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A unified modelling framework for projecting sectoral greenhouse gas emissions

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Effectively tackling climate change requires sound knowledge about greenhouse gas emissions and their sources. Currently, there is a lack of comprehensive, sectorally disaggregated, yet comparable projections for greenhouse gas emissions. Here, we project sectoral emissions until 2050 under a business-as-usual scenario for a global sample of countries and five main sectors, using a unified framework and Bayesian methods. We show that, without concerted policy efforts, global emissions increase strongly, and highlight a number of important differences across countries and sectors. Increases in emerging economies are driven by strong output and population growth, with emissions related to the energy sector accounting for most of the projected change. Advanced economies are expected to reduce emissions over the coming decades, although transport emissions often still show upward trends. We compare our results to emission projections published by selected national authorities as well as results from Integrated Assessment Models and highlight some important discrepancies.

The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) paints a grim picture with regards to achieving the goals that were agreed on in the 2015 Paris agreement[1]. Limiting global warming to an acceptable degree requires swift and decisive action at all scales to reduce greenhouse gas (GHG) emissions in a sustainable and efficient manner. Specific policies to do so are often designed, decided and implemented on a national level and target particular sectors. It appears therefore pertinent for policy-makers to have sound evidence about current and future trends of emissions on a sectoral level. In combination with detailed knowledge of country characteristics, these are crucial to inform the design of targeted policies aimed at reducing GHG emissions in specific sectors. However, comprehensive and globally consistent projections of sectoral emissions that would allow for benchmarking are lacking.

Scenario-based projections of future GHG emissions are typically derived from Integrated Assessment Models (IAMs) by various institutions and are assessed in reports by the IPCC. These models explicitly take anticipated future policy changes into account and derive scenario trajectories for GHG emissions on a global, regional or national level. They are crucial, inter alia, for the assessment of mitigation technologies, policies and international cooperation needed to achieve goals regarding the climate and sustainable development[2,3]. However, the quantification of uncertainty for IAMs is conceptually difficult due to their complexity and rich model structure[4–6]. Advances have been made to approach the quantitative assessment of uncertainty, e.g. by using ensembles of models, thereby recognizing that robust findings require a diversity of scenarios and modelling approaches[3,7,8]. In this regard, a newly established database collecting outcomes of various IAMs allows for an eased assessment across them (see Supplementary Note A). Downscaling methods to derive nationally and sectorally resolved scenarios exist[9–11], and projections at these more granular levels are recognized to constitute an important contribution to an evidence-based climate policy discussion[12,13]. However, the added (assumption-based) layers required for this breakdown also amplify complexities with respect to uncertainty quantification already present at the regional or global scale[14]. Despite the advances of the IAM community, further improvements in these aspects are crucial[3].

The number of studies presenting models aimed at forecasting carbon or GHG emissions for individual countries and sectors has substantially increased in recent years[15–18], with an emphasis on the highest emitting countries[3]. The models employed for this purpose span a wide range of methodologies, geographical and sectoral resolutions, underlying data sources, and temporal coverage in terms of observation and projection periods[3]. These efforts include estimation frameworks for national

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emissions reported in official communications of countries to the United Nations Framework Convention on Climate Change (UNFCCC) regarding their Nationally Determined Contributions (NDCs). The diversity in terms of coverage and methodological approaches of country-specific modelling frameworks hinders cross-study comparisons, thereby also impeding the drawing of coherent conclusions on a regional or global level. Furthermore, the leeway in the creation of projections is prone to be used by countries to inflate benchmark projections against which they formulate their pledged reductions as part of their NDCs, making them in turn less stringent[19].

Responding to these issues, the climate science community has taken measures to enhance the understanding of quantitative differences across country-level studies, but also in comparison to global models. This notably includes the establishment of a database that collects country-level mitigation scenarios (see Supplementary Note A). These efforts are crucial, given the importance of considering country-specific determinants of GHG emissions for the formulation and design of specific mitigation policies at a national level[20]. Partly to address the lack of cross-country comparable projections, recent contributions have developed fully probabilistic models to jointly model dynamics of carbon emission intensity, gross domestic product (GDP) per capita and population[21,22]. These modelling frameworks derive nationally resolved, comparable projections of CO_2 emissions for a global sample of countries. However, the focus of these contributions on aggregate carbon emissions abstracts from important differences across sectors and precludes other GHGs that would need to be addressed in the design of efficient policies to combat climate change. Furthermore, while the approach used has the advantage of explicitly accounting for uncertainty in future population and income dynamics, this also introduces a certain lack of comparability to projections based on established socioeconomic trajectories commonly used in climate research, the Shared Socioeconomic Pathways (SSPs)[23].

In this contribution, we present projections of sectoral emissions derived from a unified statistical framework. We compile projections for 173 economies and five main sectors until the year 2050, capturing 99% of global GHG emissions in 2018 (excluding those from land use, land use change and forestry, LULUCF). Building upon sector-specific Kaya identities, we characterize total emissions in a given sector as the product of their main drivers: total population, average gross domestic product (GDP) per capita as a measure of affluence, and sector-specific emission intensities, whose change is related to technological and structural dynamics at the sectoral level[24]. We augment these specifications with economy-wide information on the demographic structure of the corresponding country and model interdependencies between components explicitly using large panel vector autoregressive models (see the "Methods" section). We employ a hierarchical Bayesian prior setup which pools information across countries within sectors, while simultaneously allowing for country heterogeneity where historical evidence deems it necessary. The proposed model setup is used to obtain projections of sectoral emissions, conditioning on trajectories of socioeconomic and demographic variables given by the SSPs[23,25]. With this unified framework that relies on a limited set of assumptions, we aim to bridge the gap between IAMs and country-specific modelling exercises, providing an addition to the toolkit usable for evidence-based climate policy-making.

For our projections, we focus on the SSP2 scenario, which describes a "Middle of the Road" trajectory. The nature of our setting implies that the model projects sector-specific trends for emission intensities assuming no major abrupt technological shifts or unprecedented policy responses in the future, beyond the narrative embodied in the assumptions of the SSP2 scenario[23]. The resulting sectoral emissions, retrieved from the sector-specific Kaya identities, can thus best be thought of as a "business-as-usual" (BAU) case for future GHG emissions. The minimal set of assumptions and straightforward uncertainty quantification embodied in our modelling strategy facilitates the assessment of projections as computed by other models. However, the accompanying credible bands serve as a lower bound for uncertainty surrounding them, given that we abstract from uncertainty regarding future socioeconomic and demographic dynamics by relying on economy-wide trends for them that characterize the narrative of the SPP2 scenario. The proposed vector autoregressive specification would be able to incorporate additional uncertainty regarding the drivers of emissions intensity but would thereby sacrifice consistency with the established SSP narratives. Keeping this in mind, our results can serve as benchmarking and validation tools for estimates of GHG emissions under BAU scenarios derived by national authorities[19] or for reference scenarios derived from IAMs.

Having detailed projections for future GHG emissions at hand can effectively inform policymakers regarding the sectors that necessitate action most urgently. In conjunction with recent approaches to identify policy mixes that have proved to be effective in reducing GHG emissions in the past[26], this information can guide policymakers in their quest to formulate effective mitigation strategies. As is the case for projections based on IAM scenarios[27], our results should not be viewed as representing the most likely outcome in the future and they have no likelihood of actually realizing attached to them. By conditioning on exogenously given paths for some of the socioeconomic drivers of emissions, the associated uncertainty surrounding the projections should be understood as a lower bound to the variability of GHG emissions and interpreted within the narrative given by the SSP2 scenario. As such, our projected emission paths depict a potential future in which technological advancements, their roll-out and other climate policies do not deviate strongly from those expected using past trends. Whether or not these pathways are to be realised is conditional on technological advancements and their dispersion, as well as policy-making being geared towards reducing GHG emissions more strongly than in the past or not.

Results

Our main contribution is the establishment of comprehensive projections that allow for the assessment of sectoral emission trends within individual countries while retaining global consistency across them. Given the vast amount of country-sector results available, we only present a subset of them in the next subsection before describing more aggregated results on a regional and sectoral scale in the subsequent subsection. The results of the analysis can be further explored on the World Emissions Clock (https://worldemissions.io/), an interactive data visualization tool that includes comparisons to emission trajectories derived from IAMs. These alternative projection paths correspond to a scenario where countries fully implement their (unconditional) NDCs and one that is compatible with limiting global warming to 1.5 °C by the end of the century.

