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Analysis

Re-examining the impact of annual weather fluctuations on global livestock production

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ABSTRACT

Attempts to analyze the effect of weather shocks on livestock production have been carried out using integrated assessment models (IAMs) or the cross-sectional (Ricardian) method. However, these methodologies are fraught with obvious shortcomings, such as omitted variable bias, amongst others. This paper, therefore, re-examines the relationship between weather changes and global livestock production using an established econometric strategy that takes care of the pitfalls inherent in the conventional approaches. Using country-level data and a variety of specifications, we find that a 1 °C increase in temperature will lead to a 9.7% reduction in global beef production on average. These adverse effects are amplified in hot, poor, and agriculture-dependent countries. Besides, we find that a marginal increase in annual precipitation would lead to a 2.1% increase in beef production in tropical countries but a 1.9% decrease in temperate ones. Also, our forecasts show that climate change will reduce animal output by a further 20% in the mid-century and an additional 40% by the end of the century assuming no adaptation other than the degree of adaptation observed in the historical period.

1. Introduction

The rate of increase in the earth's average surface temperature in the last 30 to 40 years has far outstripped that of any other period for the last 20,000 years (IPCC, 2022). Many climatologists forecast a further rise in global temperature in the near future (IPCC, 2022; Allen et al., 2014). Similarly, rainfall patterns have become more erratic and unpredictable (Lobell and Asseng, 2017; Lobell et al., 2013; Roudier et al., 2011). These weather fluctuations and the associated extreme events have been evidenced in previous studies as major influencers of agricultural production (Emediegwu et al., 2022; Aragón et al., 2021), economic growth (Kalkuhl and Wenz, 2020; Smith and Ubilava, 2017; Dell et al., 2012), mortality (Emediegwu, 2021; Barreca, 2012; Deschênes and Greenstone, 2011), and conflict (Harari and Ferrara, 2018; Hsiang et al., 2013, 2011). The agricultural sector bears the largest economic impact of changing climate because of the size, significance, and sensitivity of the sector, especially in rural communities situated in low latitudes (Mendelsohn, 2008).

Agriculture is of global importance as it employs more than 70% of the world population, with more concentration on the rural poor in developing regions (International Labour Office, 2017). The sector also accounts for 4 percent of global gross domestic product (GDP) and more than 25% of GDP in some developing countries (WDI, 2017). In addition, OECD/FAO (2016) documents that livestock production currently accounts for some 40 percent of the gross value of agricultural production. This share is more than 50 percent in some industrial countries and about 33 percent in most developing countries. Further, livestock is often kept as a form of wealth and food "buffer" stock in the event of crop failures, thus forming an important part of consumption smoothing behavior.

Besides the fact that more than half of the world's land surface is used for grazing livestock or growing crops for animal feeds (FAOSTAT, 2018), the importance of livestock production can also be viewed within the context of global animal consumption. FAOSTAT (2018) documents the annual, global meat consumption between 1988 and 2018 to be around 350 million tonnes, with the expectation that consumption could reach up to 570 million tonnes by 2050. The expected remarkable increase in meat demand has been associated with population and income growth, as well as lifestyle and dietary

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[1] Although some non-animal proteins may be consumed, animal proteins (including dairy) are still essential because they constitute about 70% of all protein consumption (Hoy et al., 2021). Besides, some food nutrients can only be obtained from animal proteins.

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habits changes (FAO, 2018). More importantly, to meet global meat consumption by 2050 would require a doubling of meat production from the 2008 level (FAOSTAT, 2018).[1] Consequently, given the importance of livestock production in the global economy and the reality of a changing climate, detailed attention needs to be paid to the relationship between the duo.

Climate change in Africa particularly has drawn significant interest from researchers and policymakers due to the peculiar fragility of its economy, making adverse effects of climate change even more severe. Global warming affects several agro-related outcomes such as the increasing incidence and severity of droughts, floods, and other extreme weather events. This paper sheds more light on the effects of weather shocks on livestock.

There have been attempts to quantify the damage estimate of climate change on livestock production using integrated assessment models. This approach uses biophysical livestock simulation models in conjunction with economic models to estimate animals' responsiveness to climate change (see, St-Pierre et al., 2003; Rötter and Van de Geijn, 1999; Klinedinst et al., 1993; Johnston, 1958, for empirical examples). The attractiveness of this modeling approach is that it takes advantage of the large amount of information available from the animal sciences regarding the likely effects of weather fluctuations on livestock (Antle and Stöckle, 2017). However, a major weakness pointed out by Chimonyo et al. (2015) is that most biophysical simulation models are tailored towards mono cultural practices, making them impracticable for multi-livestock analyses. Other deficiencies associated with process-based models are the limited number of animal models available and the problem of external validity, given that models need to be carefully calibrated to reflect local conditions (Mendelsohn and Dinar, 2009).

An alternative approach to improve on the shortcomings of the IAMs is the cross-sectional (or Ricardian) approach introduced in Mendelsohn et al. (1994),[2] and applied in several studies (Feng et al., 2021; Taruvinga et al., 2013; Kabubo-Mariara, 2009; Seo and Mendelsohn, 2008).[3] This approach, which introduces the revealed preference technique in estimating the impact of climate change on agriculture, exploits cross-sectional variation across spatial units (households, counties, countries, *etc.*) to evaluate the effect of long-run climate on average livestock values. Despite the attractiveness of the Ricardian model because of its ability to capture long-run farmer's adaption, it severely suffers from the problem of omitted variables bias.[4] The omission of relevant variables (e.g., closeness to river source) that are correlated with both climatic factors and the dependent variable (e.g., farmland value) can bias climate impact estimates. Dell et al. (2014) also submit that even in the absence of omitted variable bias, it is unlikely to obtain a true estimate of how climate change will impact agricultural activities in the long run (e.g., next 50 or 100 years) because the historical equilibrium the cross-section represents may depend on mechanisms that act differently. These limitations are addressed in fixed effect panel data models.

Unlike the Ricardian model, panel data analysis uses group fixed effect (FE) to account for omitted variables that correlate with climatic and response variables (Blanc and Schlenker, 2017). Panel data models exploit the exogeneity of cross-time variations in weather to identify the causal effects of weather variables, such as temperature and precipitation, on several economic outcomes, including agricultural output. This established econometric approach has been popularly used in the climate econometrics literature to estimate the impact of weather fluctuations on several economic outcomes.[5] Despite these interesting works, rigorous empirical work on the impact of weather shocks on global livestock production is lacking. Such work would help understand the effect of changing weather at a global rather than a local level, as exemplified in previous studies that employed integrated assessment models or cross-sectional analysis.

This paper achieves this objective using a panel of national livestock production and local weather fluctuations from 187 countries. Empirically, we address some specific shortcomings in previous literature with respect to methodology, data, temporal and spatial scale. The methodology accounts for omitted variable bias; the spatial and temporal dimension of our dataset allows for substantial variation through which we can identify the effects of short-term weather shocks on livestock production.

Our results show a robust negative effect of temperature changes on global livestock production and a positive impact of rainfall fluctuations. We offer further evidence that the effect of temperature is more concentrated in hot, poor, and agricultural-dependent countries. Also, we find that climate change will reduce animal output by a further 20% in the mid-century and an additional 40% by the end of the century. Also, while the benefits of rainfall in the tropical regions moderate temperature-caused adverse effects, these adverse affects are further aggravated by rainfall in the temperate regions.

