Figure 5. The direction and significance of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in mean annual flow across catchments outside the RFA regions, estimated for individual catchments.

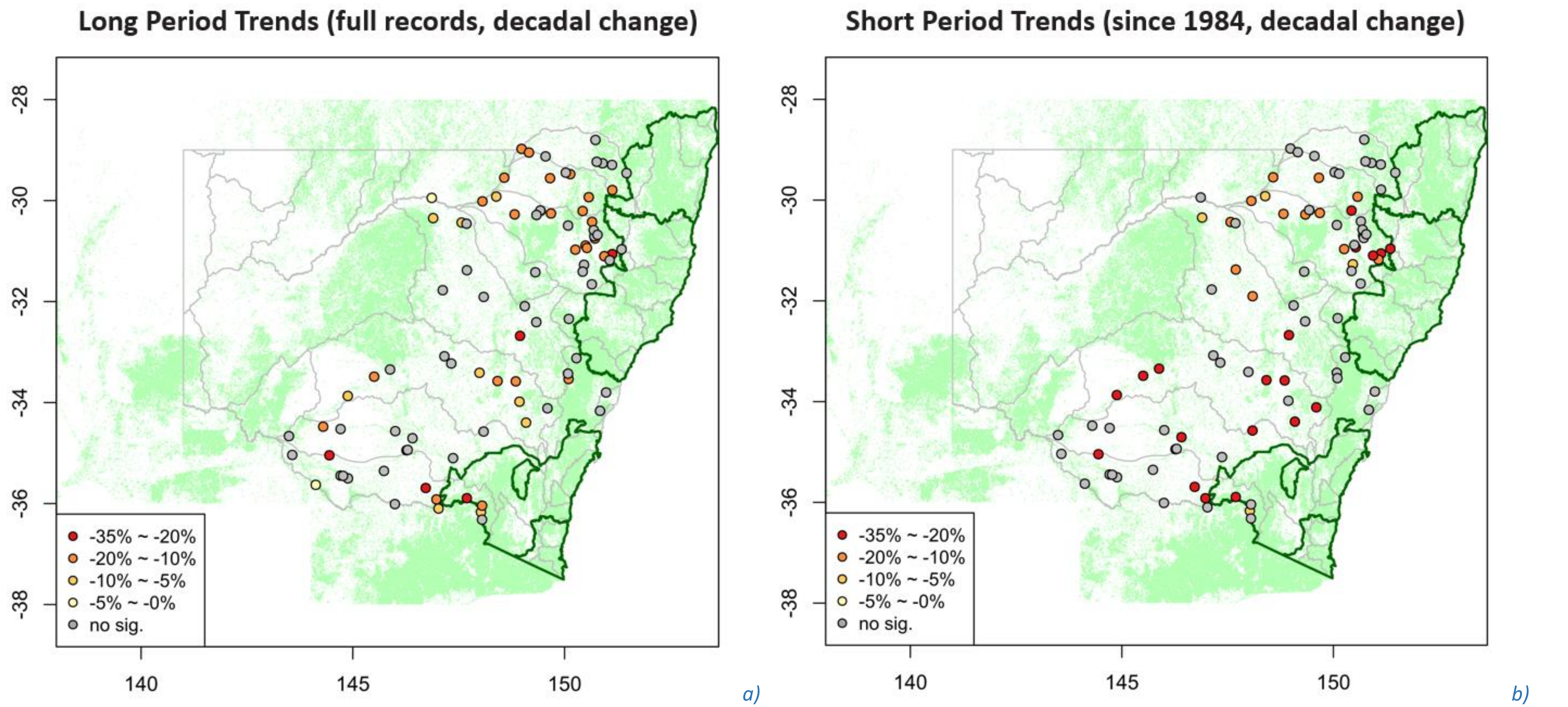


Figure 6. The magnitudes of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in mean annual flow across catchments outside the RFA regions. All trend magnitudes are in percentage change per decade, relative to the long-term average of mean annual flow for individual catchments.

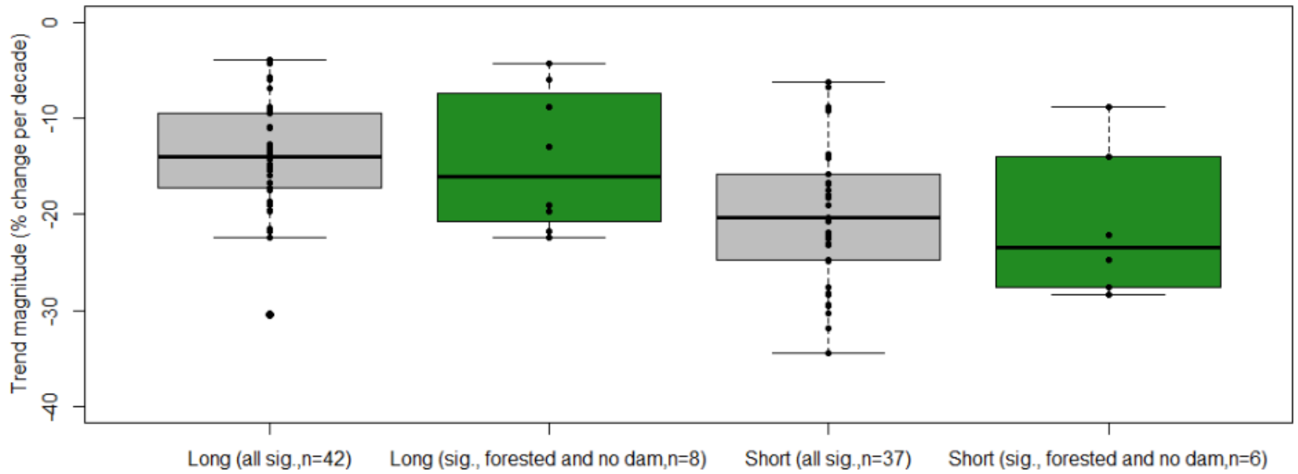
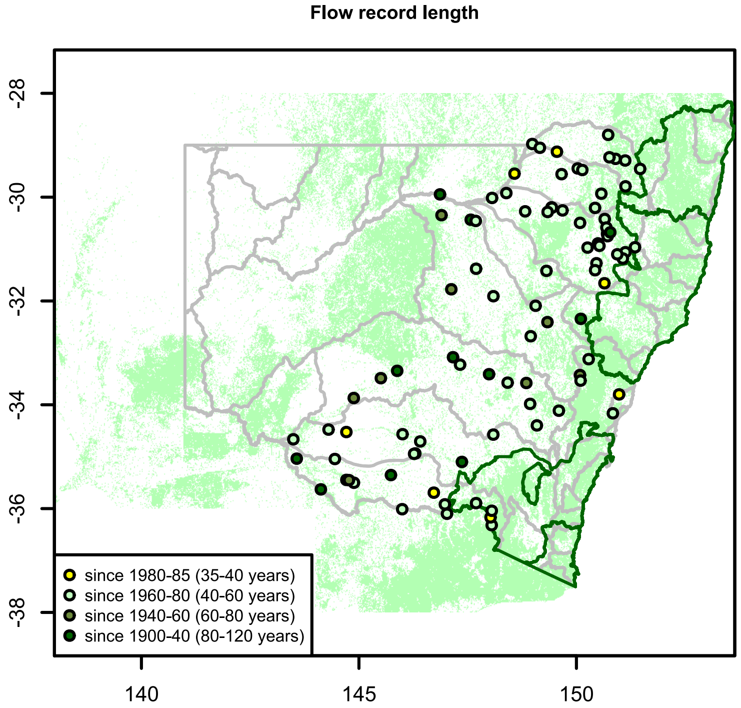


Figure 7. The magnitudes of significant long trends (full record periods of individual sites) and significant short trends (since 1984 for all sites) in mean annual flow, for all catchments, and for predominantly-forested and unmodified (no large dam) catchments only, with n specifying the number of catchments included for each group. Only significant trend magnitudes are shown. All trend magnitudes are in percentage change per decade, relative to the long-term average of mean annual flow for individual catchments.



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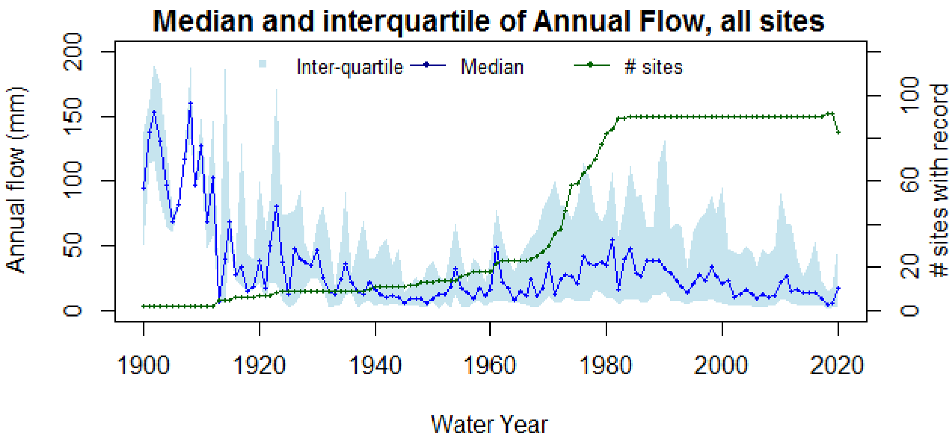


b)

Figure 8. Trend differences due to analysis periods of annual flow (mm) for the water quantity trends, comparing a) flow record length; and b) median and interquartile of annual flow in all sites. In a), different colours indicate different length ranges of flow record. In b), the blue solid line indicates the median across the catchments with 25th and 75th percentile range shown in shades. This inter-quartile range indicates the variability in annual flow each year across all forest catchments studied. The green solid line indicates the number of sites with record.

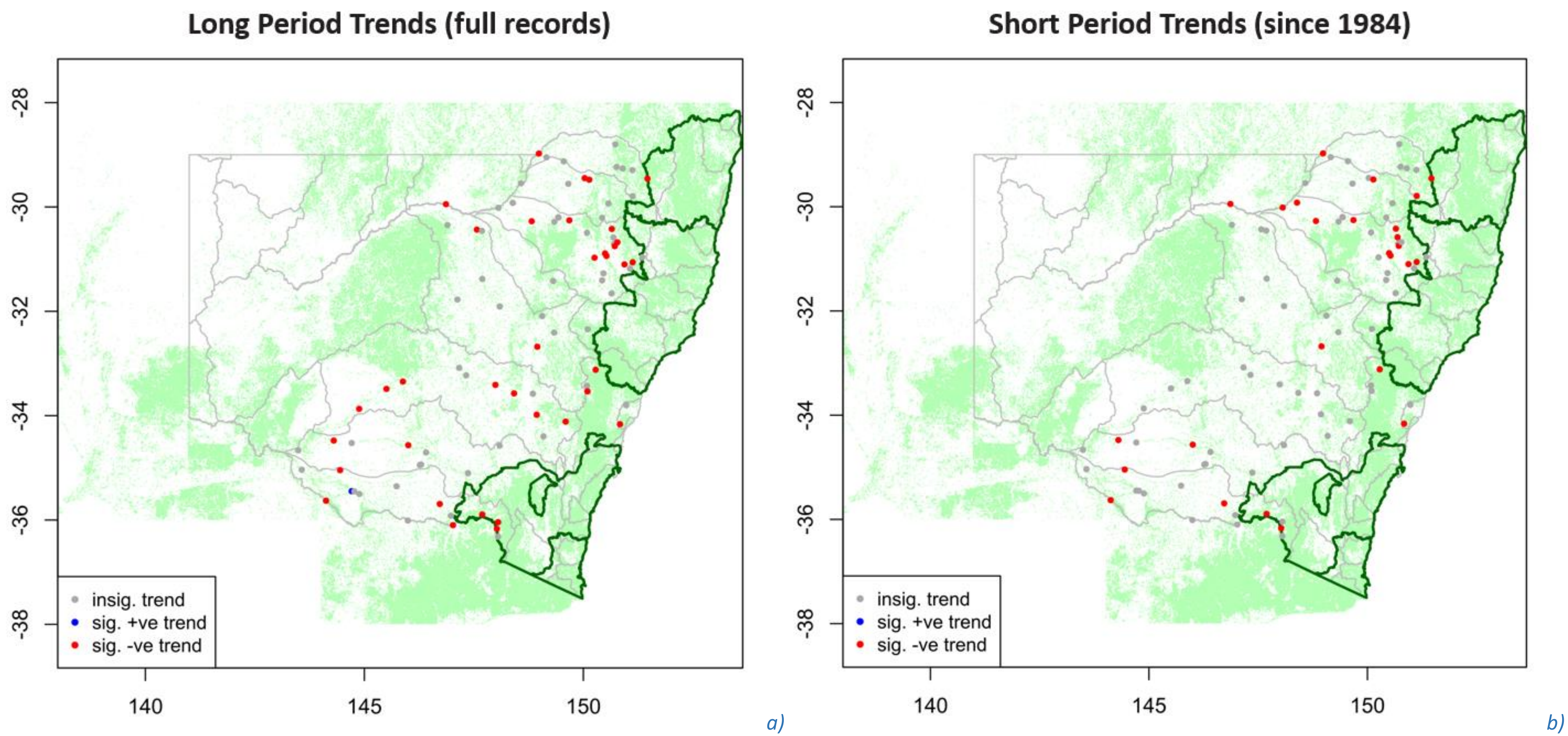


Figure 9. The direction and significance of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in annual rainfall-runoff residuals across catchments outside the RFA regions, estimated for individual catchments.

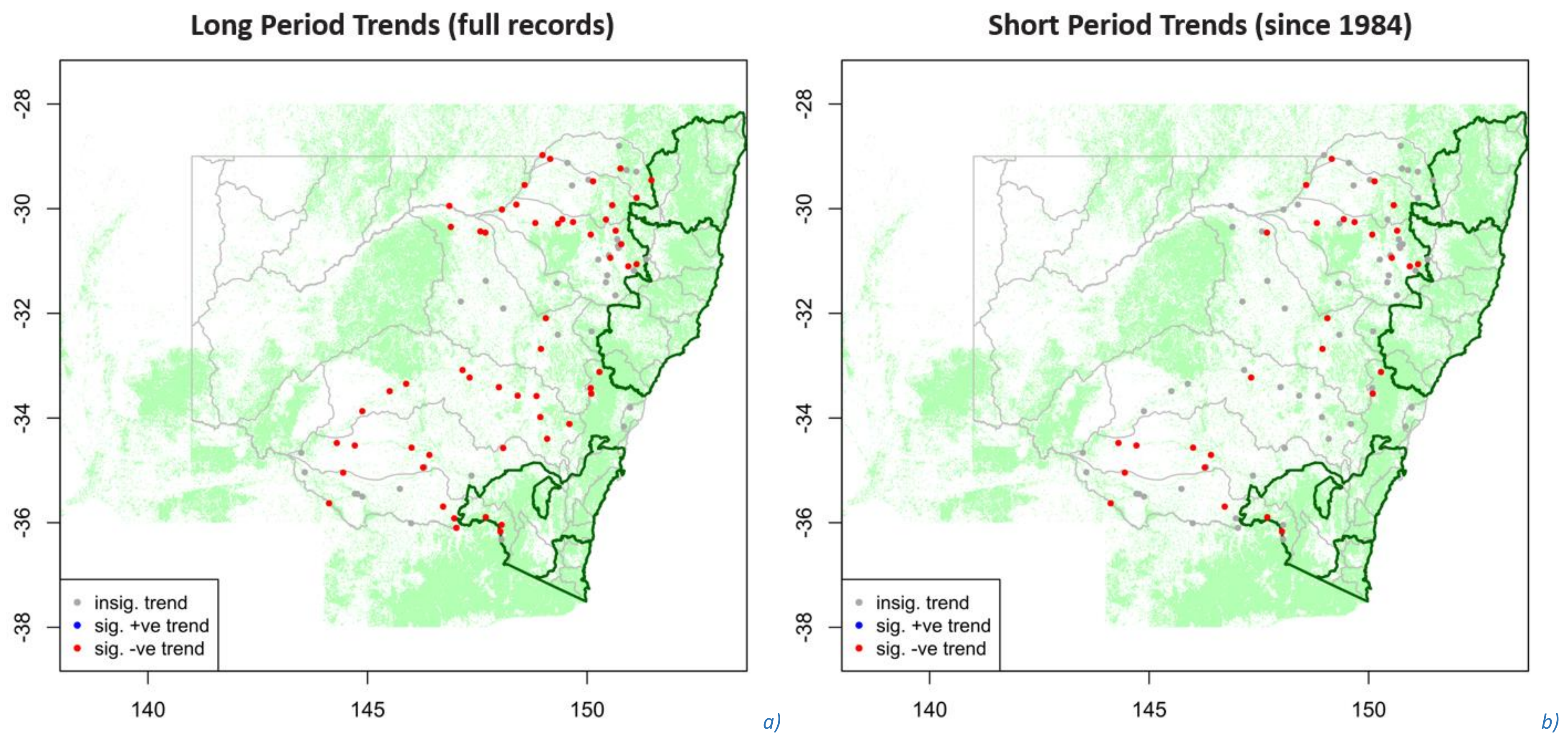


Figure 10. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in high flow across catchments outside the RFA regions. High flow Q90 is the annual 90th percentile of all daily flow, estimated for individual catchments.

