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## Classification of Changes in Extreme Heat Over Southeastern Australia

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### Abstract

Over half of Australia's population lives in its southeastern quadrant. Temperature records for the 55-year period 1958-2013 indicate that hot summers have occurred increasingly since the 1990s with daily maximum temperatures reaching 10 °C above normal. The extreme nature of the change in monthly mean maximum temperatures (~1 to 1.5 °C above the long term mean) far exceeds the natural variability expected over a half century. Numerous maximum temperature records have been set and the extreme heat poses a major socioeconomic threat. This work examines changes in mean values of maximum daily temperatures for each summer month, in southeastern Australia. A 10-site dataset, for 1958-2013, was drawn and resampled to quantify temporal changes and uncertainty in decadal monthly maximum temperatures. Resampling methods documented the historical uniqueness of the maximum temperatures in recent decades. Results suggest strongly that, in recent decades, the maximum temperatures exceeding the upper quartile of the historical data is greater than expected by random chance. The findings confirm the regional nature of the warming. The increase in summer temperature is partly related to changes in atmospheric blocking.

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### 1. Introduction

Since the early 1990s, extreme temperatures in southeastern Australia have been set and then subsequently broken in following years [1]. The increasing mean monthly maximum temperatures at each of ten selected observation sites over much of southeastern Australia, in both the warmer and cooler seasons, motivate this study. We seek to document if the temperature anomalies since the early 1990's are significantly warmer than the preceding decades. Traditionally, extremes in temperature have been fitted and modeled using extreme value distributions [2] [3]. Moreover, detection of changes in extremes is most often based on parametric statistics. Such statistics make distributional assumptions that are rarely met. In this work, we present a data driven method to detect and assess changes in extremes, rather than fitting extreme values. The method uses resampling of monthly

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mean maximum temperatures (the warmest temperature for each day) to find the uncertainty associated with those temperatures. We present this methodology to quantify the mean and variability in mean monthly maximum temperatures over the study region for the summer months. Additionally, we relate these temperature anomalies with atmospheric blocking, a major pattern associated with the extreme heat.

## 2. Data and Methods

### 2.1. Data

The data set consists of the monthly means of the daily maximum temperature at ten locations in southeast Australia (Fig. 1). The period of record is the 55 summer “seasons” (each season is 6 months, November through April) for 1958–2013. An atmospheric pattern, associated with above normal temperature in southeast Australia, is investigated through a blocking pattern index [4] centered at longitude 140 E for the same months as the temperature data. The temperature data have a strong intraseasonal signal (e.g., January is always warmer than November); hence, the summer is divided into individual months and each month is analyzed separately.

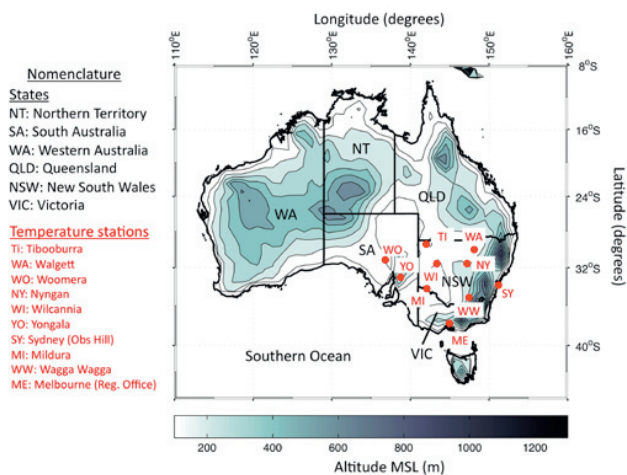


Fig. 1. Map of Australia showing the 10 stations used in this study.

