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Climate change increases North Korea's hunger: implications for social resilience

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29 **Abstract**

30 Adaption based on social resilience is proposed as effective measures to mitigate hunger and avoid
31 disaster caused by climate change. But these have not been investigated comprehensively in climate-
32 sensitive regions especially necessary-quantitative paths. North Korea (NK, undeveloped) and its
33 neighbors (SK, South Korea, developed; China, developing) represent three economic levels that
34 provide us with examples of how to examine climatic risk and quantify the contribution of social
35 resilience to rice production. Our data-driven estimates show that climatic factors determined rice
36 biomass changes in NK, while non-climatic factors dominated biomass changes in NK's neighbors.
37 If no action is taken, NK will face a higher climatic risk (with continuous high temperature heatwaves
38 and precipitation extremes) by the 2080s with high emission scenario when rice biomass and
39 production are expected to decrease by 20.2% and 14.4%, respectively, thereby potentially increasing
40 hunger in NK. The contribution of social resilience to food production in the undeveloped region
41 (15.2%) was far below the contribution observed in the developed and developing regions (83.0%
42 and 86.1%, respectively). These findings highlight the importance of social resilience to mitigate the
43 negative effects of climate change on food security and human hunger, and provide necessary-
44 quantitative information.

Main Text:

Extreme climate and high-frequency meteorological disasters occurring from abnormal changes in temperature and precipitation are reported to decrease agricultural productivity and increase inter-annual variability of crop production¹⁻³. By the 2050s, predicted increases in frequency and intensity of climate extremes are projected to increase global food prices and place billions of people at risk of hunger⁴, especially in poor countries, regions, and households, exacerbating risk owing to lower ability to adapt to climate change⁵⁻⁷.

Indeed, regional famine and hunger normally arise from the combined effects of climate and economic vulnerabilities^{8,9}. Further, the adaptive ability that depends on social-economic resilience is consistently regarded as a crucial factor in coping with climatic risk and safeguarding food security. Social-economic resilience includes not only traditional financial assets and infrastructure¹⁰, but also demographic structure, resource utilization, technology, education, and attitudes and perceptions of risk in order to change adaptive behaviors^{11,12}. However, few studies have integrated social resilience into the climate risk framework to quantify the contribution of regional food production due to inherently hard-to-quantify human behavior and risk recognition. Moreover, the potential of social-economic resilience to mitigate the adverse effects of climate change, in particular climate extremes, and to ensure food security remain largely unknown.

North Korea (NK), located in a climatic-vulnerable region of Eastern Asia (Figure 1), has been strongly affected by climate change. Many meteorological disasters have occurred that have induced more severe famine over the past decades, including typhoons, heavy precipitation events, and river floods¹³. It has been reported that NK suffered from a freezing disaster in 1993, hail in 1994, severe floods during 1995 to 1996, a typhoon and drought in 1997, frost in 1998, etc¹⁴. Even in the 21st century, NK's grain production still cannot meet the needs of the population, and food deficits still loom large and are even a growing trend^{15,16}. With large-scale intensification of extreme high temperature and precipitation events in the future, more scholars take a pessimistic attitude towards food self-sufficiency for NK¹⁵. Due to the particularity and importance of its geographical location and social-economic policies, the unstable famine and poverty issues in NK may increase risks to global stability that include required extensive international aid¹⁴, humanitarian relief¹⁷, and open international trade¹⁸, especially in the context of the global pandemic of COVID-19.

NK (the undeveloped region) and its neighbors (South Korea, SK, the developed region; China, the developing region) represent different levels of economic development, and also provide us with a natural example for investigating the impacts of climate extremes and their link to social-economic behavior. Additionally, the similar climatic conditions¹⁹ of these regions also rule out uncertainties in social-economic assessments due to differences in climate vulnerability. Comparing economic vulnerability based on social resilience among the three regions excepting climate risk is a valuable approach, i.e., the ability to adapt to climate risk for food security resulting from climate and economic vulnerability. Rice (*Oryza sativa* L.) is one of the most important foods in NK. Rice composes more than 60% of the total grain production, and directly affects food security for NK in terms of planting area and production²⁰. Importantly, the adverse impacts of climate change on rice systems is increasing²¹.

It is well-known that obtaining reliable statistics and survey data from NK is difficult due to NK's politics and economics. Therefore, this study attempted to fully use remote sensing and climate data with openly available statistical information to examine and assess climatic risk and food security with interaction between climate and social-economic vulnerability for NK and its neighbors (Table

89 S1). In addition, the method presented in this study can be used in regions of the world that lack
90 official information to evaluate climatic risk and food security status. In this research, we need to
91 answer three key questions: (1) How has climate change (climate extremes) affected rice production
92 in NK? (2) What is the future projection of rice production loss? and (3) How have human activities
93 (adaptation based on social-economic resilience) exacerbated or ameliorated food deficits in NK and
94 its neighbors. Specifically, we focus on normal and extreme climate changes in NK over the past 18
95 years (2000–2017), and attribute rice biomass changes to climatic factors resulting from high-
96 frequency climate extremes and increased vulnerability. Furthermore, we introduce 27 global climate
97 models (GCMs) under two future scenarios (SSP245 and SSP585 from CMIP6) to assess climate
98 changes and production losses in the future from a climatic risk perspective. Finally, the contribution
99 of social resilience based on five factors (population development, resource use, science and
100 education, economic development, and agricultural input) to rice production is explored
101 quantitatively by contrasting the differences between NK and its neighbors (SK and China). Further
102 details of the data used, methods, and model robustness checks can be found in the Methods and
103 Supplementary Information.

104 Results

105 **When food famine occurs.** The first challenge relative to analyzing food security is to determine the
106 time of the food crisis occurrence, i.e., when food famine occurred. To do this, we employed a general
107 method with food self-sufficiency rate and national-level statistics from FAO to identify the degree
108 of food self-sufficiency in NK and SK, and defined the years when the rice self-sufficiency rate was
109 less than 70% as famine years (see Methods). Over the period from 1984 to 2017, we obtained an
110 impressive result in which the rice self-sufficiency rate in NK was the highest in 1988 and then
111 declined dramatically to the lowest point in 2000 (less than 70%) (Figure 2a). After 2000, NK's self-
112 sufficiency rate gradually increased, but it still fell sharply in some years, especially in 2007 (again
113 less than 70%). In contrast, SK's self-sufficiency rate has remained stable and close to 100% (Figure
114 2a). From 1984 to 2017, the self-sufficiency rate for rice in NK was below 90% in fifty percent of the
115 years, but in SK the self-sufficiency rate was higher than 90% in all the years. We identified two
116 famine years in NK (2000 and 2007), and used data from those two years to study the causes of the
117 famines.

