Analysis of changes in high-intensity rainfall events in South Australia

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Goyder Institute for Water Research
Technical Report Series No. 2025/1.

www.goyderinstitute.org

Goyder Institute for Water Research Technical Report Series ISSN: 1839-2725

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Citation
McInerney D, Thyer M, Westra S and Leonard M (2025) *Analysis of changes in high-intensity rainfall events in South Australia.* Goyder Institute for Water Research Technical Report Series No. 2025/1.

DOI: 10.25909/29095580

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Respect and reconciliation

Aboriginal people are the First Peoples and Nations of South Australia. The Goyder Institute for Water Research acknowledges the range of First Nations' rights, interests and obligations as well as the cultural connections that exist between First Nations and Aboriginal peoples across South Australia and seeks to support their equitable engagement. Aboriginal peoples' spiritual, social, cultural and economic practices come from their lands and waters, and they continue to maintain their cultural heritage, economies, languages and laws which are of ongoing importance.

Executive Summary

This report describes the findings of a pilot study that examined trends in high-intensity, short-duration observed rainfall events in the Greater Adelaide region, using data from weather stations and radars. Understanding trends in high-intensity rainfall events is important for flood planning, stormwater management, and infrastructure design. National and international studies indicate that extreme rainfall has intensified and will continue to do so due to climate change. Australia's national flood guidance document, Australian Rainfall and Runoff (ARR), has recently updated its guidance to factor increases in the intensity of design rainfall events due to climate change across Australia. The local analysis performed in this study has the potential to improve our understanding of changes in observed high-intensity rainfall events in the Greater Adelaide region, with likely implications for design rainfall events that are crucial for infrastructure design.

Station analysis. The study used sub-daily rainfall data from four sites in the Greater Adelaide region: Adelaide Airport, Kent Town, Parafield Airport, and Hindmarsh Valley. These sites were selected based on having the highest number of years of reliable data (30-40 years). The analysis focused on trends in high-intensity rainfall across multiple durations (12 minutes, 30 minutes, 1 hour, and 3 hours) and several metrics, including annual maximum rainfall and values exceeded 2 and 6 times per year.

The results indicated there were 'likely' increasing trends for high-intensity rainfall, primarily for the more extreme shorter duration events (e.g. annual maximum, 12 min duration), although it is important to note there is a high level of uncertainty due to the relatively short duration of data records. As an example, at Parafield Airport, the best-estimate trend for the annual maximum 12-minute duration storm event showed an increase of 30%/ºC of global temperature increase. As the duration of rainfall events increased (e.g., to 3 hours), the increasing trends became smaller and approached zero. In contrast, most stations showed a decreasing trend in mean annual rainfall, with best estimates around a reduction of 15%/ºC of global temperature increase.

These findings for high intensity rainfall trends analysed in this study are broadly in line with the ARR climate change guidelines. The ARR guidelines are based on a large number of studies throughout Australia and therefore have a higher level of evidence than the small number of sites analysed in this local study. Hence, it is recommended to use the ARR guidelines for estimating future changes in design rainfall in the Greater Adelaide region rather than specific trends from this study (with this recommendation based on the absence of sufficient evidence to the contrary).

Radar analysis. In addition to station data, we explored the potential of using rainfall radar data from the Buckland Park and Sellicks Hill radar stations to identify trends in high-intensity rainfall. The rainfall radar data showed considerable potential for detecting large rainfall amounts that were not recorded by stations and demonstrated some ability to capture high-intensity rainfall metrics. However, the length of the available calibrated rainfall radar data (4 to 6 years) was insufficient to derive reliable long-term trends. Longer records of radar data are available, but they require calibration to be used to estimate rainfall.

Recommendations. In the short-term we recommend evaluating the impact of changes in design rainfall events provided by the ARR guidelines, as these could significantly affect stormwater infrastructure design and management in Greater Adelaide. A stress-testing approach could be used to account for catchment-specific factors such as design annual exceedance probability, land use, and catchment losses. A medium to longer term recommendation is to reduce uncertainty in high-intensity rainfall trend analysis by developing methods to integrate station, radar, and climate model data for improved insights into rainfall changes in the region.

Acknowledgments

We gratefully acknowledge the support of the South Australian Department of Environment and Water and the Stormwater Management Authority. In particular, we thank Graham Green for initiating this project and securing the radar data. We appreciate the advice and guidance provided by the project steering committee members Belinda Skilton, Martin Allen, Darren Ray, and Shabnam Saffarpour. Our thanks go to Alec Rolston and Bryony Cotterall from the Goyder Institute for Water Research for their support in managing this project. We also thank Rory Nathan and David Kemp for their thoughtful feedback during the external review of this report.

1 Introduction

Recent studies indicate increases in extreme rainfall events across Australia (e.g., Wasko et al., 2024b), which are particularly significant for urban areas as they can play a crucial role in effective urban planning, infrastructure design, and emergency management.

This pilot study analyses trends in high-intensity, short-duration rainfall within the Greater Adelaide region using both station and radar data. Given the variability of climate drivers across different locations, local data analysis has the potential to enhance our understanding of these changes and their potential implications. This study seeks to contribute to the body of evidence that has analysed trends in observations of high intensity rainfall events, with likely implications for design rainfall events which play a key role in infrastructure design.

The objectives of this pilot study are as follows:

1. **Data and station selection**: Identify rainfall monitoring station data and radar products that are suitable for trend analysis, based on record length and quality assurance/control measures in the Greater Adelaide region.
2. **Evaluate trends in high-intensity sub-daily rainfall at stations**: Assess trends in high-intensity subdaily rainfall using data from multiple monitoring stations. This will involve analysing rainfall over various durations (e.g., 30 min, 60 min, 120 min) and calculating high-intensity metrics, such as annual maximum and number of exceedances per year.
3. **Evaluate trends in spatially variable high-intensity radar rainfall:** Investigate the capability of radar data to detect trends in high-intensity subdaily rainfall, highlighting its ability to identify large rainfall amounts not captured by station data and evaluating its accuracy in key metrics.
4. **Interpretation and practical implications:** Discuss the findings in the context of national/international literature, assessing whether observed trends align with expected climate changes. Consider limitations and uncertainties related to data length and quality, discuss implications, and propose future research directions.

This project was classified as a pilot study due to its relatively brief duration of six months, which is much shorter than the typical multi-year projects carried out by the Goyder Institute. Given this limited timeframe, the scope was constrained to employing pragmatic trend analysis techniques focusing on changes in high-intensity rainfall from observed events, up to and including the annual maximum. Similar to other studies on this topic (e.g., Kamruzzaman, Beecham, & Metcalfe, 2016; Westra, Evans, Mehrotra, & Sharma, 2013; Zheng, Westra, & Leonard, 2015), we did not specifically analyse changes in design rainfall (e.g. 1 in 100-year events) that are used for infrastructure design. However, as annual maximum rainfall is often used to estimate design rainfall, we are interested in how these values may change in the future (see Section 4.2 for further discussion).

The remainder of this report is written as follows. Section 2 describes the selection of rainfall station data and evaluation of trends in high-intensity rainfall at these stations (objectives 1 and 2). Section 3 covers the selection and analysis of radar data (objectives 1 and 3). Section 4 provides interpretation of findings and future research directions (objective 4).

2 Trend analysis at stations

This section focuses on the examination of sub-daily rainfall data collected from multiple stations across South Australia. The aim is to identify and evaluate trends in high-intensity rainfall events at specific locations.

2.1 Methods

The approach for calculating trends in high-intensity rainfall using station rainfall data is shown in Figure 1 and described in the remainder of this section.

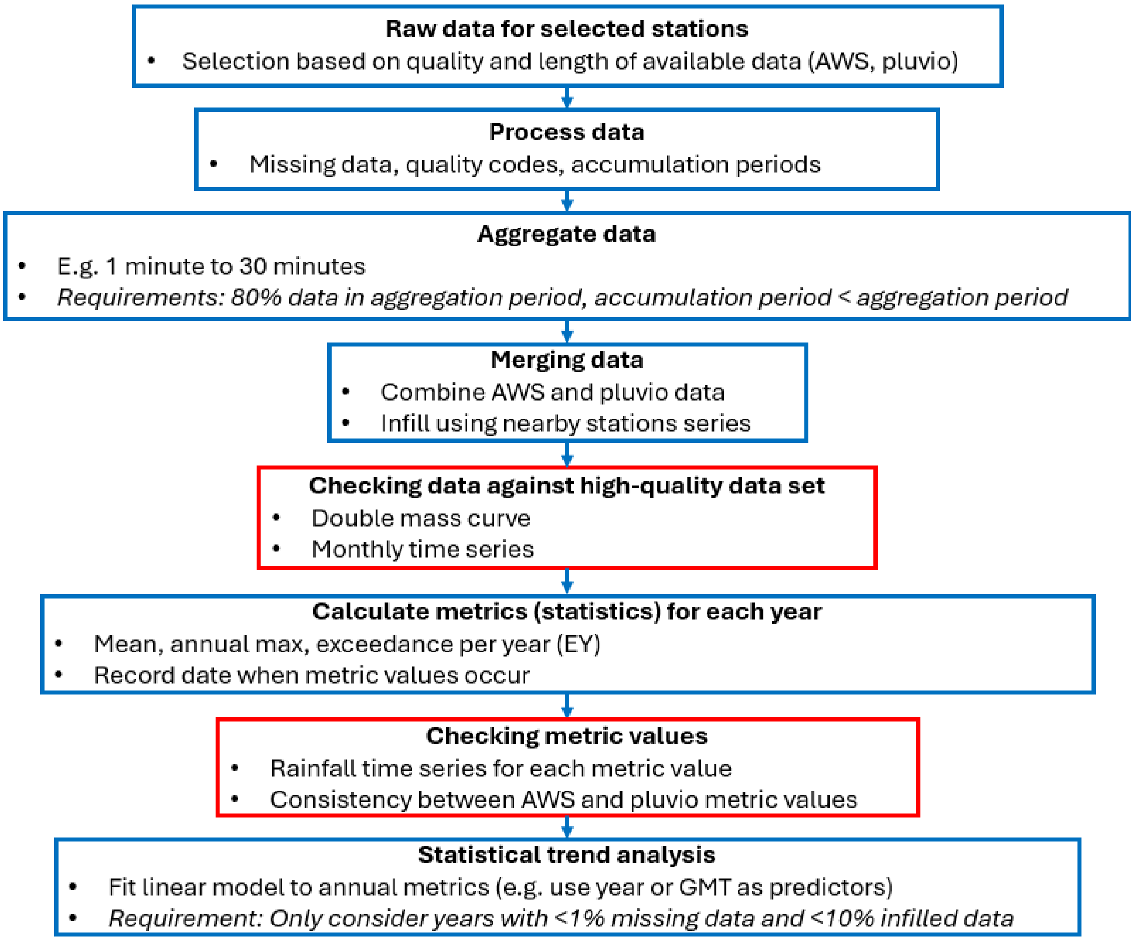

Figure 1: Approach used for processing station sub-daily rainfall data and determining trends in high-intensity rainfall metrics. The blue boxes represent steps that contribute to the statistical trend analysis, while the red boxes highlight data checks that may lead to the exclusion of certain datasets or periods of data.

2.1.1 Raw data for selected stations

Data sources

Sub-daily rainfall data was sourced from the Australian Bureau of Meteorology for approximately 150 sites across South Australia. This data was obtained from two types of instruments:

- Pluviometers, which are continuous rain gauges, consist of Dines pluviographs and tipping Bucket Rain Gauges (TBRGs). Dines pluviographs were replaced with TBRGs in the 1980s.
- Automatic Weather Stations (AWSs), which automatically and continuously record various weather variables, including rainfall.

Pluvio data is available in 6-minute intervals, with start dates varying across stations; however, data for the selected stations in this study began around 1970 and ended around 2017. AWS data is available in 1-minute intervals, starting from approximately 2004 and is currently ongoing with data until the end of 2023 used in this study.

Selected stations

The criteria for station selection included:

- A minimum of 30 years of data with sufficient data in each year to reliably calculate metrics based on having less than 1% missing data and 10% infilled data (see Section 2.1.6). It is noted that approximately 80% of sites could be excluded based solely on record length.
- An acceptable comparison with a high-quality dataset (see Section 2.1.6).

As a result, four stations were selected, as detailed in Table 1 and illustrated in Figure 2. All other stations were deemed unsuitable; reasons for exclusion are provided in Appendix A.

Table 1: Details of selected sub-daily rainfall stations.

STATION NAME (ID)	INFILL STATION (ID)	DATA SOURCE (AWS, PLUVIO)	NUMBER YEARS (1978-2023) THAT PASS CRITERIA (<1% MISSING, <10% INFILL)
Adelaide airport (023034)	Adelaide Kent Town (023090)	Both	38
Adelaide Kent Town (023090)	Adelaide airport (023034)	Both	37
Parafield airport (023013)	Adelaide Kent Town (023090)	Both	36
Hindmarsh Valley Fernbrook (023823)	Hindmarsh Valley Springmount (023824)	Pluvio	33

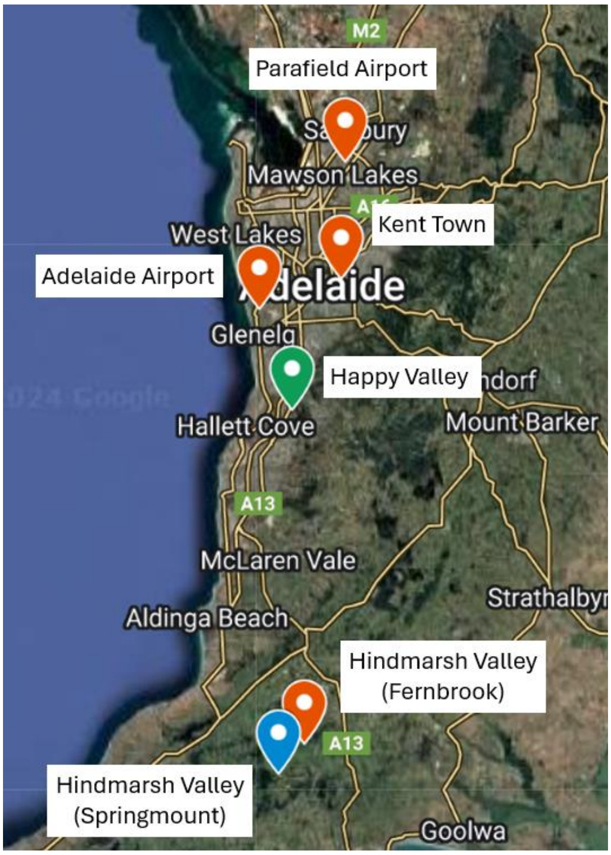

Figure 2: Locations of selected sub-daily rainfall stations and high quality daily station (Happy Valley)

2.1.2 Processing data

The raw data sets provide rainfall amounts, accumulation periods (which may the exceed 1 minute or 6-minute increments), and quality codes indicating missing data.

We only use data values which are quality controlled (specifically data with values '-9999' in pluvio files, and with quality codes other than 'Y' in AWS files are set as missing values). Accumulation is distributed over the specified period, with the accumulation period recorded accordingly.

2.1.3 Aggregating data

Data is aggregated from the original time steps (1 minute for AWS and 6 minutes for pluvio) into the following relevant durations:

- 12 minutes
- 30 minutes
- 1 hour
- 3 hours

The shortest duration, 12 minutes, is selected because it closely aligns with the 10-minute intervals considered in other studies on high-intensity rainfall (e.g., Ayat, Evans, Sherwood, & Soderholm, 2022) and is compatible with both AWS and pluvio time increments. Previous research has indicated that largest changes in high-intensity rainfall occur over short durations.

Longer durations are more relevant for assessing urban flooding and stormwater design.

The criteria for aggregation include:

1. Data from at least 80% of the time intervals must be present to allow for aggregation (based on Ayat et al., 2022).
2. The accumulation period (described in Section 2.1.2) must be less than the aggregation period.

If these conditions are not met, the aggregated value for the time period will be set as missing.

2.1.4 Merging data

To ensure extended time periods and sufficient data coverage each year, we merge multiple data sources in the following order:

1. AWS at station
2. Pluvio at station
3. AWS at nearby station
4. Pluvio at nearby station

For each station, we start with aggregated AWS data at that station. For times when AWS data at the station is not available, we use pluvio data at the station. To improve consistency between data sources, we calculate a correction factor based on the ratio of mean AWS rainfall and mean pluvio rainfall during periods when both datasets are available, then multiply the infilled pluvio data by this factor. This process is repeated for the other sources of data (i.e. to incorporate AWS and pluvio data from nearby stations). We note that the correction factors between pluvio and AWS data at the same site are close to 1, while the factors between data from nearby sites range from 0.8 to 1.3.

The nearby stations are listed in Table 1. Note that for the Hindmarsh Valley (Fernbrook) station, there is no available AWS data, so only pluvio data at this station and the nearby station are used.

This approach allows us to

- Utilise both AWS and pluvio data to extend the overall data length.

- Infill times when data is not available, so that amount of missing data is minimized. This is particularly important for the high-intensity rainfall metrics used in this study (such as annual maxima), which can be biased (underestimated) in years where data is missing.

Our infilling method is clearly more advantageous than simply omitting missing data, which could lead to an underestimation of metrics during periods with limited data. While more sophisticated methods for infilling exist, it is important to note that only small percentage of metrics are calculated using infilled data (see Section 2.1.6), which means that the results are relatively insensitive to the infilling method used.

2.1.5 Calculation of metrics

We consider the following high-intensity rainfall metrics, which are based on rainfall amounts that are exceeded a certain number of times per year (EY):

- EY1: annual maximum
- EY2: value exceeded twice per year
- EY6: value exceeded 6 times per year

We also calculate the mean rainfall, which (despite not reflecting high-intensity rainfall) provides useful comparison. These metrics are computed for each year.

Previous studies have frequently used quantiles or percentiles (e.g., 99th and 99.9th percentiles) to quantify high-intensity rainfall (e.g., Ayat et al., 2022). We have opted for EY metrics for the following reasons:

- Quantiles can be misleading when assessing high-intensity, short-duration rainfall. For instance, the 99.9th percentile of 10-minute data may sound rare, but it occurs 50 times per year. In contrast, EY metrics provide a clearer picture of how often such events happen.
- EY metrics facilitate better comparisons across different durations. It is challenging to compare quantiles across durations; for example, the 99.9th percentile occurs 50 times per year for 10-minute data, but only 9 times per year for 1-hour data.

We acknowledge that design rainfall events commonly used for stormwater management are annual maximum events occurring once every five years or more (e.g. AEP 20% and higher) – these are rarer than the events analysed in this study. However, analysing trends in these design rainfall metrics would necessitate more advanced statistical techniques that is beyond the scope of this study (see Section 2.1.7 for details of statistical trend analysis). Moreover, the uncertainty associated with trend analysis increases when considering rarer events, due to the smaller size of the dataset.

In our analysis, we only calculate metrics for years with less than 1% missing data and less than 10% nearby site data (metrics for all other years are excluded from the trend analysis). It is important that infilled data from nearby stations does not have a large influence on metrics; in our analysis, we found that nearby station data was used in only ~2% of metric values.

