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Projected changes in seasonal and extreme summertime temperature and precipitation in India in response to COVID-19 recovery emissions scenarios

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Abstract

Fossil fuel and aerosol emissions have played important roles on climate over the Indian subcontinent over the last century. As the world transitions toward decarbonization in the next few decades, emissions pathways could have major impacts on India's climate and people. Pathways for future emissions are highly uncertain, particularly at present as countries recover from COVID-19. This paper explores a multimodel ensemble of Earth system models leveraging potential global emissions pathways following COVID-19 and the consequences for India's summertime (June–July–August–September) climate in the near- and long-term. We investigate specifically scenarios which envisage a fossil-based recovery, a strong renewable-based recovery and a moderate scenario in between the two. We find that near-term climate changes are dominated by natural climate variability, and thus likely independent of the emissions pathway. By 2050, pathway-induced spatial patterns in the seasonally-aggregated precipitation become clearer with a slight drying in the fossil-based scenario and wetting in the strong renewable scenario. Additionally, extreme temperature and precipitation events in India are expected to increase in magnitude and frequency regardless of the emissions scenario, though the spatial patterns of these changes as well as the extent of the change are pathway dependent. This study provides an important discussion on the impacts of emissions recover pathways following COVID-19 on India, a nation which is likely to be particularly susceptible to climate change over the coming decades.

1. Introduction

On 25 March 2020, the Indian government announced a nationwide economic lockdown to combat the spread of COVID-19 (Times of India 2020). The lockdown forced many coal factories and industrial plants to close, while reducing transportation in the country by up to 85%, according to Apple mobility data (Apple Maps 2021). During the lockdown, the concentrations of PM2.5, NO_x, and other pollutants dropped steeply, allowing researchers to observe how India's present-day environment would react to more sustainable emission levels (IQAir 2021). Although it has been shown that emissions changes directly resulting from COVID-19 will have a negligible impact on global mean surface temperature in the long run, the lockdown may have accelerated market trends towards renewable energy and increased global political support for more sustainable policy solutions (United Nations 2020, Weber *et al* 2020). The question that arises naturally as the world recovers from COVID-19 is how countries will invest in various sectors (the electricity, transportation, industry and building sectors, for example) going forward given the global economic damage wrought in 2020 and what are the consequent regional climate impacts from these decisions.

Changes in India's summertime climate can be attributed, in part, to industrialization across Asia over the last half century. A 151.5% increase in Indian population over the last 50 years has heightened the energy demands of the nation's developing economy and consequently impacted air quality in the region (Nagdeve 2007, Appannagari 2017, Karambelas *et al* 2018, World Bank 2019). The burning of coal, solid waste, and commercial biomass have been the primary anthropogenic drivers of India's recent pollution problems (Kandlikar and Ramachandran 2000, The World Bank 2019). To combat air quality issues in the region, the Indian government has pursued a number of policies geared towards sustainability, though success so far has been mixed. Assuming a linear reduction in the price for renewable energy, India has the economic means to reduce its 2040 carbon footprint by 85% (Lu *et al* 2020). However, coal accounted for 45% of the nation's total energy consumption in 2018, and coal demand is expected to grow more in India than in any other country by 2024 (International Energy Agency 2019, Independent Statistics and Analysis 2020). This contrasts with the government's pledge to nearly triple its renewable capacity by 2030 and the nation's history of developing large scale renewable infrastructure (Gabbatiss 2021, Leonard 2021). Furthermore, in rural areas, recent policies to stabilize the water table have forced farmers to abide by strict harvest schedules, and, in many cases, resort to burning crop waste instead of disposing of it safely (Cusworth *et al* 2018, Singh *et al* 2019). Increased coal and biomass burning have dampened the positive effects of India's solar and wind infrastructure initiatives on both public health and climate.

At a daily resolution, extreme weather events can exacerbate the public health and socioeconomic impacts of seasonal climate variability (Robine *et al* 2008). While long-term precipitation projections are difficult to model accurately, it has been speculated that continued fossil-fuel emissions will increase the severity of future extreme precipitation and temperature events (Schär *et al* 2016, Roxy *et al* 2017, Yaduvanshi *et al* 2021). One of the first extreme precipitation events that started a national discourse within India on the effects of climate change was the flooding of Mumbai in July 2005, which received 40 inches of rain in the span of 1 day. The frequency of such intense events has only increased since, with particularly devastating events in Kerala and Chennai within the last few years. From 1950 to 2015, the number of extreme rainfall events tripled, killing 69 000 people and leaving 17 million more homeless (CRED 2017, Mushal 2019). In addition, summer heat waves have killed at least 6000 people since 2010, with temperatures rising above 120 °F in the pre-monsoon season (Murari *et al* 2015). There is a growing concern that these intense heat waves will increase in duration and frequency due in part to decreasing soil moisture and clearer skies (Mishra *et al* 2014, Rohini *et al* 2016). Additionally, some have posited the monsoon season could extend further into September. Rising anthropogenic emissions are known to be linked to each of these meteorological phenomena and can therefore have potentially devastating impacts on both seasonal and daily climate trends (Mishra *et al* 2014, Mukherjee *et al* 2018, CMIP 2021).

