Using climate model simulations to assess the current climate risk to maize production

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Supplementary material

Region definitions

Table S1: 2004-2013 (inclusive) regional statistics. Information taken from USDA NASS and the National Bureau of Statistics of China; rainfed values extracted from MIRCA2000 (Portmann et al 2010)

| Region     | Production % National | Total area % National | Rainfed area % | Coordinates (N, S, E, W) |
|------------|-----------------------|-----------------------|----------------|--------------------------|
| Iowa       | 18.2                  | 16.3                  | 99             | (43.5, 40.5, -91., -96.5) |
| Illinois   | 16.0                  | 15.0                  | 98             | (42.5, 38.5, -87.5, -91.) |
| Nebraska   | 11.7                  | 10.9                  | 36             | (43., 40., -95.5, -99.)   |
| Minnesota  | 10.0                  | 9.3                   | 97             | (45.5, 43.5, -91.5, -96.5) |
| Indiana    | 7.3                   | 7.1                   | 96             | (42., 38.5, -84.5, -87.5) |
| Ohio       | 4.1                   | 4.1                   | 99             | (42.0, 39.0, -82.0, -85.) |
| Jilin      | 12.4                  | 9.8                   | 78             | (45.5, 42.5, 127., 123.)  |
| Heilongjiang| 11.7                  | 12.6                  | 66             | (48., 45., 128., 124.5)   |
| Shandong   | 10.9                  | 9.3                   | 28             | (38., 34.5, 120., 115.5)  |
| Henan      | 9.2                   | 9.2                   | 12             | (35.5, 32.5, 116.5, 112.5) |
| Hebei      | 8.6                   | 9.4                   | 24             | (40.5, 37.5, 119., 114.5) |
| Liaoning   | 7.2                   | 6.5                   | 63             | (43.5, 41., 124.5, 121.)  |
| Shanxi     | 4.3                   | 4.6                   | 43             | (39.5, 35.5, 114., 111.)  |
| Shaanxi    | 3.0                   | 3.7                   | 49             | (35.5, 32.0, 111., 106.5) |

Table S2: Additional regions utilised for deriving the agro-climatic indicator

| Region       | Coordinates (N, S, E, W) |
|--------------|--------------------------|
| Wisconsin    | (45., 42.5, -87.5, -92.) |
| Missouri     | (41., 38., -90., -96.)   |
| Michigan     | (44.0, 41.5, -82.5, -87.) |
| South Dakota | (46., 42.5, -96., -100.5) |
| Kentucky     | (38.5, 36., -85., -89.5) |
| Kansas       | (40.5, 36.5, -94., -102.5) |
| Jiaozuo      | (35., 33., 120.5, 116.5)  |
| Anhui        | (35., 32.5, 118.5, 115.)  |
Using climate model simulations to assess the current climate risk to maize production

**Irrigated and rainfed yield anomalies**

To assess the relationship between irrigated and rainfed yield anomalies, all available state and county level yields were extracted from the USDA NASS database for the period 1960-2013. Samples in which the harvested area was less than 10000 hectares, or the ratio between irrigated and rainfed areas less than 100, were removed. Yield anomalies are derived using the rolling mean detrend method with a window of 5 years. This results in 230 samples at the state scale and 630 at the county level (Figure S1). Removal of the area constraints results in 1623 county level samples with a correlation score between irrigated and rainfed yields of 0.49.

![Figure S1: Irrigated versus rainfed maize yield anomalies. State scale (left) and county scale (right) de-trended yield anomalies calculated from USDA NASS data for the time period 1960-2013.](image)

**Indicator verification**

To increase the sampling and better constrain the thresholds for the water stress indicator, annual yield anomalies, and seasonal meteorological values, were extracted for the following regions: Iowa, Illinois, Indiana, Minnesota, Ohio, Wisconsin, Missouri, Michigan, South Dakota, Kentucky, Jilin, Liaoning, Heilongjiang, Jiangsu, and Anhui. This results in 504 yield and meteorological values. The information was categorised in the form of a 2x2 contingency table, counting the occurrences of events where the temperature and precipitation satisfy the criteria for severe water stress (or not, \(I_{crit}\), and the observed yield anomalies exceed -1t/ha (or not). Using this approach, “hits”, “misses”, “false alarms” and “correct rejections” are defined as shown in Table S3. The relative numbers in each category are a function of the value of \(I_{crit}\). For example, as \(I_{crit}\) increases, the number of hits and false alarms will likely decrease, while the number of misses and correct rejections will increase. The ratio of events in each category affects the skill of the indicator. Therefore, by varying the temperature and precipitation thresholds, we can identify the values which maximise the skill. In this case, we demonstrate the method using the Heidke skill score. For completeness, the Heidke skill measures the fractional improvement of the forecast over the standard forecast, is quantified using:

\[
HSS = \frac{(a+d)/n - [(a+b)(a+c)+(b+d)(c+d)]/n^2}{1 - [(a+b)(a+c)+(b+d)(c+d)]/n^2}
\]

