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Analysis

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Priority areas for investment in more sustainable and climate-resilient livestock systems

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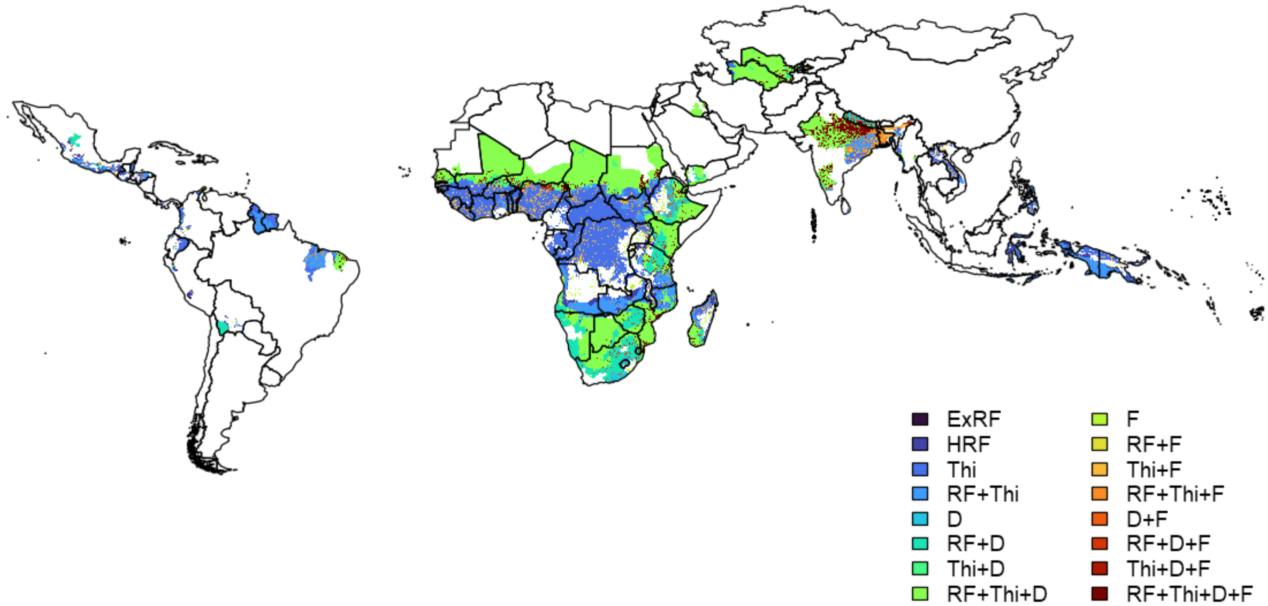
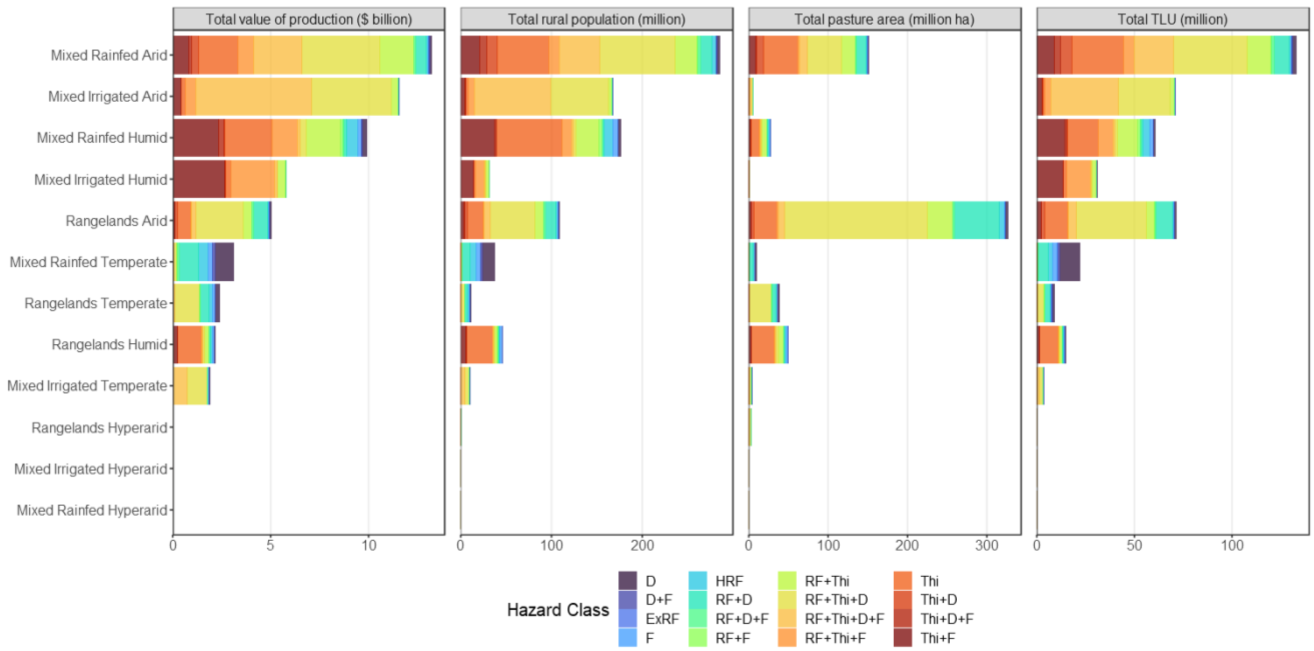
Contents



Supplementary Figure S1: Potential climatic hazards within low- and middle-income countries with low and medium adaptive capacity (poverty headcount ratio of US$1.90 per day above 10 %, dataset ID=010 in Table S3). ExRF = extremely high rainfall variability (derived from dataset ID=006); HRF = high rainfall variability (derived from dataset ID=006); Thi = livestock heat stress (derived from dataset ID=009); RF = extreme or high rainfall variability (combination of ExRF and HRF classes); D = drought, i.e., areas with an average of over 25 days with no rain per month (derived from dataset ID-007); F = flooding, i.e., areas with risk of flooding over zero (derived from dataset ID=008). Thi is projected for 2030 under an 8.5 RCP scenario = areas with a Thi ≥ 79.

To produce this figure, we combine individual climate hazard layers (dataset IDs 006, 007, 008, and 009 in Supplementary Table S3, also listed in Supplementary Table S5) into a single 16-class hazard layer. Next, we subset the combined hazard layer to low/medium adaptive capacity areas (poverty headcount ratio >10%, see dataset ID=010 in Supplementary Table S3). Each color in Fig. S1 refers to a specific combination of hazards.

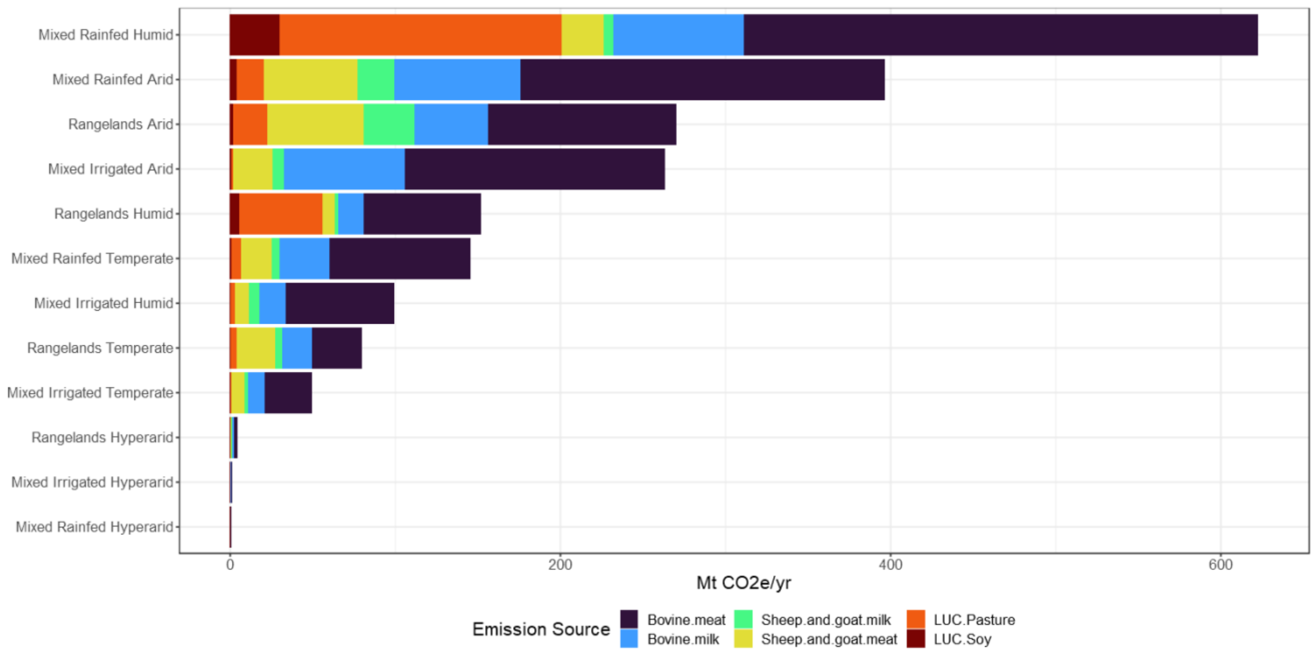
For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.