Here, we analyze six models that have taken part in the Coupled Model Intercomparison Project, Phase 6 (CMIP6) CovidMIP project (Forster *et al* 2020, Lamboll *et al* 2020), to study the effects of COVID-19 emissions recovery pathways on India's summertime climate. We leverage a multimodel ensemble to account for the intermodel variability present in temperature and precipitation projections (Forster *et al* 2020, Climate Change Knowledge Portal 2021, Pandey *et al* 2021). Each of these models is run for three future global recovery pathways following the COVID-19 lockdown: fossil-fuel based, moderate green, and strong green emission control pledges (with details of each scenario included in table 1) (Forster *et al* 2020). We compare each of these recovery pathways to a low emissions baseline scenario (SSP245) to evaluate prospects for seasonal and daily climatic changes in India for the summer when both major temperature and precipitation events take place (Riahi *et al* 2017).

This paper focuses on the impact of these various climate recovery scenarios on precipitation and temperature projections in the summer monsoon season. We first analyze summertime aerosol optical depth (AOD) as an integrative property of the air pollution loading and precipitation projections across India in the near-term (2020–2025) and the long-term (2045–2040) to distinguish human-induced climate trends from natural variability. We then compare the magnitude and frequency of severe summertime temperature and precipitation events across the multimodel ensemble. Impacts of projected changes are discussed in the context of India's geospatial population projections. Our study aims to thoroughly assess the implications of realistic, policy-based emissions changes on long-term summertime climate over the Indian subcontinent in the context of both seasonally-aggregated changes as well as short-term extreme events.

2. Method

Our study utilizes six models from the CovidMIP project to understand the role of global emissions perturbations on Indian climate over the next 30 years (there are a few other models in the CovidMIP ensemble, but these have been excluded in the analysis presented here as they were missing either certain scenarios or years in the Earth System Grid Federation (ESGF; https://esgf-node.llnl.gov/search/cmip6/), a

Table 1. Summary of the multimodel ensemble studied here.

Model	Resolution (lon × lat)	# Baseline members	# Fossil members	# Modgreen members	# Strgreen members
ACCESS-ESM1-5	1.241° × 1.875°	30	10	10	10
CanESM5	2.813° × 2.813°	50	50	50	50
MPI-ESM1-2-LR	1.875° × 1.875°	10	10	10	10
MRI-ESM2-0	1.125° × 1.125°	6	6	6	6
NorESM2-LM	1.875° × 2.500°	10	10	10	10
UKESM1-0-LL	1.25° × 1.875°	17	12	15	10

data center for climate model output and observations). Each of these models simulates four different global climate recovery scenarios from COVID-19, which are based on individual nations' commitment to renewable energy (Forster *et al* 2020). Our baseline scenario follows the so-called 'middle-of-the-road' scenario that assumes historical emissions policies continue into the future (SSP245, henceforth referred to as the baseline scenario; O'Neill *et al* 2017). The fossil-fuel scenario (COV-FOSSIL) assumes that emissions will increase to 4.5% above baseline levels by 2022, a recovery similar to that following the 2008–2009 global recession. The moderate green stimulus scenario (COV-MODGREEN) assumes a gradual shift towards low-carbon technologies through a 35% reduction in GHG emissions relative to the baseline by 2030. The strong green stimulus scenario (COV-STRGREEN) simulates a 50% reduction in GHG emissions relative to the baseline by 2030, with the end goal of reaching global net-zero carbon emissions by 2050. Further details of all four of these scenarios are provided in Forster *et al* (2020).

Due to the differing spatial resolutions present in these models, we rescale and interpolate each model (using a bilinear interpolation approach) to a standard 1.25° × 1.875° resolution. Climatic changes in the near- (2020–2025) and long-term (2045–2050) are calculated using the multimodel mean of summertime (June–July–August–September) simulation outputs. Scenarios from each model are comprised of multiple ensemble members (see table 1 for numbers specific to any given model), which represent the slight variations in initial atmospheric conditions. Whilst they may be generated via slight variations in initial atmospheric conditions they represent a measure of the model internal variability. And the goal here is to compare the effects of the emission scenarios to this internal variability. Having a sufficiently large ensemble size for each model-scenario combination should allow for us to distinguish between the emissions-driven responses and internal variability. To avoid overweighting models with more ensemble members, we take the mean across all ensemble members for each model prior to aggregating the models together in figures 1–3.

Our initial analysis focuses on projected changes in summertime (JJAS) AOD at 550 nm (AOD) and precipitation over continental India at a monthly resolution. We first compute the difference in AOD between the multimodel average of each scenario and the baseline scenario over the periods 2020–2025 and 2045–2050. Similar calculations are performed also for precipitation to evaluate the sensitivity of these quantities to projected emissions changes. To evaluate how realistically the models can simulate AOD and precipitation at a monthly resolution over India, we compare the multimodel summertime average and standard deviation for historical AOD and precipitation levels to observations compiled by the NASA Moderate Resolution Imaging Spectroradiometer and Global Precipitation Climatology Centre, respectively (figures S1–S4 (available online at stacks.iop.org/ERL/16/114025/mmedia)) (GPCC 2011, Moderate Resolution Imaging Spectrometer 2021). While there are discrepancies in the magnitude of AOD and precipitation, particularly in southern India for AOD and northern India for the variance in precipitation, the spatial patterns are generally consistent between the model means and standard deviations and the observations.

