

Chronicle of the Causes of Famine in the World during 1840–2019 and their Risks

Soma Funahashi

The University of Tokyo

Misato Okaneya

Cookpad Inc.

Taikan Oki (✉ oki@civil.t.u-tokyo.ac.jp)

The University of Tokyo <https://orcid.org/0000-0003-4067-4678>

Article

Keywords: Sustainable Development Goal, Quantitative and Long-term Analysis, Risk Factors, Famine Database, Soil Water

Posted Date: November 21st, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-105823/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Abstract

Famine still exists in this world, hindering the achievement of sustainable development goal 2: zero hunger. The history and mechanism of famine have been broadly studied; however, few studies have focused on quantitative and long-term analysis of the general characteristics of famine. This study aims to analyze the factors influencing famine and estimate its risk. We developed a famine database and estimated the probability of the occurrence of famine through logistic regression with physical and social factors. Herein, we identified a few factors that are strongly related to the occurrence of famine and found that soil water and gross domestic product per capita are the most influential. By extrapolating the logistic regression to a future scenario, we revealed that although the number of countries with high famine risk would decrease, some countries in sub-Saharan Africa would remain at high famine risk for a while.

Introduction

Famine is one of the oldest and most catastrophic forms of disaster worldwide. The history of famine can be dated back to 1700 BC [1] and many people have died from the lack of food since the dawn of human history. Approximately 70–80 million people died of famine in the 20th century, and this figure is far greater than that of any previous centuries [2].

Eradicating hunger is included in the UN Sustainable Development Goals (SDGs); SDG 2 [3] aims to achieve “Zero Hunger.” However, the number of undernourished people has increased since 2015, and 821 million people were suffering undernourishment in 2017 [4], with famine as one of the leading causes. Hunger is estimated to rise in some regions due to the COVID-19 pandemic [5]. With the rising concerns about food insecurity, exacerbated by population growth, climate/environmental changes, and the pandemic, the elimination of famine will remain a challenge even in the 21st century.

It is essential to assess the future risk of famine in each country to achieve this goal, and the investigation of past famines is necessary. The causes of famine and its processes have been widely examined [6]; however, most of the previous studies are descriptive and detailed for individual events rather than quantitative and comprehensive. Although some studies conducted quantitative analysis on past famines, most of them revealed facts and insights about famines, but not their risks. The Famine Early Warning System [7] adopts a scenario-based approach to assess the risk of food insecurity; however, the system is designed to support the administrator’s decision in urgent food insecure situations and does not offer future prospects longer than six months.

The purpose of this study is to identify the essential components of past famines and their changes and to assess the risk of famine in the future. This study consists of two parts. In the first part, data on major famines since 1840 were assembled into a famine database based on literature review, and their causes and processes were analyzed. In the second part, a logistic regression analysis was applied using physical and social factors related to famine, and the result was validated by the famine database. We

also assessed the future risk of the famine in each country by applying the logistic regression model under a few socio-economic scenarios and concentration pathways.

Analysis Of Past Famines

The word “famine” has several definitions. In this study, to clarify the criteria for adoption into the database, the term “famine” was defined by a mortality-based definition [8], which defines a famine as an event in which more than 10,000 people died.

We developed a famine database targeting major famines since 1840. This database consists of two parts: factor and description. In the factor section, major factors that triggered the famine, such as drought or conflict, were attributed to each famine. The categorization of factors, shown in Supplementary Table 1, was defined according to the chapter division of “Theories of Famine” [9], that provides a comprehensive and organized overview of famine factors. The perspective given by DeRose [10] was also used to organize the categories. In the second section, auxiliary information is provided: pre-famine situation, shock, and social response against the famine are summarized.

Fig. 1.a shows the average number of factors that contributed to each famine every 20 years since 1860. Overall, recent famine were caused by a combination of various factors, which is consistent with the insights by Devereux [11]; famine causality is becoming more complex than ever. The trends in causes can be broadly divided into three periods by the combination of causes. In the first period, from 1860 to 1899, environmental triggers, such as droughts, were the leading causes of famines. In the second period, from 1900 to 1959, the number of social triggers and domestic responses, including war or development failure, aggravated due to colonization, revolution, and the two World Wars. In the third period, after 1960, the factors became more diverse; environmental factors further increased, international responses increased, and social triggers decreased. As for the breakdown of the factors in each category (see Fig. 1.b–e), famines in the third period seem to be triggered by various factors; however, the number of the social triggers, domestic response, and international response decreased from the 1960s to 2000s, while there is consistently more than one environmental factor in each famine. The environmental factors primarily consist of drought, and in other categories, the proportion of each element varies depending on the period. In the social triggers, factors such as inadequate infrastructure and market failure increased, while the share of war or conflict was relatively constant after 1900.

Assessing The Risk Of Famine

Regarding the assessment of the risk of famine, in this study, basic theories of famine and studies on risk were reviewed to define the “famine risk.”