118 **Attribution of famine occurrences to climate.** In order to attribute changes in rice growth and major
119 climate in NK, Liaoning and Jilin provinces in China (CH_1_2), and SK (Figure 1), the phenology-
120 and pixel-based paddy rice mapping (PPPM) algorithm was first applied on the Google Earth Engine
121 cloud platform to extract rice paddy map referencing used by Dong et al. (2016)²² in which they
122 adequately verified this algorithm and the accuracy of rice maps for ensuring robust application in
123 large-scale fields (Figure S1a). Further, we adopted an eLUE model to simulate the biomass of the
124 study areas in 2000 and 2007, and calibrated this model. Figure S1b demonstrated that the eLUE
125 model had good robustness and accurately reproduced the light use efficiency of ecosystems
126 monitored by eddy covariance (EC) towers (10-fold cross-validation: $R^2 > 0.75$, $nRMSE < 0.4$, $P <$
127 0.01). Consequently, we reestablished the distribution of gross primary productivity (GPP) in 2000
128 and 2007 using this model for the study regions (see Methods).

129 The twelve climatic variables (including three average and nine extreme variables) were
130 incorporated in the analysis to determine climate attribution of famine years (Table S2). We then
131 conducted a multicollinearity analysis of all climate variables to exclude high collinearity for machine

learning modeling, i.e., variance inflation factor more than 10 (Table S3). Although the eLUE model is driven by remote sensing and flux data, it introduces solar radiation into the simulation. We therefore additionally analyzed the impact of solar radiation on attribution to climate. In the two famine years (2000 and 2007), similar accuracy was found for the model with and without solar radiation (Table S4). In the famine years, climate variables produced different levels of explanation of GPP changes in NK, CH_1_2, and SK, with 73%, 43%, and 44%, respectively, explained in 2000, and 65%, 44%, and 55% explained in 2007 (Figure 2b). This meant that climate variability was responsible for nearly three quarters of rice GPP changes in NK, while approximately half of GPP changes in CH_1_2 and SK in the famine years were due to climate change.

We next fully examined the spatial-temporal changes of each climatic factor by comparing the baseline using anomalies to attribute the famine (see Methods). The gray bands in Figure 2c represent the period from heading to tillering during the rice growing season (GS). This period is usually sensitive to climate change, and especially sensitive to high temperatures that can cause plant death. Heat wave caused by sustained high temperatures dominated decreasing in rice production in 2000 for NK. Total solar radiation and average air temperature during GS were not observed to be different from the baseline during the heading to tillering stages in 2000 (Figure 2c). The temperature extremes, annual minimum value of daily minimum temperature (TNn) and annual maximum value of daily maximum temperature (TXx), also did not demonstrate significant increases (Figure 2c), yet their duration increased substantially such as for TR20 (annual count of days when $TN > 20^{\circ}\text{C}$) and SU30 (annual count of days when $TX > 30^{\circ}\text{C}$), resulting in a heat wave for nearly five months in 2000 (Figure 2c). In addition, a few long-term periods of rainfall hardly alleviated the high temperatures and heat wave in local areas (Figure 2c). In terms of the spatial distribution of anomalies, the frequency of abnormal increases for TXx, TR20, SU30, and FD0 (annual count of days when $TN < 0^{\circ}\text{C}$) in 2000 accounted for 27%, 35%, 37%, and 54%, respectively, of the entire region (Figure S2). Specifically, the occurrence of extreme high temperatures increased abnormally in southwest NK, and the anomalies of TXx, TR20, and SU30 were all more than three standard deviations, with the anomalous occurrences covering the rice growing regions (Figure 2c). Significant increases for precipitation and precipitation days were observed in the non-rice region of northeast NK, and this also explains why precipitation did not alleviate the reduction in production caused by the high temperatures and the heat wave (Figure 2c). Precipitation extremes caused by increasing precipitation days with the extra precipitation dominated decreasing in rice production in 2007 for NK. Specifically, high-temperature days were significantly reduced in the heading-tillering stages in 2007 compared with the baseline (Figure 2c). And an important cause of the reduced temperatures was the large amount of precipitation that regulated surface temperatures, decreasing maximum temperatures (TXx) and increasing minimum temperatures (TNn) (Figure 2c). Furthermore, the long-term and substantial amount of precipitation produced conditions that made plants highly susceptible to crop root rot and flood damage. TP (total precipitation during GS), R50 (annual count of days when $R \geq 50\text{mm}$), and R25 (annual count of days when $R \geq 25\text{mm}$) in 2007 accounted for 87%, 72%, and 80%, respectively, of the entire region (Figure S2). This was similarly evidenced by the spatial distribution of rainfall extremes that covered the west/southwest rice-growing region in 2007 (anomaly was more than three standard deviations) (Figure 2c).

If NK maintains its current level of rice production, what risks will be faced for future production under climate change? This section focuses on climate change and the potential for warning of food security issues in the future. Here, we show the effects of climate change regarding production losses under two climate scenarios (SSP245 and SSP585) using 27 GCMs (Table S5). Future climate would

177 see marked increases in temperature and precipitation in the vulnerable climatic region of NK.
178 Specifically, AAT, TNn, and TXx would increase by $2.96 \pm 0.93^{\circ}\text{C}$, $2.32 \pm 0.59^{\circ}\text{C}$, and $3.81 \pm 1.12^{\circ}\text{C}$,
179 respectively, under the SSP585 scenario in the 2080s (Figure S3a, d, e). Most surprisingly, SU30
180 would increase by $97.6 \pm 43.77\%$ and $221.94 \pm 77.09\%$ under SSP245 and SSP585, respectively, in the
181 2080s, indicating that the number of high temperature days would double and triple in the future
182 compared with the 1979–2018 period (Figure S3g). Additionally, TP, R50, and R25 would increase
183 by $19.93 \pm 7.74\%$, $7.57 \pm 12.53\%$, and $13.42 \pm 9.75\%$, respectively, in the 2080s under SSP585, yet R1
184 would decrease by $19.23 \pm 0.86\%$ (Figure S3c, i, j). In general, no matter which climate scenario is
185 considered, the risk of high temperatures and extreme rainfall due to future warming will increase.

