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Article

Quantifying the impacts of COVID-19 on Sustainable Development Goals using machine learning models

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A B S T R A C T

The COVID-19 pandemic has posed severe threats to global sustainable development. However, a comprehensive quantitative assessment of the impacts of COVID-19 on Sustainable Development Goals (SDGs) is still lacking. This research quantified the post-COVID-19 SDG progress from 2020 to 2024 using projected GDP growth and population and machine learning models including support vector machine, random forest, and extreme gradient boosting. The results show that the overall SDG performance declined by 7.7% in 2020 at the global scale, with 12 socioeconomic SDG performance decreasing by 3.0–22.3% and 4 environmental SDG performance increasing by 1.6–9.2%. By 2024, the progress of 12 SDGs will lag behind for one to eight years compared to their pre-COVID-19 trajectories, while extra time will be gained for 4 environment-related SDGs. Furthermore, the pandemic will cause more impacts on countries in emerging markets and developing economies than those on advanced economies, and the latter will recover more quickly to be closer to their pre-COVID-19 trajectories by 2024. Post-COVID-19 economic recovery should emphasize in areas that can help decouple economic growth from negative environmental impacts. The results can help government and non-state stakeholders identify critical areas for targeted policy to resume and speed up the progress to achieve SDGs by 2030.

1. Introduction

The global progress to achieve the United Nations (UN) Sustainable Development Goals (SDGs) by 2030 has been stalled by the coronavirus disease 2019 (COVID-19) pandemic. As of May 2022, COVID-19 has already caused over 516 million confirmed cases and 6.3 million deaths [1]. As a result of mitigation measures such as lockdown, COVID-19 has also greatly affected the global economy. The world's gross domestic product (GDP) declined by 3.1% in 2020, almost twice that in the Great Recession (−1.6% in 2008) [2]. Consequentially, financial and institutional resources that would be available to enhance SDGs will likely go away by a large extent. Achieving SDGs by 2030 post COVID-19 becomes more challenging if not impossible.

Several studies have assessed the impacts of COVID-19 on SDGs [3–14]. For example, the UN's 2020 annual report on SDGs showed worrisome initial impacts of COVID-19 on some specific goals and targets [3]. Naidoo and Brendan developed a qualitative framework and gave a comprehensive appraisal on the impacts of COVID-19 on SDG targets [6]. Nundy et al. evaluated the impact of COVID-19 on SDGS with specific focus on socioeconomic, energy-environment and transport sectors in 2020 [13]. Khetrapal and Bhatia assessed the pandemic impact on SDG3 (Good Health and Well-being) from the perspectives of health of children and women, support of health system, and management of emergencies [14]. Elavarasan et al. analyzed the path of renewable and sustainable energy transition, digital transformation of the energy sector, and energy affordability in the post-COVID world [10]. However, most of these studies are qualitative assessments with limited quantitative examinations. Elavarasan et al. performed a hybrid qualitative and quantitative impact analysis in terms of the targets of the SDGs with a

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ranking methodology [11]. However, the key impact assessment score in this study was evaluated by subjective expert knowledge rather than an objective evaluation framework. In addition, the impacts were only evaluated at the global level, without knowing the impacts for various types of countries. Without an objective and comprehensive evaluation, it is difficult to understand the impacts on specific SDGs, SDG targets, and SDG indicators for developed and developing economies. Such an understanding is urgently important for the government and non-state stakeholders to identify critical areas for targeted policy to resume and speed up the progress to achieve SDGs by 2030.

One of the challenges for a quantitative assessment of COVID-19 impacts on SDGs is that the complex non-linear relationship among SDG indicators makes the traditional linear statistical evaluation and prediction models less effective. For example, Storm et al. stated that the econometric analysis is not sufficiently flexible to capture the non-linearities, which were so common to the processes in environmental systems [15]. Compared with the traditional methods, machine learning approaches can better capture complex non-linear relationship between responses and predictors so as to show better accuracy [16–20].

To fill this knowledge gap, this research quantified the impacts of COVID-19 on SDGs at the indicator level using machine learning. The prediction is based on the expected changes in GDP and population, because both historical data and future projections related to GDP and population are widely available for developing models and the success of SDGs highly depends on economic growth. The model can predict 42 SDG indicators in 31 targets and 16 SDGs with reasonable accuracy (Material and methods, Table S1 and Fig. S1). Other indicators were thus excluded due to either lack of data or low prediction accuracy (testing $R^2 < 0.6$) including all indicators in SDG 5 (Gender Equality). As a result, the analysis focused on these 42 SDG indicators which are most relevant to GDP and population. Specifically, this research addressed two research questions. First, what are the short- and middle-term impacts of COVID-19 on each SDG at the global level? Second, how do the impacts differ between emerging market and developing economy (EMDE) and advanced economy (AD)?

To answer these questions, the research first used historical data to develop and test a variety of supervised machine learning models with cross-validation to predict each SDG indicator (response) based on four predictors (population, GDP, annual GDP growth rate, and time). Then, this research predicted each SDG indicator between 2020 and 2024 using the best model and projected GDP and population. To reflect the impact of COVID-19, this research used four sets of GDP projection data to represent one no-COVID-19 scenario and three post-COVID-19 scenarios. Note that the post-COVID scenarios include during-COVID and post-COVID scenarios. Specifically, the International Monetary Fund (IMF) released two GDP projections in October 2019 and October 2020 [21, 22] which were used to represent the no-COVID-19 scenario and a COVID-19 (S1) scenario, respectively. Specifically, the COVID-19 (S1) scenario is very optimistic that the GDP will quickly recover to the pre-COVID-19 trajectory in 2021 with a global GDP growth rate of 5.2%. Given the continuation of the COVID-19 pandemic worldwide, mitigation measures affecting the economy are likely to be continued at least until 2022 [23]. Therefore, this research also examined two less optimistic COVID-19 scenarios in which the GDP recovers to the pre-COVID-19 trajectory in 2022 (COVID-19 (S2)) and 2023 (COVID-19 (S3)), respectively. Note that the GDP projections of the three COVID-19 scenarios in 2020 are the same. As the uncertainty of longer GDP projection becomes increasingly higher, this study did not predict the SDG indicators beyond 2024.

