Between June 2019 and March 2020, thousands of wildfires spread devastation across Australia at the tragic cost of many lives, vast areas of burnt forest, and estimated economic losses upward of AU$100 billion. Exceptionally hot and dry weather conditions, and preceding years of severe drought across Australia, contributed to the severity of the wildfires. Here we present analysis of a very large ensemble of initialized climate simulations to assess the likelihood of the concurrent drought and fire-weather conditions experienced at that time. We focus on a large region in southeast Australia where these fires were most widespread and define two indices to quantify the susceptibility to fire from drought and fire weather. Both indices were unprecedented in the observed record in 2019. We find that the likelihood of experiencing such extreme susceptibility to fire in the current climate was 0.5%, equivalent to a 200 year return period. The conditional probability is many times higher than this when we account for the states of key climate modes that impact Australian weather and climate. Drought and fire-weather conditions more extreme than those experienced in 2019 are also possible in the current climate.

### INTRODUCTION

The 2019–2020 wildfire season in Australia was among the most catastrophic in recorded history, causing severe social, environmental, ecological and economic impacts across the continent. An area larger than the size of the United Kingdom was burned (estimates range from 24 to 34 million hectares), including at least 21 percent of Australia’s temperate forests, and over 3000 homes. Thirty-three deaths occurred as a direct result of the fires. Hundreds more deaths, and thousands of hospital and emergency-department admissions, have been attributed to the extreme levels of air pollution resulting from the wildfire smoke. The estimated death toll for animals is in the billions, with fears that some species have been driven to extinction. Recent estimates of the total economic loss to Australia resulting from the 2019–2020 wildfires are in the order of AU$100 billion.

Two key factors have been linked to the severity of the 2019–2020 wildfires. First, the exceptionally dry conditions in the years and months leading up to the fire season produced very low fuel-moisture content, especially in eastern Australia. The widespread drought conditions have been connected to the states of the El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) in the years and months preceding 2020. Second, the extremely hot and dry weather conditions experienced across Australia during the 2019–2020 summer were particularly favorable to fire ignition and spread. A number of extreme weather records were broken over this period, which included Australia’s highest national daily-averaged temperature (41.9 °C) and record-high values of the Forest Fire Danger Index (FFDI) in areas of all Australian States and Territories. The Southern Annular Mode (SAM), which was strongly in its negative phase during the spring and summer of 2019, has been implicated in the unusually hot and dry conditions across eastern Australia.

Many studies have investigated how climate and weather conditions favorable to wildfires in Australia have changed historically and how they will continue to change into the future. Paleoclimate records indicate an increase in the last century in the occurrence of the fire-promoting phases of both ENSO and the IOD. These increases may continue in the coming decades. Observed records since the mid-twentieth century show a trend towards more dangerous fire-weather conditions for much of Australia and a corresponding reduction in the time between major wildfires. Future projections of Australian fire weather are strongly region- and model-dependent, but generally indicate increased severity in southeast Australia.

Estimates of the likelihoods of increased susceptibility to fire from extreme climate and weather are essential for policy makers, contingency planners, and insurers. However, such likelihoods are difficult to quantify from observed records, which are limited to approximately the past century and thus provide few samples of extremely susceptible conditions in a given region. There was, for example, no direct observational precedent for the high values of FFDI nor the low annual accumulated rainfall total that was, for example, no direct observational precedent for the high values of FFDI nor the low annual accumulated rainfall total that was observed in southeast Australia in 2019. Further, assessment of likelihoods is compounded by nonstationarity in the observed record, resulting, for example, from climate change. Even if past likelihoods could be well determined from the observed record, they may not be representative of current wildfire susceptibility.

Climate models can provide large samples of plausible conditions over short time periods that can be used to reduce uncertainties in quantifying risk. Previous studies have used ensemble seasonal and weather prediction systems to estimate return periods of surge levels in the Netherlands and of significant wind and wave heights globally. More recently, the approach of quantifying risks of extremes using ensemble climate simulations has been popularized under the acronym UNSEEN, standing for UNprecedented Simulated Extremes using ENsembles. The UNSEEN approach has been used to assess the risk of droughts and heat waves and to quantify likelihoods of

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extreme meteorological events, such as instances of unprecedented rainfall\textsuperscript{45,46} and temperature\textsuperscript{47}, and sudden stratospheric warming in the Southern Hemisphere\textsuperscript{48}.

In this paper, we use a decadal ensemble climate forecast model to quantify the likelihood of concurrent extreme drought and fire weather in a region of southeast Australia where the 2019–2020 wildfires burned significant area (Fig. 1). We focus on two indices averaged over this region (below, overlines denote regional averaging). Our drought index, $\text{DI}$, is defined as the total accumulated rainfall from January to December and quantifies how preconditioned for fires the landscape may be leading into the wildfire season of a given year. We use the December-average FFDI, $\text{FFDI}_{\text{Dec}}$, to quantify how severe fire-weather conditions are near the peak of the fire season of a given year. These indices were selected to capture the unprecedented nature of the drought and fire weather in southeast Australia in 2019.