Supplementary Figure S2: Total value of production (dataset ID=002, Table S3), total rural population (dataset ID=004), total pasture area (dataset ID=003), and tropical livestock units (TLU) (dataset ID=001) exposed to climate hazards by livestock production systems and with low/medium adaptive capacity (poverty headcount ratio of US$1.90 per day above 10 %, dataset ID=010). ExRF = extremely high rainfall variability (derived from dataset ID=006); HRF = high rainfall variability (derived from dataset ID=006); Thi = livestock heat stress (derived from dataset ID=009); RF = extreme or high rainfall variability (combination of ExRF and HRF classes); D = drought, i.e., areas with an average of over 25 days with no rain per month (derived from dataset ID-007); F = flooding, i.e., areas with risk of flooding over zero (derived from dataset ID=008). Thi is projected for 2030 under an 8.5 RCP scenario = areas with a ThI $\geq$ 79.

To produce this figure we combine individual climate hazard layers (dataset ID=006, 007, 008 and 009 in Supplementary Table S3, also listed in Supplementary Table S5) into a single 16-class hazard layer. Next, we totalize each of the exposure datasets, namely, total livestock units (ID=001), livestock value of production (ID=002), total pasture area (ID=003), and rural population (ID=004) at the global level for each of the livestock production systems in the dataset (dataset ID=005). Finally, we produced a stacked bar plot for each exposure variable, with the exposure variable in the *x*-axis, the livestock systems in the *y*-axis, and each bar split by the different hazards to which each production system is exposed.

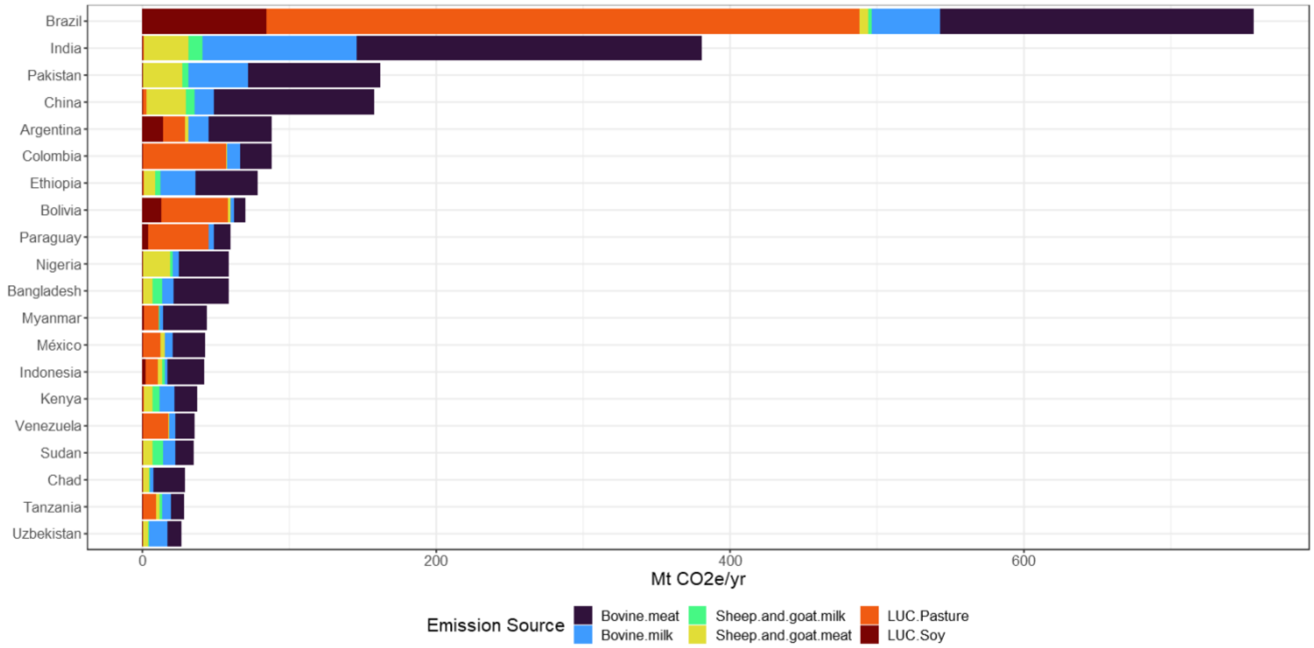
For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.



Supplementary Figure S3: Total megatons of carbon dioxide equivalent emissions per year (Mt CO_2e/yr) broken down into direct (dataset ID=011, and ID=012 in Table S3) and indirect emissions (dataset ID=013, 014, 015, 016, and 017) by livestock production systems.

To produce this figure, we totalize individual emissions sources as reported by the emissions datasets (direct and indirect, as shown in Supplementary Table S3) by livestock production system (dataset ID=005 in Table S3). We then plot a stacked bar plot with emissions in the *x*-axis, the livestock systems in the *y*-axis, and each bar split by the emissions sources.

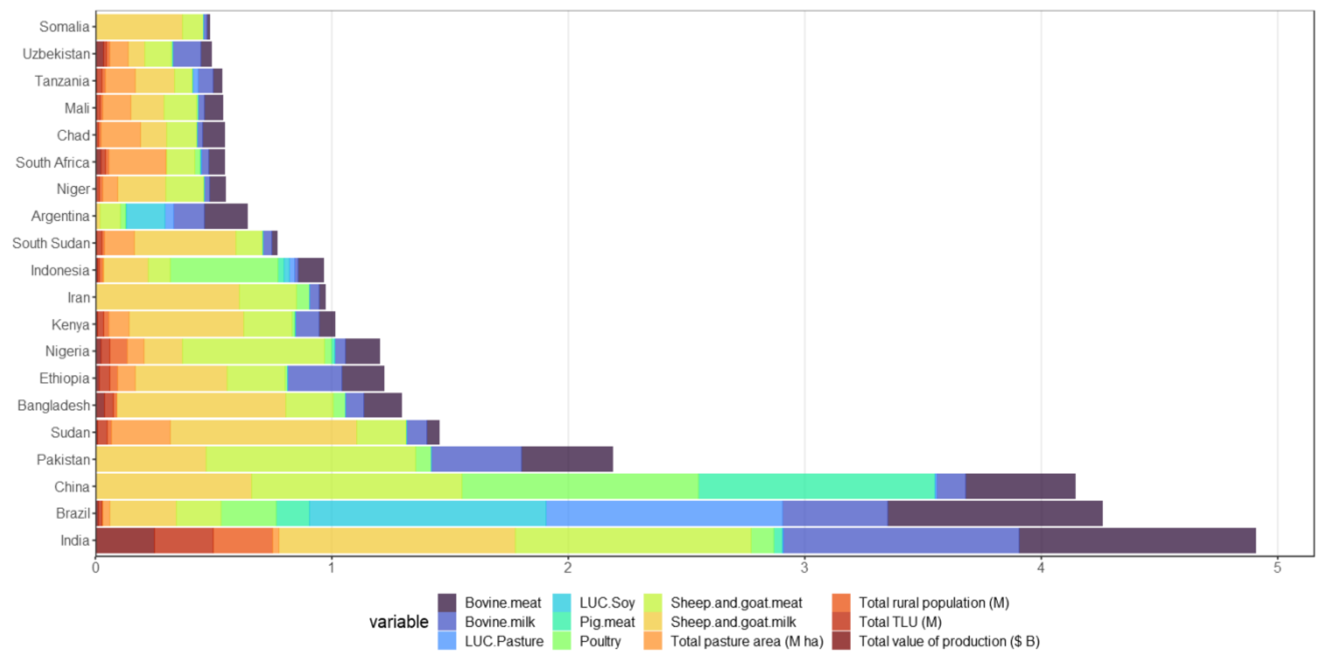
For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.



Supplementary Figure S4: Total megatons of carbon dioxide equivalent emissions per year (Mt CO_2e/yr) broken down into direct (dataset ID=011, and ID=012 in Table S3) and indirect emissions (dataset ID=013, 014, 015, 016, and 017) for the top 20 countries.

To produce this figure we totalize individual emissions sources as reported by the emissions datasets (direct and indirect, as shown in Supplementary Table S3) by country (dataset ID=018 in Table S3). We then plot a stacked bar plot with emissions in the *x*-axis, the countries in the *y*-axis, and each bar split by the emissions sources.