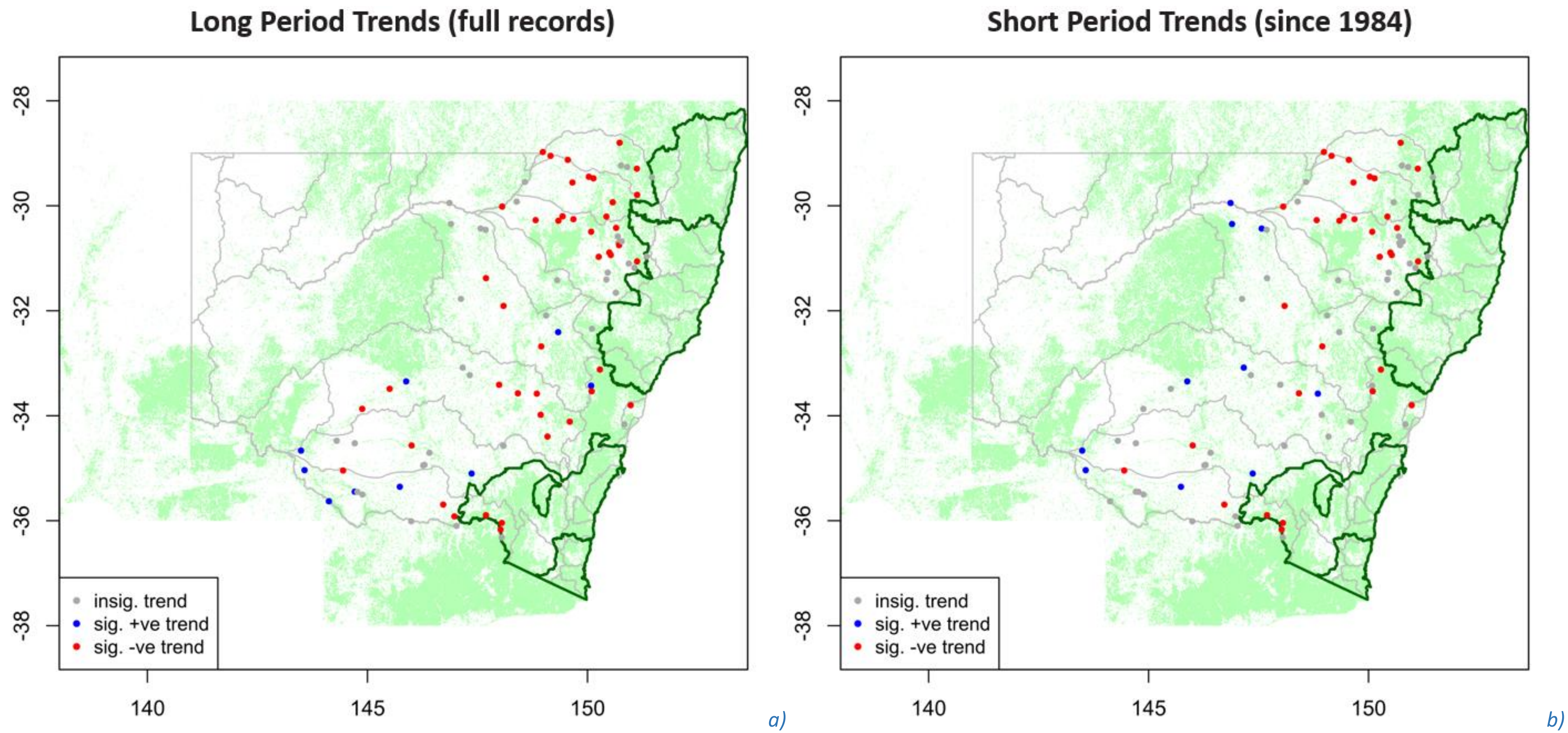


Figure 11. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in low flow across catchments outside the RFA regions. Low flow Q10 is the annual 10th percentile of all daily flow, estimated for individual catchments.

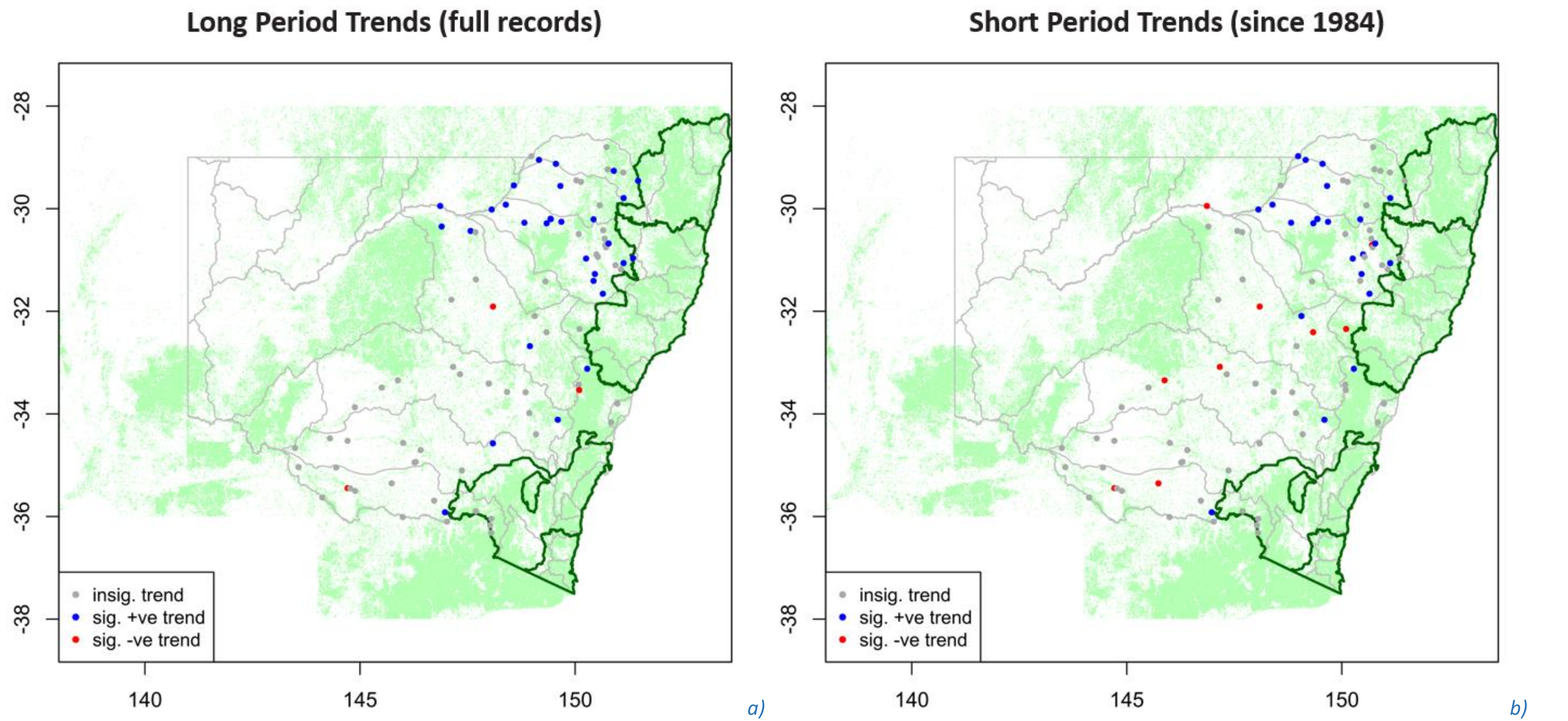


Figure 12. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in cease-to-flow across catchments outside the RFA regions, estimated for individual catchments. Cease-to-flow is the number of days with no flow in each year.

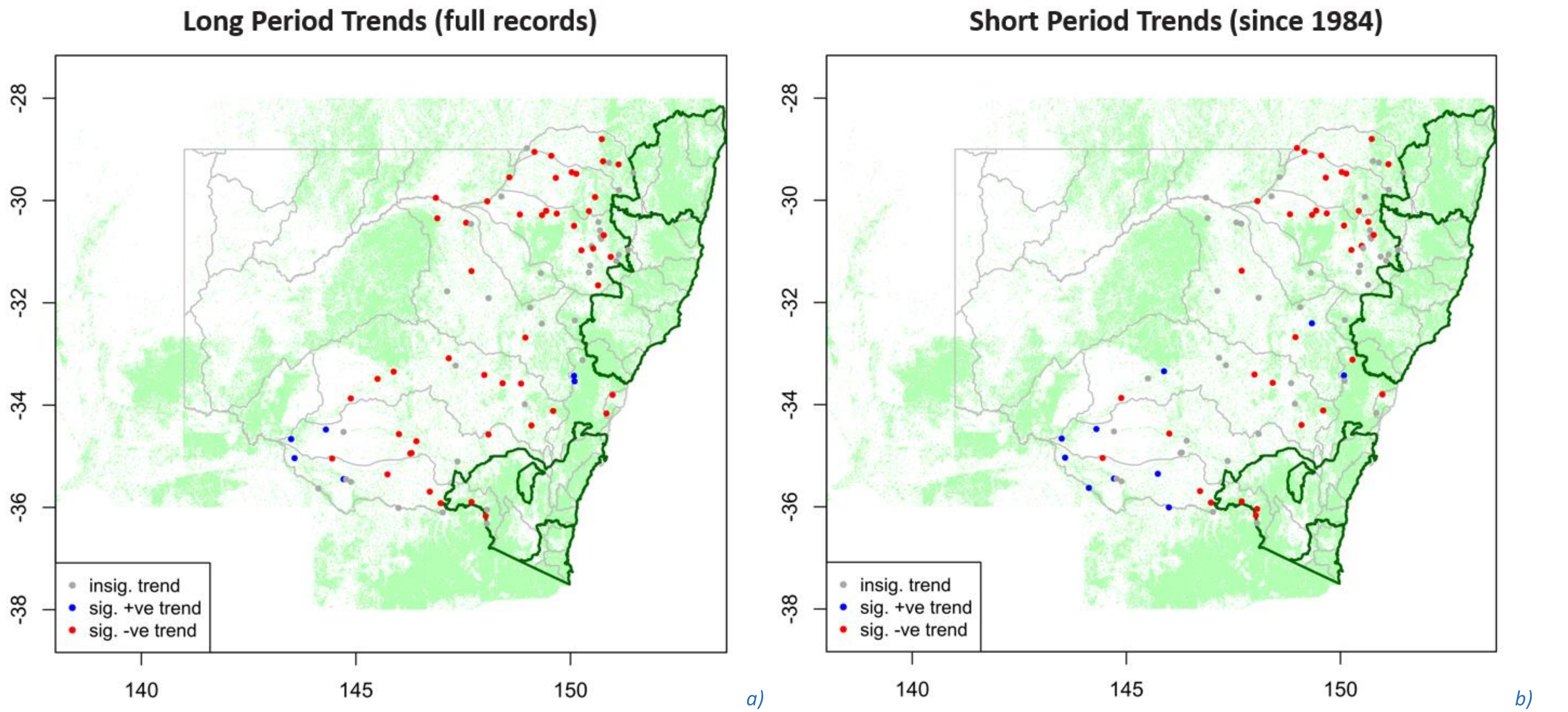


Figure 13. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1984 for all sites) in 7-day low flow across catchments outside the RFA regions, estimated for individual catchments. 7-day low flow is the average flow over the 7 days in each year for which have the lowest flows.

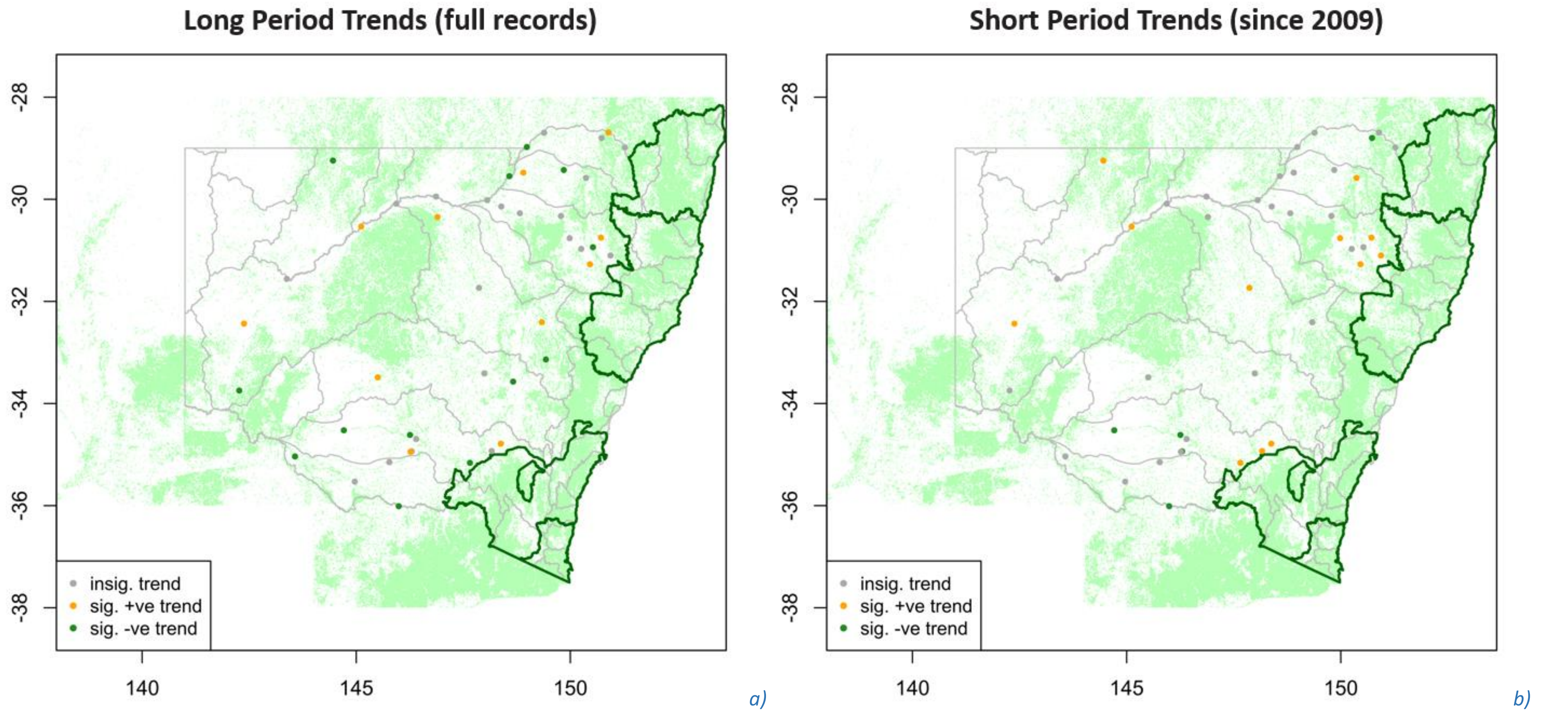


Figure 14. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1990 for all sites) in total phosphorus (TP) across catchments outside the RFA regions, estimated for individual catchments.