Simultaneous low values of $\text{DI}$ and high values of $\text{FFDI}_{\text{Dec}}$ indicate elevated susceptibility to wildfires in southeast Australia. Therefore, hereafter, we will refer to their vector as simply “fire susceptibility”.

Our climate forecast dataset comprises 10-year long, daily forecasts, each with 96 ensemble members, initialized at the beginning of every May and November over the period 2005–2020. By pooling forecast ensemble members and lead times, these forecasts provide up to 1920 times more samples of $\text{DI}$ and $\text{FFDI}_{\text{Dec}}$ in the current climate than are available from observed records (“Methods”). After first checking that these many samples provide accurate and independent representations of the real world (“Model fidelity”), we use them to estimate the likelihoods of exceeding extreme values of $\text{DI}$ and $\text{FFDI}_{\text{Dec}}$, including the unprecedented values experienced during the 2019–2020 wildfires (“Likelihoods of exceedance”). The very large number of forecast samples yields many years with $\text{FFDI}_{\text{Dec}}$ and $\text{DI}$ that are simultaneously more severe than the observed 2019 values. This enables us to test the correspondence between unprecedented drought and fire weather in southeast Australia and the states of ENSO, IOD and SAM (“Extreme susceptibility to fire and climate drivers”).

RESULTS

Historical record of fire susceptibility

The historical record of $\text{FFDI}_{\text{Dec}}$ and $\text{DI}$ is shown in Fig. 2. These data are calculated from high quality atmospheric reanalysis and gridded rainfall data (“Methods”) and are referred to hereafter as “observations”. The data points in Fig. 2 are shaded according to the year for which they are calculated, with colored shading for years in which severe wildfires occurred in summer in southeast Australia.

Severe fires have generally been associated with extreme values of $\text{FFDI}_{\text{Dec}}$ and $\text{DI}$ (Fig. 2). The values of both indices recorded in 2019 were the most extreme in the 63 years (1958–2020) of observational data available for both indices (Fig. 2a). Indeed, there was no precedent for the 2019 $\text{DI}$ values in the full 121 years (1900–2020) of data available for this index (see Supplementary Fig. S1). A large proportion of Australia experienced unprecedented values of December-averaged FFDI in 2019 (Fig. 2b). Similarly, much of eastern and central Australia accumulated the lowest rainfall annually in 2019 relative to all other years in the joint historical record (Fig. 2c). Over much of our region of interest, the minimum $\text{DI}$ occurred in 1980 and 1982, which were also years in which unplanned summer fires burned extensive areas of southeast Australia. We can quantify the joint extremity of $\text{DI}$ and December-average FFDI in a given year as the normalized distance from the mean index values over 1958–2020: $\sqrt{\text{FFDI}^2_{\text{Dec}} + \text{DI}^2}$, where primes indicate the difference from the mean index over 1958–2020, normalized by the standard deviation of the index over the same period. Even at a local scale, this joint quantity was unprecedented in 2019 over much of southeast Australia (Fig. 2d).

The small number of samples in the observed record makes quantification of the probabilities of extreme $\text{FFDI}_{\text{Dec}}$ and $\text{DI}$ events very difficult. It is not possible, for example, to directly determine the likelihood of an event more severe than that observed in 2019 simply because no such event has ever been observed. Statistical techniques enable extrapolation of fitted distributions, but require assumptions about the shape of the distribution and still suffer from large uncertainties when the sample size is small\textsuperscript{49–51}. Issues with sampling become increasingly restrictive as dimensionality—that is, the number of variables —increases\textsuperscript{52}. With its very large sample size, our forecast model (hereafter “model”) provides many in-sample estimates of rare extreme events, allowing for the probabilities of these events to be determined directly from the empirical probability density function\textsuperscript{53}.

Model fidelity

In order to provide reliable estimates of likelihoods of fire susceptibility, the model samples must be stable, independent and realistic estimates of the real world\textsuperscript{45}. Stability here refers to an absence of systematic changes in the estimates of $\text{FFDI}_{\text{Dec}}$ and $\text{DI}$ with model lead time. Model stability is necessary for pooling samples at different lead times. Dependence between model samples inflates the sample size without adding new information and arises at short lead times because the ensemble forecasts are initialized from similar initial conditions. We remove dependent samples by considering only model lead times for which ensemble members are uncorrelated (≥37 months: Fig. 3, see also “Methods”).

To assess the model fidelity, we compare the modeled joint and marginal distributions of $\text{FFDI}_{\text{Dec}}$ and $\text{DI}$ to the observed distributions over a common time period (Fig. 4). Initial
assessment of the marginal distributions revealed a systematic dry bias in the modeled DI that was corrected for by applying a simple additive adjustment to the mean DI at each lead time ("Methods"). With this correction applied, we compare the distributions using the 96-member forecasts—denoted f1980→10 mem—in Fig. 4a–c. These model distributions show little dependence on lead time (colored lines) and agree generally with the observed data. However, because these forecasts are initialized over a relatively short period of time (2005–2020), there are very limited observations to which they can be compared. Only data within the 7-year period 2014–2020 (comprising 9408 model samples) are shown in Fig. 4a–c so that the distributions at each lead time are constructed from the same number of samples, thus enabling comparison of the distributions across lead times ("Methods").