As for the famine theory, the Food Entitlement Declining (FED) theory, which was developed by Crichton [12], was applied to this research. Before the FED theory, the Food Availability Decline (FAD) theory, which argues that food production decrease would lead to famine, was primarily used; however,

this theory had several issues [13]; Crichton [12] suggested that FAD is neither necessary nor sufficient for famine. The lack of “entitlement,” which means “the set of alternative commodity bundles that a person can command in a society using the totality of rights and opportunities that he or she faces” [14] would lead to famine.

There are many definitions for “risk.” In the context of disaster management, Devereaux [15] defined risk as a combination of three aspects: hazard, exposure, and vulnerability (risk triangle), whereas Sen [16] defined it as the composition of hazard, vulnerability, preparedness, and capability. Considering the feasibility of quantitative analysis on risk, we defined the famine risk as the recurrence probability affected by hazard and vulnerability. This is due to the partial lack of numerical data on the scale of famine, such as the number of casualties.

Based on this, we conducted a logistic regression analysis on the risk of famine. We assumed that hazard and vulnerability, including food availability and entitlement, can be explained by the datasets shown in Supplementary Table 2. The definitions of hazard and vulnerability in this research and the dataset explaining each aspect are given below. Due to data availability, the target period of past famine analysis was set from 1961 to 2014.

Hazard refers to the direct triggers of the decline in food production. Based on the database we developed, hazards can be primarily divided into droughts and conflicts. As for the drought index, the amount of soil water in cropland was used [17]. As conflict is challenging to quantify, the ratio of years of conflict in the country during the target period was used to approximate the likelihood of the occurrence of conflict in each country.

Vulnerability is defined as the sensitivity of society to food insecurity. The correlation coefficient of agricultural water input (AWI) and the value of agricultural production (VAP) was selected as the indices that can explain the vulnerability of food production, based on the suggestion of Nyariki and Wiggins [18], suggesting that food production varies with rainfall in food insecure regions in sub-Saharan Africa. We hypothesized that, if this coefficient is large, production is influenced by climatic conditions. Cereal import dependency (CID) was also used as an indicator of vulnerability, hypothesizing that a lower CID ratio would lead to food supply instability. Gross domestic product (GDP) per capita was selected as the indicator of the resilience of society against food insecurity, assuming that higher GDP would make it possible to import more food under food insecure situations. The urban population rate is expected to be an indicator of the ease of distribution of food or the proxy of access to food through the market. The Gini coefficient, which represents the income inequality in each country, was also adopted based on the assumption that income inequality results in the intensification of famine. Herein, GDP per capita, urban population rate, and Gini coefficient are expected to explain the people's capacity to gain food: the food entitlement.

Fig. 2 shows the relationship between each variable of hazard and vulnerability. The average of available year's data is plotted. Fig. 2.a illustrates the two indices of hazard: soil water and conflict frequency. Most famines occurred in countries where the conflict frequency is greater than zero. Famine-experienced

countries have relatively small soil water or high conflict frequency, indicating that these hazard values relate to famine occurrence. The indices of vulnerability are shown in Fig. 2.b–2.e. CID and the correlation coefficient between AWI and the value of agricultural production (CAV) are shown in Fig. 2.b. Countries with higher CAV experienced famine, supporting our hypothesis that CAV can be a proxy for production unstableness. Famine-experienced countries have a low CID value (approximately zero), implying that a self-sufficient agricultural supply is likely to result in an unstable food supply. However, countries with negative CID, such as cereal-exporting countries, did not have experienced famine in the target period. There may be possible explanations; the surplus of cereal production can be a buffer for food insecurity, and countries where mass production of cereal is possible to have high GDP per capita, which reduces the countries' vulnerability to the famine. CID and GDP per capita are plotted in Fig. 2.c to support the second explanation, showing that countries with negative CID have a higher value of GDP per capita. As shown in Fig. 2.d, famine-experienced countries have lower GDP per capita and urban population rate. The Gini coefficient in famine-experienced countries shown in Fig. 2.e is slightly higher than those without, even though they do not have distinct differences.

Risk Assessment Of Famine

The former section illustrates that listed indices of hazard and vulnerability have some relationships with famine occurrence. Herein, we define the risk as the possibility of famine and applied a logistic regression analysis to estimate the probability of famine occurrence. In the logistic regression analysis, seven indices of hazard and vulnerability were adopted as explanatory variables.

Table 1 shows each case's estimated probability of famine and whether the case was a famine case or not. In each probability band, the ratio of the famine case is within the range; therefore, it can be supposed that the probability of famine occurrence is well estimated.

Fig. 3 shows the variation in the estimated probability of famine in each country. Famine-experienced countries have a higher value than those without; however, some countries with low probability have experienced famine. For example, North Korea experienced famine in 1995–1999 and 2012; however, the estimated probabilities in these cases were approximately 0.002, which is relatively low. This is likely due to the oversight of other components of famine; these famines occurred due to an economic crisis or political scheme that keeps the economic differential between civilians and people in the government and the military, which is difficult to quantify numerically.

Fig. 3 illustrates the probability map. Overall, the probability of famine has decreased with time. South Asian countries and sub-Saharan countries have had higher values of famine risk, and the risk in sub-Saharan countries remained high in 2010, which is consistent with the UN's warning indicating the rising risk of hunger in this area [19].