Following the monthly aggregated analysis, we then assess changes in the magnitude and frequency of summertime extreme events in India in the long-term. Using data at a daily temporal resolution, we examine changes in extreme precipitation events and daily peak temperature across the multimodel ensemble. We have defined the threshold for an extreme event at the model level (that is, a 95th percentile event for a model is computed across all individual ensemble members of a given model). Direct human impacts from changing extreme events are then evaluated in the context of expected population dynamics changes across India. To quantify the population impacts of extreme events from the different emission scenarios, we calculate the number of people affected by an extreme event on a daily basis at each grid cell. We then sum the number of people affected by a daily extreme event at each grid cell over the summertime 2045–2050 period to yield a metric in units of people-days (i.e. the number of people affected by extreme events from 2045 to 2050 times the number of extreme event days in that period). This number represents the total long-term scenario-dependent impacts of COVID emissions recovery. The population trends applied are driven by the Shared Socioeconomic Pathways (SSP), which

provide decadal projections of population changes at a one-eighth degree resolution.[33] These pathways highlight climate vulnerabilities, impacts, and sustainable developments under multiple scenarios. Our study uses SSP2 as a baseline framework, which is designed to simulate a world in which social, economic, and political rhetoric do not shift markedly from their historical trends. We acknowledge that analysis should be extended to assess climate impacts in other SSP scenarios in the future.

3. Results

3.1. Projected seasonally-aggregated summertime air quality and precipitation changes

We start with an evaluation of how projected summertime Indian AOD at 550 nm differs between various emissions pathways. The differences in summer AOD between the three emissions pathways relative to the SSP245 baseline provide a range of trajectories for air quality in India in the future according to these emissions trajectories, and are presented in figure 1. In the near term, the multimodel difference in AOD relative to the baseline in each of the three recovery pathways is negative (implying a lower AOD relative to that of in the SSP245 trajectory), specifically in the Bengal region. That being said, the magnitude of these changes is relatively weak compared to the differences found in the longer term, suggesting that the various recovery pathways will not have a marked near-term impact on Indian AOD, consistent with the findings in Jones *et al* (2021).

However, in the 2045–50 time frame, the fossil recovery pathway indicates greater AOD values than either of the green recovery pathways. While both of the green stimuli projections indicate a robust reduction in AOD relative to the baseline scenario by 2045–2050, the COV-STRGREEN ensemble amplifies this result across the Indian subcontinent. While the deviations observed in the COV-FOSSIL scenario are not statistically robust, it is notable that the fossil recovery case predicts greater AOD relative to the baseline scenario. We expect AOD to decrease in the green stimuli cases, as is expected in a scenario with reductions in fossil-based emissions. We also observe that the magnitude of the multimodel deviation from the baseline increases from the southwest to the northeast portion of the Indian subcontinent, with the greatest deviations taking place in the eastern portion of the Indo-Gangetic Plain. This result is consistent with the current AOD hotspots in India; because the Indo-Gangetic Plain contains many of the nation's largest cities and since it is shielded by both the Himalayas and the Deccan Plateau, it creates a geographic funnel for air pollutants.

It is expected that these varying concentrations of air pollutants should also have climate impacts (Sherman *et al* 2021). Figure 2 indicates changes in seasonally-aggregated summertime precipitation in India relative to the SSP245 baseline. In the near term, we do not observe any consistent or discernible trends in summertime precipitation projections for the three recovery scenarios. While the COV-MODGREEN scenario projects that there will be more precipitation than the COV-FOSSIL scenario, the COV-STRGREEN pathway shows on average lower projected precipitation across India. Because spatial precipitation changes associated with COV-STRGREEN contradict the results from COV-MODGREEN, we cannot identify a clear relationship between summertime precipitation and the levels of commitment to green technologies in the near term. Therefore, it is likely that the discrepancies present in the 2020–2025 period across the multimodel ensemble are attributable to natural climate variability rather than anthropogenic forcing.

In the longer term, the effects of each policy scenario on summertime precipitation levels are more apparent. The COV-FOSSIL scenario indicates less precipitation in central India than the baseline, a conclusion that is supported by multiple robust points in the region. In the COV-MODGREEN simulation, this same conclusion is not seen with statistical robustness, as this scenario projects roughly similar precipitation levels to the baseline across the Indian subcontinent. Higher rainfall levels relative to the baseline are projected throughout contiguous India in the COV-STRGREEN pathway, with robust points found in the same region as the COV-FOSSIL pathway. Thus, we conclude that in the long term, more aggressive low-carbon policies will likely lead to a higher Indian summertime precipitation than would be experienced without these policies. We can further analyze this result to infer the interconnection of aerosols and GHGs on seasonal precipitation trends. The COV-FOSSIL pathway—which results in higher aerosol and GHG concentrations than the baseline—projects less summertime precipitation than the greener COV-STRGREEN pathway, which results in lower aerosol and GHG concentrations than the baseline. Increased GHGs raise the average summertime temperature in the COV-FOSSIL scenario, which should increase water vapor in the atmosphere and result in greater precipitation (e.g. Sherman *et al* 2021). However, the lower precipitation in the COV-FOSSIL scenario relative to the baseline may show that realistic potential changes in anthropogenic aerosol emissions might be a more significant forcing agent on summertime precipitation in India relative to realistic changes expected from GHG emissions by 2050. It is worth noting that there is less statistical robustness stippling in figure 2 relative to figure 1, which makes sense as AOD responds directly to emissions changes, while precipitation changes are a more secondary order effect in response to emissions changes.

