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Net benefits to US soy and maize yields from intensifying hourly rainfall

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Many varieties of short-duration extreme weather pose a threat to global crop production, food security and farmer livelihoods[1–4]. Hourly exposure to extreme heat has been identified as detrimental to crop yields[1,5]; however, the influence of hourly rainfall intensity and extremes on yields remains unknown[4,6,7]. Here, we show that while maize and soy yields in the United States are severely damaged by the rarest hourly rainfall extremes (≥50 mm hr^{-1}), they benefit from heavy rainfall up to 20 mm hr^{-1}, roughly the heaviest downpour of the year on average. We also find that yields decrease in response to drizzle (0.1–1 mm hr^{-1}), revealing a complex pattern of yield sensitivity across the range of hourly intensities. We project that crop yields will benefit by ~1–3% on average due to projected future rainfall intensification under climate warming[8,9], slightly offsetting the larger expected yield declines from excess heat, with the benefits of more heavy rainfall hours outweighing the damages due to additional extremes. Our results challenge the view that an increasing frequency of high-intensity rainfall events poses an unequivocal risk to crop yields[2,7,10] and provide insights that may guide adaptive crop management and improve crop models.

Crop production is sensitive to variation in climate and weather, with 30–40% of the variability in global crop yields attributable to monthly and seasonal climate[11,12]. Recent research has emphasized the important impacts of short-duration weather extremes on crop yields, particularly the steep reductions from hourly exposure to high temperatures[1,5]. However, the influence of short-duration rainfall intensity and extremes on yields remains scarcely understood and is widely omitted from historical analyses, crop models and climate risk projections[2,4,6,7,13,14].

Assessments of the effects of rainfall variability on crop yields have focused on monthly to seasonal total accumulation, detecting regionally variable and often weak relationships[1,5,11,12,15,16]. However, rainfall occurs in events with a mean duration of several hours that vary in intensity by up to three orders of magnitude, from less than 1 to over 100 mm hr^{-1} (refs. [17,18]). The response of crop yields to both extreme and common rainfall intensities remains obscured by analyses using longer-term rainfall totals. Given that the largest changes to rainfall climatology under global warming are projected to occur at subdaily timescales[9,19], anticipating and adapting to the impacts of climate change on global crop production require a detailed understanding of the yield response to short-duration rainfall intensity.

In this study, we assess the sensitivity of crop yields in the United States to hourly rainfall intensity and extremes over 2002–2017. Combining high-spatial-resolution hourly rainfall observations with county-level maize and soy yield data, we identify threshold intensities of extreme downpours with damaging effects on yields and two additional non-extreme intensity zones with significant impacts ($P<0.05$). We then illustrate the importance of hourly rainfall intensity to crops by comparing its influence with that of rainfall distribution across other timescales. Finally, we project future crop yield impacts under three scenarios of changing rainfall intensity in response to climate warming.

We find substantial deleterious effects of the most extreme rainfall events on crop yields. County-level maize yields decline by 23–45 bushels (bu) per acre per hour of exposure to rainfall with intensities of 80–90 mm hr^{-1} ($P<0.05$, Fig. 1a,b and Supplementary Table 1), or 16–32% of the national mean yield. Soy yields decline at lower-intensity thresholds of 50–70 mm hr^{-1} and by a smaller amount of 2 to 4 bu ac^{-1} per hour of exposure, or 5–10% of the national mean ($P<0.01$, Fig. 1c,d and Supplementary Table 1). This yield reduction is similar for soy and larger for maize compared with daily exposure to extreme temperatures of 40 °C (~7% per day)[1].

The impacts of such extreme rainfall events may result from direct damage to plant tissue, either by rainfall or by the wind and hail that often accompany such storms[20]. Indirect mechanisms such as waterlogging and rhizosphere anoxia[7,21] or soil erosion[22] and soluble nutrient leaching[23] may also cause or compound the yield reduction. These potential mechanisms may explain the differing responses between crops: soy may be damaged at a lower intensity than maize due to its broader foliar configuration and weaker stems, while the magnitude of damage may be mitigated by its nitrogen fixation capacity[23,24].

The damaging rainfall extremes exceed the 99.95th percentile of hourly intensity, representing once-per-decade to once-per-century events (Figs. 1 and 2, and Supplementary Table 2). In contrast, crop yields benefit from heavy rainfall up to the 99.5th percentile of hourly intensity, roughly a once-per-year event. Yields increase by ~1 bu ac^{-1} hr^{-1} for maize and ~0.1 bu ac^{-1} hr^{-1} for soy from exposure to heavy rainfall ranging from 5 to 20 mm hr^{-1} ($P<0.001$, Fig. 1a–d). Meanwhile, exposure to very light drizzle (0.1 to 1 mm hr^{-1}) corresponds to significant yield reductions in both maize (~0.1 bu ac^{-1} hr^{-1}, $P<10^{-8}$) and soy (~0.01 bu ac^{-1} hr^{-1}, $P<10^{-8}$). This drizzle effect is significant from 0.1 to 2.2 mm hr^{-1} for maize and 0.1 to 1.4 mm hr^{-1} for soy, and largest in magnitude between 1 and 2 mm hr^{-1} (Supplementary Fig. 1).

Our analysis thus reveals a pattern of yield responses to rainfall intensity that varies substantially across the range of hourly intensities and is broadly consistent between the two crops. The estimated magnitudes of yield responses to drizzle and heavy rainfall are at least as large as those to the more widely studied seasonal total rainfall and multiday extremes (Fig. 3). Crucially, we find positive or statistically insignificant yield sensitivities to the annual maxima of hourly and daily rainfall (Fig. 3), probably because these measures capture beneficial heavy hourly intensities[2,10] (the mean national maximum hourly rainfall is 29 mm hr^{-1}, Fig. 2 and Extended

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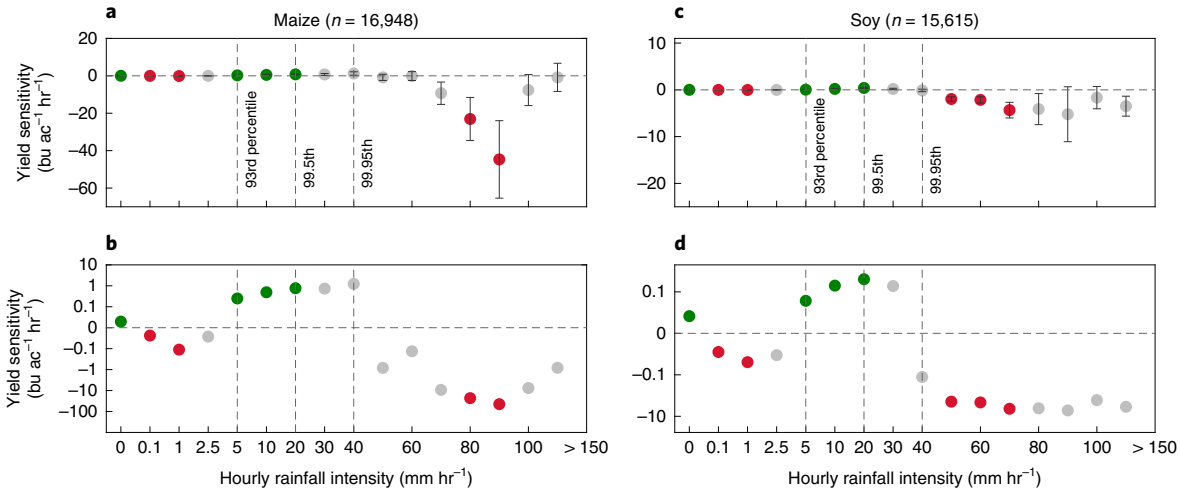