Table 2 shows the weight of each variable in the logistic regression analysis. The uncertainties of these values were calculated by the non-parametric bootstrap method (see Method), and the mean and variance of these coefficients are shown here. GDP per capita and soil water have the largest absolute values, approximately 0.9, indicating that they are the major factors for famine occurrence. However, the means of the CID and the Gini coefficient are smaller than those of the others. As for CID, it is assumed that cereal-exporting countries (with negative CID value) have rooms for food supply, and cereal importing countries (with high CID value) have rather stable food supply; merely using the size of CID does not lead to a clear classification. As for the Gini coefficient, famine-experienced countries have a relatively high Gini coefficient (see Fig. 2.e), as stated in Nyariki and Wiggins [18]. However, in this study, high Gini coefficients does not mean that there is a higher risk of famine, and some countries without famine have higher Gini coefficients than countries with famine (Fig. 2e).

Future Projection

We conducted the future projection of famine risk from 2020 to 2050 by applying logistic regression analysis and the datasets of future scenarios (Supplementary Table 5).

Fig. 4 represents the results of future projection, considering the socio-economic (SSPs) and climate change scenarios (RCPs). The figures of each SSP show the number of countries with famine probabilities ranging from 0.010 to 0.025, from 0.025 to 0.050, and above 0.050. We see that the risk of famine will generally decrease in the future. Notably, the number of countries with a high probability of famine occurrence will decrease in SSP1, whereas the number of such countries will be less likely to decrease in SSP3, and SSP2 is in between. This changing trend is primarily due to the increase in GDP per capita and urban population rate, and differences among SSPs are due to the different growth of GDP per capita in each scenario.

Countries that are estimated to have relatively larger famine risk are located in Africa, especially in sub-Saharan countries (see Supplementary Fig. 2). There are no distinctive differences in the famine risk distribution among different scenarios.

Discussion And Conclusions

In this research, a famine database was developed, the details of past famines were examined, and logistic regression analysis was applied to estimate the risk of famine by employing seven factors of hazard and vulnerability.

Famine is not a state, but an urgent event. This research focused on the events and did not analyze the famine's extent, such as the number of casualties, due to the lack of sufficient information. An estimation of a famine's magnitude should be included in future work focusing on quantitative assessment of famine. Additionally, quantitative studies should be conducted on undernourished populations as well as on the famine, as it has been suggested that the number of famine casualties is decreasing [20], but

undernourishment is prevailing in sub-Saharan Africa [21]. Considering the time-series processes of famine, the relationships among each factor are also critical. In this study, we evaluated the risk of famine from merely the annual value of each factor; however, the magnitude of the risk could be different depending on the seasonality of the parameters during the famine due to the lack of detailed data in monthly or weekly spans. Additionally, it is important to assess the causal relationships among these factors, including process-based analysis in the estimation of global long-term famine risk to obtain a clearer view of famine in the future.

Although there is room for a finer assessment, our study shows the comprehensive characteristics of famine, the general risk of famine, and its prospects. The famine database revealed that the factors triggering famine have become diverse. The past famine during 1961–2014 is explained by the logistic regression analysis based on risk assessment theories and famine showing that GDP per capita and soil water are the largest explanatory values. In the future, the rate of decrease in famine risk will be faster in SSP1 than in SSP2 or SSP3, and the sub-Saharan area would be the last part of the world to suffer from famine. This research is the first step in the long-term assessment of famine risk, and it could guide in outlining the measures to help eradicate hunger from all countries in the long term.

Methods

Famine database

The detailed description of the famine database is as follows:

Year

The starting year for smaller famines is stated differently from literature to literature, and the end year is also different for larger famines. We selected the one that is most frequently used in the literature.

Country

Although many famines occurred in only a part of a country, each famine was attributed to the country/countries rather than regions, as statistical data are available at the country scale.

Number of deaths

The number of deaths significantly differ in literature. For some famines, there is no record at all. As famine often occurs during the war, it is challenging to separate famine deaths from war deaths. Additionally, countries that experienced famine often lack the administrative capacity or political will needed for record-keeping. Therefore, the number of deaths was estimated from the available data and used only as a reference.

Contributing factors

Various explanations have been offered in literature for the mechanism and causalities of famine. To summarize these explanations into a comparative form, a literature study was performed, and each famine case was checked against 10 factor categories under four groups (Supplementary Table 1). Two or three studies were referred to for each famine, and if the literature included a keyword listed under a factor category as a cause, the famine received a score of one for that factor.

