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ORIGINAL PAPER

An epidemiologic approach to environmental monitoring: cyanobacteria in Australia's Murray–Darling basin

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Abstract

Risk based management of aquatic resources for ecosystem and public health requires water managers and health professionals to work together. Using an epidemiologic time-series modelling approach, we assess patterns of risk for alert-level cyanobacterial abundance with water temperature. We focus on six sites along the Murray–Darling Drainage Basin, using the longest continuous record of algal abundance in Australia. Alert-level cyanobacterial abundance showed a non-linear and lagged response to water temperature across all six sites, after controlling for relative water discharge. For three sites there was a positive relationship of high-water temperature with the risk of alert-level abundance. These three sites also showed a substantial lagged effect, with the risk remaining high at a lag of 1 month following high water temperatures. The higher than average risk of alert-level cyanobacterial abundance with extreme water temperature and the persistence of this effect for 1 month highlight the applicability of these models to understand non-linear and time-dependent relationships in complex systems which are managed for ecosystem and population health. The site-specific relationships provide guidance for local authorities to develop water quality-related environmental and public health responses to a variable climate.

Keywords Environmental · Epidemiology · Climate · Water · Health · Temperature

1 Introduction

Cyanobacterial blooms can cause major problems for water quality. Recent evidence suggests that cyanobacterial blooms are increasing in frequency, magnitude and duration globally. Several environmental factors including increased nutrient inputs, higher water temperatures and low flow conditions, as well as rising CO_2 concentrations have been identified as drivers of blooms (Huisman et al. 2018). In addition to aquatic life, blooms have a considerable impact on human health and well-being. A changing environment and climate will degrade water quality, resulting in increased cyanobacterial blooms (Soranno et al. 1996, Hofer 2018), with potential implications for ecosystem and public health (Brooks et al. 2016).

Recent environmental events around Australia have made international headlines. Record temperatures were reached across Australia, with severe atmospheric heatwaves reported across the country, to the mass fish deaths in freshwater lakes in the Murray Darling Basin in early 2019. The fish deaths in the 30 km stretch of Menindee Lakes have been attributed to the die-off of an algal bloom caused by falling temperatures, and subsequent mixing of oxygen-depleted bottom water with surface oxygenated water, leaving inadequate levels of oxygen for fish respiration (DPI 2019). The initial bloom had been partly attributed to a combination of low flow conditions, prolonged drought and high than average water temperatures in the region.

Integrated water resources management requiring cross-sector collaboration is essential for sustainable development (Hall et al. 2018). Australian State and Territory

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Environmental departments are responsible for ecological monitoring of waterways, however the guidelines and thresholds of algal abundance for recreational water quality are set by the country's National Health and Medical Research Council (NHMRC). The council recognises the importance of clean water for human health and well-being. This division between health and environmental agencies regarding setting of guidelines and monitoring of waterways respectively, makes it important for water managers and health agencies to talk across disciplines. Despite this critical need for a common language, siloed perspectives focussed on either ecosystem or human health aspects continues to dominate water research.

The main aim of this study is to use the epidemiologic concept of Relative Risk (RR) to examine an environmental association most frequently assessed by environmental scientists using metrics of 'abundance'; an uncommon term in epidemiology. As applied here, the concept of RR is appealing as a conceptual tool for understanding the risk of alert level abundances relative to a site-specific baseline rather than absolute counts, where data are transformed prior to analysis, reducing the interpretability of associations. The concept of risk is easily understood by both water managers and health professionals.

Here, we focus on the relationship between water temperature and alert level algal abundances, against the backdrop of the recent fish kills in the Murray-Darling Drainage Basin. In this study, RR represents the ratio of the probability of an outcome (alert level algal abundances) with changing water temperature to the probability of this outcome at average water temperature. For each site, at average water temperature the RR is 1. Values greater than 1 represent a higher than average risk and values less than 1 indicate a lower than average risk. Using RR, we examined the short-term and lagged response of algal abundances to water temperature at six sites along the lower Murray-Darling Drainage Basin. This analysis is based on recent advances in statistical modelling to account for the heterogeneous temperature–algal abundance relationship. We use the results from this study to highlight how epidemiologic methods can inform environmental decision making. (Fig. 1)

2 Results

2.1 Cyanobacterial abundance and relationship between environmental variables across sites

Figure 2 shows the seasonal variation in cyanobacterial abundance across sites with a clear autumn peak in abundance for the mid and upstream sites of Yarrawonga, Torrumbarry, Heywoods and Swan Hill. Figure 3 illustrates the close relationship between relative flow and relative discharge for all sites. Apart from the most downstream site of Morgan, all other sites showed an inverse relationship of cyanobacterial counts with relative flow. Apart from the most downstream site of Morgan, all other sites showed a nearly perfect correlation between relative flow and relative discharge.

