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Title: Estimating the effects of extreme weather on food security

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Text:

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1 **Both governments and the private sector urgently require better estimates of the likely**
2 **incidence of extreme weather events¹, their impacts on food crop production and the**
3 **potential consequent social and economic losses². Current assessments of climate change**
4 **impacts on agriculture mostly focus on average crop yield vulnerability³ to climate and**
5 **adaptation scenarios^{4,5}. Also, although new-generation climate models have improved**
6 **and there has been an exponential increase in available data⁶, the uncertainties in their**
7 **projections over years and decades and at regional and local scale, have not**
8 **decreased^{7,8}. We need to understand and quantify the non-stationary, annual and**
9 **decadal climate impacts using simple and communicable risk metrics⁹ that will help**
10 **public and private stakeholders manage the hazards to food security. Here we present**
11 **an ‘end-to-end’ methodological construct based on weather indices and machine**
12 **learning that integrates current understanding of the various interacting systems of**
13 **climate, crops, and the economy to determine short to long-term risk estimates of crop**
14 **production loss, in different climate and adaptation scenarios. For provinces north and**
15 **south of the Yangtze River in China, we have found that risk profiles for crop yields**
16 **that translate climate into economic variability follow marked regional patterns, shaped**
17 **by drivers of continental-scale climate. We conclude that to be cost-effective, region-**
18 **specific policies have to be tailored to optimally combine different categories of risk**
19 **management instruments.**

20

21

22 An increasing body of scientific evidence, derived from both observations and model
23 simulations, indicates that the climate system never was, nor is it likely to ever be,
24 statistically stationary¹⁰. Moreover, statistical characterization of slowly changing weather
25 extremes is fraught with difficulties¹¹. These stem partly from the potentially large effects

26 caused by lack of stationarity and partly from the existence of complex nonlinear processes
27 and threshold effects. The assessment and the prediction of such effects, both deterministic
28 and stochastic, on weather extremes depend on a number of interconnected drivers. For
29 example, changes in weather variability season-to-season and year-to-year that affects food
30 production derive from shifts in the statistics of decade-to-decade climate processes^{12,13}.
31 Thus, changes in the large-scale climate processes that drive both regional and global climate
32 variability affect the annual onset of rainfall in the tropics and subtropics, as well as rainfall
33 patterns in temperate latitudes, so playing a significant role in the variability of regional rain-
34 fed crop production¹⁴. The risk estimation methodology proposed here integrates large- and
35 small-scale information, and is based on both observed and simulated data for weather,
36 climate, crop vulnerability and economic conditions.
37 The overall, end-to-end methodological construct is illustrated in Fig. 1. It relies on machine
38 learning involving weather indices that characterize the vulnerability of crops to weather
39 variability in different technological scenarios (Fig 1a).

40

41 **Figure 1 near here**

42

43 We here used a stochastic “weather-within-climate” downscaling approach that quantifies the
44 interaction of low- and high-frequency climate variability (Fig. 1b) to determine the crop
45 loss, risk profiles (Fig. 1d) for future climate scenarios. These are then used to model the
46 direct and indirect economic impacts subject to supply loss shock (Fig. 1e) and to determine
47 optimum mix of risk transfer and mitigation policies in a particular region or country (Fig.
48 1f). We assessed the potential of this methodological construct by using data for weather,
49 crops, and the economy in four provinces (Shandong, Hebei, Guangdong, and Guangxi) of
50 the People’s Republic of China, north and south of the Yangtze River.

51

52 Existing Integrated Assessment Models (IAMs) have attempted to provide first estimates of
53 future possible costs of climate impacts on the economy subject to different global warming
54 scenarios^{15,16}. However, the sensitivity of these IAMs to individual economic parameters,
55 such as the discount rate, has limited their usefulness. Taking this into account, the
56 methodology presented in Fig. 1 focuses on the economic impacts driven by the local and
57 regional characteristics of weather variability and climate state changes, the local response of
58 the system considered (e.g. the crop production sector), and different scenarios of
59 technological risk mitigation.

60

61 Weather indices were devised as proxies of physical crop response to two of the main drivers
62 of yield variability: precipitation variability and exposure to excess-temperatures. Other
63 hazards such as cold shocks or radiation variability are not considered here. Observed
64 historical daily weather data and soil databases for the studied provinces are used to simulate
65 crop yields using mechanistic crop modelling. Daily precipitation and temperature data are
66 used to build pixel-level databases of precipitation and temperature variability indices. Each
67 index captures exposure to deficit precipitation or excess temperature during different time
68 intervals of crop growth.