Fig. 1 | Sensitivity of maize and soy yields to hourly rainfall intensity. a, National mean county-level maize yield sensitivity (±s.e.m.) to hourly rainfall intensity per hour of exposure over 2002–2017. **b**, Same as in **a**, but on symmetric logarithmic axes. **c**,**d**, Same as in **a**,**b**, but for soy. The vertical dashed lines denote the indicated percentiles of climatological rainfall intensity. The sensitivities are inferred from a model controlling for exposure to beneficial and excessive heat and seasonal total rainfall. The sample sizes reflect county-year pairs. The dark-green and red points indicate significant positive and negative sensitivities (two-sided $P < 0.05$, Supplementary Table 1). Transformed standard error estimates are omitted in **b** and **d** for clarity.

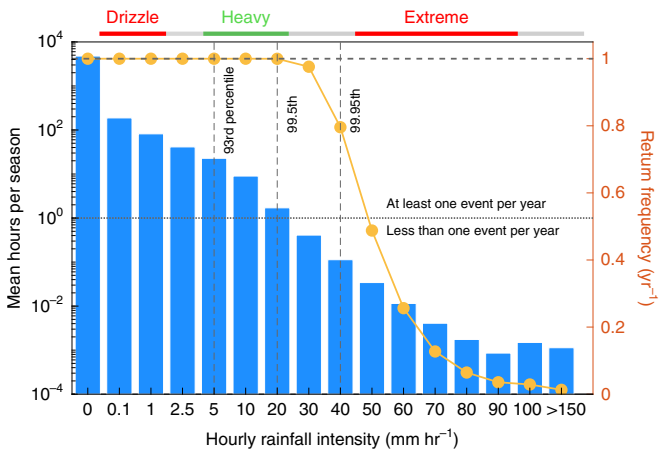

Fig. 2 | Frequency distribution of hourly rainfall intensities. National average county-level number of exposure hours per season (blue bars) and estimated national return frequency (yellow curve) for each hourly rainfall intensity bin over 2002–2017. The horizontal dotted line represents a once-per-year occurrence (mean hours per season of 1), such that bars above the line occur annually on average while bars below the line occur less than once per year. For the return frequency, a value of 1 (horizontal dashed line) indicates an event that occurs in every year for each county in the sample. The vertical dashed lines denote the indicated percentiles of climatological rainfall intensity.

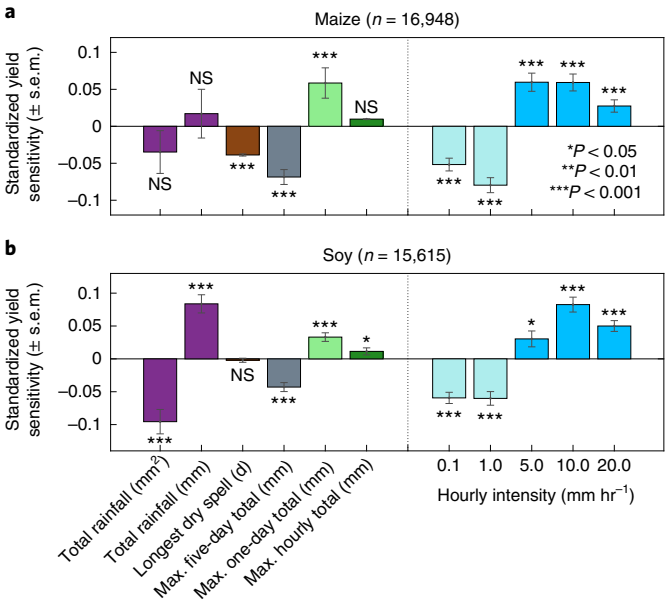

Fig. 3 | Crop yield sensitivity to rainfall distribution across timescales. **a**,**b**, Yield sensitivity estimates (±s.e.m.) to five measures of subseasonal rainfall distribution and select hourly intensities over 2002–2017 for maize (**a**) and soy (**b**). The subseasonal measures include seasonal total rainfall, duration of the longest dry spell and seasonal maxima of five-day, one-day and hourly total accumulations. The sensitivities are standardized to enable comparison among measures of differing units and variances. All P values are two-sided. NS denotes coefficients with $P > 0.05$.

Data Fig. 1). These findings underline the importance of accounting explicitly for subdaily intensity in understanding and projecting the impact of rainfall on crops, as simple annual maxima or percentile-based definitions may conceal crucial complexities and nonlinear responses[2,10,13,14].

Because we control for seasonal total rainfall, our estimated yield sensitivities reflect the yield impact of an incremental hour at a given rainfall intensity aside from its contribution to integrated moisture conditions. Our results thus suggest that heavy rainfall benefits crops because of its intensity, not merely because it contributes greater moisture than lower intensities. The significant benefits to crop yields from zero-rainfall hours are consistent with this interpretation (Fig. 1): given the seasonal total rainfall control and the fixed total number of hours per growing season, each incremental dry hour reduces the incidence of damaging drizzle and increases that of beneficial heavy rainfall (Fig. 1).

Regional differences in the pattern of yield response to rainfall intensity suggest that heavy rainfall benefits yields by providing moisture that is more plant-available than drizzle[25,26]. A higher fraction of heavier rainfall infiltrates the root zone, while a higher