Where a, b, c and d are defined in Table S3 and n is equal to a+b+c+d.
Using climate model simulations to assess the current climate risk to maize production

Table S3: 2x2 contingency table definition

| Yield anomaly < -1 t/ha | Indicator > I_{crit} | Indicator < I_{crit} |
|-------------------------|----------------------|----------------------|
| Hit (a)                 | Miss (c)             |
| Yield anomaly > -1 t/ha | False Alarm (b)      | Correct rejection (d) |

The Heidke skill score was found to be maximal for temperatures greater than or equal to 23°C and precipitation less than or equal to 250mm. Re-sampling the contingency table 1000 times, for each threshold, using a multinomial distribution (based on the observed probabilities for a, b, c and d given a sample size of 34 years) provides an estimate of uncertainty due to the limited availability of observations. The 1000 Heidke skill score samples are normally distributed meaning that skill scores within one standard deviation of the mean value can be considered to be statistically indistinguishable. In turn, this “counting uncertainty” enables us to quantify the uncertainty in the temperature and rainfall thresholds used to define the agro-climate indicator.

Another important measure of indicator performance is the so-called “frequency bias”, quantified by (hits + false alarms)/(hits + misses). In this case, the bias measures the ratio of the number of events for which the indicator is above I_{crit}, to the number of negative yield anomalies of at least -1 t/ha. To ensure that the indicator identifies the appropriate frequency of negative yield anomalies, the bias should be close to unity.

The HSS and frequency bias was calculated for a range of temperature and precipitation thresholds for both precipitation datasets. The results as described in Figure 2, but for the CRU precipitation, is shown in Figure S2.

Figure S2: As Figure 2 but using the CRU precipitation dataset.

It is important to note that we would not expect or want the indicators to capture all negative yields anomalies, since there are other important drivers including floods and non-climate factors, as well as artefacts from the detrending procedure. The distribution of yield anomalies captured within each indicator is shown in Figure S3.

For both SWS and SWS_{lin} the indicator captures a sub-sample of yield events which are statistically different from the remaining yield anomalies in a number of ways. Firstly, the mean value of the yield anomaly in the water stress category is statistically different from that of the remaining yield anomalies at the 95% level. Secondly, sub-sampling from the entire sample of anomalies indicates that the likelihood of obtaining the mean yield anomaly, or less, of the points in the water stress category by random chance is less than 10^{-4}. Thirdly, using a Kolmogorov-Smirnov test, the
Using climate model simulations to assess the current climate risk to maize production

distribution of yield anomalies in the water stress category is statistically different at the 95% level from the remaining anomalies.

Figure S3: de-trended yield anomaly distributions associated with the water stress indicators SWS (left) and SWS<sub>lin</sub> (right).

Climate model performance assessment

Table S4: Model performance against observations. WFDEI value followed by 1400 member ensemble range from 10000 bootstraps provided in brackets. * indicates model data is consistent with observations.