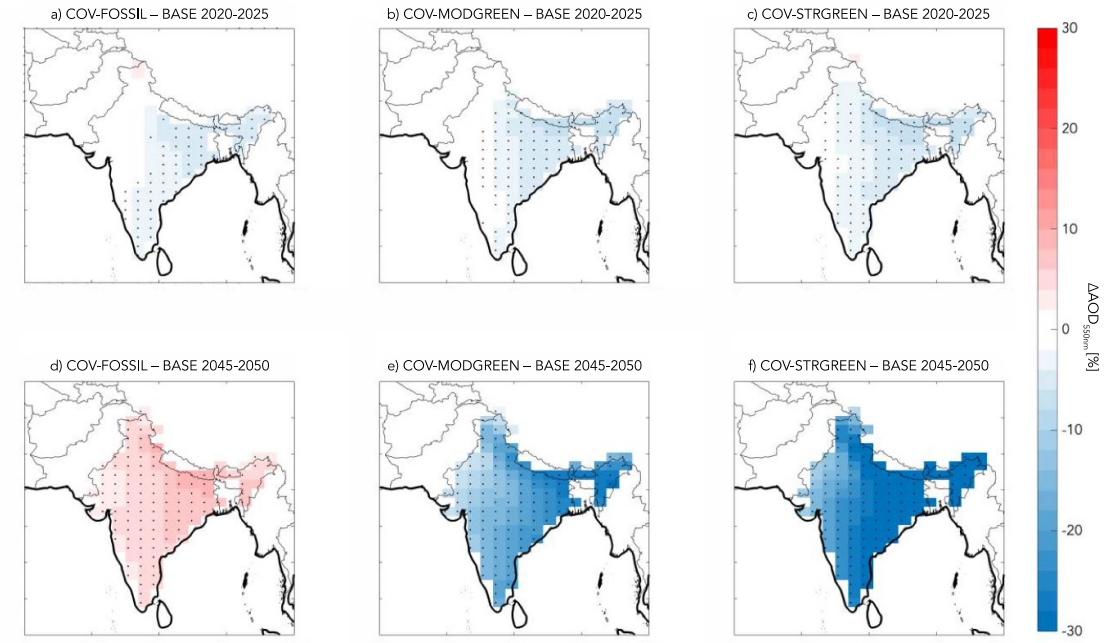

Figure 1. The multimodel mean percent change in summertime (JJAS) AOD at 550 nm between (a) and (d) COV-FOSSIL, (b) and (e) COV-MODGREEN and (c) and (f) COV-STRGREEN and the BASE scenario. The top row indicates summertime AOD changes over the period 2020–2025, while the bottom row indicates the same for the period 2045–2050. Stippling denotes regions of a statistically robust change, defined here as at least five of the six models agreeing on the direction of change.