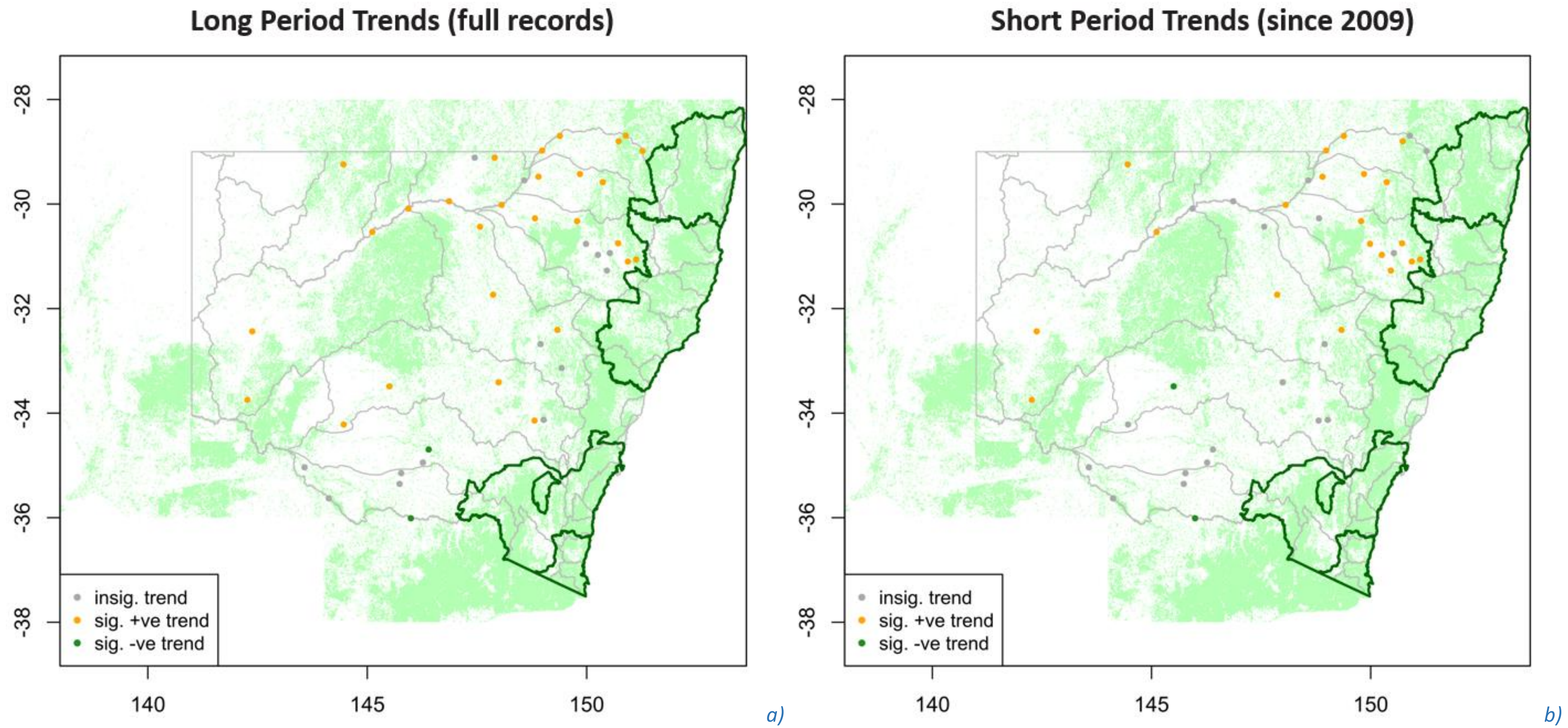
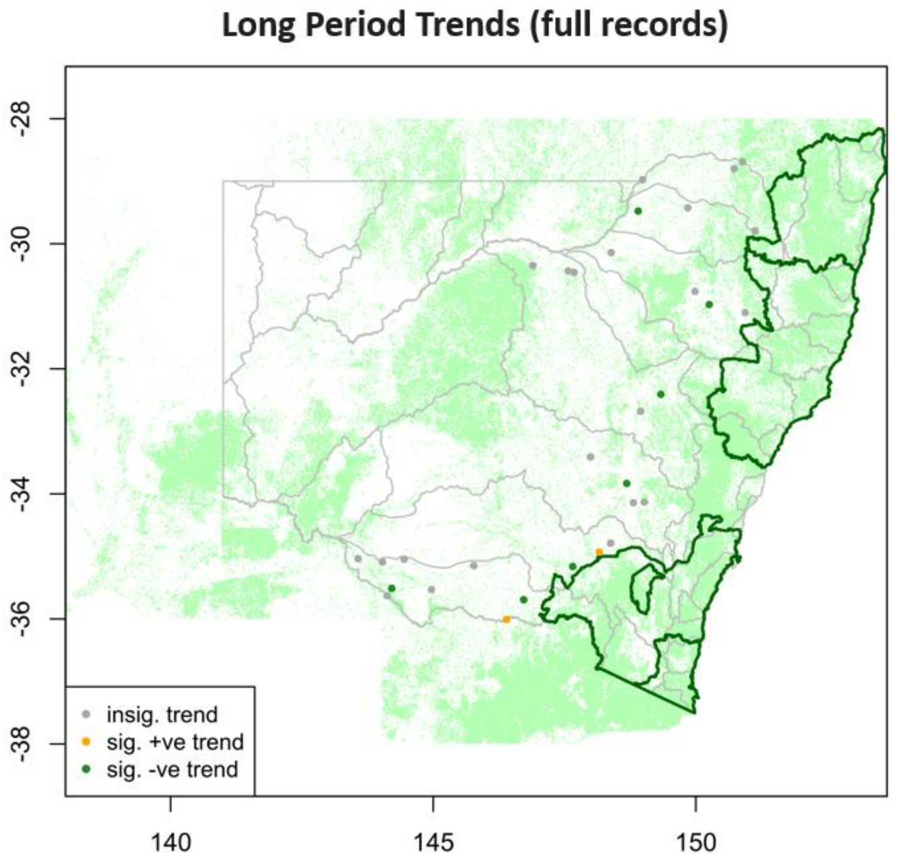


Figure 15. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1990 for all sites) in total nitrogen (TN) across catchments outside the RFA regions, estimated for individual catchments.



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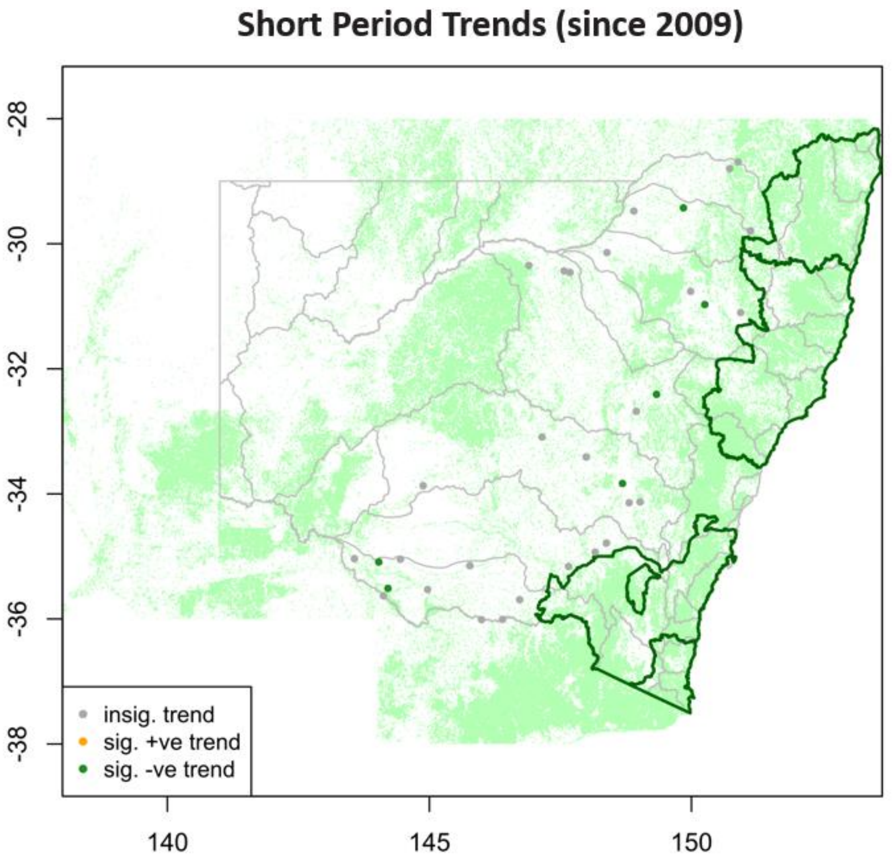

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Figure 16. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1990 for all sites) in electrical conductivity (EC) across catchments outside the RFA regions, estimated for individual catchments.

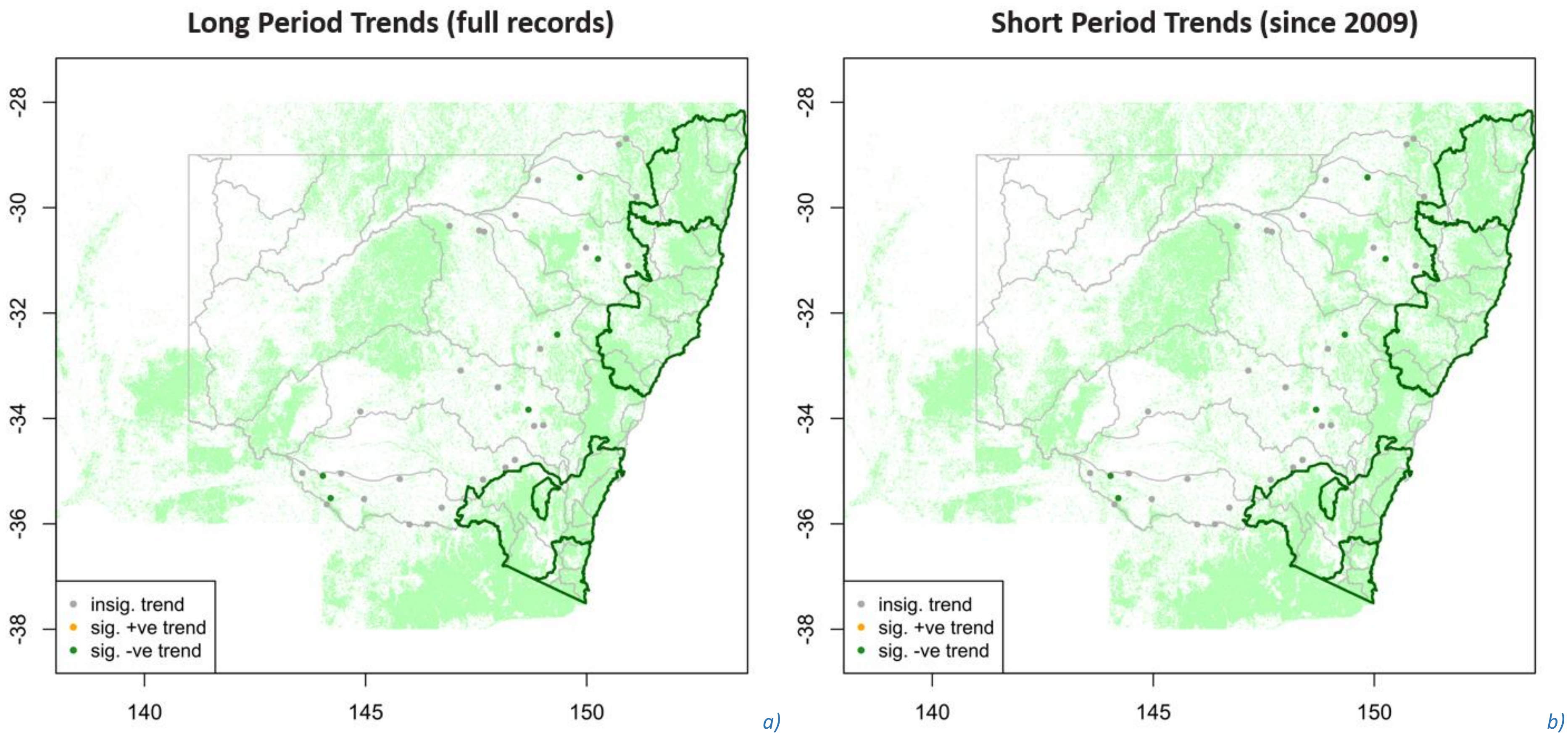

Figure 17. The direction of a) long trends (full record periods of individual sites); and b) short trends (since 1990 for all sites) in water temperature (WTemp) across catchments outside the RFA regions, estimated for individual catchments.

3.2 Trend attribution

3.2.1 Explaining spatial difference in flow trends with catchment characteristics

As highlighted in the trend results (Section 3.1), the number of monitoring sites for individual water quality indicators is generally insufficient to reveal spatial patterns of water quality trends; therefore, this analysis aiming to explain the spatial differences in trend magnitudes was performed only for water quantity, specifically, on the trend magnitudes for annual flow (Figure 6) as that is the most important water quantity indicator. Table 7 summarizes the best predictors that we identified for explaining the long and short trends in annual flow, along with the directions of their effects on these trends. Our analysis suggests that the mean annual flow, the percentage of plantation forest and the percentage of grazing area are the key catchment characteristics that can explain the differences in the percentage decline in annual flow across catchments. These three key explanatory variables are consistent for flow trends estimated for both the short and long analysis periods; meanwhile, forest coverage and the percentage area of natural land, although identified as important to explain the spatial differences in flow trends over the short analysis period, are not recognized for the long analysis period. Thus, the subsequent discussion focuses on the three key common explanatory variables between the short and long trends (i.e., mean annual flow, plantation forest, grazing land), while not further discussing the effects of natural land and forest coverage. As explained in the description of the approach of this analysis (Section 2.4.1), we included a comprehensive set of catchment characteristics as the potential factors driving the spatial differences in flow trends, which consisted of some highly-correlated variables (e.g., % forest and mean annual rainfall). However, our multi-variate analysis has effectively filtered out influences from these 'similar' variables and identified the key driving variables that are relatively independent to each other (e.g., mean annual flow and % plantation forest, correlation = -0.006; % plantation forest and % grazing land, correlation = -0.1). Thus, the final sets of key catchment characteristics selected (Table 7) are likely exhibiting different effects of these characteristics on catchment hydrology and the trends in flow. Nevertheless, the implication of these results should be also interpreted with consideration of the ranges of each spatial characteristics across all catchments (Figure A4 in the Appendix). It is worth noting that the mean annual flow and percentage of grazing land both have relatively wide ranges of values which are likely capturing a variety of catchment conditions; in contrast, the percentages of plantation forest vary only a little across the catchments analysed, taking <10% of the corresponding areas in most catchments; it remains questionable whether such small variation of values would offer much power in explaining the spatial differences in flow trends. Therefore, the effect of plantation forest identified with our statistical analysis is likely due to a statistical artefact rather than indicating true impact of plantation forest. Combining the above results and discussions, we can conclude that within the catchments for which we analysed long-term flow trends, wetter catchments and catchments with higher proportions of grazing areas generally experienced greater percentage declines in flow. These results also indicate that catchment land use could potentially modulate the effects of climate in influencing water quantity.