Next, this research normalized and aggregated the predicted SDG indicators into SDG performance. Specifically, the SDG performance is a metric based on multiple SDG indicators to represent the overall performance towards achieving each SDG. A higher value is more desired indicating closer to achieving an SDG (see details in the Methods). This research quantified the impact of COVID-19 using the predicted SDG performance and indicators in the no-COVID-19 and the COVID-19 scenarios in the same year. In other words, this research exclusively focused on how the SDGs would be with COVID-19 as compared to how they would be without COVID-19 during 2020–2024, rather than how the SDGs will change from 2019.

Compared with the existing research, the innovation and contribution of this study lie in the following two aspects. First, this study applied machine learning approaches to estimate the non-linear relationships between predictors and responses, which improves the estimation accuracy. Second, to the best of our knowledge, this is the most comprehensive quantitative evaluation of the impacts of COVID-19 on SDGs both at the global level and country groups level, which depicts a more specific picture of impacts.

2. Material and methods

2.1. Indicator selection and data sources

This study proposed three criteria to select predictors including 1) the availability of both prediction and historical data; 2) the association with global sustainable development; and 3) low correlation among predictors. The population- and economy-related indicators meet both the first two criteria [24–27]. For the population-related indicators, this study selected the “Total population”, “Urban population”, “Female population”, “Male population”, “Population ages 0–14″, “Population ages 15–64, “Population above 65″ and “Annual population growth rate (%)”as candidates. For the economy-related indicators, this study selected “GDP (current US$)”, “GDP (constant 2010 US$)”, “Annual GDP growth rate (%)”, “GDP per capita (constant 2010 US$/capita)”, and “GDP per capita (current 2020 US$/capita)” as candidates. In addition, the indicator “Time (measured by year)” was also incorporated to capture the potential variation associated with time. The final predictors are indicators “Total population”, “GDP (constant 2010)”, “GDP growth rate” and “Time (measured by year)”. The specific selection process is shown in the Supplementary material (Figs. S1 and S2).

This study selected candidate SDG indicators (responses) from datasets provided by the UN [28], World Bank [29], and the 2020 SDG Index and Dashboards Report [5]. The 2020 SDG Index and Dashboards Report was published by the Sustainable Development Solutions Network which operates under the UN auspices to promote the implementation of the SDGs and the Paris Climate Agreement. There are in total 42 SDG indicators in the dataset covering 16 SDGs and 31 SDG targets for 213 countries and regions. The temporal coverage of individual SDG indicators varies in the dataset, with the longest from 1990 to 2019. The historical data of all the predictors are from the World Bank [30]. The projected data of the predictor “GDP growth (%)” and “GDP (constant price)” under the COVID-19 (S1) scenario are from the IMF World Economic Outlook database released in October 2020 [21]. This research also considered two less optimistic scenarios in which GDP recovers to the 2019 level in 2022 and 2023, respectively (Fig. S3). The hypothetical projected GDP data under the no-COVID-19 scenario are from the same source released in October 2019 before COVID-19 [22]. The projected data of the predictor “Total population” are from the UN’s World Population Prospects database in 2019 [31]. This study collected the projected data for 187 countries and regions (Table. S2). The classifications of EMDE (149 countries and regions) and AE (38 countries and regions) are from IMF [21]. This study predicted the annual value of each SDG indicator from 2020 to 2024 based on the available data for these predictors.

2.2. Machine learning models for prediction

This study developed and tested three types of widely used machine learning models, including support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGBoost), to model the historical relationship between the four predictors (GDP, GDP growth rate, Total population, and Time) and the response (each SDG indicator). For each response, this research selected the best model (with the highest R^2 on test sets) for prediction.

In particular, SVM represents complex non-linear patterns in a hypothetical space which is a form of linear or non-linear function in a high dimensional feature space, where the complex non-linear patterns can be simply represented [32]. In the new space, SVR aims to construct an optimal hyperplane that fits data and predicts with minimal empirical risk and complexity of the modeling function [32]. RF is an ensemble decision tree-based model for classification and regression tasks by taking the average estimation of the individual trees [33]. It can reduce the sum of variance induced by a single decision tree, correct the decision tree's habit of overfitting to their training set, and handle conditions with a large amount of missing data [33]. XGBoost generates an estimation model in the form of an ensemble of weak decision tree-based estimation models and constructs the final estimation in an iteration process [34]. For each iteration, it first finds the best splitting points via information gain, and assigns a prediction score to the two new leaves, then prunes the tree by deleting the nodes with negative gain [34].