2.1.6 Data checking

We conduct the following checks on the aggregated data to evaluate its suitability for analysis:

- **Comparison with high-quality daily rainfall data.** We compare station data used in our analysis with high-quality rainfall data at the Happy Valley station (023721) from The Australian Climate Change Site networks, hosted by the Bureau of Meteorology (http://www.bom.gov.au/climate/change/hqsites/). These high-quality datasets have undergone rigorous quality control and homogenisation to ensure they are consistent over time and free from non-climatic influences (such as changes in site location or instrumentation). Specifically, we perform the following analyses:
  - **Double mass curves**: These evaluate the stability of the relationship between recorded rainfall at multiple stations, based on the hypothesis that climate change should not cause markedly different changes at closely located stations. To do this, cumulative rainfall from the sub-daily station of interest is compared against

cumulative rainfall from the HQ daily station. Any change in this relationship (which should remain linear) indicates that the sub-daily rainfall station has undergone change (e.g. change in instrumentation) that has influenced properties of rainfall. Examples of double mass curves are provided in Appendix B. We exclude stations that do not pass this test.
    - **Monthly total comparison**: We compare monthly totals to the high-quality data, looking for periods where recorded rainfall is noticeably different from the HQ site. Problematic periods are omitted.
- **Time series examination**: We conduct a visual inspection of the time series of rainfall for the dates leading to the metrics, excluding any periods with obvious issues.
- **Correlation check**: We assess the correlation between AWS and pluvio metrics to ensure that merging the data from these sources is appropriate. Correlation values are found to be above 0.9 for the majority of metrics/durations.

2.1.7 Statistical trend analysis

We use linear regression to analyse trends in annual metrics in relation to global mean temperature (GMT), assessing the uncertainty in the trend parameter. GMT is commonly used as an indicator of the magnitude of global climate change, with global temperature preferred to local temperature for reasons discussed in Wasko et al. (2024b).

This approach facilitates comparisons with existing literature. Notably, Wasko et al. (2024b) conducted a meta-analysis that synthesized results from multiple studies to provide quantitative estimates of potential future changes in extreme rainfall. Their findings have been integrated into the Australian Rainfall Runoff national guidelines. The estimated median and likely range of changes in extreme rainfall per degree of global mean temperature (GMT) increase, as reported by Wasko et al. (2024b), are presented in Table 2.

Table 2: ARR changes in extreme rainfall per degree of global mean temperature (GMT) increase based on meta-analysis reported by Wasko et al. (2024b).

	≤ 1 HR (%/^{O}C)	> 1 HR AND < 24 HRS (%/^{O}C)	≥ 24 HRS (%/^{O}C)
Central (median) estimate	15	Interpolation zone	8
'Likely' range (~ 66 % range)	7-28	Interpolation zone	2-15

To compare trends with those reported by Wasko et al. [2024b], we will also consider the 66% range for uncertainty in trends. The implications of this comparison are discussed in Section 4.

We obtain GMT data from NASA GISS https://data.giss.nasa.gov/gistemp/graphs_v4/graph_data/Global_Mean_Estimates_based_on_Land_and_Ocean_Data/graph.txt.

Each station is analysed separately; we do not incorporate a model that captures dependencies between stations.

We acknowledge that the use of linear regression to analyse trends is based on the assumption that the residuals (i.e. the differences between the fitted linear model and observed metrics) follow a Gaussian distribution. Appendix C evaluates this assumption of Gaussian residuals for the models used in this study. This evaluation shows the Gaussian assumption is reasonable, except for some evidence suggesting that the residuals contain more extreme values than would be expected from a Gaussian distribution. Given the limited timeframe of this pilot study, it is considered beyond the scope to explore alternative distributions that better capture the behaviour of the residuals – this is left to future work. In the authors' opinion, such an approach might refine uncertainty estimates but is unlikely to significantly affect the overall conclusions of the analysis.

While our primary focus is on annual metrics, we also examine trends for each season.

2.2 Results

2.2.1 Trends in high-intensity rainfall

Figure 3 and Figure 4 illustrate representative results for annual metrics from Adelaide Airport and Kent Town, respectively. These figures show high-intensity rainfall metrics for both the minimum duration of 12 minutes and the maximum duration of 3 hours, along with the mean annual rainfall, which is independent of duration. A comprehensive set of results for annual metrics across all stations and durations is provided in Appendix D.

Insights from these figures are:

1. Shortest duration (12 minutes): The line-of-best-fit indicates an increase in high-intensity rainfall metrics, particularly for the annual maximum at the Kent Town station.
2. Longest duration (3 hours): The trends are mixed. Kent Town shows a slight increase in annual maximum rainfall, while EY2 and EY6 exhibit slight decreases, while Adelaide Airport shows no changes or slight decreases in high-intensity metrics.
3. Mean annual rainfall: A decreasing trend in mean annual rainfall is observed for both stations.

Trends in rainfall metrics per year (i.e. the best fit line Figure 3 and Figure 4) are included for visualization purposes only. A detailed trend analysis based on GMT, including uncertainty assessments, is presented next.

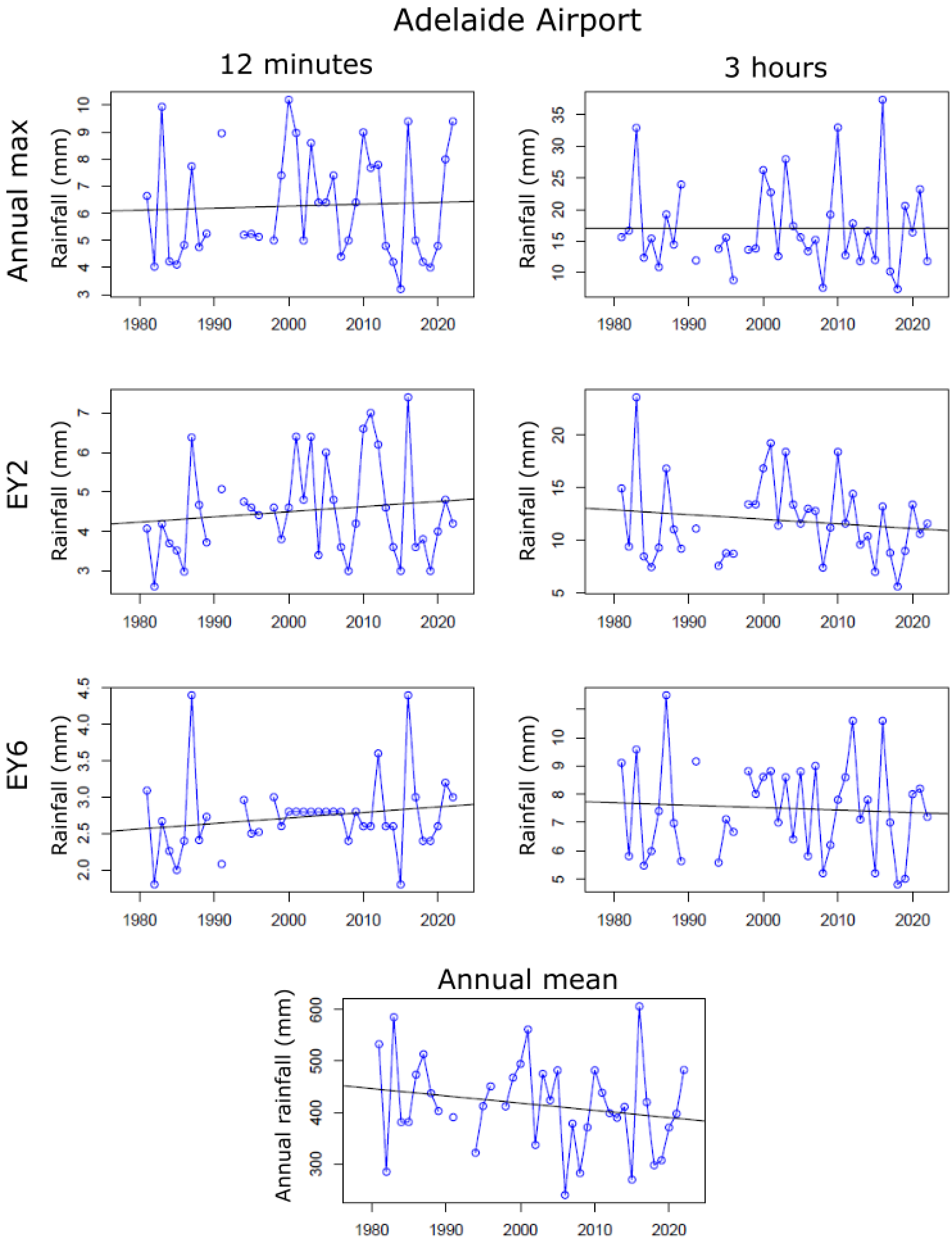

Figure 3: Annual rainfall metrics for Adelaide Airport with durations of 12 mins (left) and 3 hours (right) considered. A line of best fit (black line) is shown to indicate trends through time.

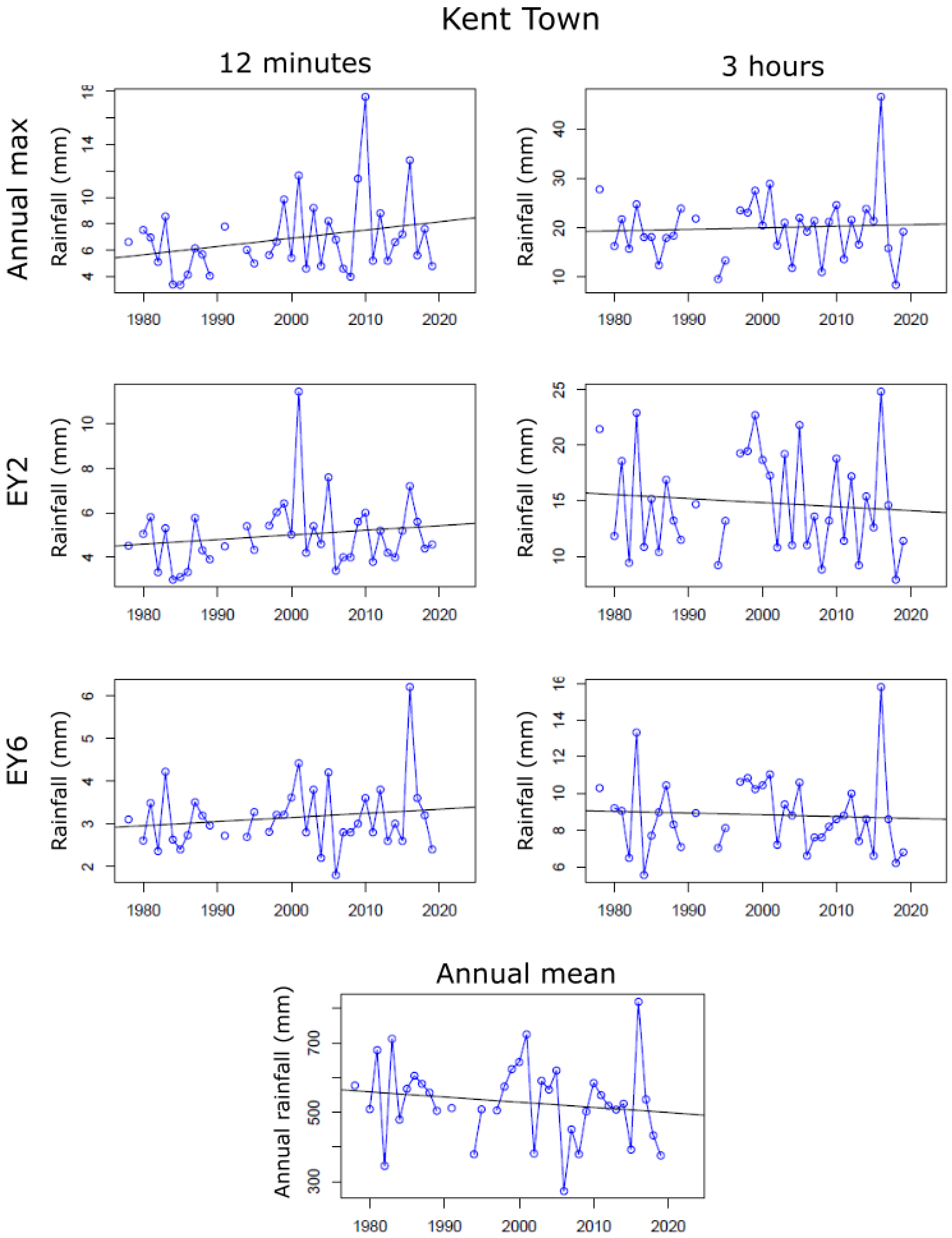

Figure 4: Annual rainfall metrics for Kent Town with durations of 12 mins (left) and 3 hours (right) considered. A line of best fit (black line) is shown to indicate trends through time.

The complete set of trends in annual metrics, expressed as change in each metric per change in GMT, is shown in Figure 5. Key results are summarized below:

- **High intensity short duration rainfall (annual maximum, 12 minutes)**: There is an increasing trend for Kent Town, Parafield Airport, and Hindmarsh Valley. For example, at Parafield Airport, the best estimate of this trend is approximately 30%/°C. The lower limit of the 'likely' range is above zero for these three stations. In contrast, Adelaide Airport shows slightly different trends, with the best estimate closer to zero.
- **Impact of duration**: As the duration increases from 12 minutes to 30 minutes, 1 hour, and then 3 hours, trends typically decrease until they are close to zero. Note that some variability exists between the results, and the 'likely' intervals generally overlap, so this finding is unlikely to be statistically significant.
- **Trends for less rare events**: A reduction in trend is also observed for less rare events; for example, at Parafield Airport the trend for the 12-minute duration drops to ~5%/°C (c.f. 30%/°C for the 12-minute duration).

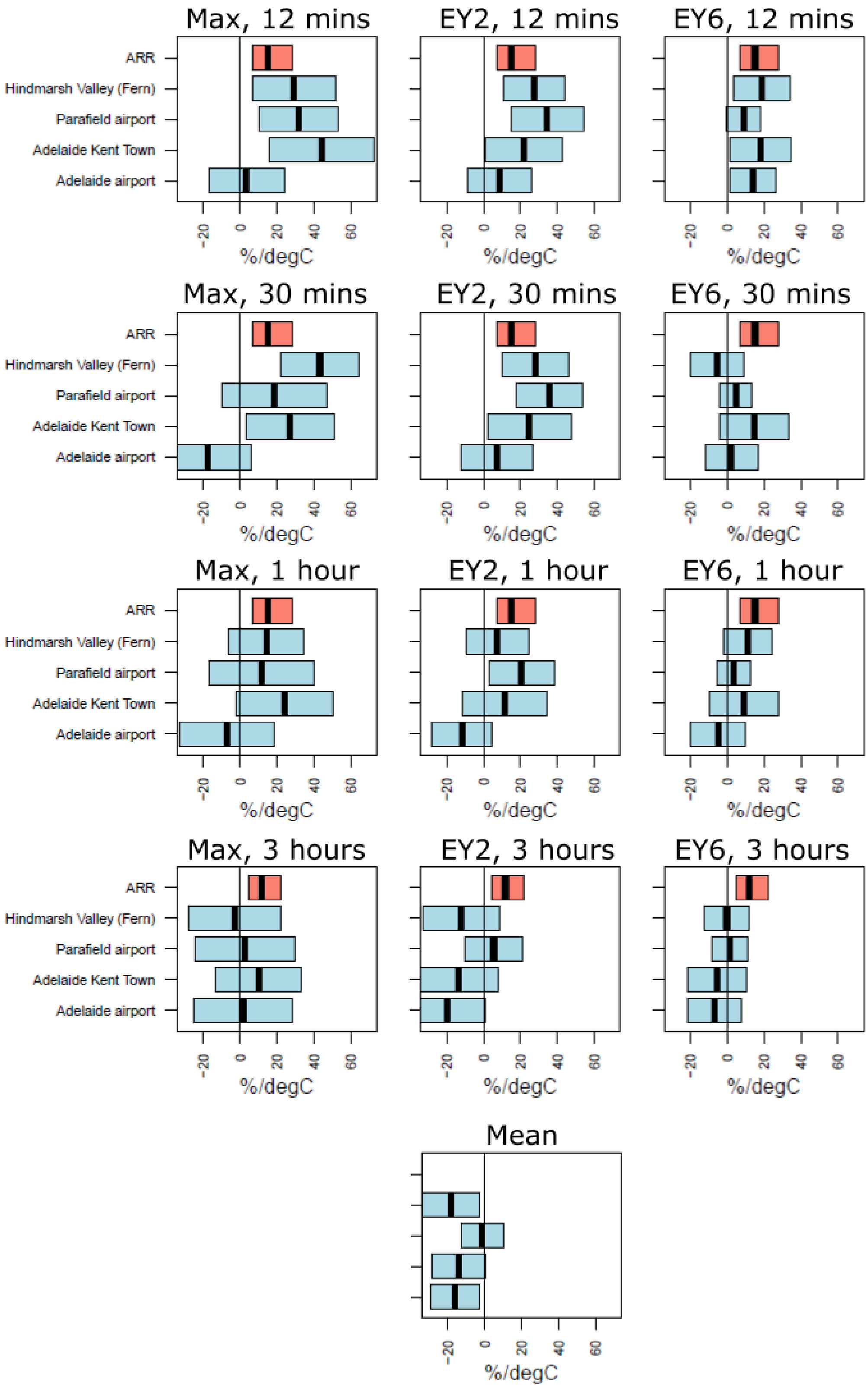

Figure 5: Trends showing change in annual metrics per change in global mean temperature. Results all shown for all 4 sites, including 3 high-intensity metrics and 4 durations, as well as mean annual rainfall. Width of boxes indicate 66% confidence limits. Trends are compared with trends from ARR.

In contrast to the results for high intensity, short duration rainfall events, there is a noted decrease in the annual mean rainfall, estimated to be between 0% and 25%. These findings highlight variations in rainfall trends based on duration and intensity, with contrasting increasing trends for high-intensity, short-duration events compared to the decreasing trends in mean annual rainfall.

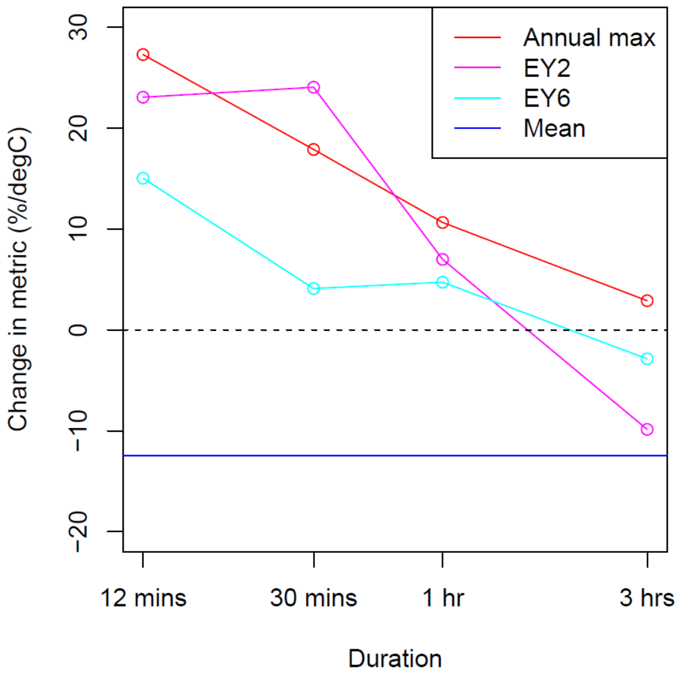

Figure 6: Trends in annual metrics per changes in GMT, averaged over the four stations, as a function of duration.