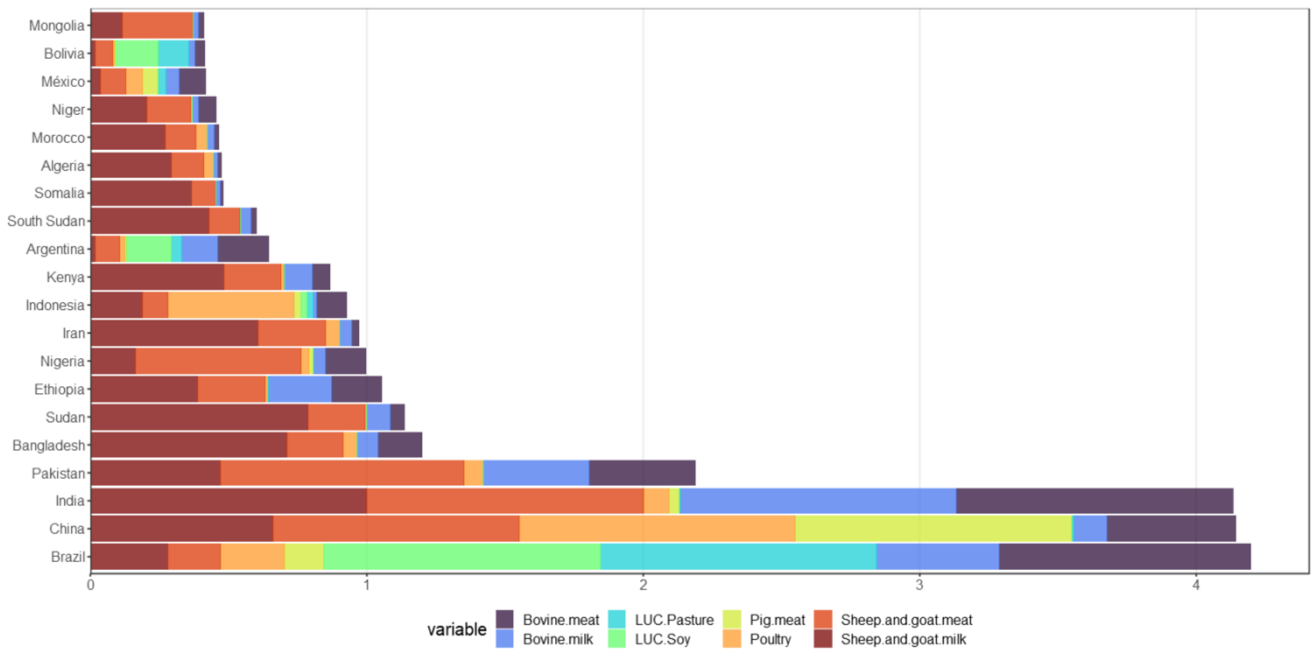
For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.



Supplementary Figure S5: Top 20 countries for adaptation and mitigation investment priorities (variable) when considering an equal weighting in adaptation and mitigation indicators.

To produce this figure we first combine individual climate hazard layers (dataset ID=006, 007, 008 and 009 in Supplementary Table S3, also listed in Supplementary Table S5) into a single 16-class hazard layer. We then calculate total exposure to climate hazards per country using four exposure indicators, namely, total livestock units (dataset ID=001 in Table S3), livestock value of production (dataset ID=002), total pasture area (dataset ID=003), and rural population (dataset ID=004). We totalize individual emissions sources as reported by the emissions datasets (direct and indirect, as shown in Supplementary Table S3) by country (dataset ID=018 in Table S3). Next, we normalize each indicator across the globe by dividing by the maximum value across all countries. We then compute a total score using equal weighting for mitigation (emissions) and adaptation (hazard exposure) normalized indicators. Lastly, we then plot a stacked bar plot with the normalized priority score in the *x*-axis, the countries in the *y*-axis, and each bar split by emissions sources or hazard exposure indicators.

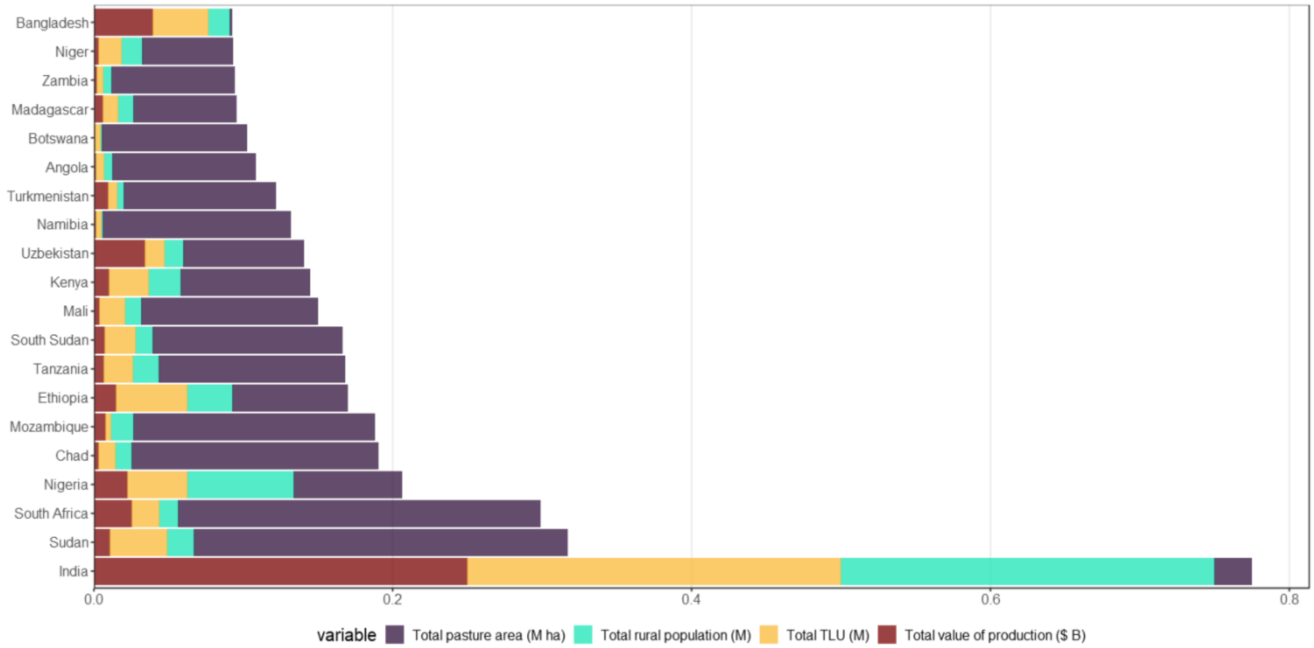
For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.



Supplementary Figure S6: Top 20 countries for adaptation and mitigation investment priorities when only considering mitigation indicators (variable).

To produce this figure we follow the same methods as for Supplementary Fig. S5, but give 100% weight to the mitigation (GHG emissions) indicators (and consequently zero weight to hazard exposure indicators).

For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.



Supplementary Figure S7: Top 20 countries for adaptation and mitigation investment priorities when only considering adaptation indicators.

To produce this figure we follow the same methods as for Supplementary Fig. S5, but give 100% weight to the adaptation (hazard exposure) indicators (and consequently zero weight to GHG emissions indicators).

For more details on methods see Supplementary Text S1, and for a detailed list of datasets see Supplementary Table S3.

Supplementary Table S1: Total value of production, total rural population, total pasture area, and tropical livestock units (TLU) exposed to climate hazards by country and with low/medium adaptive capacity, i.e., a poverty headcount ratio of US$1.90 per day above 10 %.

Country	Value of production (USD x 10^6)	Rural population (people x10^3)	Pasture area (ha x 10^6)	TLU (x10^3)
Afghanistan	168.3	94.4	213.2	50.8
Algeria	3.3	3.6	7.2	9.0
American Samoa	-	-	-	-
Angola	1,693.8	7,565.8	24,494.1	3,335.3
Argentina	1.7	4.8	23.6	1.3
Azerbaijan	161.3	14.7	56.9	10.2
Bangladesh	43,462.5	19,573.3	335.5	23,122.1
Belize	110.4	277.5	52.1	90.3
Benin	1,597.1	7,753.1	668.3	2,044.5
Bhutan	328.5	245.8	0.4	69.9
Bolivia	472.3	396.3	1,390.2	331.1
Botswana	1,044.3	1,620.6	24,764.9	2,151.4
Brazil	13,492.6	8,087.9	7,631.3	8,691.5
Burkina Faso	5,666.2	16,532.8	6,615.7	9,205.5
Burundi	196.6	1,368.1	125.6	231.6
Cote d'Ivoire	2,706.3	15,979.8	9,409.2	2,050.1
Cabo Verde	-	19.6	-	20.3
Cambodia	43.4	84.3	19.2	25.9
Cameroon	3,002.2	9,954.1	2,284.7	2,597.2
CAR	1,792.1	4,124.2	3,669.0	3,507.7
Chad	3,682.0	14,830.8	42,287.9	7,025.6
Chile	1.8	1.0	10.6	0.4
China	217.1	271.6	59.3	158.0
Colombia	3,081.5	2,273.5	2,327.2	1,071.5
Comoros	-	29.6	-	56.0
Costa Rica	-	-	-	-
Cuba	-	-	-	-
Djibouti	184.4	549.6	652.9	329.8
Dominica	-	-	-	-
Dominican Republic	127.3	106.4	30.1	86.6
Democratic Republic of Congo	1,444.7	49,330.6	8,115.1	1,498.7
Ecuador	3,703.3	1,090.7	1,387.0	663.2

Egypt	0.5	6.6	33.0	6.4
El Salvador	32.0	80.7	27.2	24.6
Equatorial Guinea	0.3	13.0	-	0.7
Eritrea	75.0	297.9	415.6	151.1
Ethiopia	16,713.3	41,444.9	19,648.3	29,367.2
Fiji	-	-	-	-
Gabon	123.2	1,245.3	460.8	130.7
Gambia	266.5	972.0	494.1	430.8
Ghana	1,894.8	10,149.1	7,018.2	1,923.7
Grenada	-	-	-	-
Guatemala	3,172.6	4,759.4	1,209.4	1,326.7
Guinea	2,768.2	7,768.2	5,484.6	3,980.7
Guinea-Bissau	418.3	1,112.6	1,220.4	736.1
Guyana	561.2	256.3	1,240.4	300.9
Haiti	2,405.2	4,017.8	450.9	1,722.6
Honduras	1,993.1	3,506.7	978.4	1,844.4
India	274,787.0	336,220.8	6,273.5	156,337.7
Indonesia	10,801.4	17,830.5	1,317.9	4,962.2
Iran	127.4	142.6	360.4	44.0
Iraq	779.8	2,985.1	326.7	452.4
Israel	-	-	-	-
Jamaica	-	-	-	-
Jordan	-	-	-	-
Kazakhstan	525.9	276.9	617.8	119.6
Kenya	11,070.8	29,393.1	22,005.1	16,650.3
Kiribati	-	-	-	-
Kuwait	0.5	0.3	0.1	0.2
Kyrgyzstan	1,391.6	420.5	192.1	227.6
Laos	2,618.5	5,228.0	692.9	2,268.1
Lebanon	-	-	-	-
Lesotho	2,079.4	1,454.1	2,028.1	718.2
Liberia	348.5	3,030.2	0.6	277.3
Libya	0.1	0.8	4.7	1.2
México	15,874.5	9,998.2	5,984.9	7,242.3
Madagascar	6,642.3	14,168.4	17,657.4	6,318.6
Malawi	1,511.1	13,071.0	1,904.6	1,412.1
Malaysia	-	-	-	-
Maldives	-	-	-	-
Mali	4,437.9	15,449.3	30,225.4	10,303.0