Notwithstanding the intuition from our results, it is important to note the following caveats. Our methodology does not account for adaptation. In the face of climate change, it is impossible to rule out the possibility of farmers taking adaptive measures (such as migrating animals to cool areas) to alleviate the adverse effects of climate change. Accounting for adaptation or mitigation measures would attenuate the damage estimate from our model.[6] However, we must state that we do not find evidence of adaptation when we apply our country-level data to other empirical strategies that account for long-run adaptation. Yet, given the scale of our observational units, the results should be interpreted cautiously since adaptation often occurs at a smaller spatial unit, such as farm or household level, rather than national level. The second caveat to note is that we do not account for inter-seasonal changes in weather, which could also amplify the adverse effect of climate change. Given these two important caveats, our results should be seen as "middle-of-the-road" estimates. Notwithstanding the caveats, our work is very informative and complements the growing literature that seeks to understand how climate change affects livestock production.

The remainder of the paper is adumbrated as follows. The next Section provides several channels through which climate change can impact livestock production. We describe the data and methodology in Section 3, while the various results are discussed in Section 4. Section 5 deals with climatic projections and predicted impacts. The paper ends with some concluding remarks in Section 6.

[2] This approach was originally applied to crop production but has been applied extensively to analyze climate change impacts on livestock production.

[3] The method follows Ricardo's observation that the present value of future net productivity is reflected by land rents (Ricardo, 1822, 1817). This, as argued by Mendelsohn and Massetti (2017), suggests that land productivity, rent, and net revenue are equivalent regardless of the type or number of crops or livestock grown in the farm, and what technology is applied since farmland value is the present value of the stream of future rents.

[4] Other shortcomings include the assumption of constant prices and non-measurement of adjustment costs from one equilibrium to another, as well as the inability to disaggregate the results into crop- or livestock-specific impacts (Carter et al., 2018; Darwin, 1999; Cline, 1996).

[5] Some previous climate-related studies that employed the panel data analysis include Kalkuhl and Wenz (2020) and Dell et al. (2012) (economic growth); Harari and Ferrara (2018) and Hsiang et al. (2013) (conflict); Emediegwu et al. (2022) and Deschenes and Greenstone (2007) (agriculture); Animashaun et al. (2022) (welfare); Emediegwu (2021), Barreca (2012) and Deschênes and Greenstone (2011) (mortality).

[6] Auffhammer and Schlenker (2014) attenuate this claim by suggesting that the introduction of nonlinear weather measures introduces cross-sectional variation in climate, hence the estimated parameters, at least, partially captures long-run adaptation. However, the extent to which the adaptation effect is captured is still a subject for debate as it depends on the size of the cross-sectional variation vis-a-vis location-specific weather variation (see, Carter et al., 2018 for more intuition).

2. Climate change and livestock production: potential channels and mechanisms

In their sixth assessment report, the Intergovernmental Panel on Climate Change (IPCC) predicted that global surface temperatures would increase by 0.3 °C to 4.8 °C by the end of the century (IPCC, 2022). Using NASA data, Hansen et al. (2010) show that earth's average global temperature has grown by over 1 °C since 1880, and two-thirds of this warming occurred since 1975, at a rate of roughly 0.15–0.20 °C every decade. These changes in climatic patterns could affect livestock in several ways, directly or indirectly.

Climate change affects livestock directly by altering their reproduction processes, feed conversion ratio,[7] and health via the emergence of new diseases (and the increase in the spread of existing ones). For example, Barati et al. (2008) show that heat stress can influence animals' oocyte growth, as well as their pregnancy rate and embryo development. Besides, as temperature increases, the activity of pathogens and parasites increase, vector-borne diseases spread faster and host resistance is diminished (Thornton et al., 2015).

On the other hand, the indirect effects include climate impacts on the availability of water, the access to and quality of feed, as well as the likelihood of morbidity when disease does occur (Rojas-Downing et al., 2017) and Walthall et al. (2012). Rojas-Downing et al. (2017) and Nardone et al. (2010), for example, detail how climate change could affect livestock health directly by increasing potential morbidity and death and indirectly by the increasing disease factors.

Agricultural activity is the largest consumer of water resources with around 70% of use (Thornton et al., 2015), and the demand for more diverse water sources for agricultural purposes is increasing due to the combination of droughts, water bodies depletion, and increasing human population. More so, livestock needs water because of its vital role in ensuring that animals survive and thrive, as well as other biological processes like fertility and milk production. For example, cows can stay up to seven days without drinking water in cool climates: however, they would require water every six hours to survive under high temperatures (Nardone et al., 2010). As temperature rises, the lack of sufficient water could cause more migration in search of water by nomadic cattle herders, leading to an increase in communal clashes and violence in developing countries (Döring, 2020; Freeman, 2017). These migratory activities and conflicts increase animals' feed conversion ratio, thereby reducing their production efficiency.

When precipitation departs from predictable patterns, agricultural activities, especially in developing countries where most crop production is rain-fed, also suffer. Besides, the composition of pastures will also be affected due to plant competition for water in drought seasons and leaching of soil nutrients during flooding (Thornton et al., 2015). In addition to the ability of the crops to grow, the quality of the forage could also be affected by changes in environmental conditions. For example, flooding could change the root structure, thereby reducing total yield and nutrient quality (Polley et al., 2013; Baruch and Mérida, 1995). Consequently, these alterations in the quantity and quality of animal feed by meteorological factors influence the growth and development of livestock.

To sum up this section, there are several channels through which weather shocks can influence livestock production: however, our intention is not to quantitatively determine the individual contributions of each channel, rather we are employing a reduced-form framework to analyze the general pass-through effect of annual weather fluctuations on global livestock production.

[7] Feed conversion ratio (FCR) is one of the methods for measuring livestock production efficiency. It is defined as the weight of feed intake divided by the animal's weight gain. Higher FCR values correspond to lower production efficiency. Typically, beef has higher FCR (6.0–10.0) than most livestock including pigs (2.7–5.0), chicken (1.8–2.0) and farmed fish and shrimp (1.0–2.4) (Fry et al., 2018).

3. Data and empirical strategy

3.1. Data sources and description

Animal Data: We draw country-level cattle average production (tonnes) from the FAOSTAT database.[8] We use cattle, generically to include the production of both beef and buffalo meat. The Food and Agriculture Organization (FAO) obtained these figures from various sources: governments through national publications and FAO questionnaires (both paper and electronic); unofficial sources; national and international agencies or organizations. Here, we focus on cattle for two main reasons. Beef is one of the most consumed forms of animal protein in most parts of the world, coming behind pork and poultry (FAO, 2018).[9] Two, aside from meat, cattle are reared for their various by-products such as dairy products, manure, hides for making leather, riding or drafting for pulling carts, and other farm implements. These value-added products raise the economic importance of cattle. Our sample covers 157 countries with at least 25 years of cattle production data, while we consider other sub-samples for robustness analysis.