Sector- and country-resolved GHG emissions projections

Figure 1 displays projections of sectoral emission intensities and resulting sectoral emissions for a selected set of some of the highest emitting countries and sectors. The top-left panel of Fig. 1 shows that the emission intensity of the Chinese energy sector, the largest GHG emitter globally, is predicted to continue its strong downward path, reducing by about two-thirds in the projection period. The corresponding GHG emission trajectory in the bottom-left panel shows that, despite the decrease in emission intensity, emissions related to the energy sector are set to increase further before the median forecast peaks at around 7.6 GT in 2036 and reduces slightly until 2050. As in many other emerging and developing countries, industrial GHG emissions are expected to rise strongly in India, in spite of notable improvements in sectoral emission intensity (middle panels of Fig. 1). Technological advancements are outweighed by strong population and GDP increases projected under the SSP2 scenario. More generally, emissions stemming from energy production and industrial activities increase in the group of developing and emerging economies, particularly in African and Asian countries such as Indonesia, Bangladesh or the Philippines. In the US, currently the second-largest emitter globally, practically all sectors (except agriculture) are predicted to continue their downward path in total GHG emissions, resulting from strong reductions in emission intensities. However, only slow expected progress in the emission intensity for the transport sector translates into comparatively slow decreases in GHG

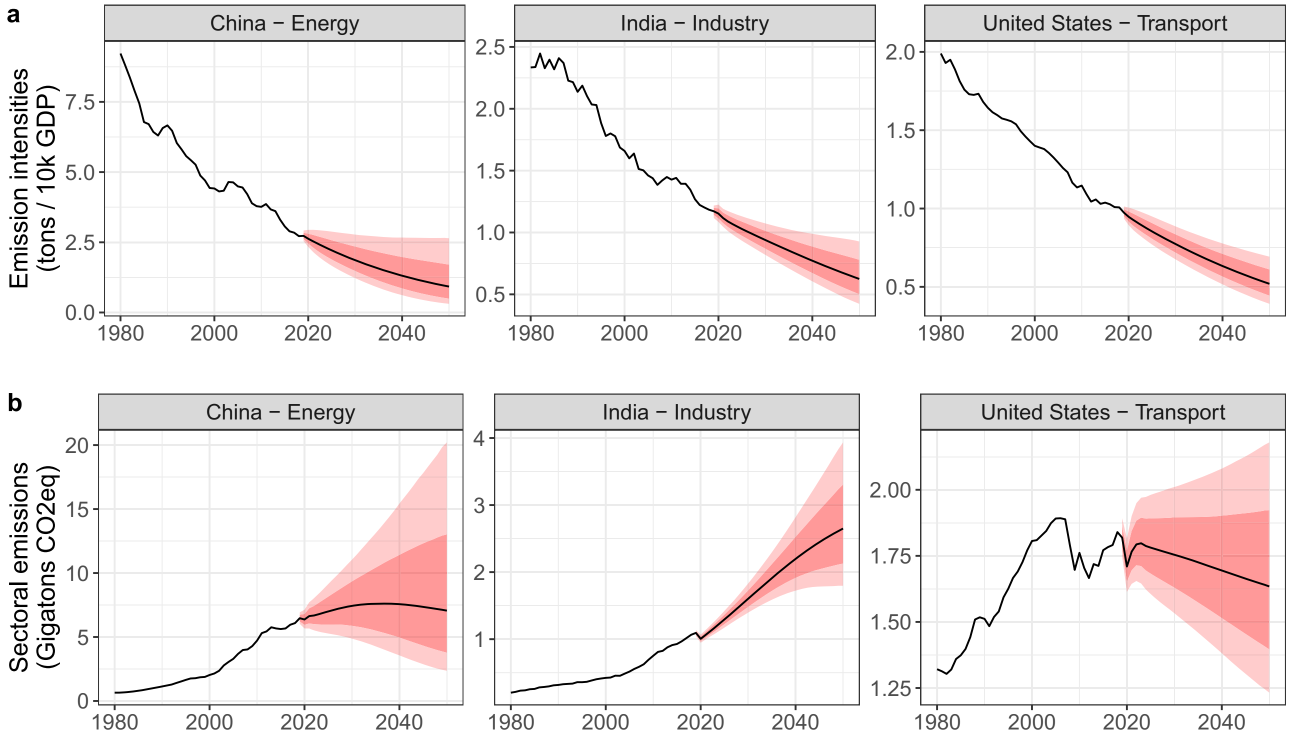

Fig. 1 | Illustrative country-sector level projections. Figure shows illustrative projections of **a** sectoral emission intensities and **b** sectoral emissions for the Chinese energy-producing, the Indian industry, and the US transport sector. Black line denotes historical values until 2018 and the median forecast thereafter. Red shaded areas denote the 68% and 90% predictive posterior intervals.

emissions, a pattern also observable in other advanced economies that show otherwise faster-declining emissions. According to our projections, transport will overtake the energy sector as the largest emitting sector in the US in 2047.

Emission projections only lead to small changes in the list of top-emitting countries and sectors over the coming decades. Table 1 shows the top 15 emitting country/sector pairs in 2018 (the end of the observation period in Minx et al. 2021[28,29]) and 2050. Under BAU, the identity of some of the highest-emitting sectors within countries will remain unchanged in the future. Despite peaking in 2036, Chinese energy-related emissions are the largest single contributor to global GHG emissions in 2050. Indian energy emissions take second place in this respect, replacing the Chinese industry sector, which, notwithstanding sizable reductions until 2050, remains the third-largest emitting sector. However, according to our projections, there are also some notable differences in the composition of top emitters. In emerging economies such as Indonesia, India, Iran or Vietnam, strong increases in energy-related emissions are projected, placing them further up in this list. Sectors in some economically advanced countries such as Japan (energy emissions) or Saudi Arabia (energy and industry emissions) also exhibit rising emissions, both in absolute and relative terms, moving them upwards in the ranking for 2050. Current major emitters such as the United States or Russia, on the other hand, show reductions in at least some of their major emitting sectors but remain large contributors to global GHG emissions.

Only a few countries exhibit sustained decreases in GHG emissions under BAU. Achieving the goals set down in the Paris Agreement requires strong and sustained reductions in emissions across countries and sectors in the coming decades. However, only a few countries have managed to sustain long-term decreases in emissions, most of them advanced economies that account for a large share of past GHG emissions but a small portion of current ones[30]. Learning from these past experiences can prove crucial for gearing economies on track to reduce their sectoral emissions as well. The few countries that achieved sustained reductions of GHG emissions in the past (when excluding LULUCF emissions) are located in Europe, with the exception of the United States and Jamaica[31]. Our emissions projection exercise reveals that following current decarbonization trends and given the expected global socioeconomic and demographic developments under SSP2, only a few countries would add to the list of overall emissions-reducing economies. These are mainly small countries such as Switzerland, Luxembourg or Cuba, but also a few larger emitters such as Australia, Poland, or Taiwan (see Supplementary Fig. S7).

Some countries have reversed their patterns of decreasing emissions in the past. In contrast, some of the countries that were deemed to have had sustained reductions in GHG emissions in the past[31], are predicted to increase their emissions again in the projection period (see Supplementary Fig. S8). This group includes countries in the periphery of the European Union, which were hit hard by the global financial crisis and the subsequent European debt crisis. The economic recovery after the crisis in countries such as Portugal and Greece (but also Cyprus, Hungary or Slovenia) was accompanied by increases in GHG emissions in the recent past, a trend that, according to our projections, extends into the future in the absence of active climate policy actions. A similar development is projected for Jamaica and North Macedonia, the only countries outside the group of high-income economies that attained sustained reductions in GHG emissions in the past[31]. Only modest reductions in emission intensities for these countries, particularly in the transport sector, are offset by expected strong GDP growth in the coming decades. These predictions underline the necessity of strong policy support for structural changes in energy use and a reduction of the fossil share in the energy mix going forward, especially for economies where output growth picks up after times of economic slowdown[30].

Short-term fluctuations in GHG emissions due to geopolitical events can be substantial. Our modelling approach is also able to assess the effects of specific events that led to abrupt changes in GHG emissions on a national scale, insofar as output dynamics are affected by these events or are forecast to be in the near future (see the "Methods" section). The drop in emissions due to the COVID-19 pandemic has been particularly pronounced for advanced economies (see also Supplementary Fig. S1). Our median forecast for total GHG emissions in the European Union shows a reduction of

Table 1 | Top emitting sector/country pairs in 2018 and 2050

Rank	Emissions in 2018 (GT)			Emissions in 2050 (GT)		
1	CHN	Energy	6.09	CHN	Energy	7.06
						(3.77–13.02)
2	CHN	Industry	5.29	IND	Energy	3.57
						(2.59–4.85)
3	USA	Energy	2.48	CHN	Industry	3.05
						(1.05–8.26)
4	USA	Transport	1.84	IND	Industry	2.65
						(2.13–3.31)
5	IND	Energy	1.36	CHN	Transport	2.63
						(1.06–6.58)
6	RUS	Energy	1.23	USA	Transport	1.63
						(1.4–1.92)
7	IND	Industry	1.07	USA	Energy	1.56
						(1.14–2.06)
8	USA	Industry	1.01	IDN	Energy	1.32
						(0.94–1.81)
9	CHN	Transport	0.98	IND	Transport	1.11
						(0.81–1.51)
10	CHN	Agriculture	0.90	SAU	Energy	0.88
						(0.79–0.98)
11	IND	Agriculture	0.76	SAU	Industry	0.87
						(0.62–1.25)
12	CHN	Buildings	0.65	JPN	Energy	0.86
						(0.62–1.22)
13	BRA	Agriculture	0.61	VNM	Energy	0.84
						(0.6–1.22)
14	RUS	Industry	0.60	BRA	Agriculture	0.84
						(0.6–1.19)
15	USA	Buildings	0.57	IRN	Energy	0.81
						(0.66–0.99)

The table shows the top 15 emitting country/sector pairs with historical values for 2018[28,29] as well as median projections for 2050, using ISO3 country codes. Values denote sectoral GHG emissions in Gigatons (GT), with the 68% posterior predictive interval for projections given in brackets below.

roughly 9.1% in 2020, close to the 8.8% reduction reported by the European Comission[32]. Concerning the effects of the war in Ukraine, our results imply a 10% drop in GHG emissions for Russia in 2022 compared to 2021, while for Ukraine emissions fall by more than a third as a result of economic disruptions. In both countries, the industrial sector experiences the largest drops in GHG emissions (see Supplementary Figs. S5 and S6). However, one should note that our projection model is unable to capture a potential increase in GHG emissions directly attributable to the intense fights in Ukraine[33].