Marshall Islands	-	-	-	-
Mauritania	720.4	989.4	2,306.8	697.6
Mauritius	-	-	-	-
Micronesia	-	-	-	-
Mongolia	-	-	-	-
Morocco	-	-	-	-
Mozambique	8,989.9	20,608.2	41,358.3	2,069.7
Myanmar	1,669.5	1,516.4	59.9	1,285.2
Namibia	1,861.4	1,659.8	32,106.4	2,154.3
Nepal	24,748.8	20,960.1	1,289.4	10,362.0
Nicaragua	92.0	118.3	56.5	76.4
Niger	3,476.2	19,322.7	15,523.2	9,403.5
Nigeria	24,948.6	96,621.9	18,439.8	24,783.7
North Korea	-	-	-	-
Oman	-	-	-	-
Pakistan	174.3	412.6	28.3	150.9
Palau	-	-	-	-
Palestine	-	-	-	-
Panama	107.1	147.6	126.2	50.0
Papua New Guinea	584.5	3,177.2	101.9	309.7
Paraguay	4.3	0.1	8.7	1.1
Peru	3,291.7	1,541.1	1,484.2	1,044.2
Philippines	7,453.5	11,344.6	48.6	3,285.2
Republic of the Congo	123.1	2,412.1	1,799.6	315.1
Rwanda	390.6	2,534.2	194.6	594.5
Sao Tome and Principe	-	-	-	5.7
Saint Lucia	-	43.6	-	19.0
Saint Vincent and the Grenadines	-	-	-	-
Samoa	-	-	-	-
Saudi Arabia	25.7	29.8	12.3	12.1
Senegal	3,331.1	9,170.9	5,953.0	4,252.1
Sierra Leone	775.1	4,261.8	237.7	996.5
Solomon Islands	-	-	-	-
Somalia	34.3	452.6	631.2	318.3
South Africa	28,012.6	17,681.3	62,056.6	11,301.3
South Sudan	8,014.3	16,184.9	32,509.4	12,683.0
Sri Lanka	274.7	498.4	36.0	115.8
Sudan	11,806.2	24,672.5	64,128.0	23,735.5
Suriname	166.1	315.2	34.3	115.6

Swaziland	1,239.7	1,005.2	1,206.8	536.2
Syria	-	-	-	-
Taiwan	-	-	-	-
Tajikistan	789.5	451.5	340.1	192.2
Tanzania	7,550.1	24,092.7	31,815.7	11,990.3
Thailand	152.9	388.0	20.9	190.5
Timor-Leste	396.5	908.6	185.3	357.3
Togo	1,367.5	5,000.4	931.4	1,054.1
Tonga	-	-	-	-
Tunisia	-	-	-	-
Turkmenistan	10,642.0	6,920.2	25,942.2	3,505.0
Tuvalu	-	-	-	-
Uganda	3,485.4	11,804.1	2,795.2	6,618.4
United Arab Emirates	-	-	-	-
Uruguay	-	-	-	-
Uzbekistan	37,989.0	17,382.5	20,540.5	7,925.8
Vanuatu	-	-	-	-
Venezuela	50.4	63.2	96.7	36.6
Vietnam	2,696.5	4,036.1	79.6	1,607.6
Yemen	4,433.2	8,353.6	4,198.1	1,855.5
Zambia	2,566.3	7,881.1	20,999.6	2,404.9
Zimbabwe	4,414.4	9,551.1	17,086.9	4,383.6
Total	**660,654.9**	**1,042,000.7**	**671,674.7**	**470,513.2**

Supplementary Table S2: Total megatons of carbon dioxide equivalent emissions per year (Mt CO_2e/yr) broken down into direct emissions, i.e., from meat, milk, and poultry, and indirect emissions from land-use change (LUC) due to converting forest to pasture and agricultural land for soybean production, by country.

Country	Bovine meat	Bovine milk	Pig meat	Poultry	Sheep and goat milk	Sheep and goat meat	LUC pasture	LUC soybean
Afghanistan	0.08	0.04	0	0	0.02	0.08	0	0
Angola	4.63	0.96	0.07	0.01	0.01	0.49	1.31	0
United Arab Emirates	0.16	0.12	0	0.04	0.31	0.39	0	0
Argentina	42.78	13.64	0.22	0.13	0.17	2.66	14.84	13.67
American Samoa	0	0	0	0	0	0	0	0
Azerbaijan	2.27	2.77	0	0.02	0.35	1.25	0.01	0
Burundi	0.52	0.28	0.01	0.01	0.14	0.56	0.01	0
Benin	3.2	0.51	0.03	0.02	0.08	0.53	0	0
Burkina Faso	17	2.44	0.17	0.04	0.77	4.56	0	0
Bangladesh	37.08	8.12	0	0.34	6.57	6.11	0.3	0.01
Belize	0.11	0.05	0.01	0	0	0	2.11	0
Bolivia	7.95	2.42	0.16	0.05	0.16	1.9	44.77	12.83
Brazil	213.41	46.73	4.74	1.54	2.59	5.76	403.45	84.27
Bhutan	0.4	0.12	0	0	0	0.02	0.07	0
Botswana	0.86	0.19	0	0	0	0.16	0	0
CAR	6.11	0.52	0.07	0.01	0.12	0.72	3.42	0
Chile	2.59	0.89	0.13	0.05	0.05	0.54	2.49	0.01
China	109.11	12.78	33.51	6.64	6.11	27.03	2.14	0.07
Cote d'Ivoire	1.66	0.27	0.02	0.03	0.01	0.37	1.62	0
Cameroon	7.34	0.61	0.08	0.04	0.23	1.27	0.85	0
DRC	0.93	0.09	0	0.03	0.14	0.88	1.43	0.01
Republic of the Congo	0.21	0.02	0.01	0.01	0.01	0.08	0.7	0
Colombia	21.43	8.77	0.2	0.09	0.04	0.54	56.79	0
Comoros	0	0	0	0	0	0	0	0
Cabo Verde	0	0	0	0	0	0	0	0
Costa Rica	1.28	0.54	0.02	0.01	0	0	2.42	0
Cuba	2.9	1.15	0.19	0.03	0.17	0.4	0.67	0
Djibouti	0.11	0.09	0	0	0.13	0.1	0	0
Dominica	0	0	0	0	0	0	0	0
Dominican Republic	2.36	0.93	0.07	0.06	0.03	0.07	1.1	0
Algeria	2.32	1.86	0	0.22	2.7	3.6	0.11	0
Ecuador	3.49	1.76	0.11	0.11	0.03	0.35	10.43	0
Egypt	8.09	6.07	0	0.19	0.76	1	0	0
Eritrea	1.05	0.77	0	0	0.56	0.49	0	0
Ethiopia	42.25	23.93	0	0.08	3.58	7.38	0.83	0.01

Fiji	0	0	0	0	0	0	0	0
Micronesia	0	0	0	0	0	0	0	0
Gabon	0	0	0.01	0	0.01	0.04	0.27	0.02
Ghana	3.35	0.49	0.03	0.04	0.1	1.95	0.09	0
Guinea	11.17	1.68	0	0.03	0.12	0.87	1.79	0
Gambia	0.53	0.07	0	0	0.01	0.05	0	0
Guinea-Bissau	1.02	0.16	0.03	0	0.03	0.13	0.19	0
Equatorial Guinea	0	0	0	0	0	0.01	0	0
Grenada	0	0	0	0	0	0	0	0
Guatemala	3.45	1.39	0.22	0.04	0.04	0.08	7.58	0.07
Guyana	0.11	0.03	0	0.01	0	0	0.49	0
Honduras	2.47	1.02	0.06	0.01	0	0	3.76	0
Haiti	1.04	0.41	0.04	0	0.13	0.28	0.03	0
Indonesia	25.04	1.58	0.95	3.03	1.74	2.76	8.67	1.74
India	234.6	105.26	1.25	0.62	9.22	30.42	0.89	0.01
Iran	5.99	4.52	0	0.35	5.6	7.38	0	0
Iraq	1.56	1.15	0	0	1.02	1.34	0	0
Israel	0.47	0.35	0.01	0.06	0.06	0.08	0	0
Jamaica	0.13	0.05	0.01	0	0.02	0.06	0.27	0
Jordan	0.1	0.07	0	0.06	0.33	0.43	0	0
Kazakhstan	5.28	7.06	0.15	0.02	0.53	2.85	0	0
Kenya	15.19	10.61	0.06	0.07	4.46	6.23	0.49	0
Kyrgyzstan	1.14	1.49	0.02	0	0.2	0.93	0	0
Cambodia	4.03	0.12	0.19	0.03	0	0	10.14	0.38
Kiribati	0	0	0	0	0	0	0	0
Kuwait	0.03	0.02	0	0.07	0.09	0.12	0	0
Laos	4.38	0.15	0.23	0.04	0	0	10.94	0.05
Lebanon	0.1	0.08	0	0.07	0.1	0.12	0	0
Liberia	0.01	0	0.01	0.01	0	0.13	0	0
Libya	0.31	0.23	0	0.06	0.97	1.25	0	0
Saint Lucia	0	0	0	0	0	0	0	0
Sri Lanka	1.87	0.43	0.01	0.02	0.06	0.08	0.1	0
Lesotho	0.72	0.11	0.01	0	0	0.01	0	0
Morocco	3.66	2.8	0	0.27	2.51	3.33	0.04	0
Madagascar	7.96	1.75	0.03	0.03	0	0.26	6.81	0
Maldives	0	0	0	0	0	0	0	0
Mexico	21.88	5	1.85	0.39	0.35	2.8	12.04	0.04
Marshall Islands	0	0	0	0	0	0	0	0
Mali	18.1	2.85	0	0.05	1.31	4.09	0	0
Myanmar	29.38	2.76	0.75	0.19	0.19	0.31	10.23	0.46
Mongolia	4.64	1.85	0	0	1.06	7.82	0.01	0
Mozambique	0.96	0.22	0.1	0.16	0.01	1.01	2.94	0
Mauritania	2.53	0.42	0	0	0.85	2.24	0	0