Weather Data: Our historical weather dataset is obtained from the University of Delaware Terrestrial Air Temperature and Precipitation: 1900–2017 Gridded Monthly Time Series. V4.01. This dataset provides global gridded high resolution station (land) time series data for mean air temperature and total precipitation at 0.5° resolution (approx. 56 km × 56 km across the equator).[10] We aggregate the weather data to country-year level by overlaying a world polygon with country boundaries on the average temperature and total precipitation for each grid cell and then taking a weighted average across all grid cells per country. We use cattle population-weighted weather average to account for heterogeneity in cattle population within and across countries. Our cattle population weights are from 2010 population count at 5 min of arc (~1 km at the equator) resolution extracted from FAO Gridded Livestock of the World (GLW v3) database (Gilbert et al., 2018). We also present results using several weighting measures and an alternative weather dataset in Tables A1 and A2 in the supplementary section, respectively.

Climate Change Prediction Data: We rely on the Australian Community Climate and Earth System Simulator (ACCESS-ESM1.5) of the Commonwealth Scientific and Industrial Research Organization (CSIRO) for our climate change projection data.[11] This general circulation model (GCM), which belongs to the sixth phase of the Coupled Model Intercomparison Project (CMIP6), is made up of atmospheric and land components compiled as a single executable, coupled to ocean and sea-ice executables.[12] We use the "middle-of-the-road" scenario (SSP3-7.0) of the model to construct country-year panel for average temperature and total precipitation from 1970 to 2100.[13] In the spirit of Deschenes and Greenstone (2007), we use our projected data to examine medium-term (average over 2041–2060) and long-run (average over 2081–2100) impacts of climate on cattle production.

[8] The cattle data is accessible *via* http://www.fao.org/faostat/en/#data/QL.

[9] It is recognized that this may vary between country and within age-group and depends on cultural preferences and religious beliefs.

[10] See Willmott and Matsuura (2019) for a complete description of the dataset.

[11] This data is hereafter referred to as ACCESS.

[12] In lieu of presenting detailed description of the simulation processes of these global climate models (GCMs), readers are referred to Eyring et al. (2016), whereas the dataset can be retrieved from the CMIP6 website https://pcmdi.llnl.gov/?cmip6.

[13] SSP3-7.0 is a new shared socioeconomic pathway added to CMIP6 that lies between the worst case (SSP5-8.5) and more optimistic (SSP4-6.0) scenarios.

3.2. Summary statistics

We report the summary statistics of our variables at country-level in Table 1. Most of the countries in our sample have data from 1961 to 2017, with few beginning in later years; hence our panel is unbalanced.[14] Panel A describes the historical dataset, whereas Panels B and C summarize the climate change projection data in the mid-future and by the end of the century, respectively. Over the period under consideration, the average global temperature is about 20 °C. Europe and Central Asia (ECA) is the coldest region (−7.43 °C), while Sub-Saharan Africa (SSA) has the highest average temperature (30.09 °C) and the least variation in temperature. At the same time, East Asia and Pacific (EAP) has more varied temperature range, followed by North America. In terms of rainfall, South Asia experienced more rainfall and more variation in rainfall than other regions over the sample period, while Middle East and North Africa (MENA) has the lowest rainfall. In terms of beef production, every region exceeded the world's average production, except MENA and SSA, regions with the least rainfall and the highest temperature, respectively. In terms of spatial distribution of average measures, regions in the south pole are hotter on average than their counterparts in the north pole, while there is variation in the distribution of rainfall across regions and countries (see supplementary section, Figure A1). Cattle production appears to be significantly less in Africa (SSA and part of MENA) than in other parts of the world.

Panel B shows the summary of the ACESSS SSP3.70 predicted changes in climate in the mid-future (2041–2060) across regions of the world. The model predicts a 2.2 °C rise in global temperature with North America and MENA as the leading regions to experience more warming. The Panel also shows that while other regions will benefit from a positive change in rainfall, Latin America and Caribbean (LAC) will experience a fall in total rainfall. Panel C summarizes the predicted state of climate by the end of the century (2061–2100). Based on this model, more global warming is predicted, doubling the mid-future change. North America and ECA are predicted to have the highest temperature rise. In addition, LAC and EAP will experience reduction in total rainfall by the end of the century. Figures A2 and A3 in the supplementary section show the spatial variation of the predicted climate change in the mid-future and by the end of the century, respectively.

3.3. Econometric strategy

In this sub-section, we construct a panel data model at country/year level to analyze the impact of weather changes on production. Our model takes the reduced form:

$$y_{ct} = \alpha_c + \gamma_r t + T_{ct}\beta_0 + P_{ct}\beta_1 + \epsilon_{ct} \tag{1}$$

where y_{ct} is log of beef production (in tonnes) in country c and year t, α_c are country fixed effects to control for country-specific time-invariant factors of beef production, γ_r are region-specific trends which accounts for time-changing determinants of mortality that are common within a region, and ϵ_{ct} are idiosyncratic errors. We control for possible spatial and serial correlation in the standard error terms ϵ_{it} using the approach described in Hsiang (2010) with an arbitrary distance of 1000 km and time lag of 3 years. In keeping with the conventional checks, we report results with varied cutoffs and alternative standard error corrections in the Tables A3 and A4 in the supplementary section, respectively.

Our main covariates, T_{ct} and P_{ct}, are matrices of annual average temperature (in °C) and yearly total precipitation (in mm/year), respectively, in country c and year t. These weather variables of interest also include their squared terms to capture non-linearities (Dell et al., 2014). We do not include other controls for the following reasons. First, important physical factors such as elevation are fixed over time and cannot be distinguished from country-specific effects. Hsiang (2016) and Dell et al. (2014) further argue that the addition of more controls will not necessarily move the climate change impact estimate closer to its true value if the controls (such as GDP and institutional measures) are outcomes of climate. Rather, such additions will induce an "over-controlling problem". Consequently, the standard practice in climate change applied studies using panel data is to exclude other time-varying controls (e.g., Emediegwu et al., 2022; Hsiang and Meng, 2015; Dell et al., 2012; Deschênes and Greenstone, 2011). Furthermore, we understand that some measurement errors may occur either in the quantity of beef production reported by countries or in the imputation by FAO for non-reporting countries. However, we believe that these errors are exogenous to our explanatory variables, hence such errors might only result in imprecise rather than biased estimates.

It is important to note that where reverse casualty is anticipated, then a single-equation model may not suffice to capture the impacts of weather variations on beef production. However, we have reasons to believe that our model does not suffer from such econometric issues. First, the weak exogeneity of weather variations in relation to several economic outcomes has been firmly established in economics literature at least in the short run (see, Emediegwu, 2021; Harari and Ferrara, 2018; Blanc and Schlenker, 2017). While it is conceivable to expect outcomes like manufacturing, agricultural production, etc to affect climate change in the long run, they do not impact weather variations in the short run as captured in a standard panel data model (Blanc and Reilly, 2017). Lastly, we conducted a panel Granger causality Wald test on Eq. (1), and the results show that while we cannot reject the null hypothesis that weather variation does not Granger-cause beef production, the reverse is not the case.[15]

In subsequent analysis, we estimate Eq. (1) for several countries' characteristics separately. While we do not claim strict causality in this study as it is difficult to do so with any observational study, this paper is careful to address certain empirical issues. First, we use country-specific fixed effects to account for time-invariant prevailing conditions in a country that may affect beef production. For example, hotter countries generally experience lower harvest, which indirectly affects cattle production *via* availability and pricing of grain Walthall et al. (2012). Second, there is possibility of temporal trends in both environmental factors and animal production in any region, with the latter coming from certain dynamics of growth that are unrelated to the weather agents. To mitigate the effect of such trends, we include region-specific trends which account for time-changing determinants of beef production that are common within a region.