Datasets

The datasets used in this simulation are listed in Supplementary Tables 2 and 5. The global hydrological model H08 [22] was used to calculate the agricultural water input (AWI) and soil water. A coupled simulation of the land surface process, river, crop growth, and reservoir operation was conducted with a spatial resolution of 0.5° and a time resolution of 1 day. The annual value of AWI and soil water in each country were calculated from the model's output by the nation mask with a spatial resolution of 0.5°. The future GDP data provided by the National Institute for Environmental Studies, Japan (NIES) [23] were converted into USD in 2019 to align with past data. Gridded GDP per capita in SSP1, SSP2, and SSP3 were calculated with future GDP and population data, converted into each country's value by the nation mask. Conflict frequency was calculated based on the conflict dataset provided by the Uppsala Conflict Data Program (UCDP) [24] [25]. The ratio of years when conflict occurs during the target period was considered as the conflict frequency. For all data, missing values were filled in by interpolation.

To determine the significance of each dataset, the Mann–Whitney U test was conducted under the null hypothesis that the data of famine experience countries and other countries have no significant difference. The results shown in Supplementary Table 3 illustrate that the P-values are sufficiently small that each data is significantly different between famine-experienced countries and other countries.

Logistic regression analysis

Logistic regression is a statistical regression that models the probability of a certain class, especially used for binary classification. Herein, the probability of being classified as a famine case is calculated as follows, using each parameter and coefficient:

$$p = \frac{1}{1 + \exp(-(a_1x_1 + a_2x_2 + \dots + a_nx_n + b))}. \quad (1)$$

Logit, the natural logarithm of an odds ratio, is represented by the equation below. By using the maximum likelihood method, the regression coefficient is calculated.

$$l = \ln \frac{p}{1-p} = a_1 x_1 + a_2 x_2 + \dots + a_n x_n + b. \quad (2)$$

In the regression model, the values in each year and each country were used as explanatory variables. For the data on soil water, GDP per capita, and urban population rate, we used each year's values in each country. As for the CIV and Gini coefficient data, the averaged values for each country were used for every year in the target period because the available dataset was limited to a short period. Additionally, each index was normalized so that the mean was 0, and the variance was 1, to see the weight of the indices explaining the risk of famine. The dependent variable is the occurrence of famine, which can be represented by "Famine case" or "Non-famine case," considered in the famine database developed. Herein, the year when the famine occurred and the three years before the famine were flagged as "Famine case" because the number of famine cases was small and the previous three years seem to have a high possibility of famine occurrence. There were only 76 famine cases amongst all the 8748 cases during the target period.

In the future predictions, projected datasets of GDP per capita under SSP1, SSP2, and SSP3, soil water calculated under RCP2.6, RCP4.5, RCP6.0, and RCP8.5, and urban population rate were used. The same variance and the mean of each variable's past datasets were used to standardize these future datasets. The same data as in the past were used for CIV, CID, and conflict frequency, assuming that the values will remain the same in the future.

Examination of uncertainty

A non-parametric bootstrap method was used to check the uncertainty of each coefficient. Logistic regression was applied to a half size of the random sample 100 times, and the mean and variance of each coefficient are presented in Table 2. Supplementary Table 4 shows the p-value between all the pairs of variables under the null hypothesis that there is no difference between all variables. In every pair, the p-value is much lower than 0.0001, and thus, each pair of variables has a statistically significant difference.

Declarations

Acknowledgments

This work was supported by the Japan Society for the Promotion of Science [KAKENHI; 16H06291] and the Environment Research and Technology Development Fund (JPMEERF20202005) of the Environmental Restoration and Conservation Agency of Japan.

Author Contributions

TO, MO, and SF designed the research framework, MO and SF developed the famine database and conducted data analyses, SF drafted the manuscript, and TO and MO revised the manuscript along with SF.