### 2.2. Assessing the temperature change

As warming has been noted since the early 1990s [3], the data are divided into groups for November 1958–April 1991 (summers of 1959–1991) and November 1991–April 2013 (summers of 1992–2013). These groups are investigated for change in the monthly means. Historically, changes in temperature means are tested with t-tests [5]. Whereas the Central Limit Theorem will give reasonable results for several hundred independent observations, here we have neither that many years, nor does the t-distribution fit particularly well. To assess this lack of fit, a non-parametric bootstrap approach is adopted in the following steps: (1) Two data sets are created for the 33 and 22 summers, with 198 and 132 samples, respectively, accounting for the total number of summer months in each set. (2) The station temperature data are expressed as deviations from their monthly means to remove the intraseasonal cycle. (3) Each group of summers is tested for significant autocorrelation to determine the degrees of freedom (df). (4) As the df in the t-tests are (n-1), 198 values from a  $t_{197}$  distribution are sampled and bootstrapped for 1000 replications of the mean for the first group of 33 summers. The variance of those 1000 replicates was calculated. The same process was applied the second group of 22 summers, for 132 values sampled from a  $t_{131}$  distribution that are bootstrapped to generate a set of 1000 means. From those 1000 means, a single variance is calculated. (5) Step 4 is repeated 1000 times for each group to generate 1000 variances. These 1000 variances are displayed as boxplots (Fig. 2, listed at T197 and T131, respectively). (6) Samples of 198 temperature deviations for the summers of 1959–1991 (as defined in step 2) are drawn as group 1 and from the 132 temperature deviations from the summers of 1992–2013 as group 2 (random sampling with replacement within each set), each group subject to the bootstrap of



1000 replicates to generate a sample mean for each period. From these 1000 means, a single variance of the mean is calculated for each group. (7) Step 6 is repeated 999 additional times to create 1000 values of the variance of the mean and those 1000 variances are displayed as a boxplot for each group (Fig. 2, listed as Melbourne for each group of summers). The results of steps 1 – 7 are repeated for each station. In step 3, since no autocorrelation in excess of white noise is found at any the station, the df is not reduced beyond (n-1) for the t-distributions, nor is a block bootstrap required. As all stations had similar patterns of variance, with respect to the t-distribution modeled data, only Melbourne is shown (Fig. 2). The results of that comparison for summers 1959-1991 versus 1992-2013 indicate clearly that the median variance of the anomaly data of monthly mean maximum temperatures in Melbourne is much larger (by a factor of 2 to 4) for the bootstraps of temperature data compared to those data drawn from the t-distributions (Fig. 2). As a result, the data driven approach is adopted to form empirical distributions from the monthly temperature anomalies and those distributions investigated for changes in temperature.

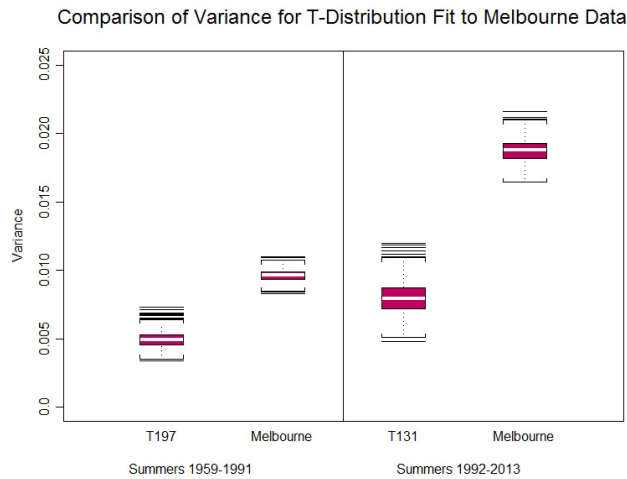


Fig. 2. Boxplots of 1000 replications of the variance for  $t_{203}$  and Melbourne empirical distribution for summers of 1959-1991 (left) and for  $t_{125}$  and Melbourne empirical distribution for summers of 1992-2013 (right).

### 3. Results

#### 3.1 Assessing spatial homogeneity of temperature anomalies

Rather than analyze all of the ten sites, an average linkage cluster analysis was applied to the ten time series to merge stations with similar temperature behavior to select a subset of stations for further analysis. The data were expressed as anomalies from the monthly mean prior to calculation of the Euclidean distances. The average linkage dendrogram indicates two large clusters for a Euclidean distance threshold value of 24 (shown as a horizontal line in Fig. 3). Additionally, Sydney and Melbourne do not cluster with other stations at that threshold distance and must be retained. Of the two large clusters, there was no reason for choosing particular stations (see Fig. 3), so we selected one station within each: Woomera and Walgett. Hence, four stations will be analyzed hereon.

