Regional disparities in climate risk to rice labour and food security

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Abstract

Ninety percent of rice is produced in Asia, where it provides half of calories consumed, making it critical to food security. The 640 million rural agricultural workers of Asia are especially vulnerable to hot and humid weather, which impacts health and productivity; we show that heat hazard exposure increased significantly from 1980 to 2019. Around half of rice production occurs in locations and months where heat hazard is strongly correlated with global mean surface warming, based on climate simulations from the Coupled Model Intercomparison Project 6 (CMIP6), including >80% of production in Southeast Asia. Limiting global warming to 1.5 C rather than 2.0 C prevents a statistically significant reduction in labour capacity of 1% across all Asia and 2% across Southeast Asia, affecting the livelihoods of around 100 million people. Our results underscore regional disparities in labour productivity from climate change resulting in rising inequality and need for climate adaptation.

Introduction

Asia produces 90% of rice, 631 million tonnes (Mt)[1,2]. A large proportion of rice cropland is tropical or subtropical (57% between 23.45 deg N and S, 95% between 35 deg N and S), see Figure 1). Agriculture employs more than 640 million rural people in the Asia and Pacific region[3], in which rice production comprises 30% of total crop gross production value[4].

Agricultural workers are especially vulnerable to hot and humid weather, which impacts health and productivity, and which will increase due to global warming[5–7]. Field studies have demonstrated the presence of heat strain and related health issues in agricultural workers in general[8,9] and rice harvest workers specifically[10]. These workers are subject to high seasonal temperatures, which can be harmful despite not necessarily being extreme statistically.

Global mean surface temperature has increased by 0.9-1.2 C relative to 1850-1900 as of 2017[11], and if anthropogenic warming continues to follow recent trends, is projected to reach 1.5 C between approximately 2030 and 2052; the estimated rate of warming is 0.2 C per decade[12]. In accordance with the Paris Agreement under the United Nations Framework Convention on Climate Change [13], most countries

have committed to limit global mean surface air temperature (GSAT) warming to 2 C, and to make efforts to limit warming to 1.5 C. However, given pledges of emissions reductions as of 2019, warming is on course to exceed 3.2 C by 2100[14].

Many studies focussed on the risk of occupational heat stress use wet-bulb globe temperature (WBGT), which is a heat-stress index defined by ISO 7243. WBGT is intended to combine all the factors that affect the human experience of heat, namely air temperature, radiant temperature, humidity, and air velocity[15]. As performing work generates heat, in a high WBGT environment labour must be reduced in order to maintain a safe body temperature. The ISO standard and various national regulations set limits on continuous working time at given thresholds of WBGT. Workers self-pace in order to cope with heat strain, so changes in labour capacity are a proxy for welfare, as well as being an indication of an economic impact.

Occupational heat strain depends on not only meteorological aspects, but also those factors relating to the workers themselves; including individual differences in acclimatization, work intensity, clothing, and hydration[16]. This means that estimates of heat strain are specific to an occupational context, and suggests that field data collected in specific occupational context may not be generally applicable.

Previous studies[6,17–20] have weighted exposure to heat hazard based on human population maps, and examine either the hottest month of the year, or the average of the whole year. Rice harvests occur in certain times of year, depending on location. These are not always the hottest months of the year; however, these are months in which we know that heavy physical labour is performed. We weight the result using rice harvest maps, assuming that harvested weight is a proxy for the number of workers engaged in harvesting, in order to quantify the labour capacity effect of global warming on rice harvest workers specifically.