This study split the entire dataset by years into a training set and several test sets. The number of test sets is based on the last available year of the SDG indicator. For example, if the last year of an indicator is 2018, the last six years are the period of the test sets with data in each year as a separate test set. The rest of the data as a whole is the training set. For the model training, three-fold cross-validation is used to optimize the hypermeters and avoid overfitting. Importance of the predictors can be found in Fig. S4. This research used the coefficient of determination (R^2) to evaluate the prediction accuracy. This study used 60% explained variance as the criterion for model selection (i.e., $R^2 >= 0.6$ on each test set) for each SDG indicator (Fig. S5). This means the major variation (>= 60%) of a specific indicator can be captured in the model, but the predicted value may be not as reliable for individual countries (see an example in Fig. S6). Therefore, this research only focused on the global level and country groups (AE and EMDE) level for the analysis, rather than focusing on individual countries. For the prediction, this study re-trained the best model with the entire data set for each SDG indicator. Bootstrap sampling was also used to reduce uncertainty which is a robust method to calculate confidence intervals for machine learning algorithms [35]. This research calculated the confidence intervals of the prediction results by bootstrap resampling the training set for 100 times and filtered out the 5% quantile, 50% quantile (median value), and 95% quantile prediction values. This study focused on the median value in the discussion as it will happen with the highest probability.

2.3. Normalization and aggregation

To ensure comparability across SDGs, the predicted indicator values for each SDG were normalized. This study proposed a simpler normalization method rather than using the min-max normalization method [36, 37] for two reasons. First, the purpose of the min-max method is to compare the progress of SDGs among many countries across years with a maximum value of 100. However, the main goal of this research is to analyze the effect of COVID-19 at the global level and country groups level, which means the performance of an SDG indicator in 2019 should be the base (i.e., SDG performance = 100). Second, for the min-max method, the lower and upper bound have to be selected first, which are usually set by the 2.5th quantile or top five performers [36–38]. This is impractical for us because this study only focused on five years for the prediction (2020–2024). The simpler normalization method is represented using the following formulas:

$$SDG\ indicator\ performance = \begin{cases} \dfrac{x}{x_{2019}} \times 100\ for\ postive\ directional\ indicator\ (e.g.,\ GDP\ per\ capita) \\ \dfrac{x_{2019}}{x} \times 100\ for\ negative\ directional\ indicator\ (e.g.,\ GHG\ emissions) \end{cases}$$

where $SDG\ indicator\ performance$ represents the normalized performance for a given SDG indicator, x is the value of a given SDG indicator before normalization, and x_{2019} stands for the value of the indicator in 2019. "Positive directional indicator" means larger value corresponds to desired performance (e.g., GDP per capita), while "negative directional indicator" means the opposite (e.g., GHG emissions). The direction of the indicator is shown in Table S3.

Note that this normalization method cannot be directly applied to indicators with negative value such as "GDP growth (%)"as it will mislead the performance for two reasons. First, there will be negative values which mislead the direction of the SDG indicator performance in two cases. For example, the value of "GDP growth (%)" is 2.4% in 2019 and −4.4% in 2020, which would lead to the normalized performance in 2020 of −183 using the normalization method. Another case is that the value of "GDP growth (%)" is 0.4% in 2019 and −4.4% in 2020, which means the normalized performance in 2020 would be −1100. The latter case is obviously better than the former, but the normalized SDG indicator performance shows the opposite (−1100 worse than −183). Second, the high variation of "GDP growth (%)" will mislead the performance of SDG 8. The value of "GDP growth (%)" decreases from 2.4% in 2019 to −4.4% in 2020 and back to 5.6% in 2021 under the COVID-19 scenario. This means the normalized SDG indicator performance would be −183 in 2020 and then back to 233 in 2021 (Fig. S7). The high variation will dominate the performance of SDG 8 and dilute the effects of other indicators, as shown in Fig. S7 that the performance of SDG 8 will decline by 61% in 2020 under the COVID-19 scenario and then become even higher than that under the no-COVID-19 scenario in 2021. Therefore, this research proposed a piecewise function to re-normalize the indicator "GDP growth (%)". This study assigned 0 value for the negative growth rate, and cut the change of GDP performance by 2/3 for the positive growth rate (Fig. S7). For example, if "GDP growth (%)" decreases from 2.4% in 2019 to −4.4% in 2020 and increases back to 5.6% in 2021, the renormalized value will be 0 in 2020 and 144 (100 + ((5.6% / 2.4%) – 100) / 3 = 144) in 2021 (Fig. S6). The re-normalization will not change the trend of "GDP growth (%)", but helps show the effect of other indicators in SDG 8 (Fig. S7). This research also tried other ratios like 3/4 which yielded similar results. For these cases, a piecewise function was used for normalization (Fig. S7). After normalizing all SDG indicators, the performance of related indicators was aggregated using the arithmetic mean to yield the performance for specific SDGs [36, 37]. Then this study aggregated all SDG performance using the arithmetic mean to yield an overall performance [36, 37].

3. Results and discussion

3.1. Short-term global impact in 2020

The results show that a 7.7% decline of the overall SDG performance was expected in 2020 compared to the no-COVID-19 scenario in the same year, (i.e., the difference of the SDG performance in 2020 in two scenarios compared to the SDG performance in 2020 in the no-COVID-19 scenario) (Fig. 1). At the SDG level, the performances of 12 socioeconomic-related SDGs were expected to decline by 3.0–22.3% in 2020, while those of 4 environment-related SDGs increased by 1.6–9.2%.