Figure 6 summarizes the relationship between event duration, frequency, and changes in rainfall. This analysis averages the best estimate of the trend parameters across four sites. The trend parameter declines as duration increases from 12 minutes to 3 hours and decreases with frequency from annual maximum to EY6. For the shortest duration of 12 minutes, both the annual maximum and EY2 show an average increasing trend of 22 to 28%/°C. In contrast, for the longer duration of 3 hours, both EY2 and EY6 exhibit decreasing trends, with EY6 showing a change of -10%/°C. It is noteworthy that increasing duration and more frequent events approaches the annual mean change of -12%/°C. While these metrics highlight significant trends, it is crucial to note that they should not be used directly for estimating changes, as they do not account for uncertainty and may be disproportionately influenced by data at an individual site.

2.2.2 Seasonality

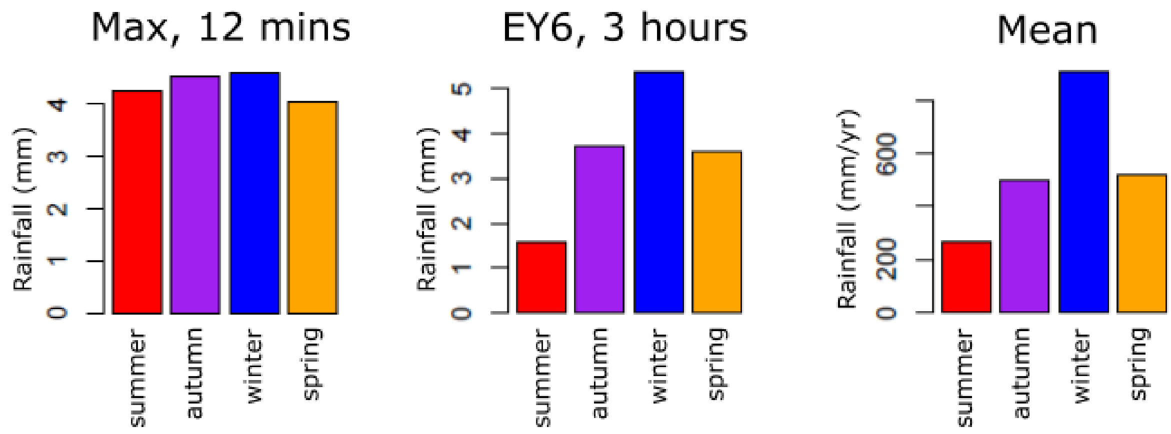

Figure 7: Seasonal variations in metric values (averaged over all sites and years). The annual maximum for 12-minute duration, EY6 for 3-hour duration and the annual mean rainfall, are shown.

Figure 7 shows the seasonality of rainfall metrics averaged across the four sites and all years for a range of metrics and durations. (Note that these metrics are presented in rainfall units to show the magnitude of events in each season, rather than as trends or relative changes.) The annual maximum 12-minute rainfall is similar for all four seasons. In contrast, the EY6 and mean seasonal rainfall are much larger in winter than summer.

Figure 8 shows seasonal trends with GMT for the same selected metrics and durations. For each season, we see that increasing duration and frequency (from maximum 12-minute rain to EY6 3-hour rain) leads to smaller magnitude increasing trends or decreasing trends, which is consistent with the annual analysis. However, there are also some notable differences across the seasons. Summer demonstrates an increase in mean rainfall, contrasting with the decreases observed in other seasons, and shows a large rise in the seasonal maximum for short durations. In autumn, there is little to no change or a decrease in the maximum for short durations, unlike the increases seen in other seasons. Winter exhibits a substantial increase of up to 60% in the 12-minute annual maximum, although it also shows a more considerable decrease in EY6 for the 3-hour duration. Spring trends are relatively similar to those observed in winter.

Seasonal variations in metric values and trends for the complete set of metrics and durations is shown in Appendix E.

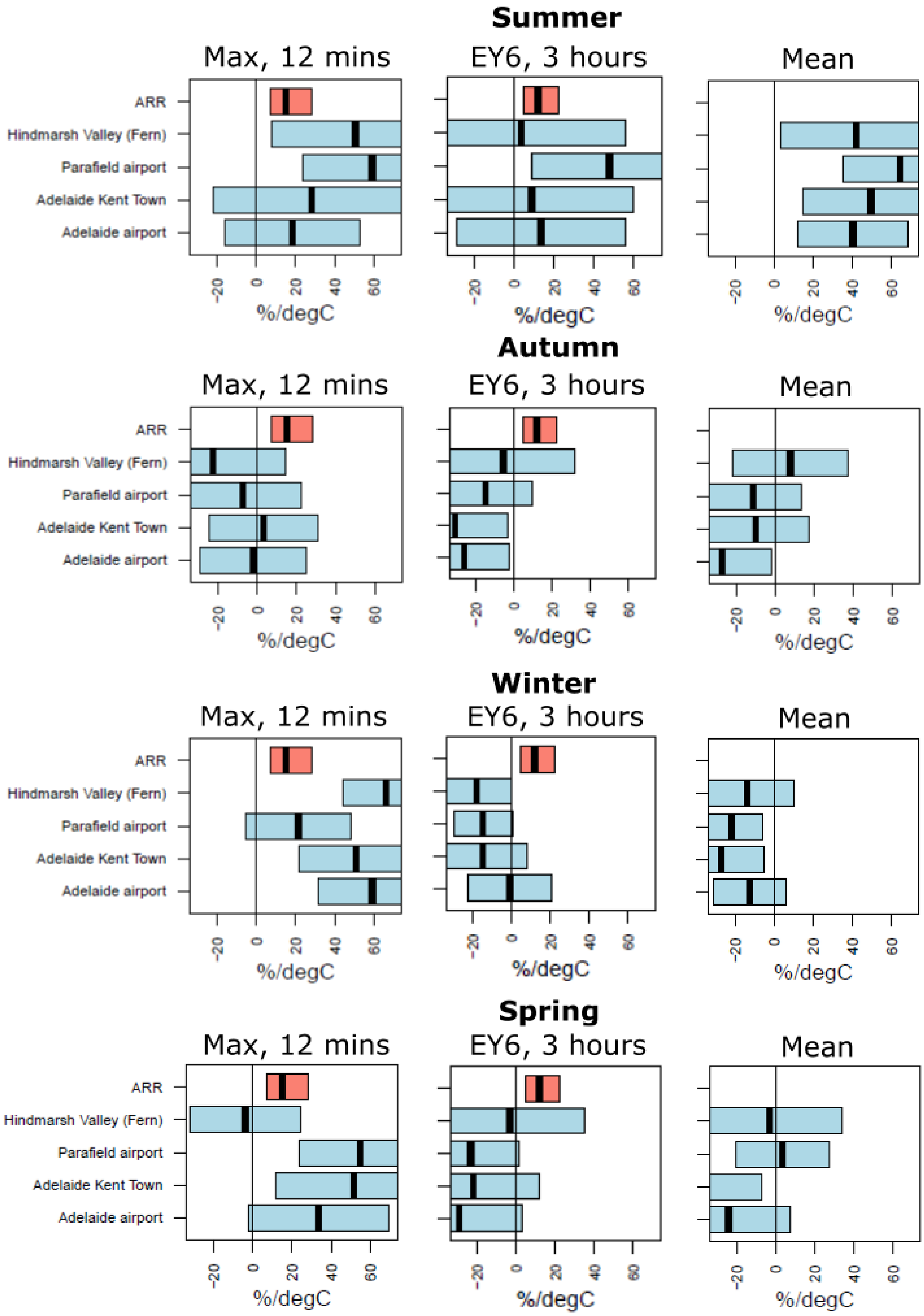

Figure 8: Trends showing change in seasonal metrics per change in global mean temperature. Results all shown for all 4 sites, focusing on seasonal maximum for 12-minute duration, EY6 for 3-hour duration, and seasonal mean rainfall. Width of boxes indicate 66% confidence limits. Trends are compared with trends from ARR.

3 Analysis of radar data

This section focuses on the use of radar data for detecting trends in high-intensity rainfall in the Greater Adelaide region. Radar rainfall data offers the potential to capture higher intensity rainfall events that may not be recorded by weather stations, particularly when storm centres pass nearby.

In the original project plan, the objective was to use radar data to identify changes in spatial patterns of high-intensity rainfall. However, as will be explained in Section 3.1.1, the data provided by the Bureau of Meteorology (BOM) proved insufficient for comprehensive trend analysis.

The revised aims of the radar analysis are as follows:

a. To demonstrate the capability of radar data to identify high-intensity rainfall amounts that are not captured by station measurements.
b. To evaluate radar data compared with AWS station data in terms of mean rainfall, correlation and ability to produce key metrics (e.g. annual maximum rainfall and the frequency of multiple exceedances per year) recognizing that the analysis will be constrained by the short (4-year) data records.
c. To summarize the limitations of using currently available radar rainfall data for trend analysis in the Greater Adelaide region, explaining why it is inadequate and outlining necessary steps for future improvement.

3.1 Methods

3.1.1 Rainfall radar data challenges

The Sellicks Hill and Buckland Park radars serve the Greater Adelaide region. Sellicks Hill is located approximately 40 km south of Adelaide, while Buckland Park is about 25 km north. Reflectivity data from Sellicks Hill has been available since 1997, and data from Buckland Park has been available since 2005. The Buckland Park radar is a more modern S-band, dual polarization radar with Doppler radar technology, compared with the older Sellicks Hill radar, which is C-band radar with only single polarization. The dual polarisation and doppler technology provide significant enhancements for using radar to detect precipitation. For further information on differences between these radars see http://www.bom.gov.au/australia/radar/info/sa_info.shtml, and for a detailed explanation on the benefits of dual polarization visit https://en.wikipedia.org/wiki/Australia%27s_weather_radars.

An empirical model is used to estimate 'radar rainfall data' from radar reflectivity. This model typically follows the form $R = aZ^b$, where R represents the rainfall rate, Z is the reflectivity, and a and b are parameters. These parameter values can with be calibrated using local rainfall station information or sourced from literature (i.e. 'uncalibrated'). The reflectivity data must also be cleaned to ensure unrealistic events are not generated.

The Bureau of Meteorology (BOM) has archived radar rainfall data for both Sellicks Hill and Buckland Park. However, this archived rainfall radar data is limited and inconsistent in the calibration approach. At Sellicks Hill, a calibrated model has provided rainfall data from June 2019 to June 2024, while an uncalibrated model was used for the period from January 2015 to December 2019. Similarly, Buckland Park has rainfall data from June 2019 to June 2024 using a calibrated model, with an uncalibrated model covering December 2013 to December 2019.

Unfortunately, the available calibrated rainfall radar data is insufficient for robust trend analysis. The inconsistencies and limited length of archived radar rainfall data (ranging from 4 to 6 years from a calibrated model) make it inadequate for trend detection. Even combining data from both calibrated and uncalibrated models would not yield a sufficiently long series for trend analysis. In contrast, we utilize station data spanning approximately 45 years (with over 30 years of reliable data), and even with this extended dataset, the trends exhibited significant uncertainty. Consequently, we do not attempt to use rainfall radar data from these sources to evaluate trends in spatial rainfall and focus on the revised aims listed above (using the calibrated model for years where all data is available, i.e., 2020-2023, for this purpose). We recommend future work to be done to provide a consistent calibrated rainfall radar data set for the Greater Adelaide region that is suitable for trend analysis (see Section 4.2).

3.1.2 Evaluation of radar rainfall data

We evaluate radar rainfall data in term of

- **Detection of higher rainfall amounts**: We will assess the radar's ability to detect higher rainfall levels compared to station data by comparing the "spatial maximum rainfall" (defined at each time as the maximum value from all gridded data within a representative spatial region) to the recorded values at the stations. The representative region encompasses the greater Adelaide region (see Figure 9) and beyond and roughly represents a region where similar rainfall to that experienced in Adelaide could occur. This analysis aims to illustrate how station data can underestimate the magnitude of storms and quantify the extent of this underestimation.
- **Comparison with station data**: We will compare radar rainfall data with observations from Adelaide Airport and Parafield Airport. AWS data for the period from 2020 to 2023 at other sites considered in Section 2 (i.e., Kent Town and Hindmarsh Valley) is not available. We will analyse time series data for selected events, compute the correlation between radar and station rainfall time series, and compare annual metrics from both sources.

3.2 Results

3.2.1 Capability to record high-intensity events

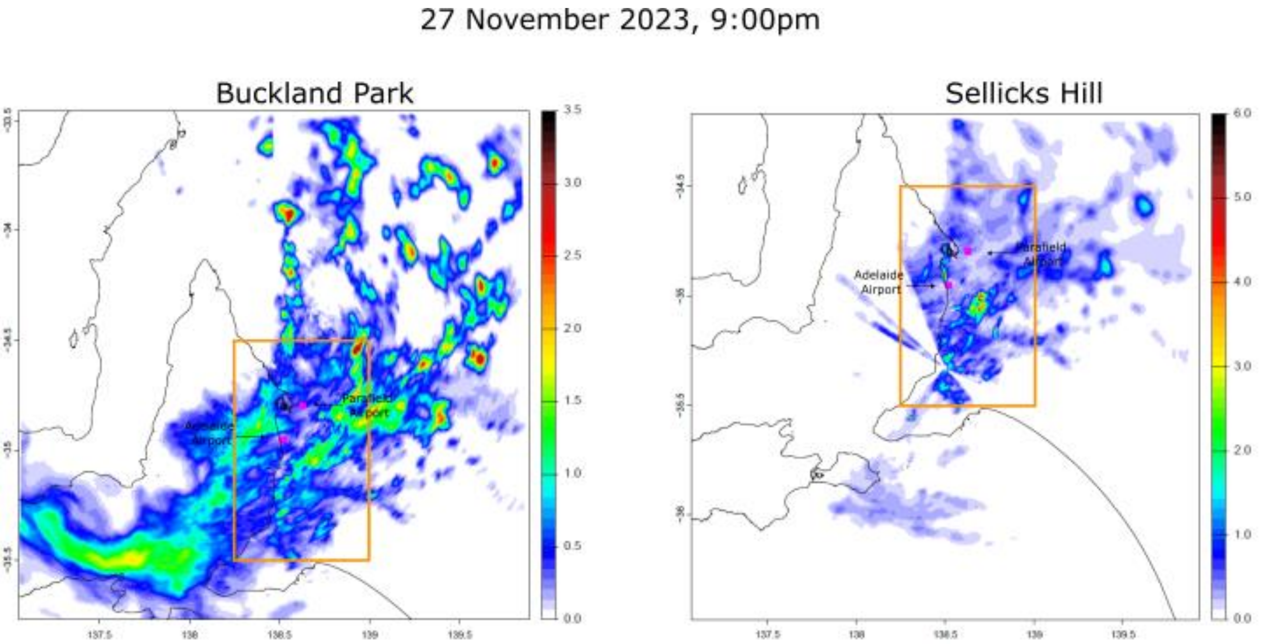

Figure 9: Rainfall rates (5 min) from the Buckland Park and Sellicks Hill radars on the 27th of November 2023

We examine two rainfall events that resulted in some of the highest estimated rainfall totals in the Adelaide region between 2020 and 2023. In this section, we first focus on the effectiveness of radar data in detecting peak storm rainfall by comparing radar readings at specific locations to those across the entire region. In Section 3.2.2, we will then compare the radar data with observations from station data.

Figure 9 shows estimated rainfall at 9 PM on November 27, 2023, based on data from the Buckland Park and Sellicks Hill radars. Both radars indicate a large storm affecting most of the selected region; however, the Sellicks Hill radar displays unusual patterns at this time, suggesting potential issues.

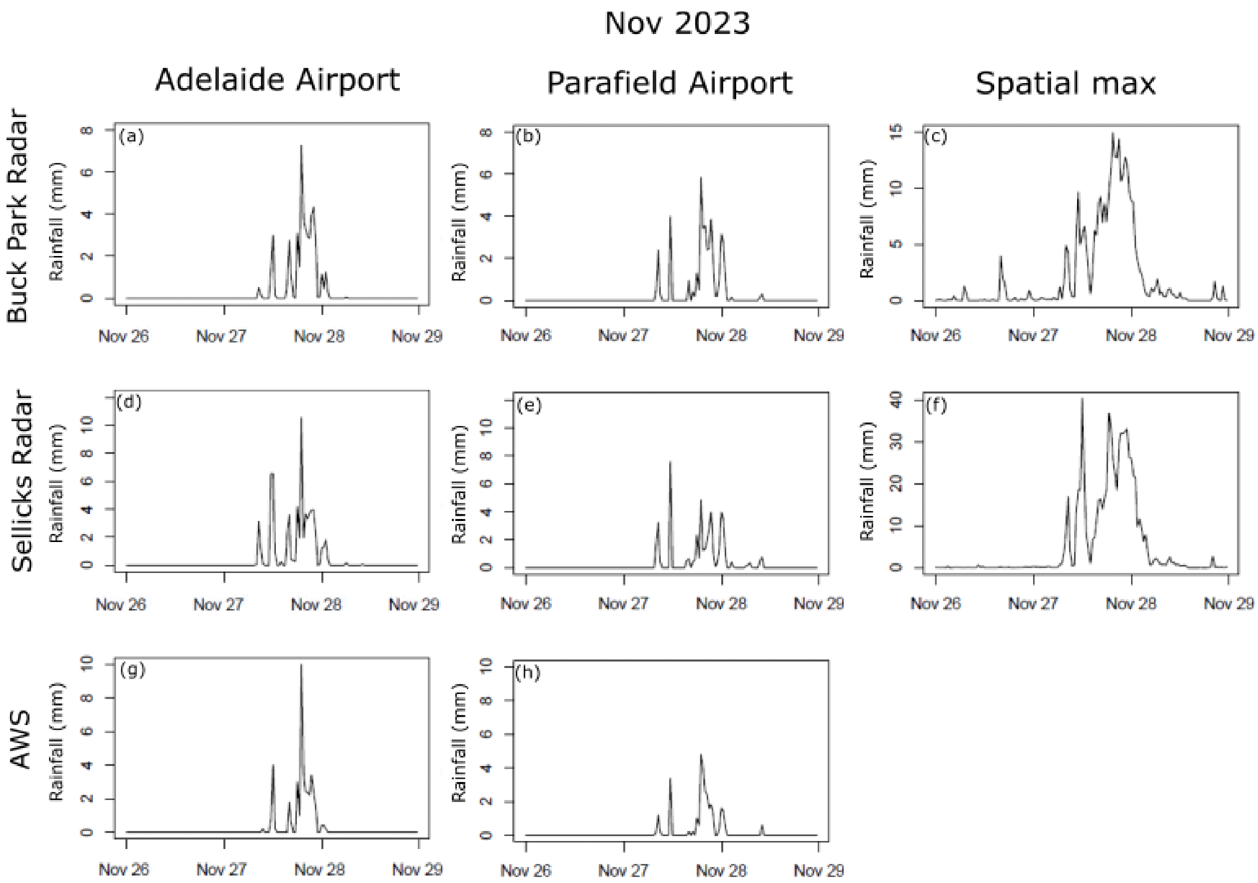

Figure 10: Comparison between 30-minute rainfall at the Adelaide Airport and Parafield Airport locations and the "spatial maximum rainfall" (as defined in Section 3.1.2) in late November 2023 based on the Buckland Park and Sellicks Hill radars, and AWS data. Note there are large differences in the *y*-limits for station locations and spatial maximum (e.g. 12mm for Sellicks radar at Adelaide Airport in panel d, and 40mm for Sellicks radar spatial maximum in panel f). The use of different y -limits for panels was chosen to highlight consistent patterns between different rainfall data sources.