Methods

In this study we analyse atmospheric data from the Coupled Model Intercomparison Project, Phase 6 (CMIP6)[21], which is comprised of global climate models that have been run in a shared experimental configuration. The model outputs used here are daily mean and maximum temperature, humidity, and surface level pressure. All CMIP6 models for which appropriate data were present in the Centre for

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Environmental Data Analysis (CEDA) archive (http://archive.ceda.ac.uk/) were included, of which there were

14. CMIP historical runs and ScenarioMIP[22] future pathways were processed. ScenarioMIP runs simulate the

future climate given assumptions about future emissions and development pathways. For each climate

model, only the first ensemble member was processed to ensure climate models were equally weighted. A

table of model runs used, with data citations, is included in the supplementary material. The Climatic

Research Unit gridded Time Series (CRUTS) 4.03[23,24], and the European Centre for Medium-Range Weather

Forecasts Reanalysis 5 (ERA5)[25], were used as the historical observational datasets.

WBGT is designed to be measured directly using specialised equipment; however, empirical

formulae for estimating it from standard meteorological variables do exist. Daily minimum and maximum

wet bulb temperature (WBT) was calculated from daily mean and max near surface air temperatures,

relative humidity, and pressure using the open source software 'psychrolib' [26] which implements formulae

from the American Society of Heating, Refrigerating and Air-Conditioning Engineers handbook. In our WBGT

calculation, we neglect the effects of solar irradiance, by assuming that the black globe temperature is

approximated by the air temperature. This means that we assume work is occurring in the shade, and

therefore underestimate WBGT by several degrees in sunny conditions[27]. Properly accounting for solar

irradiance would require either working with sub-daily data, or making further assumptions about sub-daily

variation. However, in this study we focus long term trends, which are driven by air temperature and

humidity; as there is no clear long-term trend in surface downwelling shortwave flux, it does not affect our

results.

Field measured WBT decreases with wind speed at low speed (<2 m/s, a light breeze), but higher

wind speeds have a lesser effect[27]. The WBT calculation we used assumes that the wick is well ventilated, so

variable wind speed is safely neglected.

Studies of occupational heat stress and strain under climate change often either assume a threshold

above which a worker is at risk[18], or assume that there is a simple relationship between WBGT and worker

productivity. These relationships are assumed to be representative across sectors, and are based on either a

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regulatory or advisory standard[17], limited field study or survey data, or an ad hoc fusion of the two[6,1928].

Standards attempt to minimise harm, so can appear conservative when compared to the actual conditions in which people work. Field data for the effect of heat on worker productivity are relatively sparse, and cover only a few activities: studies of small numbers of workers are used to estimate productivity effects on the entire human population.

Sahu et al[10] observed a 5% per °C WBGT decrease in the labour capacity of labourers harvesting rice between 23-33 °C WBGT. Rate of collection was measured in 124 workers in groups of 10-18, and WBGT was measured in-situ, at a single location in India. We adopt this for our labour impact metric, and assume that this is representative of manual rice harvest labour. The impact is assumed to be linear in WBGT, although this assumption must break down as WBGT approaches human skin temperature. The systematic uncertainty due to these assumptions cannot be assessed without larger scale field observations. The labour loss function is -5.14*WBGT + 218, in units of %, clipped at 0 and 100. This means that 0% loss occurs at 23 C and 100% loss occurs at 42.5 C.

Daytime temperature variation is estimated by assuming the temperature is close to the daily mean temperature, daily max temperature, and the mid-point of the two for 4 hours each, following previous studies[6]. Comparing the result of this calculation using hourly ERA5 and daily ERA5 data, we found that this is a reasonable approximation (see Supplementary Material).

The RiceAtlas dataset[1,2] provides detailed data for 31 countries in Asia, broken down into location entities with an average area of 5000 km. Information such as yield, harvested area, planting and harvesting dates are included, and many entities have multiple yearly harvests. The data are representative of the years 2010-2012. We used this to identify harvest dates. The harvest season is typically around 30 days long in this database. Figure 1 shows the distribution of rice cropped land in Asia, from the RiceAtlas dataset, with some key locations labelled.

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Location entities in RiceAtlas vary greatly in size, and many are much smaller than the grid spacing of the climate models considered. Where a location enclosed multiple GCM grid-cells, the mean is taken of the enclosed cells; otherwise, the land grid-point closest to the centroid of the location was used.