Table 7. The best predictors identified that explain the spatial differences in the long trends and short trends on catchment annual flow, and the directions of the effects of individual predictors on these trends. The grey shading highlights the three key explanatory variables of the spatial differences in flow trends across both the short and long analysis periods.

Long trend (using all historical data at individual sites)	Short trend (using only data from 1984 onwards)
▪ **Higher** *mean annual flow* -> **greater** decline ▪ **Higher** *% catchment area as Plantation Forest* -> **greater** decline ▪ **Higher** *% catchment area as Grazing Land* -> **greater** decline	▪ **Higher** *mean annual flow* -> **greater** decline ▪ **Higher** *% catchment area as Forest* -> **smaller** decline ▪ **Higher** *% catchment area as Natural Land* -> **greater** decline ▪ **Higher** *% catchment area as Plantation Forest* -> **greater** decline ▪ **Higher** *% catchment area as Grazing Land* -> **greater** decline

Further to the key drivers of the spatial differences in flow trends identified, we also assessed the ability to explain spatial differences in these trends. The corresponding best predictors identified can explain 16% spatial difference in the long trends, and 29% spatial difference in the short trends. In other words, the ability to explain the short trends with catchment characteristics is about twice as that for the long trends. Some plausible causes for this include: 1) the trends over the shorter period (1984 onwards for all sites) are less likely to be non-monotonic, likely showing stronger trend signal, which are easier to be related to catchment characteristics; 2) over the shorter analysis period, catchment climate and land characters are less likely to experience substantial changes compared with the long period, which means that catchment flow is less likely showing non-linear responses to disturbances. The relatively modest explanatory power also suggests that there are substantial catchment specific influences that are not captured by the spatial predictors considered. Other potential explanatory factors would include the detailed vegetation class and formation (as highlighted in Section 2.4.1), as well as soil, geological characteristics and seasonality of climate.

3.2.2 The 2019/2020 fire impact on flow and water quality

3.2.2.1 Fire impact on flow

To assess the impact of the 2019/20 fire on flow, we first looked at the monthly flow anomalies versus rainfall anomalies for the recent 10 years (with data since 2010 i.e., 10 years before fire) at the 9 most severely burnt forested catchments (Figure 18, see Figure A5 in the Appendix for a map of these catchments). The grey and red dots show the anomalies, as the percentage differences from the long-term average level of each catchment, before and after the 2019/20 fire respectively, with a darker red dot indicating a closer date after the fire occurrence. A visual inspection suggests that the slope going through red dots are generally steeper than the slope through the grey dots, highlighting a general increase in flow following the 2019/20 fire compared to the recent 10 years' average conditions. However, it is also worth noting that the rainfall after the fire event also increased compared to pre-fire conditions – as a substantial proportion of the red dots fall on the right side of the vertical dashed line, representing heavier rain events compared to the 10-year average condition. Therefore, it is uncertain whether the flow increase is a direct response to the fire due to changing rainfall-runoff relationship, or the heavier rainfall occurring coincidentally after the fire.

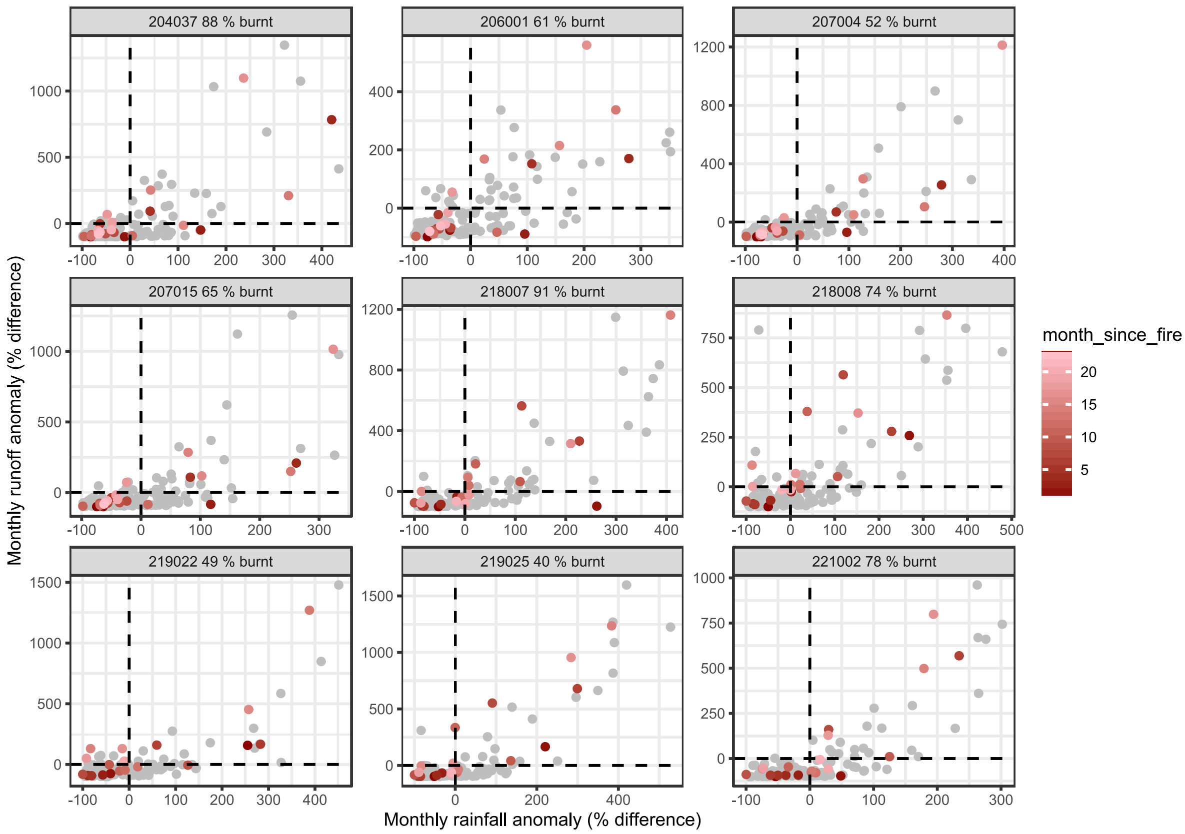

Figure 18. Comparison of the monthly anomalies of runoff against the monthly anomalies of rainfall before and after the 2019/20 fire event, at 9 catchments that have been most severely burnt in this fire event. The comparison includes all data since 2010 (10 years before fire). For both the rainfall and runoff at each catchment, the monthly anomalies are shown as % differences from the corresponding long-term average level.

When extending this analysis to the longer term – over the full record periods – the rainfall-runoff relationship after the 2019/2020 fire does not display a significant change from historical periods (Figure 18). In Figure 18, we again assessed the monthly flow anomalies versus rainfall anomalies over the full historical record period at the 9 severely burnt catchments, with the grey and red dots show the before/after fire anomalies, respectively. In contrast with the pattern in the recent 10 year's comparison (Figure 17), the red and grey dots appear to lead to similar slopes, suggesting no substantial post-fire change in the rainfall-runoff relationships at the whole catchment scale.

This result is further strengthened with an independent analysis using a model-based approach, in which we calibrated a rainfall-runoff model and assumed that we have captured the flow responses to climatic drivers, the modelled flow was then compared to the observed flow to identify any difference occurring after the 2019/20 fire (as detailed in Section 2.4.2). Figure 20 shows the model residuals (the difference between the observed and modelled flow) for the full historical record period, at each of the 9 severely burnt catchments. The green and red dots highlight residuals before and after the fire, respectively. Figure 20 shows no clear difference between the distributions of model residuals before and after the fire, suggesting that the rainfall-runoff relationship has not changed substantially after the fire when compared with the long-term climate. These results lead to the consistent conclusion that, the rainfall-runoff relationship at the whole catchment scale after the 2019/20 fire has not changed markedly when compared to the full historical period before fire.

Care is required in interpreting these results given that catchments are typically on partially burnt in any particular fire event. For the selected catchments, the 2019/20 fire affected between 40% and 91%

of the catchment area. It is quite possible that changes in runoff have occurred within the smaller portions of catchment affected by fire, but they are not sufficient to result in a clear signal at the full catchment scale to warrant a clear impact on the flow monitoring station at the catchment outlet.

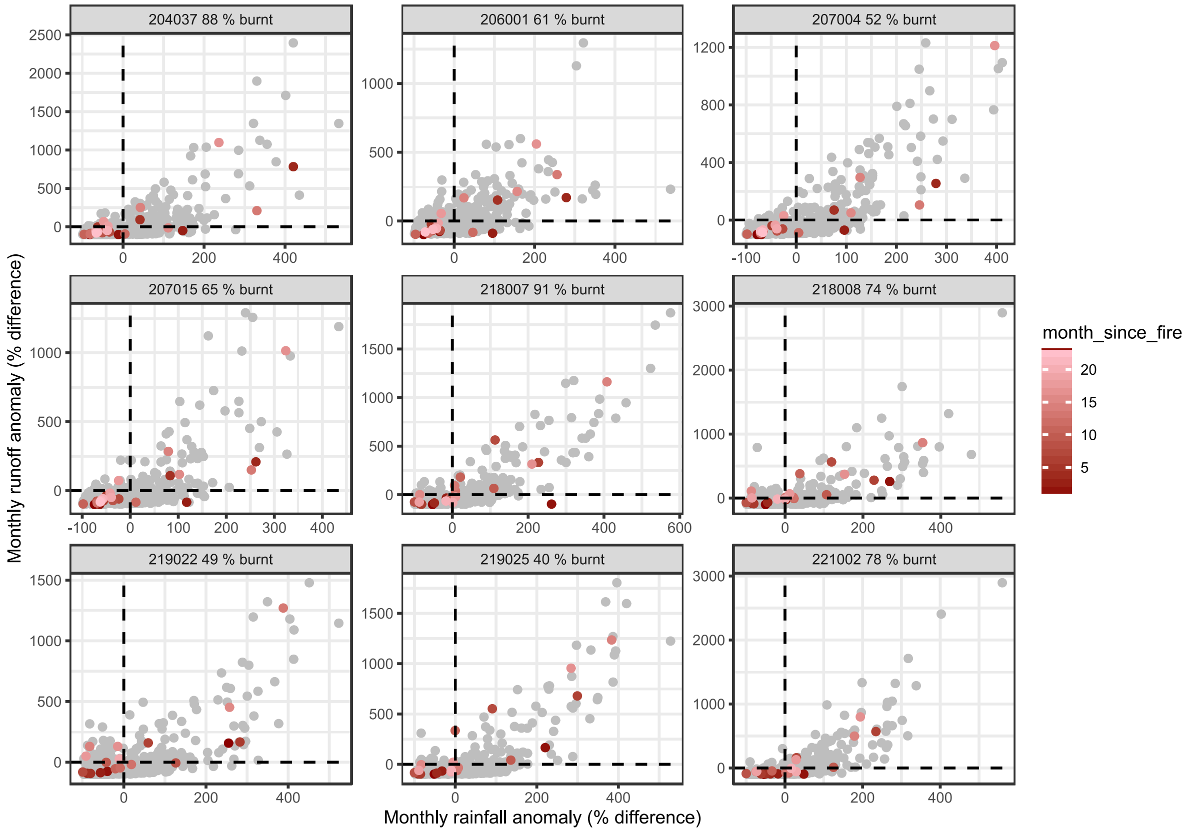

Figure 19. Comparison of the monthly anomalies of runoff against the monthly anomalies of rainfall before and after the 2019/20 fire event. The comparison includes all data over the full historical record period, at each of the 9 catchments that have been most severely burnt in this fire event. For both the rainfall and runoff at each catchment, the monthly anomalies are shown as % differences from the corresponding long-term average level.

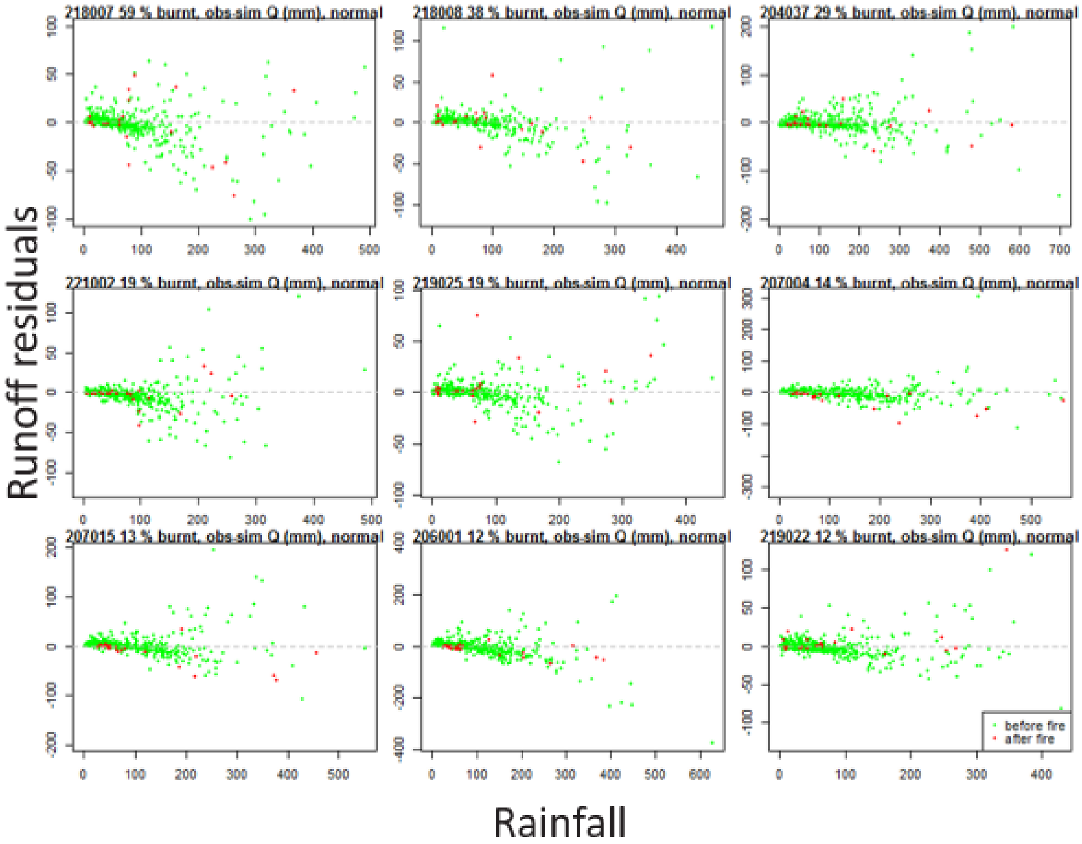

Figure 20. Comparison of the runoff model residuals (flow observed – flow modelled) vs. rainfall before and after the 2019/20 fire event. The comparisons include all data over the full historical record period, at each of the 9 catchments that have been most severely burnt in this fire event.

3.2.2.2 Fire impact on water quality

There are only five catchments (TP at #206011, turbidity at #215215, DO at #215215, DO at #215207 and EC at #410073, see Figure A6 in the Appendix for a map of these catchments) that have maintained long-term water quality records while have been severely burnt in the 2019/20 fire. Therefore, specific investigation on the water quality changes before/after the fire was performed at each catchment. Furthermore, several water quality indicators are often not sampled continuously (e.g., TP and TN often only have monthly samples), meaning that there are only a small number of samples available for analysis for each catchment; these samples are largely outside rainfall-runoff events and represent low flow conditions, which further limits the ability to detect the effect of surface runoff water quality impacts. Generally, we found the impact of the 2019/20 fire event on water quality highly catchment specific, and is also modulated by the local hydrologic conditions especially the timing of rainfall and flow events following the fire. Here we highlight two representative examples (TP at #206011, turbidity at #215215) of the catchment-specific behaviour in water quality changes following the fire; for the remaining three catchments, DO (#215215 and #215207) and EC (#410073) do not show clear changes after the fire events.