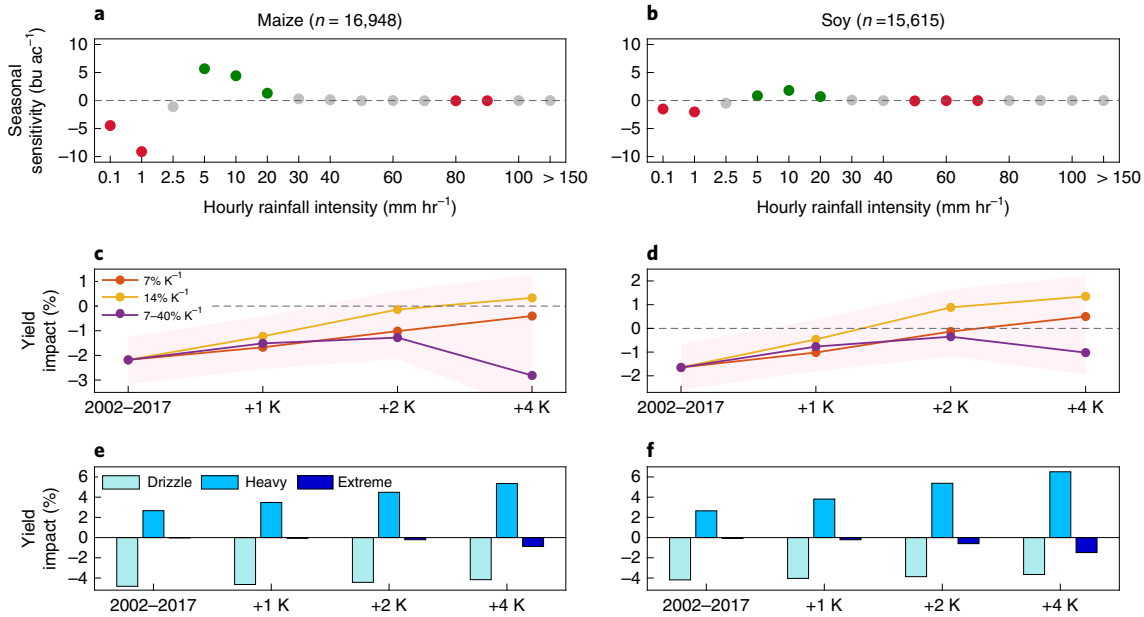

Fig. 4 | Current and projected future net yield impacts of hourly rainfall intensity. a,**b**, Integrated seasonal yield sensitivities for maize (**a**) and soy (**b**), estimated by weighting the per-hour sensitivity by total exposure hours. **c**,**d**, Net impacts across all intensities on maize (**c**) and soy (**d**) yields under the 2002–2017 climate and for 1, 2 and 4 K warming for three rainfall intensification scenarios: low change (red), high change (yellow) and amplified (purple). The shaded area shows the 90% confidence interval accounting for regression and scenario uncertainties. The net impacts are presented as percentages of the national mean yield. **e**,**f**, Same as in **c**,**d** for the 14% K^{-1} scenario, but with the yield impacts partitioned by intensity zone. For other scenarios, see Supplementary Fig. 2.

fraction of drizzle evaporates from the canopy, evading the crop. By this logic, heavy rain would offer a greater advantage to more moisture-limited crops. Indeed, we find contrasting yield responses to drizzle versus heavy rainfall consistent with the national pattern in the more moisture-limited northeastern and western portions of our study region, but not in the wetter southeast, where heavy rainfall is ~25% more frequent (Extended Data Fig. 2, Supplementary Table 3 and Methods). Consistent with this potential mechanism, we find a weaker contrast between drizzle and heavy rainfall effects on yield in more heavily irrigated counties (Extended Data Fig. 3). The damaging effect of drizzle most likely reflects a missed opportunity to receive heavy rainfall, but may also arise partly from conditions conducive to foliar fungal pathogens[27,28]. Further research into interactions between rainfall intensity and the canopy–soil continuum may clarify the mechanism behind the contrasting impacts of heavy rainfall and drizzle.

In contrast to rare, damaging extremes, drizzle and heavy rainfall occur essentially every year for each county in our sample (Fig. 2). To account for the variable incidence of differing rainfall intensities, we estimate the integrated seasonal yield sensitivity by weighting the per-hour sensitivities (Fig. 1) by the average seasonal total exposure hours for each intensity bin (Fig. 2, Supplementary Table 2 and Methods). Despite a large per-hour sensitivity to extreme rainfall, the magnitude of the integrated seasonal sensitivity to heavy rainfall and drizzle (order 1–10 bu ac^{-1}) exceeds that of extremes (order 0.01–0.1 bu ac^{-1}) due to the relative commonness of heavy rainfall and drizzle (Figs. 2 and 4a,b, and Supplementary Table 2). In the current climate, we estimate a combined net negative yield impact from the hourly rainfall intensity distribution (2.2% of the mean national yield for maize and 1.6% for soy), with the dominant negative influence of drizzle only partly offset by the benefit of heavy rainfall (Fig. 4c–f). This indicates a suboptimal hourly rainfall distribution in the current climate.

In a warming climate, heavy and extreme rainfall events are expected to intensify because the saturation vapour pressure of air increases by ~7% K^{-1}, boosting precipitable water in the atmosphere[8,9]. However, rainfall intensification may exceed this scaling as condensation and latent heating enhance convection[29,30], an effect that may be amplified for higher rainfall intensities[31,32]. We project the change in net intensity effects under three idealized intensification scenarios derived from recent empirical and modelling studies: uniform low and high change (7 and 14% K^{-1}) across the intensity distribution[29,30], and amplified change increasing with intensity from 7 to 40% K^{-1} (refs. [31–33]) (Extended Data Fig. 4 and Methods).

To assess the implications of hourly rainfall intensification for crop yields under climate warming, we apply the scaling factors for each scenario to intensities ≥5 mm hr^{-1} under idealized warming of 1, 2 and 4 K compared with the present. We keep all other variables constant to isolate the impact of rainfall intensification. We find that under all three scenarios, crop yields increase meaningfully with intensifying hourly rainfall (Fig. 4c,d), primarily due to the increased incidence of beneficial heavy events (Fig. 4e,f, Extended Data Fig. 4 and Supplementary Fig. 2). In response to rainfall intensification from 2 K warming, we project yield increases ranging from 0.9% to 2.1% across scenarios for maize and 1.3% to 2.5% for soy, approximately equivalent to recent harvests of Ethiopian maize and Russian soy. Soy yields increase by 0.7% and maize yields decrease by 0.6% under the amplified scenario with 4 K warming, the worst case among the three scenarios due to the greatest rises in damaging extremes (Fig. 4e,f, purple curve). Our projections thus suggest that, on average, yields will most likely benefit slightly from rainfall intensification itself. However, this yield boost would only partly offset the larger expected losses from heat stress (~10–30% for maize and ~0–15% for soy under 2 K warming[34]).

Several limitations of our study should be noted. First, although we focus on United States maize and soy as globally important and widely cultivated crops, attention to other crops and regions may yield important insights into the ecophysiology and generalizability of our results. Second, while our analysis focuses on the full growing season, future work may investigate the importance of the duration,

timing and sequences of hourly rainfall, especially relative to crop growth phases[35] and regionally varying growing seasons. Third, our method precludes projecting impacts due to unprecedented rainfall intensities and changes in the temporal and spatial structure of rainfall events. Interactive effects of changing heat, rainfall intensity and seasonal total rainfall on crop yields also merit further attention. Finally, variables such as hail and wind, pests and disease, soil characteristics[14], and antecedent moisture[13] are unavailable at sufficient spatial resolution for inclusion in our analysis, but probably compound or mediate the yield responses and may explain their regional variation.

We draw the following three overall conclusions from our study. First, rainfall intensity exerts an important influence on crop yields that varies substantially across the range of hourly intensities. Yields are reduced by drizzle but benefit from heavy rainfall, with damages only from exceptionally extreme events. Second, although extremes are severely damaging to crops, their rareness limits their overall influence on yields. As a result, crops are most responsive overall to drizzle and heavy rainfall rather than rare extremes. Third, rainfall intensification will on average benefit rather than harm crop yields, as damaging extremes remain much rarer than heavy rainfall under most plausible climate change scenarios. These benefits will not, however, outweigh the expected losses from higher temperatures.