186 More specifically for NK, climatic variables explained 80% of the GPP changes observed from
187 flux towers during 2000–2017 (the baseline period) (Figure 3a). In addition, temperature dominated
188 rice biomass changes in NK over the long time period as seen by the top three important variables
189 being related to temperature (Figure 3b). As a consequence, with extreme high temperatures and
190 altered precipitation in the future, rice biomass in NK would decrease by 18.9% and 20.2% in 2080s
191 under SSP245 and SSP585, respectively, compared with the baseline period. Production would
192 decrease by 13% and 14.4% in the 2080s under SSP245 and SSP585, respectively (Figure 3c). In NK,
193 where vulnerability to climate is especially high, and the frequency of extreme climate leads to low
194 production, 20.2% biomass losses may be conservatively estimated, and the fragile food system may
195 collapse and result in famine. For CH and SK, climate change did not explain the changes in rice
196 biomass, and the assessments of future rice losses are highly uncertain (Figure 2b). Therefore, the
197 future production losses in SK and CH_1_2 were not calculated in this study. However, it is worth
198 clarifying that robust results have shown that the rice production in CH_1_2 and SK was greater than
199 in NK in the context of past climate shocks, and was dominated by non-climatic factors.

200 **Analysis of adaptability in NK, CH, and SK.** Although rice production is generally subject to
201 natural-environmental change from the standpoint of a climatic risk framework, the adaptive capacity
202 at regional or national levels from social resilience is more determinant of rice production losses²³.
203 Social resilience will be driven by population, economics, technology, and culture¹². To quantify the
204 contribution of social resilience to rice production, we collected and used economic statistics from
205 FAO, World Bank, and an agricultural dataset of remote sensing that involved five factors: population
206 development, resource use, science and education, economic development, and agricultural inputs
207 (Table 1) that together constituted social resilience²⁴. The social resilience data was characterized as
208 one of two types to fully reveal the real-social situation: soft-adaptive and hard-adaptive²⁵ (Table 1).
209 Additionally, discontinuous-economic data for NK were interpolated using regression models to
210 estimate missing values (energy use, school enrollment-tertiary, access to electricity, and patent
211 applications) (Figure S4, R^2 values are respectively 0.70, 0.99, 0.99, and 0.92; P values are all < 0.01).
212 Figures S5–S7 indicate the correlations between a single social-economic variable and rice
213 production. NK showed weaker correlations between each of the variables of social resilience than
214 SK and CH ($\rho < 0.5$ and not strong significance). Moreover, an interesting result showed the huge
215 difference in the contribution direction of each economic variable to rice production (i.e., positive or
216 negative contribution) in the three regions.

217 For this purpose, we conducted a more comprehensive integrated analysis based on random
218 forest regression of economics (RF_e). The random forest model has been widely applied to ecological
219 studies to quantify the contribution of social-economic resilience to rice production (see Method
220 section, Figure 4a). Of the twelve indexes of social resilience, higher education, rural population,
221 access to electricity, and population ages 0-14 dominated rice production variations in NK (P value $>$

0.05); patent applications, population ages 0-14, GDP per capita, and energy use dominated rice production variations in SK (P value < 0.05); and population ages 0-14, rural population, net ODA received per capita, and GDP per capita dominated in CH (P value > 0.05) (Figure 4a). The level of economic development and population structure in both developed and developing regions played a more important role than in undeveloped regions, and science and education in developed regions had a greater influence on rice production than other factors (Figure 4a). The RF_e analysis further illustrated the absolute contribution of social resilience to rice production in SK and CH (explaining 83.0% and 86.1%, respectively, of inter-annual rice production variation, p value < 0.05), values which are much higher than in NK (15.2%, p value < 0.05) (see Methods section, Figure 4a). This result echoes the impact of climate change on rice production, i.e., crop production is interactively affected by climate and economic vulnerability, where rice production in undeveloped regions is controlled by climate factors (Figure 2b), and rice production in developed and developing regions is controlled by social-economic factors (Figure 4a). In addition, the robust results obtained in this study demonstrate the great potential of social resilience to increase crop production, and resist the negative effects of climate shocks and weather extremes on food security.

Rice production in NK exhibited a threshold-like response to all four of the important variables influencing rice production, including school enrollment, tertiary (Figure 4b). Rice production declined when school enrollment was higher than -0.6 units, presumably because limited capital was invested in science education and because of reduced economic investment and labor from family source in agriculture. The non-linear response of rice production in CH to population development provided coherent evidence (Figure 4b). Specifically, rice production decreased with increasing agricultural population and population ages 0-14 in the undeveloped or developing countries (NK and CH) (Figure 4b). The pressures from diet need caused by population growth and uncoordinated structure of population constrain economic development and production increase in undeveloped regions²⁶. For instance, the rural areas with relatively higher mechanization contribute to rice production and require less agricultural population²⁷. However, in the developed region (SK), one opposite result was shown in the response of rice production to population ages 0-14 (Figure 4b), and this result might be due to differences in population structure among districts. Developed regions have a greater need to increase the proportion of adolescents in the population to adjust for serious aging²⁸ so that a larger agricultural labor force is available to increase rice production. Energy use produced an increase in rice production for the developing country (CH), yet the opposite result was observed for the developed country (SK) owing to the capacity to import resources because of sufficient capital²⁹. In general, social resilience likely results in various impacts of rice production among NK, CH, and SK.

The non-linear response of rice production to agricultural inputs in the three sub-regions is shown in Figure S8. The response curves for nitrogen, phosphorus, and irrigation showed an overall increasing trend in SK and CH. However, in NK, the production responses of the three agricultural practice inputs were seen to be expressed as hump or concave curves (Figure S8). Based on the random forest model and its out of bag error, agricultural inputs (nitrogen, phosphorus, and irrigation) explained -4.8%, 51%, and 77% of rice production changes for NK, SK, and CH, respectively. The explanatory degree for NK was negative, meaning that the model was overfitted, and the three agricultural practices cannot support the increase in rice production in the current situation.

Discussion

Our results demonstrated that climate extremes reduced crop production and contributed to

266 famine under climate warming in NK. Presently, climate extremes have been known to have a
267 significant impact on the resilience of the food supply chain³⁰. Observed extreme temperatures have
268 led to increased yield variability, and occurrence of extreme temperature events is expected to
269 increase in the future³¹. However, abnormal weather and climate extremes do not always cause
270 negative consequences. Some studies relating to differing weather conditions and intensity and target
271 crops have reported different results in various areas of the globe. For instance, Schlenker and Roberts
272 indicated that high temperatures in the future will exceed the tolerable temperatures for corn (*Zea*
273 *mays* L.) and soybean (*Glycine max* L.), resulting in decreased production by 30-46% in US³². Yet in
274 the Brazil, yields of soybean, corn, and cotton (*Gossypium hirsutum* L.) have increased over the past
275 decades, even though the cumulative days of exposure to temperatures above the threshold
276 temperature have been much greater than in the US³³. Further, Lesk et al.³⁴ argued that hourly extreme
277 rainfall (> 50 mm hr⁻¹) caused severe damage to crop yield, but crop growth benefitted from heavy
278 rainfall of 20 mm hr⁻¹. Due to the projected increases in temperature and rainfall intensification in the
279 future, the impact of climate extremes on crops remains somewhat uncertain. It is difficult to identify
280 major changes in climatic sensitivity based only on production data over time because of the
281 infrequency of extreme weather³, and therefore, inductive analysis of the changes of exposure and
282 crop sensitivity to climate extremes is a prerequisite for food security assessment.