Mauritius	0	0	0	0	0	0	0	0
Malawi	2.31	0.49	0.13	0.08	0.01	0.86	0.15	0
Malaysia	0.95	0.06	0.25	0.44	0.02	0.03	1.95	0
Namibia	1.91	0.41	0	0.02	0.01	0.69	0	0
Niger	15.03	2.49	0	0.02	1.88	4.88	0	0
Nigeria	33.64	4.67	0.5	0.19	1.51	18.23	0.33	0
Nicaragua	4.31	1.77	0.05	0.01	0	0	12.89	0
Nepal	17.69	5.31	0.1	0.04	0.64	1.74	0.04	0
Oman	0.5	0.37	0	0	0.36	0.45	0	0
Pakistan	90.37	40.21	0	0.46	4.33	26.83	0	0
Panama	1.33	0.54	0.03	0.02	0	0	4.74	0
Peru	4.48	2.07	0.19	0.05	0.24	2.78	15.51	0
Philippines	6.24	0.37	1.02	0.21	0.34	0.54	0.05	0
Palau	0	0	0	0	0	0	0	0
Papua New Guinea	0.09	0	0.5	0	0	0	0.16	0
North Korea	0.57	0.08	0.23	0.02	0.02	0.39	0.17	0.02
Paraguay	11.26	3.59	0.2	0.02	0.01	0.1	41.19	3.57
Palestine	0	0	0	0	0	0	0	0
Rwanda	1.02	0.55	0.03	0	0.11	0.44	0.04	0
Saudi Arabia	0.05	0.04	0	0.23	1.25	1.61	0	0
Sudan	12.19	8.77	0	0.04	7.26	6.31	0	0
Senegal	5.46	0.81	0.01	0.03	0.34	1.65	0	0
Solomon Islands	0	0	0.01	0	0	0	0	0
Sierra Leone	0.77	0.1	0	0.02	0	0.19	0.17	0
El Salvador	0.72	0.29	0.03	0.01	0	0	0.07	0
Somalia	2.02	1.68	0	0	3.37	2.7	0	0
South Sudan	4.93	4.02	0	0.01	3.95	3.41	0.28	0
Sao Tome and Principe	0	0	0	0	0	0	0	0
Suriname	0	0	0	0	0	0	0.28	0
Swaziland	0.55	0.12	0	0	0	0.05	0.03	0
Syria	0.84	0.63	0	0.03	1.56	2.07	0	0
Chad	21.53	2.36	0	0.02	1.02	3.84	0.15	0
Togo	0.81	0.11	0.05	0.02	0.04	1	0.03	0
Thailand	6.75	0.43	0.67	0.45	0.01	0.01	0.92	0.03
Tajikistan	1.79	2.18	0	0	0.14	0.8	0	0
Turkmenistan	1.62	2.11	0	0.01	0.32	2.18	0	0
Timor-Leste	0.25	0.02	0.03	0	0.01	0.01	0.03	0
Tonga	0	0	0	0	0	0	0	0
Tunisia	0.82	0.64	0	0.1	0.67	0.92	0.01	0
Tuvalu	0	0	0	0	0	0	0	0
Taiwan	0	0	0	0.04	0.02	0.07	0	0
Tanzania	8.97	6.37	0.02	0.03	1.53	2.24	9.2	0
Uganda	9.25	6.49	0.26	0.08	1.14	3.68	0.47	0.1

Uruguay	8.96	2.95	0.04	0.01	0.07	2.16	0.05	0.03
Uzbekistan	9.83	12.61	0.02	0.04	0.65	3.38	0	0
Saint Vincent and the Grenadines	0	0	0	0	0	0	0	0
Venezuela	13.13	4.5	0.38	0.12	0.02	0.26	17.49	0
Vietnam	10.09	0.32	2.62	0.45	0	0.03	2.14	0.2
Vanuatu	0	0	0	0	0	0	0	0
Samoa	0	0	0	0	0	0	0	0
Yemen	1.44	1.06	0	0.06	1.59	2.1	0	0
South Africa	15.68	2.96	0.1	0.15	0.03	3.59	1.52	0.03
Zambia	3.05	0.68	0.02	0.05	0	0.29	5.63	0.02
Zimbabwe	4.65	0.98	0.01	0.02	0.01	0.49	0.28	0

Supplementary Table S3: Metadata of secondary data used for the prioritization analysis. For more details, see https://github.com/CIAT/livestock_prioritization. The GitHub repository contains the entirety of the data used in this paper.

ID – Source	Analysis	Dataset	Description	Unit	Time	Acquisition Date
001 – Gilbert et al. (2018)[1]	Exposure	Livestock density	The global distribution of livestock (sheep, goats, cattle, buffalo, chicken, pig, and horses) in 2010 expressed in total number of goats per pixel (5 min of arc) according to the Gridded Livestock of the World database (GLW 3). These layers are weighted and combined to give total livestock units in our analysis as per Rothman-Ostrow (2020). Available online at https://dataverse.harvard.edu/dataverse/glw	number per pixel	2010	04/08/2021
002 – Herrero et al. (2013)[2]	Exposure	Livestock value of production (VoP)	Cattle economic yield as 2005 International Dollars per terrestrial km of each grid cell. The total Value of Production (VoP) for each livestock group is divided by the total cell area of terrestrial land. Calculations are done for six cumulative farm size classifications. Dataset provided by author.	100 int. USD	2000	23/09/2021
003 – Ramankutty et al. (2008)[3]	Exposure	Pasture area	Area of pasture. Data available at http://www.earthstat.org/cropland-pasture-area-2000/	proportion	2000	23/09/2021
004 – World Pop (2018)[4]	Exposure	Total Rural Population	Rural population in 2020 as the estimated total number of people per grid-cell. Analysis data has been preprocessed to the 5 arc min resolution. Data available at https://data.worldpop.org/GIS/Population/Global_2000_2020/2020/0_Mosaicked/ppp_2020_1km_Aggregated.tif	number per pixel	2020	23/09/2021
005 – Robinson et al. (2014)[5]	(Exposure)	Global Livestock Production Systems (GLPS)	Version 5 of the Global Ruminant Production Systems (GRPS 5). This classification is widely used; finding applications in the fields of food and nutrition security; livelihoods and economic growth; human and animal health and welfare; and natural resources and environment. Available at https://dataverse.harvard.edu/dataverse/GLPS	categorical	2006	04/08/2021
006 – Funk et al. (2015) [6]	Hazards	Coefficient of variation in annual mean rainfall	The coefficient of variation in annual mean rainfall (15–30 % highly variable; > 30 % extremely variable), calculated from historical daily CHIRPS data. Input data available at https://data.chc.ucsb.edu/products/CHIRPS-2.0/	%	1981–2019	29/08/2021
007 – Funk et al. (2015)[6]	Hazards	Drought risk	Mean consecutive dry days per month calculated from historical daily CHIRPS data. Input data available at https://data.chc.ucsb.edu/products/CHIRPS-2.0/	days	1981–2019	29/08/2021