The SDGs with declining performance in 2020 due to COVID-19 all highly depended on economic development. Among them, SDG 8 (Decent Work and Economic Growth) suffered the greatest decline (−22.3%) in 2020. All its six indicators would decline (Fig. S8) with the largest for, not surprisingly, the indicator "GDP growth (%)" (−100%) (Fig. S9). However, the existing study concluded that SDG 1 is the most

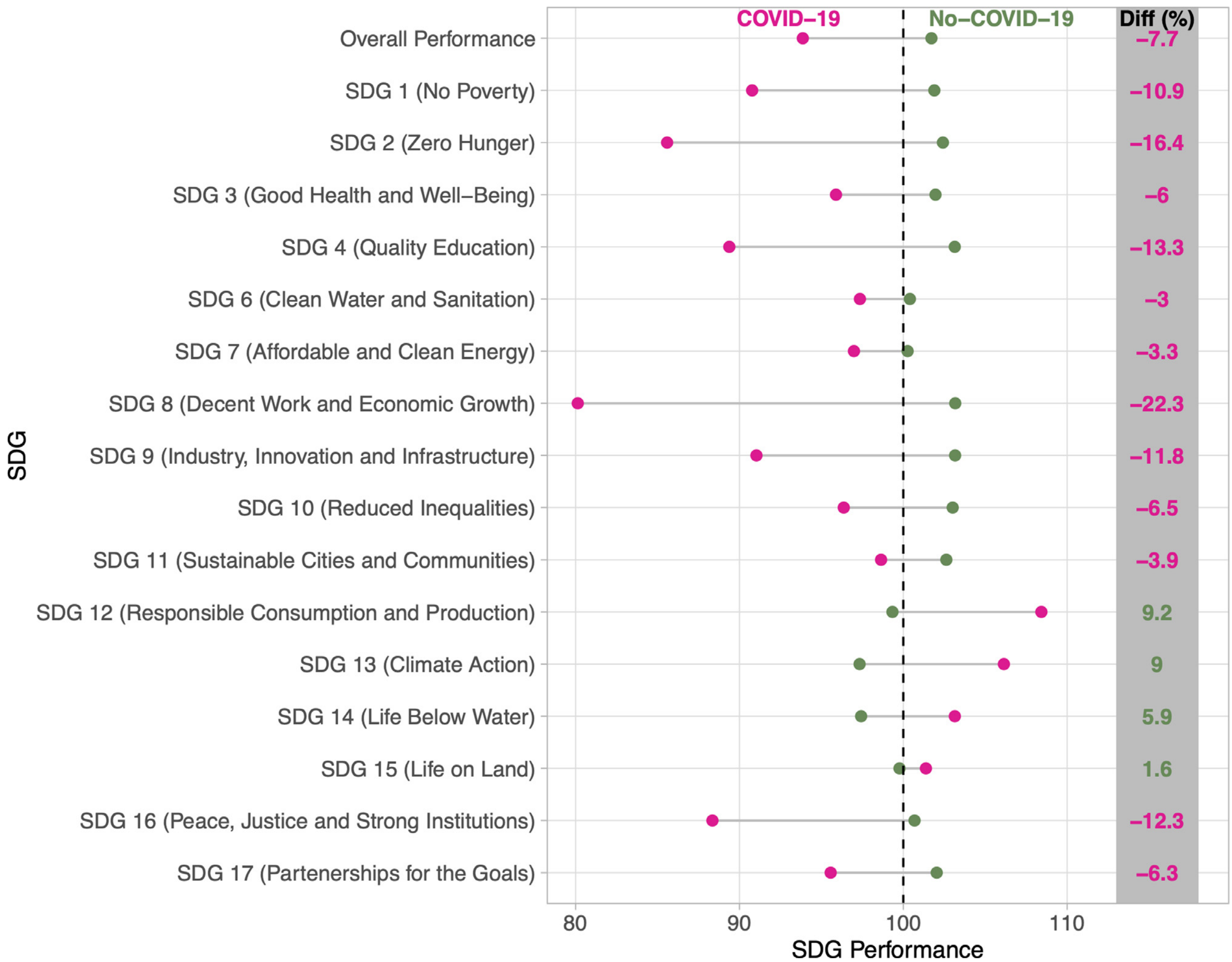

Fig. 1. Comparison of SDG performance in 2020 under the COVID-19 and no-COVID-19 scenarios. "Diff (%)" denotes the percentage change of the SDG performance in 2020 in the COVID-19 scenario as compared to that in the no-COVID-19 scenario, representing the impact of COVID-19 on the SDG in 2020. SDG performance is normalized based on those in 2019 (SDG performance = 100 in 2019). Note that SDG 5 (Gender Equality) is excluded as none of its indicators can be predicted with reasonable accuracy ($R^2 < 0.6$), and the projections of the predictors in 2020 are the same under three COVID-19 scenarios. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

affected goal by COVID-19 [11]. The difference is mainly from the definition of the impacts of COVID-19 on SDGs. This research defined the impacts with the consideration of the difference between COVID-19 and no-COVID-19 scenarios. However, the result from the current study defined the impact only with the consideration of COVID-19 scenario. The second largest predicted decline was for SDG 2 (Zero Hunger) with 16.4% decrease in its performance. Specifically, the indicator "Number of people with undernourishment" in 2020 was predicted to increase from 0.79 billion to 0.95 billion due to COVID-19 (Fig. S9). The latest UN Sustainable Development Goals Report predicted that small-scale producers are hit hard by the pandemic [3]. The performance of SDG 4 (Quality Education) decreased by 13.3% as the third largest decline. More than 8 million children were predicted to be out of school due to COVID-19 in 2020, making its indicator "Number of children out of school" up to around 60 million in 2020. This is largely due to remote learning remains out of reach for many students especially those in developing countries [3]. For SDG 16 (Peace, Justice and Strong Institutions), the next largest declining SDG (−12.3%), "Corruption perception index (worst 0–100 best)" decreased from 45.4 in the no-COVID-19 scenario to 39.8 in the COVID-19 scenario. This is reflected by studies such as Gallego et al. which found increased corruption due to relaxed public procurement rules and procedures in many places to expedite transactions for pandemic mitigation [39]. SDG 9 performance declined by 11.8% (Industry, Innovation and Infrastructure). Notably, the indicator "Air transport, passengers carried" decreased from 4.8 billion without COVID-19 to 3.0 billion with COVID-19 (Fig. S9), which was widely expected and observed due to travel restrictions during the pandemic [40]. For SDG 1 (No Poverty, −10.9%), the prediction showed about 200 million additional people were "living less than $3.20 a day" due to COVID-19 in 2020. The UN also expected that COVID-19 cause the first increase in extreme poverty in decades with 71 million people being dragged back into extreme poverty (less than $1.25 per day) [3].