Regional and sectoral trends in GHG emissions

Globally, GHG emissions have been increasing in the past decades with almost no interruptions[34–36]. Our projections indicate that these increases continue almost unhindered under BAU (see Fig. 2). This development makes achieving the Paris goals without swift and decisive action virtually impossible. Considering only CO_2 emissions and keeping gas shares as in 2018, the median of our projections indicates that the carbon budgets for limiting global warming to 1.5 °C (400 GT) or 2 °C (1150 GT) with a probability of 67%[37] are exhausted in 2030 and 2046, respectively.

Differences in emission dynamics across countries and industries change the sectoral composition of GHGs on a global scale over the coming decades. Energy production remains the largest contributor to GHG emissions in most individual countries and accounts for around 39% of global GHG emissions in 2050. This sector experiences a steep increase in emissions in many countries, especially so for developing countries and emerging economies in Asia and Africa. However, our projection exercise also reveals that reductions in emissions from this sector account for the largest portion of the decrease in countries with projected overall emission reductions. Supplementary Fig. S3 shows the evolution of GHG emissions in the energy systems sector for selected countries. While most countries tend to follow their past trend (see the first two rows of Supplementary Fig. S3), some see their emissions peak and decline in the projection period as compared to their longer-term trend (third row of Supplementary Fig. S3). The transport sector experiences the largest relative increases in global GHG emissions until 2050, reaching 13.8 GT CO_2eq, almost doubling from 7.2 GT CO_2eq in 2018, and accounting for slightly over 19% of total emissions. For most economies with projected reductions in overall emissions, the transport sector is also either the sole sector with increasing emissions in the future (see, e.g., Denmark, Bulgaria, or Czechia in Supplementary Fig. S4), or the one reducing emissions at the slowest pace (e.g. France, Great Britain, Germany, Italy). Decarbonization in the transport sector without additional policies and technological advancement is thus projected to be relatively unsuccessful. Industrial emissions remain the second-largest contributor to global GHG emissions throughout the projection period. However, their growth is substantially lower compared to the 2000s, a period that was mainly driven by strong growth in Chinese industrial emissions, and their share of total emissions reduced from 27.3% in 2018 to 24.1% in 2050. Emissions related to agriculture (excluding LULUCF) and buildings grow by 40% and 11% and account for roughly 12% and 4% of global emissions in 2050, respectively.

Emission intensities converge towards substantially lower levels in almost all regions of the world. They are expected to fall in all world regions, albeit at different paces, with the notable exception of economies in the Middle East (see Fig. 3). The oil-dependency of countries in this region, coupled with only partially successful economic diversification efforts so far, has resulted in rising or stagnating emission intensities in the past decades, a trend that continues into the future in the absence of targeted policy efforts. However, the strong downward trend in emission intensities within the other regions suggests a convergence towards less emission-intensive production patterns globally. This is also confirmed by Supplementary Figs. S9 and S10. Decreases in emission intensities are somewhat decelerating in regions such as Africa, or South-East and Southern Asian countries towards the end of the projection period. This reflects some of the structural shifts into more emission-intensive sectors such as industry or transport in these emerging economies.

Despite falling emission intensities, total emissions are increasing substantially for a majority of world regions. Countries in Southern and South-East Asia as well as Africa are projected to be the ones with the strongest growth in GHG emissions (see Fig. 4). Improvements in emission intensities are outweighed by strong projected output growth and population developments under the SSP2 scenario. Despite these increases, per capita emissions in these economies remain below the global average, causing 37% of total emissions while containing 57% of the global population in 2050. Our projections also indicate stark increases in GHG emissions for countries in Latin America and the Caribbean, as well as oil-exporting countries in the Middle East. The strong growth of emissions in the latter contrasts with the downward trend (or stagnation) that is observable in many other high-income countries. Notwithstanding a projected deceleration in overall GHG emissions growth, Eastern Asian countries (most notably China) are expected to remain the largest contributors to global emissions, accounting for more than 25% of global emissions in 2050. For Europe & Eurasia, the general downward trend that is observable in many European countries within the region is almost entirely outweighed by strong increases in a few other countries. Most notably, our projections imply that under BAU, Turkey's GHG emissions more than double from around 600 MT in 2018 to 1.3 GT in 2050. Similarly, emerging economies in

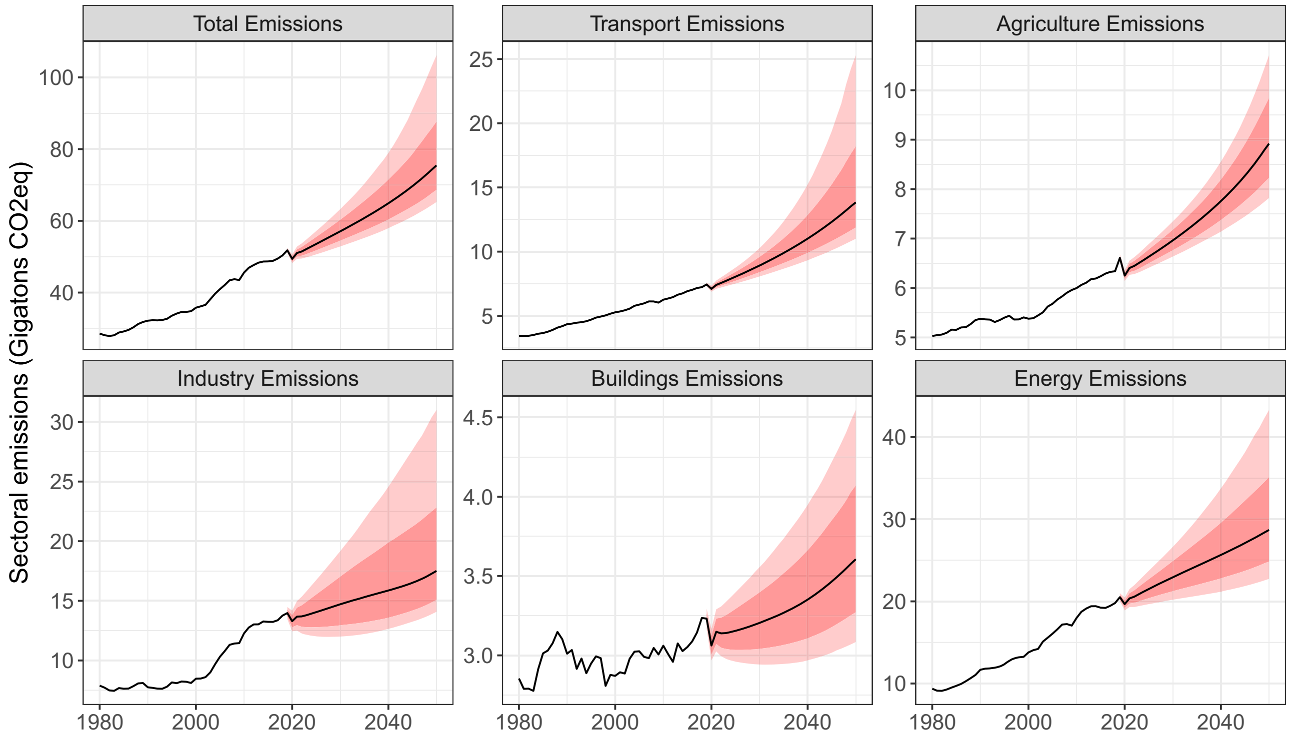

Fig. 2 | Global GHG emissions by main sectors. Figure shows total GHG emissions on a global level and separately for five main sectors. Black line denotes historical values until 2018 and the median projection thereafter. Red shaded areas denote the 68% and 90% posterior predictive intervals.

Eurasia such as Kazakhstan or Georgia are expected to increase their emissions strongly but are outweighed by projected reductions in Russia and Belarus. Although our model incorporates some of the short-term fluctuations due to economic disruptions, there is high uncertainty about longer-term developments in the region given the unclear effects of the economic sanctions imposed against Russia and its prospects of re-integration in global markets. Emissions of developed countries in Asia-Pacific, dominated by Japan and Australia, stagnate with a slight tendency to increase towards the end of the projection period. In contrast, North American countries, mainly driven by US emissions, are the only ones reducing emissions sustainably, though slowly, according to our projections, with emissions in 2050 roughly 20% lower than in 2018. Supplementary Table S1 gives an overview of the regional distribution in terms of shares of global sectoral emissions as of 2018 and the projected regional distribution in 2050.