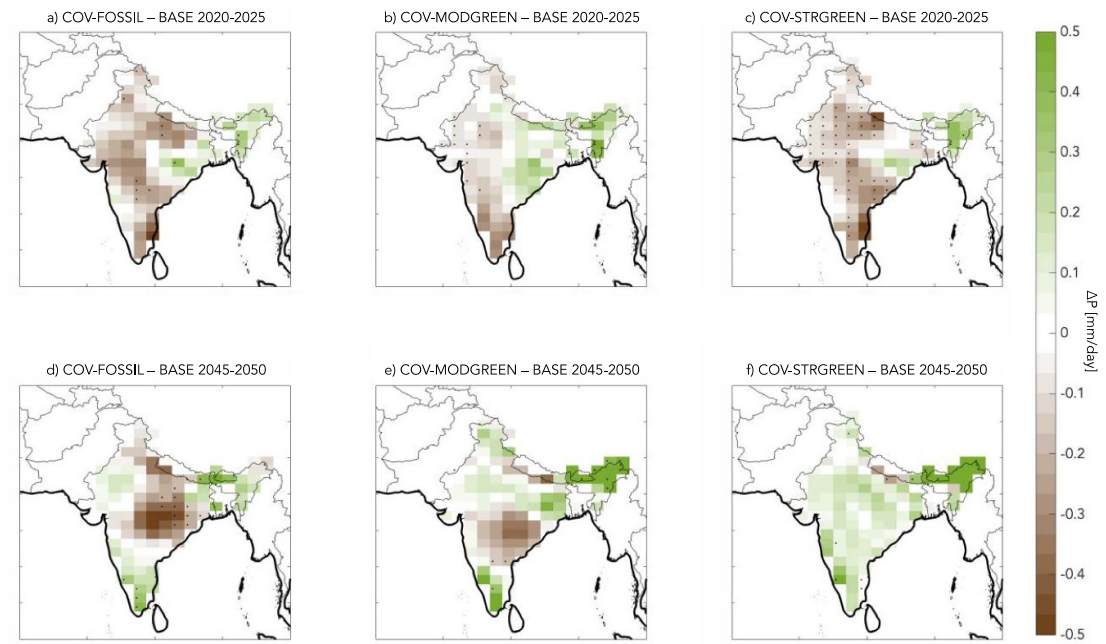

Figure 2. The multimodel mean change in summertime (JJAS) precipitation between (a) and (d) COV-FOSSIL, (b) and (e) COV-MODGREEN and (c) and (f) COV-STRGREEN and the BASE scenario. The top row indicates summertime precipitation changes over the period 2020–2025, while the bottom row indicates the same for the period 2045–2050. Stippling denotes regions of a statistically robust change, defined here as at least five of the six models agreeing on the direction of change.

3.2. Changing frequencies of extreme events

In addition to the seasonally-aggregated data, it is important also to study changes in the statistics of the precipitation data at a more granular (i.e. daily) level in the various scenarios. Changes in the magnitude of extreme temperature events have direct impacts on many people in India. Temperature changes for 95th percentile extreme events (computed at the model level and averaged across models) are indicated in figure 3, panels a–c. By 2045–2050, all three

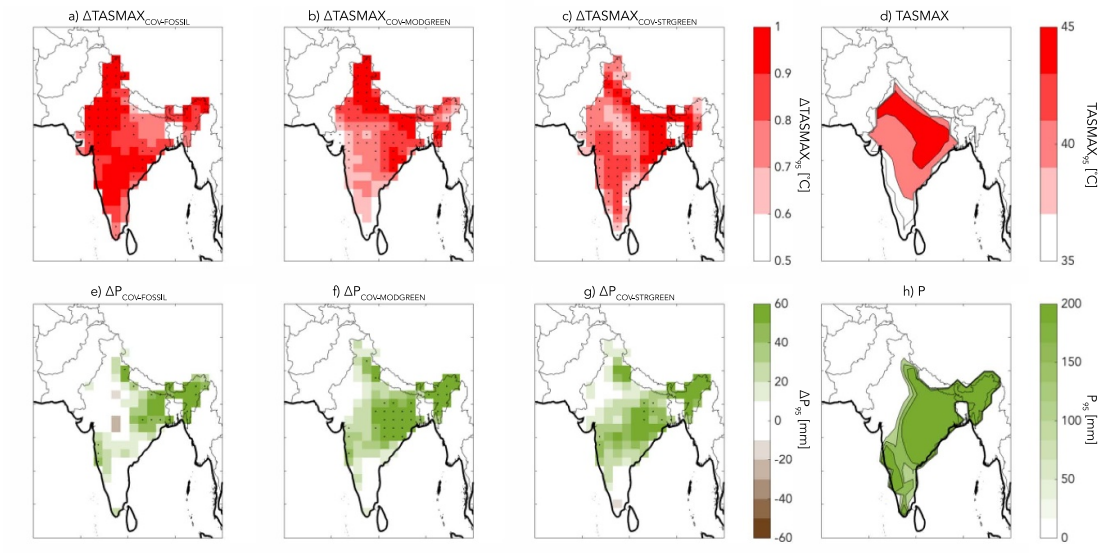

Figure 3. (a)–(c) The multimodel mean difference in 95th percentile daily maximum summertime (JJAS) temperatures (TASMAX; °C) between (a) COV-FOSSIL, (b) COV-MODGREEN and (c) COV-STRGREEEN over the period 2045–2050 and the baseline scenario over the 2020–2025 period. Contour temperature levels at 35 °C, 40 °C and 45 °C for the multimodel mean baseline scenario over the period 2020–2025 are indicated in panel (d). (e)–(g) The same as panels (a)–(c), but for precipitation (P; mm). Contour precipitation levels at 100, 150 and 200 mm for the multimodel mean baseline scenario over the period 2020–2025 are indicated in panel (h). Stippling denotes regions of a statistically robust change, defined here as at least five of the six models agreeing on the direction of change.

scenarios project a warming of 0.5 °C –1 °C in the 95th percentile daily temperature maximum relative to the 2020–2025 baseline scenario. This shows that regardless of the emissions trajectory going forward (i.e. whether we invest heavily in renewables or not), India's hottest summertime temperatures will be greater in 2045–2050 than they are today. However, the distribution and intensity of temperature extremes across India are dependent upon climate policy. In the COV-FOSSIL pathway, extreme temperatures rise by 0.8 °C–1 °C relative to the baseline in all regions of India except for the northeast portion of the Indo-Gangetic Plain. Conversely, the COV-MODGREEN and COV-STRGREEN pathways exhibit the greatest warmings on the northern border of the Indo-Gangetic Plain and the Himalayas. The two green pathways also project a smaller average increase in extreme temperatures across India than the COV-FOSSIL scenario. The COV-MODGREEN pathway shows only a 0.5 °C–0.8 °C warming in the southwest regions of India, as there is a discernible increase in 95th percentile daily maximum temperature (relative to the baseline) from the southwest to the northeast of India. The results from the COV-STRGREEN are less clear, as this model projects a larger increase in extreme temperatures on the southwest coast as compared with the north-central portion of the country.