While the SDGs depending on economic development were projected to suffer from COVID-19, other SDGs that are more relevant to the environment actually improved in 2020 during the pandemic. Specifically, the performances of SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land) increased by 9.2%, 9.0%, 5.9%, and 1.6%, respectively, in 2020 in the COVID-19 scenario compared to the no-COVID-19 scenario. The prediction shows the per capita impacts on aquatic and terrestrial ecosystems decreased by 9.2%, 5.9%, and 1.6% due to COVID-19, respectively, approximated by the predicted changes of the SDG 12 indicator "Forest rents ($/capita)", SDG 14 indicator "Fisheries production (kg/capita)", and SDG 15 indicator "Forest area as a proportion of total land area (%)" (Fig. S9). This is also reflected in Sachs et al. which considered economic decline induced by COVID-19 caused a short-term reduction in threats to the ecosystem and consumption of natural resources [5]. For SDG 13, the indicator "Energy-related carbon emissions (kg/capita)" declined from 4.9 kg/capita in the no-COVID-19 scenario to 4.5 kg/capita in the COVID-19 scenario based on the projection. This is equivalent to an annual reduction of 5.9% in global carbon dioxide (CO_2) emissions in 2020 with COVID-19 from the 2019 level. Similarly, Liu et al. estimated the global CO_2 emissions declined by 8.8% in the first half of 2020 [41], and their follow-up estimates indicated a 5.5% reduction in 2020 until October 31 compared to the same period in 2019 [42]. The UN also predicted that COVID-19 caused a 6.0% drop in greenhouse gas (GHG) emissions for 2020 [3].

3.2. Middle-term global impact by 2024

Fig. 2a and b shows the middle-term impact of COVID-19 by 2024 on SDGs. In particular, the difference of the overall SDG performance in 2021 between the COVID-19 (S1) and no-COVID-19 scenarios was only 2.5, down from 7.8 in 2020, indicating in 2021 SDGs were closer to what they would be without COVID-19 than they are in 2020. This is due to the optimistic projection of over 5% annual GDP growth in 2021 by IMF [21]. However, in COVID-19 (S2) and (S3) scenarios in which global GDP stagnated in 2021 (pandemic continues in 2021), the difference of the 2021 overall SDG performance compared to that in the no-COVID-19 scenario was 6.4 and 6.5, respectively. A prolonged pandemic slows down the economic recovery and thus slows down the global SDG progress.

Among the 12 socioeconomic-related SDGs whose performance declined in 2020 due to COVID-19, in general, quicker GDP recovery will lead to quicker SDG performance recovery (Fig. 2). For example, the differences of all the 12 SDGs in 2021 between the COVID-19 (S1) and no-COVID-19 scenario were smaller than those in 2020. None of the 12 SDG performance was able to reach the level they would be without COVID-19 in 2021 in all three COVID-19 scenarios. Among the four environment-related SDGs the performance of which increased in 2020 due to COVID-19, quicker GDP recovery would lead to quicker SDG performance decline. For example, the performance of the four SDGs in 2021 was very close to their 2019 levels under the COVID-19 (S1) scenario, but was still higher than their 2019 levels under the COVID-19 (S2) and COVID-19 (S3) scenarios.

Fig. 2c shows how long COVID-19 will make each SDG lag behind its original trajectory without COVID-19 until 2024, defined as the difference of SDG performance in 2024 with and without COVID-19 divided by the average annual change of the SDG performance between 2019 and 2024 without COVID-19. This measure indicates the time (in years) it would take for each SDG to come back to its original progress without COVID-19. Overall, global SDG progress will lag behind the original trajectory by 1.9 to 4.1 years in the three COVID-19 scenarios, roughly equivalent to delay of achieving SDGs for 1.9 to 4.1 years due to COVID-19. For individual SDGs, although SDG 2 (Zero Hunger), SDG 8 (Decent Work and Economic Growth), and SDG 9 (Industry, Innovation and Infrastructure) will be greatly affected by COVID-19 in 2020 (16.4%, 22.3%, and 11.8 declines, Fig. 1), they will recover relatively quickly compared to their original trajectories without COVID-19, making them three of the least lagged SDGs due to COVID-19 by 2024 (about 1.0 to 3.0 year). In contrast, SDG 7 (Affordable and Clean Energy) would decline only by 3.3% in 2020 due to COVID-19, but it lags behind its original trajectory for approximately 1.8 to 8.0 years by 2024 as one of the most lagged SDGs. This is because the relative slow increment in performance of SDG 7 (with the annual increment of 0.4), which could also explain the relative long lags in SDG 6. Note that the pandemic will also slow down the process of environmental deterioration and gain us more time (0.9–4.1 years) to stabilize and reverse the originally declining trajectories of SDGs 12, 13, 14, and 15. Fig. 2c also shows that the progresses of 12 socioeconomic-related SDGs will be further lagged-behind due to the slower GDP recovery, and the worsening of four environment-related SDGs (12, 13, 14, and 15) will be further slowed due to the slower GDP recovery. Nevertheless, the society will still gain some extra time from COVID-19 for the four environment-related SDGs, which provides a great opportunity to accelerate the global transition towards environmental sustainability. For example, previous studies estimated that the average annual low-carbon investment under a Paris-compatible pathway is about USD 1.4 trillion per year globally between 2020 and 2024 [43, 44], which is just about 10% of the total pledged COVID-19 stimulus to date [44] and can be further reduced considering the extra time gained from COVID-19.