The controls put in place in the model allow us to estimate the effect of a quasi-random weather variation on animal production. We further expose the models to sensitivity checks to ascertain the robustness of our results.

4. Empirical results and discussion

4.1. Main results

The main results are presented in Table 2. The Table, in addition to showing aggregate results, also displays the heterogeneous impact of weather variation on animal production based on (i) whether a country is hot or cold for most part of the year (ii) income classification (iii) agricultural role. All estimates are reported with standard

[14] Those countries with data beginning later than 1961 are mostly due to the timing of their independence. For example, many countries like North Macedonia, Ukraine, *etc.*, became independent after the collapse of the Soviet Union in 1991, hence their data starts from 1992.

[15] As suggested by one of the reviewers, we re-test for Granger causality using growth rates of beef production to control for possible serial correlation and found similar results.

Table 1
Summary statistics of dataset across regions, and predicted changes in error-corrected ACCESS SSP3.70.

	Average temperature (°C)				Total precipitation (mm)				Log animal production (tonnes)			
	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Panel A: Historical data (1961–2017)												
World	19.97	−7.43	30.09	8.03	9.14	0.06	44.32	6.18	10.80	2.83	16.32	2.19
Regions												
East Asia & Pacific (EAP)	19.04	−2.96	28.66	8.64	13.40	1.31	37.36	6.75	11.12	6.18	15.66	2.12
Europe & Central Asia (ECA)	8.27	−7.43	16.97	3.89	6.20	0.71	17.30	2.26	11.79	7.49	15.10	1.58
Latin America & Caribbean (LAC)	22.36	6.37	27.43	4.48	13.29	3.22	38.89	4.96	10.81	2.83	16.09	2.56
Middle East & North Africa (MENA)	20.73	10.40	28.36	4.82	2.53	0.06	8.58	1.72	9.82	4.56	13.65	1.95
North America (NA)	3.45	−7.27	13.38	8.52	4.66	2.34	7.72	1.78	15.01	13.39	16.32	1.19
South Asia (SA)	21.74	9.71	27.39	4.68	14.41	1.67	44.32	10.50	11.64	7.68	14.77	1.84
Sub-Saharan Africa (SSA)	24.37	10.72	30.09	3.56	8.99	0.80	34.68	4.88	9.97	3.04	13.90	1.88
Panel B: Predicted medium-term error-corrected climate change (2041–2060)												
World	2.21	0.11	3.20	0.42	0.06 (3.71)	−1.01 (−26.40)	1.20 (76.10)	0.26 (12.18)				
Regions												
East Asia & Pacific (EAP)	1.99	1.34	2.79	0.42	−0.01 (−0.98)	−0.44 (−15.96)	0.59 (6.93)	0.29 (6.29)				
Europe & Central Asia (ECA)	2.35	0.11	2.98	0.47	0.71 (3.31)	−0.09 (−4.14)	0.23 (20.26)	0.08 (4.62)				
Latin America & Caribbean (LAC)	2.09	1.32	3.20	0.40	−0.17 (−5.27)	−1.01 (−26.40)	0.27 (4.25)	0.28 (6.95)				
Middle East & North Africa (MENA)	2.47	2.13	2.93	0.23	0.03 (12.78)	−0.16 (−11.45)	0.17 (76.10)	0.08 (22.37)				
North America (NA)	3.00	2.82	3.18	0.25	0.14 (6.17)	0.12 (5.87)	0.15 (6.46)	0.02 (0.41)				
South Asia (SA)	1.70	1.02	2.31	0.39	0.18 (6.67)	−0.57 (−8.04)	0.70 (14.79)	0.42 (7.80)				
Sub-Saharan Africa (SSA)	2.14	1.63	2.84	0.29	0.21 (7.53)	−0.27 (−13.41)	1.11 (73.19)	0.28 (13.26)				
Panel C: Predicted long-term error-corrected climate change (2061–2100)												
World	4.44	2.68	6.70	0.77	0.02 (3.88)	−2.26 (−48.10)	3.11 (154.79)	0.67 (26.06)				
Regions												
East Asia & Pacific (EAP)	3.97	2.68	5.59	0.87	−0.06 (−1.23)	−1.09 (−20.11)	0.75 (13.17)	0.45 (10.84)				
Europe & Central Asia (ECA)	4.98	3.35	6.40	0.57	0.04 (2.56)	−0.35 (−19.23)	0.48 (25.96)	0.19 (9.54)				
Latin America & Caribbean (LAC)	4.17	2.83	5.78	0.75	−0.76 (−20.99)	−2.26 (−48.11)	0.53 (8.46)	0.71 (17.34)				
Middle East & North Africa (MENA)	4.85	4.22	5.50	0.34	0.07 (27.50)	−0.21 (−18.54)	0.37 (154.79)	0.16 (46.10)				
North America (NA)	6.00	5.30	6.70	0.98	0.27 (12.55)	0.23 (12.26)	0.32 (12.84)	0.06 (0.41)				
South Asia (SA)	3.68	2.94	4.74	0.59	1.00 (25.02)	0.23 (14.09)	2.31 (33.26)	0.74 (6.67)				
Sub-Saharan Africa (SSA)	4.12	3.07	5.28	0.53	0.33 (9.83)	−0.56 (−44.81)	3.10 (117.81)	0.73 (25.40)				

Note: SD denotes standard deviation. The weather and climate entries are cattle population adjusted. Figures in bracket are percentage changes from historical figures.

errors adjusted for spatial (1000 km) and serial (3-years) correlation. On aggregate, Table 2 shows that temperature has a negative and statistically significant relationship with beef production. Specifically, a 1 °C increase in temperature will lead to a 9.7% reduction in beef production. However, an in-depth look at a more disaggregated level reveals that the impact of temperature is higher in tropical regions than in temperate regions, implying that the overall negative estimate is driven by weather happenings in certain regions of the world. While a 1 °C increase in temperature will result in about a 20% fall in cattle production in tropical countries, there is no significant effect of such a rise in temperate regions. We show in the supplementary section (Table A5) that using a live animal indicator (cattle stock) as outcome variable produces similar qualitative results.[16]

On the other hand, the adverse effect of a marginal rise in temperature is evidenced in both rich and poor countries; however, the impact is stronger in the latter. We find that a 1 °C increase in temperature will reduce animal production by 27% in poor countries and 4% in rich ones. Further, our results reveal that the severity of the impact of

[16] Cattle stocks indicate the number of cattle and buffalo present in the country at the time of enumeration. It includes animals raised either for draft purposes or for meat.

Table 2
Main panel results.