Results

Figure 2 shows the Asia-wide average of the heat impact on rice harvest labour, weighted by rice production in each harvest location-season. The input climate data are CRU-TS 4.03 and ERA5. There is a statistically significant increase ($p \ll 0.01$) over the full observational period (1900-2018) of CRU-TS, and in both datasets for the common observational period (1980-2018): the heat hazard associated with the rice harvest has already increased. The long-term trend closely follows the trend in global mean temperature over the same period.

Figure 3 shows heat impact on rice harvest labour plotted against GSAT warming across various climate models. Changes are relative to the present, assumed to mean 1 C of warming over 1850-1900. The rice harvest labour impact is weighted by rice production. In Figure 3a, each point is a 20 year mean in a historical or ScenarioMIP run. All scenarios were included, but only points where GSAT change was < 4 C relative to 1850-1900. Despite the different biases and climate sensitivities of the models, they each show a linear relationship between GSAT and the rice harvest labour impact. All models have a gradient 2.0-2.7 %/C, $p \ll 0.01$, $R^2 > 0.98$. The multi-model mean (standard deviation) of the gradient is 2.3 (0.2) %/C. It is not surprising that the long-term average labour impact metric is linearly correlated with GSAT, as the labour impact metric is linear in WBGT, which itself is strongly correlated with temperature.

In Figure 3b, results for each model, shown in Figure 3a are linearly interpolated to 1.5, 2.0 and 3.0 C of warming (relative to 1850-1900) and results are shown as a multi-model boxplot. There is significant difference between the 1.0 C and 1.5 C of warming with multi-model mean (standard deviation) 1.0 (0.3) %; between 1.5 and 2.0 C of 1.3 (0.2) %; as well as between 2.0 and 3.0 C of warming 2.6 (0.4) %.

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The countries of Southeast Asia (Indonesia, Vietnam, Thailand, Myanmar, The Philippines, Cambodia, Malaysia and Laos) have high exposure. For these countries, the effect is around twice the global average: limiting warming to 1.5 C instead of 2.0 C prevents a multi-model mean (standard deviation) 2.0 (0.2) % effect, while limiting warming to 2.0 C instead of 3.0 C prevents a 3.9 (0.6) % effect.

Linear regression between the rice harvest labour impact and global mean surface air temperature (both as 20 year means), performed for individual harvest location-seasons, shows that a linear relationship is present at the local level too. Figure 4 shows the production-weighted histogram of the impact gradient (multi-model mean). There is a high level of agreement between models, with an average correlation coefficient between models of 0.95. Harvest location-seasons fall into two groups: those strongly affected by climate change (impact gradient ~ 4 %/C) and those that are not (impact gradient ~ 0 %/C, with large multi-model spread). The global mean (Fig 2) obscures this fact, as the average is over heterogeneous data. Fitting a normal distribution to the peak, we see that the strongly affected group is centred at 3.9 %/C, with a standard deviation of 0.3 %/C: we therefore identify the strongly affected group as all harvest location-seasons having a hazard gradient >3.0 %/C. The harvest location-seasons were split into two groups, split at 3 %/C. The high hazard gradient group comprises 50% of production in Asia. For locations having multiple harvest seasons, the proportion of production in the location that is in the more exposed group was calculated, and plotted in Figure 5. The proportion of production in each country that is exposed is listed in Table 1.

Exposure is generally very high in in Southeast Asia. All production in Indonesia, Sri Lanka, and Malaysia is exposed. Vietnam's production is 84% exposed, with 100% exposure in the Mekong River Delta and less in the north.

Generally, harvests that peak in September, October, and November (SON) are the least exposed due to lower seasonal temperatures. Locations at higher latitudes also on average have lower seasonal temperatures. This largely explains the spatial variation of exposure in China. Jiangsu's harvest peaking in

October is not exposed, whereas Chongqing's harvest peaks in August so is 100% exposed; multiple cropping in leads to partial exposure in Hubei, Jiangxi and Hunan. Across China, 27% of production is exposed.