283 Differences in the quantitative attribution in rice production between NK and its neighbors (SK
284 and China) reflected the importance of adaptation based on social resilience to mitigate the adverse
285 effects of extreme climate. Food security may benefit most from the changes in adaptive capacity
286 under future climate change, such as in the fields of agricultural practices, economic development³⁵,
287 resource use, and social cognition³⁶. Irrigation³⁷, fertilization, conservation tillage³⁸, and crop
288 breeding are being given much attention, with more focus given to increasing yields. For example,
289 Challinor et al. found that anthropogenic adaptability increases the average yield of crops by 7–15%².
290 However, if the focus is only on increasing crop yields, farmers will still suffer severe production
291 losses due to their low perception of risk concerning the effects of extreme weather disturbances.
292 Learning reflects the ability to produce, absorb, and transform new information about climate risk,
293 adaptation, and coping with uncertainty. This ability to learn and apply new scientific information is
294 a mitigation mechanism applicable to climate change³⁹. Capital investment depends on economic
295 development, and is a more direct approach. These investments include building early warning
296 systems and climate insurance, resource and energy use, international trade, and reducing poverty.
297 Insurance is a tool to mitigate climatic risk and restore livelihoods, especially in response to climate
298 extremes⁴⁰, but if the insurance structure is not correct, it has an inhibiting effect on risk reduction⁴¹.
299 For regions that cannot compensate for losses through trade, these years of low productivity can still
300 be devastating. Poor countries are more vulnerable and less resilient to climate change. When the
301 poor are struck, they have less support from friends, family, and the financial system. Policies meant
302 to reduce poverty under similar climatic risk conditions can also reduce the adverse impacts of climate
303 change^{42,43}. The interaction of social-economic factors from many aspects is the key to decreasing
304 economic vulnerability and increasing social resilience to mitigate climate vulnerability. In this study,
305 social resilience was shown to be enormously important for reducing hunger by contrasting the
306 situation in three regions. Future planning for food security needs to consider climate change and
307 social-economic interactions and development.

308 Surprisingly, the high-temperature index (SU30) would increase 97.6% and 221.94% under
309 SSP245 and SSP585 in the 2080s, respectively (Figure S3). SU30 was approximately 25 d for the
310 baseline period (1979-2018), and this value is approximately equivalent to an average of one month

311 of high-temperature days every year. The number of high-temperature days per year would increase
312 by nearly one month by the 2080s under SSP245, and the number would increase by two months
313 under SSP585. This is probably due to increased frequency and time extension for high-temperature
314 days affected by future temperature increases⁴⁴. This finding is also supported by results documented
315 in previous literature. Kawasaki and Uchida⁴⁵ indicated that the abnormal temperature caused by
316 global climate change has had a serious negative impact on agricultural production and quality. And
317 climate extremes will increase in frequency and intensity with rising temperature in the future⁴⁶. Our
318 results also suggested that projected GPP and production may decrease by 20.2% and 14.4%,
319 respectively, in NK in the 2080s under the SSP585 scenario. However, this result may be
320 underestimated, and could be even more serious for crops because we used the average GPP and
321 harvest index for entire regions to calculate relative changes in biomass. Similar conclusions
322 regarding future GPP losses across the study area have been stated in many previous studies. For
323 example, Zhang et al.⁴⁷ suggested that rice yield would decrease by 10.7% when CO₂ effects were
324 not considered during the 2090s under the RCP8.5 scenario in Northeast China.

325 Topography may be one of the factors that limit future rice production potential in NK due to
326 the cultivation of poor-quality land that is not suitable for planting rice. NK contains a wide range of
327 slopes compared with CH_1_2, and SK. The steeper slopes (slope >10°) accounted for 64% of the
328 country's land, and the gentler slopes (5°–10°) accounted for 15% of the country's land (Figure S9b).
329 In addition, land with DEM values greater than 500 m in NK accounted for 47% of the entire land
330 area, while those higher elevation areas in CH_1_2 and SK accounted for 23% and 16%, respectively,
331 of the entire land area (Figure S9b). Long-term deciduous broadleaf forests, deciduous needleleaf
332 forests, and mixed forests are located in regions of DEM > 500 m, and are not suitable for planting
333 crops (Figure S9a).

334 Our findings are subject to some limitations and should be considered with caution. First of all,
335 lack of sufficient ground truth data for vulnerable regions was the biggest challenge. However, in this
336 study, we used meteorological reanalysis products, openly available statistics, and high-resolution
337 images from Google Earth as a replacement to ensure robustness. The advantage of doing so is
338 extendable to other parts of the world without ground truth data limitations. With the future
339 development of multivariate data (especially remote sensing data), study regions lacking reliable data
340 will have new opportunities for analysis and evaluation. Other potential sources of uncertainty may
341 not have been resolved in our model. For example, missing short-term fertilization data and additional
342 management data are a potential source of uncertainty not considered in this study^{48,49}. Secondly, soil
343 properties may also introduce uncertainty in the results⁵⁰. The physical and chemical properties of
344 soil were different in each region, yet this variable was not included in our model. Folberth et al.⁵¹
345 found that assessing the impact of climate change on yield depended on soil type because soil
346 characteristics and moisture buffer or amplify climatic impacts³. This study also did not consider the
347 effects of rice genotype due to a lack of cultivar data, and therefore there may be potential uncertainty
348 regarding regional production differences⁵². For GPP loss estimation, we did not introduce CO₂
349 concentration in our model due to the controversy regarding the ability of increasing CO₂
350 concentration to decrease crop water demand and improve yield while reducing nutritional content of
351 grain⁵³. Not introducing CO₂ concentration effects may have affected reliable and robust estimates of
352 climate and economic vulnerability. Finally, rice maps and downscaling methods were also sources
353 of uncertainty. Specifically, uncertainties regarding rice maps may have arisen from remote sensing
354 data, poor weather, data quality, and the number of images observed^{54,55}. This study generated future
355 daily meteorological data based on statistical downscaling, but different results could be obtained

356 with different downscaling methods⁵⁶ (such as the change factor method and dynamical downscaling).
357 In the future, we plan to engage in further in-depth study of multiple climate indexes, particularly
358 extreme climate variables, combined with process-based ecological models to explain the
359 mechanisms of crop growth. However, achieving this next step will require a great deal of data
360 support.