2.2 Non-linear and delayed cyanobacterial response to water temperature

In Fig. 4 we see the cumulative short-term and delayed association of alert-level cyanobacterial abundance with temperature. Figure 5 shows the time-varying and non-linear response of alert-level cyanobacterial abundance with water temperature. Figure 6 demonstrates the pooled Relative Risk (RR) of alert-level cyanobacterial abundances corresponding to the 90th water temperature percentile of the whole time period (Panel A) and the 5th percentile of the water temperature range (Panel B) for each of the six sites. Temporal changes indicate a strong and progressive reduction in the RR of temperature-related alert level cyanobacterial abundance during the whole study period for the pooled analysis. Figure 6 shows the time-varying relationship which indicates an immediate response to high water temperatures in Morgan which persisted at a lag of 1 month at Morgan, Heywoods and Yarrawonga. Euston and Torrumbarry show a higher than average RR with water temperature at a lag of 3 months.

3 Discussion

The current study was based on the longest continuous record of algal abundance available for multiple sites in the Murray Darling Basin. This analysis provides evidence for an association of alert level algal abundance with water temperature in a range of sites with different characteristics. These results are consistent with a study in China that found site-specific association of phytoplankton with water temperature (Xiao et al. 2013). A strength of this analysis was the application of a traditionally epidemiologic approach to characterise the water temperature—abundance association. While previous studies relied on a simplified exposure–response curve or lagged relationship, applying this flexible statistical model allowed us to isolate the magnitude of the risk at specific temperatures as well as the cumulative association across different temperatures. Our analysis showed a non-linear and delayed response of alert-level cyanobacterial abundance with water temperature. The shape and magnitude of the relationship varied along the river system, with some sites showing a positive