These extreme temperature changes can be explained in part by comparing them to the deviations in AOD shown in figure 1. AOD concentrations decrease from the southwest to the northeast, and we observe that same pattern for extreme temperature in the COV-MODGREEN pathway. Decreased AOD in the green recovery pathways has likely played an important role in the hotter extreme temperature events. This suggests that, at the daily resolution, the reduction in aerosol emissions plays a major role in masking part of the overall reduced GHG trend relative to baseline. The COV-STRGREEN pathway does not indicate as robust a trend in extreme temperatures over this region, which is consistent with the logic discussed above because emissions of both GHGs and aerosols decrease in COV-STRGREEN relative to COV-MODGREEN. This suggests that, in a multimodel average of aggressive green pathways, aerosol cooling may roughly balance GHG warming, and predictions of long-term projections of the spatial distribution of extreme summertime temperature events may be more difficult.

Similarly, changes in the magnitude of extreme precipitation events could also have major consequences for the livelihoods of many people in India. These changes are shown in figure 3, panels d–f. We note a general increase in 95th percentile precipitation over the Indo-Gangetic region for all three scenarios. The spatial patterns vary further south both along the coast and inland. For the COV-MODGREEN and COV-STRGREEN simulations, we observe a sustained increase in 95th percentile precipitation of approximately 60 mm for COV-MODGREEN and 40–60 mm for COV-STRGREEN. COV-FOSSIL presents an increase in

