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Southeast Australia encapsulates the recent decade of extreme global weather and climate events

Milton Speer[1,*], Lance Leslie[1]

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Abstract

Southeast Australia (SEAUS) is a microcosm of the worldwide impacts of accelerated global warming (GW) since 2010. SEAUS experienced record rainfall and floods in La Niña years 2010–2012, followed by extreme heat and drought in 2013–2019. Catastrophic bushfires occurred in 2019–2020. Next, during successive La Nina years 2020–2023, SEAUS endured record rainfall, floods, and unseasonably cool summers. Accelerated GW amplifies the impacts of SEAUS climate drivers, depending on their phases. We used machine learning attribution to identify climate drivers responsible for a range of extreme events. Attribute detection can provide early extreme event alerts for SEAUS urban and rural communities.

Keywords: *extreme rainfall, floods, drought, heat, climate drivers, machine learning*

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Since 2010, southeast Australia (SEAUS) has witnessed a cycle of climate extremes ranging from record-breaking rainfall during 2010–2012 [1] to record low rainfall and consequent drought from 2013 to 2019. The 2010–2022 period experienced extremes at locations in SEAUS that have occurred on much shorter time scales. For example, in 2022 coastal Sydney recorded its highest ever July rainfall since records began in 1965, eclipsing its previous record July rainfall in 1950 [2]. In marked contrast, the June 2022 Sydney rainfall was in the lowest 10% [3]. At the height of the 2019–2020 bushfire season on January 4, 2020, Canberra, which is located inland approximately 150 km southwest of Sydney, broke its 80-year maximum temperature record when it climbed to 43.6°C and Penrith, an outer western Sydney suburb, was the hottest place on the Earth at 48.9°C. The 2013–2019 drought generated catastrophic bushfires in the 2019–2020 summer, which caused 34 deaths and destroyed more than 2,400 homes [4]. Next were the unprecedented rainfall and floods experienced from 2020 to 2022 [5]. Over inland SEAUS, the prolonged heat and low rainfall during 2013–2019 caused numerous major dams and river systems to either dry up or degenerate into a series of stagnant, oxygen-deprived water holes (**Figure 1**).

Millions of fish died in 2019 in the Murray–Darling River system, which supplies water to Australia's foremost important agricultural region, the Murray–Darling Basin (MDB), which occupies most of the inland SEAUS [6]. Following the fish deaths in 2019 there was a sudden return to record-breaking rainfall between 2020 and 2022, which also included record-breaking low temperatures. With very little time to transition from drought to sustained heavy rainfall, the replenished river fish stocks suffered further massive fish deaths in early 2023 owing to de-oxygenated river water. The lethal water condition arose from contamination of flood plain water runoff by fertilizers, creating the toxic "blackwater" that was returned to the Darling River and its tributaries.

The variables considered as potential attributes for the extreme weather and climate events that SEAUS has experienced since the early 1990s were the known Australian region climate drivers, namely the ocean climate drivers, Niño3.4, and the Indian Ocean Dipole (IOD). Niño3.4 is an area of sea-surface temperatures in the central equatorial Pacific Ocean that since the 1990s has increasingly been associated with El Niño episodes [7]. The phase changes in the IOD have been shown to be related to changes in the mean sea level as far away from Australia as both the Arabian Gulf and the Arabian Sea [8]. The known atmospheric climate drivers are the Southern Annular Mode (SAM) and the Southern Oscillation Index (SOI) [9], while other climate drivers are Global Temperature (GlobalT), Global Sea-Surface Temperature Anomalies (GlobalSSTA), and Tasman Sea sea-surface temperature anomalies (TSSSTA). The Tasman Sea is adjacent to the SEAUS coast. The climate drivers can act both individually and by two-way interactions of some of the drivers, defined by an asterisk (e.g., GlobalT*IOD). The interactions are intended to account for the compounded influences of drivers, as one driver often can reinforce another [10, 11]. The combining of two or more climate drivers by addition, multiplication, or both is a common practice in the attribute selection procedure when using machine learning (ML) techniques [12]. Two (or more) relatively weak attributes can become stronger in combination. Given that there are so many possible combinations, we chose just two multiplicative pairs.

[1]School of Mathematical and Physical Sciences, University of Technology Sydney, Sydney, New South Wales, Australia.
*email: Milton.Speer@uts.edu.au

Figure 1 • The dry riverbed of the Darling River in southeast Australia during the Millennial Drought of 1997–2009. Photo by Ruby Davies, Water as Life; National Gallery, Canberra.