Figure 21 shows an example at monitoring site #206011 (with contributing catchment area of 9980 km^2), with panel a) illustrating the conditions in catchment vegetation cover at three months right before the fire, 1 month after the fire and 2 months after the fire, and panel b)-d) showing the daily catchment flow, daily catchment-averaged rainfall and the measured concentration of Total Phosphorus (TP) as the water quality indicator of focus. The vegetation cover after the fire shows a clear decrease from before i.e., from around 100% to 70% over a substantial portion of the western part of the catchment; however, the affected area was rather far from the monitoring station at the far north of the catchment. Also canopy cover does not show a clear change before and after the fire in the central and eastern parts of the fire ground, likely due to different fire intensities. For stream phosphorus (panel d)), the concentration did not peak immediately after the fire started (dashed red line) but occurred about three months later, following the first major rainfall and runoff event post-fire (dashed blue line, also see panels b) and c)). A potential explanation is that the low flows and limited rainfall immediately following the fire event have limited capacity to transport phosphorus to the catchment outlet. High concentrations only occur after both the fire and flow events, because the fire has left the sediments and phosphorus in an easily mobilised condition, which were transported to the catchment outlet by high flows. The distance between the burnt region and the water quality monitoring site also seem to play an important role in affecting the timing of the delayed transport process.

Figure 22 presents another example of turbidity at monitoring site #215215 (with contributing catchment area of 5357 km^2). After the fire, the vegetation cover decreased from nearly 100% to about 60%, but only for a small proportion of the catchment near the monitoring station (panel a)). The turbidity (panel d)) peaked immediately after the fire started (dashed red line) even before the major rainfall/flow event post-fire (dashed blue line, also see panels b) and c)). This spontaneous response in turbidity could be due to the proximity of the fire-affected area to the monitoring site. However, there was also a coincident period of missing records for turbidity over a period of about 6 months before the fire event, which makes it difficult to observe the exact timing of when turbidity started to increase and adds uncertainty to our interpretation of the impact of the fire event.

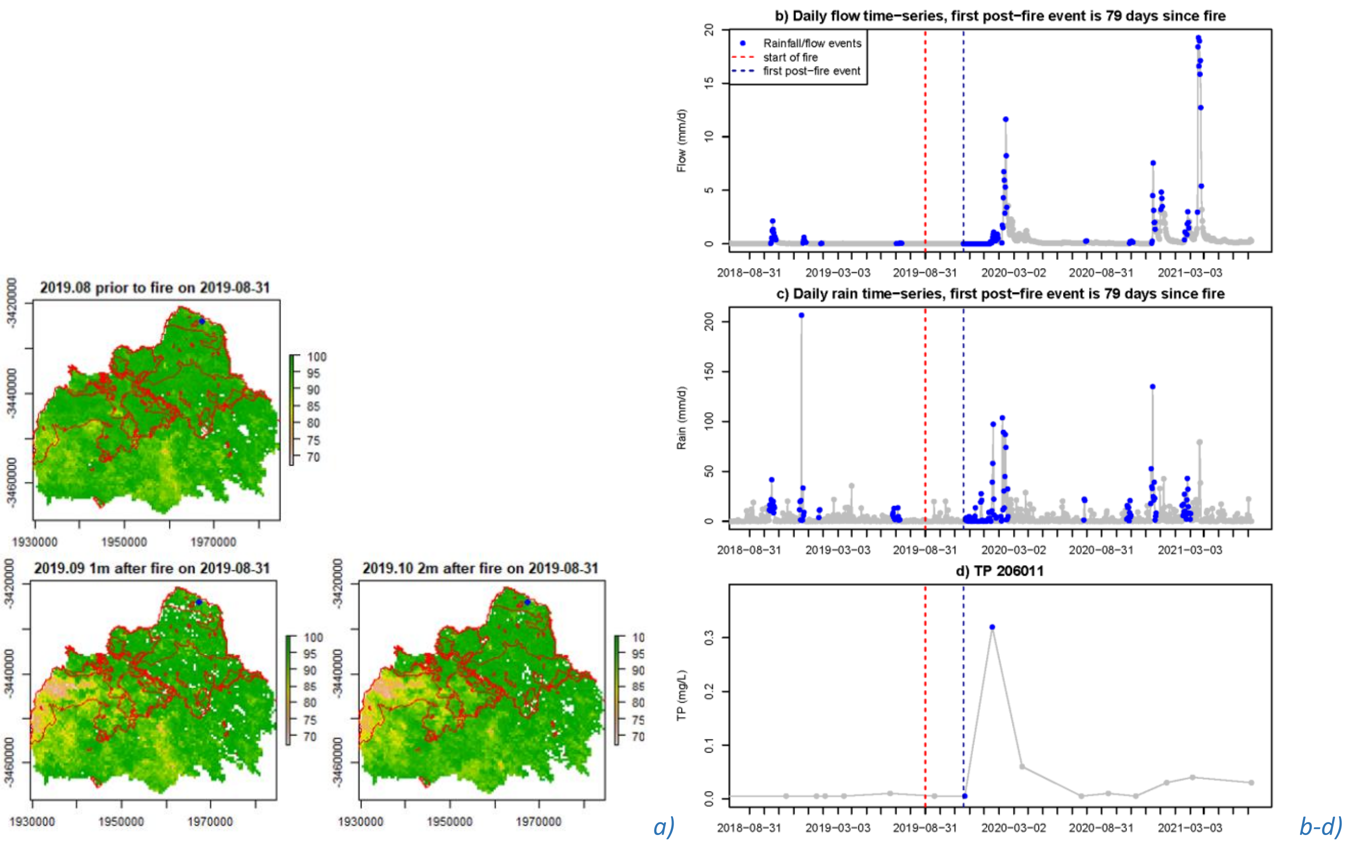

Figure 21. a) shows the vegetation cover at the contributing catchment of monitoring site #206011 (9980 km^2), where the blue dot shows the location of the monitoring site, the red boundaries highlight areas affected by the 2019/20 fire and the background map shows the fractional vegetation cover. b) shows the time-series of daily flow, daily rainfall and records of

total phosphorus concentration covering a time window of 1 year before and 2 years after the fire event. The red and blue dashed lines mark the timings of the start of the fire event and the first flow/rainfall event post-fire, respectively; blue dots in all the three panels in b) highlights the individual major flow/rainfall events.

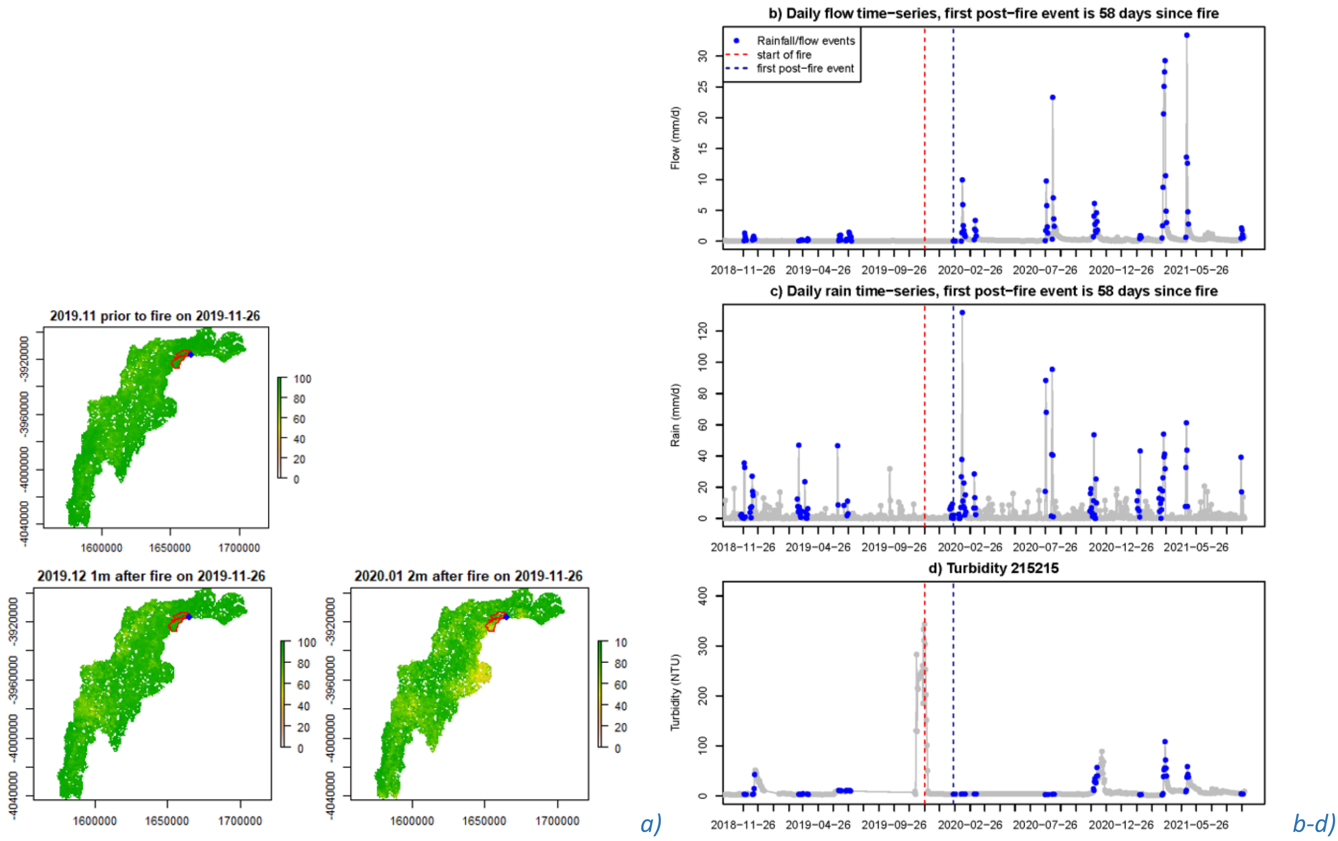

Figure 22. a) shows the vegetation cover at the contributing catchment of monitoring site #215215 (5357 km²), where the blue dot shows the location of the monitoring site, the red boundaries highlight areas affected by the 2019/20 fire and the background map shows the fractional vegetation cover. b) shows the time-series of daily flow, daily rainfall and records of turbidity concentration covering within a three-year window of the fire event (1 year before and 2 years after). The red and blue dashed lines mark the timings of the start of the fire event and the first flow/rainfall event post-fire, respectively; blue dots in all the three panels in b) highlights the individual major flow/rainfall events.

3.2.3 Linking flow changes to catchment disturbances

The final part of the trend attribution analysis was linking temporal changes in catchment flow to disturbances including climate and wildfire. As highlighted in Section 2.4.3, due to the shorter record period for the vegetation cover data, this analysis was performed for the period of 2001-2021, and at twelve forested catchments that have experienced severe fire in history; a map of these catchments is shown in Figure A7 in the Appendix. A Random Forest model was used to assess how historical catchment flow responded to various potential predictors related to climate and wildfire (see details in Section 2.4.3).

The relative importance of the potential predictors for the 12 individual catchments analysed is shown in Figure 23, where for each catchment, the sum of the importance of all predictors is 1. In general, we found that historical fire events have some influences on flow, but these influenced are generally not as big as those from the catchment storage and climatic drivers. However, there is a considerable variability between the catchments. Overall, the leading predictor for residual from the historic rainfall-runoff relationship is the catchment storage from previous year (as indicated by 7-day low flow, *low7dPrev*) with median importance of 0.3 and reaching 0.5-0.6 in selected catchments. Some other predictors related to the climate, namely the annual medium dry spell length (*medDry*) and the proportion of rainfall above 95th percentile to annual rainfall (*extremeProp*) also have marked impact in selected catchments with feature importance exceeding 0.2. In contrast, indicators related to fire i.e., change in catchment vegetation cover before/after fire (*vegDiff*) and percentage catchment area burnt in each fire event (*burnt_perc*), are showing relatively minor effects, with median importance of around 0.1 and 0.05, respectively. The effect of fire appears similar to a number of the other climatic predictors considered (*Seasonality*, *maxDry*, *extremeProp*).

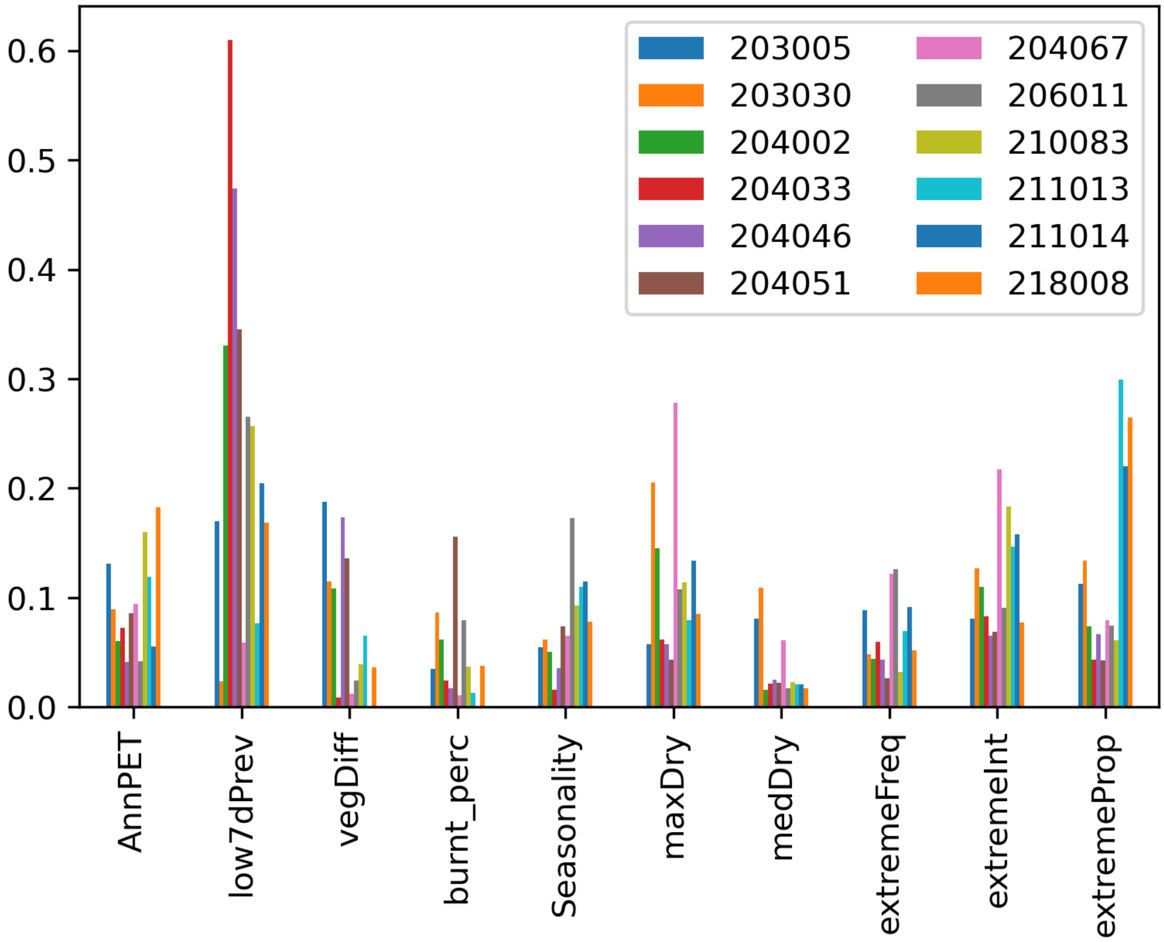

Figure 23. The relative importance of potential predictors for historical flow at 12 individual catchments considered, over the 2001-2021 analysis period. Specifically, AnnPET: annual PET (mm); low7dPrev: 7d low flow in previous year (mm); vegDiff: fire intensity represented by vegetation cover difference (%); burnt_perc: fire extent as percentage catchment area burnt (%); Seasonality: rainfall seasonality; maxDry: annual maximum dry spell length (days); medDry: annual median dry spell length (days); extremeFreq: extreme rainfall frequency (days); extremeInt: extreme rainfall intensity (mm); extremeProp: extreme rainfall proportion. See Table 5 for the full definition of individual predictors.