#### 3.2 Changes in temperature at the four locations

Because the empirical distributions of temperature are used in the detection of the monthly maximum temperature changes, we apply bootstrap resampling in each time period to establish the means and uncertainty associated with each mean. Given the strong intraseasonal cycle, each month is analyzed separately and displayed as a boxplot. The boxplots indicate the median in the center of each box, the first and third quartiles or the interquartile range, (the red box) and the data point within 1.5 times the interquartile range, known as “the fence” (the square black bracket) and any extreme values/outliers that exist beyond the fence (black lines) [6]. *If the median of the 1992-2013 summer period is outside the interquartile range of the summer 1959-1991 period, the temperature change is deemed significant.* The results for Woomera (Fig. 4) show a strong positive shift in temperature in all summer months other than March, as the median mean maximum temperature for every summer month for 1992-2013 is



larger than the third quartile of 1959-1991. In January, the warming in the last 21 years is most pronounced, as the median monthly mean maximum temperature rise is nearly 2 degrees C, which is beyond the fence of the box. Walgett (Fig. 5) shows the same strong positive warming in the 1992-2013 period in all summer months other than December and March. However, the most pronounced results are for Melbourne (Fig. 6) where the 1992-2013 median maximum temperatures in all months are significantly warmer. Most noteworthy is February, when the median is larger than the most extreme value in the earlier period (1958-1991). The boxplots for Sydney (Fig. 7) have a similar pattern to those of Melbourne, with slightly less extreme warming for most months of the summers of 1992-2013. Despite the lower mean temperature at the coastal locations, the large increase in the temperature anomalies in the 1992-2013 time period has caused considerable stress to the people living in those cities.

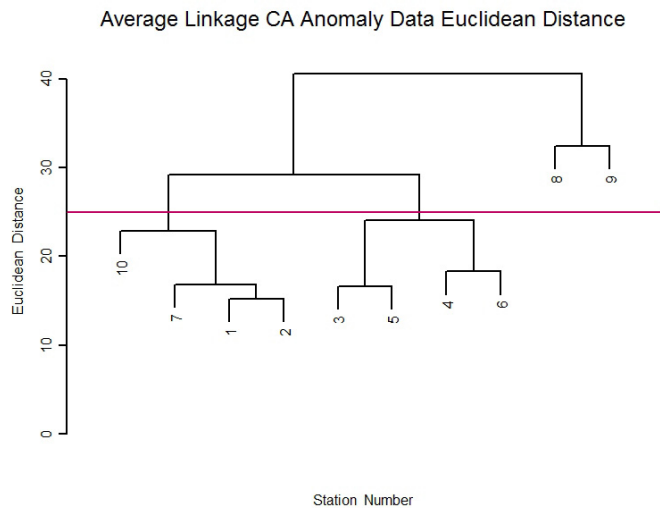


Fig. 3. Dendrogram of Average Linkage cluster analysis for all ten stations. Stations numbers listed (1-10) are: Woomera, Yongala, Wilcannia, Nyngan, Tibooburra, Walgett, Mildura, Melbourne, Sydney and Wagga Wagga, respectively.

### 3.3 Attribution of the warming

There are several possible reasons for the warming, including anthropogenic forced climate change, changes in the ocean and atmosphere patterns that favor “blocking” to local effects of ground surface feedbacks [1]. To investigate blocking, the “Blocking Index”, defined by [4], is used. The 140 E longitude is the standard choice of Blocking Index longitude for studies over southeast Australia, as it is where the cooler frontal systems are most likely to be deflected southeast, away from the Australian continent, thereby limiting the flow of cooler Southern Ocean airflow, allowing heatwave conditions to build. Negative values, especially when large, indicate inhibition of the passage of these cold fronts over southeast Australia. Similar to the temperature data, there is a strong intraseasonal cycle in the Blocking Index (Fig. 8) with the largest negative values (associated with blocking) in January. Owing to the large monthly variability in the blocking index, we examine it on a monthly basis. Note that, as the only coastal stations in the study, Sydney and Melbourne have the smallest range of mean maximum temperatures (Figs. 6 and 7) of all stations. However, both show large jumps between periods 1 and 2 in the summer months, possibly because, as coastal stations, they have more temperate summer climates than the other stations, and their summer temperatures possibly are more sensitive to changes (increases) between the two periods. We investigate the impact of blocking on the four stations. The scatterplot of blocking index versus Woomera temperature anomalies (Fig. 9) shows a moderate inverse relationship with the strongest relationships in November-January. The blocking modulates the temperature most effectively during those three months. Walgett reveals the strongest correlations are in November, January and March (Fig. 10). Melbourne has highest correlations in the months November-January (Fig. 11), whereas the Sydney correlations are highest in the period November-February (Fig. 12). The common theme among the temperature-blocking correlations is that at all stations they are largest in November-January, except for Walgett, which has a relatively low December correlation. These months are not surprising as they are the (early) summer months in which cold fronts are most frequent and possibly be blocked.