The study by Ramsay et al. [12] assessed 38 individual, additive, and multiplicative possible combinations of climate drivers. Other interactions considered but not included with reference above to the extreme weather and climate events that SEAUS has experienced since the early 1990s were three-way interactions and inverse relationships. They have not been assessed because they require prohibitive amounts of time for testing. Following the approach of Richman and Leslie [11] and Hartigan et al. [13], three ML techniques were chosen to capture both linear and non-linear effects. The ML techniques chosen all were supervised methods. They were Linear Regression (LR), Support Vector Regression (SVR), and Random Forests (RF). Each ML technique uses moving window cross-validation and both forward and backward selection methods. The advantages of LR are simplicity and effectiveness in finding relationships between the predictors and output. However, LR does not perform well in many applications because it cannot detect non-linear relationships between climate drivers and outputs. LR can be heavily influenced by outliers. SVR captures non-linear effects by defining kernels, as radial basis functions or polynomial functions and allows more flexibility in the allowable error in fitting the data. A third ML technique applied to this example was RF, which can capture non-linear processes. RF are many decorrelated decision trees and are averaged in an approach that resembles ensemble methods. Each tree is built on a set of predictors [14]. In general, they also improve predictive accuracy by reducing the variance inherent in a single tree [15]. The ML methods just described are modeled on training data, using forward and backward selection methods [16]. Forward selection begins with one climate driver and sequentially adds another, based on which additional climate driver achieves minimal error. This process continues until the testing error is minimized. Backward selection, in contrast, begins with all predictors and eliminates candidates until the testing errors rise above those with all predictors. The moving window cross-validation is applied to avoid over-fitting the attributes in a time series [17]. This technique avoids the possibility of the training data sets that falsely obtain knowledge of the future values of the time series (the testing data) when evaluating the accuracy of the predictors against the test data.

Our first study investigated the rainfall distribution of the Murrumbidgee River catchment [18] in the southern part of SEAUS. The Murrumbidgee River is a key component of the southern MDB river system and flows westward from a high country near Canberra to the western plains of the MDB. It was found that there has been a significant decrease in Murrumbidgee River heights, resulting from reduced April–May catchment rainfall [18] since global warming (GW) accelerated in the early 1990s. Our second study [19] focused on the northern part of the MDB. It also found a significant decrease in April–May rainfall since the early 1990s. In that study, we applied ML techniques to the numerous possible local and remote climate drivers, identifying the dominant attributes influencing rainfall and temperature trends in the increasingly dry April–May months. In addition to the April–May rainfall decreases, warmer April–May temperatures were shown to have occurred since the early 1990s. The attributes identified by ML included the ocean climate driver Niño3.4, an area of SSTs in the central-eastern tropical Pacific Ocean, which determines the El Niño or La Niña phase, together with the accompanying atmospheric driver SOI, and SAM, which is a measure of the latitudinal position of the mid-latitude westerly winds that influence Australia, the IOD, and both global and local SSTs. A major finding was the prominence of GW as an attribute both individually and in combination with other climate drivers. The impact of GW is modulated by the SEAUS climate drivers. For example, El Niño phases amplify the impacts of GW in SEAUS, including heat waves, drought, and bushfires. In contrast, La Niña phases amplify the GW impact on SEAUS by increasing rainfall in spring and summer, often resulting in severe flood events. When both negative IOD and La Niña phases are present in late winter/spring, the combination amplifies the impacts of the GW influence on SEAUS to generate extreme flood-producing rainfall events whereas the combination of El Niño and positive IOD amplifies heat waves, drought, and bushfire threats during spring/summer.

The 2010–2022 period is notable for an increased interest in understanding the roles of Australian region climate drivers, especially of GW, in influencing these differences between coastal and inland locations of SEAUS. One of our studies examined precipitation and temperature trends to understand drought conditions in Canberra [13], a rapidly growing region in inland SEAUS. An increase in mean temperature was established for all seasons through permutation testing for two 20-year periods, starting in 1979. It was found that the most important climate drivers were the IOD and the GW temperature attributes. Another study investigating differences between inland and coastal locations was performed as a comparative study between inland Scone and coastal Newcastle, in the Hunter region of NSW [20]. This research employed permutation testing on the differences in mean minimum and maximum temperature across three 20-year periods. It was concluded that temperatures have strongly increased in Newcastle since 1958. The inland location showed gradually increasing temperature but had weaker statistically significant evidence. This comparative study of coastal and inland locations did not attempt to link these changes to climate drivers, highlighting an overall gap in the literature.