Our findings may help identify new opportunities for climate-adaptive crop management and improved modelling. For instance, we propose potential mechanisms behind the contrasting yield responses to drizzle and heavy rainfall that, if corroborated, may help refine optimal sowing densities for both the current and future climate. Furthermore, incorporating rainfall intensity effects into crop models may enhance their experimental and predictive value[6]. Most fundamentally, our results suggest that beyond extreme events, the crop yield response to more common rainfall intensities merits further attention.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-020-0830-0.

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Methods

We employ the Stage IV gridded mosaic of radar-derived hourly rainfall data for the continental United States at 4 km resolution, obtained for 2002–2017 from the National Center for Environment Prediction[36]. The Stage IV data are bias corrected and quality controlled using gauge-based observations. The annual county-level maize and soy yield data were compiled from USDA National Agriculture Statistical Survey Quick Stats[37]. The daily temperature data were obtained from the National Center for Environment Prediction Climate Prediction Center's observational gridded dataset at 0.5-degree resolution. We also use daily 1 km gridded total incident surface shortwave radiation data from Daymet[38]. All datasets supporting the results of this paper are freely available from the references and links listed in Supplementary Table 4.

All subcounty and subseasonal-scale data were aggregated to the seasonal and county scales to correspond with the annual county-level yield data, which constituted the limiting spatial and temporal sampling resolution in the dataset. Temporal aggregation was based on the national average maize and soy growing season of March–September (that is, the full envelope of the national growing season) to avoid the erroneous exclusion of rainfall events that may result from downscaling available state-level crop progress data to the study resolution. Our reported pattern of yield sensitivities is also robust when using a growing season of March–August in the southern portion of the study region and April–September in the north (that is, a one-month shift) to broadly reflect variable cropping seasons across the region (Supplementary Fig. 4). The daily temperatures were aggregated to the growing season via growing and killing degree days (GDD and KDD) as measures of aggregate exposure to beneficial and excessive heat, respectively[39]. We do not spatially downscale the daily temperature observations used to compute GDD and KDD to the subcounty scale, as temperature is less variable on fine spatial scales than rainfall. Our estimated sensitivity to KDD on a national average concurs with estimates based on station data[39].

The hourly rainfall data were aggregated to the seasonal scale by computing intensity-binned histograms summarizing all hours in each growing season and county, and via summing across all hours for the seasonal total rainfall control. Figure 2 shows the mean intensity-binned histogram averaged across all counties and years. The intensity-binning scheme was chosen to reflect conventional meteorological classifications of rainfall (for example, 0.1 mm hr^{-1} as intensities above trace rainfall and 2.5 mm hr^{-1} to represent the upper limit of drizzle intensities), and the results are robust to varying bin widths and centres (Supplementary Figs. 1 and 3). The occurrence of extreme rainfall in our sample was relatively uniform in time over 2002–2017 (Supplementary Fig. 5). To match the county-level spatial resolution of the yield data, all final derived temperature and rainfall measures were aggregated to the county scale by averaging over all grid cells within each county. Finally, the spatial domain of the analysis was limited to counties east of the 104th meridian, as the density of radar stations west of this limit dropped sufficiently to raise concerns about data quality. The region included in the analysis comprises the majority of US maize and soy production areas.

To examine the effects on crop yields due to specific hourly rainfall intensity, we apply a linear fixed-effects multiple regression model of the form:

$$\hat{y}_{i,t,b} = C_i + T_t + \boldsymbol{\beta}_1 \mathbf{W}_{i,t} + \beta_b H_{i,t,b} \quad (1)$$

where $\hat{y}_{i,t,b}$ is the predicted yield for year t in county i and intensity bin b. The first two terms are controls, including a county-specific intercept vector (C_i) to account for time-invariant spatial yield heterogeneity and a national time fixed effect (T_t) to account for broader yield time trends (Supplementary Table 5). We account for long-term yield trends using a time fixed-effect rather than a linear or quadratic time trend, as the short time period of the analysis is insufficient for reliable trend estimation. The third term is a vector of seasonal weather measures $\mathbf{W}_{i,t}$ (with the corresponding coefficient vector $\boldsymbol{\beta}_1$) including linear terms for GDD and KDD, which together capture the nonlinear yield response to temperature, and a quadratic term for seasonal total rainfall predictors, which captures the damaging yield effects of both drought and seasonal excess moisture.

We estimate the national mean sensitivity of county-level yields to specific hourly rainfall intensities as the coefficient β_b on seasonal total exposure hours to rainfall intensities in bin b ($H_{i,t,b}$) in equation (1). This term regresses yields against each bin in the county-specific seasonal rainfall intensity histogram, resulting in a national mean estimate of county-level yield sensitivity per hour of exposure. We use names consistent with common meteorological conventions to identify the three intensity zones for which we find significant effects on yield, namely drizzle (0.1–1 mm hr^{-1}), heavy (5–20 mm hr^{-1}) and extreme (≥50 mm hr^{-1}). The binning scheme for hourly rainfall intensity was also selected to match these meteorological conventions, and we show the results under a finer binning scheme for drizzle in Supplementary Fig. 1. No significant effects on maize yields were found for rainfall above 100 mm hr^{-1}, with similar but less pronounced patterns above 80 mm hr^{-1} for soy (Fig. 1). The lack of sustained significant yield-damaging effects at these high intensities may reflect the small subgrid-scale spatial extent of such rainfall events, an insufficient sample size to detect a signal or greater propensity for error in the Stage IV data at such high intensities[40].

The inclusion of the $\mathbf{W}_{i,t}$ term enables the isolation of intensity-specific yield effects, beyond their contribution to the total rainfall. Sensitivities to $\mathbf{W}_{i,t}$ terms are reported in Supplementary Table 1 and are broadly consistent across bins. The model has a coefficient of determination (r^2) of 0.75 for maize and 0.76 for soy. The occurrence of each rainfall intensity is correlated to varying degrees with both extreme heat and seasonal total rainfall (Extended Data Fig. 1)[20]. However, we do not find a coherent relationship between the pattern of observed yield sensitivity to hourly rainfall intensity and the correlation among these variables. KDD, which reflects detrimental heat extremes, is most positively correlated with moderate rainfall intensity ($r \approx 0.2$), for which positive yield effects are observed, and most negatively correlated with drizzle ($r \approx -0.5$), for which the yield effects are negative. Meanwhile, the correlation between KDD and extreme rainfall intensities is small ($r < 0.2$). Similarly, total rainfall is positively correlated with all non-zero rainfall intensity bins, and the peak correlation between 2.5 and 10 mm hr^{-1} ($r \approx 0.9$) is not consistently aligned with the observed zones of yield sensitivity. Collinearity between rainfall intensity and total rainfall thus cannot explain the observed yield responses to intensity, suggesting independent effects of rainfall intensity on yields. The reported yield sensitivities are robust to including a linear term for the total seasonal incident shortwave radiation in equation (1) as an explicit control for solar radiation (Supplementary Fig. 6).

Our model is analogous to that in ref. [1], except that we estimate the yield sensitivity to each intensity bin separately rather than additively to eliminate the risk of type II errors from standard error inflation due to collinearity between adjacent bins (the r^2 between adjacent bins is about 0.5, generally <0.1 in the second bin and approaching 0 beyond; Supplementary Fig. 7). The observed distinct zones of sensitivity for drizzle, heavy rainfall and extreme rainfall are separated by more than the radius of considerable correlation (~2 bins, $r^2 < 0.1$). On the basis of this separation, we consider exposure hours among identified zones of significant sensitivity to be independent. Since adjacent bins within zones are not independent, however, we do not strongly interpret differences or trends in coefficient magnitudes within the zones.