	Aggregate	Hotness		Income		Agriculture-dependent	
		Tropical	Temperate	Rich	Poor	Yes	No
Temperature	−0.097	−0.199	−0.016	−0.039	−0.271	−0.141	−0.044
	[0.014]***	[0.044]***	[0.014]	[0.014]***	[0.035]***	[0.037]***	[0.013]***
Temperature squared	0.002	0.004	−0.001	−0.001	0.006	0.004	−0.001
	[0.000]***	[0.001]***	[0.001]**	[0.000]	[0.001]***	[0.001]***	[0.000]***
Precipitation	0.007	0.021	−0.019	−0.011	0.021	0.025	−0.010
	[0.007]	[0.010]**	[0.009]**	[0.013]	[0.006]***	[0.007]***	[0.012]
Precipitation squared	−0.000	−0.000	0.000	−0.000	−0.000	−0.001	−0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]**	[0.000]
Observations	8,109	4,610	3,499	4,395	3,714	4,375	3,734
Countries	157	82	75	88	69	83	74

Notes: Each coefficient is estimated from a separate (1) with country FE and region-specific trends. Standard errors are in brackets, adjusted for both spatial (1,000km) and serial (3-years) correlation. A country is defined as tropical if its median temperature is above the global median; otherwise, it is temperate. A country is rich if it is higher income or upper-middle income by World Bank classification, else it is poor. A country is agriculture-dependent if it has above median share of GDP in agriculture in 2000. Temperature is in degrees Celsius and precipitation is in mm units per year. Sample period is 1961–2017 for all specifications.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

temperature on cattle production also depends on whether a country is agriculture-dependent or not. We find that the more agriculture-dependent a country is, the greater the impact of temperature changes. On average, the adverse effect of a 1 °C increase in temperature is four times larger in agricultural economies than in non-agricultural ones. Our results imply that beef production is most seriously at risk of global warming in hot, poor, and agriculture-dependent countries. This dichotomy in the burden of impact is important in explaining possible channels (e.g., how agriculture-intensive a country is) through which weather changes affect beef production. We explore such potential channels in a later subsection.

Going back to Table 2, we explain the effect of precipitation changes on beef production. On aggregate, precipitation has a positive but insignificant effect on beef production: however, there are significant differences in results when heterogeneity is considered. For example, while a marginal rise in precipitation is beneficial to beef production in tropical countries, it is harmful in temperate economies. Specifically, where a 1 mm increase in annual precipitation would lead to a 2.1% increase in beef production in tropical countries, a similar increase in precipitation is associated with a 1.9% decline in beef production in temperate regions. Along national income lines, we find that rainfall changes have no significant effect on beef output rich countries but positively affect beef production in poor countries. This result could follow from the fact that most poor countries are situated in the tropics. This heterogeneous effect is also duplicated when considering whether a country is agriculture-dependent or not. We find that an extra mm of annual precipitation would generate a 3% improvement in beef production in agriculture-dependent countries, with no significant effect in a non-agricultural country. Overall, we find that the impacts of temperature changes are more severe in certain regions — hot, poor, and agriculture-dependent countries, as shown in Figure A4 in the supplementary section. However, the positive effect of precipitation changes in these regions means that more rainfall will attenuate the negative impact of temperature rise on beef production. Although, the extent to which this would reduce the temperature impact is an empirical question.

The quadratic term of temperature is significant across all specifications, unlike precipitation, which indicates a potential nonlinear (convex by nature) relationship between temperature and beef production. Such nonlinearity means there is a minimally beneficial level from which the effects start rising, significantly or insignificantly, in both directions.

4.2. Robustness results

In this subsection, we ascertain our results' (in)sensitivity through a series of robustness tests. Our robustness tests involve re-modeling Eq. (1) with different functional forms and panel samples.[17] The results displayed in Table 3 entail aggregate estimates and estimates for heterogeneous parts that show significant impacts.

Lagged Weather Outcomes: We test whether our estimates are sensitive to the addition of weather lags. It is possible for variability in economic outcome, like livestock production, to be coming from past weather occurrences. Livestock production is a multi-year process, which means that farmers decide what year to send animals to the slaughter house to produce meat. Hence, the need to see to what extent past weather occurrence influence current production levels. The first and second rows in Table 3 display the results with lagged weather variables added to the baseline model. With the inclusion of one-year temperature lag, the cumulative effects are broadly similar in terms of significance and sign. However, there is an increase in the size of the estimates in the heterogeneous components, but a reduction by half at aggregate level. This increase in magnitude implies that the effect of lags is reinforcing rather than diminishing. On the other hand, the effect of precipitation is qualitatively similar to the baseline estimates. The addition of a one-year lagged precipitation measure increases the magnitude of the cumulative impact of precipitation on beef production marginally, except at the aggregate level, where the effect of precipitation becomes slightly significant.[18]

Logged Weather Outcomes: We consider a log–log functional form where the weather variables are log-transformed. The implication of this transformation is a large loss of observations since the log of zero and negative temperatures is undefined. Row 3 in Table 3 reports the estimates from re-analyzing Eq. (1) using log of weather variables. In terms of interpretation, the estimates report elasticity, which is qualitatively similar to baseline estimates. Although in terms of magnitudes, the estimates here are lower than the baseline's, which is unsurprising given the loss of observations following the log-transformation.

Interaction Term: Further, we checked if our results are robust to the inclusion of an interaction term of temperature and precipitation. The results displayed in Row 4 show marginal estimates at sample mean of interaction between temperature and precipitation. The estimates are broadly consistent, except that the effect of precipitation becomes insignificant for tropical and agriculture-dependent groups.

Outliers Influence: We checked whether our estimates are driven by some outlier countries. We describe these countries as those with

[17] Results of further robustness tests can be found in the supplementary section.
[18] We use one-lag as subsequent additions do not change the results significantly.

Table 3
Robustness.

	Temperature				Precipitation			
	Aggregate	Tropical	Poor	Agriculture-dependent	Aggregate	Tropical	Poor	Agriculture-dependent
Lagged temperature (I)	−0.047	−0.214	−0.287	−0.128	0.013	0.029	0.024	0.028
	[0.015]***	[0.045]***	[0.036]***	[0.038]***	[0.007]*	[0.010]***	[0.006]***	[0.007]***
Lagged precipitation (II)	−0.026	−0.191	−0.272	−0.128	0.014	0.034	0.028	0.033
	[0.013]**	[0.044]***	[0.036]***	[0.038]***	[0.007]**	[0.010]***	[0.006]***	[0.007]***
Log temperature (III)	−0.240	−6.571	−0.831	−0.545	0.071	−0.008	−0.064	−0.015
	[0.036]***	[2.066]***	[0.198]***	[0.165]***	[0.060]	[0.065]	[0.027]**	[0.025]
Weather interaction (IV)	−0.103	−0.208	−0.273	−0.145	−0.020	0.009	0.015	0.011
	[0.014]***	[0.046]***	[0.035]***	[0.037]***	[0.009]**	[0.024]	[0.009]*	[0.015]
Outlier Countries (V)	−0.093	−0.198	−0.224	−0.126	0.002	0.023	0.011	0.016
	[0.015]***	[0.047]***	[0.044]***	[0.040]***	[0.008]	[0.009]**	[0.007]*	[0.008]**
SSA excluded (VI)	−0.086	0.064	−0.253	−0.111	−0.004	0.014	0.006	0.008
	[0.014]***	[0.069]	[0.039]***	[0.040]***	[0.008]	[0.015]	[0.006]	[0.008]
Only SSA (VII)	−0.331	−0.345	−0.301	−0.570	0.037	0.021	0.045	0.047
	[0.059]***	[0.061]***	[0.060]***	[0.077]***	[0.011]***	[0.014]	[0.011]***	[0.012]***
Balanced panel (VIII)	−0.020	−0.201	−0.251	−0.069	0.010	0.021	0.024	0.031
	[0.013]	[0.044]***	[0.035]***	[0.035]***	[0.007]	[0.010]**	[0.006]***	[0.007]***
Baseline	**−0.097**	**−0.199**	**−0.271**	**−0.141**	**0.007**	**0.021**	**0.021**	**0.025**
	[0.014] ***	**[0.044]** ***	**[0.035]** ***	**[0.037]** ***	**[0.007]**	**[0.010]** **	**[0.006]** ***	**[0.007]** ***