Figure 10a-c uses rainfall data from the Buckland Park radar to compare 30-minute rainfall totals at Adelaide and Parafield Airports against the "spatial maximum rainfall" in the selected area (indicated by the orange box in Figure 9) during a 3-day period in late November 2023. While Adelaide Airport and Parafield Airport receive some rainfall according to the Buckland Park radar (up to 6-8 mm), they do not experience the intense rainfall observed in other areas of the region, where spatial maximums reach up to 15 mm. Similarly, data from the Sellicks Hill radar in Figure 10d-f shows that rainfall at the two station locations (8-10 mm) is also significantly less than the maximum spatial rainfall of around 40 mm. There is also a notable difference in rainfall magnitudes recorded by the two radars, which will be further discussed in Section 3.2.2.

Figure 11 displays estimated rainfall at 3:30 AM on September 29, 2021. Both radars indicate scattered rainfall, with clusters of high-intensity precipitation. Notably, while certain areas of Adelaide show significant rainfall, Adelaide Airport and Parafield Airport have little to no rainfall at this time.

Figure 12a-c compares 30-minute rainfall radar data at Adelaide and Parafield Airports against the maximum rainfall observed in the selected area during this period. The comparison reveals that the maximum rainfall recorded at these sites (1-1.5 mm) is substantially lower than the peak spatial maximum of 20 mm. Similarly, data from the Sellicks Hill radar in Figure 12d-f shows that rainfall at the two station locations (approximately 4 mm) is also significantly less than the maximum spatial rainfall of around 60 mm.

The results from the two events indicate that radar data can capture higher rainfall totals across an entire region compared to those that would be recorded at individual stations.

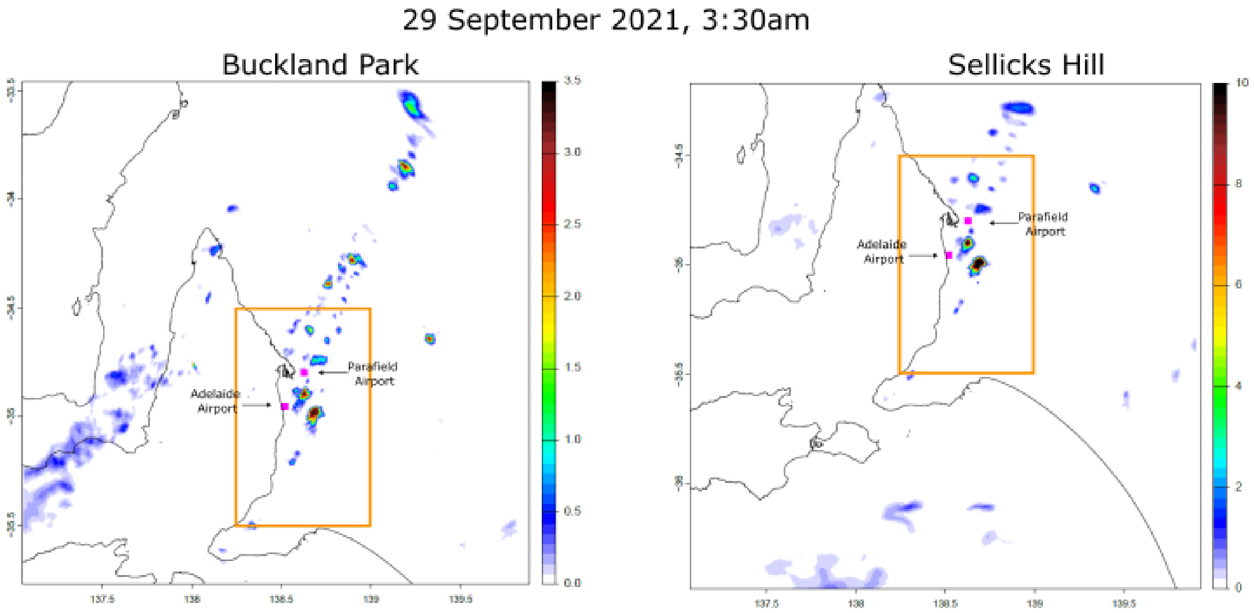

Figure 11: Rainfall rates (5 min) from the Buckland Park and Sellicks Hill radars on the 29th of September 2021

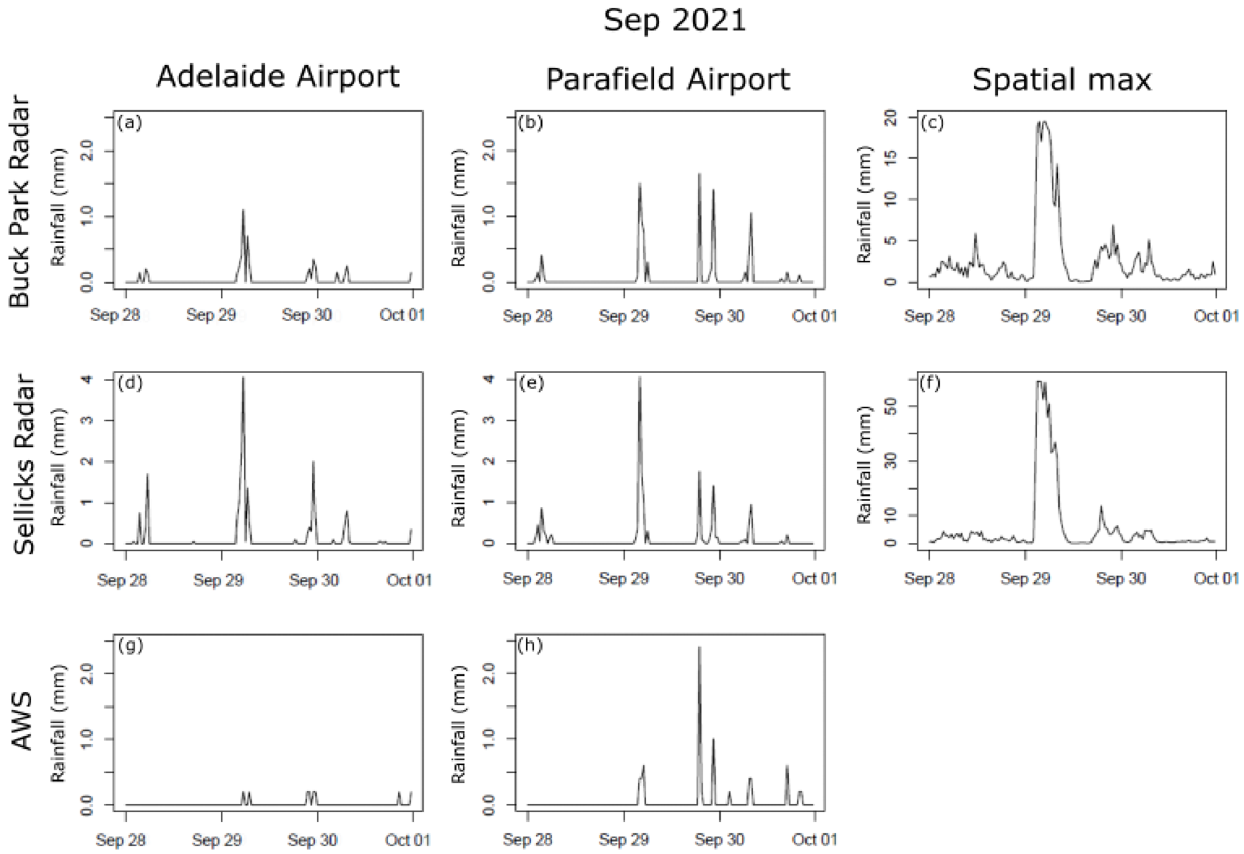

Figure 12: Comparison between 30-minute rainfall at the Adelaide Airport and Parafield Airport locations and the "spatial maximum rainfall" (as defined in Section 3.1.2) in late September 2021 based on the Buckland Park and Sellicks Hill radars, and AWS data. Note there are large differences in the y-limits for station locations and spatial maximum (e.g. 4mm for Sellicks radar at Adelaide Airport in panel d, and 60mm for Sellicks radar spatial maximum in panel f).

3.2.2 Comparison with station data

We now assess how effectively radar data captures specific aspects of the AWS data. It is important to note the differences in data sources: radar rainfall data is generated from a model based on reflectivity at multiple heights and represents average rainfall over a 500 m by 500 m grid cell. In contrast, station data is collected at ground level from a much smaller area.

Figure 10 shows rainfall from AWS stations at Adelaide Airport and Parafield Airport in November 2023. This can be compared with the estimated rainfall at these locations from radar data. At the Adelaide Airport location (Figure 10a, d, g), we see that all three sources produce similar temporal patterns of rainfall, with maximum rainfall between 7 mm and 10 mm. We also see similar patterns from the three sources at Parafield Airport. We won't focus on the event in September 2021 shown in Figure 12 since only small rainfall amounts were recorded at the stations.

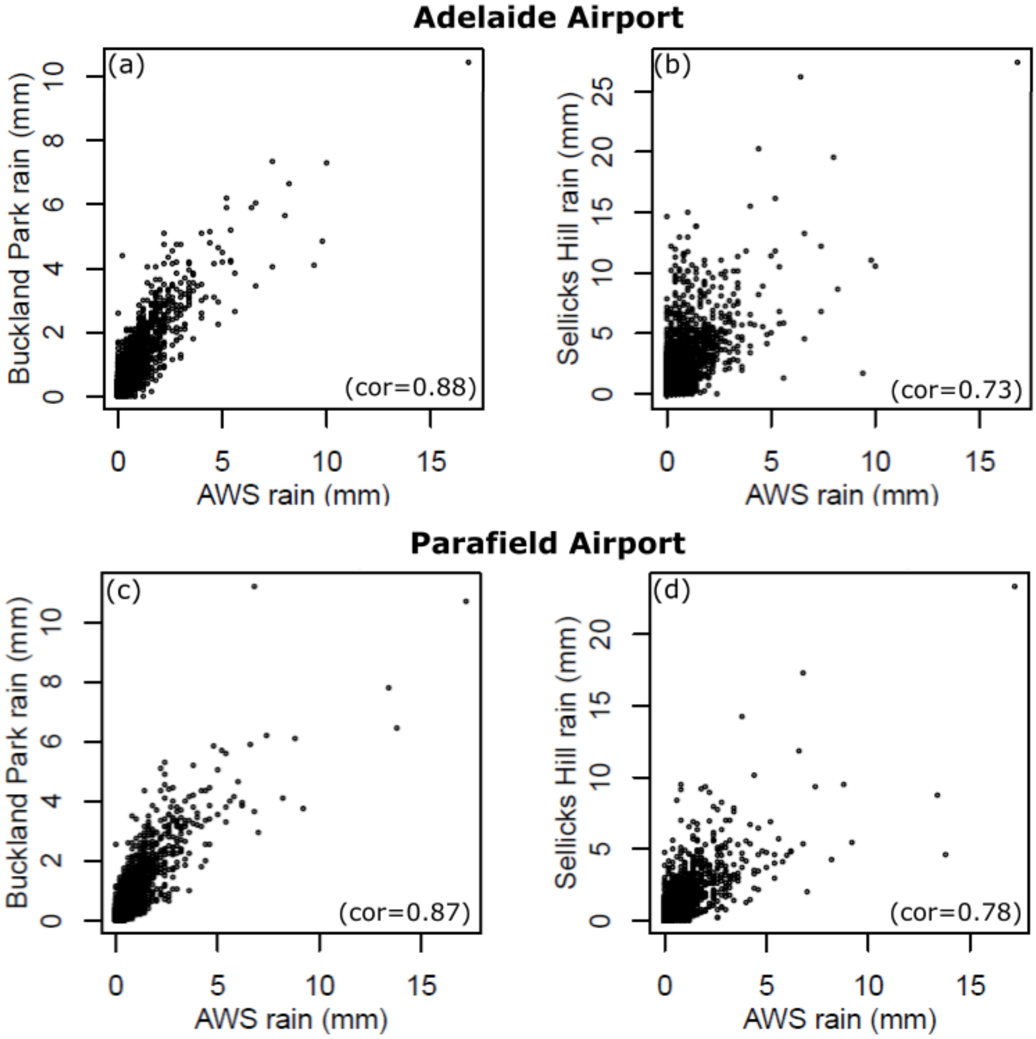

Figure 13: Comparison between AWS data and radar rainfall data, aggregated to the duration of 30 minutes. Results are shown for the Adelaide airport (top) and Parafield Airport (bottom) locations, and for the Buckland Park (left) and Sellicks Hill radars (right).

Figure 13 shows the relationship between 30-minute AWS and rainfall data at the Adelaide Airport and Parafield Airport stations for 2020-2023. Buckland Park radar shows a strong correlation with AWS at both stations (0.88 and 0.87), while Sellicks Hill (which uses older technology) has a lower correlation, but still reasonable (0.73 and 0.78).

Table 3: Mean annual rainfall based on AWS data and radar rainfall data.

	AWS	BUCKLAND PARK RADAR	SELLICKS HILLS RADAR
Adelaide Airport	441 mm	615 mm	1550 mm
Parafield Airport	466 mm	563 mm	981 mm

Table 3 presents the mean annual rainfall for Adelaide Airport and Parafield Airport based on AWS and radar data. The results indicate that radar data significantly overestimates AWS measurements, with the Sellicks Hill radar showing the largest biases. For instance, at Adelaide Airport, the Buckland Park radar overestimates rainfall by 40% (615 mm compared to 441 mm), while the Sellicks Hill radar overestimates it by 250% (1550 mm compared to 441 mm). Although the biases at Parafield Airport are smaller—particularly for the Buckland Park radar—they remain considerable.

Figure 14 and Figure 15 show metrics for 30-minute rainfall at Adelaide Airport and Parafield Airport, derived from AWS and radar data. At Adelaide Airport, Figure 14 reveals significant discrepancies in the yearly patterns of metrics obtained from radar compared to AWS data, with the Sellicks Hill radar (with older technology) performing particularly poorly. In contrast, Figure 15 demonstrates that radar data is more effective at capturing metrics for Parafield Airport compared to Adelaide Airport. Similar trends are observed across all metrics (except EY6 for the Sellicks radar), though there are notable differences in magnitude.

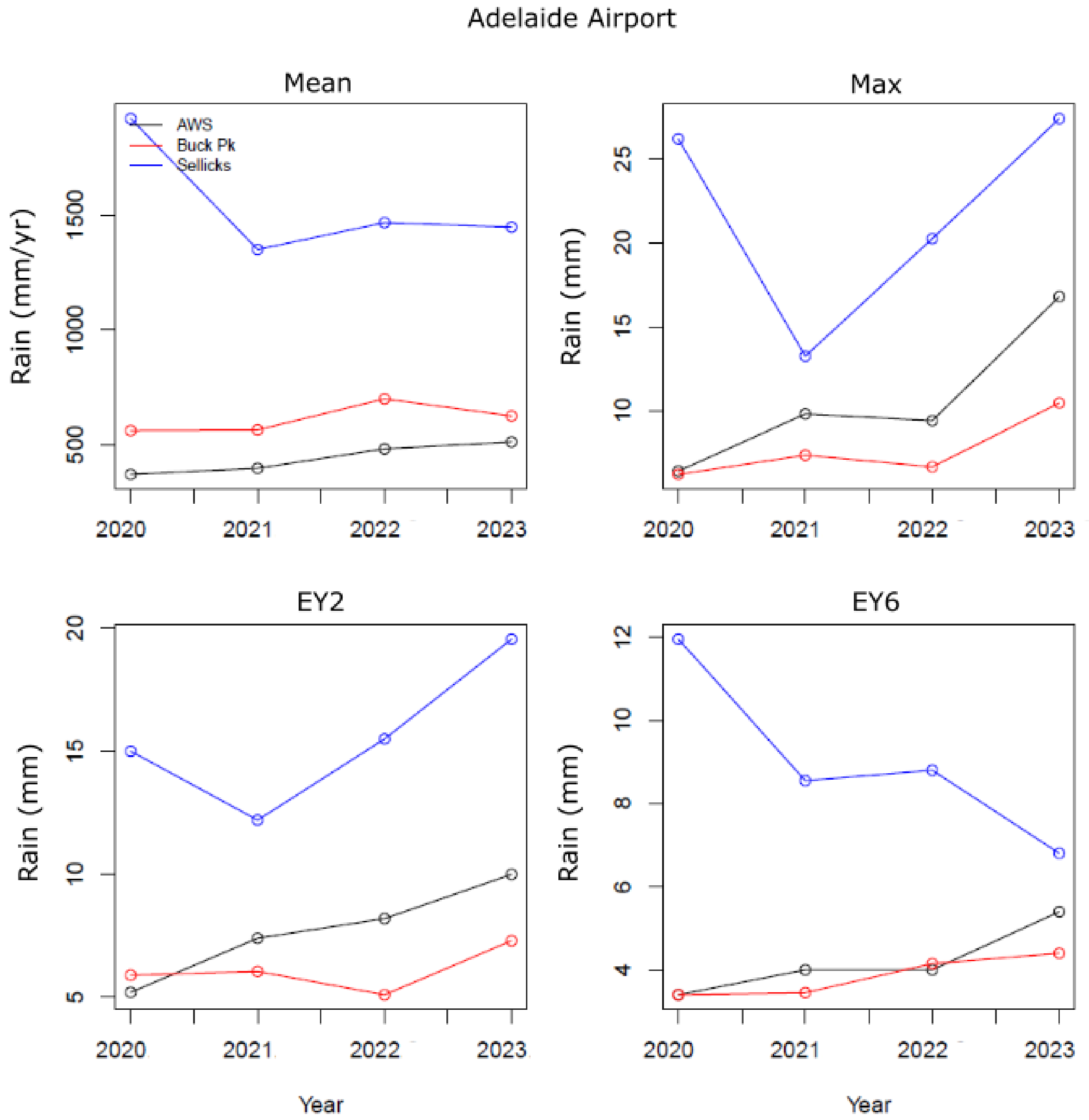

Figure 14: Metrics for 30-minute rainfall at Adelaide Airport obtained using AWS data and radar data from Buckland Park and Sellicks Hill radars.