361 Climate change is expected to increase the frequency and intensity of climate extremes that will
362 likely reduce global food production and induce famines. An accurate assessment of food insecurity,
363 must be valued in the deprived areas of the world because it is a vital link in the world food system
364 and is a major component of the United Nation's Millennium Development Goals. NK is
365 representative of the world's deprived areas, and it and its neighbors provide an excellent example for
366 studying food insecurity in undeveloped regions. Our robust results suggest that social resilience
367 provides a reliable path for understanding and mitigating the detrimental effects of extreme weather
368 shocks in the future. Using this method, we can clarify future food risks and provide quantifiable
369 pathways and goals for efforts that will contribute to improved national risk awareness, make up for
370 weaknesses in food programs, and guide adjustments to food strategies, and thereby provide further
371 guidance for optimizing social-economic policies.

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476

477 **Figure 1: Spatial patterns of geographical and climatic distribution across study area.** **a** shows
 478 climate zones. **b** shows the geographic boundaries of the study area. BSk, Cwa, Cfa, Dwa, Dw, Dwb, Dwc,
 479 Dfa, and Dfb are defined as arid and cold steppe, temperate regions with dry winter and hot summer,
 480 temperate regions with hot summer and without dry season, cold regions with dry winter and hot summer,
 481 cold regions with dry winter and warm summer, cold regions with dry winter and cold summer, cold regions
 482 with hot summer and without dry season, and cold regions with warm summer and without dry season¹⁹,
 483 respectively. NK, SK, CH_1, and CH_2 are North Korea, South Korea, Liaoning province of China, and
 484 Jilin province of China. The World Bank defines North Korea, South Korea, and China as low, high, and
 485 upper-middle income countries/regions, respectively, based on income levels.

486

Figure 2: Identification of famine years in North Korea and attribution of production losses. **a** shows rice self-sufficiency every year calculated from import, export, and production quantity data from FAO. The dash line is the 70% self-sufficiency rate (that defines the famine level). The bottom left corner inset chart in panel **a** shows an enlarged view during 1993 to 2008. **b** shows the contribution of climatic variables to rice biomass production in 2000 and 2007, which is calculated between biomass production and climate indices in all the land pixels in each region. NK, CH_1_2, and SK are North Korea, Liaoning and Jilin provinces of China, and South Korea, respectively. **c** shows the spatial and temporal distribution of climatic standardized anomalies for 2000, 2007, and the baseline period (2000 to 2007) over North Korea. The vertical gray areas in the surrounding line charts represent the period from tillering stage to heading stage, and the error bars represent one standard deviation. For detailed meanings of the twelve climatic variables, see Supplementary Table S2.

Figure 3: Projected rice production losses under four future scenarios. **a**, Observed vs. predicted rice biomass from 2000 to 2017 (baseline period). The blue and red points represent the calibration and validation data sets, respectively. **b**, Relative importance of climatic variables from non-linear modeling (the meaning of the variable abbreviations is provided in Table S2). **c**, Box plots of projected rice biomass (top panel) and production (bottom panel) losses under four different future scenarios based on non-linear modeling. Box boundaries indicate the 25th and 75th percentiles across 27 GCMs, and whiskers below and above the box indicate the 10th and 90th percentiles, respectively. The black lines within each box indicate the multi-model median.

508

Table 1 The vulnerable indexes for social resilience.

Factors of social resilience	Vulnerable indexes	Abbreviation
Rice Production	Production	Prod.
Population development (S)	Population ages 0-14 (% of total population)	Pop. 0-14
	Population ages 15-64 (% of total population)	Pop. 15-64
	Rural population (% of total population)	RP
Resources use (H)	Energy use (kg of oil equivalent per capita)	EU
	Access to electricity (% of population)	AE
Science and education (S)	School enrollment, tertiary (% gross)	SE
	Patent applications	PA
Economic development (H)	Net ODA received per capita (current US\$)	NOR
	GDP per capita	GDP
Agricultural input (H)	Nitrogen fertilizer use	N
	Phosphorus fertilizer use	P
	Irrigation	Irrigation

509 S and H represent soft-adaptive and hard-adaptive measures, respectively.

510

Figure 4: The contribution of vulnerable indexes for social resilience to rice production variability.

Twelve indexes of social resilience are from five factors, i.e., population development, resource use, science and education, economic development, and agricultural input (Table 1). **a**, The red and green bars represent significance tests for $p < 0.05$ and $p > 0.05$, respectively. The importance indicates explanation degree of the non-linear model for contribution of social resilience to rice production in the three regions. **b**, The non-linear response of rice production to standardized variables of social resilience. The black lines are smoothed representations of the response, with fitted values (model predictions) for the calibration data. The trend of the line, rather than the actual values, describes the nature of the dependence of rice production on the social resilience. The green and orange dash lines in the partial dependence plots represent rice production from the baseline and SSP585 scenarios, respectively. NK, SK, and CH represent North Korea, South Korea, and China.

Methods

Data sources. We used daily reanalysis data to analyze climate variables over the years of the study. The daily reanalysis data were obtained from the European Center for Medium-Range Weather Forecasts (ECMWF) gridded dataset at 0.1-degree resolution, and included daily 2-m temperature (24-hour maximum, minimum, and mean temperature), precipitation flux, and solar radiation flux from 1979 to 2018. See Table S1 for more details. We selected the ECMWF's ERA-5 dataset for two reasons: 1) ground data are not readily available; 2) by using the global dataset, we can apply our methods to other areas with limited data. Our primary analysis focused on calculating normal and extreme climate indexes for 2000–2017 (Table S2), and statistical downscaling of data from 1979–2018 was conducted to project future climate change using ERA-5.

For remote sensing information, we employed the MODIS gridded mosaic including 8d_surface reflectance, 8d_leaf area index, and 8d_gross primary productivity accessed from Google Earth Engine (GEE) for 2000–2017. We used MODIS surface reflectance to calculate vegetation indexes, i.e., normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), land-surface water index (LSWI), and the near-infrared reflectance of vegetation (NIR_v). The specific formulas are:

$$EVI = G \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + C_1 \times \rho_{Red} - C_2 \times \rho_{Blue} + L} \quad (1)$$

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (2)$$

$$LSWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad (3)$$

$$NIR_v = NDVI \times \rho_{NIR} \quad (4)$$

where ρ_{Red} , ρ_{NIR} , ρ_{SWIR} , and ρ_{Blue} are the surface reflectance values of the red band, near infrared band, shortwave infrared band, and blue band in the MODIS imagery. L is the canopy background adjustment that addresses non-linear, differential near infrared and red radiant transfer through a canopy. C_1 and C_2 are the coefficients of the aerosol resistance term that uses the blue band to correct for aerosol influences in the red band⁵⁷.

