Precipitation trends determine future occurrences of compound hot–dry events

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Compound hot–dry events—co-occurring hot and dry extremes—frequently cause damages to human and natural systems, often exceeding separate impacts from heatwaves and droughts. Strong increases in the occurrence of these events are projected with warming, but associated uncertainties remain large and poorly understood. Here, using climate model large ensembles, we show that mean precipitation trends exclusively modulate the future occurrence of compound hot–dry events over land. This occurs because local warming will be large enough that future droughts will always coincide with at least moderately hot extremes, even in a 2 °C warmer world. By contrast, precipitation trends are often weak and equivocal in sign, depending on the model, region and internal climate variability. Therefore, constraining regional precipitation trends will also constrain future compound hot–dry events. These results help to assess future frequencies of other compound extremes characterized by strongly different trends in the drivers.

To estimate the influence of internal climate variability, each of the seven SMILEs is run multiple times from different initial conditions, resulting in multiple ensemble members that span a range of plausible climates and associated future compound hot–dry (HD) uncertainties, which arise due to model-to-model differences in the intermodel range of the ensemble mean of future climate models (see Methods for details).

We focus on land masses and characterize hot–dry events on the basis of temperature and precipitation means over the warm season (the climatologically hottest three consecutive months), which is when the impacts from the compound event are generally most pronounced. We highlight that our main conclusions also apply to the wettest season, which for some regions may be the season where impacts from the compound event are largest. To study the concurrence of hot and dry conditions, we compute $f_{HD}$ as the empirical frequency (%) of concurrent extremes, that is, the count of simultaneous exceedances of temperature over its historical 90th percentile and precipitation below its historical 10th percentile (individual extremes occurring every ten years on average) divided by the total number of considered seasons.

Uncertainty in historical estimates

The global average of $f_{HD}$ over land during the historical period (1950–1980) is about 3% (Fig. 1a; compound events occurring every 33 years on average), which implies compound hot–dry events are three times more likely to occur than expected under independence between temperature and precipitation (1% probability). These estimates are in line with earlier results based on observations and climate model simulations and are controlled by the negative correlations between temperature and precipitation over land (cor = −0.42 on average) caused by a combination of atmospheric processes and land–atmosphere interactions.

Using large-ensemble simulations from multiple models demonstrates that large sample sizes are crucial for robust estimates.
Overall, model differences in \( f_{HD} \) are relatively small (Fig. 1b). By contrast, estimates of \( f_{HD} \) based on a single climate realization are highly uncertain because of internal climate variability (Fig. 1c), indicating a wide range of possible compound-event risk estimates. For example, the compound-event frequency \( f_{HD} \pm U_{IV} \), where the range \( \pm U_{IV} \) is an estimate of the 68% uncertainty range (Methods), is 3.6 ± 3.5% at the grid cell containing Paris, France. At the global scale, the relative uncertainty \( 2 \times U_{IV}/f_{HD} \) is 2.3 on average. Notably, the same metric for the frequency of (univariate) hot extremes derived from the same 31 years of data is 1.1, whereas to reach a relative uncertainty of 1.1 in \( f_{HD} \) requires 130 years of data (Extended Data Fig. 1). This highlights that estimates of compound-event frequencies are substantially more uncertain than related univariate estimates.

The uncertainty in local \( f_{HD} \) is reflected in estimates at the regional scale, which are often of interest for defining climate adaptation strategies\(^{31}\). For example, for Central Europe, Central North America and Amazon, which are at a relatively high risk of compound hot–dry events\(^{32,33}\) (Fig. 1a), the bottom 7% regionally averaged \( f_{HD} \) estimates among the ensemble members indicate frequencies in line with independence between temperature and precipitation (stippling in Fig. 1d–f), which are up to 13 times smaller than in the top 7% members (Fig. 1g–i). We conclude that estimates of the occurrence of compound hot–dry events based on relatively short climate data such as observations (<130 years) can be highly misleading as they may, by chance, indicate low compound-event risk in areas that are, instead, at high risk (or vice versa).