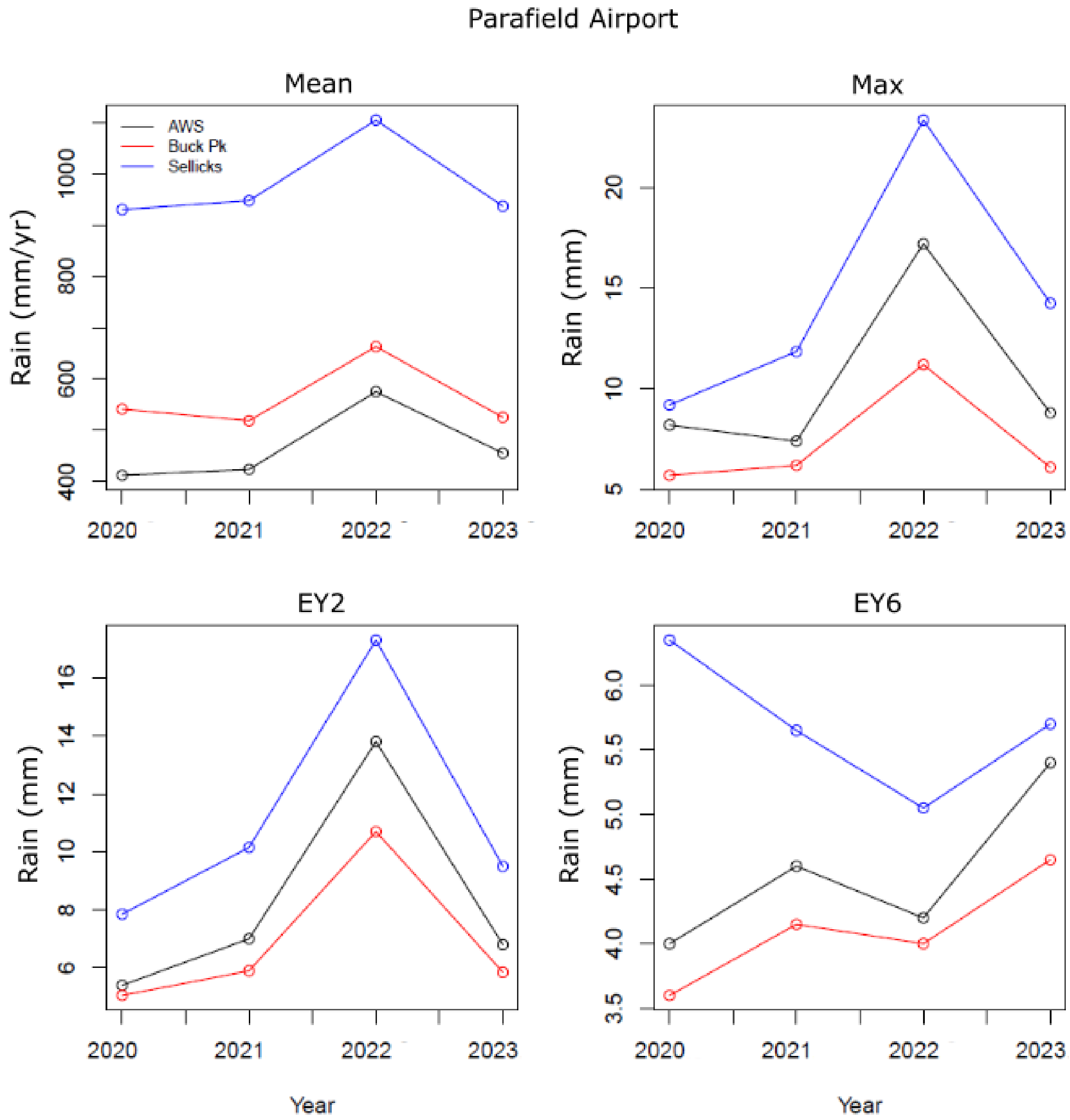

Figure 15: Metrics for 30-minute rainfall at Parafield Airport obtained using AWS data and radar data from Buckland Park and Sellicks Hill radars.

3.2.3 Potential and current limitations of radar data for trend analysis

The results from Sections 3.2.1 and 3.2.2 can be summarised as follows:

1. **Detection of large rainfall amounts**: Radar can identify large rainfall intensities that may be missed by stations, especially when storms do not pass directly over those stations.

2. **Ability to capture features of station data**: Radar can capture some aspects of station rainfall data, showing reasonable correlations with AWS data for 30-minute rainfall, although there are substantial biases in annual totals. Radar can somewhat represent annual changes in high-intensity rainfall metrics, performing well at Parafield Airport but not as effectively at Adelaide Airport.

The primary limitation of using radar data for trend analysis is the short length of the dataset, as described in Section 3.1.1.

4 Interpretation of findings and recommendations for future research

4.1 Comparison with existing knowledge on changes in high-intensity rainfall

The station-based trend analysis aligns broadly with the recently updated Australian Rainfall and Runoff (ARR) climate change guidelines, and the literature that informed these guidelines, in two main respects. First, this analysis has shown that the 'likely' range of trends from station analysis is consistent with the 'likely' range provided by ARR. Second, the analysis demonstrates that short-duration high-intensity rainfall events are exhibiting a greater magnitude of increasing trends compared to longer-duration events (Wasko et al., 2024a), consistent with previous studies (largely in Eastern Australia), including Westra and Sisson (2011), Yilmaz and Perera (2014) and Laz, Rahman, Yilmaz, and Haddad (2014). It is interesting to note that in terms of previous analyses in the Greater Adelaide region, Jayaweera, Wasko, Nathan, and Johnson (2023) found no significant trend in annual maximum short duration (6-minute) rainfall at Adelaide Airport, which aligns with our findings for short-duration rainfall (12 minutes). However, our study found increasing trends at the other three sites (not considered by Jayaweera et al., 2023), underscoring the importance of considering multiple sites in the greater Adelaide region.

In line with other local rainfall trend analyses (e.g., Kamruzzaman et al., 2016), our study also identified significant uncertainty in these trends. This uncertainty is due to the limited number of high-quality sub-daily rainfall monitoring sites and their relatively short records. In the Adelaide/Fleurieu Peninsula region, only four sites met the criteria of having over 30 years of reliable data, none of which were longer than 38 years. To enable clear and consistent interpretation of these uncertain trends, we have employed the IPCC's terminology to describe the likelihood of different outcomes, as summarized in Table 4.

Table 4: Likelihood Scale based on IPCC terminology

TERM	LIKELIHOOD OF THE OUTCOME
Virtually certain	99-100% probability
Very likely	90-100% probability
Likely	66-100% probability
About as likely as not	33 to 66% probability
Unlikely	0-33% probability
Very unlikely	0-10% probability
Exceptionally unlikely	0-1% probability

In our study, we found the following:

- **High-intensity short-duration events**: These show largest increasing trends. For example, at Parafield Airport the best-estimate trend for the annual maximum 12-minute rainfall is 30%/°C. Based on Table 4, we can classify it as 'likely' (66%-100% probability) that the trend in these high-intensity short duration events is greater than zero at three out of four sites.
- **Longer duration events**: Trends weaken as duration increases. For all stations, the 3-hour rainfall event, the best-estimate trend in annual maximum for all four sites is close to zero, with zero falling within the 66% confidence limits, indicating no significant trend.
- **Annual rainfall:** For annual mean rainfall it is 'likely' that there is decreasing trend at three out of four stations.

It is important to recognise that there is a large difference in the strength of evidence between this local analysis and the strength of evidence provided by ARR. The ARR guidance (Wasko et al., 2024a) was developed through a systematic review of over 300 distinct peer-reviewed scientific studies published largely from 2011 onwards, together with a more detailed quantitative meta-analysis of over 40 unique peer-reviewed studies, comprising a combination of gauge-based, radar and modelling (GCM and RCM) data. Some of the individual studies were based on several hundred rain gauges across Australia. The systematic review[1] and meta-analysis[2] themselves were peer reviewed in the international literature (Wasko et al., 2024b). This is considered a high level of evidence. In contrast, this pilot study considered 4 sites for the Greater Adelaide area, which is a much lower level of evidence than the ARR guidance.

There is considerable regional variability in extreme rainfall, and ARR addresses this through representing regional changes in IFD curves based on a large database of station data. However, there are no clear spatial patterns associated with observed rates of *change* of extreme rainfall, other than perhaps slightly greater rates of change in the tropical north of Australia (see Wasko et al., 2024b for further discussion on this). Whilst it is plausible that there are geographic variations in rainfall trends, this local analysis does not provide sufficient evidence to recommend against the ARR findings. **Therefore, this study recommends adopting the ARR guidelines for estimating future changes in extreme rainfall for the Greater Adelaide region.**

4.2 Implication for impacts

It is important to recognise that infrastructure design, such as stormwater systems, relies on design rainfall events. As defined in ARR (Ball et al., 2019), design rainfall events are statistically based estimates of the likelihood that a specific rainfall depth will occur at a particular location over a defined duration. These events are generally classified by an Annual Exceedance Probability or exceedances per year (EY). Design rainfalls are therefore not real (or observed) rainfall events, but are statistical estimates based on observed data and probabilistic methods.

The focus of this study has been on rainfall events that occur more frequently than those considered in design rainfall calculations. For example, the most extreme event analysed in this study is the annual maximum rainfall event, while design rainfall events typically consider annual maxima with a 20% to 1% AEP.

Since design rainfall event estimation is based on frequency analysis of annual maximum rainfalls, understanding how these values might change in the future is of great interest. Our analysis has identified trends in high-intensity rainfall events that suggest design rainfall values will also change. There are opportunities for further research using more advanced probabilistic techniques, such as models that analyse data from two distinct time periods (Guerreiro et al., 2018) or incorporate non-stationary parameters (Jayaweera et al., 2023). However, given the inherent uncertainty in annual maximum rainfall data, it is expected that trends in rarer design rainfall events would come with even greater uncertainty. This challenge could potentially be addressed by integrating multiple data sources, as discussed in Section 4.3).

4.3 Recommendations for future research

The following options are recommended for future research:

1. **Evaluate impacts of extreme rainfall changes on water management in Greater Adelaide**
   We recommend evaluating the impacts of the ARR climate change guidance on water management in the Greater Adelaide region.

   Stormwater infrastructure in metropolitan Adelaide is a major expense, with a replacement cost estimated at $4.2 billion (as of 2018) and metro councils spending over $100 million annually from 2014/15 to 2018/19 (DEW, 2021). The design and management of this infrastructure heavily rely on estimates of extreme rainfall. Changes in ARR climate change guidance (Wasko et al., 2024a) suggest that the level of flood protection for these systems may differ significantly from what was assumed during their planning or design. However, the impacts will vary based on several factors, including catchment land-use (urban or rural), the Annual

[1] A systematic review is an authoritative account of existing evidence using reliable, objective, thorough and reproducible research practices.
[2] Meta-analysis is the formal, quantitative, statistical combination of results from two or more separate studies.

Exceedance Probability (AEP) used for design (minor or major storm), and the critical storm duration (typically between 30 minutes to 2-3 hours).

For instance, in predominantly urban catchments, increased extreme rainfall will likely lead to higher peak flows. Conversely, in catchments with significant non-urban land-use (such as rural or forested areas, typical of peri-urban catchments in eastern Adelaide), changes in antecedent catchment moisture conditions—expected conditions before an extreme rainfall event—must be considered. ARR indicates there is evidence of drying antecedent moisture across Australia, especially in regions with decreasing annual or seasonal rainfall (as found in this study—see Section 2.2.2). This will increase the loss parameters, reducing the impact of rainfall intensities, particularly for frequent floods or systems whose performance depends on both flood volume and peak flow.

It is recommended that a 'bottom-up stress-test' (McInerney et al., 2024; McInerney et al., 2023; O'Shea, Nathan, Wasko, Ho, & Sharma, 2024) by undertaken to determine how these range of factors influence flood volumes/peaks and hence stormwater infrastructure design in Greater Adelaide. This could include consideration of Smart Design and Smart Control of Stormwater Systems as an adaptive approach to handle climate change (Liang, Maier, Thyer, & Dandy, 2024; Liang, Thyer, Maier, Dandy, & Di Matteo, 2021). This will aim to identify the most vulnerable areas and identify the opportunities to target investments.

This is considered high priority in short to medium term as it is evaluating the practical impact of the recently released ARR climate change guidance for metro Adelaide.

Other areas of water management in Greater Adelaide that will need to adapt to changes in high-intensity rainfall events include (but are not limited to) emergency response management, flood plain management, dam spillways and any other major works whose design and/or management is sensitive to intense rainfall events.

2. **Utilise multiple sources of information to address limitations of individual data sources, reduce the uncertainty for future extreme rainfall changes**

   In longer term, we recommend that efforts be made to develop and utilise techniques for integrating multiple lines of evidence (multiple high-quality datasets, including station, radar and regional climate models) to better quantify and reduce the uncertainty in local changes in historical and plausible future extreme rainfall for the region. In particular, Australia's radar network, which spans over 60 radars covering major urban centres, is an under-utilised resources that has the potential for improving rainfall data analysis. Many of these radars have been operational for decades, providing long-term datasets that are comparable in length to those from sub-daily rainfall gauges. However, the radar data used in this study was not suitable for trend analysis due to short time series and inconsistencies with station-based data. Moving forward, efforts should be made to address these limitations, as radar data has considerable potential to enhance the spatial coverage of extreme rainfall analysis, particularly in areas where sub-daily stations are sparse. This future research needs to include analysis of more extreme rainfall events that are critical for infrastructure design (e.g. AEPs of 20%, 10% and 1%).

5 Conclusions

Changes in high-intensity, short-duration rainfall events can significantly impact urban flooding, with important implications for infrastructure design and emergency management. Recent studies indicate an increase in extreme rainfall intensity across Australia. Given the variability of climate drivers across different regions, local data analysis can enhance our understanding of local changes and their potential consequences. This pilot study focused on analysing trends in observations of high-intensity, short-duration rainfall within the Greater Adelaide region by utilizing both station and radar data. Since high-intensity rainfall is often used to estimate flood frequency, the outcomes of this study can inform future estimation of trends in design rainfall events, crucial for infrastructure design.

Evaluation of station data: We utilized data from Automatic Weather Stations (AWS) and pluviometers across four stations over approximately 45 years, examining multiple durations (12 mins – 3 hours) and metrics (annual maxima, and other amounts exceeded multiple times per year). The results indicated there were 'likely' increasing trends for high-intensity rainfall, primarily for the less frequent shorter duration events (e.g. annual maximum, 12 min duration). However, it is important to note there is a high level of uncertainty due to the relatively short duration of data records and low number of sites with high quality data. As duration and frequency increase, the increasing trends reduce in magnitude or even become decreasing trends, which aligns with the observed decline in mean annual rainfall.

These findings for high intensity rainfall trends from observed events are broadly consistent with the ARR climate change guidelines. The ARR Guidelines have a higher level of evidence at the national scale than the smaller number of sites analysed in this local study. In addition, the rainfall events analysed in this study occur much more frequently than the design rainfall events typically used for design purposes. Hence for design purposes, we recommend using the ARR guidelines for estimating future changes in extreme rainfall in the Greater Adelaide region, rather than the specific trends found in this study.

Radar data evaluation: We also explored the potential of using radar rainfall data for trend analysis but deemed that the available period of the more reliable calibrated radar data was too short (4-6 years) to provide reliable trends, even though long periods of radar reflectivity are available. Our analysis showed that radar rainfall data has considerable potential for detecting large rainfall events not captured by station measurements. While radar rainfall data demonstrated some capability in capturing high-intensity rainfall metrics, there were notable biases in rainfall amounts.

In light of these findings, we recommend that future work focus on the following topics. In the short to medium term, high priority should be placed on evaluating the impact of ARR guidance on potential changes in design rainfall and associated losses, as this will be vital for effective water management and planning in Greater Adelaide. In the longer term, ongoing development of methods to integrate various rainfall data sources—particularly under-utilized longer records of radar rainfall—will be essential for reducing uncertainty around trends in high-intensity rainfall events and its impact on design rainfall estimates that are relied upon for design purposes.

List of shortened forms and glossary

ARR	Australian Rainfall and Runoff (ARR). National guideline document for the estimation of design flood characteristics in Australia.
AWS	Automatic weather station. Source of sub-daily rainfall used in this study.
EY	Metrics used to express rainfall intensity that has X Exceedances per Year (EY). For example, a design event (rainfall or flood) with a 6-month recurrence interval will be expressed as having 2 Exceedances per Year (EY2).
GMT	Global mean temperature.
Pluvio	Pluviometer. Source of sub-daily rainfall used in this study.

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Appendix A: Selection of stations

Table A.1: Details of sub-daily stations in South Australia with over 30 years of data that were omitted from the case study, along with the reasons for their exclusion from this study.

STATION NAME	STATION ID	DATA SOURCE	YEARS > 90% DATA (1978-2023)	REASON FOR OMISSION
Adelaide West Terrace	023000	Both	8	No data between 1980 and 2017
Ceduna	018012	Both	24	Not enough years with sufficient data. Lots missing at start.
Cleve	018116	Pluvio (AWS not in purchased dataset)	24	Not enough years with sufficient data
Coonawarra	026091	Pluvio (AWS not in purchased dataset)	22	Not enough years with sufficient data
Edinburgh RAAF	023083	Both	42	Poor double mass c.f. Hope Valley
Heathfield	23843	Pluvio	18	Not enough years with sufficient data
Hindmarsh Valley Springmount	23824	Pluvio	31	Chose to use Hindmarsh Valley Fernbrook instead
Jamestown	021060	Pluvio	28	Many years ~5% missing data. No nearby site to infill.
Karoonda	025006	Pluvio (AWS not in purchased dataset)	8	Not enough years with sufficient data
Langhorne Creek	024515	Pluvio	37	Many years ~5% missing data. No nearby site to infill.
Lenswood	023801	Pluvio	39	Poor double mass c.f. Hope Valley
Loxton	024024	Both	28	Not enough years. No nearby site to infill.
Marla	016085	Pluvio	-	Very dry climate
Mount Crawford	023763	Pluvio	19	Not enough years with sufficient data
Mount Gambier	026021	Both	29	Lots of missing data at start. Insufficient data for infilling from nearby site (e.g. 026082).
Oodnadatta	017043	Both	-	Very dry climate
Policeman Point	026049	Pluvio	27	Not enough years with sufficient data. Lots missing at end
Rosedale	023343	Pluvio	33	Many years ~5% missing data. No nearby site to infill.
Straun	026082	Pluvio	24	Not enough years. Many years ~5% missing data.
Woomera	016001	Both	-	Very dry climate