To test the influence of collinearity between the rainfall intensity zones on the estimated yield sensitivities, we conduct a post hoc rebinning of the drizzle, heavy and extreme significant impact zones into a single model (in contrast to the individual estimation in equation (1)). The model is of the form:

$$\hat{y}_{i,t} = C_i + T_t + \boldsymbol{\beta}_1 \mathbf{W}_{i,t} + \beta_D D_{i,t} + \beta_H H_{i,t} + \beta_E E_{i,t},$$

where D, H and E represent the county total seasonal exposure hours in the drizzle, heavy and extreme zones of significant impact (summed across bins within each zone), with corresponding coefficients from which sensitivity is inferred (Supplementary Fig. 3). The estimated yield sensitivities to each zone are consistent with those estimated using equation (1) (Fig. 1), suggesting limited influence of collinearity between rainfall intensity zones on the results.

The hourly rainfall intensity percentiles are estimated as the fractional rank of a given rainfall intensity within the national mean intensity distribution excluding zero-rainfall hours, averaged across all counties (Figs. 1 and 2). The national mean return frequency is estimated as the ratio of the number of county-years with non-zero exposure hours to the total county-years in the sample for each intensity bin (Fig. 2, yellow curve)—that is, only accounting for binary occurrence and not the number of events per season. This measure reflects the rareness of heavy and extreme rainfall intensities on a national average relative to the common events that occur each year and in each county.

The regional analysis divides the spatial domain of the dataset into three regions with roughly equal sample sizes, with the west defined as west of the 93rd meridian, the northeast as east of the 93rd meridian and north of the 40th parallel, and the southeast as east of the 93rd meridian and south of the 40th parallel (Extended Data Fig. 2a). These regional boundaries correspond approximately to climatological rainfall contours, with seasonal mean rainfall ± s.d. of 660 ± 200 mm, 750 ± 167 mm and 850 ± 200 mm in the west, northeast and southeast, respectively. For this analysis, we applied the regression model in equation (1) limited to bins less than 50 mm hr^{-1}, as the sample sizes for extreme rainfall bins were insufficient for data stratification. Beyond this limitation, the yield sensitivity to extremes probably differs regionally as well, for instance because the southeast experiences the most extremes among the regions (on average 47% of the total extreme hours per season, Supplementary Fig. 5) and may be somewhat more strongly represented in the national-scale sensitivity estimates. The regional results reveal certain general patterns that probably mask spatial variability at the county scale, which we cannot explicitly analyse due to a limited time series (15–16 years) in the rainfall data.

Our stratification based on irrigated crop area (Extended Data Fig. 3) followed an analogous method to the regional analysis. We first computed the percentage of harvested area that is irrigated for each county, averaged across available censuses (2002, 2007, 2012 and 2017), using data from USDA–NASS (ref. [39]). We excluded 5,706 counties with no available irrigation data from this analysis. We then stratified the sample of 11,242 counties using the irrigated area threshold of 5% (which resulted in two samples of similar size) and applied the regression model in equation (1) separately for the two groups.

For the comparison of hourly rainfall within the overall growing season weather (Fig. 3), we applied five indicators of rainfall distribution across timescales based on CLIVAR climate extremes indicators[41]: (1) seasonal total rainfall, (2) the duration in days of the longest dry spell, (3) the maximum five-day total rainfall, (4) the maximum one-day total rainfall and (5) the maximum

hourly rainfall (Fig. 3). We regressed the county crop yields against the suite of subseasonal rainfall distribution measures using the equation:

$$\hat{y}_{i,t} = C_i + T_t + \boldsymbol{\beta}_1 \mathbf{W}_{i,t}$$

where $\hat{y}_{i,t}$ is the predicted yield for year t in county i, and $\mathbf{W}_{i,t}$ is the vector of rainfall distribution measures with the corresponding coefficient vector $\boldsymbol{\beta}_1$, from which the yield sensitivities are inferred. As in equation (1), we controlled for temperature by including GDD and KDD in $\mathbf{W}_{i,t}$ (these coefficient estimates are omitted for clarity). To aid the comparison of estimated yield sensitivities across measures with differing units, we present dimensionless standardized coefficients of each measure ($\mathbf{B}_1$), estimated by multiplying the absolute coefficient estimates by the ratio of weather measure to yield standard deviations (the national mean of the within-county time standard deviations, denoted $\overline{\sigma_{\mathbf{W}}}$ and $\overline{\sigma_y}$, respectively):

$$\mathbf{B}_1 = \boldsymbol{\beta}_1 \frac{\overline{\sigma_{\mathbf{W}}}}{\overline{\sigma_{\mathbf{y}}}}$$

Various combinations of weather metrics were tested in candidate models to examine the robustness of the coefficient sign and magnitude; individual indicator coefficients from candidate submodels are generally consistent with the full model.

Our estimated yield sensitivities to the duration of the longest dry spell are consistent in sign and approximate magnitude with other recent estimates[4]. However, in contrast to refs. [2,4], we find a significant negative yield response to the maximum five-day total rainfall, probably because we control for seasonal total rainfall. This result thus probably reflects the yield-reducing influence of short-duration moisture excess[7,13], separate from the contribution of the multiday rainfall extremes to seasonal moisture conditions. The standardized yield sensitivities to drizzle and heavy rainfall are comparable in magnitude to five-day maximum rainfall and longest dry spell, whose impacts are more broadly recognized in recent research[10]. We conclude that daily and hourly maxima correlate positively with yields because they capture beneficial heavy rainfall, rather than damaging extremes. The mean national maximum hourly rainfall is 29 mm hr^{-1}, which corresponds to insignificant yield responses between the heavy and extreme rainfall intensities. Furthermore, the maximum daily rainfall most strongly correlates with the incidence of heavy rainfall ($r \approx 0.5$–0.6) rather than extremes ($r \approx 0.1$–0.4, Extended Data Fig. 1).

We estimate integrated seasonal sensitivities (Fig. 4a,b) by weighting the β_b sensitivities by the hourly exposure $H_{i,t,b}$ averaged nationally over 2002–2017 for each bin (Fig. 2, blue bars). For each intensity bin, this procedure converts the per-hour yield sensitivities into estimated total yield impacts, accounting for the total number of exposure hours across the growing season. Because adjacent bins in each intensity zone with significant yield effects cannot be treated as independent (Supplementary Fig. 7), we compute net intensity effects by first averaging integrated seasonal yield sensitivities for drizzle, heavy rainfall and extreme bins separately, and finally summing the average sensitivities across the three independent intensity zones (Fig. 4c–f).