| Region     | Precipitation (mm) | Temperature (°C) |
|------------|-------------------|-----------------|
|            | Mean              | Standard Deviation | Mean | Standard Deviation |
| Iowa       | 346.67 (223.17, 270.21) | 99.04 (50.52, 86.09) | 22.85 (23.91, 25.00) | 1.07 (1.22, 1.92) |
| Illinois   | 312.92 (222.66, 267.64) | 83.87 (50.15, 82.85) | 23.69 (24.30, 25.24) | 1.03 (1.07, 1.72) |
| Indiana    | 319.57 (237.71, 286.32) | 69.93 (53.53, 91.82)* | 23.18 (23.07, 23.94)* | 1.04 (0.98, 1.56)* |
| Minnesota  | 337.47 (225.48, 272.06) | 80.35 (49.98, 89.68)* | 21.67 (21.85, 22.87) | 1.19 (1.17, 1.85)* |
| Ohio       | 301.82 (260.86, 309.04)* | 61.31 (54.12, 89.76)* | 22.39 (22.47, 23.28) | 0.96 (0.90, 1.44)* |
| Nebraska   | 298.49 (204.29, 248.69) | 74.96 (49.20, 82.96)* | 23.56 (25.02, 26.19) | 1.05 (1.30, 2.06) |
| Jilin      | 398.49 (381.06, 449.59)* | 74.17 (75.02, 126.04) | 22.01 (21.71, 22.40)* | 0.74 (0.78, 1.23) |
| Liaoning   | 406.97 (415.26, 501.74) | 90.50 (93.34, 158.07) | 22.59 (22.49, 23.15)* | 0.72 (0.74, 1.18) |
| Heilongjiang | 353.44 (335.95, 396.56)* | 64.75 (66.30, 112.10) | 21.01 (21.09, 21.83) | 0.76 (0.83, 1.33) |
| Hebei      | 325.26 (378.34, 475.88) | 80.25 (104.66, 183.44) | 23.64 (23.30, 23.84)* | 0.60 (0.57, 0.97)* |
| Shanxi     | 292.54 (341.63, 406.76) | 76.37 (70.75, 119.56)* | 19.33 (19.13, 19.61)* | 0.70 (0.54, 0.91)* |
| Shandong   | 407.39 (333.79, 413.27)* | 101.27 (87.10, 149.74)* | 24.47 (24.58, 25.12) | 0.53 (0.59, 1.00) |
| Henan      | 421.21 (331.45, 418.46) | 99.84 (95.83, 163.83)* | 25.05 (25.21, 25.85) | 0.50 (0.71, 1.17) |
| Shaanxi    | 391.13 (393.09, 462.66) | 92.98 (77.50, 125.30)* | 21.05 (20.92, 21.42)* | 0.70 (0.56, 0.90)* |

Climate model adjustment

For regions in which this condition was not met, model data was adjusted. Seasonal temperature values were adjusted by shifting the mean and scaling the variance to the observations (Hawkins et al 2013b):

\[
\tilde{T}_{GCM} = \frac{\tilde{T}^{OB}}{\sigma_{T,GCM}} \sigma_{T,OB} (T_{GCM} - \tilde{T}_{GCM})
\]
Using climate model simulations to assess the current climate risk to maize production

where $T^{GCM}$ is the model temperature, $\bar{T}^{GCM}$ and $\bar{T}^{OBS}$ are the mean model and observed values respectively, $\sigma_{T,GCM}$ and $\sigma_{T,OBS}$ are the respective standard deviations of seasonal temperature, and $\bar{T}^{GCM}$ is the corrected model temperature. Due to the requirement of positive rainfall totals, the modelled precipitation was instead corrected using a multiplicative method (Hempel et al 2013):

$$\bar{P}_{T,GCM} = \frac{\bar{P}_{T}^{OBS}}{\bar{P}_{T}^{GCM}} \bar{P}_{T,GCM}$$

where $P_T^{GCM}$ is the model precipitation, $\bar{P}_{T}^{GCM}$ and $\bar{P}_{T}^{OBS}$ are the mean model and observed values respectively and $\bar{P}_{T,GCM}$ is the corrected model precipitation. Constraining the large ensemble to the characteristics of a small observational sample raises a question of appropriateness. The sensitivity of the results to the small observational sample was tested by re-sampling the observations (removing one) and repeating the bias correction methodology. The sensitivity of the derived event probabilities was found to be small compared to the uncertainty range (5th-95th percentile) by randomly selecting 10,000 samples from a multinomial distribution.

The distribution of rainfall and temperature, across all regions and 1400 members, for the raw and adjusted model data is shown in Figure S4. It can be seen that for precipitation the bias correction reduces the number of very low amounts and slightly reduces the occurrence of more extremely high values. This reduces the number of samples less than the SWS threshold of 250mm from 5,371 to 3,615. The bias correction greatly reduces the occurrence of high temperatures but has little impact in the cooler regions. The number of samples greater than the SWS threshold of 23°C is reduced from 10,531 to 8,547.