The results are largely based on post-COVID-19 GDP projections. The results imply the pivotal role of rapid economic recovery on SDGs. Indeed, continuous economic growth is considered as one of the necessary conditions for the success of SDGs [6, 43]. With a slower economic recovery, the recovery of SDGs will be slower and the gap caused by COVID-19 will be larger. Note that economic growth is also a barrier for improving certain environmental conditions, as indicated by the findings of improved SDG 12, 13, 14, and 15 due to COVID-19. Post-COVID-19 economic recovery should emphasize in areas that can help decouple economic growth from negative environmental impacts.

3.3. Impacts on emerging markets and developing economies and advanced economies

When our model is tested for EMDE and AE countries separately, fewer SDG indicators can be predicted with reasonable accuracy (R^2 >= 0.6): 27 indicators in 14 SDGs for EMDE and 18 indicators in only 8 SDGs for AE (Figs. S10 and S11). This is largely because of smaller sample size in split datasets for the two country groups. Therefore, this study only compared the impacts of COVID-19 in EMDE and AE countries on the performance of individual SDG indicators (2019 = 100).

The results show COVID-19 had severe negative impacts on SDG indicator performance for both EMDE and AE countries in 2020, with EMDE countries hit harder (Fig. S12). Specifically, the median declines of individual SDG indicator performance in 2020 due to COVID-19 were −6.3% and −5.1% for EMDE and AE, respectively. This indicates EMDE countries are more vulnerable to economic downturn in sustainable development. The indicator "GDP growth (%)" in SDG 8 declined the most for both EMDE (4.5% no-COVID-19 vs. −3.2% COVID-19) and AE (1.7% no-COVID-19 vs. −5.8% COVID-19) in 2020 among all the predicted SDG indicators (Fig. S11). The other indicator that declined the most for both EMDE and AD is "Air transport, passengers carried (billion people)" in SDG 9, from 2.5 billion for EMDE and 2.2 billion for AE without COVID-19 to 1.5 billion with COVID-19 in 2020, respectively. The indicator "Undernourishment (%)"in SDG 2 increased from 2.8% to 5.6% due to COVID-19 in 2020 for AE, making its performance declining by 50.0%, while the decline of the performance of the same indicator in EMDE was only 14.3%. However, the percentage of population undernourished in EMDE (14.1%) was still much higher than that in AE (5.6%) in the COVID-19 scenario in 2020. On the other hand, the performance of environment-related SDG indicators increased for both EMDE and AE in 2020. In particular, the performance of indicator "Forest rents ($/capita)" in SDG 12 had the largest increases for both EMDE and AE (18.9% and 22.7%, respectively), indicating lessened impact on terrestrial ecosystems in both country groups (Fig. S11).

As shown in Fig. 3a-c, by 2024, the median changes of SDG indicator performance compared to the no-COVID-19 scenario are −2.3% to −5.5% and −1.5% to −2.8% for EMDE and AE, respectively. The largest decline for AE will be the performance of the indicators "Exports of goods and service ($/capita)" (−7.4% to −7.5%) and "Triadic patent (per thousand people)" (−5.9% to −11.8%) in 2024 due to COVID-19. For EMDE, the performance of the indicators "Manufacturing ($/capita)" and "Labour ($/capita)" will decline the most (−11.4% to −18.8% and −7.5% to −20.4%) in 2024 due to COVID-19. These results represent long-lasting impacts of COVID-19 on the global production and consumption system. Indicator "GDP growth (%)" will increase the most (7.1% to 28.1%) for AE in 2024. The largest increase for