008 – UNEP/DEWA/ GRID-Europe (2011)[7]	Hazards	Flood risk	This dataset includes an estimate of the global risk induced by flood hazards. Unit is estimated risk index from 1 (low) to 5 (extreme). This product was designed by UNEP/GRID-Europe for the Global Assessment Report on Risk Reduction (GAR) and modeled using global data. Available at the UNEP/GRID data platform https://preview.grid.unep.ch/index.php?preview=data&events=floods&evcat=5&lang=eng	ordinal risk scale (0-5)	Unknown	23/09/2021
009 – Thornton et al. (2021)[8]	Hazards	Thermal heat stress index	The thermal index (0–100 %) indicates "extreme stress" for livestock. See section 2.4 of the publication linked in the Methods column for details on THI and its calculation. THI is estimated for 2030 under RCP 8.5. Dataset provided by author.	%	2030	23/09/2021
010 – World Bank[9]	Adaptive Capacity	Poverty headcount ratio of US$1.9 per day	People living on US$1.90 per day or less. This dataset is at the Administrative Unit Level 1, based on international poverty line(s). Administrative Unit Level 1 refers to the highest subnational unit level, e.g., state, governorate, province figures. Data available at https://maps.worldbank.org/projects.	%	2018	23/09/2021
011 – Herrero et al. (2013)[2]	Emissions (Direct)	Livestock direct emissions	Methane and nitrous oxide emissions (global rasters). Data provided by author.	CO_2eq/ km^2/yr	2000	21/02/2015
012 – FAOSTAT (2021)[10] & Tubiello et al. (2022)[11]	Emissions (Direct)		FAOSTAT TIER 1 emissions stats for items Enteric Fermentation, Manure applied to Soils, Manure left on Pasture and Manure Management and elements Emissions (CO2eq) from CH4 (AR5) and Emissions (CO2eq) from N2O (AR5). FAOSTAT data accessed from https://fenixservices.fao.org/faostat/static/bulkdownloads/Emissions_Totals_E_All_Data.zip	1,000 tons	2000–2019	30/09/2021
013 – Soto-Navarro et al. (2020)[12]	Emissions (Deforestation)	Above-ground biomass carbon density	Above-ground living biomass carbon stock density of combined woody and herbaceous cover in 2010. This includes carbon stored in living plant tissues above the Earth's surface, e.g., stems, bark, branches, and twigs. This does not include leaf litter or coarse woody debris once attached to living plants but now deposited and no longer living. Data available at https://datadownload-production.s3.amazonaws.com/WCMC_carbon_tonnes_per_ha.zip	Mg C/ha	2010	14/10/2021
014 – Soto-Navarro et al. (2020)[12]	Emissions (Deforestation)	Below-ground biomass carbon density	Below-ground living biomass carbon stock density of combined woody and herbaceous cover in 2010. This includes carbon stored in living plant tissues below the Earth's surface, i.e., roots. This does not include dead and/or dislocated root tissue or soil organic matter. Data available at https://datadownload-production.s3.amazonaws.com/WCMC_carbon_tonnes_per_ha.zip	Mg C/ha	2010	14/10/2021

015 – Hansen et al. (2013)[13]	Emissions (Deforestation)	Forest tree cover	Tree canopy cover for the year 2000 is defined as canopy closure for all vegetation taller than 5 m. Data available at https://storage.googleapis.com/earthenginepartners-hansen/GFC-2021-v1.9/download.html (now https://glad.earthengine.app/view/global-forest-change)	%	2009	14/10/2021
016 – Goldman et al. (2020)[14]	Emissions (Deforestation)	Pasture-driven forest loss	Annual rate of forest conversion to pasture. This dataset is provided at subnational unit level, e.g., state, governorate, province figures. Data provided by author.	ha	2001-2015	29/07/2021
017 – Goldman et al. (2020)[14]	Emissions (Deforestation)	Soy-driven forest loss	Annual rate of forest conversion to soy. This dataset is provided at subnational unit level, e.g., state, governorate, province figures. Data provided by author.	ha	2001–2015	29/07/2021
018 – Global Administrative Areas (2021)[15]	Administrative Regions	Administrative Regions	Global Administrative Areas (GADM 4.1) aggregated to different administrative scales worldbank regions, countries or admin 1 areas. Available at https://gadm.org/download_world.html	NA	2021	05/08/2021

Supplementary Table S4. Indicators used to represent the adoption constraints for available adaptation and mitigation options by country. Source: World Bank (https://data.worldbank.org/indicator).

Constraint	Indicators	Variable Description	Unit	Timeframe
Accessibility	Research and development expenditure	Gross domestic expenditures on research and development (R&D). This includes both capital and current expenditures in the four main sectors: business enterprise, government, higher education, and private non-profit. R&D covers basic research, applied research, and experimental development.	% of GDP	2010–2021
Cost	GDP per capita, PPP (constant 2017 International Dollars)	GDP per capita, based on purchasing power parity (PPP). PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates. An International Dollar has the same purchasing power over GDP as the US$ has in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in the country, plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without deducting for the depreciation of fabricated assets or the depletion and degradation of natural resources. Data are in constant 2017 International Dollars.	USD	2010–2021
Knowledge	Total adult literacy rate	The adult literacy rate is the percentage of people aged 15 and above who can read, write, and understand a short, simple statement about their everyday lives.	% of people aged 15 and above	2010–2021
Labor	Employment in agriculture	Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether they were at work during the reference period or not at work due to temporary absence from a job. The agriculture sector consists of activities in agriculture, hunting, forestry, and fishing, under division 1 (ISIC 2) or categories A–B (ISIC 3) or category A (ISIC 4).	% of males and females in agriculture	2010–2021

Land tenure	Rule of Law	Rule of Law captures perceptions of the extent to which agents have confidence in and abide by society's rules, particularly the quality of contract enforcement, property rights, the police, the courts, and the likelihood of crime and violence.		2010–2021

Supplementary Text S1: Detailed Methods

In this section, we provide a fully detailed description of methods. For enhanced reproducibility we provide a more detailed description of the datasets and specific calculations employed in this analysis. Note all references used in this section can be found in Table S3.

The analysis can be reproduced using a shiny R Markdown script[1]. See the Session Info (appended at the end of this document) section for the exact environment in which the analysis was conducted.

The analyses presented in the main paper are divided into two major parts: (1) quantification of exposure to climate hazards in areas of low and medium adaptive capacity; and (2) quantification of total emissions from livestock. The quantitative output of these two analyses is normalized and used to produce country rankings, which are in turn used to draw our main conclusions.

1. Analysis of exposure to climate hazards in areas of low adaptive capacity

The analysis of climate hazard exposure required first defining areas of low adaptive capacity, followed by an assessment of exposure to climate hazards in these areas.

Adaptive Capacity was defined using the 2018 headcount poverty rate from the World Bank Poverty Global Practice (Data for Goals) and Development Economics Division (PovcalNet)[2] (dataset 010 in Supplementary Table S3). These data are available at https://maps.worldbank.org/projects and correspond to the percentage of the population in the survey representative area living on less than $1.90 a day at 2011 international prices. We used the poverty headcount ratio as a proxy of adaptive capacity because poverty typically implies the lack of several capitals (social, natural, economic) needed to adapt to climate variability and change. We defined areas of low and medium adaptive capacity as those with poverty headcount ratios above 10% (i.e., >10% of people on $1.90 per day or less). We chose this threshold to indicate moderate to high poverty and therefore some limitation to adaptive capacity is present.

Four climate hazard layers were used to characterize all main hazards to which livestock systems are typically exposed. These are listed in Supplementary Table S5.

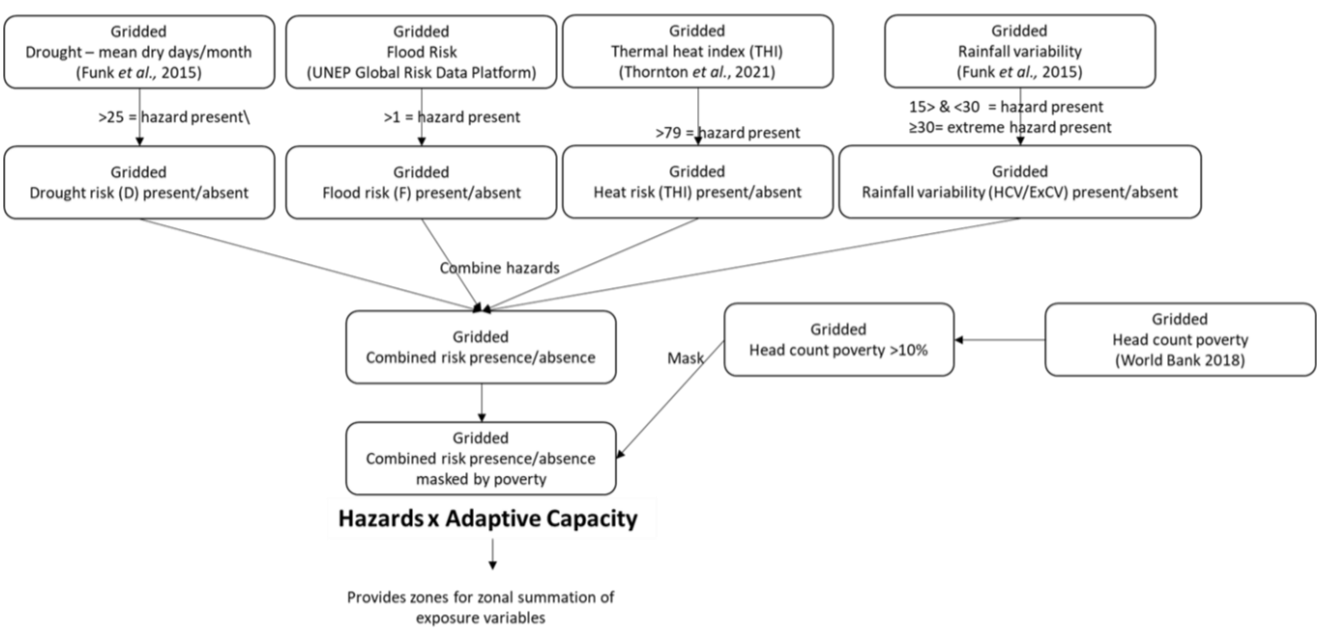
These hazard layers were processed and combined as shown in Figure S8. More specifically, for each hazard, we define a threshold to separate low and/or moderate intensities from high intensity areas, and then used these thresholds to create categorical hazard layers. Next, we combined all categorical layers together into a single layer, resulting in 16 hazard categories in total. The combined hazard layer was then masked by the adaptive capacity layer. This produced a hazard layer that covered only medium to low adaptive capacity areas.