Emission dynamics differ markedly across countries by development level and economic structure, but also across sectors within nations. Considering the dynamics of GHG emissions by income classes, low and lower-middle-income countries show the strongest increases in GHG emissions, in line with their expected economic catch-up dynamics, low roll-out of emission-reducing technologies and slow climate policy adoption (see Supplementary Fig. S1). Upper middle-income countries, the largest group in terms of total GHG emissions, also see increases in the projected period, although at a slower pace. High-income countries see slight increases in GHG emissions after the pronounced drop caused by the COVID-19 pandemic. Further differentiating them by oil dependence, it becomes clear that increases in oil-exporting countries (most of them located in the Middle East) are the driving force behind this evolution (see Supplementary Fig. S2). Oil-importers among high-income countries are projected to follow their path of reduction in emissions after peaking in the early 2000s. However, GHG emissions from the transport sector are still increasing in this group of economies. Given the relative size of this sector and its fast expansion dynamics in other country groups, the need for a faster roll-out of technology and policy adoption geared towards net-zero transportation is evident. Crucially, however, the electrification of the transport sector has to be accompanied by a more sustainable energy mix for electricity production to avoid the paradox of potentially increasing overall emissions as a result[38].

Region and sector-specific differences in dynamics imply shifts in the distribution of aggregate and per capita emissions at the global level. Figure 5 shows aggregate emissions differentiated by sector and world regions for the years 2018 and 2050. One can see that emission increases in emerging economies of Africa, South-East and Southern Asia together with Middle Eastern countries are expected to account for the bulk of global emissions growth until 2050. Sectoral shifts in GHG emissions can be discerned for Eastern Asia, with the transport sector becoming more important as opposed to industry, or Southern Asia, where fast-growing industry emissions overtake agricultural emissions as the second-largest contributing sector. Figure 6 shows that in 2018, the average footprint of a North American was the largest, with almost 20 tons per person, but this figure is expected to reduce by more than one-third until 2050. Our projections indicate that Middle Eastern per capita emissions surpass them by then, after increasing by almost 50% from their level of 13.4 tons in 2018 to 19.3 tons in 2050. This figure is already twice as high as the global average in 2018, 6.72 tons per capita, but is projected to become almost 2.5 times higher than the global average in 2050, 8.04 tons per capita. Africa remains the region with the lowest GHG emissions footprint but also increased it from roughly 2.5 to 3.8 tons per capita.

Discussion

A swift and sustained reduction of GHG emissions is imperative for any attempt to limit global warming to an acceptable degree. At the heart of the framework designed to structure global climate policy are the NDCs that countries submit to the UNFCCC, where they specify to which extent they intend to reduce their GHG emissions. These are typically accompanied by an intended set of (sector-specific) measures aimed at achieving this goal. One approach, often (but not exclusively) chosen by emerging market economies, is to specify reductions in relation to a BAU trajectory. Thus, there might be incentives for these countries to inflate BAU projections such that pledged reductions in their NDCs are less stringent than they might appear to be[19]. Our modelling framework provides projections for

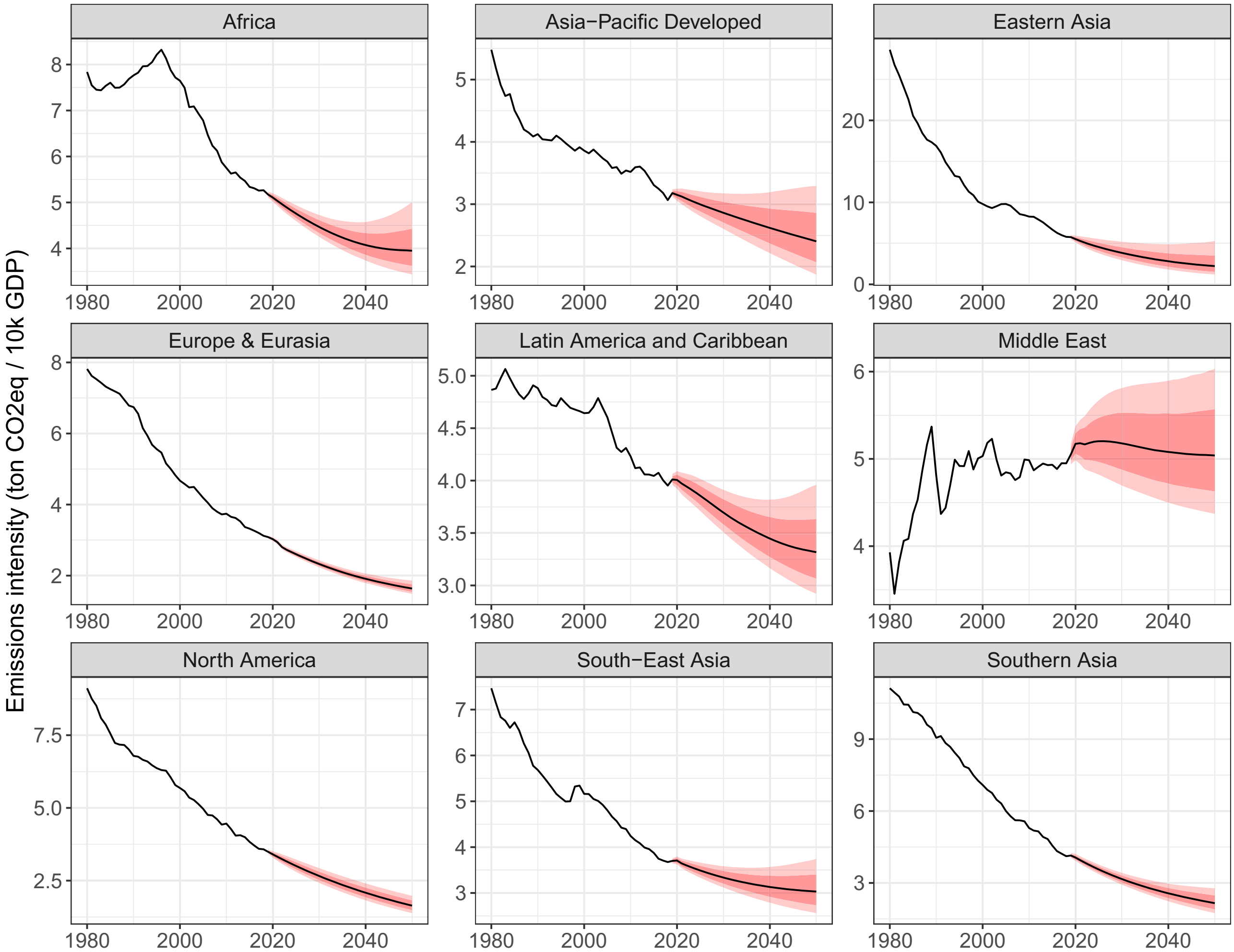

Fig. 3 | Regional GHG emissions intensities. Figure shows GHG emissions intensities by regions, with "Europe & Eurasia" comprising the respective IPCC regions for expository reasons. Black line denotes historical values until 2018 and the median forecast thereafter. Red shaded areas denote the 68% and 90% posterior predictive intervals.

sectoral GHG emissions that can serve as a benchmark for such estimates by abstracting away from the potentially idiosyncratic assumptions that might drive national BAU GHG projections.

Figure 7 presents a comparison of our projections with those of three selected countries for total GHG emissions up until 2030, the year for which most NDCs are formulated. The comparison of projected GHG emission trends shows that national BAU projections (blue line) appear exaggerated compared with our projected paths. The BAU estimates for GHG emissions of Indonesia, Iran and Turkey as presented in their NDCs or similar documents exceed the median of our projections by more than 50% by 2030. Our results imply that all these countries might overachieve their pledged emission reduction as part of their (unconditional) NDCs (green line) without substantial changes in policy-making or technological advancements, which raises questions about their ambition level. The sectoral breakdown of our projections would also allow us to assess national BAU estimates at a more granular level if they are available. Supplementary Fig. S11 presents such a comparison for Mexico, showing that most of the difference across scenarios for total GHG emissions stems from the projected paths in emissions from energy production. In this sector, the dynamics of emissions under BAU derived from our framework differ markedly from the ones reported in Mexico's updated NDC.

The quantification of uncertainty for projections of emission intensities, and by extension GHG emissions, is another important contribution of the methodological framework proposed. Predictive uncertainty entails various dimensions, including parameter uncertainty, which is not typically assessed in the framework of IAMs. Rather, uncertainty is often assessed by comparing projections for particular variables across simulations of different IAMs[3]. Our modelling setup allows for a straightforward quantification of projection uncertainties and thus lends itself for comparison and potential validation of IAM results. In the setting chosen to compute our projections, it should be noted that by conditioning on SSP paths for the socioeconomic and demographic variables included, the credible bands surrounding our projections should be viewed as a lower bound resulting from uncertainty about future trends of emission intensities only (see Methods). We compare our projections to scenario projections of GHG emissions involving baseline dynamics in socioeconomic and demographic variables as well as no substantial shifts in the energy mix or technological advancement for five widely used IAMs (see Supplementary Discussion G for more details). This exercise shows that the simulated scenario trajectories generally align well with our results on a global level, with all IAM outcomes but one falling within the one standard deviation range of our projections (see Supplementary Fig. S12). At the regional level, however, discrepancies become more apparent, especially so for the OECD region and economies of Eastern Europe and the former Soviet Union. These results can provide insights that may be helpful to revise some of the assumptions baked into IAMs, as well as for methods that downscale global or regional results from IAMs to the country-sector level.