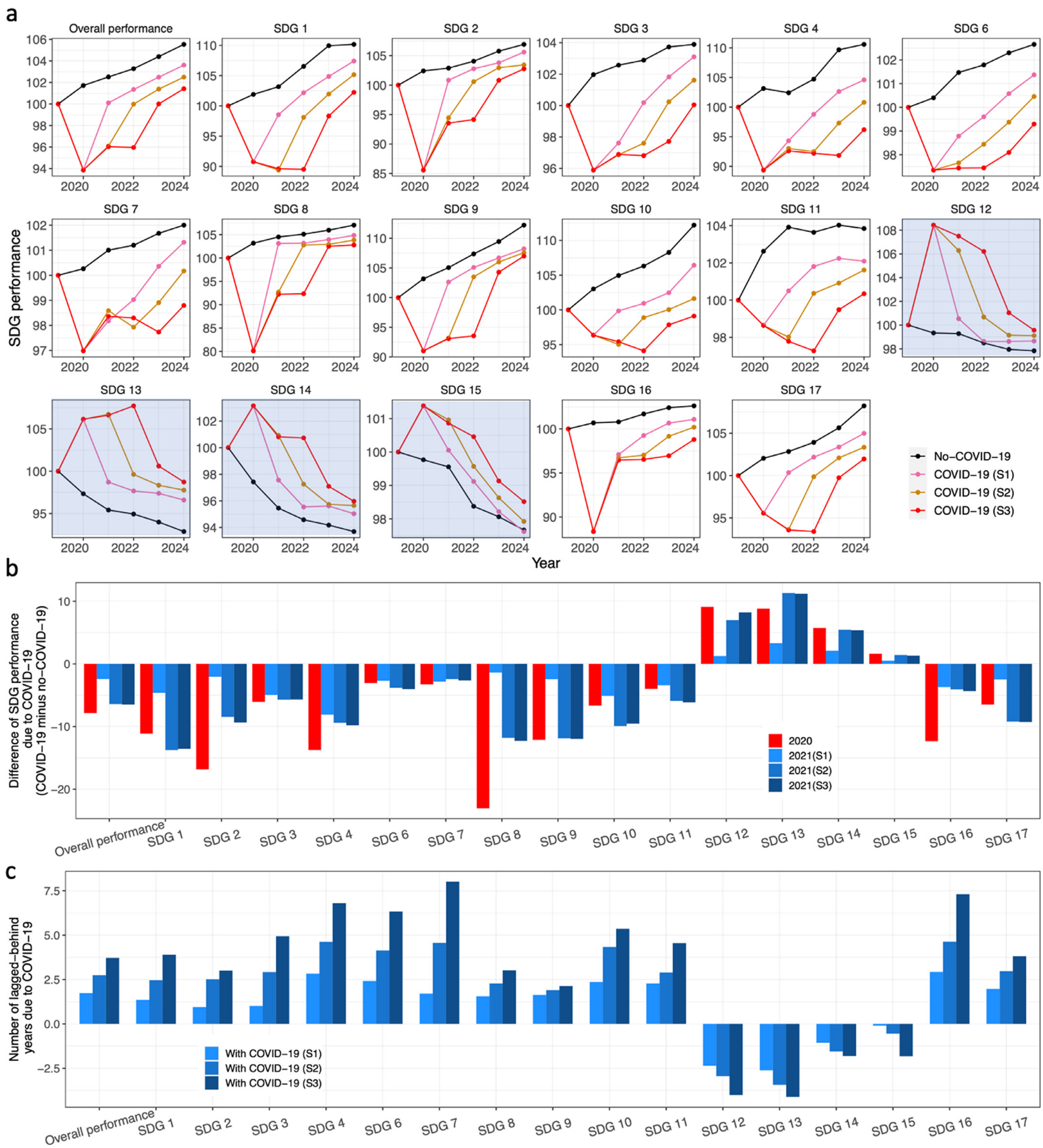

Fig. 2. Middle-term impact of COVID-19 on SDGs by 2024. (a) Comparison of SDG performance between the no-COVID-19 and three COVID-19 scenarios from 2020 to 2024. Four environment-related SDGs with declining performance in the no-COVID-19 scenario are differentiated with different background colors. (b) Difference of SDG performance between the no-COVID-19 and each of the three COVID-19 scenarios in 2020 and 2021. Note that the projections of predictors are the same in 2020 under the three COVID-19 scenarios. (c) Number of years lagging behind the original trajectory for each SDG by 2024 due to COVID-19 under the three COVID-19 scenarios. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