[1] Available at https://github.com/CIAT/livestock_prioritization

[2] World Bank (2018) published a global subnational poverty headcount ratio dataset based on primary household survey data obtained from government statistical agencies and World Bank country departments. The reported number is calculated for survey representative areas based on the country's lineup estimates of 2018 released in Oct 2020.

Supplementary Table S5 Hazard layers included in the analyses of exposure to climate hazards

Variable	Description	Timeframe	Source – ID from Table S3	Threshold(s)
Rainfall variability (CV)	The coefficient of variation in annual mean rainfall.	1981–2019	Derived from CHIRPS 2.0 – ID= 006	Highly variable (HCV) = 15>CV<30 Extremely variable (ExCV) = RF≥30
Heat stress (THI)	The thermal index (0–100 %) indicates "extreme stress" for livestock.	2030 RCP8.5	Thornton, P. et al (2021) – ID=009	THI ≥ 79
Drought (D)	Mean days per month without rain	1981–2019	Derived from CHIRPS 2.0 – ID=007	D>25
Flood risk (F)	Flooding risk is ranked from 0 (no risk) to 5 (extreme)	2010	UNEP/DEWA/GRID-Europe – ID=008	F>0

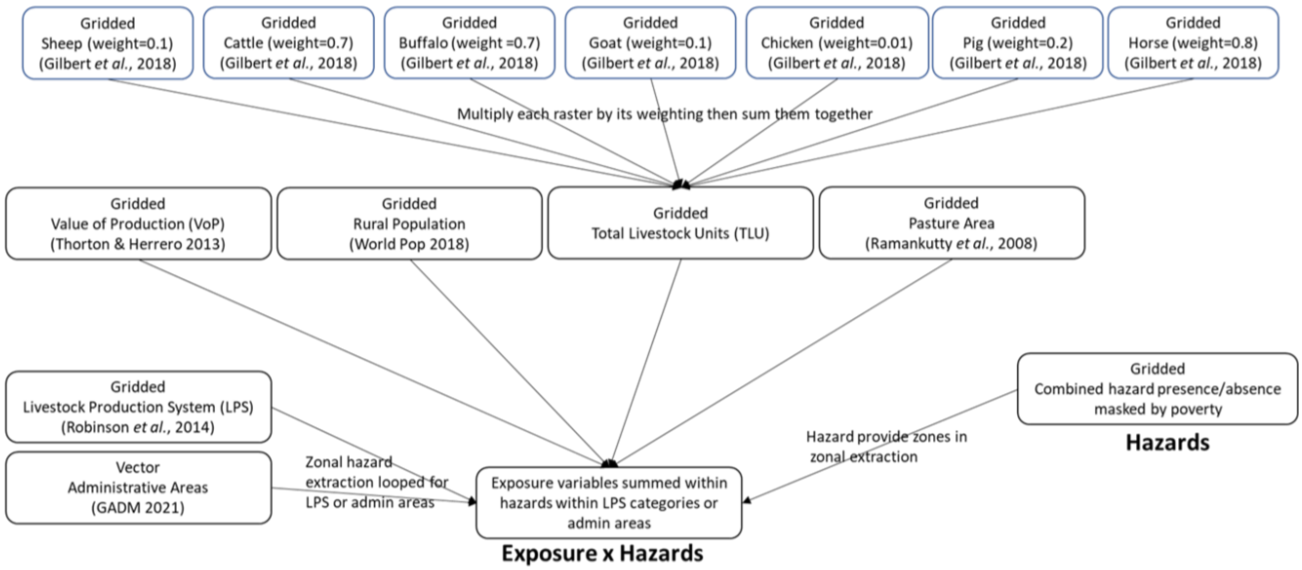


Supplementary Figure S8: Workflow for the processing of climate hazards data

Exposure data layers (Supplementary Table S6) were used to compute exposure levels within medium to low adaptive capacity areas exposed to climate hazards (derived from the process of Fig. S8), following the process outlined in Fig. S9. More specifically, we gathered and organized the exposure data, geospatially subset the exposure variable to those areas of climate hazard exposure and medium/low adaptive capacity, and finally totalized the exposure variable for each country. This gave the total value of exposure variables exposed to different hazards within a country or livestock production system (LPS).

Supplementary Table S6 Exposure datasets in the analyses of exposure to climate hazards

Variable	**Description**	**Timeframe**	**Source – ID from Table S3**
Value of Production (VoP)	Total value of livestock production (int. USD) derived from summing the value of sheep, goats,chickens, pigs, cattle, horse, and buffalo.	2000	Thornton & Herrero (2013) – ID=002
Pasture	Area of pasture.	2000	Ramankutty et al. (2008) – ID=003
Total Rural Population	Rural population in 2020 as the estimated total number of people per grid-cell.	2020	World Pop (2018) – ID=004
Total Livestock Units	Sheep, goats, cattle, buffalo, chicken, pig, and horses numbers are weighted and combined to give total livestock units as per Rothman-Ostrow (2020): TLU = Cattle*0.7 + Buffalo*0.7 + Sheep*0.1 + Goat*0.1 + 0.01*Chicken + 0.2*Pig + 0.8*Horse.	2010	Derived from Gilbert et al. (2018) – ID=001



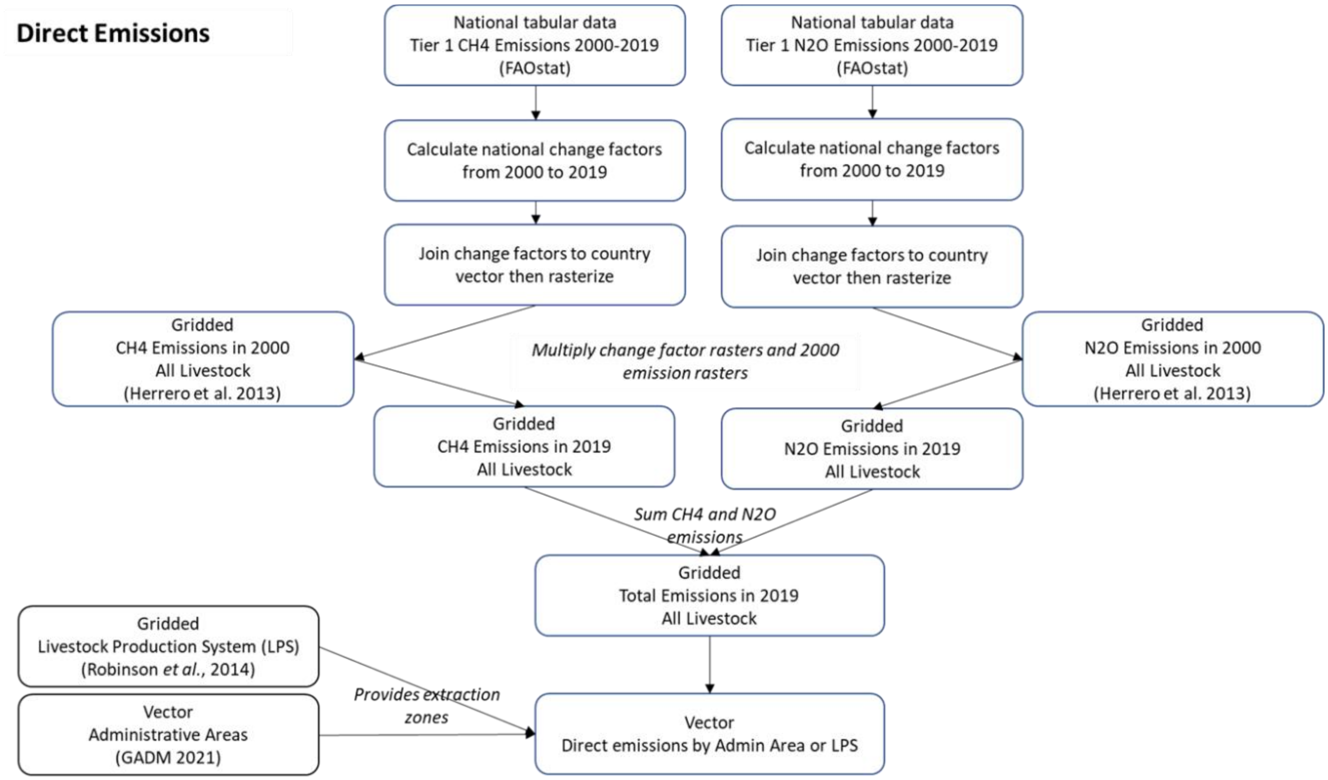
Supplementary Figure S9: Workflow for analysis of exposure and intersection with hazards

2. Quantification of total emissions from livestock

We calculated total emissions from livestock through a three-step process, as follows,

1. First, gathered direct livestock GHG emissions.
2. Estimated GHG emissions from land conversion to soy and pasture.
3. We compute total emissions by adding the direct emissions of Step 1 and the indirect emissions of Step 2.

Direct CH_4 and N_2O emissions (step 1) from all livestock in 2000 data from Herrero et al. (2013) (dataset ID= 011 in Table S3) were updated to 2019 using a proportional change in emission factor calculated between 2000 and 2019 and derived from FAOSTAT Tier 1 emissions statistics (dataset ID=012 in Table S3) for CH_4 and N_2O summed for enteric fermentation, manure applied to soils, manure left on pasture, and manure management (see Supplementary Fig. S10). FAOSTAT emissions data is available at the national level, so tabular change statistics were joined to a vector of country boundaries which was then rasterized and used to multiply the gridded direct emission data.