Appendix B: Double mass curve analysis

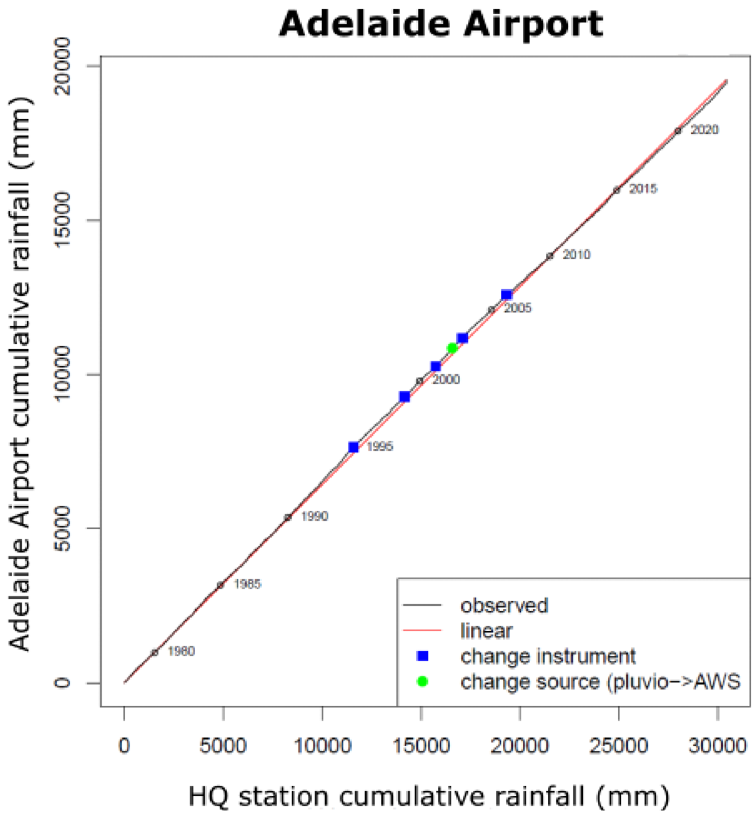

Figure B.1: Double mass curve analysis for Adelaide Airport

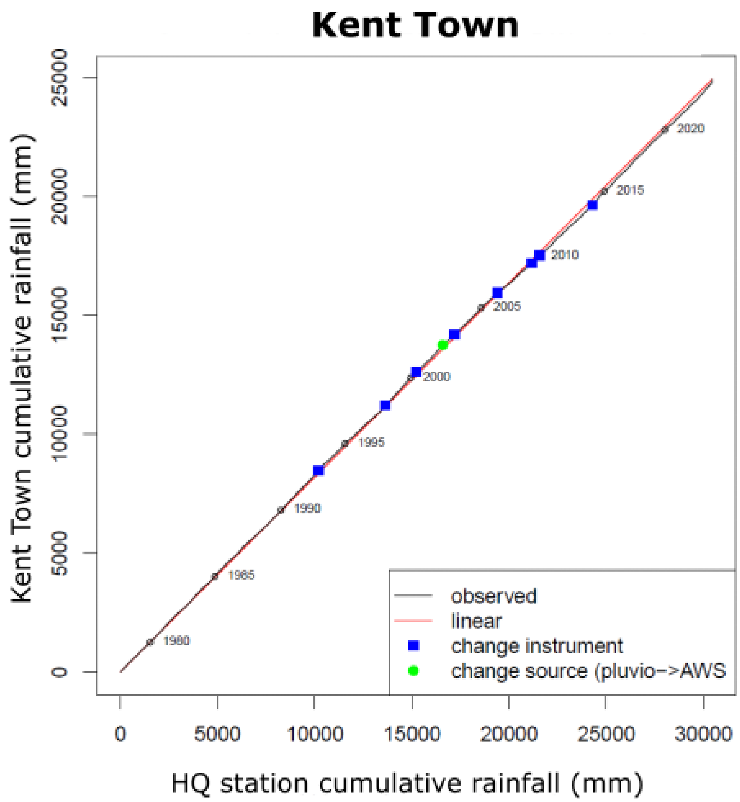

Figure B.2: Double mass curve analysis for Kent Town

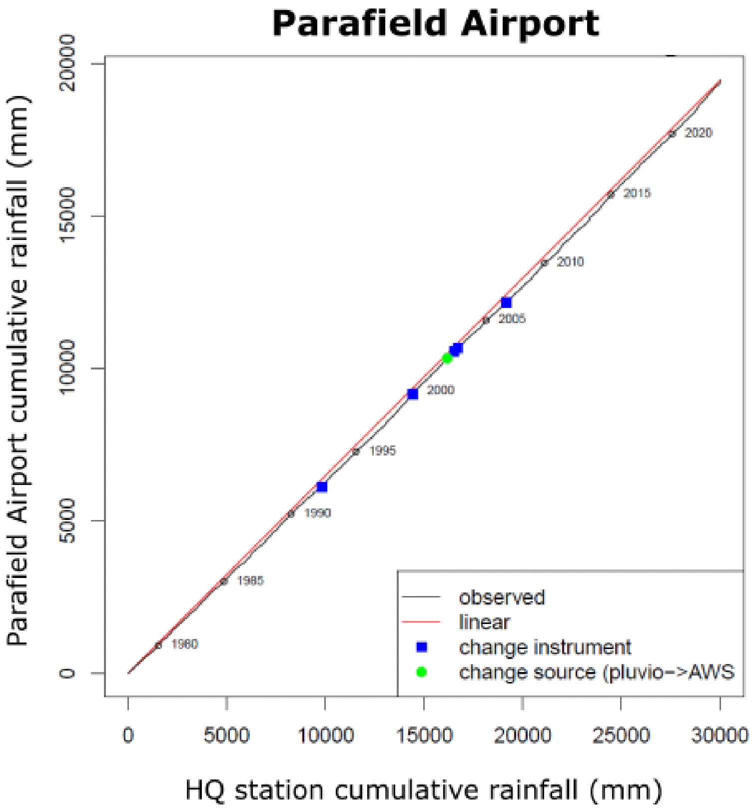

Figure B.3: Double mass curve analysis for Parafield Airport

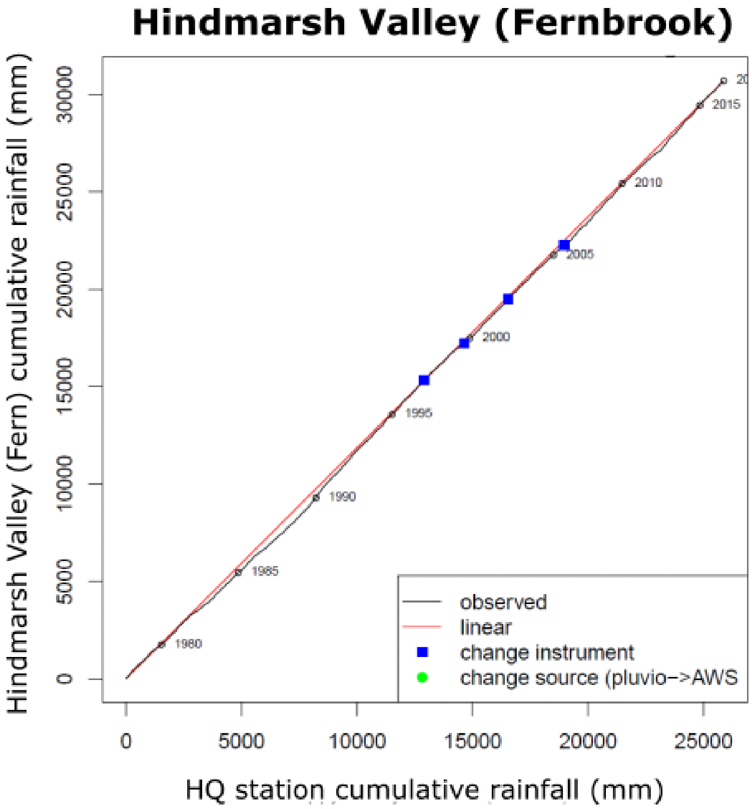

Figure B.4: Double mass curve analysis for Hindmarsh Valley (Fernbrook)

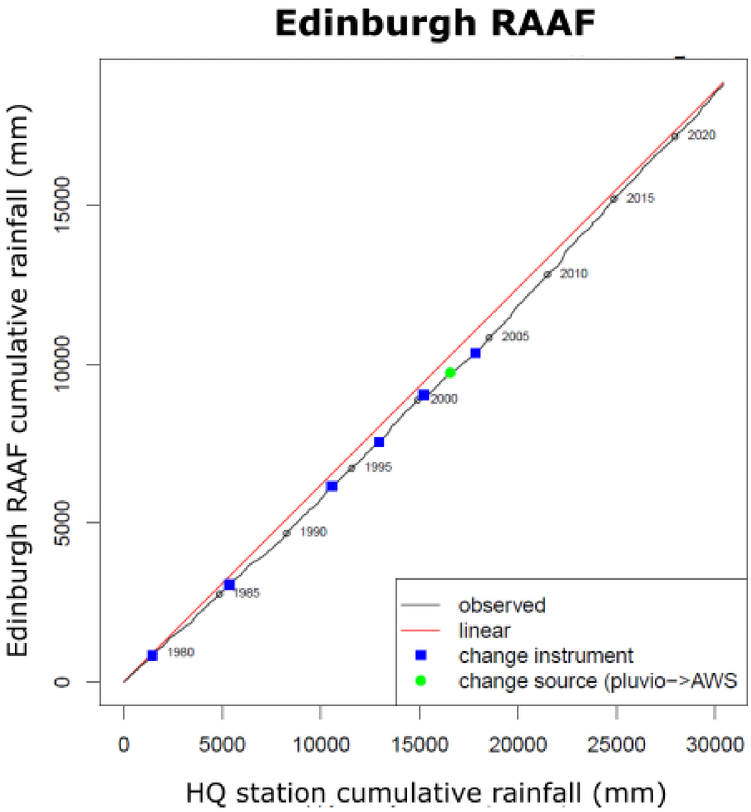

Figure B.5: Double mass curve analysis for Edinburgh RAAF

Appendix C: Residual diagnostics

In this study, we employed linear regression to analyse trends in annual rainfall metrics in relation to global mean temperature. Linear regression assumes that the residuals—the differences between the observed values and the values predicted by the model—follow a Gaussian (normal) distribution. To evaluate whether this assumption holds, we used Quantile-Quantile (QQ) plots, which compare the quantiles of the residuals against the quantiles of a theoretical Gaussian distribution.

In a QQ plot, a close fit to the 1:1 line indicates that the residuals are approximately normally distributed, meaning the assumption of Gaussianity is satisfied. Figures C.1 to C.4 present QQ plots for all metrics, sites, and durations. Most of the points on these plots fall close to the 1:1 line, which suggests that for many cases, the residuals do follow a distribution like the Gaussian one. However, a common feature in many of the plots is that the highest residuals (on the right-hand side of the plots) tend to be more extreme than expected from a normal distribution, as they lie well above the 1:1 line. For example, in the QQ plot for annual maximum 12-minute rainfall (Figure C.1, 1st row, 2nd column), the highest residuals significantly deviate from the expected Gaussian distribution. This suggests that the Gaussian assumption underestimates the occurrence of extreme residuals. This mismatch in the Gaussianity assumption implies that the linear regression model may not adequately capture the full range of extreme values in the data, particularly for higher rainfall events.

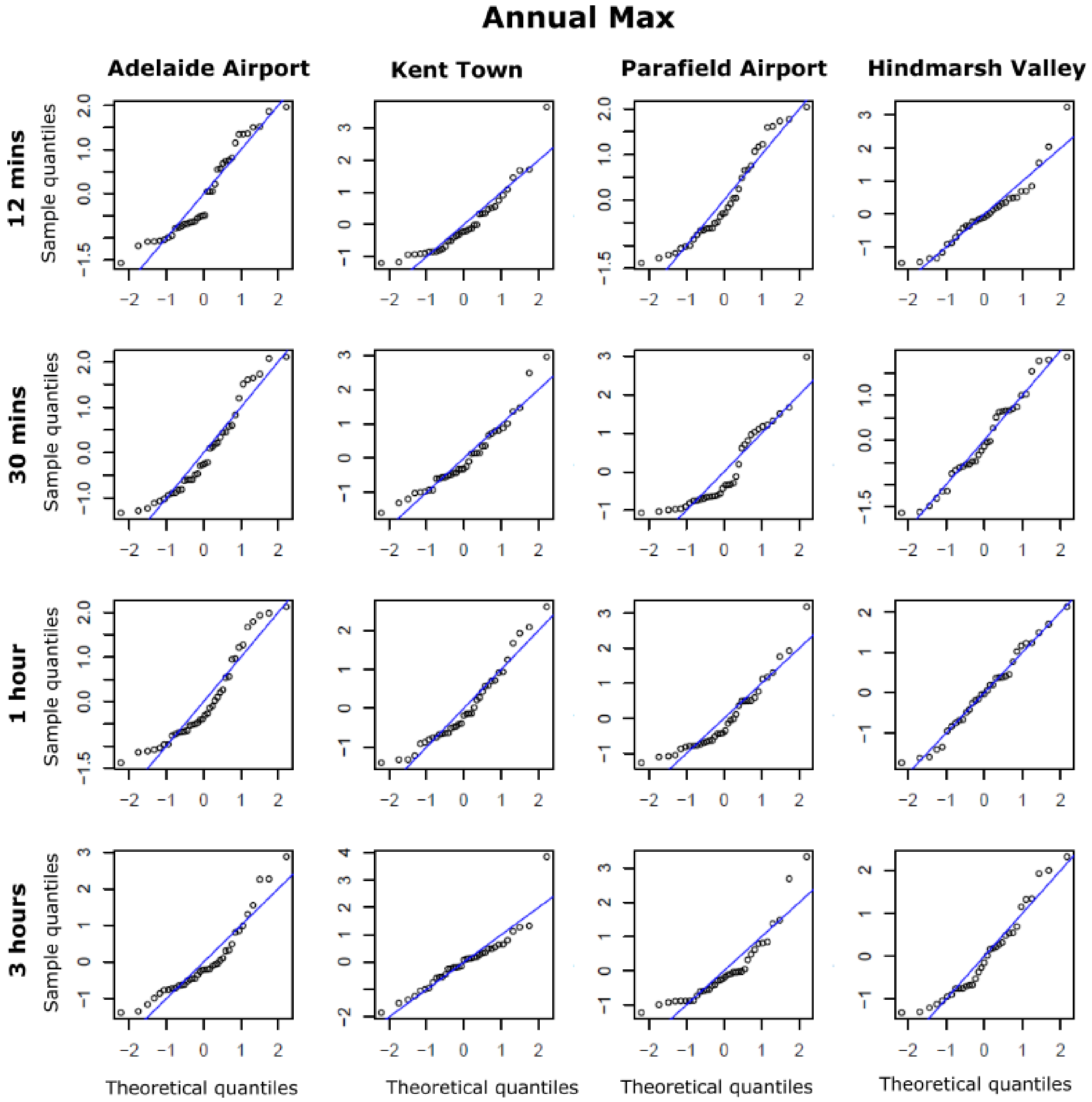

Figure C.1: Quantile-quantile plots that evaluate the assumption of Gaussian residuals for the model for annual maximum rainfall. Results are shown for all sites (columns) and durations (rows).

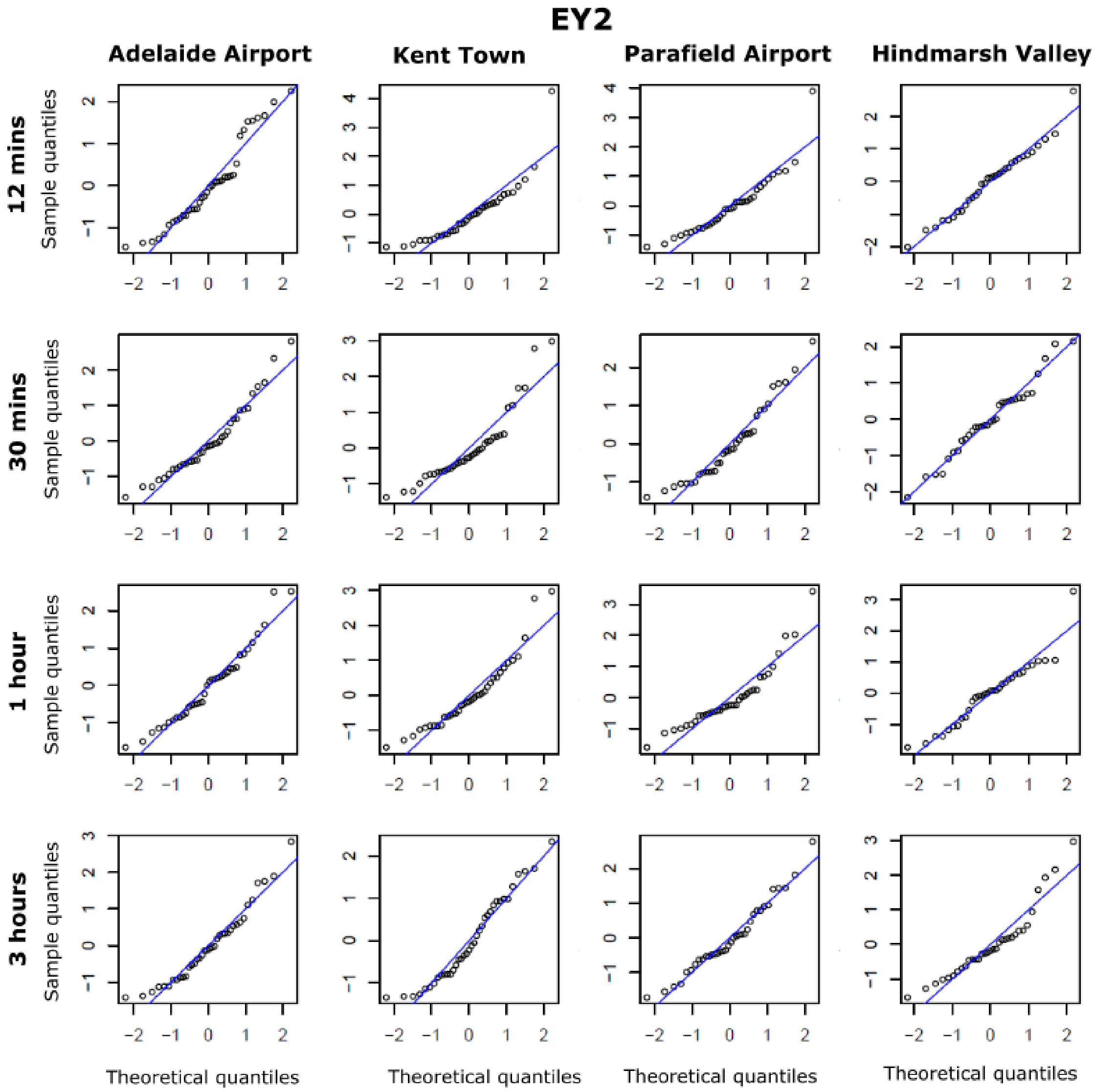

Figure C.2: Quantile-quantile plots that evaluate the assumption of Gaussian residuals for the model for EY2 rainfall. Results are shown for all sites (columns) and durations (rows).

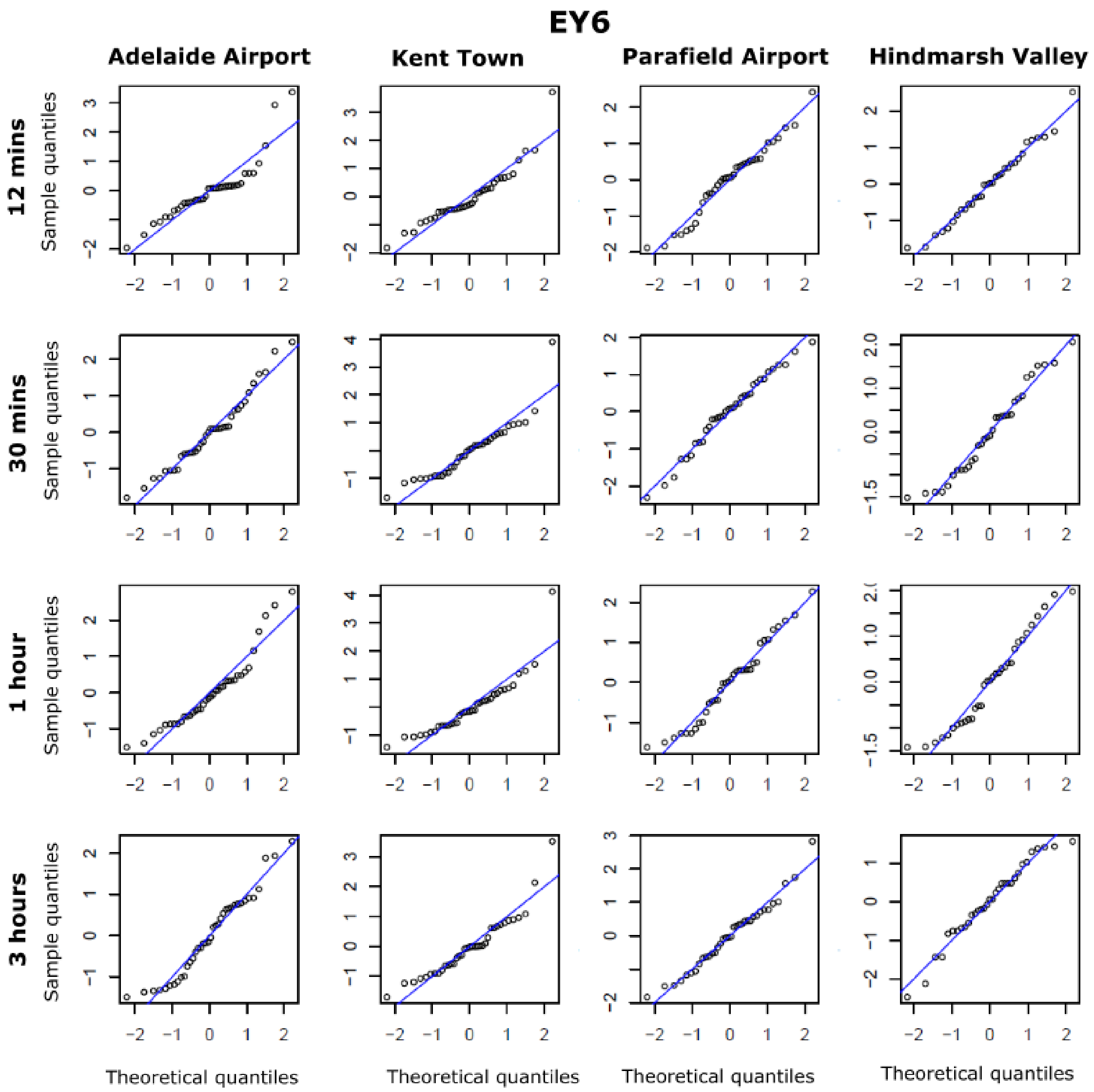

Figure C.3: Quantile-quantile plots that evaluate the assumption of Gaussian residuals for the model for EY6 rainfall. Results are shown for all sites (columns) and durations (rows).