References

- [1] Gráda, C. O. *Famine: A Short History* (Princeton University Press, 2009).
-
- [2] Gráda, C. O. Making famine history. *J. Econ. Lit.* **45**, 5–38 (2007).
-
- [3] United Nations, Goal 2: Zero hunger, 2020. [Online]. Available: <https://www.un.org/sustainabledevelopment/hunger/>. [Accessed 4 9 2020].
-
- [4] United Nations, Food, 2019. [Online]. Available: <https://www.un.org/en/sections/issues-depth/food/index.html>. [Accessed 06 2020].
-
- [5] World Food Programme, United Nations, New report shows hunger is due to soar as coronavirus obliterates lives and livelihoods, 2020. [Online]. Available: <https://www.wfp.org/news/new-report-shows-hunger-due-soar-coronavirus-obliterates-lives-and-livelihoods>. [Accessed 4 9 2020].
-
- [6] Devereux, S. *The New Famines: Why Famines Persist in an Era of Globalization* (Routledge, 2006).
-
- [7] USAID, Famine Early Warning System Network, [Online]. Available: <https://fews.net/>. [Accessed 18 8 2020].
-
- [8] Ravallion, M. Famines and Economics, *J. Econ. Lit.* **35**, 1205–1242 (1997).
-
- [9] Devereux, S., *Theories of Famine* (Harvester Wheatsheaf, 1993).
-
- [10] DeRose, L. E. M. a. S. M. *Who's hungry? And How do We Know? Food Shortage, Poverty, and Deprivation* (United Nations University Press, 1998).
-
- [11] Devereux, S. *Famine in the twentieth century* (Institute of Development Studies, 2000).
-
- [12] Crichton, D. The risk triangle. In: Ingleton, J. (Ed) *Natural Disaster Management* (Tudor Rose 1999).
-
- [13] de León, J. C. V., Bogardi, J., Dannenmann, S., Basher, R. Early warning systems in the context of disaster risk management. *Entwicklung and Ländlicher Raum* **2**, 23–25 (2006).
-
- [14] Sen, A. *Poverty and Famines: An Essay on Entitlement and Deprivation* (Oxford University Press, 1982).
-
- [15] Devereux, S. Entitlements, Availability and Famine: A Revisionist View of Wollo, 1972–1974, *Food Policy* **13**(3), 270–282 (1988).
-
- [16] Sen, A. *Resources, Values, and Development* (Harvard University Press, 1997).
-
- [17] Sheffield, J., Eric, F. *Drought: Past Problems and Future Scenarios* (Routledge, 2012).
-
- [18] Nyariki, D. M., Wiggins, S. Household Food Insecurity in Sub-Saharan Africa: Lessons from Kenya. *Brit. Food J.* **99**, 249–262 (1997).
-
- [19] Food and Agriculture Organization of the United Nations, New UN report reveals that hunger in Africa continues to rise, 13 2 2019. [Online]. Available: <http://www.fao.org/news/story/en/item/1180443/icode/>. [Accessed 26 8 2020].
-
- [20] Hasell, J. Famines, Our World in Data, 2013. [Online]. Available: <https://ourworldindata.org/famines>. [Accessed 31 08 2020].
-
- [21] United Nations, Indicator 2.1.1 - Prevalence of undernourishment, 2020. [Online]. Available: <http://www.fao.org/sustainable-development-goals/indicators/211>. [Accessed 31 08 2020].
-
- [22] Hanasaki, N., et al. An integrated model for the assessment of global water resources 0- Part 1:

Model description and input meteorological forcing. *Hydrol. Earth. Syst. Sc.* **12**, 1007–1025 (2008).

[23] Murakami, D., Yamagata, Y. Estimation of gridded population and GDP scenarios with spatially explicit statistical downscaling. *Sustainability* **11**(7), 2106 (2019).

[24] Gleditsch, N. P., Wallensteen, P., Eriksson, M., Sollenberg, M., Strand, H. Armed conflict 1946-2001: A new dataset. *J. Peace. Res.* **39**, 615–637 (2002).

[25] Pettersson, T., Öberg, M. Organized violence, 1989–2019. *J. Peace. Res.* **57**, 597–613 (2020).

[26] Food and Agriculture Organization of the United Nations, Value of Agricultural Production, 2020. [Online]. Available: <http://www.fao.org/faostat/en/#data/QV>. [Accessed 01 04 2020].

[27] Food and Agriculture Organization of the United Nations, Suite of Food Security Indicators, 2020. [Online]. Available: <http://www.fao.org/faostat/en/#data/FS>. [Accessed 01 04 2020].

[28] World Bank, GDP per capita (current US\$), 2020. [Online]. Available: <https://data.worldbank.org/indicator/NY.GDP.PCAP.CD>. [Accessed 01 04 2020].

[29] World Bank, Urban population (% of total population), 2020. [Online]. Available: <https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS>. [Accessed 01 04 2020].

[30] World Bank, GINI index (World Bank estimate), 2020. [Online]. Available: <https://data.worldbank.org/indicator/SI.POV.GINI>. [Accessed 01 04 2020].

[31] Gosling, S., et al. ISIMIP2a Simulation Data from Water (global) Sector (V. 1.1), GFZ Data Services, 2019. [Online]. Available: <https://doi.org/10.5880/PIK.2019.003>. [Accessed 01 04 2020].

[32] United Nations, World Urbanization Prospect 2018, 2018. [Online]. Available: <https://population.un.org/wup/>. [Accessed 01 04 2020].

Tables

Table 1 Probability of famine

For each country, each year was counted as one case, and the number of all cases was 8748 (162 countries, 54 years). Famine cases refer to the year within three years of famine, and non-famine cases are the others. Ratio is the proportion of famine cases out of all cases in each probability band. Note that this famine case includes the years within three years before famine (description about the dependent variables is in Method).

Estimated probability	Famine case	Non-famine case	Ratio
0.000–0.010	14	4852	0.003
0.010–0.025	17	1762	0.010
0.025–0.050	41	924	0.042
0.050–1.000	140	998	0.123

Table 2 Coefficient of each variable in the logistic regression

Variables	Mean of coefficient	Standard deviation of coefficient
Soil water	-0.8425	0.0573
Conflict frequency	0.4170	0.0378
Correlation coefficient b/w AWI and VAP	0.3289	0.0433
Cereal import dependency	-0.0723	0.0410
GDP per capita (log.)	-0.9276	0.1168
Urban population rate	-0.3245	0.1100
Gini coefficient	-0.0112	0.0401