For geographic information, we also used the Digital Elevation Model (DEM) with 90-m spatial resolution from SRTM Digital Elevation Data Version 4 in the GEE platform to calculate slope for every grid cell. All datasets supporting the results of this paper are freely available in Supplementary Table 1.

We accessed the observations of daily net ecosystem CO₂ exchange and ecosystem respiration from two eddy covariance (EC) towers from the Chinese FLUX Observation and Research Network (ChinaFLUX) for 2003–2010 to calibrate and simulate the biomass of the study areas without meteorological inputs (except solar radiation). The EC towers were located close to North Korea in Yucheng, Shandong province of China (116°34'12.72"E, 36°49'44.4"N) and at Changbai Mountain, Jilin province of China (128°05'45"E, 42°24'9"N) with farmland and forest ecosystem, respectively. We used the daily net ecosystem exchange and heterotrophic respiration from the flux towers to calculate the gross ecosystem CO₂ exchange. We refer to gross ecosystem CO₂ exchange as gross ecosystem primary productivity.

The phenological periods of the main crops were obtained from the China Meteorological Data Sharing Service System (<http://cdc.cma.gov.cn/home.do>) in Panjin Plain, Liaoning Province of China to determine the rice growing and transplanting seasons in the study area. We redrew the crop calendar

based on Table S3 of Zhou et al., 2016⁵⁵. The reason for choosing these sites was based on the similar climate zone in the study area (Fig 1) and the lack of real data in North Korea. All data was strictly examined to meet the standards for further analysis, including cross-validation and comparison with existing data.

The statistical data were obtained from the Food and Agriculture Organization (FAO) of the United Nations (including rice production (1984-2017), rice imports and exports (1984-2017), and population (2000-2017) in country-level), the United Nations Statistics Division (GDP and imports/exports of goods and services (\$) from 2000 to 2019), and the World Bank (including Population ages 0-14, Population ages 15-64, Rural population, Energy use, Access to electricity, School enrollment, Patent applications, and Net ODA received per capita) (Table 1). Additionally, nitrogen and phosphorus fertilizer application for agriculture production were provided by Lu and Tian²⁴, which they developed the global gridded data at $0.5^\circ \times 0.5^\circ$ resolution from 1961-2013 and published for free. The production, imports, and exports were used to calculate rice self-sufficiency rate to identify famine years, and the other statistical data were used to analyze social-economic attribution. FAO's data quality is generally divided into 10 categories: "Unofficial figure, Symbol for indigenous or liveweight meat, Official data, Aggregate (may include official; semi-official; estimated or calculated data), Calculated, FAO estimate, Calculated data, FAO data based on imputation methodology, Data not available, and Trend". More than 95% of the data used in this study were from the "Official data" and "Aggregate" categories to ensure high quality.

For further analysis of non-climate attribution, we considered the effect of irrigation on rice growth. We used water consumption coefficient (WCE) of rice paddy to replace irrigation because of the lack of irrigation data over the study areas, and because of the large uncertainty in irrigation timing, amounts, and methods. The irrigation period for these maps was from 2001-2017, and the ratio of evapotranspiration (from MOD16A2, Table S1) to precipitation was used to calculate the WCE. Furthermore, we averaged WCE of rice paddy in the study areas.

Rice paddy mapping and estimating biomass. Rice paddy maps were produced on the GEE cloud platform based on vegetation index (see formula 1-3) and rice phenophase (Table S6) calculated from MODIS reflectance bands. For more details, see Dong et al., 2016²², where clear steps and full verification are provided. Existing biomass products usually are calculated using meteorological data. However, a misleading result can be obtained when analyzing which climate variables dominate biomass changes using these products, i.e., the climate variables that dominate biomass changes are highly correlated with the climate factors used for calculation. Therefore, we considered using a vegetation index from remote sensing to estimate gross primary productivity without including climatic factors. Traditional light use efficiency (LUE) models need to estimate fAPAR and ϵ separately when calculating GPP. Furthermore, using $VI_s \times PAR_{TOC}$ to estimate GPP means that vegetation indexes (VIs) can be more clearly used as a measure of ecosystem light use efficiency (eLUE)⁵⁸. eLUE is defined as the ratio between GPP and PAR_{TOC} :

$$eLUE_{TOC} = \frac{GPP}{PAR_{TOC}} = f(VI_s) \quad (5)$$

We averaged daily GPP (GPP_{EC} , $g\ C\ m^{-2}d^{-1}$) and daily PAR_{TOC} ($MJ\ m^{-2}d^{-1}$) from two EC towers as 8-day values to calculate $eLUE_{TOC}$ ($g\ C\ MJ^{-1}$). $f(VI_s)$ was from the regression of $eLUE_{TOC}$ to VIs. Once $eLUE_{TOC}$ was estimated, the eLUE relationship with PAR_{TOC} (formula 5) was rearranged to predict GPP:

$$GPP = eLUE_{TOC} \times PAR_{TOC} \quad (6)$$

$f(VIs)$ is the coupling relationship between eLUE and VIs. Past research has focused on the linear model^{58,59}. However, multiple variables have non-linear relationships in the natural environment, and large-scale areas contain multiple complex ecosystems. The performance of the linear model can no longer meet the practical application in large-scale regions and be extended to other districts. We converted $f(VIs)$ into a non-linear model (i.e., random forest model), and incorporated a variety of VIs into the model (NVI, EVI, LAI, and NIRv). Random forest has good performance and fewer parameters compared with other nonlinear models. In recent years, it has been widely used in different regions to solve natural science problems at global scale⁶⁰. For a more detailed explanation of this model, see Breiman (2001)⁶¹

For establishing the relationship between eLUE and VIs (calibrating the eLUE model) and providing independent verification, we randomized EC tower data (397 samples), and then divided the data into two subsets to be used as calibration and validation datasets. To evaluate non-linear model performance, we used a stratified 10-fold cross-validation. Two statistical parameters were used to evaluate the results of cross-validation: (1) coefficient of determination (R^2_{CV}); and (2) normalized root mean squared error (nRMSE_{CV}), where the CV subscript represents the data obtained from the cross-validation datasets^{56,60,62,63}. We used the Cal subscript to represent the data obtained from the calibration datasets. These parameters were calculated as:

$$R^2 = \frac{[\sum_{i=1}^n (x(i) - x_m)(y(i) - y_m)]^2}{\sum_{i=1}^n (x(i) - x_m)^2 \sum_{i=1}^n (y(i) - y_m)^2} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (pe_i - p_i)^2}{n}} \quad (8)$$

$$nRMSE = \frac{RMSE}{pe_i} \quad (9)$$

Identification of Famine Years. To identify famine years, we relied on statistical data (Rice, paddy index) at the nation-level from the Food and Agriculture Organization of the United Nations (<http://www.fao.org>) to calculate food self-sufficiency (FSS). FSS is defined differently due to the differences in disciplines, economy, and food application. FAO (1999)⁶⁴ states that "food self-sufficiency is generally considered to be the degree to which a country can meet its own food needs from domestic production". Generally, FSS is closely related to food security.