69

70 The translation of the metrics of physical-loss risk into metrics of direct and indirect
71 economic loss is carried out through macroeconomic modelling of exogenous, supply-side
72 shocks. Probabilistic and scenario-based risk modelling is cascaded from climate to
73 agricultural and finally economic loss through data clustering, by using machine learning
74 techniques of recursive partitioning¹⁷ and Nonhomogeneous Hidden Markov Models¹⁸
75 (NHMMs), as illustrated in Supplementary Fig. 1. The joint effects of precipitation variability

76 and excess temperature were modelled through stochastic-copula dependency; see **Methods**
77 and Supplementary Fig. 2. Finally, complete province-level profiles of economic-loss risk
78 were obtained by considering several technological scenarios for climate risk mitigation.
79 While a historical climate scenario is presented here, the same methodological construct is
80 applicable to obtain risk profiles in future climate scenarios by using simulated large scale
81 climate driver NHMM covariates.

82

83 Vulnerability of crops to weather variability varies strongly over their growing period. The
84 length of this period and of the occurrence of stages of development such as flowering and
85 maturity is also constrained by local weather variability and environmental conditions, as
86 well as by genetic traits. In addition to extreme weather events, slight changes in planting
87 season and duration of weather patterns may also reduce yields¹⁹. The weather indices are
88 used to capture the response of crop growth to different features of weather variability.
89 Excess heat indices are built by counting the number of days where the maximum
90 temperature, T_{max} , surpasses a critical threshold, T_c , of 30 or 35°C – for instance the number
91 of days with $T_c > 30^\circ\text{C}$ from day 10 to day 40 of crop development. Precipitation deficit
92 indices account for cumulative rainfall during a given period of crop growth. **Supplementary**
93 **Figure 3** summarizes the different periods of aggregation of weather indices and the colour
94 code used in **Figure 2**.

95

96 The machine learning methodology applied here to select pixel-level weather indices shows
97 that the weather indices which best capture weather-driven yield variability exhibit spatial
98 heterogeneity relative to the portion of the growing cycle accounted in the index. For
99 instance, the optimal indices for the effects of precipitation variability (Fig. 2a) and excess
100 heat (Fig. 2b) on maize yield variability in the northeastern province of Shandong are

101 heterogeneous, with several pixels spatially clustered according to different periods of the
102 growing season (Supplementary Fig. 3) during which the crop is most sensitive to climatic
103 effects. The spatial clustering of indices appears to follow topographical features of
104 Shandong province. For instance, the central mountainous and the westernmost regions of the
105 province are dominated by precipitation indices capturing vulnerability during, respectively,
106 the middle and the end of the crop development. This spatial pattern of precipitation indices
107 also depends on the technological scenario considered (i.e. local rain-fed variety, local
108 irrigated variety, switched rain-fed variety), as shown in Supplementary Fig. 4. In contrast, a
109 marked index spatial homogeneity is observed regarding the choice of critical temperature
110 used to build heat wave indices. For each pixels, two sets of 25 heat wave indices using 30 or
111 35°C as critical temperature was used to determine the optimum heat wave index. 30°C
112 appears is homogeneously selected across all Shandong province (Figure not shown).

113

114 **Figure 2 near here**

115

116 Heat wave–driven variability in rice yield in the Southern provinces of Guangxi and
117 Guangdong possesses similar spatial variability; see Supplementary Figs. 5a,b. Estimated
118 impacts of weather variability and climate change on crop production are usually based in
119 IAMs which implies spatially homogenous hydrometeorological indicators²⁰. Doing so is
120 likely to underestimate local-to-regional yield losses. In effect, the rate of succession of
121 phenological growth stages in crops depends on the accumulation of temporal photo-thermal
122 units¹⁹; this accumulation, in turn, depends on the interaction of local environmental
123 variables. Therefore, the use of homogenous hydrometeorological indicators may fail to
124 systematically capture times of peak vulnerability, e.g., during reproductive stages that vary
125 with location.

126

127

128 Results obtained for northern Shandong (Fig. 2) and Hebei (not shown) provinces illustrate
129 the importance of modelling the joint impacts of precipitation variability and excess
130 temperature stresses on rain-fed crops. Under the baseline scenario of the currently grown,
131 rain-fed maize variety, average yield variation throughout Shandong province, subject to the
132 stress of precipitation variability alone, produces slightly positive yield anomalies, while the
133 joint modelling of excess temperature and precipitation variability leads to spatially
134 homogenous negative anomalies. Supplementary Figure 4 illustrates the latter.

135

136 The nonlinearity of maize yield losses due to drought and heat stress is captured by our
137 modelling and is consistent with agricultural field studies^{22,23}. The relatively homogenous
138 yield losses for irrigated rice subject to increasing heat wave exposure throughout the
139 southern Guangdong (not shown) and Guangxi provinces in Supplementary Fig. 5 are
140 consistent with existing literature^{24,25} and might actually be underestimated²⁶.