As an additional test, all regions were adjusted using the define method, and the results compared against those previously obtained. Adjustment of regions which had passed the appropriateness test was found to have a small impact on the derived event probabilities (less than 4% in absolute terms) and often had overlapping uncertainty estimates. The impact at regional, national and multi-breadbasket scales was found to be negligible.
Using climate model simulations to assess the current climate risk to maize production

Sub-national event probabilities

Table S5: Estimated SWS annual probabilities from observations (CRU, GPCC), 1400 model simulations, and the range derived by estimating the uncertainty due to bias correction

| Region   | CRU    | GPCC   | Model     | Bias(min) | Bias(max) |
|----------|--------|--------|-----------|-----------|-----------|
| Iowa     | 8.8 (2.9-17.6) | 5.9 (0.0-11.8) | 11.8 (10.4-13.2) | 10.6       | 13.6      |
| Illinois | 20.6 (8.8-32.4) | 17.6 (8.8-29.4) | 23.7 (21.9-25.6) | 22.1       | 25.8      |
| Indiana  | 20.6 (8.8-32.4) | 20.6 (8.8-32.4) | 20.1 (18.4-21.9) | 19.4       | 21        |
| Minnesota| 5.9 (0.0-11.8)  | 5.9 (0.0-11.8)  | 7.0 (5.9-8.1)    | 6          | 7.8       |
| Ohio     | 17.6 (8.8-29.4) | 17.6 (8.8-29.4) | 15.1 (13.5-16.6) | 14.1       | 15.6      |
| Nebraska | 17.6 (8.8-29.4) | 20.6 (8.8-32.4) | 30.6 (28.6-32.6) | 28.9       | 34.1      |
| Jilin    | 0.0 (0.0-0.0)  | 2.9 (0.0-8.8)   | 3.9 (3.1-4.8)    | 3.5        | 4.4       |
| Liaoning | 0.0 (0.0-0.0)  | 0.0 (0.0-0.0)   | 0.4 (0.1-0.6)    | 0.2        | 0.5       |
| Heilongjiang | 0.0 (0.0-0.0) | 11.8 (2.9-20.6) | 24.1 (22.2-26.1) | 23.4       | 25.9      |
| Hebei    | 14.7 (5.9-26.5) | 11.8 (2.9-20.6) | 24.1 (22.2-26.1) | 23.4       | 25.9      |
| Shandong | 2.9 (0.0-8.8)  | 5.9 (0.0-11.8)  | 14.3 (12.8-15.9) | 14.3       | 14.3      |
| Henan    | 0.0 (0.0-0.0)  | 0.0 (0.0-0.0)   | 0.0 (0.0-0.0)    | 0          | 0         |
| Shaanxi  | 0.0 (0.0-0.0)  | 0.0 (0.0-0.0)   | 0.4 (0.1-0.7)    | 0.4        | 0.4       |

National scale event probabilities

Table S6: Estimated SWS lin annual probabilities from observations (CRU, GPCC), 1400 model simulations, and the range derived by estimating the uncertainty due to bias correction

| Region   | CRU    | GPCC   | Model     | Bias(min) | Bias(max) |
|----------|--------|--------|-----------|-----------|-----------|
| Iowa     | 8.8 (2.9-17.6) | 5.9 (0.0-11.8) | 10.7 (9.4-12.1) | 10         | 12.4      |
| Illinois | 20.6 (8.8-32.4) | 20.6 (8.8-32.4) | 24.2 (22.4-26.1) | 22.9       | 26.4      |
| Indiana  | 20.6 (8.8-32.4) | 17.6 (8.8-29.4) | 22.4 (20.6-24.3) | 22         | 23.1      |
| Minnesota| 5.9 (0.0-11.8)  | 5.9 (0.0-11.8)  | 5.9 (4.9-6.9)    | 4.9        | 6.6       |
| Ohio     | 11.8 (2.9-20.6) | 11.8 (2.9-20.6) | 14.3 (12.8-15.9) | 13.8       | 14.7      |
| Nebraska | 14.7 (5.9-26.5) | 23.5 (11.8-35.3) | 30.0 (28.0-32.0) | 27.7       | 32        |
| Jilin    | 0.0 (0.0-0.0)  | 0.0 (0.0-0.0)   | 1.0 (0.6-1.4)    | 0.9        | 1.3       |
| Liaoning | 2.9 (0.0-8.8)  | 2.9 (0.0-8.8)   | 2.6 (1.9-3.4)    | 2.4        | 2.9       |
| Heilongjiang | 0.0 (0.0-0.0) | 0.0 (0.0-0.0)   | 0.7 (0.4-1.1)    | 0.6        | 0.9       |
| Hebei    | 14.7 (5.9-26.5) | 11.8 (2.9-20.6) | 22.8 (20.9-24.7) | 22.3       | 24.2      |
| Shandong | 8.8 (2.9-17.6) | 8.8 (2.9-17.6) | 19.0 (17.4-20.7) | 18.6       | 19.2      |
| Henan    | 8.8 (2.9-17.6) | 8.8 (2.9-17.6) | 19.1 (17.3-20.8) | 18.2       | 19.6      |
| Shaanxi  | 0.0 (0.0-0.0)  | 0.0 (0.0-0.0)   | 0.5 (0.2-0.9)    | 0.4        | 0.5       |