4. Discussions

4.1 Implications of the long-term trends in water quality/quantity

Our analysis suggested a large-scale decline in water quantity in the forest catchments across NSW outside of the RFA regions (Section 3.1). These widespread declining trends were also observed in the preceding Project 3 (Guo et al., 2021b). Therefore, the two projects together strengthen the finding of declining streamflow over NSW. Our further analysis on trend attribution suggested that the hydro-climatic conditions, specifically catchment storage from previous year, played a more important role than the impacts of fire in explaining temporal variation in flow (Section 3.2.3).

Our finding on the large-scale declining streamflow is in line with existing literature on the trends of water availability in south-eastern Australia (Chiew et al., 2009; Zhang et al., 2016; Gao et al., 2022).

Most catchments that have significant long-term flow declines show 10-20% decrease per decade, relative to the long-term mean annual flow of individual catchments. It is, however, difficult to compare the trend magnitudes estimated across studies due to potentially different datasets (e.g., selection of catchments and record period) and the trend analysis approach used. For example, Zhang et al. (2006) used the same Sen's slope approach to estimate the magnitude of long-term linear trends in average flow at 222 catchments across Australia. Based on the significance level of the estimated trends, Zhang et al. (2006) concluded that the declining trends in annual flow are the strongest for catchments in the Murray–Darling Basin. Zhang et al. (2006) also summarized the magnitudes of the linear trends of annual flow estimated for 22 catchments with a 0.01 significance levels (i.e., the 22 catchments with the most statistically significant trends) – within which, only three NSW catchments were included, with significant decadal change in annual flow of -12%, -16% and -17% relative to their individual long-term mean annual flows. Although none of these sites were included in our analyses or being identified as having significant long-term trend, the range of estimated decadal trends in Zhang et al. (2006) is consistent with our estimates.

The Australian Bureau of Meteorology (BoM) analysed the long-term changes in catchment streamflow around Australia and published them within its Hydrologic Reference Stations (HRS) dataset (BoM, 2020c), which provides another point of reference to our trend estimates. The record period and trend model employed in HRS are different to our analysis. Specifically, in HRS, the trend was estimate for each catchment by fitting a linear model relating the historical annual flow with time. We focused on 10 catchments that showed the greatest long-term declines in flow in our results, and compared our results with the corresponding trend estimates from the HRS analysis (Table 8). There are only five catchments in common to enable this comparison, but the trend magnitudes estimated across the two studies are highly consistent, given the differences in the record period and statistical approach used.

Table 8. Comparison of trend magnitude estimates (as % change in annual flow per decade relative to the long-term mean annual flow) from this study and from Bureau of Meteorology's Hydrologic Reference Stations (HRS), at 10 catchments that show the greatest long-term flow decline in this study. Only five catchments are common across the two studies.

Site	This Study		HRS		
	Record period	Trend magnitude, % per decade	Record period	Trend magnitude, ML/yr	Trend magnitude, % per decade
410091	1982-2020	-30.4	1981-2019	-3	-26.5
419016	1974-2020	-22.4	1973-2019	-1.42	-22.4
401013	1973-2020	-21.7	1972-2019	-1.1	-21.7
421018	1974-2020	-21.5	1973-2019	-1.91	-19.7
410134	1979-2020	-21.5	-	-	-
418027	1971-2020	-19.7	1970-2019	-0.45	-13.9
416001	1974-2020	-19.6	-	-	-
419024	1974-2020	-19.1	-	-	-
419006	1973-2020	-18.7	-	-	-
422003	1982-2020	-17.5	-	-	-

Chiew et al. (2009) took a contrasting approach to analyse change in streamflow. In contrast to our analysis which only relied on historical records, Chiew et al. (2009) used a model-based approach combined with climate projections to predict changes in catchment runoff from the 1895-2006 condition to that under a 0.9°C global warming scenario. The study predicted a decreasing runoff for most catchments in south-eastern Australia, with the magnitude of change ranging from -17% decrease to 7% increase in the mean annual runoff averaged across the study area, for a 0.9°C global warming. The declines in runoff estimated in Chiew et al. (2009) is much smaller compared to our results, but we acknowledge that the approaches used in the two studies are too different (e.g., model-based vs. data-driven; prediction vs. analysing historical observations) to enable a fair comparison of the results. Nevertheless, the above comparison between this study and existing literature can provide independent lines of evidence suggesting that water availability in NSW is at risk under a changing climate which is known to lead to reducing rainfall. This has major implications for the future water security for the state.

Further to the overall decline, when analysing the differences in flow trends across catchments, our results highlighted greater percentage declines in flow in catchments that are wetter catchments and catchments with higher proportional areas used as grazing land (Section 3.2.1). These results suggest that catchment land use could potentially modulate the effects of climate on the changes in flow. As a potential implication for management, this finding also indicates a possibility for targeted management of catchment water resources by the specific land use categories; for example, catchments that are predominantly used for grazing could be prioritised in developing long-term strategies to cope with potentially further flow reduction in the future.

The number of water quality monitoring sites in NSW regions outside the RFA regions is generally low and large-scale patterns in temporal water quality trends are not evident. Trend detection is also hampered by infrequent sampling. Similar remarks were also made in the previous Project 3 (Guo et al., 2021b), suggesting that the monitoring for water quality indicators is insufficient to form a clear state-wide assessment. Combining these, we again emphasize the value and the need for improved effort in long-term water quality monitoring throughout NSW.

4.2 Key drivers of changes in water quality/quantity

Our analyses show that after the 2019/20 fire event, turbidity and phosphorus concentrations peaked at two individual catchments, but the timings of these increases are highly dependent on the catchment hydrological conditions (Section 3.2.2.2). The frequency and availability of water quality sampling data is generally inadequate to detect water quality impacts during runoff events and thus it is not possible to draw clear conclusions on the impact of fire on water quality from the data analysed.

Regarding water quantity, there has been a general increase in flow after the 2019/20 fire, compared to the average conditions over the recent 10 years (Section 3.2.2.1). However, the post-fire period is also associated with heavier rainfall, leaving it uncertain whether the flow increase is a direct response to the fire due to changing rainfall-runoff relationship, or due to the heavier rainfall occurring coincidentally after the fire. In contrast to the short-term analysis, the 2019/20 fire did not seem to result in substantial change in catchment flow at the whole catchment scale when compared with the long-term average condition.

The above contrasting conclusions regarding the impact of the 2019/20 fire events on flow from using a shorter and a longer analysis periods highlighted the importance of referencing period when assessing the effects of forest disturbances, and the potential need to adapt management to changing scenarios. Here we further assess the sensitivity of these results (which were based on data up to Sep 2021) to the more recent wet periods in NSW (Bureau of Meteorology, 2022b), by updating the data till end of April 2022 and re-assess the relationships between the monthly rainfall and runoff anomalies at each catchment with the short-term and the long-term data, respectively (Figures 23 and 24). In general, these update results suggest consistent conclusion with those in Section 3.2.2.1, that: 1) over the short-term (Figure 24), the post-fire period is generally characterised by heavier rainfall and increased flow, as visual inspection generally suggests a steeper slope of going through the red dots (post-fire) compared with that for the grey dots (pre-fire), at each catchment; 2) compared with the long-term (Figure 25), the post-fire rainfall is still consistent with the average condition, and there is no substantial increase in flow. It is worth noting, however, that after extending the data to April 2022, the increasing flow compared to the short-term conditions (Figure 25) in 1) seems more evident than previously shown with data up to Sep 2021 at a few catchments. Specifically, when comparing the results based on the extended data to those based on the previous data (Figure 25 and Figure 18, respectively), catchments #219022 and #219025 both experienced several more extreme post-fire rainfall events between Sep 2021 to Apr 20222, with increasing number of red dots to the right of the vertical dashed lines in each panel. In both catchments, the number of red dots above the horizontal vertical dashed lines also increased in Figure 25 with the extended data, suggest a more evident increase in post-fire flow when the data was extended to include a wetter period in both catchments.

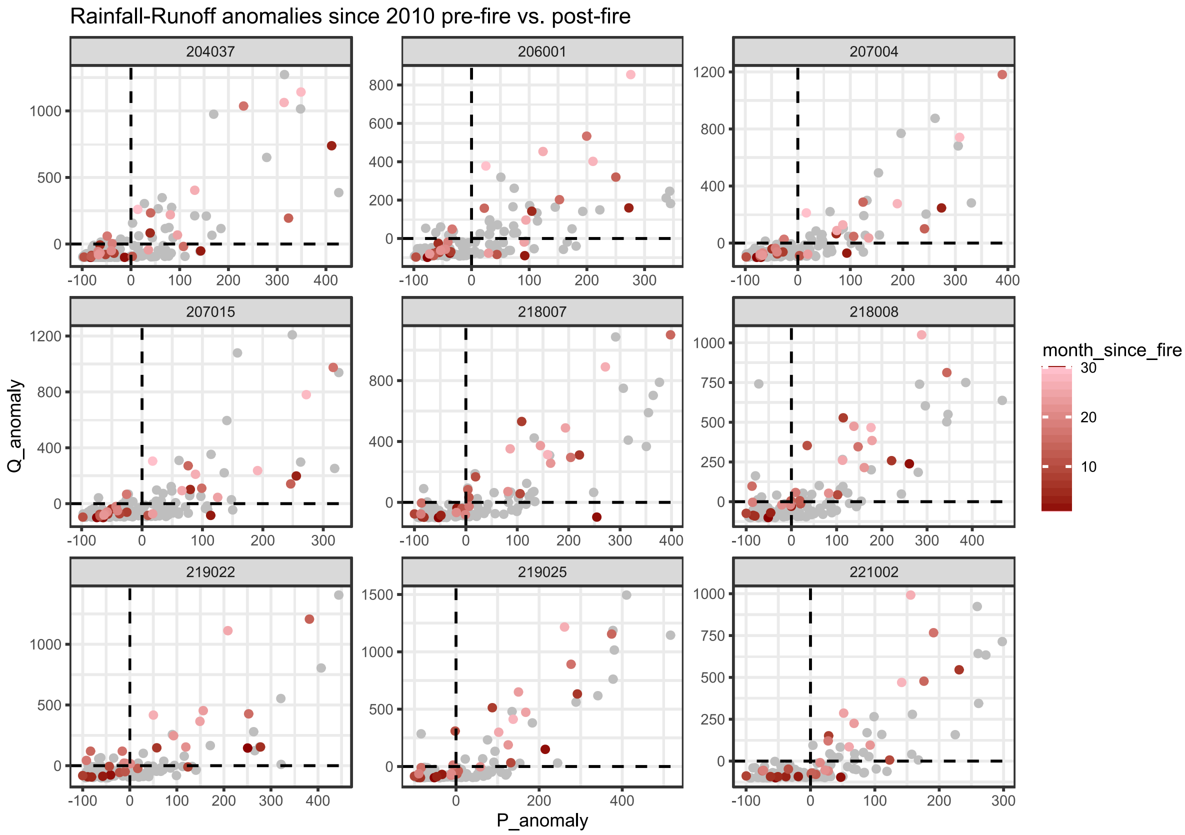

Figure 24. Comparison of the monthly anomalies of runoff against the monthly anomalies of rainfall before and after the 2019/20 fire event, at 9 catchments that have been most severely burnt in this fire event. The comparison includes all historical data at each catchment up to April 2022.

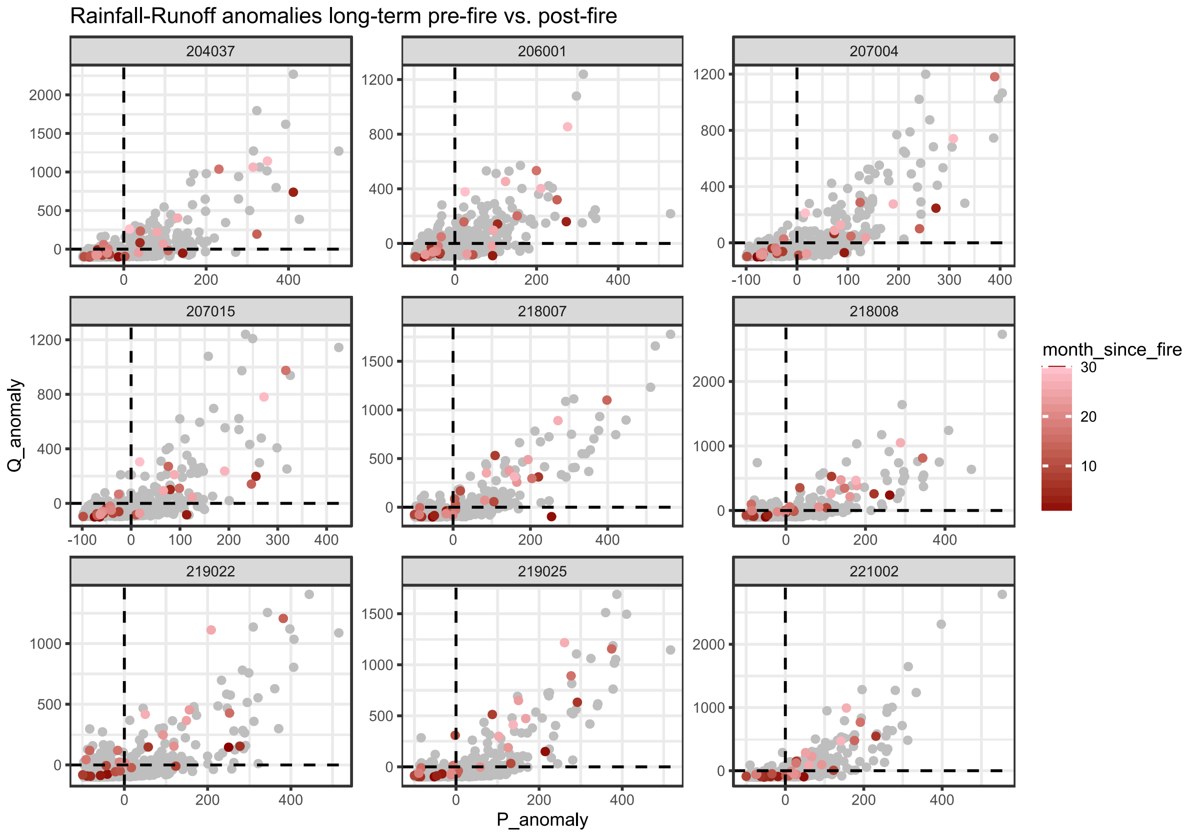

Figure 25. Comparison of the monthly anomalies of runoff against the monthly anomalies of rainfall before and after the 2019/20 fire event, at 9 catchments that have been most severely burnt in this fire event. The comparison includes all data from 2010 (10 years before fire) to April 2022.

Besides focusing on the 2019/20 event, we also assessed the impact of fire over longer historical period (Section 3.2.3). Our analyses suggested that climate variability is generally more important in driving changes in catchment flow in history, compared with individual wildfire events (Section 3.2.3). Therefore, a general conclusion from both analyses (over the 2019/20 event period and the long-term) is that fire is unlikely the most important driver of large-scale changes in water quantity at the full catchment scale, in forested catchments across NSW. A key management implication of this result is the importance of considering the future impact of a changing climate, which exhibits stronger, long-term and landscape-scale effects on water resources; in contrast, the effects of fire are more likely localized.