A more pragmatic understanding of FSS is that domestic food production equals or exceeds 100% of a country's food consumption⁶⁵. This concept can be reflected by the self-sufficiency ratio (SSR)⁶⁶:

$$SSR = P/D \times 100 \quad (10)$$

where SSR is the self-sufficiency ratio, P represents food production, and D represents food demand. Food demand can be further refined as food production, food exports, food imports, and fluctuations in domestic food storage⁶⁷. Therefore, the clear definition of food demand is:

$$D = P + I - E - \Delta S \quad (11)$$

where I is food imports, E is food exports, ΔS represents annual change in food storage.

However, SSR focuses on key crops in order to give an approximate value for a country's grain self-sufficiency⁶⁵. In NK and SK, rice is the dominant food produced and affects food security²⁰. We assumed that the annual food storage remains constant due to difficult-to-obtain inventory fluctuations for a country. Then the rice self-sufficiency rate (RSSR) formula is:

$$RSSR_i = \frac{P_i}{P_i + I_i - E_i} \times 100 \quad (12)$$

where i is a specific year from 2000 to 2017.

We used RSSR to evaluate the degree of rice self-sufficiency. RSSR indirectly reflects the state of national food security under the conditions of external environmental changes. In this study, we defined 100%–90%, 90%–80%, and 80%–70% of RSSR to be high self-sufficiency, medium self-sufficiency, and low self-sufficiency. RSSR less than 70% was defined as a famine year. It is worth noting that FSS cannot only consider the numbers (i.e., RSSR). It also needs to weigh natural conditions, industrialization level, market operations, and other actual conditions for a country. These factors will not be studied for the time being.

Attributing predominant climate variables. To demonstrate the responses of GPP to climate change, we assessed the importance of each climate variable to biomass changes. To check the multicollinearity and achieve a simple model, we first removed the climatic variables whose variance inflation factors (VIF) indicated the degree of multi-collinearity of any independent variable with the other independent variables in a regression model was greater than 10. The VIF formula was:

$$VIF = \frac{1}{1-R_i^2} \quad (13)$$

where R^2 represents the coefficient of determination between the i th independent variable and other independent variables.

All gridded climatic variables with resolution of 0.1°pixel were resampled to 500 m resolution using the bilinear interpolation method to match biomass. We then used 75% of the random climate and biomass data from 2000–2017 as training data and 25% of the data as validation data to test model performance. We used this model to predict future biomass and production losses. The coefficient of determination values (R^2) were used to evaluate the results of validation (formula 12). Finally, the machine learning model, random forest regression of climate and baseline (RF_c and RF_b), was used to analyze GPP changes controlled by climatic factors (Table S7). The random forest regression model generated different regression trees by using random multiple training sets and features, and each regression tree was sampled independently and distributed identically⁶¹. Each regression tree produced different results through branching, and the prediction from the random forest regression model was the average of all trees⁶¹. The unbiased estimate of random forest performance was from out of bag error, and this result was similar to k fold cross-validation. For more details about the random forest model, please see Breiman (2001)⁶¹ and Shi (2020)⁶⁰. Specifically, the RF_c and RF_b models were used to determine the fit between biomass and climatic variables with the parameters “ $mtry$ = the square root of the variables, $n tree=500$ ” in the R package “randomForest”. The RF_c model was built based on spatial pixels over NK’ rice between biomass and climatic variables in 2000 and 2007 to attribute climatic contribution in the two years, and the RF_b model was built based on spatial pixels over NK’ rice from 2000 to 2017 to project future rice losses with climate change (Table S7). We further used function importance that was quantified as the Gini index to compute the variable importance. Compared with linear regression, RF explained the non-linear response of climate variables and unraveled the influence of related variables.

In order to attribute climatic factors in famine years (that is, to identify climate anomalies), we initially calculated normal and extreme meteorological factors for 2000–2017 (for more details, see Table S2). We then calculated the mean value in non-famine years as the baseline. The ratio of the difference between baseline and famine years to the standard deviation of baseline was used to determine the climate anomaly. Therefore, if the anomaly was >1 or <-1 , we considered that the values in famine years were clearly greater than or less than the baseline values (2000–2017 except

famine years)⁶⁸. Specifically, we used the threshold of one standard deviation by assuming that the variations of climatic factors under normal conditions were generally located in the ranges of one standard deviation about the multi-year mean⁶⁹.

Future climate projection. We used the statistical downscaling (SD) model NWAI-WG, developed by Liu and Zuo⁷⁰, to downscale global climate models (GCMs) monthly gridded data to daily climate data for 1299 meteorological observing grid points from reanalysis data in NK. SD consisted of three major components: spatial downscaling, bias correction, and temporal downscaling. Spatial downscaling used inverse distance-weighted (IDW) interpolation based on the center of the nearest four grid points in GCMs to improve accuracy⁷⁰, and then applied bias correction to generate bias-corrected monthly data using a relationship between observations and GCM data for a historical training period, in this case 1979–2018. Finally, the time series daily for maximum and minimum temperature, precipitation, and solar radiation for each pixel were downscaled from the bias-corrected monthly GCM projections using a modified version of the stochastic weather generator⁷¹. For a more detailed description of SD, please see Liu and Zuo⁷⁰.

We downscaled 27 GCMs of the Coupled Model Intercomparison Project Phases 6 (CMIP6) based on the SD method as two future climate scenarios (SSPs, the combination of shared socioeconomic pathways, where SSP245 represents SSP2 + RCP4.5, an intermediate development pathway; SSP585 represents SSP5 + RCP8.5, a high development pathway). Further, the daily normal and extreme climate variables were calculated for two climate scenarios during 2021 to 2100 according to the climatic index as described above for Table S2. We then assessed climate change and production loss in the future for the 2040s (2021-2060) and the 2080s (2061-2100). Specially, for climate change in the future, the relative changes of temperature (maximum and minimum temperature) were calculated by subtracting the means of the historical period (1979-2018) from the future temperature. And for precipitation, solar radiation, SU30, and R50, the relative changes were derived from the ratio of future means to historical means. For production loss in the future, we first obtained the inferred mean value of harvest index (noted as α) from statistical production and estimated GPP (i.e., α as the ratio of GPP to production). The formula is:

$$P_{sta} = \sum B_{t1} \times \alpha_i \times A \quad (14)$$

$$\alpha_{mean} = \sum_{i=0}^n \alpha_i \div n \quad (15)$$

where P_{sta} is statistical production from FAO. $\sum B_{t1}$ represents the sum of each gridded GPP. α_i represents harvest index for every year, and α_{mean} is average harvest index calculated by α_i for every year (2000 to 2018). n is the number of years and A is the pixel area.