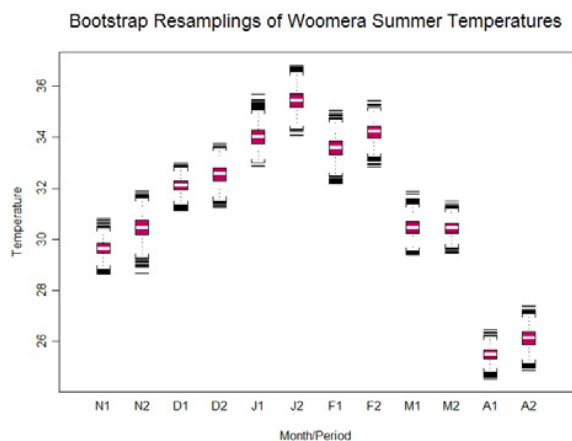


Fig. 4. Bootstrap resamplings of monthly mean maximum temperatures in Woomera for the summer months (Nov. – Apr.). N1 refers to November for period 1 (1958-1991), N2 to November for period 2 (1991-2013), D1 to December period 1, D2 to December period 2, etc.

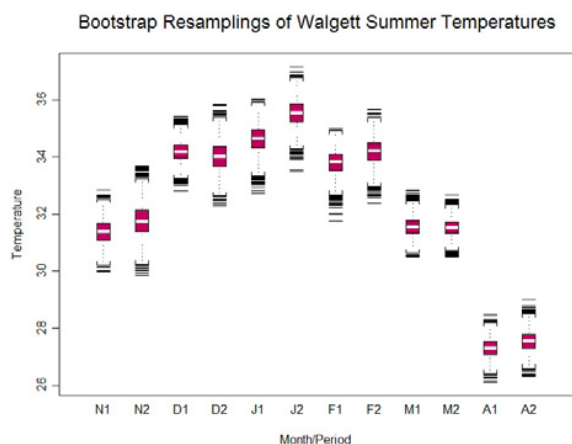


Fig. 5. Same as Fig. 4 for Walgett for summer months (Nov. – Apr.).

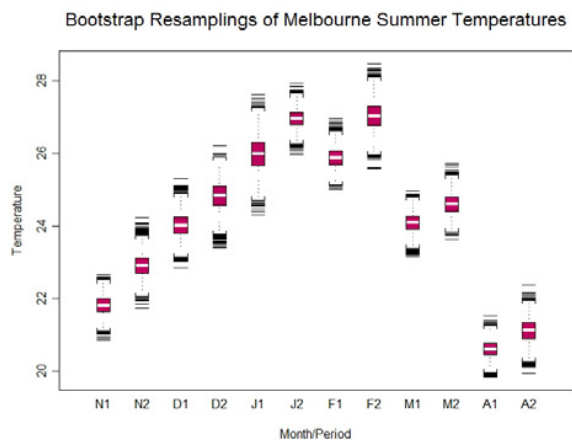


Fig. 6. Same as Fig 4 for Melbourne for summer months (Nov. – Apr.).



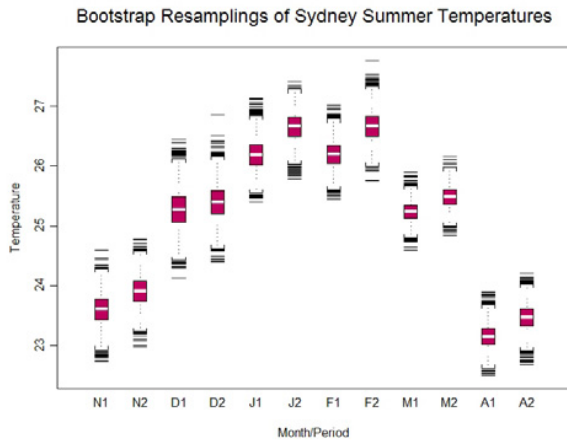


Fig. 7. Same as Fig. 4 for Sydney for summer months (Nov. – Apr.).