We therefore also assess the distributions computed from another set of forecast model data, denoted f1980→10 mem. These data are produced using the same decadal forecast system and initialization dataset as f2005→96 mem. However, they have only 10 ensemble members and they are initialized over the longer period 1980–2020. The latter enables comparison to a much larger set of observed values of FFDI Dec and DI. In Fig. 4d–f we compare the f1980→10 mem distributions over the period 1989–2020 (comprising 4480 samples) with observations over the same period ("Methods"). As for the f2005→96 mem data, the f1980→10 mem data distributions are stable and show good agreement with observations over the matched time period.

We use a two-dimensional, two-sample Kolmogorov–Smirnov (KS) test54,55 to test the null hypothesis that the modeled and observed joint distributions (gray and white points in Fig. 4) are the same ("Methods"). Proxy time series are generated by randomly subsampling the model data for sets of equal length to the observed record. These sets are compared with the full model distribution to produce a null distribution for the KS-statistic, K. The KS-statistic calculated between the observed and modeled distributions, Kobs, is compared with the null distribution. For both f1980→10 mem and f2005→96 mem, the observed KS-statistic falls below the 95th percentile of the null distribution (p-value > 0.05) and hence the model is considered to provide values of FFDI Dec and DI that are consistent with the observed record (Fig. 4g). The KS test also confirms consistent modeled and observed distributions when applied using model data at each lead time independently (Fig. 4h), indicating that the independent model samples are both realistic and stable.
Likelihoods of exceedance
In 2019 unprecedented values of $FFDID_{Dec}$ and $DI$ were observed that were respectively 19% higher and 8% lower than previous record values (since 1958). These record values coincided with one of the worst wildfire seasons in recorded history. Our model simulations show that the likelihoods of experiencing $FFDID_{Dec}$ or $DI$ values equal to or more extreme than those experienced in 2019 are 7.8% and 1.5%, respectively, in the current climate (2014-2023 comprising 13,440 samples, Fig. 5a, b). The likelihood of exceeding both simultaneously is roughly 0.5%, indicating a return period for the 2019 event of approximately 200 years (Fig. 5c). Note that for $DI$ to be “more extreme” or to “exceed” is to have a lower value, since lower values of $DI$ indicate drier conditions that are more conducive to wildfires.

Values of $FFDID_{Dec}$ and $DI$ substantially more extreme than observed records occur within the model sample (Fig. 5d). This is especially true for $FFDID_{Dec}$, for which nearly 8% of all model samples are more extreme than the observed 2019 value, with some model realizations up to twice as high. Indeed, there are realizations from the model where $FFDID_{Dec}$ and $DI$ are

Fig. 4 Model fidelity testing. The joint (a) and marginal (b, c) distributions of observed (white circles and bars) and modeled (gray circles and lines) $FFDID_{Dec}$ and $DI$ from the bias-corrected $f_{2005-96}$ mem model dataset over the period 2014-2020. Lines show probability densities from the model for each lead time (colors) and for all lead times together (black dashed). For the joint distribution, probability densities are from a two-dimensional kernel density estimate and are presented with contour levels at 0.5e-4, 2e-4, and 4e-4 (enclosing approximately 92%, 63%, and 27% of the model data across all lead times). d-f As in a-c, but using $f_{1980-10}$ mem data over the period 1989-2020. g Null distributions of the Kolmogorov–Smirnov statistic, $K$, resulting from bootstrapping the $f_{1980-10}$ mem (purple shading) and $f_{2005-96}$ mem (pink shading) datasets using all independent lead times. h As in g, but for each lead time separately. In g and h, the distributions are presented as a difference between $K$ and the KS-statistic calculated between the observed and model data, $K_{obs}$ such that the vertical black line (at $K - K_{obs} = 0$) indicates the location of $K_{obs}$ in the distributions of $K$. Colored numbers show the right-tail $p$-value for the $f_{2005-96}$ mem (pink) and $f_{1980-10}$ mem (purple) distributions.
simultaneously 60% higher and 20% lower, respectively, than in 2019, though such events are very unlikely (<0.05% chance, or >2000 year return period). What such extreme events would mean for the severity of wild fires in southeast Australia is an important question that requires further investigation.

Extreme susceptibility to fire and climate drivers
Climate and weather extremes prior to and during the fire season in southeast Australia are influenced by multiple drivers of climate variability, including the El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Southern Annular Mode (SAM)\textsuperscript{15,27}. The positive phase of ENSO (El Niño) is associated with warm and dry conditions across eastern Australia, generally leading up to and during the fire season (spring and summer)\textsuperscript{56}. Similarly, positive IOD events reduce atmospheric moisture availability to the continent and are generally concomitant with drier conditions in southeast Australia\textsuperscript{56,57}. Negative phases of the SAM in spring and summer are characterized by an equatorward shift of both the westerly storm track and the descending branch of the southern hemisphere Hadley Cell, resulting in dry westerly winds and warm conditions over eastern Australia\textsuperscript{58}. These three climate drivers are not independent and the compounding effects of their co-occurrence can impact wildfire susceptibility\textsuperscript{15}. Positive phases of ENSO and IOD tend to co-occur\textsuperscript{59}, for example, as do the fire-promoting states of ENSO and SAM\textsuperscript{60,61}.