We project a range of plausible future hourly rainfall intensification using three scenarios of rainfall intensity scaling with mean temperature, representing current empirical and modelling uncertainty over the response of convective and mesoscale dynamics to warming. We apply the scenarios to intensities ≥5 mm hr^{-1} consistent with reported distinct temperature scaling of high-percentile rainfall intensities with temperature beginning between the 90th and 99th percentiles[9,29]. The uniform low-change scenario reflects a simple scaling of high-percentile rainfall intensity with precipitable water equal to the 7% K^{-1} increase in saturation vapour pressure, governed by the Clausius–Clapeyron relation. The high-change and amplified scenarios reflect potential additional rainfall intensification mainly due to convective enhancement and associated horizontal moisture convergence from latent heating in the ascending air column. Under the high-change scenario, a uniform 14% K^{-1} intensification (double the Clausius–Clapeyron scaling) is applied[29,30], while in the amplified scenario, intensification is linearly increased from 7% K^{-1} at 5 mm hr^{-1} to 40% K^{-1} at 90 mm hr^{-1} (refs. [31–33]). On the basis of our yield analysis, this final scenario represents the most disadvantageous plausible scenario for crops, serving as a limiting case for projected net yield impacts.

We project future changes in the incidence of heavy and extreme hourly rainfall (≥5 mm hr^{-1}) by shifting the observed 2002–2017 frequency distributions by the intensity scaling factors following:

$$I_{\text{bin,scen}}^{\text{future}} = I_{\text{bin}}^{2002-2017}(1 + f_{\text{scen}})^{\Delta T}$$

Future bin-centre intensities $\left(I_{\text{bin,scen}}^{\text{future}}\right)$ are projected by increasing the observed 2002–2017 bin-centre intensities $\left(I_{\text{bin}}^{2002-2017}\right)$by the scaling factors ($f_{\text{scen}}$) under assumed mean temperature increases of 1, 2 and 4 K relative to the present day (ΔT). The increased incidences at the original 2002–2017 bin centres are then estimated by linearly interpolating from the shifted distributions (Extended Data Fig. 4). Our method thus preserves the observed relative decay in frequency of rainfall with increasing intensity (Fig. 2). The projected intensification results in 4–27 additional heavy and extreme rainfall hours per season, depending on the scenario and warming magnitude.

To isolate the impact of changing rainfall intensities, we conserve the climatological total rainfall hours by subtracting the projected increase in heavy and extreme hours from the 2002–2017 drizzle hours, consistent with projected declines in the frequency of light precipitation under mean warming[32,42]. Importantly, while seasonal total rainfall, KDD and GDD are likely to change in the future, we keep these variables constant in our yield projections to isolate the impact of rainfall intensification. Our projected yield changes from rainfall intensification should thus be interpreted as only one component of climate-induced yield changes, which must be considered in the context of impacts from changing extreme heat and drought.

Projected future yield impacts from the intensification scenarios are finally estimated by reweighting the intensity-specific per-hour sensitivities by the projected intensified hourly rainfall distributions, as for Fig. 4a,b. This approach assumes that the per-hour yield sensitivities estimated over 2002–2017 remain constant into the future. Projected net yield changes are estimated as the sum of the intensity-zone mean impacts (Fig. 4c,d). To represent uncertainty in these estimated impacts, we include an estimated 90% confidence interval from an ensemble of projections in which intensity-specific yield sensitivities are permuted to reflect estimation uncertainty. The permutation involves generating 1,000 pseudorandom yield sensitivities from a normal distribution with a mean equal to the coefficient estimate and a standard deviation equal to the standard error of the estimate. We recompute the net impact using the 1,000 sensitivity permutations for each scenario to yield an ensemble of 3,000 impact projections, the 5th to 95th percentiles of which we include as a shaded area in Fig. 4c,d. We also present partitioned impacts for each intensity zone by averaging the impacts across bins in the drizzle, heavy and extreme zones (see Fig. 4e,f for the 14% K^{-1} scenarios; the other scenarios are shown in Supplementary Fig. 2). Supplementary Fig. 8 provides a visualization of the methods, data and assumptions employed in this study.

Future changes in hourly rainfall intensities may not be uniformly distributed across the growing season, with potential consequences for daily to multiday rainfall statistics and their yield impacts. Such potential future changes in the temporal structure of rainfall across timescales may alter the rainfall intensities that contribute most to extreme daily rainfall totals. For example, one-day rainfall totals may become damaging to crops in the future if they are more strongly driven by short-duration extremes than at present (Fig. 3). Future research may investigate the influence on crop yields of variation in the time structure of rainfall from hourly to seasonal scales, especially as the observational, theoretical and model bases for reliably projecting these changes improve.

Our results provide an example of a climate-sensitive system essential to human health and well-being that is sensitive to hourly rainfall intensity. While the incorporation of hourly rainfall data into climate risk assessment is presently common in hydrological modelling and engineering[9], our results suggest that rainfall on this timescale merits further attention in crop research and in plant science and ecology more generally. Finally, our results highlight the value and applicability of increasing climate model resolution, expert elicitation and improved spatial and temporal completeness of observational and reanalysis data for understanding and projecting the shifting distribution of hourly rainfall under climate warming and the associated impacts on human and natural systems.

Data availability

All datasets supporting the results of this paper are freely available from the references and links listed in Supplementary Table 4. The compiled dataset is available at https://github.com/clesk/crop-hourly-rainfall. Source data are provided with this paper.

Code availability

The processing and analysis codes are hosted at https://github.com/clesk/crop-hourly-rainfall.

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Author contributions
C.L. and E.C. designed and coordinated the research and conducted the analysis. All authors discussed the results and wrote the manuscript.

Competing interests
The authors declare no competing interests.