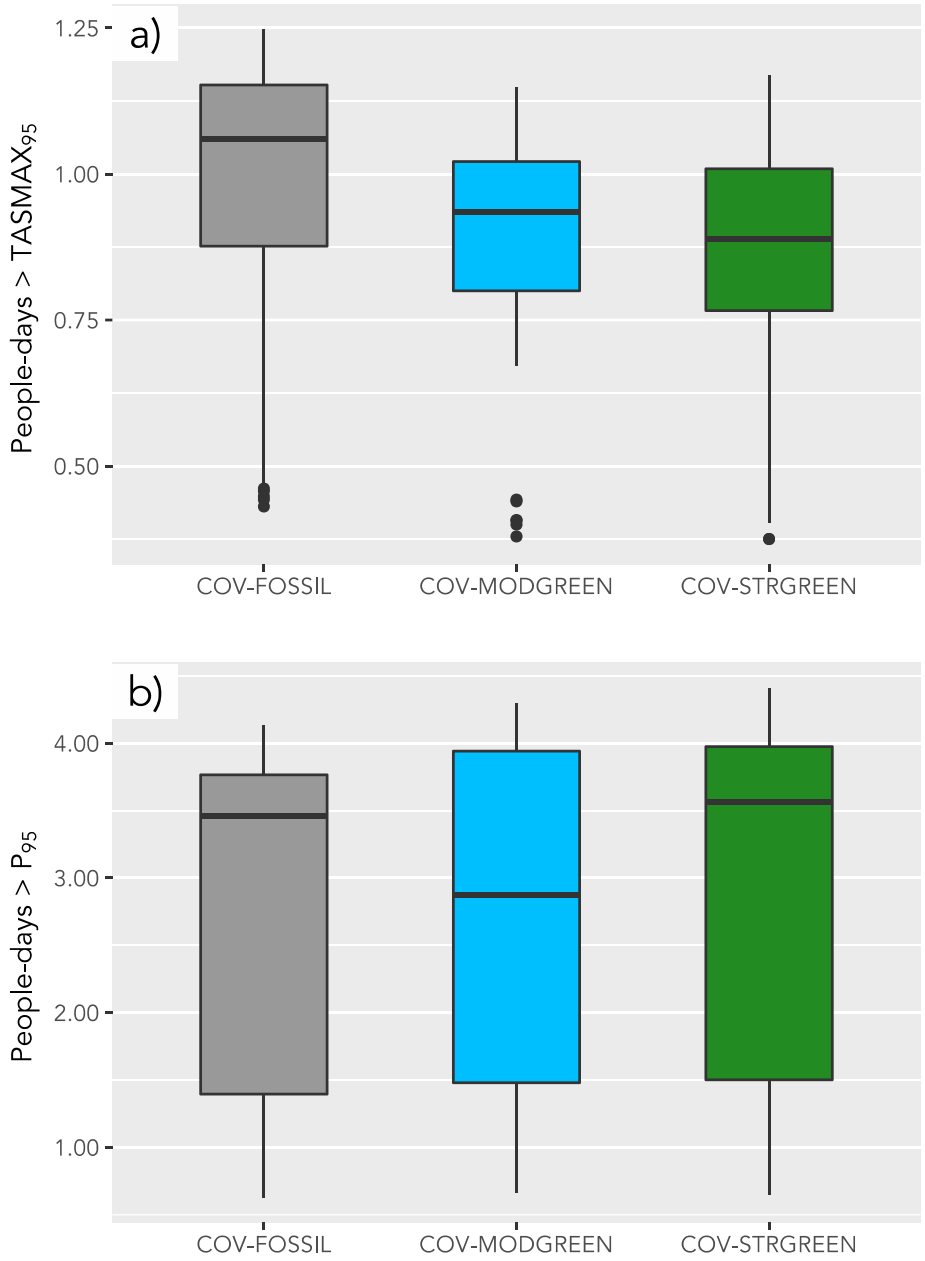

Figure 4. Boxplots of the number of people-days affected by 95th percentile baseline scenario 2020–2025 summertime (JJAS) extreme events for COV-FOSSIL, COV-MODGREEN and COV-STRGREEN in the period 2045–2050 summertime over continental India. The boxplots illustrate the distribution of people-days in all individual ensemble members from all of the models studied. Panel (a) indicates the number of people-days affected by 95th percentile temperature extremes and panel (b) indicates 95th percentile precipitation events. Dots in the figures represent outliers, which in the case of panel (a) all correspond to individual ensemble members from MRI-ESM-2-0. Values have been normalized by dividing all boxplots by the mean people-days affected by 95th percentile temperatures in the COV-FOSSIL scenario (i.e. dividing by the mean of the COV-FOSSIL data from panel (a)).

95th percentile precipitation as well, though it is confined to a smaller area and weaker in magnitude, peaking at an increase of about 40 mm. Notably, there is a small area in central India that exhibits a slight decrease. However this is not corroborated by data from other surrounding areas, and should probably not be treated as robust. Lastly, we observe that for all simulations, there seems to be no apparent change in extreme precipitation in the south or northwest.

3.3. Impacts on population-dense regions

Changes in the frequency of extreme events will also play an important role on the potential human impacts of future climatic changes in India. Changes in the number of people-days affected by 95th percentile temperature extremes are indicated in figure 4(a). To do this, we multiplied the number of days exceeding the threshold extreme value at each grid cell by the corresponding population value. We then aggregated over all of India to

obtain a single value in units of people-days for each ensemble member of each model. The impacts of extreme temperature have clear responses across the three scenarios, ordered, as expected, according to the amount of fossil fuels emitted. COV-FOSSIL has the largest increase; there are 11.8% more people-days affected by extreme temperatures in the median COV-FOSSIL scenario relative to the median COV-MODGREEN scenario and 16.1% more relative to COV-STRGREEN. These results are consistent with expectations that the severity and impact of extreme temperature events are likely to coincide with greater GHG emissions. That is to say, in the least sustainable pathway (COV-FOSSIL), not only will the magnitude of extreme temperature events increase (figure 3(a)), but also the number of people-days impacted by these extreme events will increase as well.

While the models in aggregate confirm this hypothesis, natural variability in population and extreme temperature projections across India are expected to play an additionally important role. The interquartile ranges shown in figure 4(a) indicate that there is overlap in the extreme temperature impacts for the different scenarios, suggesting that natural variability can allow for summers in a renewably-driven pathway that are just as hot as summers in a fossil-driven pathway. However, while it is important to note the significance of natural variability in extreme temperature projections, this does not detract from the clear discernible trend of increased people-days affected by extreme temperatures as we move from a greener to a more fossil-fuel oriented COVID-19 recovery plan.

Impacts from extreme precipitation events are indicated in figure 4(b). It is important to note that people in India are more exposed to extreme precipitation events relative to extreme temperature events, as can be seen by the number of people-days affected in each scenario. This is consistent with the fact that the most populous regions in India are along the coastline and the Indo-Gangetic Plain. Unlike extreme temperature events, there does not appear to be a clear relationship between scenario and people-days affected. The interquartile ranges for all three scenarios almost completely overlap and the bottom quartiles are nearly identical. Additionally, the median for the COV-MODGREEN scenario is lower than for the other two scenarios, making it difficult to distill a relationship between green policy and the impacts of extreme precipitation events.

These extreme precipitation results are also consistent with the data presented in figure 3, panels d–f. All three scenarios predict an increase in the magnitude of extreme precipitation events primarily over the east and south. These regions host some of most densely populated environments in all of India, and this is especially the case for the Indo-Gangetic region. As such, the slight variances in other regions do not have a large effect on the number of people-days due to the low number of people impacted. Given the relatively uniform projected change in the magnitude of extreme precipitation events, regardless of scenario, it follows that the human impacts of these events should also be experienced relatively uniformly.

4. Discussions and conclusions

The main purpose of this study was to understand potential ramifications of COVID-19 motivated emissions changes on summer-aggregated and daily extreme climate in India. We leveraged output from the CovidMIP multimodel ensembles running a set of four emissions recovery trajectories following COVID-19. We focused specifically on two periods, one representing the near future (2020–2025) and one representing the long-term (2045–2050), to evaluate how climatic changes will affect population-dense regions under various recovery pathways.