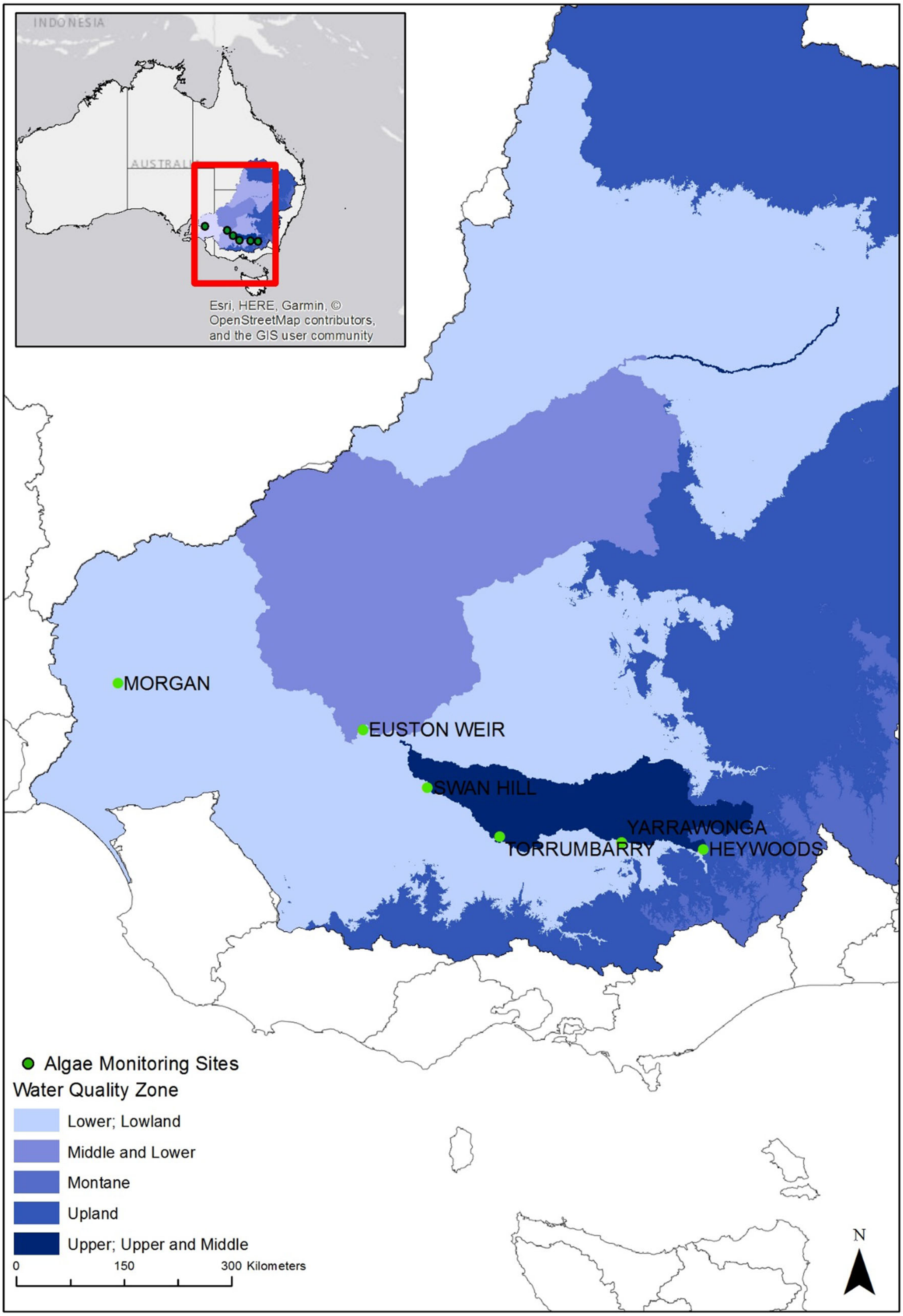

Fig. 1 Location of phytoplankton monitoring sites in the Murray-Darling Drainage Basin used in this study

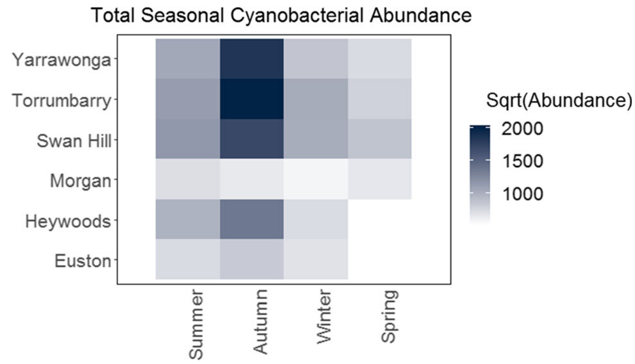

Fig. 2 Seasonal cyanobacterial abundance by season across the six sites

association with high water temperature (90th percentile of temperature range), compared with the risk estimated at average temperature.

Managing cyanobacterial risk is a major challenge for water quality managers. Comparison with previous studies that report association of cyanobacterial abundance with water temperature is limited by many factors. This includes varying environmental study designs and actual abundance as the outcome of interest. Studies on the Murray River in South Australia have identified water temperature and river flow as dominant factors controlling the magnitude and duration of cyanobacteria growth (Maier et al. 1998). A recent study showing water quality parameters such as sediments and nutrients provide a poor explanation of the variance in cyanobacteria, with increased cyanobacterial presence in the Murray River during drought periods further supports these findings (Bowling et al. 2016). Biotic factors such as bacterial community composition are also important drivers of cyanobacterial abundance in this area (Woodhouse et al. 2016). In addition to cyanobacterial abundance, water temperature may also be used to predict microcystin release, indicating a potential to use water temperature to forecast the severity of a bloom in areas where blooms can last year-round (Walls et al. 2018). Water temperature also plays a significant role in cyanobacterial abundance across multiple sites, with no effect from site-specific factors in 16 sites across four South Korean rivers (Cha et al. 2017). We found a similar effect of water temperature, although the magnitude and the timing of the peak in risk varied across sites.

The most downstream and upstream sites showed a strong positive association with high temperature over a three-month period. The risk of alert-level cyanobacterial abundance showed an immediate response to high water temperature, at the most downstream site, Morgan. In contrast, the most upstream site, Heywoods, showed a delayed, but substantial response to high water temperature. This contrast suggests that, whereas cyanobacterial abundance responds directly and positively to high water temperatures downstream, water temperature may have indirect effects on abundance upstream due to other factors such as residence time (Havens et al. 2019). It is also possible that higher nutrient loads downstream facilitate alert-level abundances at higher water temperatures. The sustained higher than average risk across the three-month period at Morgan, Heywoods and Yarrawonga demonstrate the potential for targeted surveillance following high temperatures and support localised management in the Basin. Locally, the integration of the alert-level quantitative risks generated by the epidemiologic approach described in this paper has the potential to provide empirical risk estimates for periods of operational relevance to both environmental and public health. For example, such estimates can inform the timing and duration of recreational water closures as well as water safety promotion messages. Understanding the relationships between environmental parameters and blooms can provide crucial planning time to implement public health measures (Tamerius et al. 2007). Local management would allow water managers to engage with relevant health authorities, to inform the development of public health and environmental responses to climate change. In addition, increased water temperatures are associated with both an increase in air temperatures as well as flow conditions (Liu et al. 2018). Our results can help inform water diversion schedules and the timing of operational releases form dams to minimise risk to public health.