Another attribution study we made to assess and attribute the marked differences in observed maximum summer (December–March) temperature trends in coastal Sydney and western Sydney used ML techniques applied to known Australian region oceanic and atmospheric climate drivers [21]. This study found that there is a marked disparity in the number and percentage of summer days above the 95th percentile during the accelerated climate change period (1992–2021) between western Sydney (+35%), as represented by the official Bureau of Meteorology observing station data at Richmond and coastal Sydney (−24%), as represented by the official Bureau of Meteorology observing station data at Observatory Hill, relative to 1962–1991 when compared with the period 2010–2022. The detected climate drivers were similar for both coastal and western Sydney but, not surprisingly, coastal Sydney was more affected than western Sydney by the oceanic climate drivers, both individually and through two-way interactions of some of the drivers.

In the coastal/western Sydney study, the window of the training data set was moved until the entire time series was used in the modeling approach, with a fixed size of the test data set. An initial training window of size 20 and testing window of size 20 began with training a model in the years 1962–1976 and testing in 1977–1981. It was expanded until the method trains a model in the years 1962–2014 and tests on data from 2015 to 2019. The sliding window method was applied to a range of training and testing window sizes. The most influential attributes for coastal Sydney are the Tasman Sea sea-surface temperature anomalies (TSSSTA), the IOD, and the interactions between global temperature and TSSSTA (GlobalT*TSSSTA), Niño3.4*SOI, and SAM*SOI. Western Sydney appears most influenced by the IOD and Niño3.4 and the interactions between GlobalT*SAM and Niño3.4*SOI. Additionally, SAM*SOI IOD*GlobalSSTA, and GlobalSSTA*TSSSTA have a similar strong influence on western Sydney mean maximum temperature (**Table 1**).

Table 1 • Attribute selection for the coastal Sydney data represented by the official Bureau of Meteorology observing station of Observatory Hill using the eight different machine learning techniques

Attributes	LR F	SVM RBF F	SVM Poly F	RF F	LR B	SVM RBF B	SVM Poly B	RF B	Mean	Std Dev
IOD	92	46	69	41	74	21	38	77	57.37	24.32
GlobalSSTA	10	59	77	51	38	21	44	77	47.12	24.17
GlobalT	51	54	77	33	36	26	49	62	48.40	16.59
Niño3.4	21	64	67	49	51	31	56	74	51.60	18.26
SAM	8	44	72	49	21	15	46	90	42.95	28.21
SOI	46	49	64	51	13	28	51	85	48.40	21.56
TSSSTA	31	64	72	54	77	15	62	97	58.97	25.97
IOD*GlobalSSTA	33	49	49	31	51	23	33	74	42.95	16.26
IOD*GlobalT	36	38	46	38	77	18	36	64	44.23	18.38
IOD*Niño3.4	38	46	69	49	18	21	49	85	46.79	22.47
IOD*SAM	0	33	69	46	18	10	46	82	38.14	28.50
IOD*SOI	18	54	67	46	36	62	51	87	52.56	20.70
IOD*TSSST	3	54	62	49	44	33	44	87	46.79	24.08

GlobalSSTA*GlobalT	21	36	59	44	33	33	49	79	44.23	18.32
GlobalSSTA*Niño3.4	33	44	59	38	33	41	64	79	49.04	16.70
GlobalSSTA*SAM	13	38	44	46	15	33	44	85	39.74	22.18
GlobalSSTA*SOI	26	44	64	41	23	44	69	82	49.04	20.94
GlobalSSTA*TSSSTA	13	59	62	64	46	28	38	95	50.64	25.15
GlobalT*Niño3.4	51	38	51	41	26	54	56	64	47.76	12.10
GlobalT*SAM	41	38	54	36	56	62	56	85	53.53	15.77
GlobalT*SOI	49	41	41	36	8	41	41	77	41.67	18.83
GlobalT*TSSSTA	64	67	49	59	5	59	59	92	56.73	24.38
Niño3.4*SAM	18	38	41	46	15	15	62	82	39.74	23.82
Niño3.4*SOI	31	62	72	51	10	54	72	87	54.81	24.63
Niño3.4*TSSSTA	13	49	56	49	21	21	64	87	44.87	25.46
SAM*SOI	46	44	56	51	44	41	64	90	54.49	16.20
SAM*TSSSTA	87	41	67	54	3	15	67	82	51.92	30.42
SOI*TSSSTA	8	54	64	59	8	33	64	82	46.47	27.46
Mean	32.14	48.08	60.62	46.52	32.14	32.05	52.66	81.78		
Std Dev	23.28	9.48	10.54	7.98	21.65	15.23	10.84	8.67		

The percentage of moving windows selecting the attribute is shown for each of the eight methods (columns 2–9). The mean percentage of the eight different methods for each attribute is shown in column 10. The first few attributes with mean percentages greater than 50% have the most influence. Here, the six most influential climate drivers identified by machine learning (i.e., those with ≥50% success rate) are TSSSTA, IOD, GlobalSSTA, GlobalT*TSSSTA, Niño3.4*SOI, and GlobalT*SAM.