Both the comparison of our projections to BAU estimates by countries and to results from IAMs highlight important potential use cases for them. While we provide a brief exploratory analysis here, we leave a more comprehensive comparison exercise as a promising avenue for further research. In a similar vein, collating results from other cross-country studies[21] can

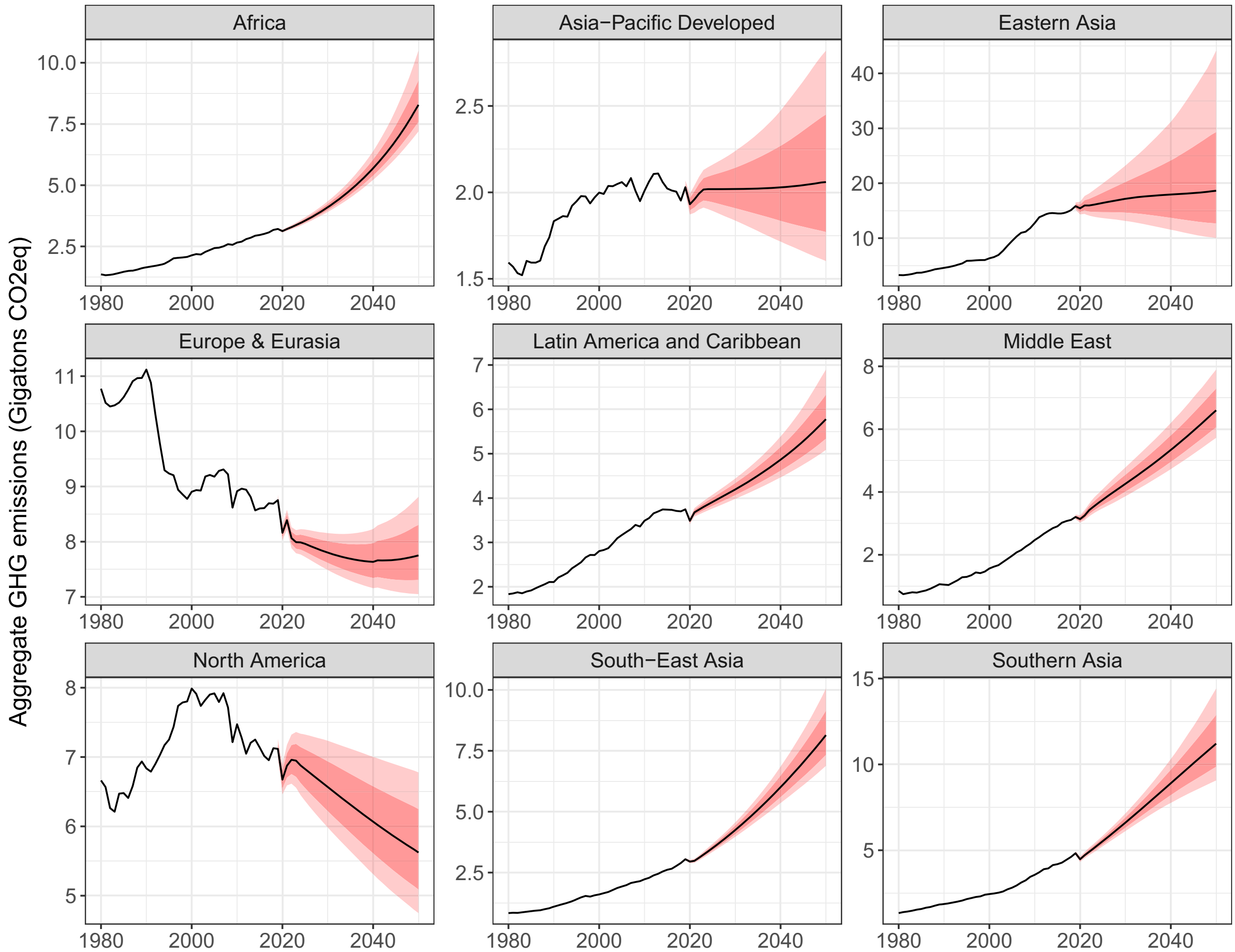

Fig. 4 | Regional GHG emissions. Figure shows total GHG emissions by regions, with "Europe & Eurasia" comprising the respective IPCC regions for expository reasons. Black line denotes historical values until 2018 and the median forecast thereafter. Red shaded areas denote the 68% and 90% posterior predictive intervals.

yield interesting insights into discrepancies among them. A detailed analysis of differences across assumptions about socioeconomic and demographic developments, the sources of these discrepancies and their effects would shed light on the realism of existing emission projections. Carrying out extensive comparison exercises, both across country-specific and cross-country studies as well as with IAM results (on the global, regional and local level), is a potentially fruitful avenue for further research and would also be in line with recent endeavours within the climate science community (see Supplementary Note A).

The flexibility of our modelling approach in terms of assumptions and input data addresses the need for methodological contexts that can be regularly updated when new data are observed[27]. However, the relative simplicity of our approach does not come without drawbacks. Characterizing sectoral GHG emissions simply as a product of their main drivers, expanded with demographic dynamics, and inferring dynamics based on this decomposition may ignore important aspects driving the evolution of GHG emissions in the future. Changes in human behaviour in general and consumption patterns in particular are aspects that have been found to be of importance for emissions mitigation[39] and more research into demand-side oriented solutions to climate change is being called for[40]. Our model does not consider the possibility of such behavioural changes besides the impact they could have on the macroeconomic and demographic quantities included in the analysis. However, it highlights some sectors where additional efforts, both concerning technological advancement and behavioural changes, are particularly pressing. With emissions from the transport sector expected to increase strongest, globally but also within many economies, it is vital to scrutinize potential decarbonization strategies for it. Simulations from IAMs have shown that even in the most ambitious case, emissions from transport amount to 4.2 GT per year in 2050[41], a non-negligible decrease from current levels and far below our BAU estimate of 13.8 GT. Yet, it is far off from a full decarbonization of the sector. More efficient urban demand management (e.g. the provision of public transport) and measures for steering the demand for individual transportation (e.g. by increasing fossil fuel taxes) are important alleys to be explored but their potential is hard to assess quantitatively[41].

Another limitation of our analysis regards the exclusion of LULUCF emissions. Besides the technical limitation that our model is not able to assess negative emissions in an internally consistent manner, there are also conceptual differences in the accounting of these emissions, both between IAMs and country GHG inventories as well as within the latter[42], though recent approaches have been proposed to bridge this gap[43]. This lack of consensus obstructs the construction and availability of comparable and reliable time series on LULUCF emissions for the global sample of countries we strive for. The absence of this sector in the current projection model neglects an important part of the discussion on future climate policies, considering that pledges regarding this sector represent about a quarter of total emissions reductions included in countries' NDCs[43,44]. Deriving projection scenarios for national LULUCF emissions that have a narrative which is coherent with the ones provided here is thus a relevant topic of future research.

Our study provides projections of nationally resolved, sectoral GHG emissions for a global sample of countries, together with estimates for the lower bound of their uncertainty. Similar to IAM scenarios, they are not meant to be an outlook for the most likely future, but instead outline a