Every sample from our model provides a simulated realization of the earth system, including the ocean and atmosphere. We can quantify for every modeled sample of FFDI\textsubscript{dec} and DI the corresponding states of ENSO, IOD and SAM over the period leading into the wildfire season using the Nino 3.4, DMI and SAM indices (defined in “Methods” and assessed in Supplementary Figs. 2 and 3). The model provides 66 simulated Earths over the period 2014–2023 with values of FFDI\textsubscript{dec} and DI worse than the most extreme event in the observed record (2019). Of these samples, approximately 80% are associated with simultaneous positive ENSO, positive IOD and negative SAM states (Fig. 6a). Composites of sea surface temperature and 500 hPa geopotential height anomalies generated from years of unprecedented FFDI\textsubscript{dec} and DI
Fig. 6 Correspondence with climate drivers. a Values of average Nino 3.4 over September–December (SOND), average DMI over September–November (SON) and average SAMI over SOND from the model data (gray dots, 2014–2023) and from observations (white dots, 2014–2020). Indices are normalized by their standard deviation, $\sigma$ (calculated over 2014–2023 for the model data and over 1980-2020 for the observed data). Colored dots show the subset of model data points for which both $\text{FFDIDec}$ and $\text{DI}$ are unprecedented—i.e., values more extreme than the respective observed 2019 values—where the color indicates the normalized distance from the mean modeled $\text{FFDIDec}$ and $\text{DI}$ over 2014–2023. The text in each quadrant gives the percentage of colored points that fall within each quadrant. Where no text is given, the percentage is 0%. Dashed black lines show contours of two dimensional kernel-density estimates using the model forecast data with levels at $2 \times 10^{-2}$, $5 \times 10^{-2}$, $1 \times 10^{-1}$ and $2 \times 10^{-1}$.

b Composite of average sea surface temperature anomalies over September–November from forecast years in the period 2014-2023 with unprecedented values of $\text{FFDIDec}$ and $\text{DI}$. Dashed boxes show the regions used to calculate the Nino 3.4 and DMI indices. c As in b but showing the composite of average 500-hPa geopotential height anomalies over September–December. Dashed lines at $40^\circ$S and $65^\circ$S show the locations of the longitudinal averages used in the calculation of $\text{SAMI}$. 
Conditional likelihoods of exceedance. The likelihoods of simultaneously exceeding 2019 FFDI\textsubscript{Dec} and D\textsubscript{T} conditions given that one or more of Nino 3.4, DMI and −SAM\textsubscript{i} are positive (purple shading) or strongly positive (>1 standard deviation, pink shading) over the period leading into the wildfire season (September, October, November, and December for Nino 3.4 and SAM\textsubscript{i}; September, October, and November for DMI). Likelihoods and standard deviations are calculated using model data over the period 2014–2023 and error bars show 2.5–97.5% confidence bounds ("Methods"). Numbers show the number of years in the 63-year historical record (1958–2020) that satisfy each condition, where underlines indicate that 2019 is one such year.

Exhibit the typical patterns associated with these states (Fig. 6b, c). While these results indicate a clear correspondence between extreme susceptibility to fire and the driver states, there is little evidence that the strength of the driver states is related to the joint magnitude of unprecedented FFDI\textsubscript{Dec} and D\textsubscript{T} (as quantified by the normalized distance from the mean—see the shading of points in Fig. 6a). That is, the severity of extreme wildfire susceptibility is apparently associated mostly with the concurrency of fire-conducive Nino 3.4, DMI, and SAM\textsubscript{i} states and not with their individual magnitudes, a characteristic of compound events previously described in frameworks for understanding extreme impacts.62–64.

Conditioning on the states of ENSO, IOD, and SAM has a large impact on the likelihood of simultaneously experiencing unprecedented values of FFDI\textsubscript{Dec} and D\textsubscript{T} (Fig. 7). The SAM\textsubscript{i} appears to be the strongest driver; when SAM\textsubscript{i} is strongly negative (<=−1 standard deviation) over spring the likelihood of an unprecedented event is over 5 times higher (nearly 3%) than if the state of the SAM\textsubscript{i} is not considered. Likelihoods are higher still when conditioned on more than one of the drivers being strongly in their fire-conducive phases (up to approximately 4% for strongly positive Nino 3.4 and strongly negative SAM\textsubscript{i}). In 2019, both the IOD and SAM were strongly in their fire-conducive phases (Fig. 6a). According to the model, the likelihood under such conditions of the unprecedented values of FFDI\textsubscript{Dec} and D\textsubscript{T} in 2019 was approximately 3%.

**DISCUSSION**

We have used a very large ensemble of climate model simulations to quantify the likelihood of high susceptibility to wildfire from concurrent extreme fire-weather and drought in southeast Australia. Our analysis shows that the likelihood of experiencing the unprecedented conditions that occurred leading into and during the catastrophic 2019–2020 wildfire season was approximately 0.5% in the current climate. Substantially more extreme conditions are also realized by the model, and the impact of such conditions on the severity of wildfires in southeast Australia is a potential area for future research. A very high proportion (~80%) of the model realizations with more extreme fire susceptibility than that observed during 2019 occur when ENSO, IOD and SAM are all in their fire-promoting phases—positive, positive and negative, respectively—during the austral spring and early summer. Accounting for the observed phases and strengths of these climate modes, the likelihood of the fire-weather and drought conditions experienced in 2019 was approximately 3%.