Overall, **Table 1** highlights the influence of ENSO, the Indian Ocean, SAM, and the Tasman Sea on temperatures in both coastal and western Sydney. There also are influences from GW on both sites, although the influence appears strongest for western Sydney (**Table 2**) with numerous GW indicators (including interactions with other predictors) among the most frequently selected attributes.

Table 2 • Attribute selection for western Sydney data represented by the official Bureau of Meteorology observing station of Richmond using the eight different ML techniques

Attributes	**LR F**	**SVM RBF F**	**SVM Poly F**	**RF F**	**LR B**	**SVM RBF B**	**SVM Poly B**	**RF B**	**Mean**	**Std Dev**
IOD	100	62	64	36	62	46	54	79	62.82	19.81
GlobalSSTA	21	49	67	44	26	28	38	77	43.59	19.96
GlobalT	41	41	51	41	31	18	41	74	42.31	16.22
Niño3.4	79	62	69	46	46	31	56	82	58.97	17.71
SAM	23	56	67	44	23	8	49	79	43.59	24.33
SOI	21	56	64	31	31	28	46	72	43.59	18.84
TSSSTA	38	64	67	46	46	26	36	85	50.96	19.36
IOD*GlobalSSTA	62	72	62	41	44	23	59	56	52.24	15.44
IOD*GlobalT	59	59	51	44	59	23	36	77	50.96	16.59
IOD*Niño3.4	13	62	72	36	18	28	46	92	45.83	27.67
IOD*SAM	18	62	64	44	21	5	44	87	42.95	27.54
IOD*SOI	13	59	54	36	33	64	49	82	48.72	21.28
IOD*TSSST	8	62	64	59	26	23	49	90	47.44	26.86
GlobalSSTA*GlobalT	21	51	41	49	41	31	56	79	46.15	17.71
GlobalSSTA*Niño3.4	44	44	59	38	38	26	54	85	48.40	17.79
GlobalSSTA*SAM	3	46	64	41	41	28	59	85	45.83	24.61
GlobalSSTA*SOI	21	46	51	46	31	38	64	82	47.44	19.19

GlobalSSTA*TSSSTA	28	56	59	44	44	51	49	87	52.24	17.00
GlobalT*Niño3.4	23	38	56	36	23	44	54	72	43.27	16.87
GlobalT*SAM	49	41	51	49	59	36	69	77	53.85	13.84
GlobalT*SOI	15	46	49	41	13	26	51	77	39.74	21.23
GlobalT*TSSSTA	46	38	59	44	10	31	46	85	44.87	21.45
Niño3.4*SAM	28	44	62	41	38	18	44	82	44.55	19.72
Niño3.4*SOI	36	62	56	54	15	38	72	92	53.21	23.61
Niño3.4*TSSSTA	5	44	69	44	21	15	64	87	43.59	28.75
SAM*SOI	62	44	64	41	51	26	54	79	52.56	16.39
SAM*TSSSTA	15	72	62	54	0	46	56	79	48.08	27.30
SOI*TSSSTA	10	56	64	38	10	36	67	90	46.47	28.00
Mean	32.14	53.30	60.07	43.04	32.14	30.04	52.20	81.14		
Std Dev	23.54	9.83	7.27	6.10	16.03	12.75	9.57	7.39		

The percentage of moving windows selecting the attribute is shown for each of the eight methods (columns 2–9). The mean percentage of the eight different methods for each attribute is shown in column 10. The first few attributes with mean percentages greater than 50% have the most influence. In this case, the six most influential climate drivers (i.e., those with ≥50% success rate) identified by machine learning are IOD, Niño3.4, Niño3.4*SOI, SAM*SOI, GlobalSSTA*TSSSTA, and IOD*GlobalSSTA.

In summarizing the studies described above, ML was confirmed as a very effective approach to provide a scientific basis for supporting public policy and decision-making, because of its capacity to reveal the complex relationships between climate drivers and extreme weather and climate events, and their impacts, on a range of timescales. It was found that GW enhances the impacts of the known SEAUS climate drivers, depending on the phases of the climate drivers and whether the climate drivers are mutually supportive of their impacts. The climate drivers revealed by ML therefore can inform policy makers of the kinds of impacts when dealing with extreme weather and climate events.

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Conflict of interest

The authors declare no conflict of interest.

Data availability statement

Data supporting these findings are available within the article, at https://doi.org/10.20935/AcadEnvSci6155, or upon request.

Institutional review board statement

The study was conducted according to the guidelines of the Declaration of Helsinki for studies not involving humans or animals.

Informed consent statement

Not applicable.

Sample availability

The authors declare no physical samples were used in the study.

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