**Trends in mean precipitation as key modulator**

In a warmer climate, the global average frequency of compound hot–dry events is projected to increase to a land average of about 12% (multimodel range: 10–14%), or about four times higher compared with 1950–1980 (Fig. 2a)\(^4\). Compared with the historical period, the uncertainty in the \( f_{HD} \) estimates can be enhanced by model differences in the response to climate change and particularly in the projected regional mean warming and mean precipitation trends\(^{18}\). This would be expected as, for both temperature and precipitation, trends in mean conditions drive changes in extremes\(^{23,24}\), and therefore uncertainty in trends can affect future occurrences of univariate and compound extremes. Accordingly with this expectation, the uncertainty in local temperature trends leads to a large
In particular, models projecting a stronger increase in mean precipitation are associated with a lower frequency of concurrent hot and dry events in the future, and vice versa (mean correlation of −0.8, Fig. 3f). This relationship also holds when considering higher thresholds to define extremes, that is, potentially more impactful compound events, compound hot–dry events during the wettest season (Extended Data Fig. 4a–d) and other warming levels, as long as local warming trends are large compared with local precipitation trends (Extended Data Fig. 5 and Supplementary Information). Furthermore, while the underlying negative correlations between temperature and precipitation may favour the exclusive control of precipitation trends on future $f_{\text{HD}}$, results are similar when assuming zero correlation (Extended Data Figs. 5 and 6 and Supplementary Information). This indicates that a similar mechanism may govern the future dynamics of other compound events that are affected by global warming and for which trends in the drivers differ strongly in magnitude, regardless of the underlying dependencies between the compound-event drivers \cite{2,3}.

For example, the results are similar when considering compound hot–dry events defined on the basis of soil moisture rather than precipitation, that is, on the basis of soil moisture drought rather than meteorological drought (Extended Data Fig. 4e,f). Other events may include, for example, compound high-temperature and low-chlorophyll extremes in the ocean, which threaten marine ecosystems\cite{3}, sequential flood–heatwave events that slow recovery times and amplify damages\cite{4} as well as emerging novel combinations of extreme weather such as tropical cyclone–deadly heat compound events\cite{5}.

Overall, our results imply that improved modelling of precipitation trends is needed\cite{6,7,8}, to reduce uncertainties in the projection of future $f_{\text{HD}}$. However, we also find that about half of the uncertainty in precipitation trends (Extended Data Fig. 7c), and therefore in the future $f_{\text{HD}}$ (Fig. 2b), is driven by internal climate variability over the majority of land masses. This means that even if precipitation trends could be constrained for some regions\cite{9,10}, uncertainties would remain high for most land areas due to ‘certain uncertainty’ from unpredictable internal climate variability\cite{11}. Hence, given model and internal variability uncertainties, for practical risk assessment, considering distinct plausible precipitation trends, that is, different climate storylines\cite{12,13}, may be a way to plan for plausible future compound-event risk.

**Estimating future compound-event occurrences**

Across all large-scale regions commonly used in the Intergovernmental Panel on Climate Change, the regional average of the future $f_{\text{HD}}$ associated with different model ensemble members depends on mean precipitation trends (Extended Data Fig. 8). For example, this relationship holds over Central Europe (correlation $\text{cor}(f_{\text{HD}}, \Delta P_{\text{mean}}) = -0.9$, Fig. 4a), where model differences and internal climate variability equally contribute to uncertainties in future $f_{\text{HD}}$ (Fig. 2b). If mean precipitation weakly increases according to a ‘wet storyline’, compound hot–dry summers would occur in one out of ten years over Central Europe on average ($f_{\text{HD}} = 10\%$, Fig. 4d). Alternatively, an equally plausible ‘dry storyline’ characterized by decreasing mean precipitation would result in more than twice as many compound hot–dry summers ($f_{\text{HD}} = 26\%$, Fig. 4g). Future $f_{\text{HD}}$ is also controlled by mean precipitation trends over Central North America (correlation $\text{cor}(f_{\text{HD}}, \Delta P_{\text{mean}}) = -0.8$, Fig. 4b). According to the wet and dry storylines, regionally averaged compound-event frequencies range from 11% to 18%, respectively (Fig. 4e,h). The Amazon is a notable region where, contrary to most other regions, model differences dominate the uncertainties in precipitation trends (Extended Data Fig. 7c) and $f_{\text{HD}}$ (Fig. 2b). As a result, for the Amazon, improving the representation of the processes dominating mean precipitation trends, particularly the plant physiological response to $\text{CO}_2$, and changes in the Atlantic meridional overturning circulation\cite{14},...
is essential for constraining estimates of future compound risk. Here, compound-event frequencies range from 20% to 42% (Fig. 4f), according to a wet and a dry storyline (cor \(f_{\text{HD}}; \Delta P_{\text{mean}}\) = –0.9, Fig. 4c).

We focused on the frequency of concurrent extremes on the basis of historical exceedance thresholds, which is a widely used indicator of the frequency of impactful compound events\[58,101,128\]. The modulation of the future frequency of concurrent extremes from trends in one of the two compound-event drivers, here precipitation, is expected to hold for other compound events as long as the trends in the drivers differ strongly in magnitude (Extended Data Fig. 5). In general, the magnitude of some compound-event-related impacts may still be affected by the magnitude of exceedance in the driver with the strong trend, here temperature. Furthermore, adaptation of human and ecological systems may render historical hazard thresholds obsolete\[65\]. However, given that many impacts are characterized by threshold behaviour in response to climate stressors, for example tree mortality\[5\], crop yields\[61\], heat stress in humans and other species\[57\], landslides\[68\] and floods\[69\], estimating compound-event frequencies on the basis of historical exceedance thresholds can be considered a suitable impact indicator\[6,9,11,13,19,31\]. We thus conclude that the mechanism identified here provides relevant information to scientists and practitioners to reduce uncertainties when dealing with complex compound-event risks in the future.