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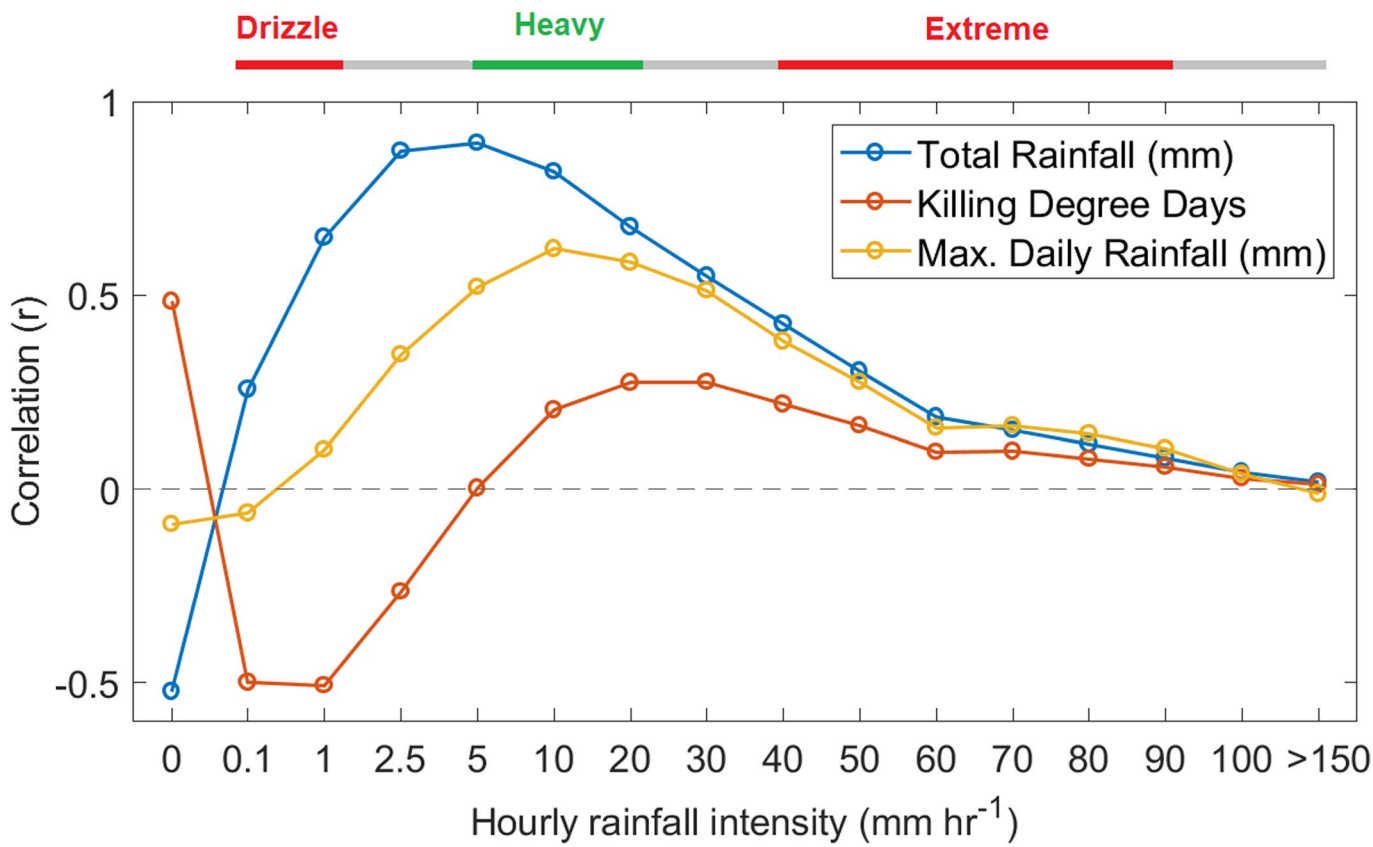
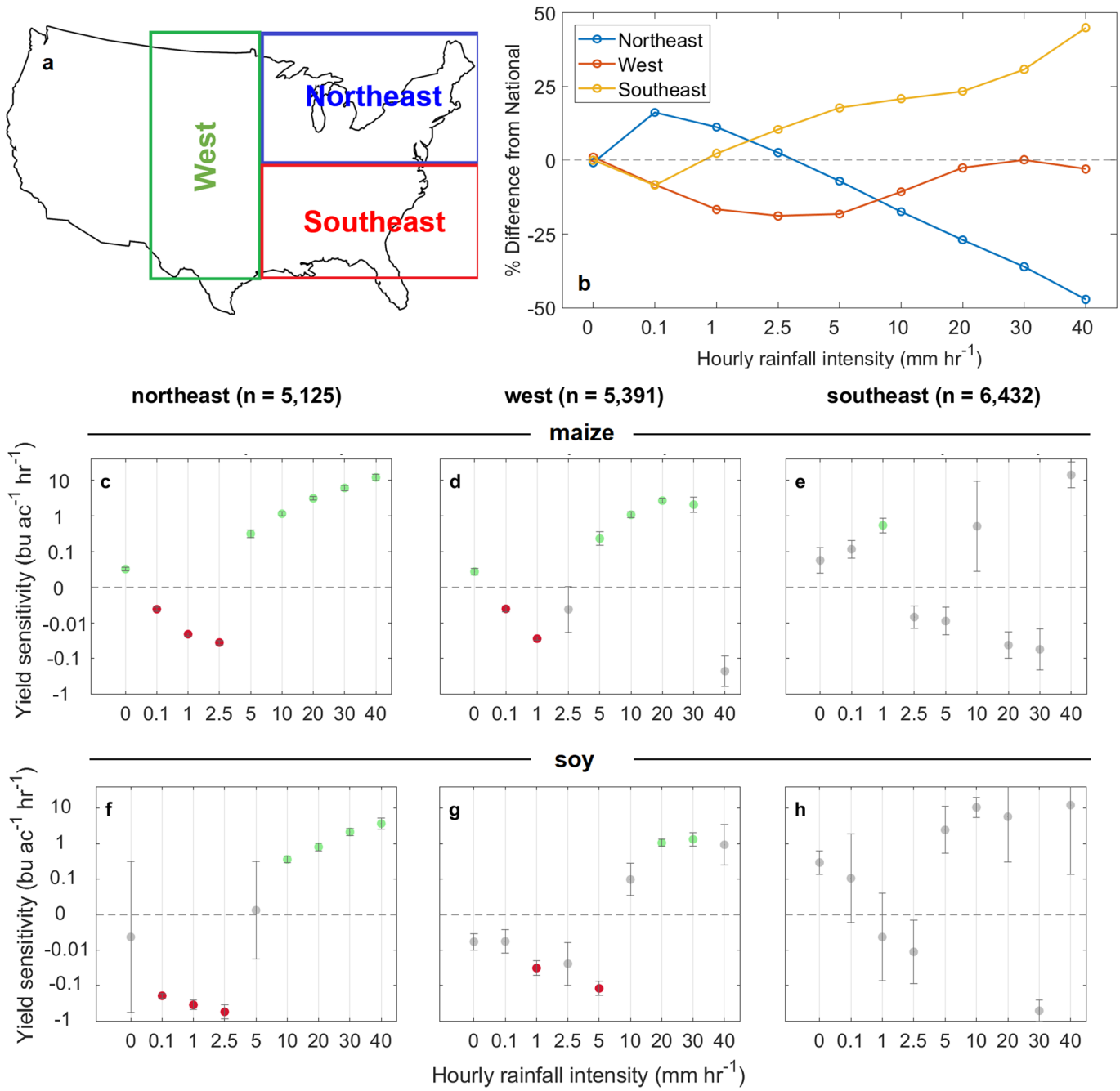
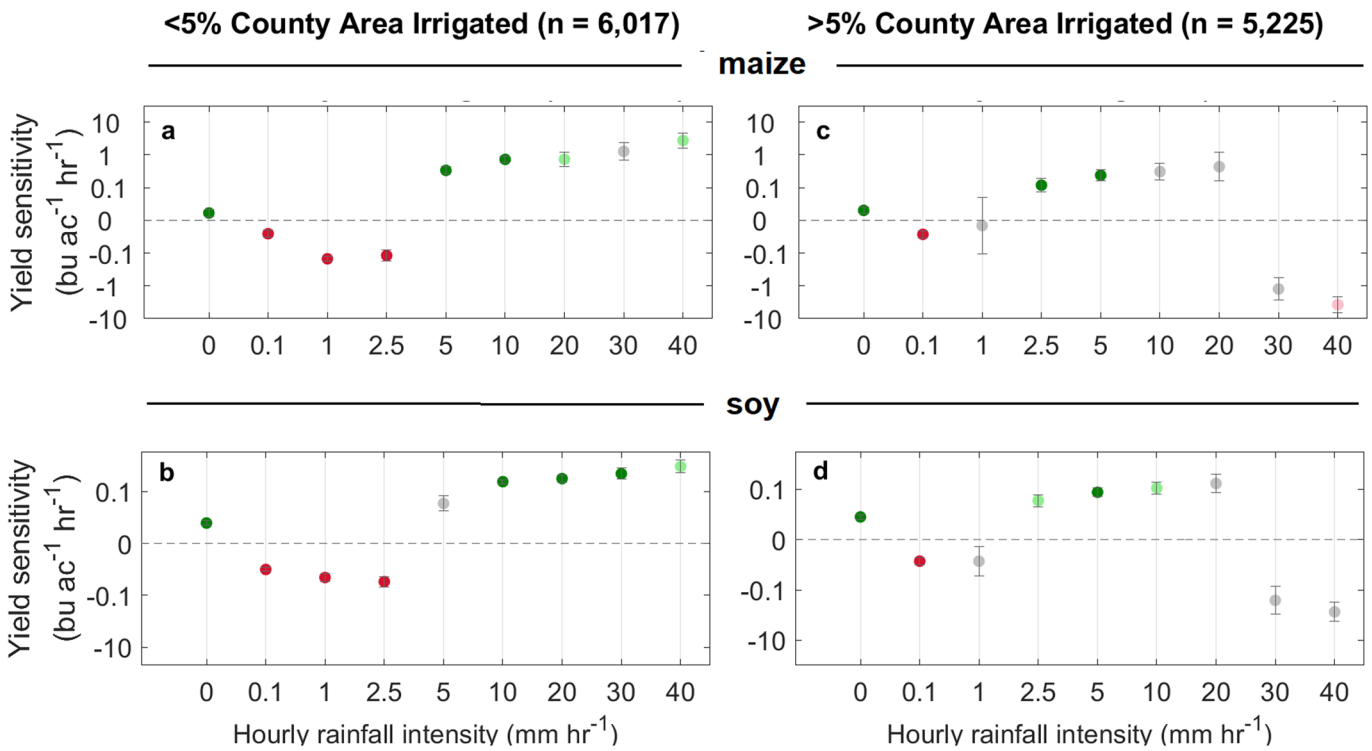