Figures

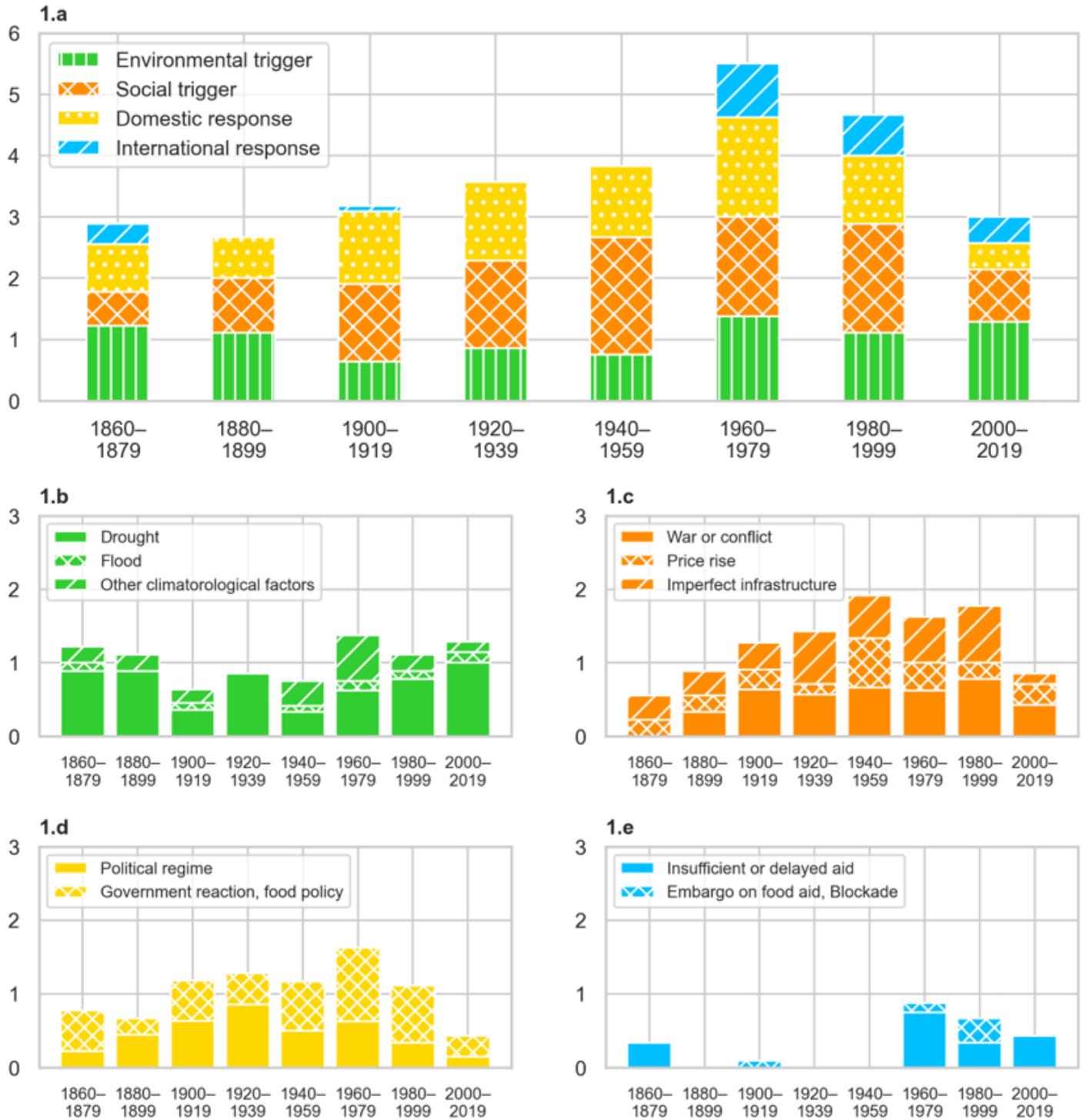


Figure 1

Average number of four categories in each famine The average number of causes contributing to each famine was counted according to the four categories in every 20 years from 1860. Fig. 1.a shows the sum of each category and 1.b–1.e illustrates the breakdown of each category. Note that the result from 1840 to 1859 was omitted because there was only one famine in the period.