141

142 **Figure 3 near here**

143

144 The results demonstrate that important variations in province-level risk profiles depend on the
145 regional features of weather and climate variability.

146

147 To capture dependence on large-scale, low-frequency climate variability, we have
148 constructed and applied an NHMM¹⁸; see **Methods** and Supplementary Fig. 6. In the
149 northeastern provinces of Shandong (Fig. 3) and Hebei (not shown), the effect of low-
150 frequency climate change, modelled by this NHMM, is masked by high-frequency weather

151 variability. In fact, northeastern China is strongly affected by mid-latitude weather systems,
152 as well as by teleconnections from the Tropical Pacific^{27,28}.

153

154 In contrast, for the southern Guangdong and Guangxi provinces, risk driven by weather
155 variability depends strongly on the climate state. For a given state, the risk profiles in the
156 southern provinces exhibit minimum variation for varying return periods of weather events,
157 whereas drastic jumps, of 0.18 % and 1.15 % in losses of provincial gross domestic product
158 (GDP) occur in Guangdong and Guangxi, respectively, as central-Eastern Pacific sea surface
159 temperatures shift from a warm to a cold event, as captured by the Niño-3.4 index in our
160 NHMM²⁹ and illustrated in Supplementary Figs. 6 and 7.

161

162 We have considered three different technological scenarios: (i) continuing use of a local rain-
163 fed variety; (ii) switching to another, more drought tolerant rain-fed variety; and (iii) the use
164 of a local irrigated variety. Their effects on the risk profiles are illustrated in Fig. 3a and
165 Supplementary Fig. 4.

166

167 The probabilistic risk profiles of economic loss obtained by the present methodology are
168 strongly driven by the physical-loss risk. But the different magnitudes of aggregated direct
169 and indirect losses also reflect the shares of agriculture within each province's GDP (Figs.
170 3a,b).

171

172 Our results should help formulate fiscal policy and public budgeting for these extreme
173 weather risks. Risk management instruments can be used to minimize and cap the cost of
174 weather and climate impacts on society, government and producers.

175

176 Investments in infrastructure that increases physical resilience are effective in mitigating
177 risk³⁰. Our results indicate a maize production loss generated by a 1-in-50-year event of
178 excess temperature and precipitation variability produces an aggregate 0.7 % loss of
179 Shandong provincial GDP (see Fig. 3b). They also indicate that in under an irrigation
180 scenario, production and aggregate economic losses are cancelled. As shown in
181 Supplementary Table 1, estimations of the cost of deploying new irrigation infrastructure and
182 restoring existing decaying structures could be performed at a cost of up to 0.73 % of
183 Shandong GDP.

184

185 The economic efficiency of risk mitigating investments decreases, however, with the risk
186 level considered and is only justifiable up to certain risk level³¹. In order to manage the
187 residual risk, instruments of risk transfer and risk forecast can decrease the ex-post event
188 costs of damage.

189 We propose a “three-pillar”-based approach for rural development and food security risk
190 management. The three pillars are: (i) risk mitigation, (ii) risk forecast, and (iii) risk transfer
191 instruments. These need to be tailored and combined to respond to specific climate risk
192 profiles characterizing a given region. We believe the results of the end-to-end probabilistic
193 risk assessment methodology presented here will be particularly effective in setting the
194 balance of these three pillars. The implications of this work are of concern for farmers and
195 policy makers, as well as for the whole value chain of the food-and-fibre industry, and for its
196 long-term sustainability. The crucial importance of providing such detailed end-to-end
197 information to stakeholders is further summarized in the **Supplementary Discussion**.

198

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302

303

304

305

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314

315 **Author contributions:**

316 EC, GC and MG designed the study. EC obtained the data and carried out the calculations.
317 MS provided further insights into the application of risk profiles to market practice. All four
318 authors contributed to the writing.

319

320 **Competing interest declaration**

321 None of the authors declare any competing financial interest.

322

323

324 **Figure Legends and Tables**

325

326 **Figure 1. Schematic diagram of the end-to-end methodology for deriving crop**

327 **production and economic-risk profiles.** Panel (c) uses input from panels (a) and (b) to

328 produce grid-to-province PDFs of yield loss captured by weather indices, conditional on

329 large-scale interannual climate processes. Panel (d) uses panel (c) grid-level yield loss PDFs

330 and yield response functions subject to GHG and technological scenarios to derive regional-

331 level risk profiles of production loss. If the region matches an economic administrative unit

332 (e.g. province, country), panel (e) uses (d) to derive distributions of province-level economic

333 losses. Panel (f) uses panel (d) and/or, if relevant, panel (e), to determine optimum

334 combinations of risk mitigation and transfer instruments to minimize risk of climate-driven

335 losses.