National scale event probabilities

Table S7: Region scale event probabilities (%) for severe water stress indicator SWS : Corn Belt

| Number of states | 0     | 1     | 2     | 3     | 4     | 5     | 6     |
|------------------|-------|-------|-------|-------|-------|-------|-------|
| Model (central)   | 54.14 | 18.29 | 9.14  | 8.29  | 5.79  | 2.43  | 1.93  |
| Model (lower)     | 51.9  | 16.6  | 7.9   | 7.1   | 4.8   | 1.8   | 1.4   |
| Model (upper)     | 56.4  | 20    | 10.4  | 9.5   | 6.8   | 3.1   | 2.6   |
| GPCC              | 67.65 | 11.76 | 5.88  | 5.88  | 2.94  | 0     | 5.88  |
Using climate model simulations to assess the current climate risk to maize production

|         | 67.65 | 8.82 | 8.82 | 5.88 | 2.94 | 0  | 5.88 |
|---------|-------|------|------|------|------|----|------|
| Random  | 29.47 | 40.96| 22.43| 6.18 | 0.9  | 0.07| 0    |

Table S8: Region scale event probabilities (%) for severe water stress indicator SWS: NECP

| Number of provinces | 0     | 1      | 2     | 3   |
|---------------------|-------|--------|-------|-----|
| Model (central)     | 95.57 | 3.29   | 1     | 0.14|
| Model (lower)       | 94.6  | 2.5    | 0.6   | 0   |
| Model (upper)       | 96.4  | 4.1    | 1.4   | 0.4 |
| GPCC                | 97.06 | 2.94   | 0     | 0   |
| CRU                 | 100   | 0      | 0     | 0   |
| Random              | 94.36 | 5.56   | 0.07  | 0   |

Table S9: Region scale event probabilities (%) for severe water stress indicator SWS: NCP

| Number of provinces | 0     | 1      | 2     | 3     | 4     | 5   |
|---------------------|-------|--------|-------|-------|-------|-----|
| Model (central)     | 66.43 | 21.57  | 7.57  | 4.14  | 0.29  | 0   |
| Model (lower)       | 64.3  | 19.8   | 6.4   | 3.3   | 0.1   | 0   |
| Model (upper)       | 68.5  | 23.4   | 8.7   | 5.1   | 0.6   | 0   |
| GPCC                | 85.29 | 11.76  | 0     | 2.94  | 0     | 0   |
| CRU                 | 85.29 | 11.76  | 2.94  | 0     | 0     | 0   |
| Random              | 57.35 | 35.44  | 6.79  | 0.42  | 0     | 0   |

Table S10: Region scale event probabilities (%) for severe water stress indicator SWS: China

| Number of provinces | 0     | 1      | 2     | 3     | 4     | 5     | 6     | 7     | 8   |
|---------------------|-------|--------|-------|-------|-------|-------|-------|-------|-----|
| Model (central)     | 64.36 | 21.79  | 8.57  | 4.21  | 0.93  | 0.14  | 0     | 0     | 0   |
| Model (lower)       | 62.2  | 20     | 7.4   | 3.4   | 0.5   | 0     | 0     | 0     | 0   |
| Model (upper)       | 66.5  | 23.6   | 9.8   | 5.1   | 1.4   | 0.4   | 0     | 0     | 0   |
| GPCC                | 82.35 | 14.71  | 0     | 2.94  | 0     | 0     | 0     | 0     | 0   |
| CRU                 | 85.29 | 11.76  | 2.94  | 0     | 0     | 0     | 0     | 0     | 0   |
| Random              | 54.12 | 36.63  | 8.42  | 0.8   | 0.03  | 0     | 0     | 0     | 0   |