All locations in Bangladesh have an exposed harvest, but overall exposure is 61% due to multi-cropping: harvests in March-May are exposed, harvests in November-December less so. Although in India, a large amount of production is exposed in West Bengal and Andhra Pradesh, production further north in Punjab and Uttar Pradesh is not identified as exposed, meaning that the overall exposure of India is just 36%. The rice harvest in Punjab and Uttar Pradesh is in October-December, a cooler time of the year; West Bengal has rice harvests in between April and July.

Due to the resolution of climate models, results are not reliable for locations closest to the Himalayas. Temperatures are averaged across a grid-cell that includes both mountains and plains, but rice agriculture mainly occurs in plains and valleys.

In some cases, especially wheat in Punjab, rice is multi-cropped with another crop not covered in this study, which may have its harvest exposed. Studies have suggested that changes to planting and harvesting dates[29], and crop choice[30], could be used to adapt to climate change and mitigate negative effects on yields. Changes to planting and harvesting dates could lead to workers being exposed to heat stress in locations where they currently are not, and this should be taken into account when planning adaptive measures.

These results are comparable to those of similar previous studies, but with a different focus. Previous studies either average over the whole year or focus on the hottest part of the year. However, different parts of the year are not equally important in terms of agricultural labour. Planting and harvesting typically take up the most labour, and they cannot be delayed or displaced.

Orlov et al[31] project a decrease in work productivity of approximately 9.5% and 12% for South Asia and Southeast Asia respectively, in the crops sector by 2050 under the CMIP5 high-emission scenario (their figure 9). Assuming this corresponds to 2 C of warming relative to the present gives an impact gradient of 4.7 and 6.0 %/C respectively. Wind and surface downwelling shortwave radiation was included in the calculation of

the WBGT, but the calculation used daily average irradiance withthe Sun assumed to always be at its zenith. The general picture and conclusions of our work are unchanged when the labour impact function is changed to the one used by Orlov et al for the crops sector. A function based on fitting a curve to an ad-hoc combination of data from the Sahu et al study and a study of miners, and has a similar gradient from 29-32 C WBGT.

In the study by Dunne et al[17], much more dramatic reductions in labour capacity were projected, as industrial safety guidelines for WBGT were used as the labour impact function. If the same function is applied in our analysis, a strong correlation is still seen between the calculated impact and the GSAT, but with a higher gradient. Clearly, the choice of labour impact function is very important and has a strong impact on the final result. The labour impact function used by Dunne for heavy labour reaches 100% at 33 C WBGT, at which WBGT the function from Sahu et al is 52%.

Our study is limited by the accuracy, coverage, and granularity of the rice crop data. However, by focussing on long-term trends with high levels of multi-model agreement, we largely avoid the issue of climate model bias. The assumed linear effect of WBGT on labour productivity comes from a single field study, and cannot be accurate as WBGT approaches known human physiological limits.

Conclusion

The growing impact of heat on rice harvest labour will be very unevenly distributed, mainly falling on poor rural workers who will be least able to adapt, and therefore contributing to widening economic inequality. Given agriculture employs hundreds of millions of people in the region, a few-percent shift in their labour capacity is equivalent to the labour of millions of people.

Vulnerability may be higher in those locations with low levels of farm mechanization, but we note that high quality international data on the level of farm mechanization are lacking. Farm mechanisation in Asia over the past 50 years has been largely driven by small internal combustion engines, which have already alleviated much of the human drudgery of farming, reduced the use of draft animals, and increased yields[32,33]. However, more fatal injuries occur when using powered machinery[33], and the use of internal

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combustion engines contributes to greenhouse gas emissions. Labour productivity decreases due to climate change will compound other environmental impacts on rice production, including declining yields as direct result of increasing temperature, water stress, and sea level rise[12]; contributing to the unequal loss and damage created by climate change.