ENSO and IOD are predictable on seasonal timescales, particularly during austral winter and spring when any event has already started to establish itself and persistence plays a first order role in predictability.65,66. The neutral ENSO and positive IOD conditions experienced during spring (SON) of 2019, for example, were predicted by the Australian Bureau of Meteorology in June67, and their implications on the fire season were foreshadowed in August68. SAM events are generally shorter lived and less predictable, although there is evidence that the significant stratospheric polar vortex weakening in spring 2019 and subsequent development of negative SAM was forecast as early as late July69. Thus the corresponding quantitative increases in likelihoods of extreme fire susceptibility demonstrated in this paper were potentially predictable months in advance of the peak in the 2019–2020 fire season.

The work in this paper builds on a growing area of research using climate simulations to assess and explore extreme events. There is enormous value to policy planners and decision makers in the ability to quantify the probability of impactful climate and weather events, particularly those that are unprecedented in the observed record. However, the use of climate models to quantify real-world risk is not without its difficulties. Foremost, the accuracy of estimates of probabilities is dependent entirely on the climate model’s ability to realistically represent the full range of plausible states that could be experienced in the real world. This is inherently very difficult to test because limited observed records provide very few samples of real world states and one is left trying to verify model states that have never been observed. We designed a statistical test to check for consistency between our modeled and observed indices and applied this in a way to maximize the number of observations in the test period. However, our test still suffers from small numbers of observations, particularly of extreme events. Thus, there is still some inherent reliance on the model’s ability to simulate the indices used.

Ideally, a climate model should be able to represent the real world without any correction, and indeed this can be the case for specific models simulating specific variables in specific regions.45,69. But more generally, climate models have systematic biases that must be accounted for prior to their use. In this study we used relatively low resolution climate simulations because of our focus on the 2019–2023 time period, error bars show 2.5–97.5% confidence bounds ("Methods"). Numbers show the number of years in the 63-year historical record (1958–2020) that satisfy each condition, where underlines indicate that 2019 is one such year.
influences. Projections indicate that winter and spring rainfall over Australia’s eastern seaboard will decrease\textsuperscript{70} and that drought duration and frequency across southern Australia are likely to increase\textsuperscript{71}. Increases in mean and extreme temperatures this century are virtually certain\textsuperscript{70} and likely to contribute to increases in the number and severity of dangerous fire weather events\textsuperscript{15,31–34} and drier, more volatile, fuel loads\textsuperscript{72}. Indeed, some studies suggest that temperature may play an increasing role over precipitation in global fire occurrence over the next century\textsuperscript{16,73}. Exactly how these changes will impact wildfire risk is a potential area for future research.

\section*{METHODS}

\subsection*{Burnt area data}

To produce Fig. 1, burnt forest areas are taken from FireCCI v5.1 provided by the European Space Agency Climate Change Initiative\textsuperscript{74} (2001–2019) and from CSIRO v1.0 provided by the Copernicus Climate Change Service\textsuperscript{30} (2020). The data are gridded monthly burnt areas for different vegetation classes with a resolution of 0.25°. Here we consider only burnt areas associated with land cover categories 50–90, corresponding to forested areas.

The burnt area data used in Fig. 2 are calculated from New South Wales National Parks and Wildlife Service Fire History data\textsuperscript{46}. These data are provided as polygons of burnt areas of wildfires and prescribed burns, sometimes including associated start and/or end dates, over the period 01/01/1920–18/02/2021. The polygon data are converted to a gridded product with 0.05° resolution in latitude and longitude. We consider only wildfire data and exclude data that have start or end dates that do not fall within 28 days of December or do not span a period encompassing December. The regional burnt areas used in Fig. 2 are calculated by summing the 0.05° resolution data over the region shown in Fig. 1.

\subsection*{Calculation of forest fire and drought indices}

The daily McArthur Forest Fire Danger Index\textsuperscript{76,77}, FFDI, is defined here as:

\begin{equation}
\text{FFDI} = \frac{T - 10}{0.9} \exp \left(0.03387 - 0.0345W + 0.0234W + 0.243147\right),
\end{equation}

where \(T\) (°C) is the maximum daily temperature; \(H\) (%) is the daily average relative humidity at 1000 hPa; \(W\) (km/h) is the daily average 10m wind speed; and \(D\) is the rolling 20-day total precipitation scaled to range between 0 and 10, with larger \(D\) for lower precipitation totals.

Note that this formulation differs from standard formulations of the FFDFI\textsuperscript{76,77} in a number of ways, principally in its use of daily average humidity and wind speed. These changes were necessitated by the data that were available to us across the various datasets used in this paper. FFDI estimates herein are likely to be attenuated relative to the standard formulation as a result of these differences. We calculate the FFDFI from equation (1) from both the forecast model data (see “Use of forecast model data”\textsuperscript{78}) and the Japanese 55-year reanalysis (JRA-55)\textsuperscript{17,19} which spans 1958–2020. For the latter, the 1.25° resolution fields of the individual components in equation (1) are first interpolated linearly to the forecast model grid (the only exception to this is in Fig. 2, where the FFDI is presented at the JRA-55 grid resolution). For both the forecast and JRA-55 data, the regional December-averaged FFDI, FFDIDec, is calculated for a given year by averaging all daily December values of FFDI over the four model grid cells in Fig. 1.