Seasonal climate models have been used to predict water quality as well as disease outbreaks. Such forecasts can help to reduce the risk of blooms by increasing planning and response times to better target high risk areas. To date, there are few localised studies in this region that quantify the associations between subseasonal environmental factors and alert-level risk of cyanobacteria, with most studies focussing on absolute abundance, with no empirical estimates of bloom risk. In the absence of a comprehensive evidence base, the opportunity to use climate information to predict bloom risk remains limited as is the chance to develop climate-driven early warning systems for cyanobacteria. This is an area for future research in the Basin, along with the adaptability of this approach to model the risk of cyanobacteria and other microbiological contaminants in other areas.

Limitations of the current study must be acknowledged. First, although this study examined the relationship of water temperature and the risk of alert level algal abundance across six sites accounting for site-specific relative discharge, we did not examine the relationship with other biotic and abiotic factors. Although our results suggest substantial site-specific variation of risk in association with high water temperatures, the models did not characterise

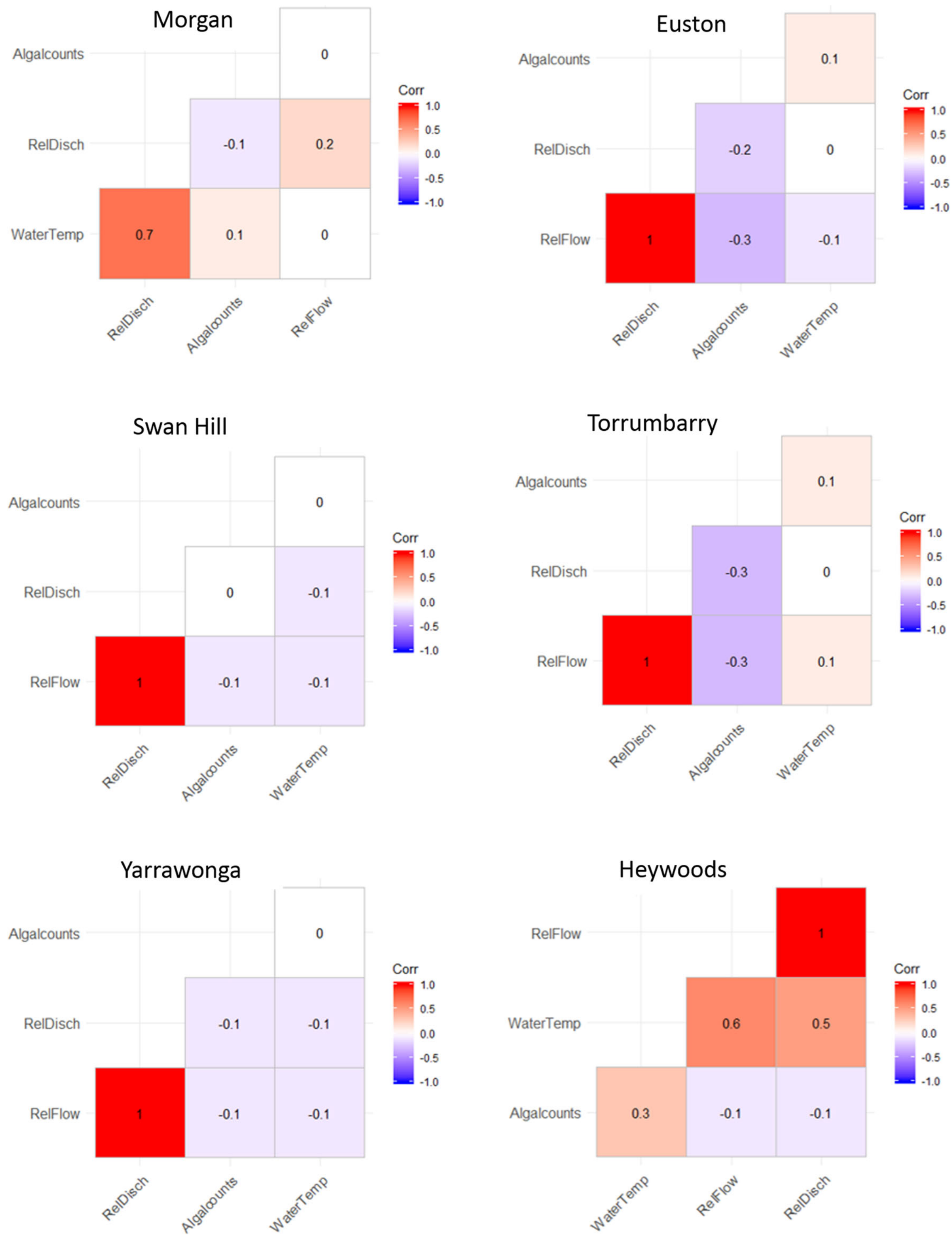

Fig. 3 Pair-wise cross correlation matrix for environmental variables

these differences to identify determinants of increased or decreased risk. Such limitations may be addressed in future research that can include additional site-specific biotic and abiotic factors. Results from such analyses would add to the evidence provided by the current study.

Our parsimonious model for studying the temporal dynamics of the risk of alert-level algal abundances in response to water temperature highlights that epidemiologic methods could potentially offer environmental and public health authorities a tool to measure or even predict

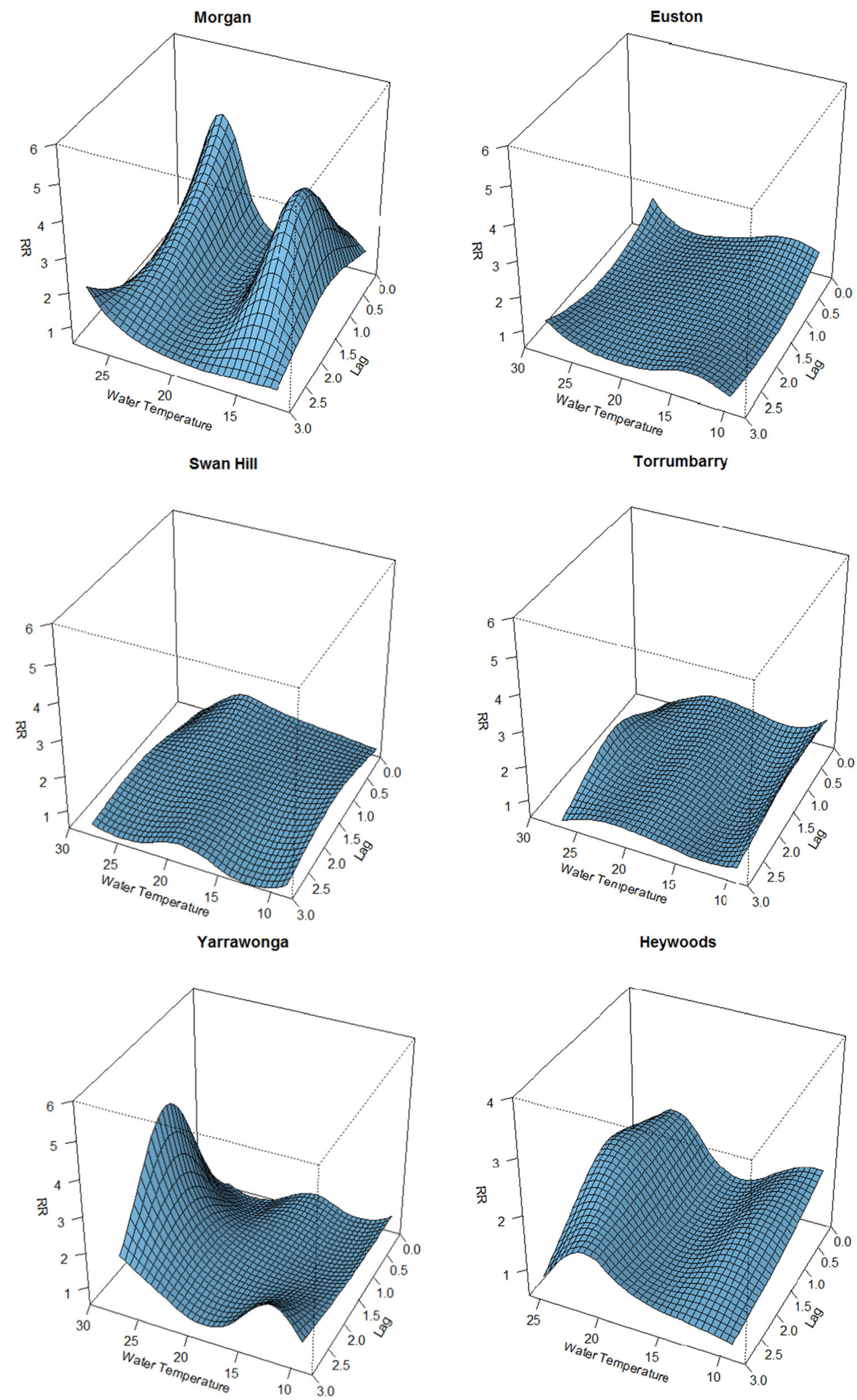

Fig. 4 Cumulative short-term and delayed association of alert-level cyanobacterial abundance with temperature