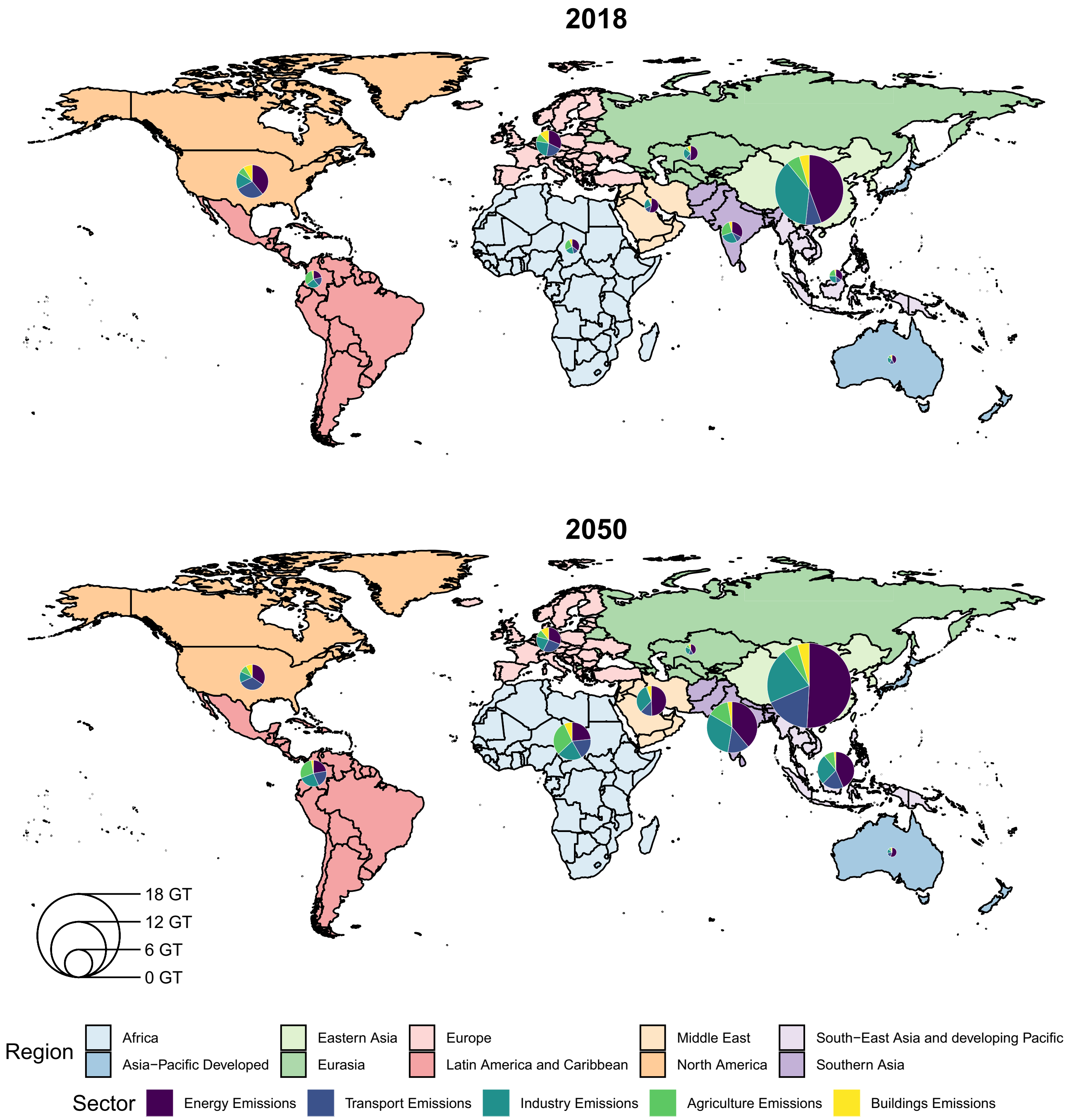

Fig. 5 | Regional overview of aggregate GHG emissions. Figure shows the distribution of aggregate GHG emissions in 2018 and 2050 for IPCC regions.

possible future under a particular scenario narrative in which policy efforts and technological advancements broadly follow past trends. Whether or not this future trajectory is to realize is subject to the actions policymakers and the public take today. In this contribution, we deliberately abstain from providing structured policy advice based on the projections, thus acknowledging that this requires additional knowledge on the particular institutional factors governing the sectoral mix at the country level, an analysis which is out of scope for the present study. However, it provides useful information about the relative importance of sectors and thus complements recent efforts in developing methods to identify effective policy interventions at the sectoral level[26]. We believe that our projection exercise will prove valuable for national policy-makers in identifying the most critical sectors within and across countries in order to formulate effective policies aimed at reducing future GHG emissions.

Methods

Characterizing sectoral GHG emissions

The conceptual framework for obtaining projections of GHG emissions is closely related to the one proposed one by Raftery et al. (2017)[21]. We rely on a simple form of the Kaya identity[24] to express sectoral GHG emissions in a given country as a product of their main drivers:

$$E_s = \frac{E_s}{G} \times \frac{G}{L} \times L, \tag{1}$$

where E_s denotes emissions in sector s, G is a measure of total output (gross domestic product, GDP), with E_s/G being the corresponding emission intensity, L denotes total population and G/L output per person. We introduce identical, economy-wide population and affluence dynamics for

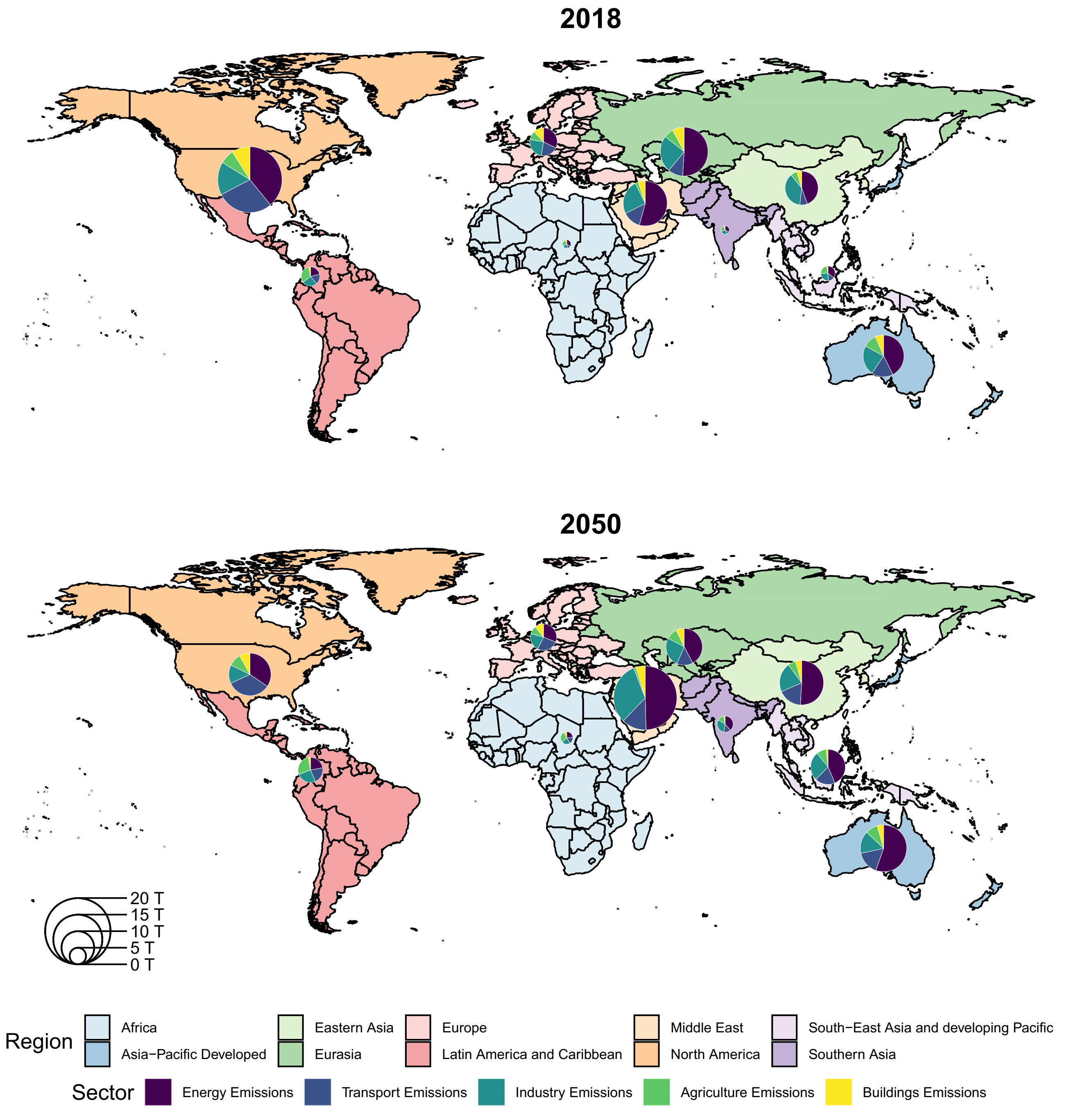

Fig. 6 | Regional overview of per capita GHG emissions. Figure shows the distribution of per capita GHG emissions in 2018 and 2050 for IPCC regions.

all sectors and approximate them using total national population and GDP per capita, while emission intensity is computed for each sector separately, implying sector-specific versions of the Kaya identity. This decomposition carries the notion of distinct technological levels and innovation (dispersion) dynamics in sectors, as well as capturing potential economy-wide structural changes (e.g. moving from an industry-based economy towards a service-oriented one).

Our specification of the Kaya identity notably excludes a measure for energy or energy intensity. Limited data availability for energy consumption for the global sample of countries over the full historical observation period we cover, as well as SSP-consistent national pathways, prevented us to include such a measure that would allow deeper insights into the specific drivers of sectoral GHG emissions. In order to capture the effects of human capital and other demographic trends on the development of emission intensities, we enrich the empirical specification of our framework with additional demographic variables. In particular, we include information about the age and educational structure of an economy as well as the degree of urbanization.

All these variables have been shown to be important determinants of emission intensities and energy consumption. In particular, a higher educational level of individuals correlates negatively with emission levels after controlling for income differences and lifestyles[45]. The rationale behind this correlation is that more educated societies tend to be more environmentally conscious and conserve energy more efficiently, all other things kept constant. The age structure of a population has also been commonly identified as an important determinant of emissions and emission intensities[46]. However, it is not entirely clear upfront how the aging of a society affects emissions, and whether these effects are the same across different sectors.