336 Words: 114

337

338 **Figure 2. Results of weather index–based modelling of maize yield in Shandong**

339 **province.** (a, b) Maps of indices selected to best capture on a $0.25^\circ \times 0.25^\circ$ longitude-latitude

340 grid (a) deficit precipitation, and (b) excess temperature–driven yield variability. Color scale

341 (see Supplementary Fig. 3) indicates the phase of crop growth in which the selected index

342 captures highest sensitivity. (c) Map of 10-year return period production (see **Methods**) of

343 ~200 to ~1,400 tons/pixel. Panels (d)–(g) present computations for a heat wave index. (d)

344 Mixed univariate distributions of the index, subject to each NHMM state. (e) Viterbi-

345 weighted sum of each distribution. The convolution of (f), the response function of yield to

346 heat wave, with (e) allows obtaining the distribution of yield (g). Results shown for a single
347 local maize variety rainfed technological scenario.

348 Words: 132

349

350 **Figure 3. Risk profiles of province-level physical production and aggregate economic**

351 **loss in China's northeast Shandong province.** (a) Risk profiles of maize provincial

352 production loss, driven by the joint impacts of excess temperature and precipitation

353 variability, subject to three different technological scenarios: (i) continuous line – local rain-

354 fed variety; (ii) dotted line – switched rain-fed variety; and (iii) long-dashed line – local

355 irrigated variety. (b) Risk profiles of direct and indirect aggregate economic loss expressed as

356 percentage of provincial gross domestic product (GDP_{2008}): (i) black bars – local rain-fed

357 variety; (ii) yellow bars – switched rain-fed variety; and (iii) red bars – local irrigated variety.

358 Words: 97

359

360

361 **Methods**

362 Word Count: 840

363 **Data sources**

364 Daily observed weather data on precipitation, radiation, and maximum and minimum

365 temperatures were used. The data set was provided by the National Climate Centre (NCC) of

366 the China Meteorological Administration (CMA) on a $0.25^\circ \times 0.25^\circ$ longitude-latitude grid,

367 available from 1961 to 2012; it covered the two northeastern provinces of Shandong and

368 Hebei, and the two southern provinces of Guangxi and Guangdong. Grid-level maize and rice

369 yields were simulated in those northeastern and southern provinces, respectively, using a

370 mechanistic crop model called DSSAR-CERES.

371 **Random forest-based indices selection**

372 We selected the most effective pixel-level pairs of indices to capture the effects of deficit
373 precipitation and excess temperature on yield variability by a random-forest algorithm. This
374 algorithm uses ensemble-based recursive partitioning and thus permits one to circumvent the
375 issues of cross-correlation between indices and of a large number of variables vs. a small
376 sample size.

377

378 **Extreme value multivariate modelling**

379 Robust stochastic characterization of the interannual variability of the optimum grid-level
380 weather indices was carried out using univariate distributions of mixed, exponential–
381 Generalized Pareto Distribution (GPD) type. The latter allows one to accurately estimate the
382 risk of occurrence of events that are both rare and extreme, within a modified Generalized
383 Pareto Distribution framework across the whole gridded domain studied. The stochastic
384 dependence of deficit precipitation and excess temperature is characterized by coupling their
385 univariate mixed distributions F_X and F_Y within a Gumbel-Hougaard copula model, as
386 described in the equations (1) and (2) below.

387

$$F(X, Y) = C_\theta(F_X, F_Y) \quad (1)$$

388

389 Here C_θ is the Gumbel-Hougaard Archimedean extreme value copula,

390

$$C_\theta = \left\{ - \left(\left((-\log(u_X))^\theta + (-\log(u_Y))^\theta \right)^{-1/\theta} \right) \right\} \quad (2)$$

391

392 The coefficient of dependence is $\theta \geq 1$, where $\theta = 1$ characterizes independence of the
393 uniform transforms u_X and u_Y of the mixed univariate F_X and F_Y distributions of precipitation
394 and heat wave grid-level indices, respectively.

395

396 The Gumbel-Hougaard Archimedean copula enables us to characterize dependence in both
397 the upper and lower tails without assuming independence of extreme-value occurrences, as is
398 the case in Gaussian copulas. An example of stochastic dependence of two weather indices, at
399 the same location and subject to a technological scenario, is presented in Supplementary Fig.
400 2.

401

402 **Nonhomegenous Hidden Markov Model “weather-within-climate” modelling**

403 Historical univariate or multivariate distributions of weather indices are derived by adopting a
404 “weather-within-climate” modelling framework. The distributions are modelled conditionally
405 on hidden regional weather states, S_t that capture seasonal variability. These states are
406 conditioned themselves on observed or simulated continental and planetary-scale climate
407 drivers that capture interannual modes of variability. A Nonhomogenous Hidden Markov
408 Model (NHMM) is used to achieve this two-step conditioning and enable the introduction of
409 non-stationarity, as illustrated in Supplementary Figure 1 across a gridded domain and
410 equation (3) below.