The Drought Index, DI, of a given year is defined as the accumulated total precipitation (mm) between January and December (both inclusive) of that year. Thus, lower values of DI indicate drier conditions. We calculate DI using the daily forecast data and using data from the Australian Gridded Climate Dataset (AGCD), which provides interpolated in situ observations between 0 and 10, with larger DI for lower precipitation totals. These changes were necessitated by the data that were available to us across the various datasets used in this paper. FFDFI estimates herein are likely to be attenuated relative to the standard formulation as a result of these differences. We calculate the FFDFI from equation (1) from both the forecast model data (see “Use of forecast model data”\textsuperscript{78}) and the Japanese 55-year reanalysis (JRA-55)\textsuperscript{17,19} which spans 1958–2020. For the latter, the 1.25° resolution fields of the individual components in equation (1) are first interpolated linearly to the forecast model grid (the only exception to this is in Fig. 2, where the FFDI is presented at the JRA-55 grid resolution). For both the forecast and JRA-55 data, the regional December-averaged FFDI, FFDIDec, is calculated for a given year by averaging all daily December values of FFDI over the four model grid cells in Fig. 1.

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The large-ensemble FFDFI\textsuperscript{17,19} dataset comprises 10-year long forecasts, each with 10 ensemble members, initialised at the beginning of every May and November over the period 1980–2020. The FFDFI\textsuperscript{17,19} dataset provides many estimates of plausible values of FFDFI and DI under contemporaneous anthropogenic and natural forcings that enable the likelihoods of exceeding rare events (like those in 2019) to be estimated empirically. Our methodology is similar to those introduced in previous papers using the UNSEP approach\textsuperscript{44}.

1. Remove model samples at short lead times where there is dependence between forecast ensemble members due to their similar initial conditions (see “Testing of ensemble member independence”). Dependence between samples artificially inflates the sample size without adding new information.

2. Test that the model provides stable (with lead time) and realistic estimates of FFDFI\textsuperscript{17,19} and DI. We apply a simple bias correction to the modeled DI (see “Bias correction”) and check that the joint distributions of modeled FFDFI and DI are consistent with the observed record (see “Testing of model fidelity”).

3. Calculate likelihoods of exceedance (see “Calculation of likelihoods of exceedance”).

When using forecast data for the purpose of providing multiple realizations of a given time period, it is important that equal numbers of samples are included for each year in the period, since this avoids over/under-sampling the conditions of a particular year. Figure 8 shows the number of samples per calendar year for the F1980 and F1980−10 mem (pink labels) and F2005 and F2005−96 mem (purple labels) datasets after removing lead times with dependent ensemble members. Fewer samples are available for calendar forecast years toward the start and end of each forecast period because these years have fewer lead time available. For both FFDFI\textsuperscript{17,19} and DI, we define the lead time of a given forecast as the number of elapsed months between initialization and December of the forecast year (e.g., the 2020 forecast initialised in Nov 2020 is at 1-month lead). Note that no DI forecast is available at 1-month lead, since this index requires the accumulation of rainfall from January to December. Thus, the shortest available lead time for DI is 13 months.

The F1980−10 mem dataset provides 140 simulations (14×10 lead times×ensemble members) for every year over the period 1989–2023. Likewise, the F2005−96 mem dataset provides 1344 simulations (14×96) for every year in 2014–2023. Thus, when testing the fidelity of the F1980−10 mem and F2005−96 mem datasets in Fig. 4g we use the periods 1989–2020 and 2014–2020, respectively, since these periods provide maximum and equal numbers of realizations per year and overlap with the observed record. To calculate the likelihoods of the 2019 FFDFI\textsuperscript{17,19} and DI conditions using the F2005−96 mem data, we consider all lead times together and use the 10-year period centered on 2019 (2014–2023) as representative of current climate conditions.

\subsection*{Testing of ensemble member independence}

Each multi-member forecast is initialised from a set of initial conditions that seek to estimate the state of the climate at the time of initialization and the uncertainty about that state. As such, ensemble members of a given forecast at short lead times are strongly dependent on each other. Inclusion of dependent ensemble members in our analysis results in
artificial inflation of the sample size, without adding new information. To determine the lead time at which the ensemble members can be considered independent, we apply a simple statistical test that the correlation between ensemble members at a given lead time is zero. For each forecast lead time, we estimate the mean DI bias as the difference between the mean f1980 to f1990 and observed DI over the period 1990–2020. These biases (which range between −141 mm and −68 mm, depending on the lead time) are subtracted from both the f1980 and f2005 forecasts to produce unbiased estimates of DI. No bias correction is necessary for FFDIDec. Note that the f1980 model dataset is used here so that the biases can be estimated using a relatively long time period (31 years). The f2005 model dataset is a shorter period (2005–2020), so provides, for example, only seven years of data at 115 months lead (2014–2020) that could be compared with observations to estimate biases (see Fig. 8).