We see a strong relationship between heat hazard and global mean surface temperature change in the rice harvest seasons and locations comprising 50% of the Asian harvest, with a high level of agreement between climate models. Historical observational data shows already shows a statistically significant increase in our labour impact metric. Understanding disparities in the exposure of workers and industries around the world will be important for climate adaptation strategy, as well as estimation of loss and damage. Overall, the exposure of such a large proportion of rice agriculture, and the workers engaged therein, provides an argument for strong mitigation of climate change.

Tables

Table 1: Rice production exposed to high hazard gradient by country, and Asia total. Countries with less than 1 million tonnes of annual rice production are not included. Rice production from RiceAtlas[1].

Country	Exposed production (%)	Total production (million tonnes)	Exposed production (million tonnes)
Asia	50	646	325
Indonesia	100	67	67
China	27	200	55
India	36	151	55
Vietnam	83	42	35
Thailand	79	36	28
Bangladesh	61	45	27
Myanmar	71	32	23
Philippines	94	17	16
Cambodia	84	9	7
Sri Lanka	100	4	4
Japan	33	8	3
Malaysia	100	3	3
Laos	25	3	1
Taiwan	70	2	1
Pakistan	0	9	0

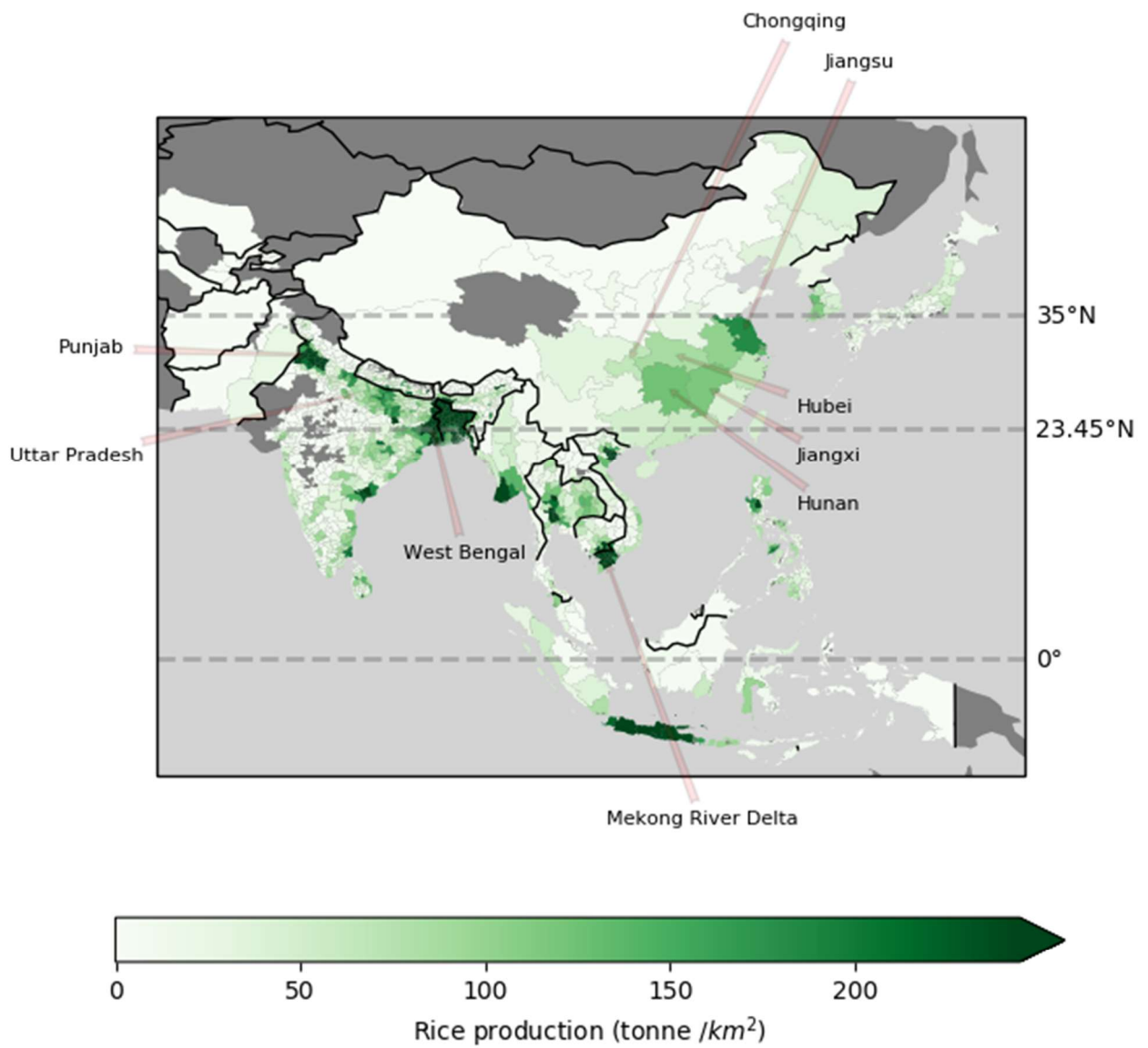|			
South Korea	0	6	0
Nepal	0	5	0
Iran	0	3	0
North Korea	0	2	0
Turkey	0	1	0
Afghanistan	0	1	0