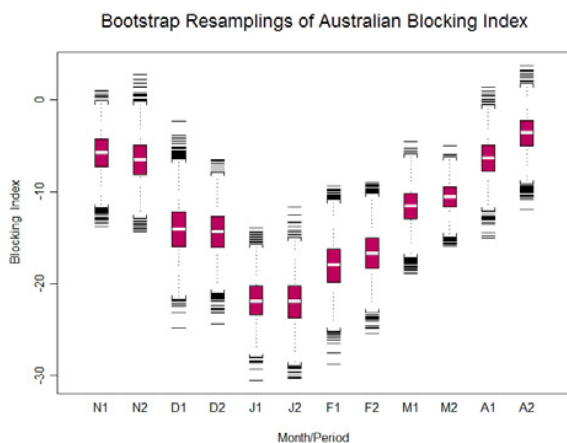


Fig. 8. Bootstrap resamplings of monthly blocking index at 140 E for summer months (Nov. – Apr.). N1 refers to November for period 1 (1958–1991), N2 to November for period 2 (1991–2013), D1 to December period 1, D2 to December period 2, etc.

#### 4. Conclusions

In the past several decades, southeastern Australia has recorded extreme summer mean monthly maximum temperatures that carry a range of risks including drought, fire danger, and human exposure to potentially lethal heat waves. This study uses a data driven approach to classify and to analyze trends in summer mean monthly temperatures. Such an approach avoids any of the traditional distributional assumptions and provides empirical estimates of both the trends and the range of extreme values. The approach can be applied other types of data to allow for determination of the uncertainty associated with any statistic. For the present study, the major known, but not sole, contributor to the increasing trend is extreme atmospheric blocking. Approximately 20 to 50% of the monthly maximum temperature anomaly variance is related to the blocking in early summer (Nov. – Jan.), suggesting additional research will be required to account for the remaining variance by determining the additive role of other atmospheric and ocean processes, (e.g., El Niño phases, the Pacific Decadal Oscillation, MODOKI, the Southern Annular Mode, and the Indian Ocean Dipole, as they are known to affect the atmospheric heights and winds over Australia [7]). It is important to note that the increase in temperature is consistent with IPCC projections [1] for Australia. However, the interaction of global warming with blocking and the aforementioned atmospheric and oceanic processes is not well understood, as the atmosphere and ocean represent a fully coupled system.



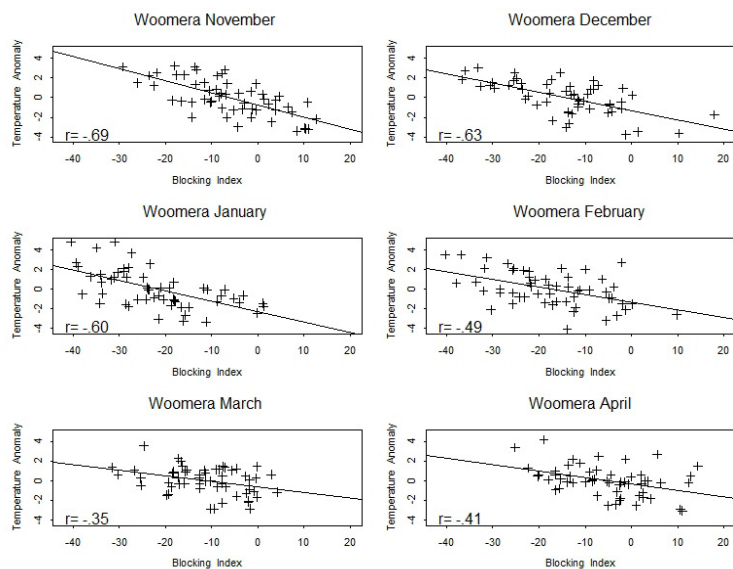


Fig. 9. Scatterplots of blocking index monthly maximum temperature anomaly in Woomera for the summer months (Nov. – Apr.). The correlations are between the blocking index and the temperature anomalies.