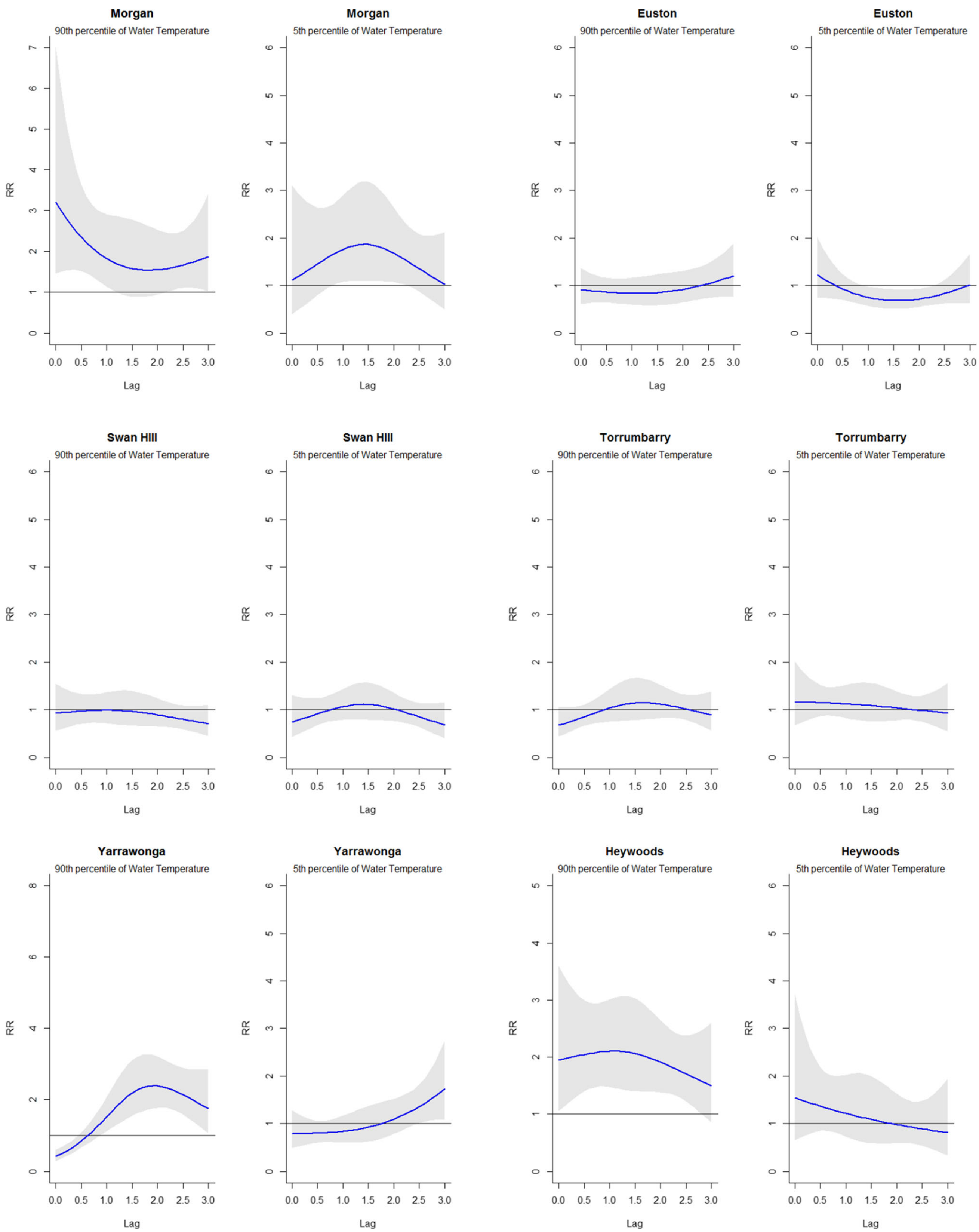

Fig. 5 Non-linear response of alert-level cyanobacterial abundance to extreme water temperatures (90th and 5th percentile of temperature range) across the six sites