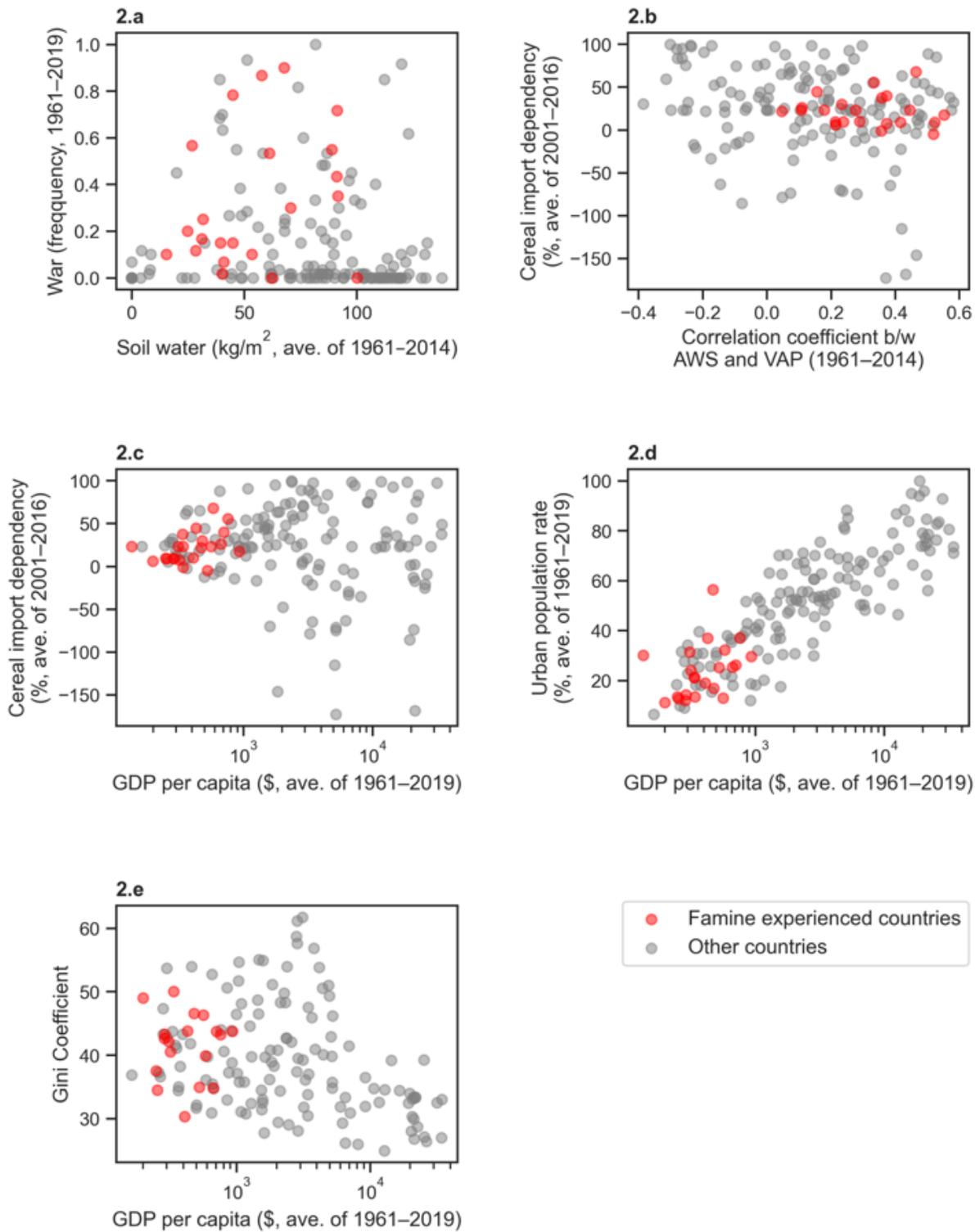


Figure 2

Indices of hazard and vulnerability Indices for each country are shown. The red plot indicates the countries that experienced famine during the target period (1960–2014).