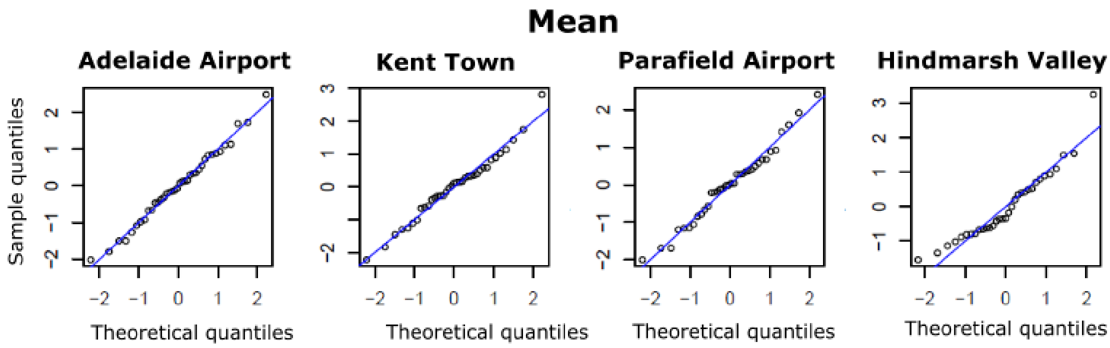

Figure C.4: Quantile-quantile plots that evaluate the assumption of Gaussian residuals for the model for mean annual rainfall.

Appendix D: Complete set of high-intensity rainfall metrics

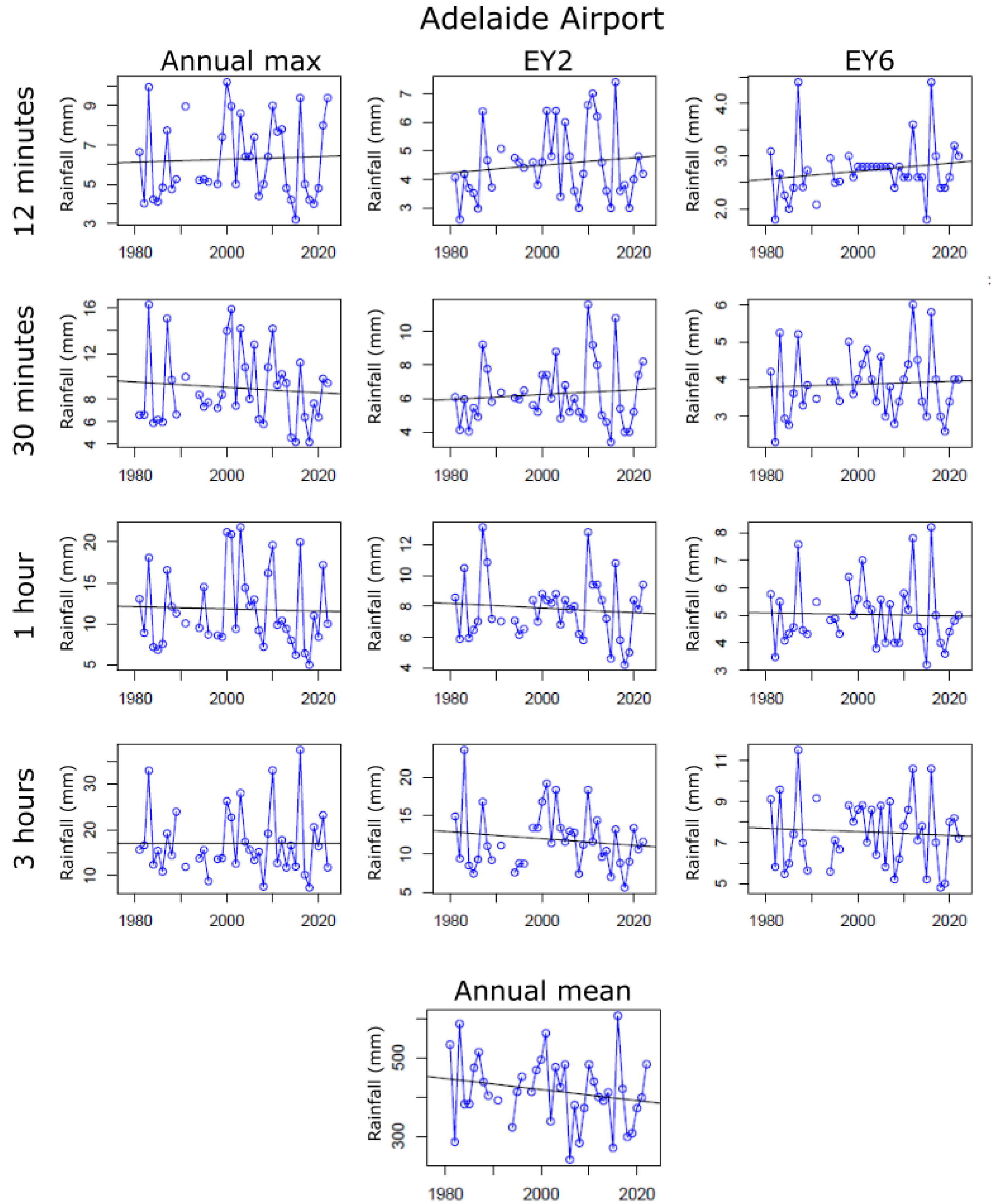

Figure D.1: Annual rainfall metrics for Adelaide Airport for complete set of metrics and durations considered in case study. A line of best fit (black line) is shown to indicate trends through time.

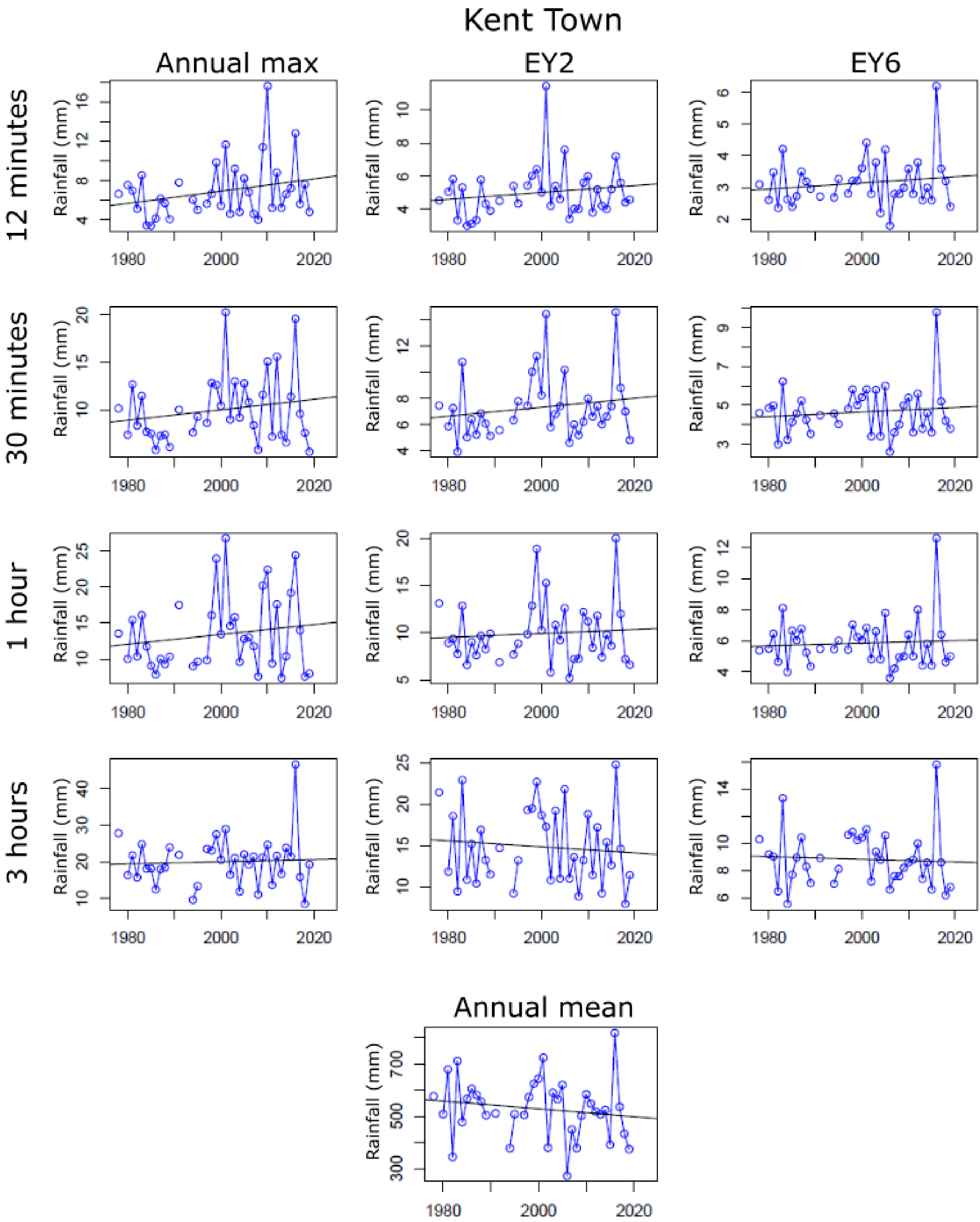

Figure D.2: Annual rainfall metrics for Kent Town for complete set of metrics and durations considered in case study. A line of best fit (black line) is shown to indicate trends through time.

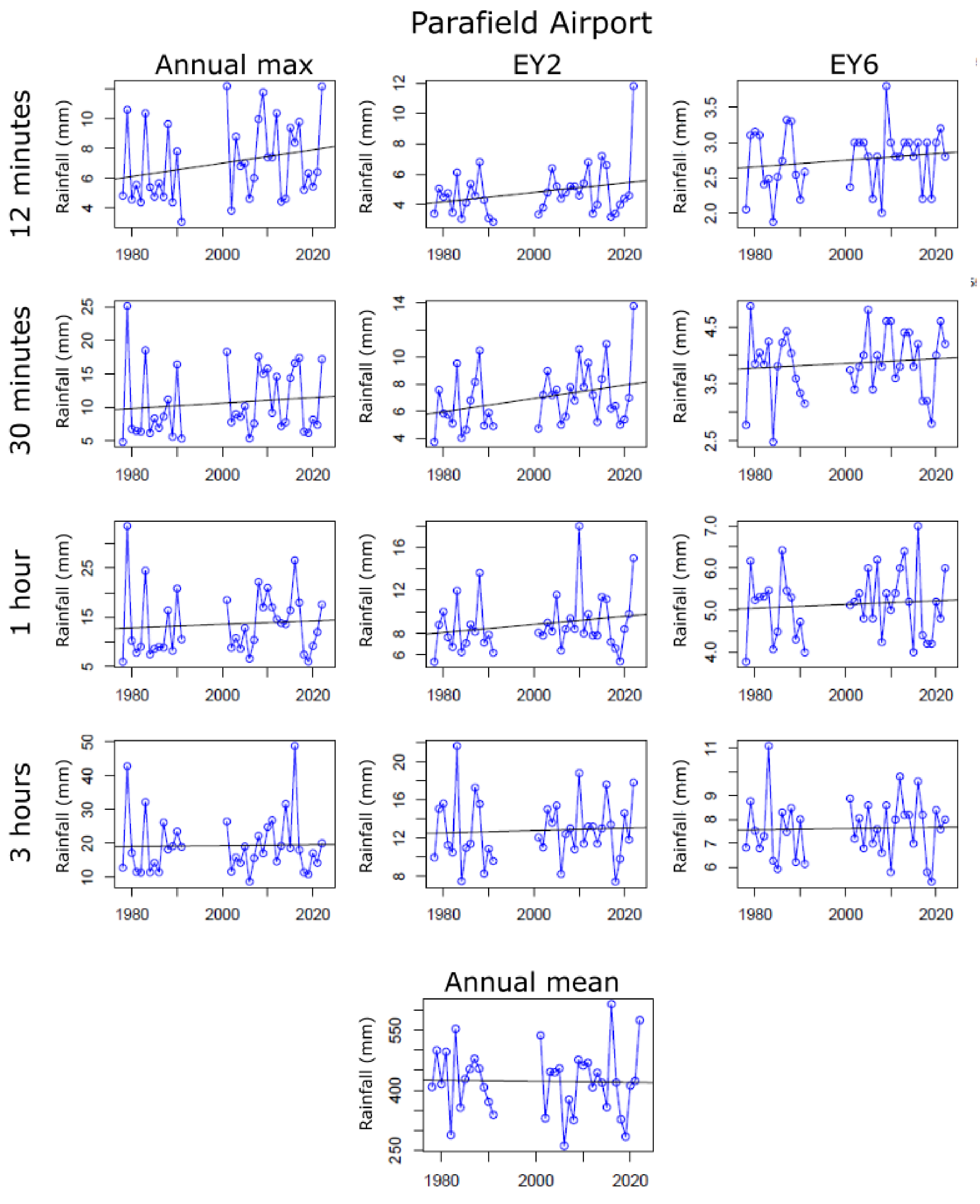

Figure D.3: Annual rainfall metrics for Parafield Airport for complete set of metrics and durations considered in case study. A line of best fit (black line) is shown to indicate trends through time.

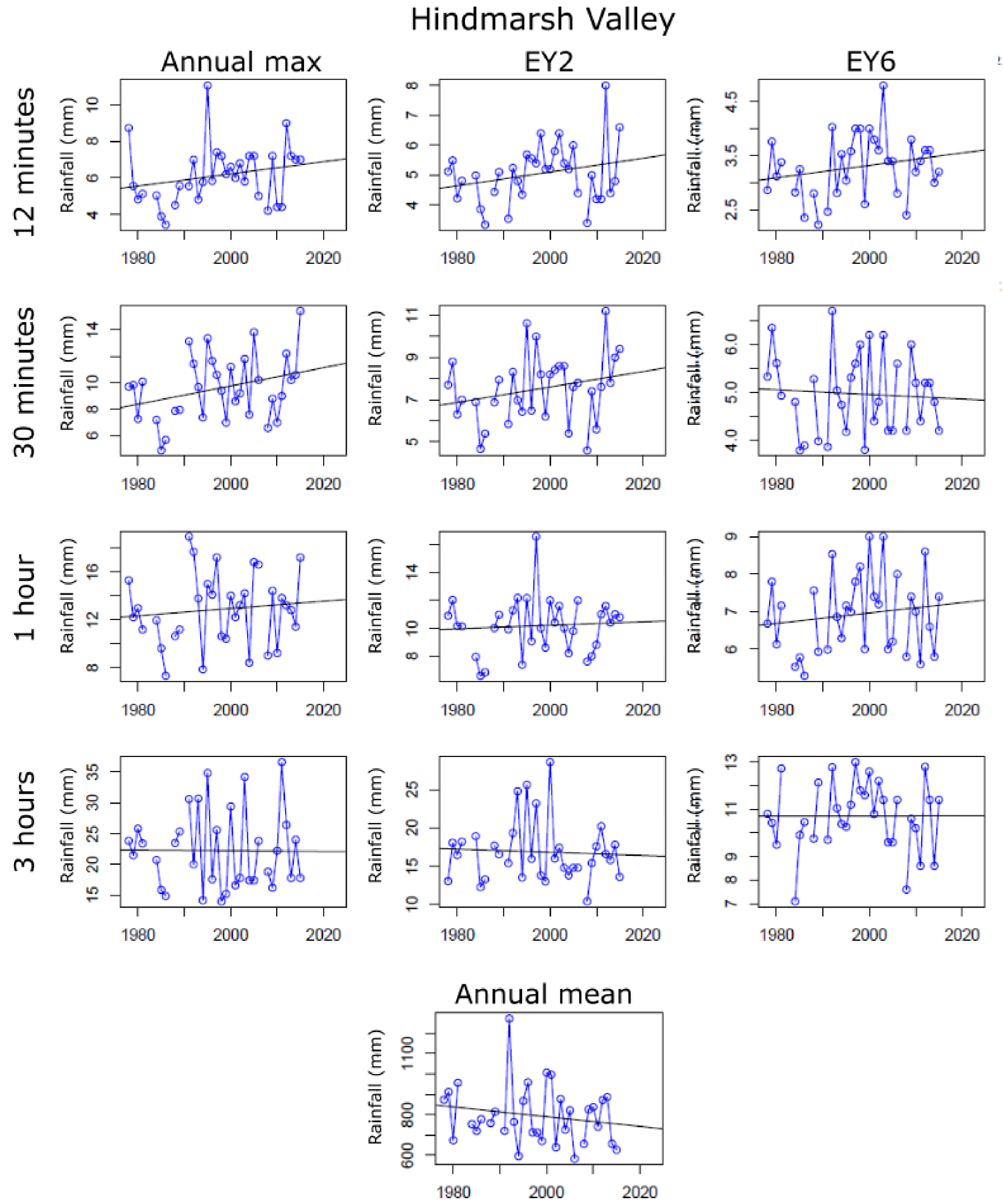

Figure D.4: Annual rainfall metrics for Hindmarsh Valley for complete set of metrics and durations considered in case study. A line of best fit (black line) is shown to indicate trends through time.