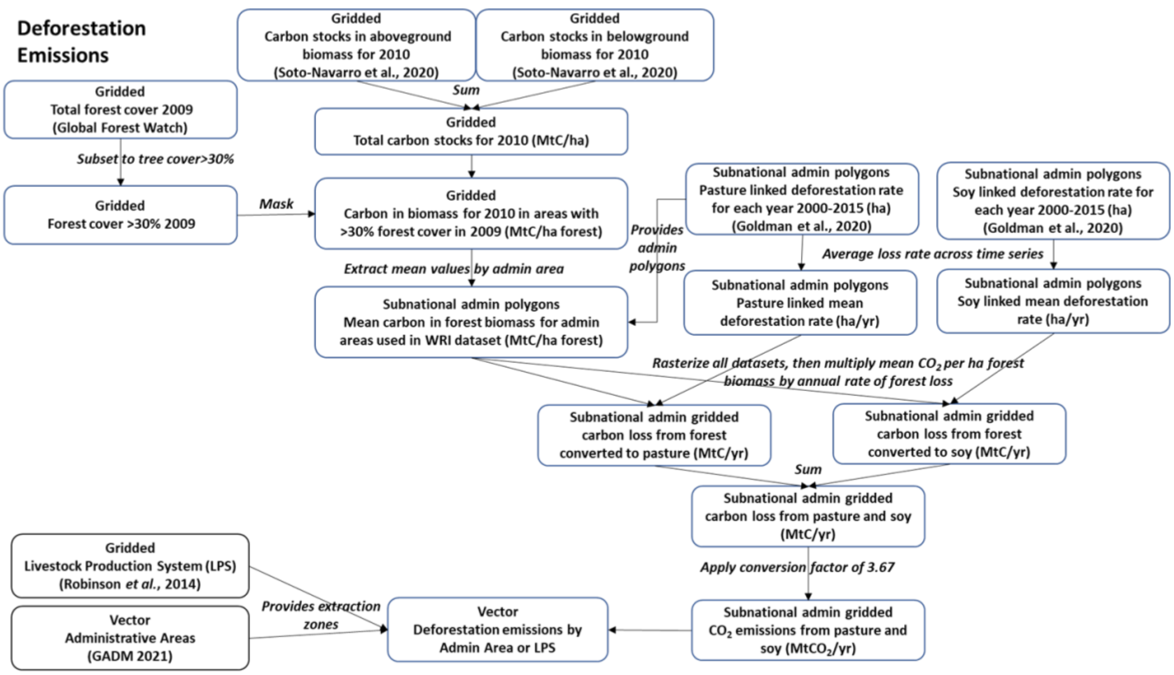
Supplementary Figure S10: Workflow for analysis of direct livestock emissions

Emissions from commodity linked deforestation (step 2) were estimated by combining three geospatial datasets, namely, (1) carbon in above and below ground biomass (dataset ID=013 and ID=014 in Table S3); (2) tree cover (dataset ID=015 in Table S3); and (3) commodity linked deforestation rates (dataset ID=016 and dataset ID=017 in Table S3). This is a transparent and simple analysis, unlikely to be subject to significant uncertainties (other than from the original datasets). The process was as follows,

1. Sum 2010 estimates of carbon in above and below ground biomass (Soto-Navarro *et al.*, 2020).
2. Create a mask of forest area in 2009 using global forest watch tree canopy cover data (Hansen *et al.*, 2013). Areas with >30%* tree cover were classified as forest.
3. Calculate mean pasture and soy linked forest loss rate (ha yr^{-1}) 2000-2015 for each subnational administrative area in the commodity linked deforestation dataset of Goldman *et al.*, 2020.
4. Calculate the average carbon in biomass (Mt C ha^{-1}) within the forested area mask for each subnational administrative area present in the commodity linked deforestation dataset.
5. Multiply 3. and 4. to get average annual rate of carbon loss from forest converted to pasture or soy per administrative area.
6. Sum carbon loss from soy and pasture.
7. Convert carbon to CO_2 using a factor of 3.67.

Goldman *et al.* (2020) considered tree cover losses only in areas with at least 30 percent tree canopy cover for most analyses, as that matches the default statistics presented by Global Forest Watch. For the detailed soy and pasture analyses, they used a tree cover canopy density of 10 percent to better capture the conversion of less-dense woody vegetation in South American biomes such as the Chaco and

Cerrado, which have faced widespread deforestation for commodity expansion. The tree cover loss dataset measures the first instance of complete removal of tree cover canopy at a 30-meter spatial resolution for all woody vegetation over 5 meters in height.



Supplementary Figure S11: Workflow for analysis of livestock linked deforestation emissions

As specified in the Main Text (see Methods), it is likely that the input data sources come with inherent errors and uncertainties. Individual dataset errors and uncertainties are unfortunately not available from these original data sources and studies, and this precludes a comprehensive uncertainty analysis. We note, however, that our analysis is unlikely to introduce additional uncertainties as we are not introducing new parameters or equations. From the seven steps outlined above, steps (1), (2), and (3) are subject to uncertainties in one single input data source only (Soto-Navarro et al., 2020 for step [1], Hansen et al. 2013 for step [2], and Goldman et al., 2020 for step [3]); step (4) is subject to uncertainties in outlining forest area which would affect estimates of average carbon at each subnational unit; step (5) combines uncertainties from all datasets but separately for soy and pasture; step (6) combines the resulting uncertainties for soy and pasture into a single total; and step (7) applies a constant, which does not add any uncertainties.

Lastly, our spatial overlay of the emissions data means that there could be methodological or data incompatibilities from original data sources. Nevertheless, we do not see any glaring incompatibilities, nor we see that our use of these data is outside of the possible uses of these data. Furthermore, our GHG estimates are consistent with previously published studies[16] once we consider that our analysis excludes direct CO_2 emissions from cropland used for feed (see ref. [2n]), and that we focus on LMICs only (in comparison to the global estimates of ref. [16]).

4. **Normalization and combination of exposure and emission data (Figure 2):**

To allow side-by-side comparison exposure and emissions data, values were normalized by dividing by the maximum value for the variable in question. For example, if emissions were extracted and summed by country, then each country's total emissions were divided the maximum emission value across all countries.

When creating the adaptation and mitigation potential shading for Figure 2 adaptation was the average of the four normalized exposure variables and mitigation the average of normalized direct and deforestation linked emission. The '*bi_class*' function of the '*biscale*' R package was used to generate breaks in the shading using the "Fisher" method.

5. **R Session Info:**

```
## R version 4.2.1 (2022-06-23 ucrt)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 22621)
##
## Matrix products: default
##
## locale:
## [1] C
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] viridis_0.6.2      viridisLite_0.4.1  terra_1.6-17       stringr_1.4.1
##  [5] sf_1.0-8           RColorBrewer_1.1-3 raster_3.6-3       sp_1.5-0
##  [9] plotly_4.10.1      ggpubr_0.4.0       ggplot2_3.3.6      DT_0.25
## [13] data.table_1.14.2  cowplot_1.1.1      colourpicker_1.2.0 Cairo_1.6-0
## [17] biscale_1.0.0      pacman_0.5.1       shiny_1.7.2
##
## loaded via a namespace (and not attached):
##  [1] httr_1.4.4         tools_4.2.1        backports_1.4.1    bslib_0.4.0
##  [5] utf8_1.2.2         R6_2.5.1           KernSmooth_2.23-20 DBI_1.1.3
##  [9] lazyeval_0.2.2     colorspace_2.0-3   withr_2.5.0        tidyselect_1.2.0
## [13] gridExtra_2.3      compiler_4.2.1     textshaping_0.3.6  cli_3.4.1
## [17] labeling_0.4.2     sass_0.4.2         scales_1.2.1       classInt_0.4-8
```

```
## [21] proxy_0.4-27        systemfonts_1.0.4  digest_0.6.29      rmarkdown_2.17
## [25] pkgconfig_2.0.3     htmltools_0.5.3    fastmap_1.1.0      htmlwidgets_1.5.4
## [29] rlang_1.0.6         rstudioapi_0.14    jquerylib_0.1.4    generics_0.1.3
## [33] farver_2.1.1        jsonlite_1.8.2     crosstalk_1.2.0    dplyr_1.0.10
## [37] car_3.1-0           magrittr_2.0.3     s2_1.1.0           Rcpp_1.0.9
## [41] munsell_0.5.0       fansi_1.0.3        abind_1.4-5        lifecycle_1.0.3
## [45] stringi_1.7.8       yaml_2.3.5         carData_3.0-5      grid_4.2.1
## [49] promises_1.2.0.1    crayon_1.5.2       miniUI_0.1.1.1     lattice_0.20-45
## [53] knitr_1.40          pillar_1.8.1       ggsignif_0.6.4     codetools_0.2-18
## [57] wk_0.7.0            glue_1.6.2         evaluate_0.17      vctrs_0.4.2
## [61] httpuv_1.6.6        gtable_0.3.1       purrr_0.3.5        tidyr_1.2.1
## [65] assertthat_0.2.1    cachem_1.0.6       xfun_0.33          mime_0.12
## [69] xtable_1.8-4        broom_1.0.1        e1071_1.7-11       rstatix_0.7.0
## [73] later_1.3.0         ragg_1.2.3         class_7.3-20       tibble_3.1.8
## [77] memoise_2.0.1       units_0.8-0        ellipsis_0.3.2
```

Supplementary References

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