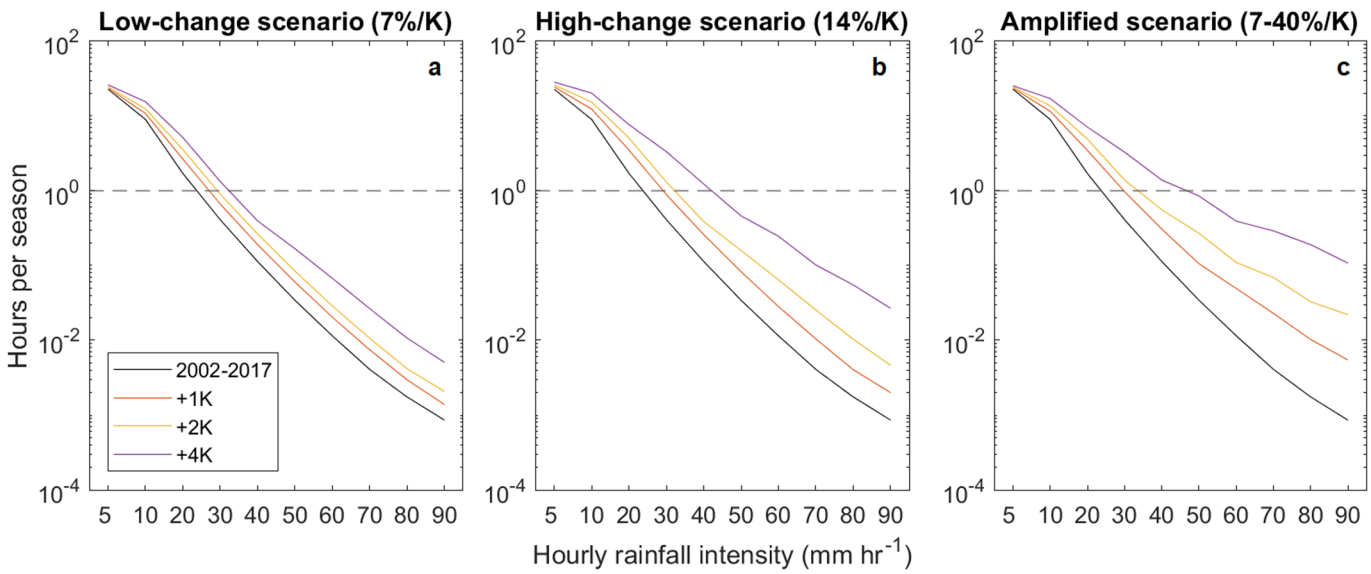
Extended Data Fig. 1 | Correlation between the incidence of hourly rainfall intensities and seasonal total rainfall, extreme heat, and maximum daily rainfall. Correlation coefficient of seasonal occurrence (hours) of rainfall of given intensities with seasonal total rainfall, killing degree days, and maximum daily rainfall, with annotated zones of significant positive (green) and negative (red) yield response ($P < 0.05$).



Extended Data Fig. 2 | Regional maize and soy yield sensitivity to drizzle and heavy rainfall. a) Schematic map of regional boundaries. Northeast is defined as latitude ≥40°N, east of 93°W, southeast as latitude <40°N, east of 93°W, and west as 93 to 104°W. **b**) Regional variation in the incidence of differing rainfall intensities, as percent deviation from the national mean incidence (Fig. 2). Regional mean county-level yield sensitivity (±SE) to hourly rainfall intensity per hour of exposure for **c**–**e**) maize, and **f**–**h**) soy. Extreme rainfall bins >40 mm hr^{-1} are omitted due to insufficient data for sample stratification. Sensitivities are plotted on symmetric logarithmic axes, with correspondingly transformed relative error bars. Green and red points indicate significant positive and negative sensitivities (two-sided $P < 0.05$).



Extended Data Fig. 3 | Maize and soy yield sensitivity to drizzle and heavy rainfall among counties with more and less extensive irrigation. Mean county-level yield sensitivity (±SE) to hourly rainfall intensity per hour of exposure for **a**, **b**) counties with less than 5% of crop area irrigated, and **c**, **d**) counties with more than 5% crop area irrigated (see Methods). Results are shown for maize in **a**) and **c**), and for soy in **b**) and **d**). Extreme rainfall bins >40 mm hr^{-1} are omitted due to insufficient data for sample stratification. Sensitivities are plotted on symmetric logarithmic axes, with correspondingly transformed relative error bars. Dark green and red points indicate significant positive and negative sensitivities (two-sided $P < 0.05$), while pink and light green points denote weakly significant effects (two-sided $P < 0.1$). The total counties analyzed is less than for the other analyses as irrigation data is not available for all counties.



Extended Data Fig. 4 | Projected future incidence of heavy and extreme rainfall under climate warming. Intensified distributions of heavy and extreme hourly rainfall under idealized warming of 1, 2 and 4 K projected by shifting the 2002–2017 baseline distribution (black curve, Fig. 2) under **a**) the uniform low-change scenario, **b**) the uniform high-change scenario, and **c**) the amplified scenario with greater intensification for higher intensities.