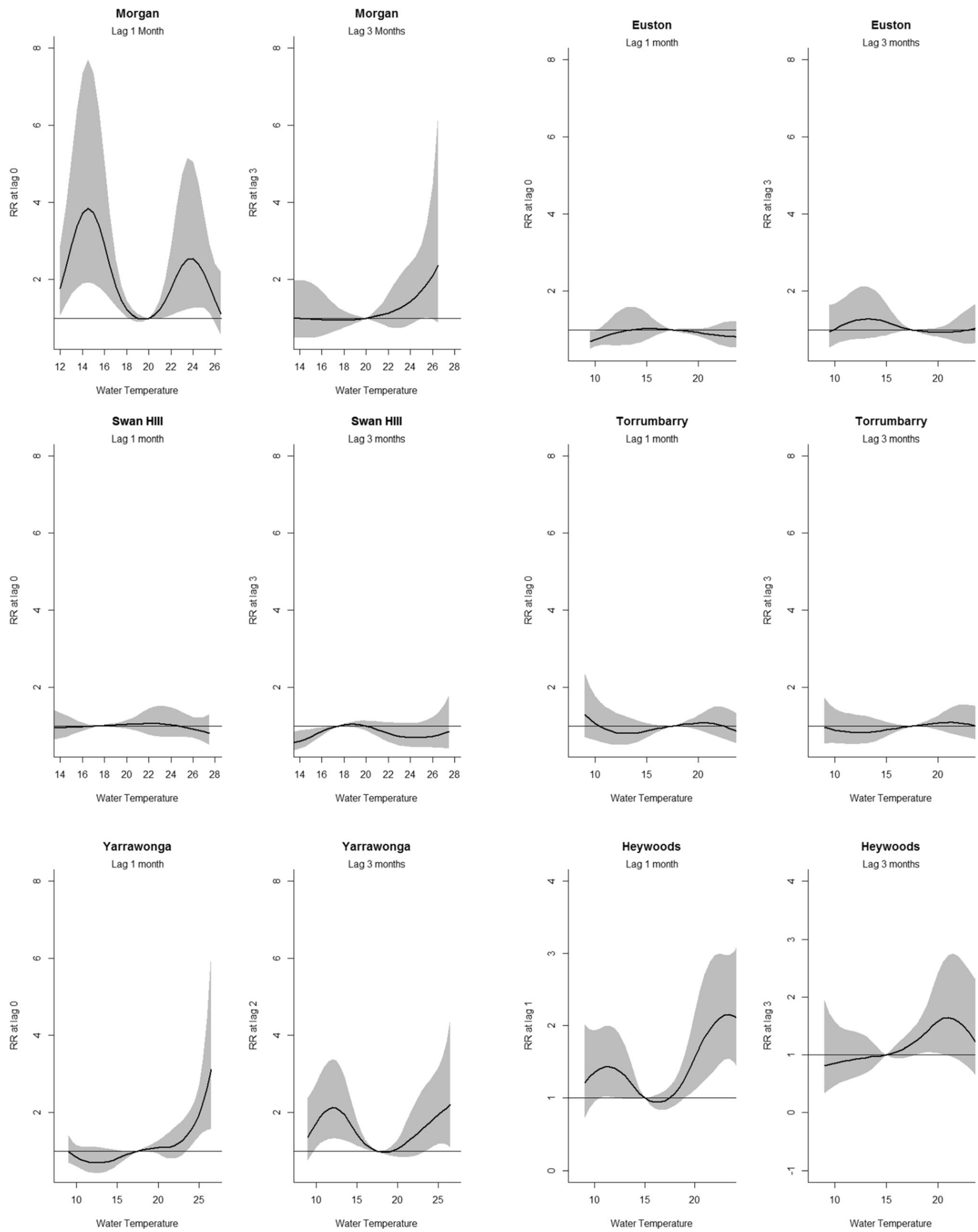

Fig. 6 Lagged response (Lag 1 month and Lag 3 months) of alert-level cyanobacterial abundance with water temperature

fluctuations in the risk of alert-level cyanobacterial abundances seen in the Murray-Darling Basin. Such quantification of risk, when combined with site-specific biotic and abiotic factors known to influence algal abundance, can help optimize the efficiency of water safety and public health policies and interventions designed to reduce the impact of blooms. The disciplines of ecology and epidemiology have traditionally crossed over when understanding vector-borne diseases (Chancey et al. 2015; Schotthoefer and Frost 2015; Wilson et al. 2015). Here, we present an emerging statistical approach to better understand water-environment-health interactions.