The non-linear model (RF model, as described above for GPP changes analyzed by the machine learning model) was then established through historical gridded climate data, and GPP was estimated by the eLUE model to assess rice GPP in the future. Future production was projected by using mean harvest index and predicted GPP:

$$P_{pre} = \sum B_{t2} \times \alpha_{mean} \times A \quad (16)$$

where P_{pre} is future production. $\sum B_{t2}$ represents the sum of each predicted GPP. Finally, we used future and historical GPP and production to calculate relative changes as the losses.

The contribution of social resilience to rice production. We interpolated missing statistics from FAO and World Bank based on linear regression (four social-economic variables: energy use, school enrollment, access to electricity, and patent applications). Given that the effects of social resilience effects on rice production are often nonlinear, the random forest model was expected to perform well

736 in assessing the nonlinear relationship. On the obtained robust explanation and significance, this study
737 modelled the relationship between social-economic variables and rice production using the random
738 forest regression of economics (RF_e), and significance was tested for a single variable and the full
739 model (Table S7). Details about the random forest regression model and its parameters were provided
740 in the above section. This process was conducted using R software using the "A3" package. The
741 parameters of non-linear models (ntree and mtry) were set as 500 and the number of the square root
742 of the variables, respectively. The Gini index was further used as an index to evaluate variable
743 importance measures to rice production. The partial dependence (i.e., marginal effect) was
744 constructed to assess the non-linear response between rice production and each of the first four
745 variables. This process was accomplished using the "partialPlot" function of the "random forest"
746 package in R.

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749 **Data Availability**

750 All original MODIS reflectance and other MODIS products that were provided by NASA LP DAAC at the USGS
751 EROS Center in this study are freely accessible on the GEE platform at <https://developers.google.cn/earth-engine/datasets>.

752

753 The observational, DEM, and reanalysis data are publicly available from the following sources:

754 -EC data, <http://www.cnern.org.cn/index.jsp>

755 -ERA5 reanalysis

756 <https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-agrometeorological-indicators>

757 -DEM data, <https://srtm.csi.cgiar.org/>

758

759 The downscaled 27 GCMs of CMIP6 were kindly provided by the co-authors of Liu et al.⁷⁰ who downscaled them
760 based on the original CMIP6 at <https://esgf-node.llnl.gov/projects/cmip6/>.

761

762 The statistical data are freely available from the following sources:

763 -rice production, rice imports and exports, fertilizer application, and population from FAO,
764 <http://www.fao.org/faostat/en/>

765 -GDP from United Nations Statistics Division, <https://unstats.un.org/unsd/snaama/Basic>

766 -Population ages 0-14, Population ages 15-64, Rural population, Energy use, Access to electricity, School
767 enrollment, Patent applications, and Net ODA received per capita from World Bank, <https://data.worldbank.org/>.

768

769 **Code Availability**

770 The first and corresponding authors are prepared to respond to reasonable requests for code.

771

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Competing interests: Authors declare no competing interests.

Figures

Figure 1

Spatial patterns of geographical and climatic distribution across study area. a shows climate zones. b shows the geographic boundaries of the study area. BSk, Cwa, Cfa, Dwa, Dwbc, Dwc, Dfa, and Dfb are defined as arid and cold steppe, temperate regions with dry winter and hot summer, temperate regions with hot summer and without dry season, cold regions with dry winter and hot summer, cold regions with dry winter and cold summer, cold regions with hot summer, cold regions with dry winter and warm summer, cold regions with dry winter and cold summer, cold regions with hot

summer and without dry season, and cold regions with warm summer and without dry season¹⁹, respectively. NK, SK, CH_1, and CH_2 are North Korea, South Korea, Liaoning province of China, and Jilin province of China. The World Bank defines North Korea, South Korea, and China as low, high, and upper-middle income countries/regions, respectively, based on income levels.

Figure 2

Identification of famine years in North Korea and attribution of production losses. a shows rice self-sufficiency every year calculated from import, export, and production quantity data from FAO. The dash line is the 70% self-sufficiency rate (that defines the famine level). The bottom left corner inset chart in panel a shows an enlarged view during 1993 to 2008. b shows the contribution of climatic variables to rice biomass production in 2000 and 2007, which is calculated between biomass production and climate indices in all the land pixels in each region. NK, CH_1_2, and SK are North Korea, Liaoning and Jilin provinces of China, and South Korea, respectively. c shows the spatial and temporal distribution of climatic standardized anomalies for 2000, 2007, and the baseline period (2000 to 2007) over North Korea. The vertical gray areas in the surrounding line charts represent the period from tillering stage to heading stage, and the error bars represent one standard deviation. For detailed meanings of the twelve climatic variables, see Supplementary Table S2.

Figure 3

Projected rice production losses under four future scenarios. a, Observed vs. predicted rice biomass from 2000 to 2017 (baseline period). The blue and red points represent the calibration and validation data sets, respectively. b, Relative importance of climatic variables from non-linear modeling (the meaning of the variable abbreviations is provided in Table S2. c, Box plots of projected rice biomass (top panel) and production (bottom panel) losses under four different future scenarios based on nonlinear modeling. Box boundaries indicate the 25th and 75th percentiles across 27 GCMs, and whiskers below and above the box indicate the 10th and 90th percentiles, respectively. The black lines within each box indicate the multi-model median.

Figure 4

The contribution of vulnerable indexes for social resilience to rice production variability. Twelve indexes of social resilience are from five factors, i.e., population development, resource use, science and education, economic development, and agricultural input (Table 1). a, The red and green bars represent significance tests for $p < 0.05$ and $p > 0.05$, respectively. The importance indicates explanation degree of the non-linear model for contribution of social resilience to rice production in the three regions. b, The

non-linear response of rice production to standardized variables of social resilience. The black lines are smoothed representations of the response, with fitted values (model predictions) for the calibration data. The trend of the line, rather than the actual values, describes the nature of the dependence of rice production on the social resilience. The green and orange dash lines in the partial dependence plots represent rice production from the baseline and SSP585 scenarios, respectively. NK, SK, and CH represent North Korea, South Korea, and China.

Supplementary Files

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