411 The weather index distributions, $P(O_{1:T}, S_{1:T} | \lambda, z_{1:T})$, thus use continental-scale climate
412 variables, $z_{1:T}$, observed or, potentially, simulated by high-end general circulation models,
413 subject future greenhouse gas scenarios⁴⁵. The non-stationary univariate distributions of
414 pixel-level precipitation and excess heat, $O_{1:T}$, follow the mixed GPD-exponential univariate
415 framework presented above. The copula-characterized stochastic dependency between
416 marginal is considered stationary across weather states.

417

418

419

420 Here $1961 \leq t \leq 2012$ while S_t are the hidden states of the two-states Markov chain, z_t is the
 421 non-stationary NINO3.4 index acting as covariate, and $\lambda = \{a_i, \pi_i\}_{i=\{1,2\}}$ contains the
 422 transition parameters a_i , and initial probabilities π_i , of the NHMM, and b_{S_t} the distribution of
 423 the observed weather indices at time t , depending on the state S_t as follows:

$$P(O_{1:T}, S_{1:T} | \lambda, z_{1:T}) = \pi_i(z_1) b_{S_1}(O_1 | z_1) \prod_{t=1}^{T-1} a_{ij}(z_t) b_{S_t}(O_{t+1} | z_{t+1}) \quad (3)$$

424 And where

- 425 • $a_{ij}(z_t)$ is the transition probability from state i at time t to j at time $t + 1$ of a first-
 426 order Markov chain as a function of the non-stationary covariate z_t ;
- 427 • $\pi_i(z_1)$ is the probability that the initial hidden state at $t = 1$ is i , $S_1 = i$; and
- 428 • $b_{S_t}(O_{t+1} | z_{t+1})$ is a component of the vector of observed weather indices
 429 characterized by mixed densities F_X and F_Y cited above, and dependent on the value
 430 of the non-stationary covariate z_{t+1} .

431

432 **Generalized Additive Mixed crop response modelling**

433 In order to model the vulnerability functions of crop yield to the combined or individual
 434 effects of precipitation variability and excess temperature exposure, Generalized Additive
 435 Mixed Models (GAMMs) are used. The use of a GAMM $g(\mu_i)$ enables capturing non-linear
 436 response of crop yield μ_i to the varying values of a single or several weather indices, cf. Fig.
 437 2 (f),

438

$$439 \quad g(\mu_i) = X_i\theta + f_1(x_{1i}) + f_2(x_{2i}) + \dots \quad (4)$$

440

441 Here $\mu_i \equiv E(Y_i)$, with Y_i the rice or maize yield response variable following an exponential-
442 family probability distribution function with and y_i is the i^{th} observation of the rice or maize
443 yield variable, X_i is the i^{th} row of the model matrix with its corresponding θ parameter vecto
444

445 Also, in order to model the univariate model of rice or maize yield response to heat waves or
446 deficit precipitation, a smoothing basis composed of natural cubic splines is used. Ultimately,
447 the convolution of the GAMM-based yield response function with the distribution of the
448 corresponding grid-level indices results in the distribution of yield loss as a function of
449 indices values.

450

451 **Input-Output-based economic impact modelling**

452 An Input-Output modelling approach is used to assess direct and indirect Province-level
453 economic impacts due to weather-driven maize production shortfall. Additional details
454 concerning the methodology can be found in the **Supplementary Information** section.

455

456

1 Title: Estimating the effects of extreme weather on food security

2 NCLIM-14111599 revised manuscript

3 **Authors:** Erik Chavez^{1*}, Gordon Conway², Michael Ghil^{3,4}, Marc Sadler⁵

4 **Supplementary Information**

5 Words: 1,413

6 **Supplementary Methods**

7 **Data sources**

8 The datasets contain less than 0.1 % data gaps¹. The quality of the datasets was controlled by
9 the CMA following Qian and Lin (2005)². The temperature data homogeneity was controlled
10 by CMA using the method of standard homogeneity test³, the moving *t*-test⁴, and departure
11 accumulating method⁵. Precipitation datasets are not adjusted, while temperature datasets
12 were homogeneity-adjusted¹.

13 The mechanistic crop model used has been calibrated with observed yield and soil data at the
14 Chinese Academy of Agricultural Sciences^{6,7,8}.

15

16 **Random forest-based indices selection**

17 In each pixel, two sets of databases of (i) 25 precipitation indices, and (ii) 50 excess heat
18 indices are built based on the pixel-specific date of planting, The 25 different periods of
19 aggregation of the weather indices across the crop growing period are represented in

20 **Supplementary Figure 3.** Datasets of excess temperature indices are computed in each pixel
21 using two critical temperatures $T_c = 35^\circ\text{C}$ or $T_c = 30^\circ\text{C}$, and accounting for the numbers of
22 days with $T_{max} > T_c$ during each of the aggregation periods. Precipitation indices are built by
23 computing cumulative precipitation during the same 25 different aggregation periods.