Our study expands on prior research through a multimodel climate analysis of four scenarios, each with several ensemble members. By analyzing geospatial multimodel projections at the seasonal and daily resolution, we assess potential summertime climatic changes across the Indian subcontinent over the coming decades. We found that fossil fuel based recovery pathways lead to higher summertime AOD concentrations in the long term, while greener scenarios lead to lower AOD concentrations in the long term. This is consistent with the rise in fossil fuel combustion, agricultural waste burning and non-renewable transportation prevalent with a fossil-fuel driven recovery pathway. The greener scenarios may actually drive a positive feedback loop where the solar PV capacity factor improves with reduced air pollution, incentivizing further investment in renewables which should further reduce AOD. Precipitation projections are inherently noisier than projections of AOD, though the results suggest that in the long-term, seasonally-aggregated summertime precipitation may, on average, increase slightly across India increase in greener scenarios relative to fossil fuel focused policies. This suggests that realistic changes in emissions of aerosols and its precursors will likely play a more dominant role on precipitation over India in the coming decades relative to the changes expected for greenhouse gases (because relative changes in GHG emissions are expected to be smaller than that of aerosol emissions). The magnitude of these trends is larger in the long-term relative to the near-term, highlighting how the implementation of sustainable policies today will be more impactful in the future. The full CMIP6 ensemble under a range of future scenarios (SSP126, SSP245, SSP585) shows large uncertainty, but little differences between mean summertime precipitation projected by the three SSP scenarios before 2060 (Almazroui *et al* 2021). This result is generally

consistent with the changes found here, which are largely masked by noise. It is, however, of note that the most fossil-intensive scenario (SSP585) yielded higher mean summertime precipitation in the far-term (2080–2099) (Almazroui *et al* 2021).

At a daily resolution, we conclude that maximum summertime temperatures will generally be higher in fossil-fuel recovery scenarios than for greener alternatives. However, this result varies spatially; extreme temperature events in less sustainable pathways are more severe in southwest India, and less severe further north. The extreme temperature changes in the north correlate with the AOD changes in the various scenarios, suggesting that perturbations to the aerosol forcing could play a major role in future extreme temperature events in that region. We also observe that extreme precipitation events are more severe in greener recovery scenarios compared to their fossil recovery counterparts, specifically in the northeast and central regions of India. Finally, by overlaying Indian population data onto our spatial extreme temperature and precipitation projections, we observe that more people-days are affected by heat waves in fossil recovery pathways, compared to greener alternatives. Additionally, extreme precipitation events, when averaged across models and scenarios, affect more than triple the amount of people-days than extreme temperature events. These results make sense in the context of India's volatile monsoon season that has been known to bring short spurts of torrential downpours throughout the summer.

This projected increase in the intensity of future extreme precipitation events is consistent with the results of prior studies. While there have historically been several metrics used to define extreme events, both global CMIP5 (Mukherjee *et al* 2018) and regional (Woo *et al* 2019, Rai *et al* 2020, Maharana *et al* 2021, Shahi *et al* 2021) models project an increase in both the frequency and intensity of extreme events over India. Comparisons between different carbon emissions pathways used by CMIP, RCP4.5 (lower carbon forcing) and RCP8.5 (higher carbon forcing) project a similar range for the frequency of extreme events under both of these scenarios (Woo *et al* 2019). This is consistent with the results presented here, which finds that, because of high variance in model projections, the number people-days affected by extreme precipitation predicted overlaps under the emissions scenarios studied.

We note here a few caveats from this study which should be considered for future analysis. First, due to the coarse spatial resolution of GCMs, there may be issues in simulations of summer monsoon precipitation, particularly the frequency and magnitude of extreme events, given India's complex orography (Prell and Kutzbach 1992). We find, however, general consistency in the spatial patterns of precipitation between multimodel mean and observations (figures S1 and S3) over the historical period as well as the variability (figures S2 and S4). Second, all scenarios studied here follow emissions trajectories branching from SSP245, a middle-of-the-road CMIP6 emissions pathways. Future work should explore similar COVID-19 recovery scenarios for the worst-case SSP scenarios to understand the reasonable upper limit of human-induced climate change on the Indian monsoon. Third, some chemistry-climate feedbacks remain heavily unconstrained in GCMs due to our limited understanding of indirect aerosol effects. For example, while past studies have found the precipitation response to sulfate aerosol emissions to be persistent across models (Kim *et al* 2007, Shawki *et al* 2018), impacts from black carbon are more difficult to evaluate (Xie *et al* 2020, Sherman *et al* 2021). The representation of cloud microphysical processes represents a well-recognized limitation of current GCMs (Wilcox *et al* 2015), and is likely one of the main components responsible for model-dependent precipitation responses to BC emissions perturbations (Sherman *et al* 2021). Fourth, intermodel bias could affect the results presented here. We have briefly studied this in figure S5 in the SI, which shows precipitation and AOD aggregated over India for each of the models investigated. This shows that some models are biased relative to the rest of the ensemble (particularly, precipitation in CanESM5 aggregated over India is roughly 50% lower relative to the rest of the multimodel ensemble), though the models are generally consistent. As we mainly studied projected changes relative to a baseline, model bias should generally be accounted for in the analysis presented in our paper, though future work could be implemented to expand on this further.

The long-term economic recovery from COVID-19 can prospectively take many forms, and these decisions can have important implications for future climate change. These results should be valued as important considerations in our future emissions trajectory globally as well as regionally in India. The projected changes we find in the summertime temperature and precipitation extremes can be studied further and could have broad consequences for India from perspectives of both agriculture and human health.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.llnl.gov/search/cmip6/.

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Conflict of interest

The authors declare that they have no conflicts of interest.

Author contributions

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