Figures

Figure 1: Geographical distribution of rice production across Asia (green shading). Sub-national locations mentioned in the article are labelled. Data sourced from RiceAtlas[1].
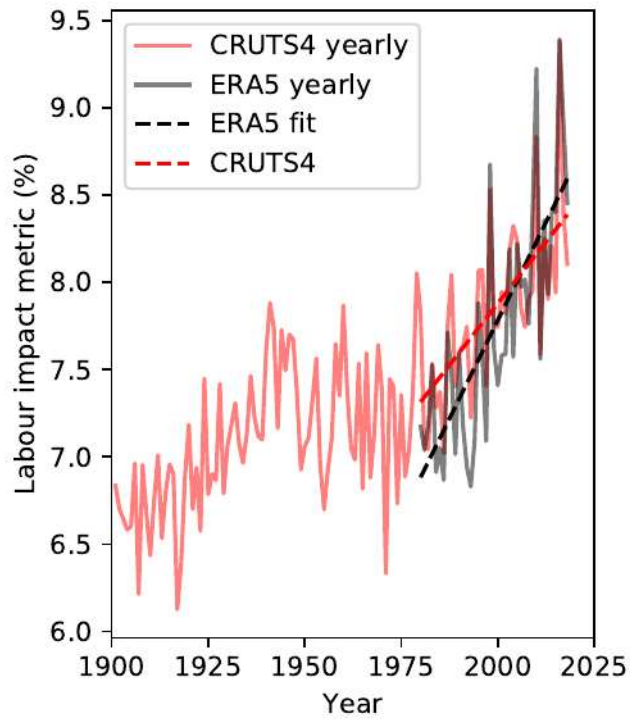
Figure 2: Annual global mean labour impact metric, weighted by harvest weight, calculated from CRU-TS 4.03 (red lines) and ERA5 (black line), with trend lines (dashed) shown for the period 1980-2018.
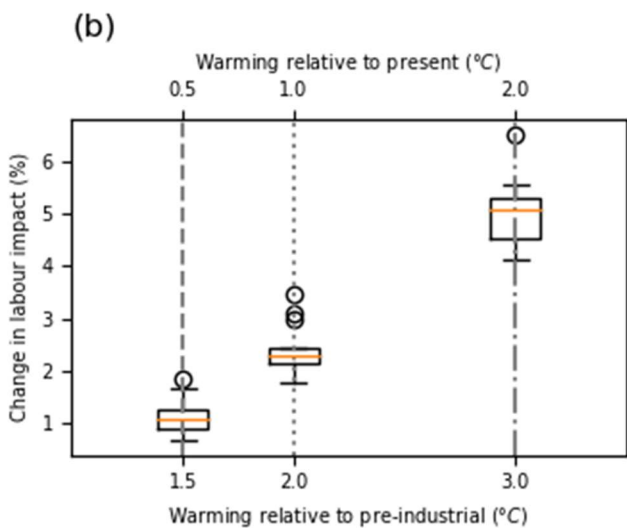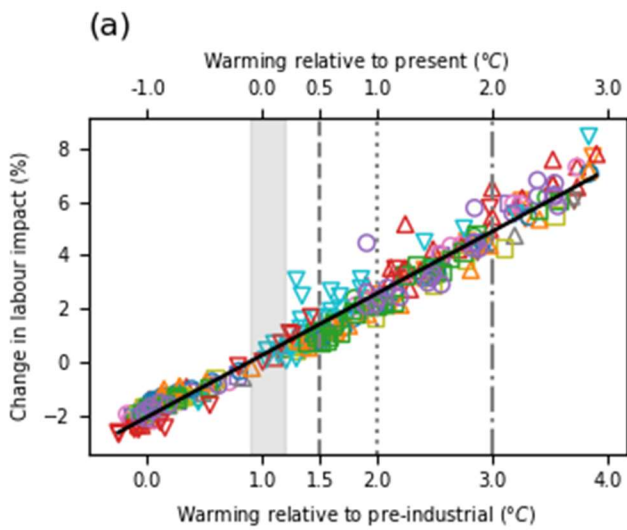
Figure 3: Relationship between rice labour impact and GSAT change in the 14 analysed CMIP6 climate models; each shape/color corresponds to a different model. Changes are relative to 1.0 C of warming relative to 1850-1900, which is assumed to be representative of the present. Three levels of warming relative to 1850-1900 and relative to the present are shown for