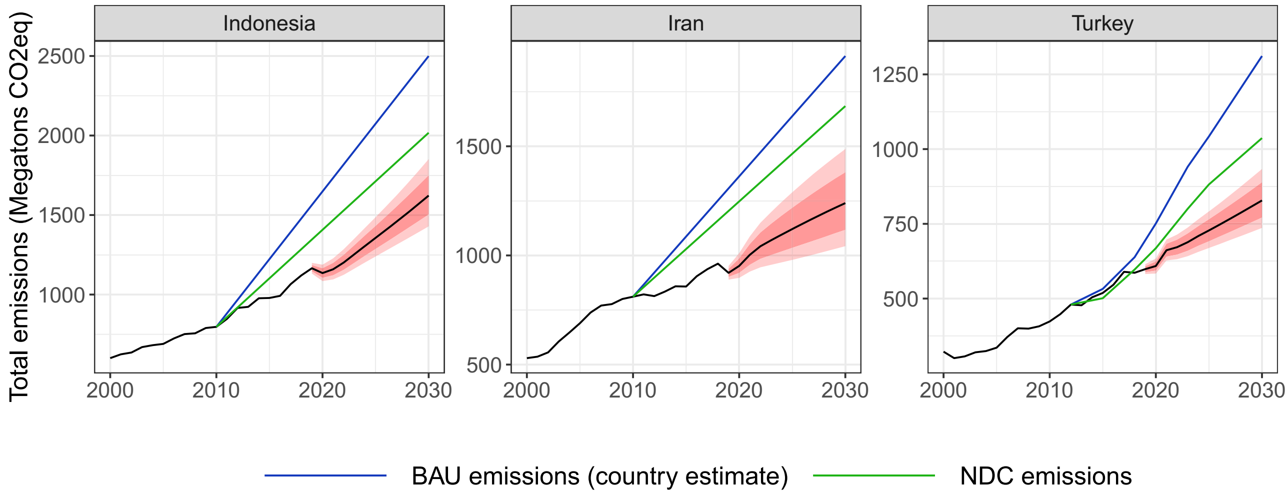

Fig. 7 | Comparison of BAU emission trajectories. Figure shows total GHG emissions projections compared to national BAU scenarios (GHG emission levels scaled to historical values as reported in Minx et al. (2021)[28,29] for the base year used in the respective country's NDC). Black line denotes historical values until 2018 and the median projection thereafter. Red shaded areas denote the 68% and 90% posterior predictive intervals. Blue line denotes the national BAU scenario, green line the pledged reduction under the unconditional NDC.

For example, an increasingly aging population could require more heating in the residential sector[45] but at the same time, older persons tend to be less mobile and thus cause fewer transport emissions. Similarly, it is conceivable that urbanization can have unclear effects on energy consumption or emissions. An increased spatial concentration of the population could decrease transport emissions stemming from less commuting but urban households could also have a higher energy consumption due to facilitated access and higher income. It has also been shown that the effects of urbanization differ along the developmental stages of an economy[47]. The flexible nature of our proposed statistical model (see next subsection) accommodates such potentially different effects across economies and sectors. The choice of variables is also dictated by the availability of comparable historical data and future trajectories. Projections based on SSP narratives are available on a national scale for all additional indicators included in our model[48–51]. Furthermore, while the inclusion of energy consumption in our specification would allow us to gain more insights into the specific drivers of sectoral GHG emissions, we do not think that it would change our results substantially as we capture the most important drivers of energy consumption with economic output and population.

Model specification

We rely on a unified multivariate time series model capturing the joint dynamics of GDP per capita, population and sectoral emission intensity, augmented with human capital and demographic variables (age structure and urbanization), inspired by models used in the macroeconomic literature[52,53].

We collect our endogenously modelled variables for each country $i = 1, \ldots, N$ and sector $s = 1, \ldots, S$ in the vector $\boldsymbol{y}_{i,s,t}$ ($t = 1, \ldots, T_i$). It thus captures $M = 6$ variables, of which the socioeconomic and demographic variables are the same across sectors, whereas emission intensities are not. We assume that $\boldsymbol{y}_{i,s,t}$ follows a vector autoregressive (VAR) process of order p:

$$\boldsymbol{y}_{i,s,t} = \sum_{j=1}^{p} \boldsymbol{A}_{i,s,j}\boldsymbol{y}_{i,s,t-j} + \boldsymbol{B}_{i,s}\boldsymbol{w}_{i,s,t} + \boldsymbol{\varepsilon}_{i,s,t}, \quad \boldsymbol{\varepsilon}_{i,s,t} \sim \mathcal{N}(0, \boldsymbol{\Sigma}_{i,s}). \tag{2}$$

Here, $\boldsymbol{y}_{i,s,t-j}$ denotes the jth lag of the endogenous variables, with the corresponding autoregressive coefficients collected in the $M \times M$ matrix $\boldsymbol{A}_{i,s,j}$. The deterministic terms $\boldsymbol{w}_{i,s,t}$ include country-specific intercepts and linear time trends, with the corresponding coefficients contained in $\boldsymbol{B}_{i,s}$. The vector $\boldsymbol{\varepsilon}_{i,s,t}$ is composed of Gaussian noise with zero mean and variance-covariance matrix $\boldsymbol{\Sigma}_{i,s}$ specific to country i and sector s.

The potentially large number of parameters to estimate and the rather short sample period available for individual countries raises concerns with regard to the efficient estimation of parameters, a problem commonly known as the curse of dimensionality. Our modelling strategy aims to alleviate this issue by pooling information across countries in a data-driven fashion using Bayesian methods. For that, we assume that the autoregressive coefficients for each sector arise from a common global distribution, with country-specific deviations. Specifically, let $\boldsymbol{\alpha}_{i,s} = \text{vec}([\boldsymbol{A}_{i,s,1}, \ldots, \boldsymbol{A}_{i,s,p}])$ for all i and s, then:

$$\boldsymbol{\alpha}_{i,s} | \bar{\boldsymbol{\alpha}}_s, \boldsymbol{\Omega}_{\alpha_{i,s}} \sim \mathcal{N}(\bar{\boldsymbol{\alpha}}_s, \boldsymbol{\Omega}_{\alpha_{i,s}}), \tag{3}$$

where $\bar{\boldsymbol{\alpha}}_s$ denotes a mean vector that is common across countries but sector-specific. The diagonal country and sector-specific matrices $\boldsymbol{\Omega}_{\alpha_{i,s}}$ effectively control the deviations of individual country coefficients from this common mean. A standard Normal-Gamma prior on the diagonal elements of the matrix is specified[54],

$$\left[\boldsymbol{\Omega}_{\alpha_{i,s}}\right]_j = \frac{2\left[\psi_{i,s}\right]_j}{\lambda_{i,s}^2}, \; \lambda_{i,s}^2 \sim \mathcal{G}(a_\lambda, b_\lambda), \; \left[\psi_{i,s}\right]_j \sim \mathcal{G}(a_\psi, b_\psi), \tag{4}$$

where $[\boldsymbol{\Omega}_{\alpha_{i,s}}]_j$ corresponds to the jth diagonal element of $\boldsymbol{\Omega}_{\alpha_{i,s}}$. This setup imposes shrinkage for country-specific coefficients towards the common mean governed by the global shrinkage parameter $\lambda_{i,s}$. The parameter $[\psi_{i,s}]_j$ in turn governs the strength of shrinkage for individual coefficients and allows for deviations of the jth element of $\boldsymbol{\alpha}_{i,s}$ from the common mean when the data are informative. For instance, a large $[\psi_{i,s}]_j$ corresponding to the lag of GDP per capita in the emission intensity equation of country i and sector s implies less regularization of the associated coefficient towards the global within-sector mean. Coefficients related to the deterministic terms included in the model are left unregularized, allowing for flexible capture of country-specific intercepts and linear time trends.

Another layer of hierarchy is imposed by placing a similar Normal-Gamma prior on the common mean vector $\bar{\boldsymbol{\alpha}}_s$ in order to flexibly push coefficients towards zero. This has been shown to improve forecasting performance in the context of VAR specifications[55]. To complete the model setup, an inverse-Wishart prior is imposed on the variance-covariance matrix of the error terms. To facilitate computation, a triangularization scheme is used to decompose $\Sigma_{i,s}$ into $\boldsymbol{HSH}^{\top}$. On the free off-diagonal elements of $\boldsymbol{H}$, a variant of the Normal Gamma prior is imposed, while for the elements of the diagonal matrix $\boldsymbol{S}$ inverse-Gamma priors are used. Analytical results of the resulting posterior distributions and efficient sampling schemes are available for this class of models[55].

Following our conceptual framework based on sector-specific Kaya identities, we estimate the model for each sector separately, thus accounting for potentially substantial differences in the sectoral dynamics of GHG emissions. In addition, within a sector panel, separate models are estimated for groups of countries where sectoral emission intensities have already peaked. We determine whether sectoral emission intensity in a given country has peaked in a similar vein as previous studies[21]. In particular, we locate the potential maximum in emission intensity after applying a loess-based smoother on the original series. If sector-specific emission intensity peaks only after 2005 or shows substantial increases after an initial peak early on, we assume that there is not enough evidence that the peak has occurred. Models for country/sector pairs where emission intensity has already peaked are estimated using data only for the *post-peak* period to better capture more recent patterns in the drivers of GHG emissions. Furthermore, the specifications for the two groups of countries are assigned different deterministic terms to capture the difference in dynamics. The models for countries where sectoral emission intensities have already peaked also include a linear trend in addition to the country-specific intercept, which all specifications include irrespective of whether a peak within a sector was observed. This difference in modelling parametrizations further captures the notion that sectoral emission intensities of countries after a sustained peak have the tendency to continue a downward trend.