Testing of model fidelity

We test the ability of our forecast model to simulate the real world by comparing the forecast and observed distributions of FFDIDec and DI over a common period of time. Previous studies assessing likelihoods of extremes using forecast ensembles have tested that the observed mean, standard deviation, skewness and kurtosis of the variable in question falls within 95% confidence intervals from bootstrapped distributions of each statistic computed from the forecast model. We apply a different test for two reasons. First, our focus in this paper is on compound events and thus we seek to assess the fidelity of our model in simulating the joint distributions of FFDIDec and DI. Second, because the approach of previous studies simultaneously tests multiple statistics, each with their own statistical significance, it suffers from issues with multiple testing. Indeed, Monte–Carlo simulations applying the above test to samples and bootstrapped distributions drawn from the same Gaussian population show that the rejection rate is approximately 18% (not 5%), with little dependence on sample size. For two variables, the rejection rate is higher still.

For these reasons, we instead apply a two-dimensional Kolmogorov–Smirnov (KS) test to compare the joint distributions of FFDIDec and DI. The f2005 model dataset provides 96 (member) forecasts for the 7-year period 2014–2020 at all independent lead times (see Fig. 8). We calculate the two-dimensional KS statistic between the observed and forecast distributions, Kobs, using all data in this period. To derive a p-value for this statistic, we bootstrap 10,000 7-year pseudo-timeseries of FFDIDec and DI from all forecasts that fall within the same period. For each

dataset to produce 10,000 estimates of the mean Spearman correlation for each variable in the same manner as above. Because these estimates are constructed from randomly drawn data, they represent the distribution of mean correlation values for uncorrelated data (i.e., the null distribution). Ensemble members of each variable are considered to be independent (i.e., the null hypothesis of independence is rejected) at a given lead time if ρ = 0, and is consistent with the real world. For each lead time the mean DI bias as the difference between the mean f2005 and observed DI over the period 1990–2020. These biases (which range between −141 mm and −68 mm, depending on the lead time) are subtracted from both the f2005 and f1980 forecasts to produce unbiased estimates of DI. No bias correction is necessary for FFDIDec. Note that the f1980 model dataset is used here so that the biases can be estimated using a relatively long time period (31 years). The f2005 model dataset is a shorter period (2005–2020), so provides, for example, only seven years of data at 115 months lead (2014–2020) that could be compared with observations to estimate biases (see Fig. 8).

Bias correction

All climate models have systematic biases relative to the real world. There is a very large range of existing methods, of varying levels of complexity, for correcting for climate model biases. Generally, these methods involve building a transfer function between the distributions of observed and model variables over a particular period of time. All such methods include potentially ad hoc assumptions regarding, for example, the shape and stationarity of the observed modeled distributions. In the present analysis, we seek to use our forecast model to learn about events that are unprecedented in the historical record and therefore have no observations to constrain their correction. Our approach to model correction is to find the simplest justifiable method that produces model distributions that are statistically consistent with the limited historical record. In doing so, we minimize the extent to which the forecast model data are manipulated, and thus rely as much as possible on the ability of the model to simulate the range of contemporaneous climate conditions. It is necessary to bias-correct the forecast DI to ensure that the simulated joint distribution of FFDIDec and DI is consistent with the real world. For each forecast lead time, we estimate the mean DI bias as the difference between the mean f2005 and observed DI over the period 1990–2020. These biases (which range between −141 mm and −68 mm, depending on the lead time) are subtracted from both the f2005 and f1980 forecasts to produce unbiased estimates of DI. No bias correction is necessary for FFDIDec. Note that the f1980 model dataset is used here so that the biases can be estimated using a relatively long time period (31 years). The f2005 model dataset is a shorter period (2005–2020), so provides, for example, only seven years of data at 115 months lead (2014–2020) that could be compared with observations to estimate biases (see Fig. 8).

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For these reasons, we instead apply a two-dimensional Kolmogorov–Smirnov (KS) test to compare the joint distributions of FFDIDec and DI. The f2005 model dataset provides 96 (member) forecasts for the 7-year period 2014–2020 at all independent lead times (see Fig. 8). We calculate the two-dimensional KS statistic between the observed and forecast distributions, Kobs, using all data in this period. To derive a p-value for this statistic, we bootstrap 10,000 7-year pseudo-timeseries of FFDIDec and DI from all forecasts that fall within the same period. For each
bootstrapped sample, we calculate the two-dimensional KS statistic, K, relative to the full set of forecasts within the period, thus providing the null distribution for our KS test. If $K_{\text{obs}}$ falls below the 95th percentile of the null distribution — i.e., the right-tail $p$-value is greater than 0.05 — we cannot reject the null hypothesis that the joint distributions are the same. In this case, we consider that our forecast model provides a good representation of plausible values of $FFDIDec$ and DI.