context. (a) Change in labour impacts against GSAT for 20 year periods. A trend for all points is shown in solid black. (b) Change in labour impacts at three levels of warming, with box plot to show climate model spread. Points are linearly interpolated to the three levels of warming. Boxes show 1st (Q1) and 3rd quantile (Q3); orange line at the median; lower whiskers at lowest point above Q1–1.5*(Q3-Q1), upper whiskers highest point below Q1+1.5*(Q3-Q1); circles are points outside the whisker range.
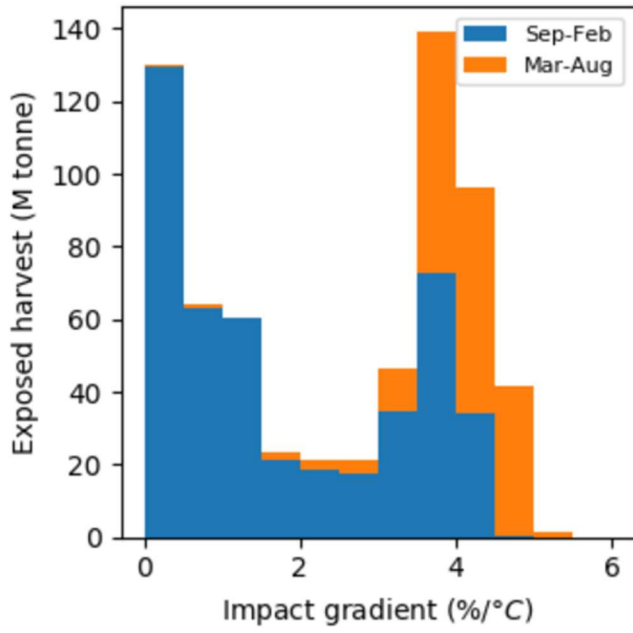
Figure 4: Labour impact was linearly regressed against GSAT independently for each harvest season-location. This histogram shows the distribution the resulting gradient. The histogram is weighted by the harvest weight in millions of tonnes. The data are divided into two groups by month, shown as a stacked histogram. Non-exposed harvests almost all peak in September-February.