Our results demonstrate that present estimates of concurrent hot and dry extremes based on relatively short climate records (<130 years) are highly uncertain as a result of internal climate variability and thus sampling uncertainty. For future estimates, given that in a warmer climate the importance of temperature variability in determining \(f_{\text{HD}}\) uncertainties vanishes, the importance of the statistical dependence between temperature and precipitation must vanish as well. That the uncertainty in future compound-event occurrence is merely a function of uncertain precipitation trends is reflected in a strong projected reduction in the relative uncertainties of the \(f_{\text{HD}}\) (that is, \(2\times U_{\text{inf}}(f_{\text{HD}})\)) that occurs despite an increase in the absolute uncertainty (\(2\times U_{\text{inf}}(f_{\text{HD}})\)) (Extended Data Fig. 9a–d). Nevertheless, relative uncertainties in the future \(f_{\text{HD}}\) due to climate model differences (\(2\times U_{\text{MD}}(f_{\text{HD}})\)) increase in a warmer climate over about 75% of land masses (Extended Data Fig. 9e–h), again reflecting the need for a better understanding of forced precipitation trends. Because uncertainty in mean precipitation trends is strongly modulated by large-scale atmospheric circulation\[30\], our results highlight that advancing our understanding of atmospheric circulation and its change is crucial for providing stakeholders with more-robust future \(f_{\text{HD}}\) estimates. This would be especially important in case we do not meet the warming targets from the Paris Agreement because, for instance at 3°C of global warming, model differences dominate the overall uncertainties over most land masses\[77,50\] (Extended Data Fig. 10). In any case, given the difficulties in constraining large-scale atmospheric circulation\[12,13\] and the omnipresent effects of internal climate variability\[55\], exploring potential impacts associated with a range of plausible storylines derived from multimodel large-ensemble simulations will offer new opportunities to develop societal preparedness for plausible worst-case scenarios.
Online content

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Methods

Data. We used seven SMILEs: CESM1-CAM551 (including 40 ensemble members), CSIRO-Mk3-6-0 (30), CanESM250 (30), EC-EARTH16 (16), GFDD-CM352 (20), GFDD-ESM2M50 (30) and MPI-ESM100. Monthly temperature and precipitation data were available for all models for the years 1950–2099, based on the representative concentration pathway53. RCP8.5 after 2005. Soil moisture over land masses (multimodel mean value). Similarly, 89% of droughts are hot that most future droughts (precipitation lower than the 5th percentile) are hot given a statistical quantity of interest

\[
X_{s,e} = \frac{1}{N_s} \sum_{e=1}^{N_s} X_{s,e}
\]

where \(N_s\) is the ensemble size of the considered SMILE model \(s\). \(X_{s,e}\) represents an estimate of the quantity \(X\) in the considered SMILE, where averaging across the ensemble members (indicated as \(\tau\)) leads to filtering out variations due to internal climate variability. When the quantity of interest \(X\) is a projected change, for example, \(\Delta P_{\text{mean}}\), it represents the forced response of \(P_{\text{mean}}\) in the considered SMILE.

The multimodel mean of \(X\) based on the \(N_s=7\) SMILEs was computed as the mean across the individual SMILE ensemble members:

\[
\bar{X}_s = \frac{1}{N_s} \sum_{e=1}^{N_s} X_{s,e}
\]

The uncertainty in \(X\) in a single realization due to internal climate variability (that is, in practice, the uncertainty in the quantity \(X\), when \(X\) is estimated from a single ensemble member of a given model) was estimated as an average of the internal climate variability effect on \(X\) in the seven SMILEs:

\[
U_{\text{IV}} = \sqrt{\frac{1}{N_{\text{mod}}-1} \sum_{e=1}^{N_{\text{mod}}} \left(\bar{X}_s - X_{s,e}\right)^2}
\]

where, in the SMILE \(s\), the spread in \(X\) due to internal climate variability was calculated as the sample standard deviation of \(X\) across the ensemble members:

\[
\sigma(X_s) = \sqrt{\frac{1}{N_s-1} \sum_{e=1}^{N_s} \left(X_{s,e} - \bar{X}_s\right)^2}
\]

Note that given that \(U_{\text{IV}}\) is obtained on the basis of the standard deviation, the value \(2 \times U_{\text{IV}}\) employed in Fig. 1c provides an estimate of the 68.2% uncertainty range in \(X\) due to internal climate variability (assuming that \(X\) is normally distributed—note that the actual distribution may deviate from normality; however, we tested a small sample size). Choosing different percentiles leads to similar patterns in the frequency of compound events16.