4.3 Limitations and further research directions

4.2.1 Interactions between climate and fire

In the statistical analysis performed, we attempted to separate the effects of climate from wildfire to understand the individual contribution to changes in catchment flow (Sections 3.2.2 and 3.2.3). However, it is worth highlighting that climate will likely interact with wildfire, particularly under a changing climate, such interactions have been reported in south-eastern Australia as well as other parts of the world.

The unprecedented 2019/20 Black Summer bushfire in southeast Australia was caused by a combination of climate variability and long-term climate trends, with an increased probability of large forest fires occurrence due to the compounding effects of two or more modes of climate variability (Abram et al., 2021). Fires have shown substantial increases in the forested regions along the coast and mountains of south-eastern Australia, which have been attributed to the influence of climatic warming and drying, as well as lightning and human ignitions (Blanchi et al., 2010; Gibbons et al., 2012; Bradstock et al., 2014).

Bradstock et al. (2014) stated that fuel types and characteristic of different vegetation types (litter vs. grass) may cause various responses of bushfires to climate change. They predicted that increased likelihood of fires caused by climatic warming and drying was more probable to happen in moist, temperate forests than in arid and semiarid woodlands (woody litter vs. herbaceous fuels). By examining burned areas (1975–2009) across south-eastern Australia, most of their results were consistent with their predictions.

Climatic change has been related to a non-linear escalation of both the fire extent and intensity, as such, fire events are likely to continue to rapidly intensify in southeast Australia in the future (Abram et al., 2021). This suggests the need to explore any joint effect of climate and fire in future studies.

The combination of fire and changing climate will likely cause long-term changes in vegetation communities. This is likely to have some impact on rainfall-runoff responses into the future. The hydrological impacts of such changes are yet to be analysed in detail and remain one of several sources of uncertainty in future hydrological behaviour of catchments.

4.2.2 CO2 fertilisation effect

Increasing level of CO2 in atmosphere is another potential factor that can influence catchment hydrology, and thus needs further exploration beyond this study. Increased atmospheric CO2 can affect both vegetation growth and water use (Leakey et al., 2009). Rising CO2 concentrations can enhance photosynthesis by stimulating carbon assimilation by plants (Farquhar, 1997). This CO2 fertilisation effect increases biomass and green vegetation cover (‘greening’), which has been globally observed (both satellite and ground observations) during recent decades (Morgan et al., 2007; Donohue et al., 2009; Buitenwerf et al., 2012). Moreover, elevated CO2 levels lower stomatal conductance and thereby reduce water loss through leaves. Therefore, the water use efficiency of photosynthesis is increased with rising CO2 concentrations, leading to increased foliage cover in warm, arid environments (Berry & Roderick, 2002; Bond & Midgley, 2000; Higgins and Scheiter, 2012). The effect of increased CO2 on vegetation manifests the most in warm, arid environments, where water is the dominant limit to vegetation growth (Donohue et al., 2013; Hovenden et al., 2014; Donohue et al., 2016). However, not all studies support a strong relationship between the CO2 effect and aridity (Morgan et al., 2004; Nowak et al., 2004; Bradley& Pregitzer, 2007).

Donohue et al. (2013) predicted that the 14% increase in atmospheric CO2 (1982–2010) led to a 5-10% increase in green foliage cover in warm, arid environments. By combining remotely sensed normalized difference vegetation index (NDVI) data and long-term water-balance evapotranspiration (ET) measurements from 190 unimpaired river basins across Australia during 1982–2010, Ukkola et al. (2016) found that the precipitation threshold for water limitation of vegetation cover has considerably decreased during the past three decades, whereas sub-humid and semi-arid basins are not only ‘greening’ but also consuming more water, leading to remarkable (24–28%) reductions in streamflow. In contrast, wet and arid basins show nonsignificant changes in NDVI and reductions in ET. These results are consistent with expected CO2 fertilisation effect on vegetation, and they suggest that the potential increases in vegetation water use, together with the projected decreases in future precipitation (Collins et al., 2013) may lead to further reduction in streamflow in water-limited areas.

4.2.3 Long-term hydrological responses and the role of groundwater

Changing relationships between rainfall and runoff have been widely observed in south-eastern Australia (Saft et al., 2015). These changes are correlated with various measures of groundwater levels, for example, 7-day low flow, durations of cease-to-flow and large-scale changes in terrestrial water store (Fowler et al., 2020). Thus, groundwater can potentially play a key role in the observed flow responses. Further, these effects of groundwater have been stronger in drier, flatter, cleared catchments to date, with fewer such effects observed in highland high runoff catchments (Saft et al., 2015). The extent to which similar changes in rainfall-runoff process might expand to high yielding mountain catchments under longer periods of sustained climatic shifts is unclear. Were such effects to become more widespread, declines in runoff are likely to be exacerbated.

5. Conclusions

This report presents the key findings and recommendations of the extension of Project 3 of the Forest Monitoring and Improvement Program by the NSW NRC. We have identified the long-term trends in water quality and quantity in forested catchments in NSW that are outside of the RFA regions. Our key findings are:

- Catchment flows display large-scale declining trends throughout study region. Out of the 90 catchments analysed, 42 catchments show statistically significant decreases at a 0.05 level.
- For catchments with significant flow decreases, the magnitudes of decline are mostly 10-35% per decade relative to the mean annual flow.
- The water quality indicators (phosphorus, nitrogen, electrical conductivity, dissolved oxygen and turbidity) generally show mixed trends which vary by indicators. Within the study region, the number of long-term monitoring sites for each indicator, and the low sampling frequency generally limit our ability to reveal large-scale patterns of trends.
- Our analyses on trend attribution, combining observations from forested catchments the RFA and non-RFA regions, suggest that:
- Wetter catchments and catchments with greater percentage area used for grazing land experienced greater percentage decline in flow.
- With the currently available data, there is little evidence that the 2019/20 fire has a substantial impact on flow at the catchment scale, compared with long-term historical conditions.
- The impact on of the 2019/20 fire on water quality is highly case specific, which is also controlled by the hydrological condition, especially the timing of recent rainfall/flow events. The frequency and availability of water quality data is generally not adequate to clearly identify water quality impacts occur during runoff events.
- Over the historical period (2001-2021 period), fire events have some influences on flow, but the impacts are generally not as big as climatic drivers.

We highlight the consensus of the large-scale declines in flow found in our study with those found in previous literature that reported similar trends in south-eastern Australia. The important implications of these findings for the water security of NSW are further discussed. Our trend attribution analysis also found that at the catchment scale, historical changes in flow are generally more heavily affected by hydro-climatic drivers than fire events. Therefore, water resources management for forested catchments should consider responses to climate conditions when assessing future water security under a changing climate.

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8. Appendix

Table A1. List of site ID and coordinates at which long-term flow data were recorded, which were used for analysing long-term water quantity trends in this project.

Site	Variable	Lat	Lon
412066	Q	-34.11	149.60
410091	Q	-35.69	146.72
422001	Q	-30.02	148.06
422003	Q	-29.55	148.58
416001	Q	-28.98	148.98
421018	Q	-32.68	148.95
410016	Q	-35.35	145.74
421023	Q	-30.35	146.90
421039	Q	-31.77	147.12
401015	Q	-35.92	146.98
212018	Q	-33.12	150.28
418052	Q	-29.13	149.55
419016	Q	-31.06	151.13
410014	Q	-34.94	146.30
420017	Q	-31.42	149.31
421019	Q	-32.41	149.33
416027	Q	-29.05	149.16
210006	Q	-32.34	150.10
419061	Q	-30.20	149.43
418042	Q	-29.45	150.03
418001	Q	-29.48	150.14
418025	Q	-29.93	150.57
418027	Q	-30.21	150.43
410112	Q	-34.57	148.09
401013	Q	-35.89	147.69
412065	Q	-34.40	149.09
412067	Q	-33.98	148.94
412004	Q	-33.41	147.99
412039	Q	-33.49	145.50
412057	Q	-33.57	148.42
410040	Q	-34.48	144.30
410021	Q	-34.57	146.00
410136	Q	-34.52	144.71
410001	Q	-35.10	147.37
419010	Q	-30.97	151.35
416012	Q	-28.80	150.73
416016	Q	-29.79	151.13
416010	Q	-29.26	150.90
421012	Q	-30.43	147.57
421031	Q	-31.91	148.09
419020	Q	-30.71	150.70
419053	Q	-30.42	150.65

419043	Q	-30.59	150.69
421088	Q	-31.38	147.69
421011	Q	-30.46	147.68
419051	Q	-30.50	150.08
418037	Q	-29.56	149.66
419027	Q	-31.27	150.46
419034	Q	-31.41	150.43
401012	Q	-36.32	148.05
401549	Q	-36.17	148.03
409016	Q	-36.10	147.02
409025	Q	-36.01	145.99
409005	Q	-35.63	144.12
419021	Q	-30.27	148.82
419001	Q	-30.97	150.26
419022	Q	-30.75	150.72
419039	Q	-30.26	149.68
419005	Q	-30.68	150.78
419059	Q	-30.20	149.44
419007	Q	-30.89	150.50
419068	Q	-30.29	149.34
213200	Q	-34.16	150.84
416020	Q	-29.23	150.76
419006	Q	-30.94	150.53
419015	Q	-31.18	151.07
419024	Q	-31.10	150.94
419049	Q	-29.92	148.39
416006	Q	-29.29	151.12
416039	Q	-29.46	151.46
421042	Q	-32.09	149.07
401014	Q	-36.04	148.05
213005	Q	-33.80	150.98
409013	Q	-35.04	143.57
409019	Q	-35.50	144.89
412016	Q	-33.23	147.33
419076	Q	-31.66	150.64
412012	Q	-33.35	145.88
409020	Q	-35.45	144.77
410015	Q	-34.95	146.27
410007	Q	-34.71	146.41

Table A2. List of site ID, coordinates and the water quality variable for which long-term records are available, which were used for analysing long-term water quality trends in this project.

Site	Variable	Lat	Lon
409005	TN	-35.63	144.12
409013	TN	-35.04	143.57

409025	TN	-36.01	145.99
410015	TN	-34.95	146.27
410016	TN	-35.35	145.74
410036	TN	-34.70	146.40
410169	TN	-35.15	145.77
412004	TN	-33.41	147.99
412027	TN	-34.13	149.02
412029	TN	-34.14	148.81
412039	TN	-33.49	145.50
412045	TN	-34.22	144.46
416001	TN	-28.98	148.98
416007	TN	-28.99	151.27
416012	TN	-28.80	150.73
416040	TN	-28.69	150.89
416048	TN	-28.70	149.39
418004	TN	-29.43	149.85
418013	TN	-29.58	150.37
418058	TN	-29.48	148.90
419001	TN	-30.97	150.26
419003	TN	-30.33	149.78
419006	TN	-30.94	150.53
419016	TN	-31.06	151.13
419021	TN	-30.27	148.82
419022	TN	-30.75	150.72
419024	TN	-31.10	150.94
419027	TN	-31.27	150.46
419032	TN	-30.76	149.98
421004	TN	-31.74	147.87
421012	TN	-30.43	147.57
421018	TN	-32.68	148.95
421019	TN	-32.41	149.33
421025	TN	-33.14	149.43
422001	TN	-30.02	148.06
422002	TN	-29.95	146.86
422003	TN	-29.55	148.58
422012	TN	-29.11	147.90
422014	TN	-29.11	147.45
424002	TN	-29.24	144.46
425003	TN	-30.09	145.94
425004	TN	-30.53	145.12
425007	TN	-33.75	142.27
425012	TN	-32.44	142.38
409003	TP	-35.53	144.97
409013	TP	-35.04	143.57
409025	TP	-36.01	145.99
410014	TP	-34.94	146.30

410015	TP	-34.95	146.27
410025	TP	-34.79	148.38
410036	TP	-34.70	146.40
410044	TP	-34.93	148.16
410047	TP	-35.16	147.66
410082	TP	-34.62	146.26
410136	TP	-34.52	144.71
410169	TP	-35.15	145.77
412004	TP	-33.41	147.99
412009	TP	-33.57	148.66
412039	TP	-33.49	145.50
416001	TP	-28.98	148.98
416007	TP	-28.99	151.27
416012	TP	-28.80	150.73
416040	TP	-28.69	150.89
416048	TP	-28.70	149.39
418004	TP	-29.43	149.85
418013	TP	-29.58	150.37
418058	TP	-29.48	148.90
419001	TP	-30.97	150.26
419003	TP	-30.33	149.78
419006	TP	-30.94	150.53
419021	TP	-30.27	148.82
419022	TP	-30.75	150.72
419024	TP	-31.10	150.94
419026	TP	-30.14	148.39
419027	TP	-31.27	150.46
419032	TP	-30.76	149.98
421004	TP	-31.74	147.87
421019	TP	-32.41	149.33
421023	TP	-30.35	146.90
421025	TP	-33.14	149.43
422001	TP	-30.02	148.06
422002	TP	-29.95	146.86
422003	TP	-29.55	148.58
422012	TP	-29.11	147.90
422014	TP	-29.11	147.45
424002	TP	-29.24	144.46
425003	TP	-30.09	145.94
425004	TP	-30.53	145.12
425007	TP	-33.75	142.27
425008	TP	-31.56	143.38
425012	TP	-32.44	142.38
409002	EC	-36.01	146.40
409003	EC	-35.53	144.97
409005	EC	-35.63	144.12

409013	EC	-35.04	143.57
409014	EC	-35.09	144.03
409045	EC	-35.51	144.21
410025	EC	-34.79	148.38
410044	EC	-34.93	148.16
410047	EC	-35.16	147.66
410091	EC	-35.69	146.72
410134	EC	-35.04	144.45
410169	EC	-35.15	145.77
412002	EC	-33.83	148.68
412004	EC	-33.41	147.99
412027	EC	-34.13	149.02
412029	EC	-34.14	148.81
416001	EC	-28.98	148.98
416012	EC	-28.80	150.73
416016	EC	-29.79	151.13
416040	EC	-28.69	150.89
418004	EC	-29.43	149.85
418058	EC	-29.48	148.90
419001	EC	-30.97	150.26
419024	EC	-31.10	150.94
419026	EC	-30.14	148.39
419032	EC	-30.76	149.98
421011	EC	-30.46	147.68
421012	EC	-30.43	147.57
421018	EC	-32.68	148.95
421019	EC	-32.41	149.33
421023	EC	-30.35	146.90

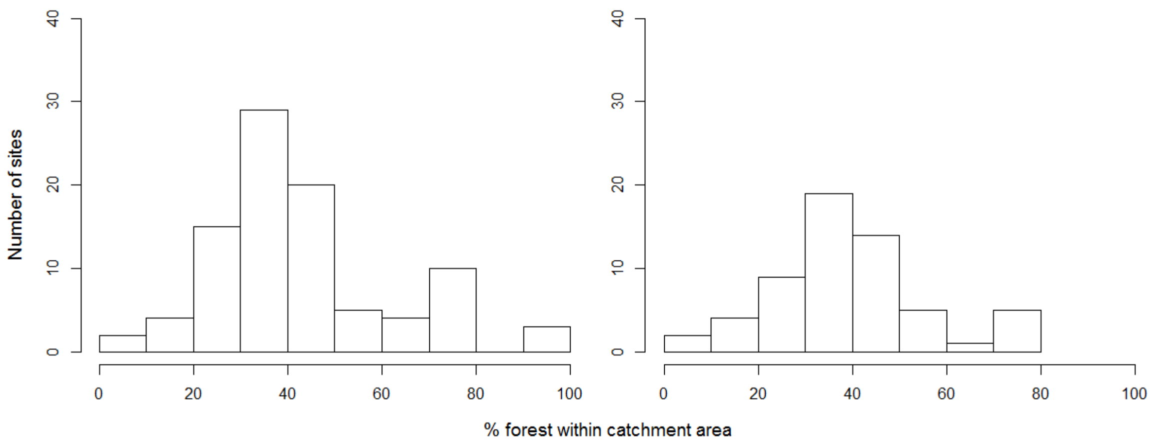

Figure A1. Distribution of forest coverage of the contributing catchments, as % catchment area covered by forest for a) the 90 catchments used for analysing long-term trends in water quantity; b) the 59 catchments used for analysing long-term trends in water quality. Spatial data source: National Forest and Sparse Woody Vegetation v3.0.