Notes: Each coefficient is estimated from a separate (1) with country FE and region-specific trends. Standard errors are in brackets, adjusted for both spatial (1,000km) and serial (3-years) correlation. A country is defined as "tropical" if its median temperature is above the global median, "poor" if it is classed as a lower income or lower-middle income by World Bank classification, "agriculture-dependent" if it has above median share of GDP in agriculture in 2000. Temperature is in degrees Celsius and precipitation is in mm units per year. Sample period is 1961–2017 for all specifications.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

duplicate beef production entries in the original FAO dataset. Purging our sample of the 22 countries that fall under this category do not alter our results significantly.[19] The results in Row 5 are analogous to the baseline results, confirming the stability of our baseline estimates.

Sub-Saharan Africa's (SSA) Influence: Next, we consider the influence of SSA on our results. SSA is an important region, given that most of the countries, as shown in Figure A4 in the supplementary section, are hot, poor, and agriculture-dependent. First, we re-estimate Eq. (1) without inputs from SSA. Results from Row 6 are quite similar in sign, significance, and size to the main estimates. Following, we re-estimate the main equation with SSA dataset only and found broadly analogous results, albeit with larger magnitudes than the baseline estimates as shown in Row 7. Both results indicate that while the impact of weather changes on SSA is huge, excluding the region does not cancel the general trend. Hence, our results are robust to the inclusion or exclusion of the region.

Balanced Panel: Since our dataset is an unbalanced panel, we checked whether using only countries with complete observations for the period under consideration (1961–2017) will alter our results significantly. Re-estimating Eq. (1) with a balanced panel dataset produces broadly similar estimates to the baseline results as shown in Row 8. Although, there is a marginal drop in the size of the estimates for temperature effect, which is not unexpected since some observations (8% of the original data points) were lost in the process of balancing the panel data. The effect of precipitation changes, however, remains very stable. Table A3 in the supplementary section shows similar results using various cutoffs to generate our balanced panel data.

Summarily, the results from the various sensitivity tests show that our baseline estimates that measures the impact of annual weather fluctuations on beef production are robust. Therefore, large deviations from the main estimates are unexpected.

[19] The countries excluded are Afghanistan, Bahamas, Botswana, Comoros, Dominican Republic, Equatorial Guinea, Ghana, Guatemala, Guinea, Guinea-Bissau, Haiti, Iceland, Lesotho, Liberia, Mauritania, Mozambique, North Korea, Oman, Qatar, Sierra Leone, Syrian Arab Republic, Turkey.

4.3. Investigating channels

Here, we investigate a potential source of mechanism that explains how weather changes affect global beef production. As discussed in the second section of this paper, there are several channels through which weather shocks can influence animal production. While a thorough investigation into these mechanisms is important, it is beyond the scope of this work. Here, we focus on how weather changes affect beef production vis-à-vis its impact on crop production.

4.3.1. Crop production

Weather fluctuations may influence beef output if they affect crop production via changes in the quantity and quality of feed available for cattle. Previous studies (e.g., Aragón et al., 2021; Rosenzweig and Wolpin, 1993) provide evidence that shortage of crop output could reduce livestock holding as a means of adaptation. Also, crop failure due to adverse weather conditions can lead to conflict between farmers and herders, leading to loss of lives and livestock (Harari and Ferrara, 2018; Turner, 2004). Thus, we examine the impact of temperature and precipitation on crop outputs.

Table 4 shows the impact of temperature and precipitation changes on two indices of crop production — cereal yields (ton/ha) and cereal production (kg). Dataset for both variables is from the FAO.

As expected, there is a negative impact of temperature on both yields and cereals production, although this impact is more substantial in hot countries. Specifically, a 1 °C increase in temperature is associated with a 3.7% drop in cereal yields. The impact is about 3.4 percentage points higher in tropical countries. The same trend is observable in the relationship between temperature shock and cereal output. On aggregate, a 1 °C higher temperature is associated with a 7.6% drop in global cereal production. The impact is greater in hot, poor, and agriculture-dependent countries. These results corroborate similar findings from Lobell et al. (2011), who report a 3.8–5.5% global net loss of maize and wheat from a marginal rise in temperature.

Table 4 also shows the usual positive relationship between precipitation changes and crop outcomes. A marginal increase in annual rainfall is associated with a 1.5% increase in global cereal yield. This impact is larger in tropical countries where a similar increase in annual precipitation will result in a 2.8% rise in cereal yield. While the impacts

Table 4
Impact of weather fluctuations on cereal production.

	Yield (ton/ha)				Production (kg)			
	Aggregate	Tropical	Poor	Agriculture-dependent	Aggregate	Tropical	Poor	Agriculture-dependent
Temperature	−0.0372	−0.161	−0.078	−0.035	−0.076	−0.276	−0.199	−0.127
	[0.004]***	[0.024]***	[0.014]***	[0.012]***	[0.006]***	[0.042]***	[0.022]***	[0.018]***
Temperature squared	0.001	0.003	0.002	0.001	0.002	0.005	0.005	0.003
	[0.000]***	[0.001]***	[0.000]***	[0.000]*	[0.000]***	[0.001]***	[0.000]***	[0.000]***
Precipitation	0.015	0.028	0.020	0.017	0.024	0.039	0.031	0.030
	[0.002]***	[0.003]***	[0.003]***	[0.002]***	[0.003]***	[0.005]***	[0.003]***	[0.004]***
Precipitation squared	−0.000	−0.001	−0.000	−0.000	−0.001	−0.001	−0.001	−0.001
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Observations	7,956	4,531	3,708	4,369	7,956	4,531	3,708	4,369
Countries	155	81	69	83	155	81	69	83

Notes: Each coefficient is estimated from a separate (1) with country FE and region-specific trends. Standard errors are in brackets, adjusted for both spatial (1,000km) and serial (3-years) correlation. A country is defined as "tropical" if its median temperature is above the global median, "poor" if it is classed as a lower income or lower-middle income by World Bank classification, "agriculture-dependent" if it has above median share of GDP in agriculture in 2000. Temperature is in degrees Celsius and precipitation is in mm units per year. Sample period is 1961–2017 for all specifications.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

in poor and agriculture-depend countries are larger than the aggregate effect, they are less than the impact in tropical countries. The same trend, but with larger coefficients, exists cereal production is used as the outcome variable.