We compute empirical frequencies of concurrent extremes (\(f_{\text{con}}\)) and univariate extremes. For each model, extreme events of mean temperature and precipitation were defined as values above the 90th percentile and below the 10th percentile, respectively, of the distribution obtained by pooling together data of the period 1950–1980 from all available ensemble members (hence, extreme events in a warmer climate are defined on the basis of historical percentile thresholds). Employing more extreme percentiles to define extreme events would imply the considered compound events are very rare in the historical period; for example, the global average of \(f_{\text{con}}\) over land is 0.14% (corresponding to compound events occurring every 173 years on average) when employing the 99th and 1st percentile thresholds for defining temperature and precipitation extremes, respectively.

We confirm that our main result, that precipitation trends determine future occurrences of compound hot–dry events, generally holds when employing more extreme thresholds than the historical 10th and 90th percentiles (for example, for 5th and 95th percentiles, Extended Data Fig. 4.a,b). This is in line with the fact that most future droughts (precipitation lower than the 5th percentile) are hot (temperature higher than the 95th percentile) for 94% of droughts on average over land mass (multimodel mean value). Similarly, 89% of droughts are hot when employing 1st and 99th percentiles to define precipitation and temperature extremes, respectively, and 83% of droughts are hot when employing the 10th and 99th percentiles to define precipitation and temperature extremes, respectively.

Note that the analysis of compound hot–dry events defined on the basis of soil moisture (Extended Data Fig. 4.e,f) rather than on precipitation, that is, on the basis of dry events associated with soil moisture rather than meteorological drought, was carried out exactly as the analysis based on temperature and precipitation, but swapping precipitation for soil moisture and employing only four climate models.

Calculation of ensemble mean, multimodel mean, \(U_{\text{MD}}\) and \(U_{\text{IV}}\). Following ref. 14, given a statistical quantity of interest \(X\), we quantified the contribution to its uncertainty from uncertainty due to internal climate variability (\(U_{\text{IV}}\)) and model differences (\(U_{\text{MD}}\)). Here, \(X\) can be the \(f_{\text{con}}\) in the historical or future period, the historical frequency of hot events \(f_{\text{con}}\), the projected change in mean precipitation \(\Delta P_{\text{mean}}\) or the projected change in mean temperature \(\Delta T_{\text{mean}}\).

\[
X_{s,e} = \frac{1}{N_s} \sum_{e=1}^{N_s} X_{s,e}
\]

where \(N_s\) is the ensemble size of the considered SMILE model \(s\). \(X_{s,e}\) represents an estimate of the quantity \(X\) in the considered SMILE, where averaging across the ensemble members (indicated as \(\tau\)) leads to filtering out variations due to internal climate variability. When the quantity of interest \(X\) is a projected change, for example, \(\Delta P_{\text{mean}}\), it represents the forced response of \(P_{\text{mean}}\) in the considered SMILE.

The multimodel mean of \(X\) based on the \(N_s=7\) SMILEs was computed as the mean across the individual SMILE ensemble members:

\[
\bar{X}_s = \frac{1}{N_s} \sum_{e=1}^{N_s} X_{s,e}
\]

where, in the SMILE \(s\), the spread in \(X\) due to internal climate variability was calculated as the sample standard deviation of \(X\) across the ensemble members:

\[
\sigma(X_s) = \sqrt{\frac{1}{N_s-1} \sum_{e=1}^{N_s} \left(X_{s,e} - \bar{X}_s\right)^2}
\]

The larger the ensemble size, the smaller this correction term becomes15. In a few locations where model differences are small, it can occur that \(D^2 - E^2 < 0\), resulting in \(U_{\text{MD}}\) not being defined. In these cases, we set \(E=0\). Finally, the uncertainty in \(X\) due to model differences was quantified as:

\[
U_{\text{MD}} = \sqrt{\sigma^2_{MD}}
\]

Dependence of \(U_{\text{MD}}\) on sample size. We estimated how sample size affects the \(U_{\text{IV}}\) of both \(f_{\text{con}}\) and \(f_{\text{dry}}\) in the historical period. To achieve this, we created bootstrapped ensemble members of varying sample sizes (\(N_{\text{mod}}\)) from the 31 yr historical period (1950–1980) of MPI-ESM, the model with the largest number of ensemble members (100). Specifically, for any \(N_{\text{mod}}\) of interest, we constructed 12 ensemble members with sample size of \(N_{\text{mod}}\) years through sampling without replacement from the pool of 31,100 × 3,100 years of data. We consider 12 ensemble members as it allows for exploring uncertainties associated with a large sample size. In fact, using the 3,100 available years, the procedure allows for constructing 12 independent ensemble members having a sample size up to 258 years. On the basis of the 12 ensemble members, we computed the relative uncertainty \(2 \times U_{\text{IV}}/f_{\text{con}}\) where \(f_{\text{con}}\) was obtained via equation (1) and the uncertainty due to internal climate variability via equation (3), which—given that only one model is considered here—corresponds to the sample standard deviation of \(f_{\text{con}}\) across the 12 ensemble members (analogously for the \(f_{\text{dry}}\)). Hereby, \(N_{\text{mod}}\) varies from 15 to 258 years.