In this study we identified an association of high-water temperature with the risk of alert level algal abundances that varied by site, compared with the risk at average water temperature. For three of the six sites, water temperatures at the 90th percentile were associated with a higher than average risk. Research on the association between cyanobacterial abundance and water temperature has largely relied on environmental analytical methods. Our results suggest that understanding cyanobacterial responses may be extended using epidemiologic approaches and management should account for immediate and lagged effects of water temperature. The current study provides a platform to improve analyses of water-related health and environmental risks due to climate change. Our results represent an opportunity to integrate investment in water-environment- health research, in the context of rapid environmental change.

4 Methods

4.1 Study site

The Murray–Darling Basin (MDB) is a network of 22 river catchments in south-eastern Australia (Fig. 1). The MDB landscape covers an area of over 1 million square kilometres spanning from Queensland across majority of New South Wales, all the Australian Capital Territory, across to South Australia, finishing in Victoria. The basin includes semi-arid, subtropical, temperate and cool temperate climate zones; bearing both areas prone to drought and flood (Murray Darling Basin Authority).

The Phytoplankton Monitoring Program (PMP) was established in 1978 as a key part of the water quality monitoring program for the Murray-Darling Basin and is funded jointly by the Basin governments. The program currently monitors 12 sites along the Murray and its tributaries. The present study focussed on six sites in the lower part of the Basin. These six sites were chosen for their long term data record and data completeness of associated environmental variables. For this study, all species recognised under the broad heading of 'cyanobacteria' as identified by the National Health and Medical Research Council (NHMRC) who set the guidelines and limits of cyanobacterial abundance levels for recreational water quality, including the re-classified taxa that were re-classified as cyanobacteria in 2015.

The square root of the abundance of blue-green algae (hereafter referred to as cyanobacteria) for each site across seasons is shown in Fig. 2. Using the NHMRC's classification systems for cyanobacterial bloom alerts, abundance values above 5000 cells/ml were classed as alert-level levels for cyanobacteria and used in all further analyses (NHMRC amber and red alert levels).

4.2 Environmental variables

Using the linked ID from the Bureau of Meteorology's (BoM) Water Data Online database for each of the six monitoring sites, water course discharge and water course level and water temperature were obtained. Site-specific water course level and discharge data were standardized relative to the mean for the whole time period (1992–2018). BoM's 5 km gridded monthly reanalysis air temperature data were also downloaded for each site using the reported values of latitude and longitude. The linear relationship between air temperature and water temperature was used to estimate missing water temperature data for each site (less than 2% of all data).

Pair-wise cross correlations were performed to assess the relationship between the environmental covariates. Correlations above 0.75 led to the omission of one of the covariates from the final multivariate model (Fig. 4). For most sites, relative water course discharge and level could not be used in the same model with a correlation of nearly 1, so for this study relative water discharge was chosen to control for when assessing the response of cyanobacteria to water temperature.

4.3 Modelling non-linear and delayed response

A distributed lag non-linear model (DLNM) was used to simultaneously describe non-linear and delayed dependencies in the association between monthly water temperature and algal abundance at amber and red alert levels (Gasparrini et al. 2010; Gasparrini and Armstrong 2011). Briefly, the DLNM allows the effect of an exposure (in this case, water temperature) to be distributed over a specific period of time, simultaneously estimating the different non-linear associations with water temperature at each lag period and also estimating the non-linear relationships across lags, thus providing a comprehensive picture of the exposure–response relationship (Gasparrini et al. 2010). The Relative Risk level (RR) was set at 1.0. Values above

1.0 indicate an above average risk while values below 1.0 indicate a lower than average risk. The average RR is indicated by a horizontal line on all graphs.

A DLNM with a maximum lag of three months was used to estimate the cumulative association with water temperature over the current month and the previous three months. For each site, the water temperature-algal abundance relationship was modelled using a cross-basis function where the lag and the exposure are simultaneously associated with the outcome. The exposure was described using a quadratic B-spline with two equally spaced knots and 4 degrees of freedom (df), while the temporal structure was modelled using a natural cubic B-spline with 5 df at equally spaced knots over log-values. Long-term effect was modelled using 10 df for year. The standard model using the quasi-Poisson regression is described in the equation below.

$$Y_w \sim Poisson(\mu_w)$$

$$Log(\mu_t) = \alpha + \beta T_{t,l} + S(year, 10) + relativewaterdisc\arg e \quad (1)$$

where w is the month in which the abundance was reported; Yw is the algal abundance in month w; α is the intercept; Tt,l is the matrix obtained by the DLNM using 4 df for water temperature and 5 df for the lag space for water temperature; β is the vector of coefficients for Tt, 1 and l is the lag month. S(.) is the natural cubic spline.

Author contributions A.L conceptualised this work and carried out the analysis. A.L and J.H wrote and reviewed the manuscript.

Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

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