The model is estimated using Markov Chain Monte Carlo (MCMC) methods and estimation is implemented using the statistical software R[56]. Each model run employs 150,000 MCMC draws, of which the first two-thirds are discarded as burn-in to ensure that model parameters are drawn from their stationary posterior distributions. Of the remaining draws, every fifth is retained to decrease potential serial correlation among posterior draws. Based on these posterior draws of parameters, projections are derived as described in the next section.

Projection procedure

We obtain long-term projections of GHG emissions by linking them to the established projection narratives given by the SSPs. The SSPs are scenarios that capture different potential, internally consistent trajectories for different socioeconomic dimensions[25]. Core elements of these scenarios involve, among others, population and their sociodemographic characteristics[48], economic output dynamics[49,50], and urbanization[51,57]. It is important to note that these scenarios gauge the evolution of socioeconomic quantities in the absence of the implementation of additional climate policies. Hence, the adoption of mitigation policies in our model is solely captured by changes in emission intensities as a measure of trends in technological progress and policy decisions (e.g. ones that influence the dispersion of available technologies).

In our projection exercise, we condition the country- but not sector-specific paths given by the SSP2 scenario for variables other than emission intensity. SSP2 can be loosely interpreted as a middle-of-the-road scenario in which social, economic, and technological trends are assumed not to differ markedly from historical patterns[25]. We combine long-term projections of GDP with short-term forecasts sourced from the World Economic Outlook database by the International Monetary Fund (see Data for more details). This allows us to better capture (potential) fluctuations in GHG emissions in the near future caused by the distortion of economic output dynamics, such as the temporary reductions caused by the COVID-19 pandemic[58] and other events of global or country-specific relevance.

Deriving conditional forecasts involves three steps. First, draws from the posterior distribution of the parameters of the models described in the previous subsection are obtained. Second, using these draws and the trajectories of the additional variables given by the SSPs, conditional forecasts for country-specific sectoral emission intensities are derived using established algorithms[59]. Third, total emissions per country and sector are derived as implied by the sector-specific Kaya identities. Repeating these steps a large number of times yields posterior predictive distributions of GHG emissions specific to each country and sector. From these distributions, summary statistics such as their mean, median or quantiles can be computed. This also allows for straightforward uncertainty quantification. It should be stressed that the uncertainty surrounding our projections of sectoral emissions represents a lower bound of total uncertainty for emission projections, which stems from the fact that we condition on fixed paths for the socioeconomic and demographic variables included in our model.

For a small number of country-sector pairs, this procedure resulted in unstable forecasts due to the erratic behaviour of the historical emission intensity series. For these cases, predictions of emission intensities were adjusted ex-post by using information on the evolution of emission intensities in the same sector for the five geographically nearest neighbouring countries, using the implicit assumption that geography serves as an approximation for the similarity of structural characteristics driving changes in emission intensities. Alternatively, we could also identify similar countries using the Euclidean distance for a set of standardized structural characteristics that describe the economic and demographic structure of countries.

The predictive performance of competing models is assessed in out-of-sample validation exercises using standard metrics, including comparisons of root mean squared error (RMSE) and cumulative log predictive scores (LPS) for emission intensities over a forecasting horizon of $H = 4$ years. In particular, we computed the RMSE of the emission intensity forecast for each country and sector as follows:

$$\mathrm{RMSE}_{i,s} = \sqrt{\frac{1}{H}\sum_{h=1}^{H}\left(y_{i,s,t+h} - y^{*}_{i,s,t+h}\right)^{2}}, \tag{5}$$

where $y_{i,s,t+h}$ denotes the actual value of the emission intensity of country i in sector s at horizon h and $y^{*}_{i,s,t+h}$ the respective forecast of it. We compute the RMSE at each iteration in the MCMC chain and average the RMSE over all iterations. The reported value is then the sum over all countries within a given sector. The cumulative LPS on the other hand is computed as

$$\mathrm{LPS}_{i,s} = \sum_{h=1}^{H} \log p(y_{i,s,t+h} | \bar{y}^{*}_{i,s,t+h}, \mathrm{var}(y^{*}_{i,s,t+h})), \tag{6}$$

where $y_{i,s,t+h}$ again denotes the actual value of the emission intensity of country i in sector s at horizon h, $\bar{y}^{*}_{i,s,t+h}$ and $\mathrm{var}(y^{*}_{i,s,t+h})$ denote the mean and the variance of forecasts at that horizon, and $p(\bullet)$ denotes the density of the Normal distribution. The resulting LPS scores are then summed over countries for each sector for a measure of density forecasting performance. Results are presented in Supplementary Table S2. Comparing alternative covariate choices, the model implied by the sectoral Kaya decomposition augmented with information about the age/education structure of the economy and the degree of urbanization shows the best predictive ability in terms of point forecasts (RMSE) for most sectors. For density forecasts (LPS), the model including only the Kaya components and information about the age/education structure slightly outperforms the full specification in most sectors. The full specification also has the highest proportion of countries whose 95% credible interval includes the observed value at the end of the validation period. In terms of projection trajectories until 2050, the different models yielded qualitatively similar results. However, the full specification yielded projections for some key countries and sectors (e.g., the Chinese energy sectors) that appeared to be more in line with previous projection results. We therefore opted for the full specification as our model of choice.

Data

Data are obtained from various sources. For emissions data, we rely on the synthetic dataset of GHG emissions by Minx et al. (2021)[28,29]. It covers annual information for all GHGs covered by the Kyoto Protocol (i.e., including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and a range of F-gases such as hydrofluorocarbons or perfluorocarbons) and spans a sample of 228 countries and territories at the sectoral level for the period 1970–2018, with a fast-track extension to 2019. We aggregate across GHGs using global warming potentials (GWPs) for a 100-year timescale to obtain total GHGs in tons of CO_2 equivalents emitted in five sectors: energy production, transportation, industry (including emissions from waste treatment and disposal), buildings, and agriculture. We refrain from modelling GHG emissions related to LULUCF given the lack of cross-country comparability due to conceptual differences in their quantification[42], poor data quality and the large uncertainties associated[28], as well as the distinct nature of the underlying key drivers[60].

For data on GDP, we rely on figures sourced from the World Development Indicators of the World Bank[61], with adjustments and imputations from other sources (such as the IMF) for economies where data points are missing. To ensure comparability across countries and time, GDP was converted to purchasing power parity units, expressed in 2011 US dollars. For most countries, coverage starts in 1980. For countries of the former Soviet Union and Yugoslavia, we restrict the data to start in 1995 given the unreliability of official statistics prior to the transition of these countries to a market economy and economic volatility following the break-up of communist states. Similarly, such a restriction was applied to a number of economies where data quality was deemed unreliable for earlier periods, including Eritrea, Timor-Leste, and Somalia. For the projection period, we condition on existing SSP2 projections for GDP per capita, where we use the average dynamics of two different sets of projections[49,50], combined with forecasts by the International Monetary Fund to capture anticipated short-term fluctuations in economic output (available until 2026 as of the time of writing). Similarly, SSP2-compatible paths are retrieved for the overall population as well as the age and education structure of an economy[48], and urbanization patterns within them[51], all of them adjusted to historically observed patterns.

We retrieve the data on population and additional demographic variables from the World Bank and the Wittgenstein Centre for Demography and Global Human Capital (WIC). The WIC provides information on both historical population by age, sex and education level, as well as long-term projections consistent with different scenarios of the SSPs[48]. In our model, we include the share of the population older than 40 years old and the share of the population having completed secondary schooling as covariates. Yearly values were obtained by interpolating the 5-year data available linearly. In addition, data on urbanization, defined as the share of the population living in urban centres, as well as their future trajectories consistent with the SSPs are available[51]. For a small number of countries, SSP-consistent trajectories for urbanization are missing in this dataset. Where this was the case, we rely on historical data and projections provided by the World Urbanization Prospects of the United Nations[62]. Sectoral GHG emission intensity is computed as GHGs emitted in a given sector, expressed in terms of tons of CO_2 equivalents, per US$10,000 of GDP in 2011 Purchasing Power Parity.

The only countries with a population of over 5 million which are not covered in our forecasting exercise are Eritrea, Libya, North Korea, Papua New Guinea, Syria, South Sudan and Uzbekistan, mostly due to unavailable historical demographic data. These countries and the additional 48 territories (including e.g. overseas dependencies) covered in the emissions database by Minx et al. (2021)[28,29] emitted GHGs amounting to 531 megatons of CO_2 equivalents in 2018, around 1% of global GHG emissions in that year, with the seven economies mentioned above emitting 378 megatons (more than 70% of the contribution of this group of economies). Data for Serbia and Montenegro is provided as aggregate for a single entity in Minx et al. (2021)[28,29]. In order to split those values for the individual economies, we used historical information on the compositions of sectoral GHG emissions from the World Resource Insitute for the period 1990–2018.

Data availability

The full set of results used in the analysis is available at https://doi.org/10.5281/zenodo.7846142 as R[56] binary files. The data presented in this work is featured on an online tool, the World Emissions Clock hosted by World Data Lab under https://worldemissions.io/. It is an informative and user-friendly visualization platform that allows the user to understand the progress and possible challenges related to reducing GHG emissions under different hypothetical scenarios.

Code availability

All codes required to replicate the results of our analysis are available at https://github.com/oDNAudio/GHG_sector_projections.

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