The impacts on cereal output could also serve to explain why and how weather affects beef production. For example, as higher temperatures harm crop output, the associated drop in output is passed onto beef production since cattle feed on cereals. This reduction in food could affect the quantity (via deaths or low reproduction rates) and quality (via poor health or high feed conversion ratio (FCR)) of herds. Another pass-on effect could be that as weather shocks affect crop output, farmers may substitute holding livestock for farm crops as an adaptation strategy, thus reducing beef production capacity. While there is evidence of how crop changes drive livestock holdings as evidenced in Aragón et al. (2021) and Rosenzweig and Wolpin (1993), it is not impossible to conceive of situations where livestock changes affect crop output. The investigation of such potential reversed causality is worth investigating.

Like every econometric model, there are caveats that are worth mentioning regarding our model. Not using seasonal weather measures makes our estimates overly optimistic as we do not account for seasons that are germane to crop production, an important determinant of cattle growth and development. Furthermore, we do not account for the beneficial effect of CO2 on crop fertilization which may also lower the indirect impact of weather changes on beef production via its beneficial effect on crop production. Notwithstanding the caveats, the results are very informative for policy making and complement the growing literature that seeks to understand how climate change affects livestock production.

4.4. Accounting for adaptation

A major shortfall with panel data models is that they assume away adaptation. In other words, they assume that the estimated relationship remains "stationary" regardless of changing climate. Consequently, the estimates from such models present a pessimistic view of the impacts of climate change since it rules out potential adaptive measures such as diversification of livestock and forage cropping. Besides, time-trends and country-fixed effects absorb long-run climate conditions.

Dell et al. (2014) suggest several ways to econometrically modify a standard panel data model to account for medium to long-term adaptation.[20] One of such methods is known as the long differences (LD) approach developed in Burke and Emerick (2016).[21] In what follows, we employ the LD model to check whether adaptation occurred within the period of our estimation. We only present the results here, the construction of the associated model is given in the supplementary section (Appendix A). The results of the model with several *n*-year averages are summarized in Table 5. The results from Rows 1–4 consistently show that the estimates are insignificant across all model specifications, except for the precipitation changes, where they appear to be sensitive to the choice of differencing periods. Consequently, this study does not find evidence that beef production is affected by changes in medium-term average weather conditions.

Our results are similar to extant studies (e.g., Emediegwu et al., 2022; Dell et al., 2012) that find no evidence of adaptation using country-level data. The scope of this result could differ if a more disaggregated dataset (e.g., household or farm level) is considered. For example, using farm-level dataset, Di Falco et al. (2020) and Idrissou et al. (2020) find that local farmers and herders adapt to climate change in some parts of SSA.[22] Consequently, the results we present should not be interpreted to imply the absence of adaptation to climate change but, rather, should be interpreted cautiously with the observational unit in mind.

5. Climate change projection

The last exercise is to consider the impact of projected climate change on global beef production in the mid-future (2041–2060) and by the end of the century (2081–2100). To carry out this task, we combine the regression estimates from the baseline model with forecasted climatic changes derived from a global climate model (GCM), ACCESS-ESM1.5.[23] We calculate the change in meteorological variables at different future periods by differencing the GCM's projected average weather measures over the mid-term and long-term periods for each grid cell over a historical period (1981–2010). The importance of such downscaling is to eliminate bias emanating from the GCM's current climate in some locations, since observed data and GCM's historical data for the same period may have different observations (see, Burke et al. (2015), Auffhammer et al. (2013) for more on this issue). We recognize that averaging the GCMs tends to smooth out heterogeneous spatial patterns.

[20] We thank an anonymous reviewer that pointed us in this direction.

[21] Burke and Emerick (2016) use estimates based on a long differences (LD) approach to identify how US farmers adapt to climate change.

[22] Although Gawith et al. (2020) show that climate damage is often underestimated, even in the presence of adaptation because agents respond slowly and partially to biophysical and ecological change.

[23] Kindly refer to Section 3 of this paper for a detailed description of the ACCESS-ESM1.5 GCM.

Table 5
Comparison of long differences and panel estimates of the impacts of weather variation on beef production.

	Temperature		Precipitation	
	Tropical	Poor	Tropical	Poor
15-year differences	−0.561	−0.706	0.001	0.005
	(1.260)	(0.521)	(0.007)	(0.007)
10-year differences	−0.264	−0.605	−0.001	−0.003
	(1.402)	(1.006)	(0.001)	(0.007)
20-year differences	−0.485	−0.765	0.005	0.014*
	(1.242)	(0.545)	(0.007)	(0.007)
29-year differences	−0.545	−0.939	0.004	0.014**
	(1.400)	(0.711)	(0.004)	(0.001)
Baseline	**−0.199**	**−0.271**	**0.021**	**0.021**
	[0.044] ***	**[0.035]** ***	**[0.010]** **	**[0.006]** ***

Notes: The following defines the differenced averages: 15-year diff. (1961–1975 and 2003–2017), 10-year diff. (1961–1970 and 2008–2017), 20-year diff. (1961–1980 and 1998–2017), and 29-year diff. (1961–1990 and 1991–2017) divides the entire sample into two halves. A country is defined as "tropical" if its median temperature is above the global median, "poor" if it is classed as a lower income or lower-middle income by World Bank classification. Temperature is in degrees Celsius and precipitation is in mm units per year. Sample period is 1961–2017 for all specifications.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6
Predicted climate change effect on beef production (in logs).

	Aggregate	Tropical	Temperate
Panel A: ACCESS (2041–2060)			
Temperature changes	−0.23	−0.43	−0.04
Precipitation changes	0.02	0.08	−0.07
Combined changes	−0.21	−0.36	−0.11
Panel A: ACCESS (2081–2100)			
Temperature changes	−0.47	−0.88	−0.09
Precipitation changes	0.03	0.08	−0.07
Combined changes	−0.45	−0.80	−0.16

Notes: The entries in the table are log changes from ACCESS-ESM1.5 for mid-term climate change (Panel A) and long-run climate change (Panel B) under SSP3-7.0 scenario. Changes are relative to a 1981–2010 baseline.

Table 6 reports the predicted log changes in global beef production under the ACCESS-ESM1.5 mid-term and long-run scenarios. The predicted loss in global beef production due to climate change in 2060 ranges from 11% (in temperate regions) to 36% (in tropical areas). The main agent of predicted loss is future temperature and rainfall changes in the tropical and temperate regions, respectively. Additionally, Table 6 shows that the effect of projected warming dominates that of rainfall changes by the end of the century. Also, the predicted impact of future rainfall changes on beef production is positive in the tropics while it is negative in the temperate regions. These heterogeneous impacts attest to the non-uniformity of future rainfall trends, as seen in Figures A2 and A3 in the supplementary section. Fig. 1 displays the spatial distribution of the cumulative impact of climate change under the mid-term and long-term scenarios. Important information from Fig. 1 is that the overall adverse effect of climate change on beef production is almost completely centered in tropical countries.

Another observation worth noting is that the effect of global warming stochastically dominates that of rainfall changes. A reason for this dominating effect is that while every part of the world will experience warming, though unequally, there is no unanimity on the future trend of rainfall, as seen from Figures A2 and A3 in the supplementary section. We must, however, note that one key assumption in the use of climate models for future predictions is the 'ceteris paribus' assumption, as well as the belief that climate will continue to affect livestock production in the future.