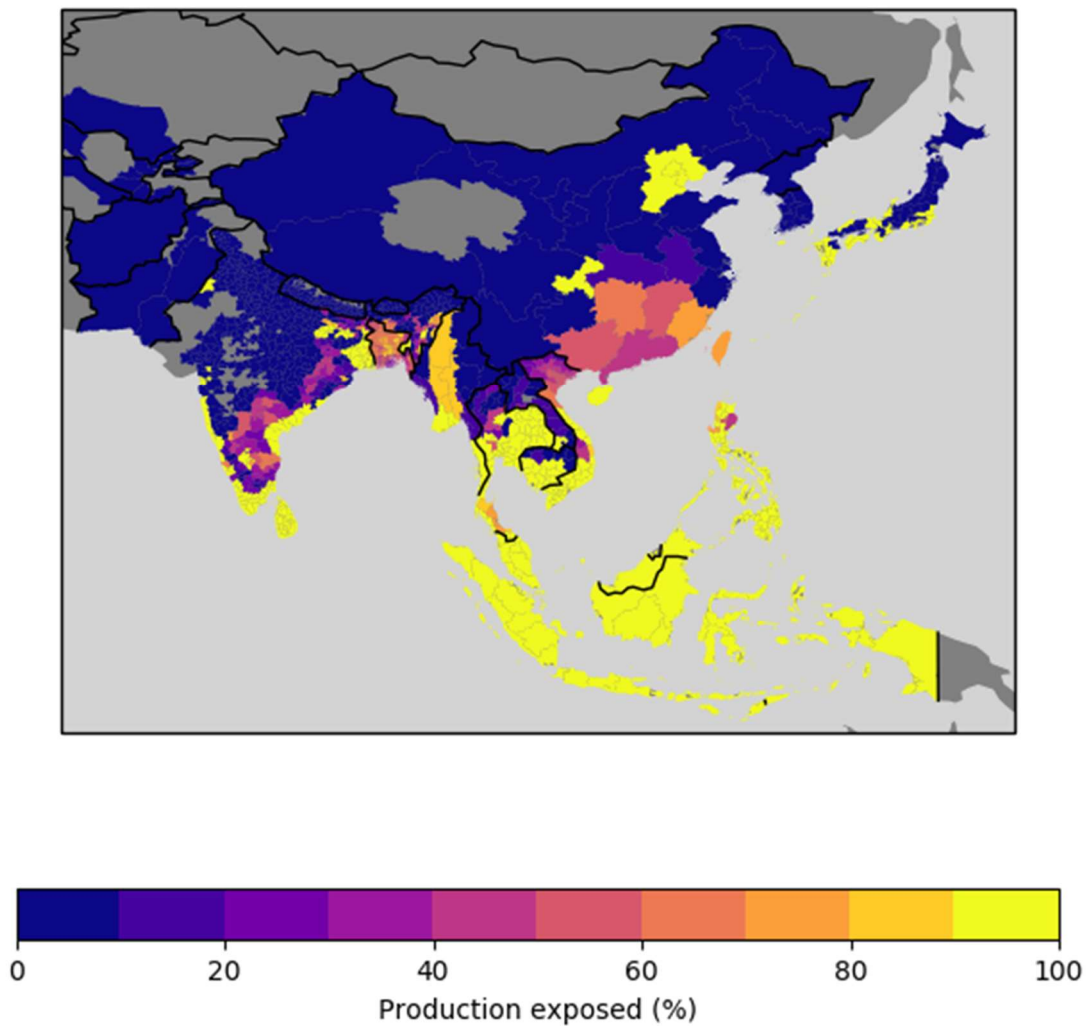
Figure 5: Map of Asia with shading representing proportion of rice production in harvests for which labour capacity is identified as having a strong relationship with GSAT (gradient >2 %/C).

Acknowledgements

Data and code availability statement

The datasets generated during the study will be available from the CEDA archive, and accession codes provided before publication. Computer code will be publicly available under the MIT license before publication.

Author contribution statement

CS performed the analysis and mostly wrote the paper. JSH, DM, RAB, and ES helped develop the ideas for the analysis, and advised on the wording and emphasis of the paper.

Competing interest statement

The authors declare no competing interests.

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