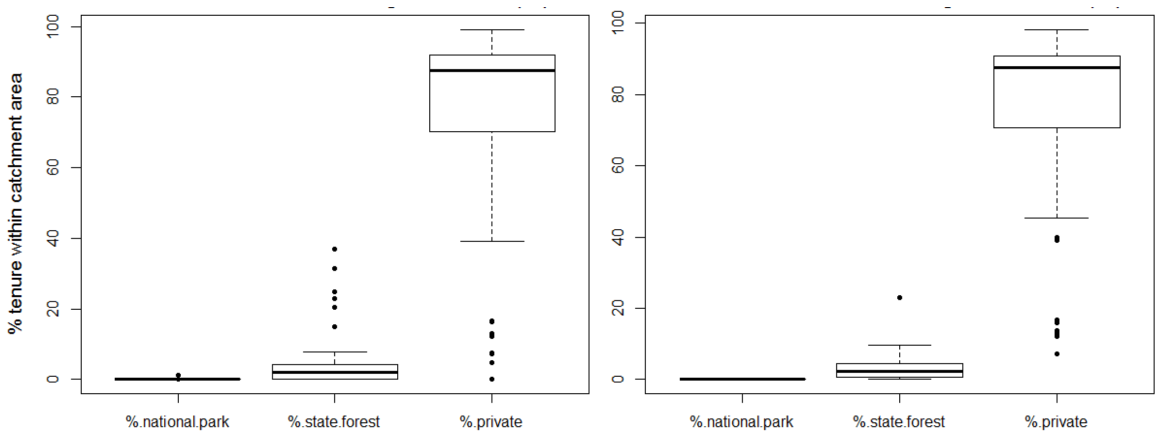

Figure A226. Distribution of key tenure types of the contributing catchments, as % catchment area for each tenure type for a) the 90 catchments used for analysing long-term trends in water quantity; b) the 59 catchments used for analysing long-term trends in water quality. Spatial data source: NSW Tenure 2019.

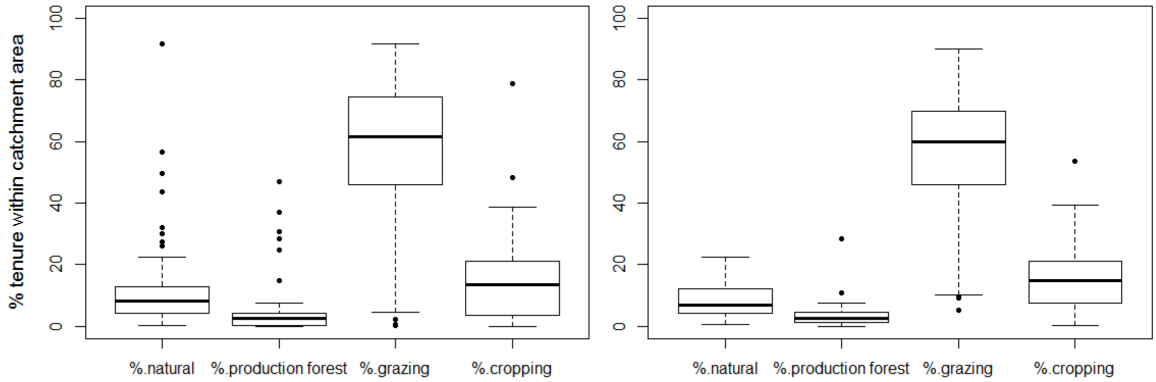

Figure A3. Distribution of key land use types of the contributing catchments, as % catchment area for each land use type for a) the 90 catchments used for analysing long-term trends in water quantity; b) the 59 catchments used for analysing long-term trends in water quality. Spatial data source: NSW Lanuse 2017 v1.2.

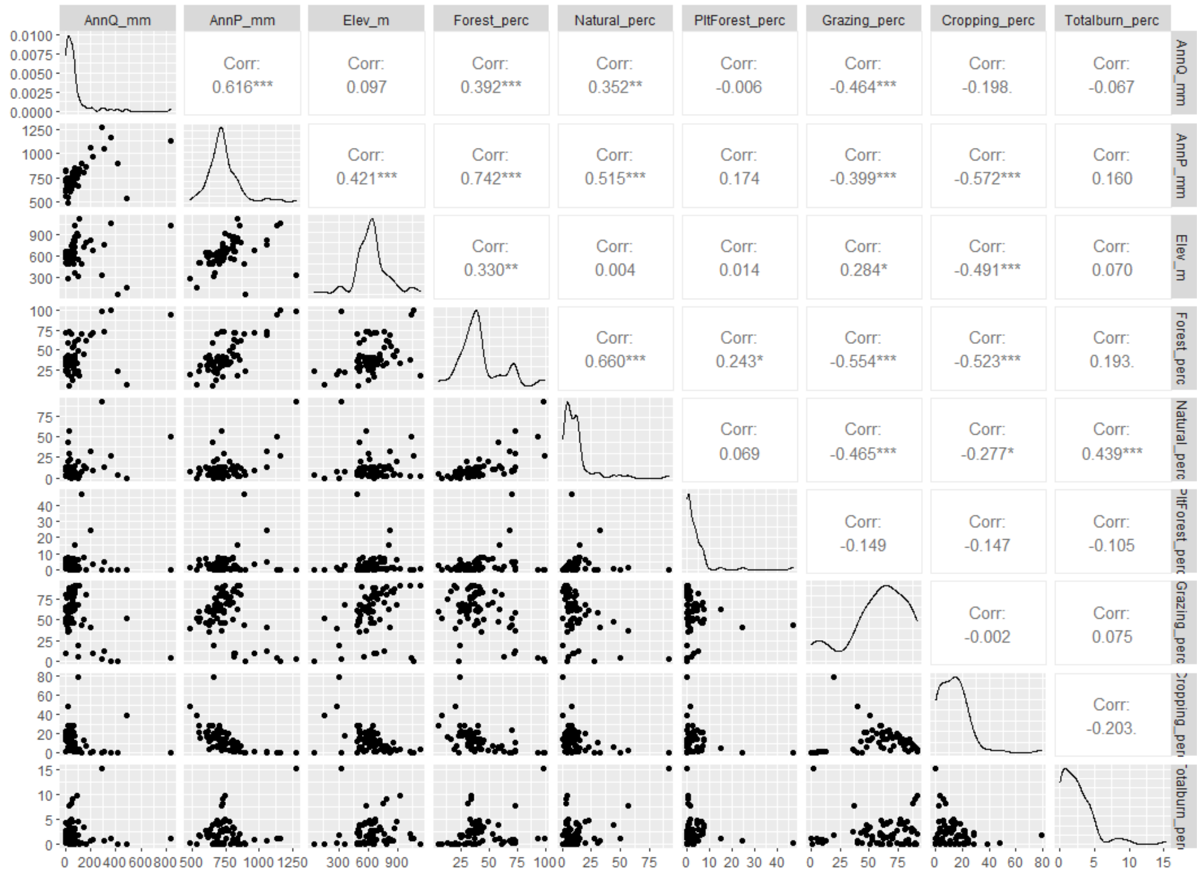

*Figure A4. The distributions of values (bottom-left triangle) and their cross-correlations (top-right triangle) of the spatial characteristics used to explain the spatial differences in water quantity trends, across individual catchments analysed. The symbols beside the correlation values indicate the correlation significances p-values, as: *** - p<0.001; ** - p<0.01; * - p<0.05; .-p<0.1; and no symbol otherwise.*

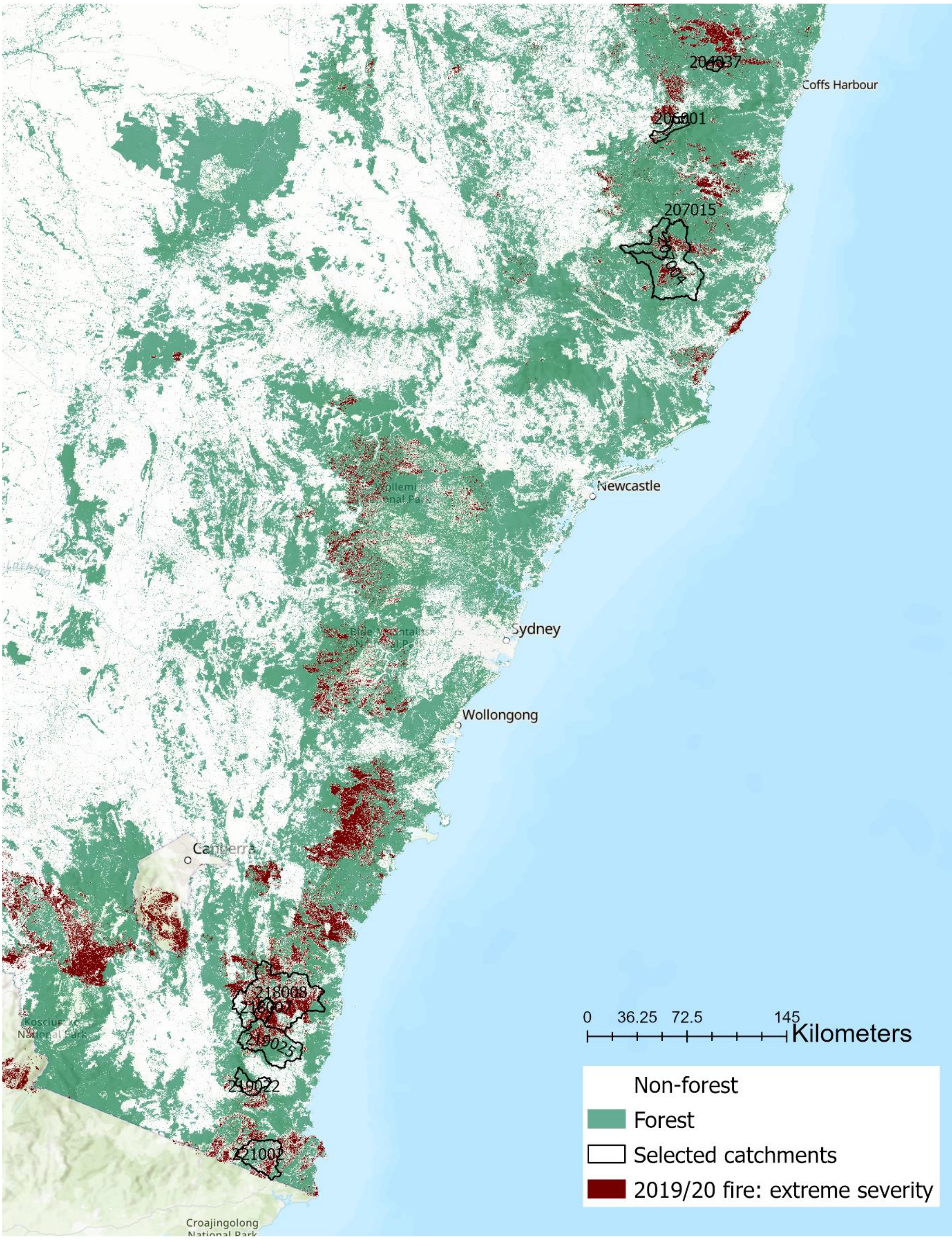

Figure A5. Map of the selected severely burnt catchments for the analysis of 2019/20 fire impacts on water quantity. The red shading highlights regions which experienced extreme fire severity during this event, which are identified with severity class = 5 within the spatial map of the 2019/20 fire intensity supplied by NRC (see Section 2.2.4).

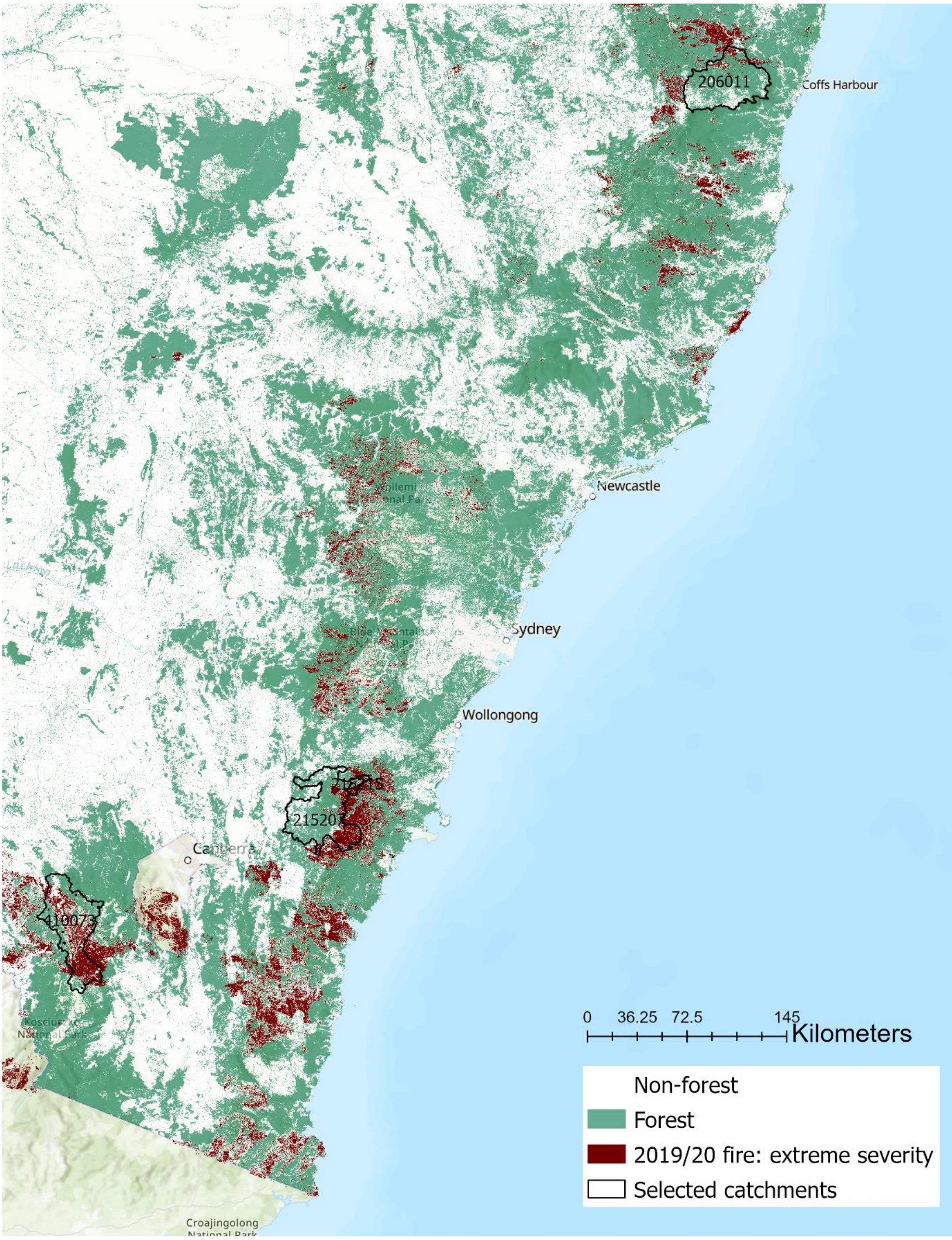

Figure A6. Map of the selected severely burnt catchments for the analysis of 2019/20 fire impacts on water quality. The red shading highlights regions which experienced extreme fire severity during this event, based on a spatial map of the 2019/20 fire intensity supplied by NRC.

Figure A7. Map of the selected forested and unmodified catchments that have experienced large fire events in history, which were used for the analysis of disturbance impacts on water quantity.