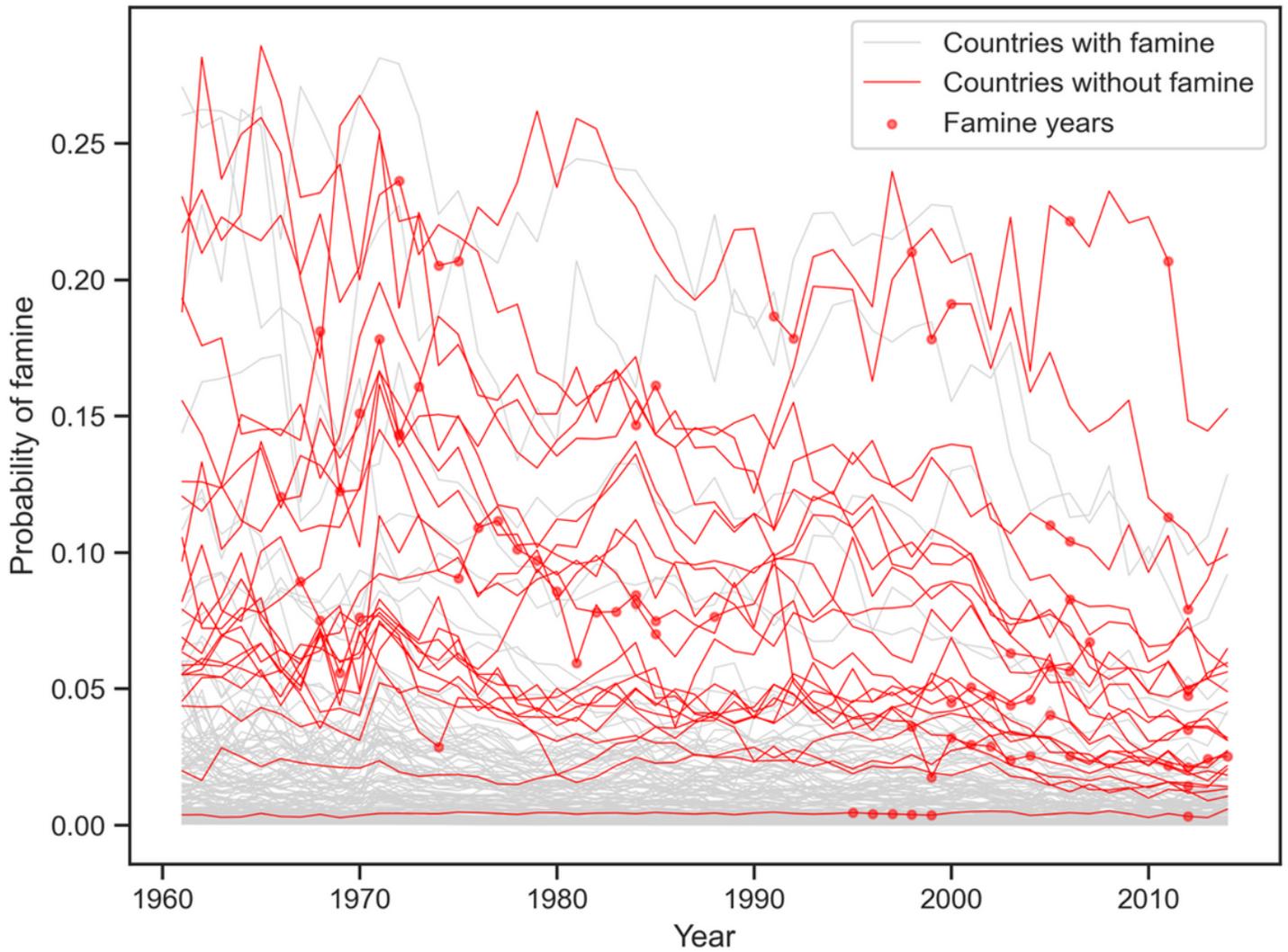


Figure 3

Probability of famine in each country Each line shows each country's variation in the estimated probability of famine. If the country has experienced famine in the target period, the line is colored red, and the others are gray. The red circles are plotted on the line of country and year in which famine occurred.

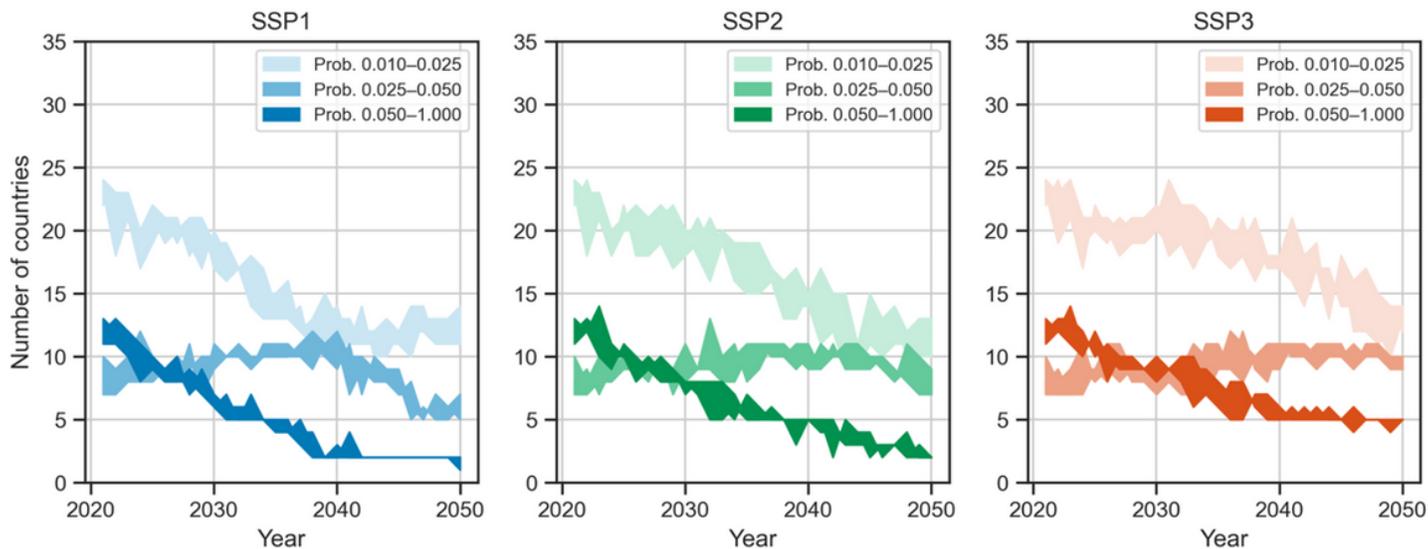


Figure 4

Future projection of the probability of famine The results of the future projections for each SSP scenario are presented. The numbers of countries with probabilities of famine ranging from 0.010 to 0.025, from 0.025 to 0.050, and above 0.050 are represented. For each SSP scenario, four RCP scenarios were used in the calculations, and the differences between the RCP scenarios were represented as bands.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [NatureSUSTSFMOTOSI2.pdf](#)
- [famineDataBaseSomaFunahashi.xlsx](#)