Note that results for \(f_{\text{dry}}\) and for the frequency of dry events are virtually identical; therefore, only \(f_{\text{con}}\) is shown in Extended Data Fig. 1b.
We tested that 12 ensemble members are enough for studying relative uncertainties. Results are robust to the random sampling; that is, the results are virtually identical when repeating the analysis multiple times. Combining results from the two randomly sampled ensemble members, the correlations of temperature and precipitation are very low on land areas. Overall, this method based on 12 randomly generated ensemble members from a single model (MPI-ESM) provides a robust estimate of the effect of internal variability, as demonstrated by the nearly identical uncertainty values obtained via the preceding method and that used in the rest of the paper for $N = 31$ years (see coloured dots in Extended Data Fig. 1b).

### Area-weighted aggregated statistics

All the statistics, such as mean, quantities and percentage of land masses, were weighted on the basis of the gridpoints surfaces, employing the R packages `wCorr` and `spatial`. We performed two experiments (results shown in Fig. 3) to quantify (1) the uncertainty range in the future $f_{\text{Hi}}$ (alike for the $f_{\text{Lo}}$) arising from the uncertainty in the change of local mean temperature, that is, uncertainty in local temperature trends, and (2) the uncertainty range in the future $f_{\text{Hi}}$ arising from the uncertainty in the change of local mean precipitation, that is, uncertainty in local precipitation trends.

At a given location, as a first step, we defined a wide range of plausible changes of mean precipitation and temperature. That is, from the pool of ensemble members introduced in the preceding section, we defined the highest, average, and lowest mean precipitation and temperature. That is, from the pool of ensemble members associated with two diverging local mean temperature changes. We first defined the uncertainty in mean temperature change $\sigma_{\text{mean}}(T)$ and $\sigma_{\text{mean}}(P)$, which were defined as in the preceding section to resemble the uncertainty around the expected changes. That is, normally distributed noise $\eta \sim N(0, \sigma_{\text{Lo}})$ and $\eta \sim N(0, \sigma_{\text{Hi}})$ is added to the 1,000 simulated $T_{\text{Lat}}$ and $P_{\text{Lat}}$. We then compute $f_{\text{Lo}}$ for the $i$-th 1,000 simulations, which is finally used to compute the correlation of the 1,000 pairs $(f_{\text{Lo}}, \eta)$ and $(f_{\text{Hi}}, \eta)$.

Finally, we tested that 12 ensemble members are enough for studying relative uncertainties. Results are robust to the random sampling; that is, the results are virtually identical when repeating the analysis multiple times. Combining results from the two randomly sampled ensemble members, the correlations of temperature and precipitation are very low on land areas. Overall, this method based on 12 randomly generated ensemble members from a single model (MPI-ESM) provides a robust estimate of the effect of internal variability, as demonstrated by the nearly identical uncertainty values obtained via the preceding method and that used in the rest of the paper for $N = 31$ years (see coloured dots in Extended Data Fig. 1b).

### Uncertainty range in local mean warming and precipitation trends

We performed two experiments (results shown in Fig. 3) to quantify (1) the uncertainty range in the future $f_{\text{Hi}}$ (alike for the $f_{\text{Lo}}$) arising from the uncertainty in the change of local mean temperature, that is, uncertainty in local temperature trends, and (2) the uncertainty range in the future $f_{\text{Hi}}$ arising from the uncertainty in the change of local mean precipitation, that is, uncertainty in local precipitation trends.

At a given location, as a first step, we defined a wide range of plausible changes of mean precipitation and temperature. That is, from the pool of ensemble members introduced in the preceding section, we defined the highest, average, and lowest mean precipitation and temperature. That is, from the pool of ensemble members associated with two diverging local mean temperature changes. We first defined the uncertainty in mean temperature change $\sigma_{\text{mean}}(T)$ and $\sigma_{\text{mean}}(P)$, which were defined as in the preceding section to resemble the uncertainty around the expected changes. That is, normally distributed noise $\eta \sim N(0, \sigma_{\text{Lo}})$ and $\eta \sim N(0, \sigma_{\text{Hi}})$ is added to the 1,000 simulated $T_{\text{Lat}}$ and $P_{\text{Lat}}$. We then compute $f_{\text{Lo}}$ for the $i$-th 1,000 simulations, which is finally used to compute the correlation of the 1,000 pairs $(f_{\text{Lo}}, \eta)$ and $(f_{\text{Hi}}, \eta)$.