6. Conclusion

This paper measures the impact of weather fluctuations on global livestock production using panel data from 1961 to 2017. In contrast to the integrated assessment and Ricardian models, the method employed in this paper exploits the exogeneity of cross-time variations in weather to identify the causal effects of temperature and precipitation on livestock production. The results show that, at the global level, a 1 °C increase in temperature will lead to a 9.7% reduction in beef production on average, with most of this effect centered in tropical countries. Poorer countries would also experience a 27% reduction as opposed to 4% in countries with higher income levels. On the other hand, an additional mm increase in annual precipitation would lead to a 2.1% increase in production in tropical countries but a 1.9% decrease in temperate ones. We also find that beef production in agriculture-dependent countries is more affected by warming than in non-agricultural economies. Overall, poor and agricultural-dependent countries located in the tropics are severely affected by warming, notwithstanding the positive effect of rainfall changes in such regions. The projections indicate that the effects of climate change by 2070 would range from 11% in temperate regions to 36% in tropical areas, with global warming playing a more significant role in determining livestock output than predicted changes in rainfall patterns in the longer term.

An important message from this study is that climate change affects livestock production and, consequently, food security, which will be even more important in the future. Global production of livestock and livestock products will be negatively impacted (due to diseases, water availability, etc.), especially in poor and tropical regions. Therefore, mitigation and adaptation policies are important to protect the sustainability of livestock production, especially in these vulnerable regions. Some ways that agricultural systems could adapt to the changing climate include adopting new and improved strategies for animal breeding, changing farmers' perception, and incorporating advances in science and technology, including improving animal nutrition and genetics. Geographic information system (GIS) and remote sensing technologies could also be adopted to optimize the timing, location, and patterns of grazing. But all of these adaptations would be inadequate if not supported at the policy-making level with appropriate policy frameworks to enhance their effects. For example, the inclusion of farmers in the decision-making process critical to understanding the issues confronting their activities and the success of any mitigating policies.

Some limitations to the study are as follow. The panel data method do not account for inter-annual tradeoffs farmers make that may be affecting the contemporaneous estimates presented in the paper. Consequent to this methodological shortcoming, this study is picking up short-run changes in inventory in the cattle herd that may not be indicative of long run changes associated with climate change. Besides,

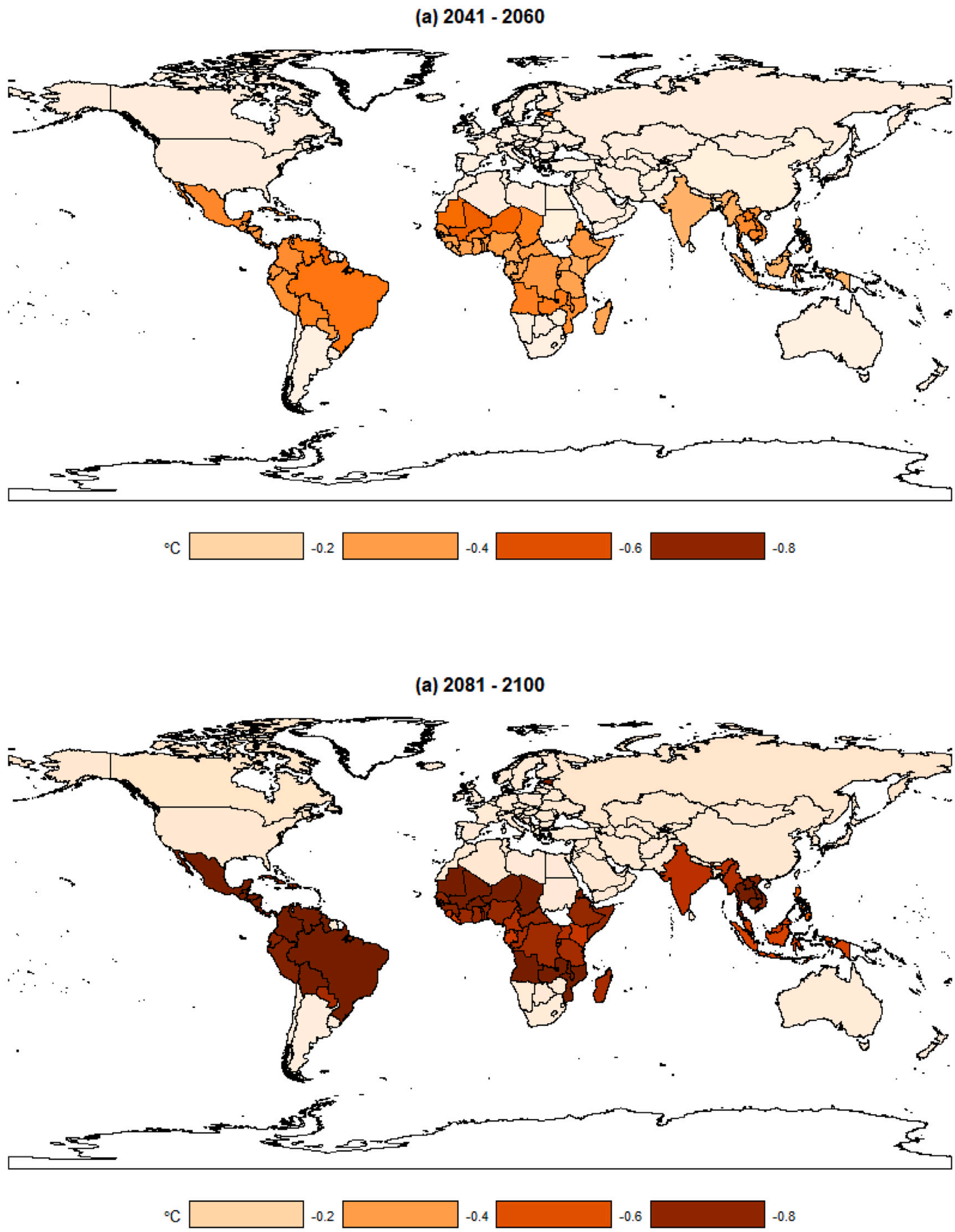

Fig. 1. Spatial distribution of predicted climate change aggregate impact on beef production (in logs).
Notes: The maps represent aggregate (temperature + precipitation) impacts (as log changes) from ACCESS-ESM1.5 for (a) mid-term climate change and (b) long-run climate change under SSP3-7.0 scenario. Changes are relative to a 1981–2010 baseline.

the panel data model does not account for adaptation to gradual changes in climate. We expect farmers to take adaptive measures (such as migrating animals to cool areas) in the face of climate change. Accounting for such adaptive techniques using long differences method did not dampen the damage estimate from our model. Although, we are careful to state that this absence of adaptation should be considered with reference to our unit of observation, country-level.

As with other empirical models, real-world agricultural processes are more complex than what models represent. There is tremendous heterogeneity in several channels through which climate change affects animals productivity. It is practically difficult for any single model to answer all the questions, prove all channels, or account for all uncertainties. Therefore, this paper contributes to the climate econometrics and agricultural economics literature that applies econometric techniques to understand the interaction between weather factors and livestock production.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary information

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