The results of the two-dimensional KS test are shown for the bias-corrected $f_{2005}^{60\text{–}10\text{ mem}}$ model data in Fig. 4 (pink shading). We run the test for all lead times together (Fig. 4g) and for each lead month separately (Fig. 4h). In the latter case, the period of time over which the test is applied is adjusted to maximize the number of observed points in the comparison. For example, $f_{2005}^{60\text{–}10\text{ mem}}$ forecasts at 37-months lead span 2008–2020 (see Fig. 8) and the KS test at 37 months lead is applied over this period. We also apply the same KS test to the bias-corrected $f_{1980}^{60\text{–}10\text{ mem}}$ data, which span a longer period of time and hence allow for comparison to a larger sample of observations (Fig. 4g and h, purple shading). For the $f_{1980}^{60\text{–}10\text{ mem}}$ data, all KS tests are applied over the period 1989–2020.

**Calculation of likelihoods of exceedance**

Likelihoods of exceeding a given event are calculated from the empirical probability distribution as the proportion of total $f_{\text{mem}}$ forecast samples that are more extreme than the event in question. For example, Fig. 5a, b, respectively, show probabilities of $P(FFDIDec > FFDIDec_{\text{hist}})$ and $P(DI > DI_{\text{hist}})$ for every sample i of the 13,440 samples in the $f_{\text{mem}}$ dataset over 2014–2023, and Fig. 5c similarly show $P(FFDIDec > FFDIDec_{\text{hist}} / A_{\text{mem}} > A_{\text{hist}})$. In the calculation of likelihoods of exceedance, we limit ourselves to the 10 year period, 2014–2023, since all independent lead times are available from the model for these years (Fig. 8).

Likelihood confidence bounds in Figs. 5 and 7 are constructed by repeatedly bootstrapping the set of $FFDIDec$ and $A_{\text{mem}}$ values used to calculate the likelihood in question and recomputing the likelihood for each bootstrapped sample to produce 10,000 resampled estimates of the likelihoods of exceedance. These resampled likelihoods are used to calculate the 2.5–97.5% percentile ranges shown in the figures. In Fig. 5c, d, the likelihoods of exceedance are interpolated onto a regular grid using the ‘griddata’ routine in the Python Scipy library.

**Calculation of climate driver indices**

We employ three simple indices for climate modes that impact Australia. To assess the strength and phase of the El Niño Southern Oscillation (ENSO), we use the Nino 3.4 index, which is the difference between the average SST anomalies over western tropical Indian Ocean Dipole is quantified using the Dipole Mode Index, DMI, which is the difference between the average SST anomalies over western (10°N–5°S, 120°–170°W) and eastern (5°N–10°S, 90°–110°E) tropical Indian Ocean regions. We represent the strength of the Southern Annual Mode (SAM, also called the Antarctic Oscillation) using a Southern Annular Mode Index, SAM, defined as the difference between the normalized monthly zonal mean sea level pressure at 40°S and 65°S.

The climate mode indices are computed from the forecast model data and from reanalysis data: Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST1) for Nino 3.4 and DMI; and JRA-55 for SAM. Anomalies are computed relative to the climatological average over the period 1990–2020. In cases where forecast model data are used, a separate climatological average is constructed using the $f_{\text{mem}}$ dataset and removed for each forecast lead time. This removes from the forecasts the mean model biases over the reference period at each lead time. We focus on the average Nino 3.4 and SAM over September, October, November and December (SOND), and on the average DMI over September, October and November (SON). Corresponding to when each index has its strongest influence on precipitation and FFDI in southeast Australia, the fidelity of the model climate driver indices relative to observations and their relationships to $FFDIDec$ and DI are assessed in Supplementary Figs. 2 and 3.

**DATA AVAILABILITY**

FireCCI v5.1 and C3S v1.0 fire burned area data are openly available from the Copernicus Climate Data Store at https://doi.org/10.24381/cds.9f3328f7. New South Wales National Parks and Wildlife Service Fire History data are available for download at https://data.nsw.gov.au/data/dataset/fire-history-wildfires-and-prescribed-burns-1e86b. JRA-55 data are available from the University Corporation for Atmospheric Research Research Data Archive at https://doi.org/10.5065/D6HH6H41. HadISST1 data are available from the Met Office Hadley Centre at https://hadleyserver.metoffice.gov.uk/hadisst/data/download.html. AGCD v1 data are accessible from Australia’s National Computational Infrastructure Data Catalogue at https://doi.org/10.25914/609900858196. AGCD v2 data are not publicly available, with access details provided by the Bureau of Meteorology at http://www.bom.gov.au/climate/australs-fire/climate-data-monthly-rainfall.shtml. The Natural Earth data used to generate the shading in the inset of Fig. 1 are in the public domain and are available at https://www.naturalearthdata.com/. The forecast datasets are not yet available publicly but are available from the corresponding author upon request, bearing in mind that these datasets comprise hundreds of terabytes of data. Postprocessed versions of all the variables and indices presented in this paper are available from the corresponding author upon request.

**CODE AVAILABILITY**

All code used to perform the analysis and generate the figures in this paper is openly available at https://doi.org/10.5281/zenodo.5566244.

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AUTHOR CONTRIBUTIONS

D.T.S. and V.K. ran the ensemble forecasts. D.T.S. devised and performed the analysis and wrote the draft paper. All authors contributed to the development of the method, the interpretation of results and reviewed the paper.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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