24 We selected the most effective pixel-level pairs of indices to capture the effects of deficit
25 precipitation and excess temperature on yield variability by a random-forest algorithm⁹.
26 Therefore, for each pixel one precipitation index and one excess heat index are selected from
27 the population of 25 precipitation 50 and excess heat potential indices.
28 For each set of 25 precipitation or 50 excess heat pixel-level indices, the Random Forest
29 algorithm was programmed to extract a subset of 5 indices randomly for 5,000 times to
30 compute regression trees. The indices importance measure is obtained after computation of
31 the average of the 5,000 initial trees.

32

33 **Extreme value multivariate modelling**

34 A dynamic mixture model¹⁰ was used to enable unsupervised threshold setting for the fitting
35 of the GPD distribution. The stochastic dependence of the exponential-GPD mixed
36 distributions of precipitation and excess heat indices is subsequently characterized using a
37 Gumbel-Hougaard copula framework¹¹.

38

39 **Nonhomegenous Hidden Markov Model “weather-within-climate” modelling**

40 Using the best fit test of Aikake Information Criteria¹², a two-state Hidden Markov Model
41 (HMM) with $S_t=1$ and $S_t=2$ was fit in each pixel on the observed time series variables of
42 weather indices $O_{1:T}$. The two pixel-level states capture seasonal patterns of indices
43 variability. For instance, at time t with $S_t = 1$, the distribution $P(O_t|S_t = 1)$ of precipitation
44 or excess heat indices, O_t , corresponds to a characteristic distribution observed during a “less
45 dry” and “less warm” season. In contrast, distribution of indices when $S_t = 2$, $P(O_t|S_t = 2)$,
46 corresponding to a “drier” and “warmer” state 2 type season. The different state-dependent
47 indices distribution during “wet-mild” (blue pdf) or “dry-warm” (red pdf) states is illustrated
48 in **Figure 2(d)**. Within the Non-homogenous Hidden Markov Model (NHMM) the sequence

49 of weather states $S_{1:T}$ is dependent upon the sequence $z_{1:T}$ of large scale climate driver
50 covariates (i.e. Niño3.4 index). These covariates can be observed or, potentially, simulated by
51 high-end general circulation models, subject future greenhouse gas scenarios¹³
52 Supplementary Figure 7 illustrates the parameters of a two-state NHMM fitted in one of
53 Shandong province 280 pixels with Niño3.4 index used as non-stationary covariate.

54

55 While the El Niño Southern Oscillation is known to be amongst the main drivers of the Asian
56 Summer Monsoon^{14,15} the seasonal and interannual variability of the summer Monsoon in
57 North East China is also associated with other drivers that are not taken into account in the
58 model used here where only one non-stationary covariate is included. Other drivers such as
59 the snow cover conditions in Eurasia and the Tibetan Plateau^{16,17}, the Indian Ocean Dipole
60 interannual oscillation¹⁸, and tropospheric cooling over Northern latitudes of China^{18,19} have
61 also been shown to exert an influence on the summer Monsoon variability in North East
62 China, in conjunction with ENSO. Given the demonstrative nature of the manuscript in
63 illustrating the methodological construct developed, only ENSO, the main driver of the Asian
64 Summer Monsoon was used, and a more detailed study would allow characterization of the
65 relative influences and interactions of the various climate drivers cited here on the Northeast
66 China Summer Monsoon variability.

67 Furthermore, the interaction of global climate forcing, derived from increased emissions of
68 greenhouse gases, with regional climate forcings^{20,21}, which result from tropospheric
69 pollution and natural climate variability, amplify the uncertainty of projections of local
70 weather variability in climate models. In particular, the prediction of local precipitation
71 variability, both seasonal and interannual, such as the dates of rainfall season onset, is
72 uncertain and represents a persistent barrier to robust forecasting of the impacts of weather
73 variability on food supply. Furthermore, the uncertainty of future tropospheric pollution and

74 the negative sensitivity of crop production to solar dimming increases the uncertainty of
75 future food production in regions such as northeast China²².