Finally, we tested that 12 ensemble members are enough for studying relative uncertainties. Results are robust to the random sampling; that is, the results are virtually identical when repeating the analysis multiple times. Combining results from the two randomly sampled ensemble members, the correlations of temperature and precipitation are very low on land areas. Overall, this method based on 12 randomly generated ensemble members from a single model (MPI-ESM) provides a robust estimate of the effect of internal variability, as demonstrated by the nearly identical uncertainty values obtained via the preceding method and that used in the rest of the paper for $N = 31$ years (see coloured dots in Extended Data Fig. 1b).

### Pool of randomly sampled ensemble members

To obtain the composite maps in Fig. 1d–f and the plots in Fig. 4a and Extended Data Fig. 8, and to carry out the experiments introduced in the next three sections, we consider a pool of randomly sampled ensemble members from the merged members of all climate models. To give the same weight to all models, each model contributes equally to the pool with 16 randomly sampled members, where 16 is the number of available ensemble members from the climate model with the lowest number of members.

#### Uncertainty range from uncertainty in local mean warming and precipitation trends

We performed two experiments (results shown in Fig. 3) to quantify (1) the uncertainty range in the future $f_{\text{Hi}}$ (alike for the $f_{\text{Lo}}$) arising from the uncertainty in the change of local mean temperature, that is, uncertainty in local temperature trends, and (2) the uncertainty range in the future $f_{\text{Hi}}$ arising from the uncertainty in the change of local mean precipitation, that is, uncertainty in local precipitation trends.

At a given location, as a first step, we defined a wide range of plausible changes of mean precipitation and temperature. That is, from the pool of ensemble members introduced in the preceding section, we defined the highest, average, and lowest mean precipitation and temperature. That is, from the pool of ensemble members associated with two diverging local mean temperature changes. We first defined the uncertainty in mean temperature change $\sigma_{\text{mean}}(T)$ and $\sigma_{\text{mean}}(P)$, which were defined as in the preceding section to resemble the uncertainty around the expected changes. That is, normally distributed noise $\eta \sim N(0, \sigma_{\text{Lo}})$ and $\eta \sim N(0, \sigma_{\text{Hi}})$ is added to the 1,000 simulated $T_{\text{Lat}}$ and $P_{\text{Lat}}$. We then compute $f_{\text{Lo}}$ for the $i$-th 1,000 simulations, which is finally used to compute the correlation of the 1,000 pairs $(f_{\text{Lo}}, \eta)$ and $(f_{\text{Hi}}, \eta)$.

#### Correlation between variability in the future $f_{\text{Hi}}$ and temperature and precipitation trends

The future $f_{\text{Hi}}$ is correlated with precipitation trends; that is, models (or ensemble members) that project a stronger increase in mean precipitation lead to a lower future $f_{\text{Hi}}$, and vice versa (Figs. 3f and 4). To demonstrate that this result stems mainly from expected changes in mean temperature being much larger than expected changes in mean precipitation, and how the spatio-temporal dependence of future precipitation affects the spatio-temporal dependence of future precipitation, we carried out an idealized experiment (results shown in Extended Data Fig. 5).

For a combination of different expected $\Delta T_{\text{mean}}$ and $\Delta P_{\text{mean}}$, we quantified the correlation between the variability around such changes and the future $f_{\text{Hi}}$. Specifically, for a given combination of $\Delta T_{\text{mean}}$ and $\Delta P_{\text{mean}}$, we obtained 1,000 pairs of future $f_{\text{Hi}}$ and variability around the expected $\Delta T_{\text{mean}}$ (analogously for $\Delta P_{\text{mean}}$), which are used to compute the correlation. To obtain each of the 1,000 pairs, we simulated 300 pairs of temperature and precipitation from a bivariate Gaussian distribution (with $\sigma(T, P) = -0.5, 0$ and 0.5 and the same standard deviations as in the preceding experiment). We prescribed the mean of the distribution as $(\tilde{T}_{\text{Lat}}, \tilde{P}_{\text{Lat}})$, where $\tilde{T}_{\text{Lat}} = \tilde{T}_{\text{Hist}} + \Delta T_{\text{mean}}$ and $\tilde{P}_{\text{Lat}} = \eta_{\text{Hist}} + \Delta P_{\text{mean}}$, where $\tilde{T}_{\text{Hist}}$ and $\tilde{P}_{\text{Hist}}$ are the historical data of the SMILE model (data of the period 1950–1980; $\tilde{T}_{\text{Hist}}$ and $\tilde{P}_{\text{Hist}}$ are obtained by merging data from all ensemble members of the SMILE model such as to get a unique reference dataset and more-robust estimates).