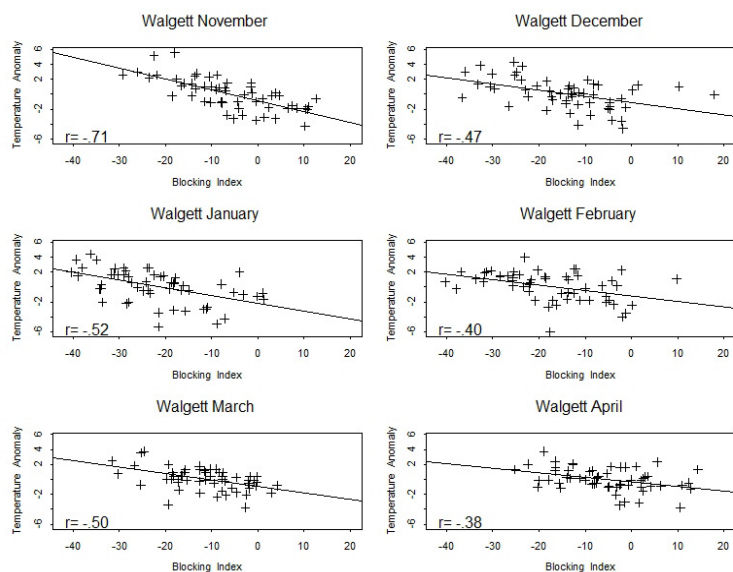


Fig. 10. Same as Fig. 9 for Walgett for the summer months (Nov. – Apr.).



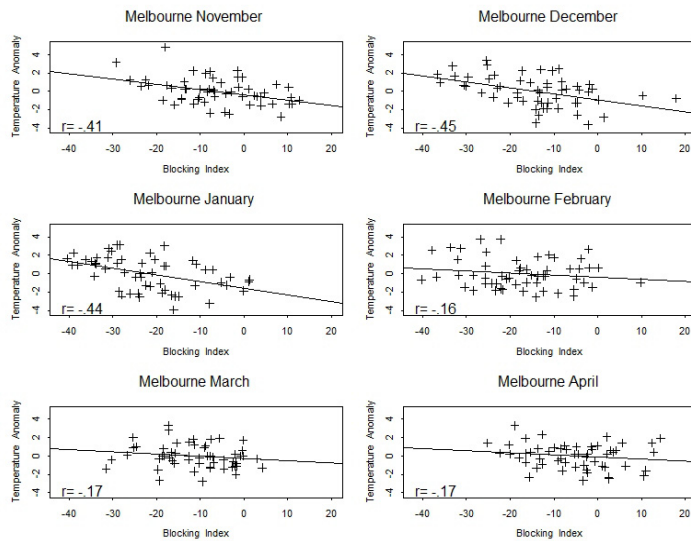


Fig. 11. Same as Fig. 9 for Melbourne for the summer months (Nov. – Apr.).

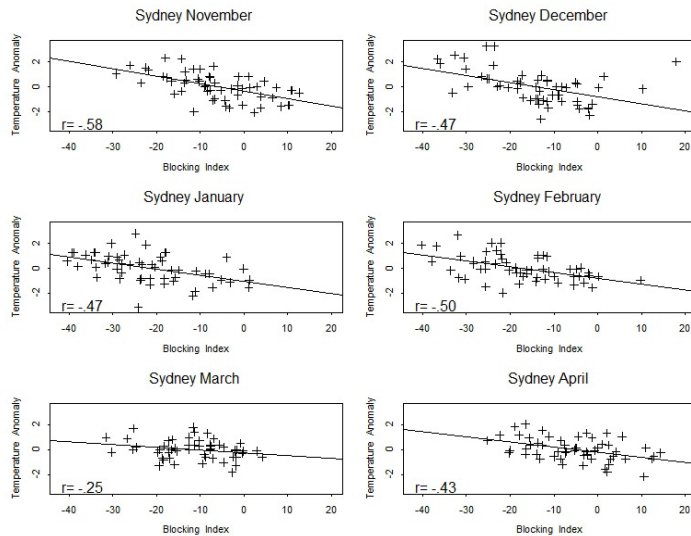


Fig. 12. Same as Fig. 9 for Sydney for the summer months (Nov. – Apr.).

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