76

77 **Generalized Additive Mixed crop response modelling**

78 Within the GAMM²³ described, f_i are smooth functions of the x_i covariates that can be
79 defined using a basis function that can be expressed linearly as follows with $b_j(x)$ the j^{th}
80 element of the basis function and β_j scalar parameter values:

81

$$f(x) = \sum_{j=1}^n b_j(x)\beta_j \quad (5)$$

82 Here a spline basis due to the ability provided to estimate the properties of f over a large
83 domain of the response variables. Cubic splines are used as smooth functions within the
84 GAMM. Cubic splines can be described as portions of cubic polynomials joined together at
85 specified *knots* in the response domain. The knots are located at specific quantiles values of
86 the response variable. Given the locations of the knots $\{x_i^*: 1, \dots, q - 2\}$ the i^{th} row of the
87 $y = \beta X + \varepsilon$ model matrix can be written using a cubic spline as:

88

$$X_i = [1, x_i, R(x_i, x_1), \dots, R(x_i, x_{q-2})] \quad (6)$$

89

90 **Input-Output-based economic impact modelling**

91 Supply-side shock is simulated using a Gosh model formulation²⁴ of province-level Input-
92 Output tables²⁵ as detailed in equation (5) below. The crops considered are singled out from
93 the rest of the economic network in order to model both direct and indirect economic losses
94 derived from supply shortages Δv . Input-Output tables were obtained from the National
95 Bureau of Statistics²⁶ repository and province-level maize and rice grain production used to

96 single out these sectors in the tables were retrieved from Provincial Agricultural Statistical
97 Records^{27,28,29,30}, and Δx below is the vector of changes in final supply for each sector
98 represented.

99

$$\Delta x = G' \Delta v \tag{7}$$

100

101 Here G is the Gosh inverse, Δx the vector of changes in final demands and productions of
102 each of the $n = 47$ represented sectors of the provinces economies, subsequent to a change in
103 supply of $\Delta v = (0,0, \Delta_{crop}, \dots, 0)'$ of supply in maize in Shandong and Hebei or rice in
104 Guangdong and Guangxi. The elements of the Gosh inverse coefficients reflect the total value
105 of production δx_j coming about in sector $j \in [1, n]$ per unit of primary input δv_i in sector
106 $1 \leq i \leq n$.

107

108 **Supplementary Discussion**

109 More frequent and broad-spread crop failures resulting from extreme weather conditions
110 require new sources and types of financial products. Here the main driver is ensuring the
111 sustainability of product sourcing by minimizing and smoothing in time, the costs caused by
112 climate and weather hazards to farmers, the food-and-fiber industry, and society. Developing-
113 country farmers are vulnerable to climate change and to the impacts of extreme events. Lack
114 of resources reduces their ability to cope with these conditions. Moreover, the occurrence of
115 natural disasters frequently forces their governments to divert planned investments to
116 immediate post-catastrophe aid and reconstruction.

117

118 The role of improved modelling of future agricultural production loss risk on food stocks at
119 both the national and international levels is becoming critically important. At the national

120 level, the ability to base policy, procurement and safety net decisions on reliable data is vital.
121 The previous existence of global food stocks and surpluses meant that shortfalls at the
122 national level could be managed through access to international markets. With the reduction
123 in global stocks and the fact that the majority of these are not liquid — as they are situated in
124 countries unlikely to allow their export — the ability of national governments to purchase
125 internationally has decreased³⁵.

126

127 With the increase of long-term investment funds in the equity markets and closer financial
128 controls resultant from the 2008 financial crisis, equity analysts are increasingly interested in
129 long-term sustainability plans of publicly listed companies, including food purchasers and
130 retailers. This will ultimately result in share price differentiation between those companies
131 who are, and those who are not, building long-term variables — such as climate change —
132 into their business models and practices.

133

134 At the international level, the use of more accurate temporal and spatial modelling of future
135 production would enable the humanitarian-aid architecture to be better planned and
136 resourced. Such accurate modelling would also enable multi-country policy dialogue to occur
137 in the case of shocks to the global food system, reducing the likelihood of volatile, “beggar-
138 thy-neighbour” policy changes. Initiatives in this direction include the Agriculture Market
139 Information System (AMIS) and Global Agricultural Monitoring (GEOGLAM) project.

140 Much more remains to be done and will require the establishment of innovative
141 collaborations between different disciplines and actors, including physical, agricultural and
142 economic researchers and institutes.

143

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253

254

255

256 **Supplementary Figures and Tables Legends**

257 **Supplementary Figure 1. Schematic of the “weather-within-climate” and index-based,**

258 **local-to-regional weather risk modelling framework.** The bottom of the figure shows grid-

259 level columns (i.e. databases) of N potential weather indices acting as proxies of weather-

260 driven crop yield loss (colour coding of indices as described in Supplementary Figure 3). The

261 most effective index is selected using an ensemble-based recursive partitioning algorithm

262 resulting in a mosaic of weather indices that capture the sensitivity of crop yield to daily

263 variability of one or more weather variables. Each selected weather index is modeled

264 (downward dashed arrows) conditionally on latent, regional-level variables capturing

265 intraseasonal weather variability in each region. The set of homogenous latent variables is

266 itself modeled conditionally on observed or simulated, time varying, large-scale variables that

267 capture interannual climate variability. The latter variables are used to project the regional set
268 of selected indices into different climate scenarios.