Finally, we defined the uncertainty range as the multimodel mean of the preceding differences.

### Regional storylines of future $f_{\text{Hi}}$

In Fig. 4a, we show plausible storylines of future $f_{\text{Hi}}$, resulting from two contrasting precipitation trends. That is, for a given region, we build the dry storyline of future $f_{\text{Hi}}$ through averaging $f_{\text{Hi}}$ spatial fields associated with the bottom 7% ensemble members of a pool of members in terms of ensemble member’s area-weighted aggregated changes. The same approach is taken to create a wet storyline, which corresponds to the top 7% ensemble members. The pool of ensemble members is introduced in the section ‘Pool of randomly sampled ensemble members.’

#### Data availability

The model data used in the study are openly available online at https://esgf-data.dkrz.de/projects/mri-ge/ (for the model MPI-GE) and https://esgf-data-explorer.nordenergy.org/dataset/acar.cgd.ccas4.EMMECLIVAR.LE.html (for the other models: CanESM2, CESM-LE, CSIRO-Mk3-6-0, GFDL-ESM2M and GFDL-CM3). The HadCRUT5 dataset is available at https://www.metoffice.gov.uk/hadobs/hadcrut5/.

#### Code availability

All custom codes are direct implementations of standard methods and techniques, described in detail in Methods.
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Author contributions
E.B. and J.Z. initiated and designed the study. E.B. carried out the analysis. E.B wrote the manuscript with contributions from J.Z. All authors (E.B, G.Z., F.L. and J.Z.) discussed the results and reviewed the manuscript.

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Extended Data Fig. 1 | Relative uncertainty due to internal climate variability in frequencies of hot events ($f_h$) and compound hot-dry events ($f_{hD}$) in the historical period. 

**a**. The same as Fig. 1c, but for $f_h$, that is the uncertainty in $f_h$ due to internal climate variability ($2 \times U_{IV}$) relative to $f_h$. The image is obtained using, as in the rest of the paper, samples of 31 years. The same palette as in Fig. 1c is used for comparison. 

**b**. Curves show the dependence of the relative uncertainty due to internal climate variability in $f_{hD}$ (green) and $f_h$ (magenta) on the sample size. To explore the relationship for large sample sizes, the curves are obtained based on a method that employs data from the model with the largest number of ensembles, that is the MPI-ESM model (Methods). The arrows indicate the difference between the sample size required to obtain fixed levels of relative uncertainty for $f_{hD}$ and $f_h$. The green and magenta dots show the relative uncertainties obtained via the method used in the rest of the paper, hence based on all seven climate models and 31 years of data. The match between the dots and the curve highlights that the estimate of the uncertainty obtained through the MPI-ESM-based method provides accurate information.
Extended Data Fig. 2 | Temperature changes in a world 2 °C warmer than pre-industrial conditions and associated drivers of uncertainties.