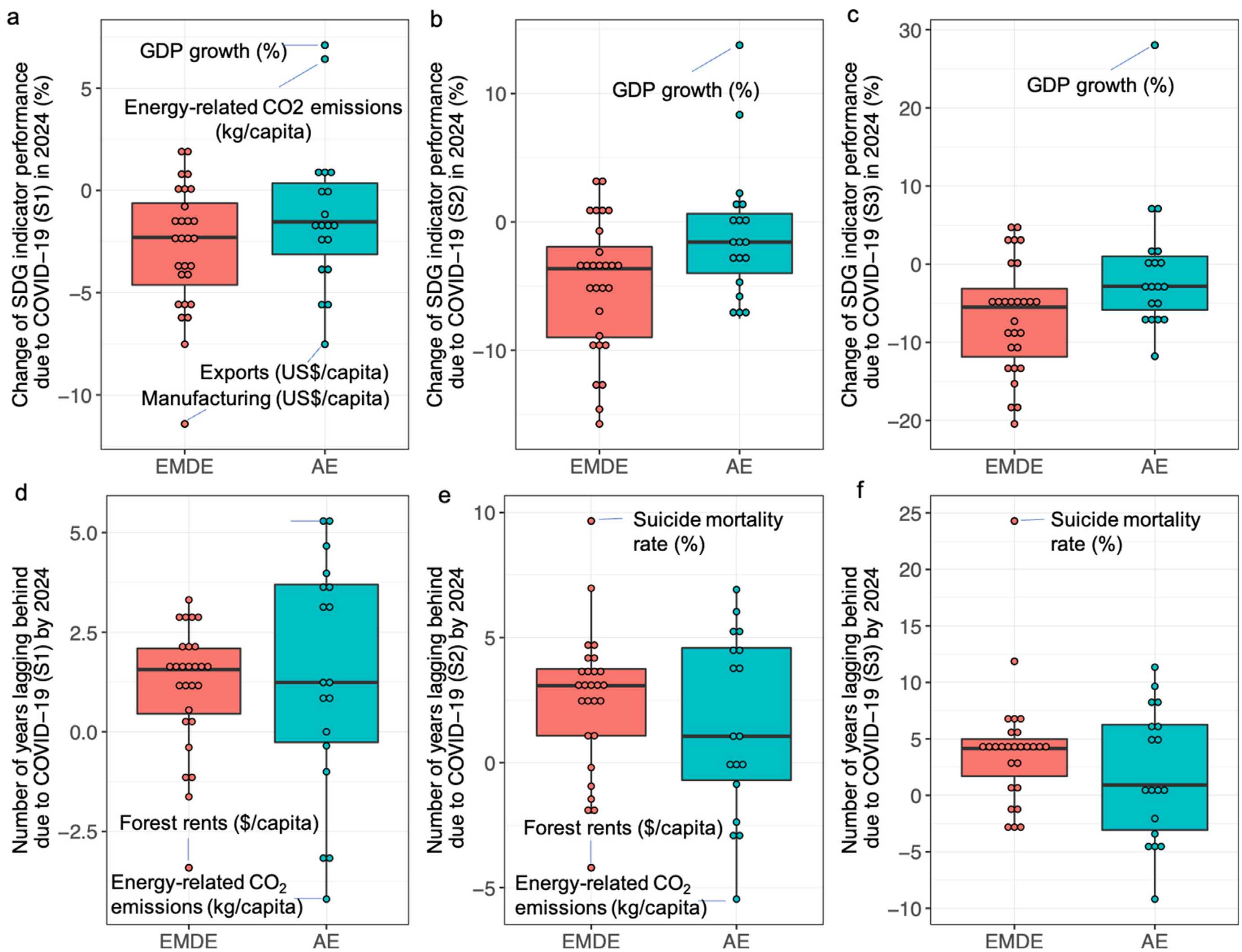

Fig. 3. Impacts of COVID-19 on SDG indicator performance for EMDE and AE. (a-c) Middle-term impacts in 2024 under the three COVID-19 scenarios (S1, S2, and S3). (d-f) Number of years lagging behind the original trajectory without COVID-19 for each SDG indicator by 2024 under the three COVID-19 scenarios (S1, S2, and S3). In each boxplot, the central rectangle box spans the first to the third quartile. The central line segment inside the rectangle represents the median value. Only the indicators with testing $R^2 >= 0.6$ are shown (Figs. S8 and S9).

EMDE will be the performance of the indicator "Energy-related carbon emissions (kg/capita)" in 2024. While economic recovery is welcome, a strong "rebound" of GHG emissions is worrisome.

Fig. 3d-f shows the number of years each SDG indicator lags behind its original trajectory without COVID-19 by 2024 for EMDE and AE. Because AE countries generally have smaller declines across all SDGs both short- and middle-term, they actually will be closer to their original trajectories by 2024 compared to EMDE countries. This is counterintuitive as the EMDE countries are predicted to own the faster post-COVID-19 economic recovery by IMF (S1). Specifically, IMF predicted that average GDP per capita of AE countries will recover to the 2019 level by 2023, but EMDE countries will be back to the same level two years earlier by 2021. The faster post-COVID-19 economic recovery for EMDE countries compared with AE countries will still remain under other two COVID-19 scenarios (S2 and S3). This may show the better resilience of the AE countries on the pandemic, which highlights the importance of sustainable development. The slower economic recovery for AE countries also explains additional time gained for SDG indicators such as "Energy-related carbon emissions (kg/capita)" with nearly 4 to 5 years. Note that the indicator "Suicide mortality rate (%)" will be lagged most for EMDE countries under COVID-19 scenarios (S2 and S3), which is due to the originally slow progress in the no-COVID-19 scenario (annual increment of 0.4).

4. Conclusions

This study predicted SDG indicators from 2020 to 2024 in a no-COVID-19 scenario and the three COVID-19 scenarios based on projected GDP and population in each country or region. Prior to this work, most existing studies have only qualitatively evaluated the impact of COVID-19 on SDGs. This study showed COVID-19 led to short-term declines of 12 socioeconomic-related SDG performances in 2020. SDGs and SDG indicators closely related to economic growth were affected the most, such as SDG 8 (Decent Work and Economic Growth) and SDG 2 (Zero Hunger). On the other hand, four environment-related SDGs would actually be improved, likely due to reduced human activities during COVID-19, including SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land). After 2020, the quicker GDP recovers, the quicker non-environment-related SDG performance will recover and the quicker the environment-related SDG performances will worsen. By 2024, there will still be one to eight years lagging behind for most SDGs compared to the situation without COVID-19. At the same time, the downward trajectories of the four environment-related SDGs will be slowed down for up to 4.1 years. The impacts of COVID-19 on SDGs are different for countries. In short-term, EMDE countries will be affected almost twice more than AE counties are in 2020. The recovery of EMDE countries is relatively slower than that of AE countries. By 2024, SDGs of the AE countries will be closer to their pre-COVID-19 trajectories than those of the EMDE countries.

The results rely on machine learning models with GDP and population as key predictors. Other factors, such as technology development and new policy intervention, could also play critical roles in driving SDGs, but are excluded in our model due to the lack of reliable future projections. Future research should explore ways to incorporate other relevant variables in the prediction. The results are also based on the assumption that the tested relationship between the predictors (GDP, population, etc.) and each of the responses (SDG indicators) will remain in the future. In addition, this study also finds pandemic-related indicators are scarce in existing SDG indicators, especially for SDG 3 (Good Health and Well-Being). Currently, there is no indicator in SDG 3 directly on pandemics. Future efforts should consider including pandemic-related indicators in the suite of SDG indicators to better reflect the impact of pandemics on sustainable development.

Data availability

The datasets analyzed in this study are publicly available as referenced within the article. All data and code are available from the corresponding author on request.

Ethic approval

Ethic approval is not applicable.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest in this work.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.fmre.2022.06.016.

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