269 **Supplementary Figure 2. Bivariate distributions of the indices for heat wave and**
270 **precipitation variability, associated with a single pixel in Shandong province, subject to**
271 **rain-fed local variety scenarios.** (a) Joint cumulative distribution of dependence between
272 heat wave and precipitation variability indices, using a Gumbel copula model. (b) Return
273 period of joint occurrence of the indices for heat wave and precipitation variability.

274

275 **Supplementary Figure 3. Weather index color code, as illustrated by sample building**
276 **for a cumulative weather index, namely the deficit rainfall for the 135 daylong growing**
277 **period of a given crop.** The color code of each weather index is calibrated on the yellow-
278 red-blue color scale located above all the indices. If an index recording deficit precipitation is
279 at the beginning of the crop growth cycle (i.e. during the first third of the 135- day period) its
280 color is yellow and tends to green. For deficit precipitation at the middle (i.e. during the
281 second third of the growth cycle, including the reproductive stages) the color is red. Finally,
282 for deficit precipitation during the last third of the crop cycle the color is blue. Overlapping
283 deficit precipitation indices capture periods are indicated by corresponding colour proportions
284 Brown colored “NaN” is used to encode lack of data.

285

286 **Supplementary Figure 4. Matrix of the impact of weather conditions and technological**
287 **scenario on the maize yield in northeast China’s Shandong province.** Rows indicate the
288 technological scenario, while the columns indicate the individual, (a)-(f), or combined, (g)-
289 (i), weather hazards (i.e. precipitation, heat or both).

290

291 **Supplementary Figure 5. Results of weather index–based modeling of rice yield**
292 **response to excess temperature in South China’s Guangxi province.** (a) Map of Guangxi
293 with indices selected at pixel level to best capture rice yield variability driven by excess
294 temperature. The colour scale is fully displayed in Supplementary Fig. 3 and indicates the
295 phase of the crop growth cycle during which the selected weather index captures most
296 significantly higher sensitivity to excess heat: beginning – green-yellow; middle – red-purple;
297 end – purple/blue-dark blue; and grey: whole season. (b) Map of the 10-year return period for
298 rice production, derived from the pixel-level distributions of weather indices for rice yield
299 response, and pixel-level sown area; light-yellow–to–dark-orange scale from ~200 to ~1,400
300 tons/pixel. Results shown for a single local irrigated technological scenario, of local rain-fed
301 rice.

302 **Supplementary Figure 6. Schematic diagram of the Nonhomogenous Hidden Markov**
303 **Model (NHMM) used.** **R1** and **R2** represent the observed uni- or multivariate distributions
304 of the weather indices. **S1** and **S2** are hidden variables that describe regional weather
305 variability on intraseasonal scales, while $X(t)$ is a time-varying covariate that captures
306 interannual climate variability. The vertical arrows represent conditional dependence, while
307 the horizontal arrows linking **S1** and **S2** represent transition probabilities between the two
308 latent variables; self-transition probabilities are represented by circular arrows. The Niño-3.4
309 index, based on Tropical Pacific sea surface temperatures, is used as $X(t)$, while **S1** and **S2**
310 are derived from the observed **R1** and **R2** weather indices.

311
312 **Supplementary Figure 7. Schematic diagram of the two-state NHMM for a grid point in**
313 **Guangxi province.** (a) Transition probabilities for the two states of the NHMM conditioned
314 on central-eastern Pacific sea surface temperatures, as captured by the Niño-3.4 index. (b)

315 Most probable sequence of states on the same grid point as decoded using the Viterbi
316 algorithm³².

317

318 **Supplementary Table 1. Cost estimates for new development and renovation of**
319 **irrigation infrastructure in Shandong province, expressed in millions of 2008 USD**

320 **(USD×10⁶) and percentage of 2008 aggregate provincial GDP (% GDP); the latter**

321 amounted to 3.09 trillion Yuan in 2008 (i.e. 0.46 trillion 2008 USD). Sown area figures are

322 extracted from the USDA ERS statistical database³³. Irrigated land areas are extracted from

323 the National Bureau of Statistics²⁶ (NBS) and FAO's AquaStat³⁴, respectively, lower and

324 upper bound estimates for the year 2001. The FAO irrigation infrastructure cost database is

325 used to access potential costs of deployment and renovation/modernization of irrigation

326 infrastructure in Shandong province used here³⁵: (i) average cost of new infrastructure for

327 underground pumped water irrigation in Asia of 550 USD/ha; and (ii) average cost of

328 rehabilitating and modernizing underground pumped water irrigation projects in China of

329 1,670 USD/ha.