a. Multimodel mean projected change in frequency of hot extreme events (relative to 1950–1980). Stippling indicates locations where at least six out of seven models agree on the sign of the change. b. As in panel a, but for changes in mean temperature. c. Uncertainty in the change in mean temperature due to model-to-model differences ($U_{MD}$) relative to the sum of $U_{IV}$ (uncertainty due to internal climate variability) and $U_{MD}$ (expressed in percentage; see Methods).
Extended Data Fig. 3 | See next page for caption.
Extended Data Fig. 3 | Uncertainty in the frequency of compound hot-dry events ($f_{HD}$) in idealised experiments. (Note that an in-depth interpretation of the figure is provided in the Supplementary Material.) Given a present-day bivariate Gaussian distribution of temperature $T$ and precipitation $P$ with a correlation $\text{cor}(T, P)$ of -0.5 (first row), 0 (second row), and 0.5 (third row), shading shows the uncertainty in the future $f_{HD}$ associated with uncertainty in the change of mean temperature (left column) and mean precipitation (right column) at given levels of expected changes in mean temperature (shown on the $x$-axis) and mean precipitation (y-axis). Magenta isolines show the expected $f_{HD}$ resulting from the expected changes in mean temperature and precipitation (they are the same on right and left columns for a given $\text{cor}(T, P)$). The second axes show changes in units of present-day standard deviations. The closed contour shows the kernel density containing 90% of the multimodel mean projected changes in mean temperature and precipitation in units of relative present-day standard deviations over land grid-points (actual changes in °C and mm/day are shown in Extended Data Figure 2b and 7b, respectively). The green line indicates changes of equal magnitude in temperature and precipitation, in units of present-day standard deviations. (Note that the difference in magnitude of uncertainty from temperature (left column) and precipitation (right column) results from the fact that the uncertainty in the change of temperature is relatively large compared to the uncertainty in the change of precipitation).
Extended Data Fig. 4 | Effect of uncertainty in local warming and precipitation or soil moisture trends on future \( f_{HD} \). a-b, The same as Fig. 3c,f, but for extreme events of temperature and precipitation that are defined as values above and below their individual 95th and 5th percentiles, respectively. c-d. The same as Fig. 3c,f, but when considering compound hot-dry events during the wettest, instead than the hottest, season. e-f, The same as Fig. 3c,f, but when considering soil moisture rather than precipitation and based on four rather than seven available climate models.
Extended Data Fig. 5 | See next page for caption.
Extended Data Fig. 5 | Correlation between the future frequency of compound hot-dry events ($f_{HD}$) and changes in mean temperature and precipitation in idealised experiments. (Note that an in-depth interpretation of the figure is provided in the Supplementary Material.) Pairs of temperature $T$ and precipitation $P$ are simulated from a bivariate Gaussian distribution with a given $\text{cor}(T, P)$ which considers an expected future change in mean precipitation and temperature and variability around this change. For a given mean temperature change of $+2 \, ^\circ\text{C}$ and no change in mean precipitation, panel a,b show how future $f_{HD}$ depends on the exact change in temperature and precipitation, respectively (given $\text{cor}(T, P) = -0.5$). For different values of $\text{cor}(T, P)$ of -0.5 (c,d), 0 (e,f), and 0.5 (g,h), shading shows the correlation between the future $f_{HD}$ and the change in temperature (left column) and precipitation (right column) at given levels of expected changes in mean temperature (shown on the x-axis) and mean precipitation (y-axis). For example, the correlation coefficient of the pairs in a is reported in panel c. Axes, green lines, and closed contours are the same as in Extended Data Figure 3. Stippling indicates where at least 90% of the $f_{HD}$ values from the Gaussian distribution are equal to 0%.
Extended Data Fig. 6 | Effect of uncertainty in local warming and precipitation trends on future $f_{10}$ under no dependence between temperature and precipitation. The same as Fig. 3c,e,f, but in a scenario within which the warm-season mean temperature $T$ and precipitation $P$ time series are uncorrelated. That is, for each model ensemble member, the thirty-one pairs $(T,P)$ of the period 1950-1980 and in the warmer climate period are randomly shuffled prior to proceeding with the rest of the analysis.
Extended Data Fig. 7 | Precipitation changes in a world 2 °C warmer than pre-industrial conditions and associated drivers of uncertainties. The same as Extended Data Figure 2, but for precipitation.
Extended Data Fig. 8 | Relationship between regional future frequency of compound hot-dry events ($f_{HD}$) and mean precipitation trends. Similar to Fig. 4, but for all of the regions used in the Intergovernmental Panel on Climate Change (IPCC). That is, in a world 2 °C warmer than pre-industrial conditions, regionally averaged future $f_{HD}$ against changes in mean precipitation (relative to 1950-1980) are shown for all IPCC regions (differentiated by colored symbols), based on a pool of ensemble members from different climate models (Methods). The image highlights that the relationship is non-linear, in line with theoretical expectations (Figure Extended Data Figure 5b). Such a non-linear behaviour is not well evident when considering individual regions given the more limited range of uncertainty of precipitation trends.
Extended Data Fig. 9 | See next page for caption.
Extended Data Fig. 9 | Sources of uncertainty in the frequency of compound hot-dry events ($f_{HD}$) in the historical period and in the future (a world 2°C warmer than pre-industrial conditions). a,b. Uncertainty due to internal climate variability (2 × $U_{IV}$) relative to $f_{HD}$ in the historical and future periods, respectively. Panel a is the same as Fig. 1c. c,d. Uncertainty due to internal climate variability (2 × $U_{IV}$) in historical and future periods, respectively. e,f. Uncertainty in $f_{HD}$ due to model-to-model differences (2 × $U_{MD}$) relative to $f_{HD}$ in the historical and future periods, respectively. g,h. Uncertainty in $f_{HD}$ due to model-to-model differences (2 × $U_{MD}$) in the historical and future periods, respectively.
Extended Data Fig. 10 | Drivers of uncertainties in future frequency of compound hot-dry events ($f_{HD}$) and mean precipitation trends in a world 3 °C warmer than pre-industrial conditions. a,b, As in Fig. 2b and Extended Data Figure 7c, respectively, but in a world 3 °C warmer than pre-industrial conditions. That is, uncertainty due to model-to-model differences ($U_{MD}$) relative to the sum of $U_{IV}$ (uncertainty due to internal climate variability) and $U_{MD}$ for future $f_{HD}$ in a and mean precipitation trends in b. $U_{MD}$ is larger than $U_{IV}$ over 67% and 77% of landmasses for future $f_{HD}$ and mean precipitation trends, respectively.