Appendix E: Complete set of seasonal trends in high-intensity rainfall metrics

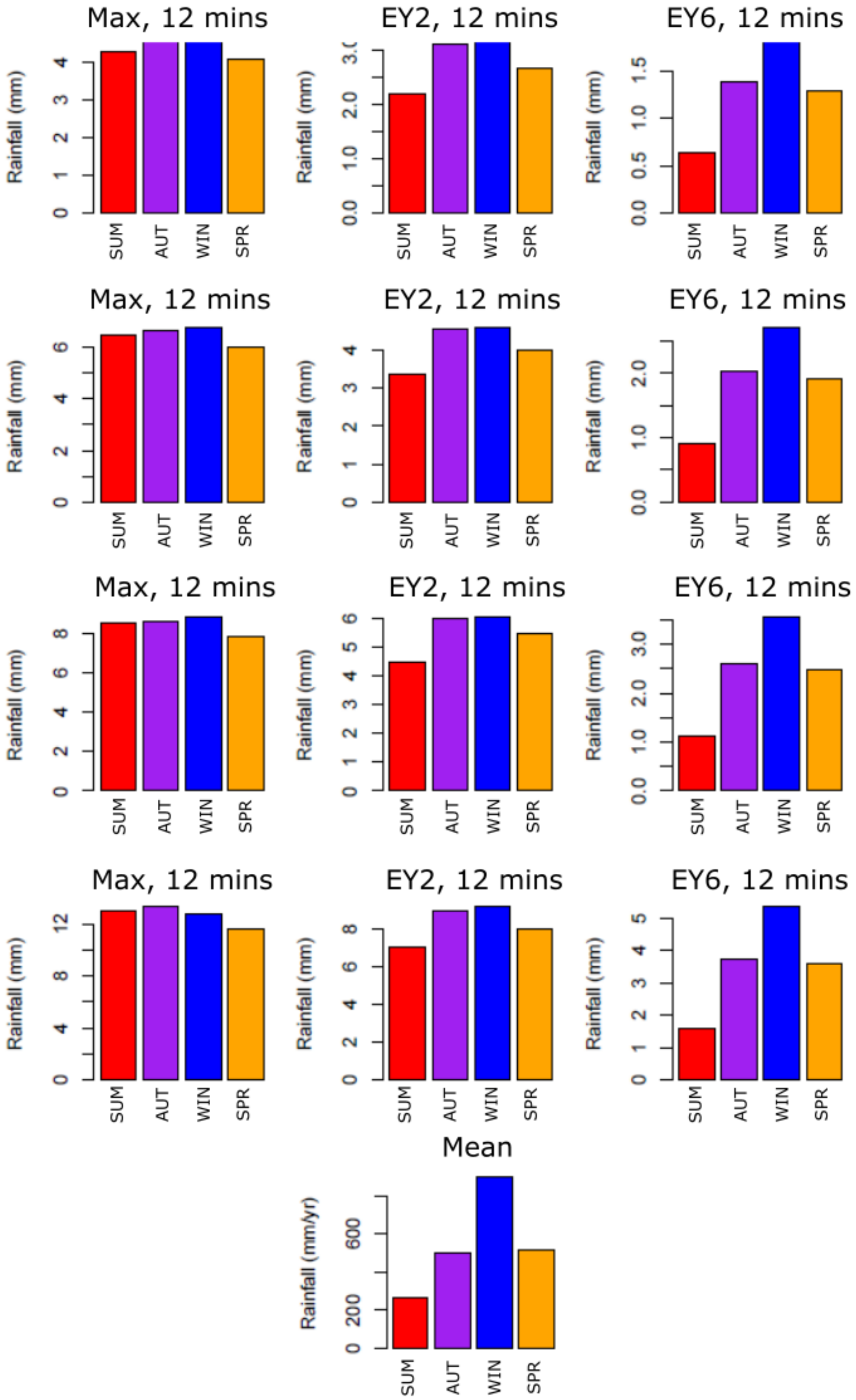

Figure E.1: Seasonal variations in metric values (averaged over all sites and years) for all durations and metrics considered in the case study.

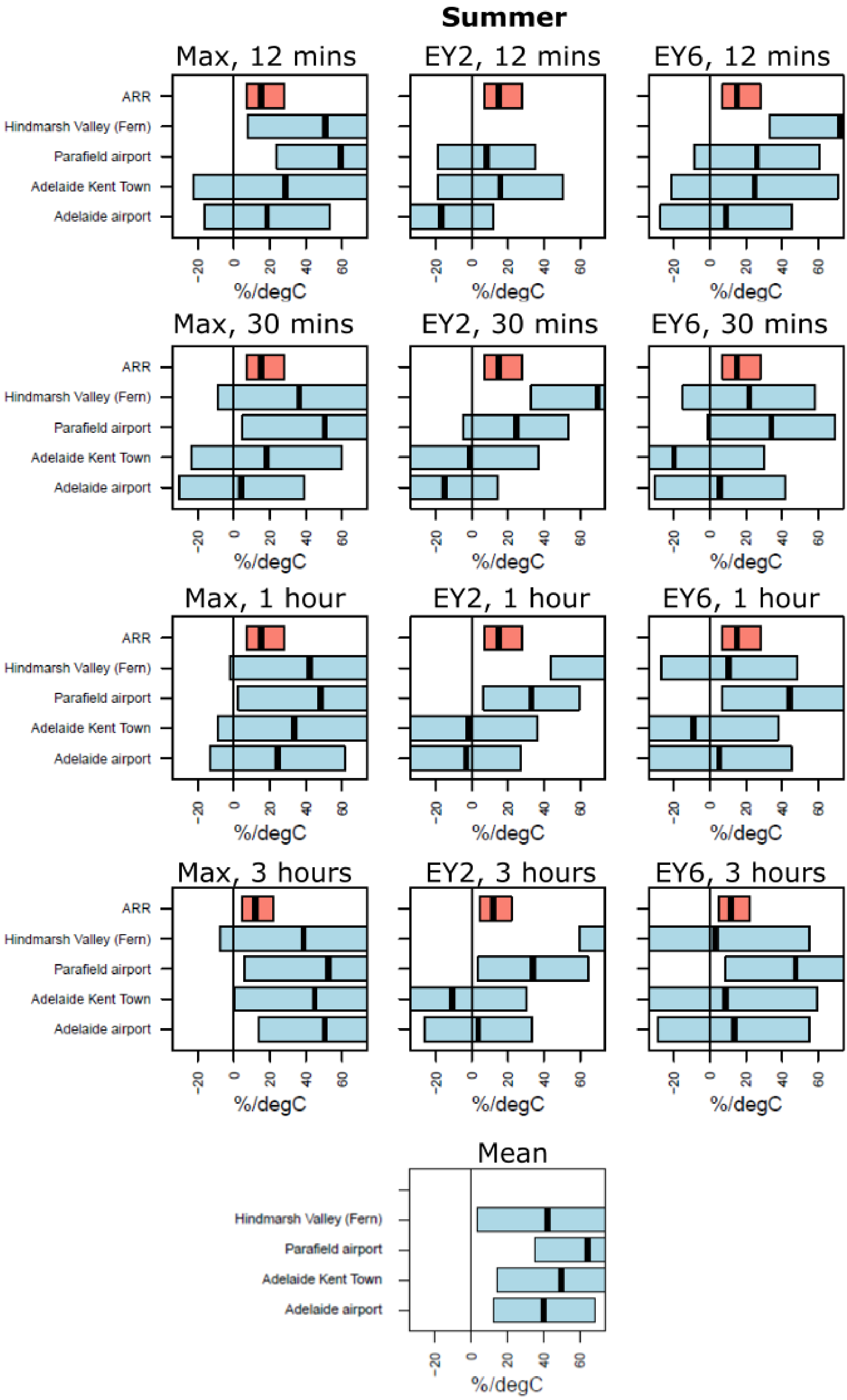

Figure E.2: Trends showing change in summer metrics per change in global mean temperature. Results all shown for all 4 sites, metrics and durations. Width of boxes indicate 66% confidence limits. Trends are compared with trends from ARR.

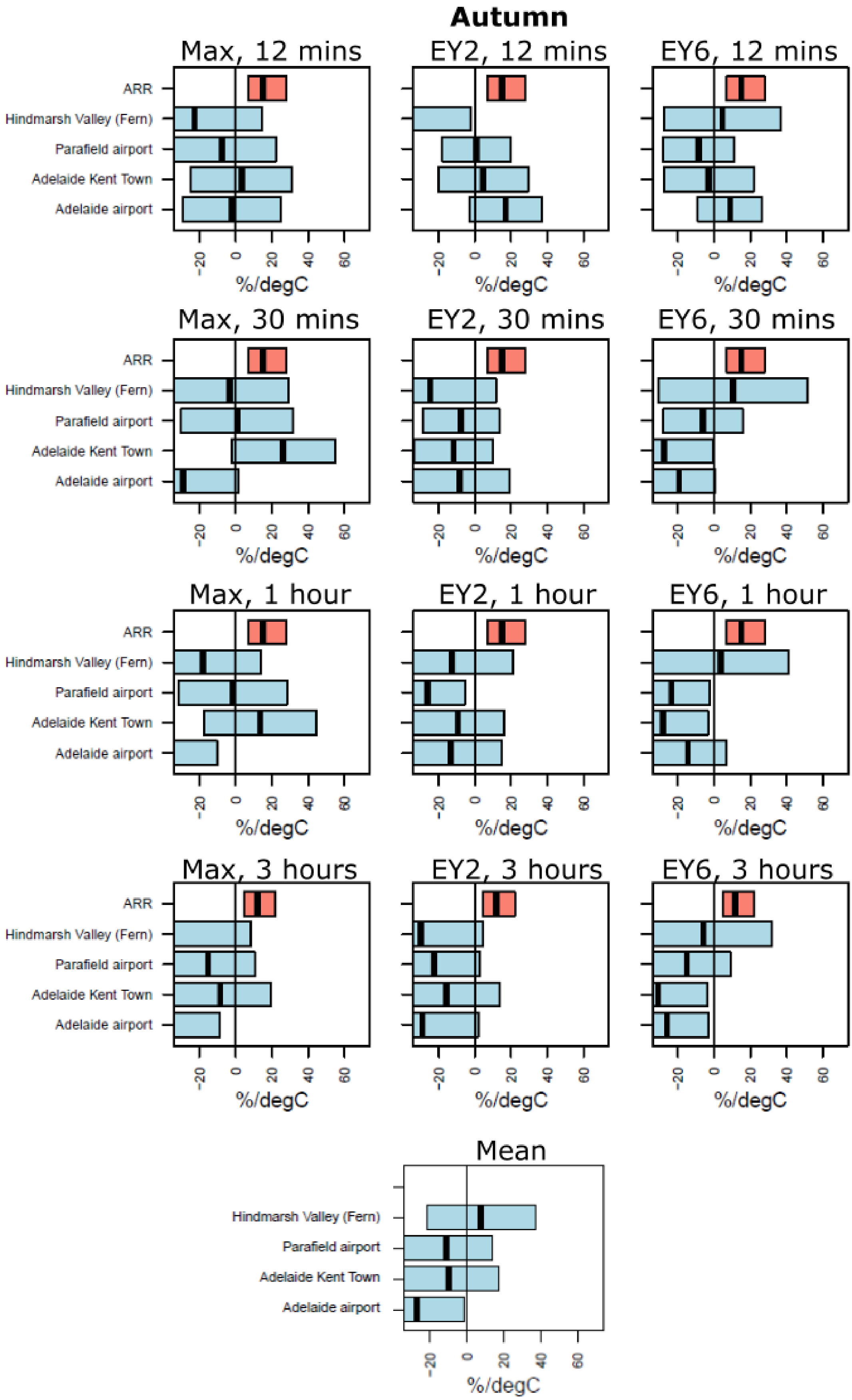

Figure E.3: Trends showing change in autumn metrics per change in global mean temperature. Results all shown for all 4 sites, metrics and durations. Width of boxes indicate 66% confidence limits. Trends are compared with trends from ARR.

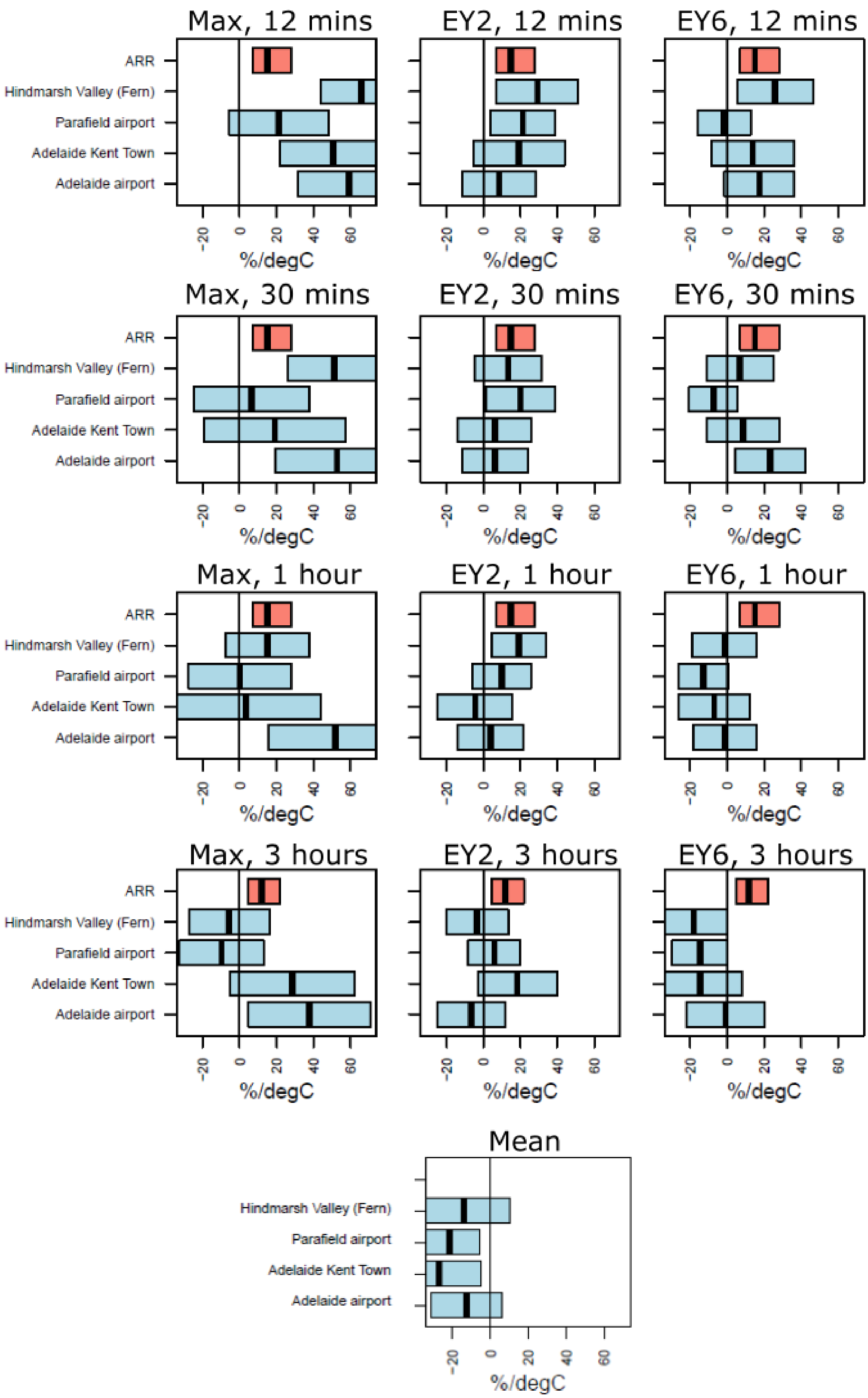

Figure E.4: Trends showing change in winter metrics per change in global mean temperature. Results all shown for all 4 sites, metrics and durations. Width of boxes indicate 66% confidence limits. Trends are compared with trends from ARR.

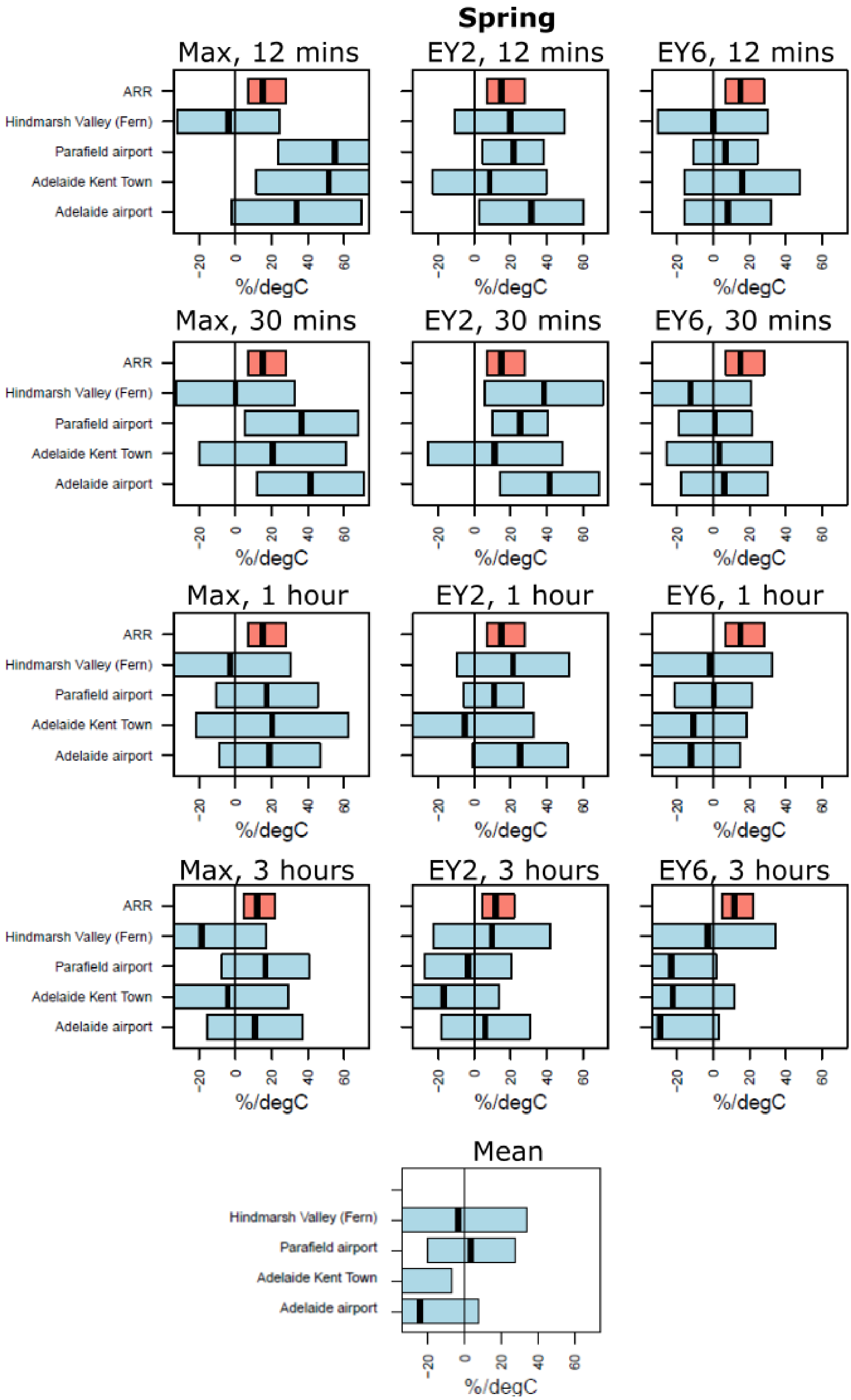

Figure E.5: Trends showing change in spring metrics per change in global mean temperature. Results all shown for all 4 sites, metrics and durations. Width of boxes indicate 66% confidence limits. Trends are compared with trends from ARR.

The Goyder Institute for Water Research is a research alliance between the South Australian Government through the Department for Environment and Water, CSIRO, Flinders University, the University of Adelaide and the University of South Australia.