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Estimating CO₂ emissions from emergency-supply transport: The case of COVID-19 vaccine global air transport

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ARTICLE INFO

Handling Editor: Zhifu Mi

Keywords:
COVID-19
IPAT analysis
“Expression of uncertainty in measurement (GUM)’’
Monte Carlo simulation
Natural and unnatural disaster
Sustainability

ABSTRACT

The environmental cost of disaster-related emergency supplies is significant. However, little research has been conducted on the estimation of emergency-supply transportation-related carbon emissions. This study created an “emergency supply emission estimation methodology” (ESEEM). The CO₂ emissions from the global air dispatch of COVID-19 vaccines were estimated using two hypothetical scenarios of one dose per capita and additional doses secured. The robustness of the model was tested with the Monte Carlo Simulation method (MCM) based one-sample t-test. The model was validated using the “Expression of Uncertainty in Measurement (GUM)” and GUM’s MCM approaches. The results showed that to dispatch at least one dose of the COVID-19 vaccine to 7.8 billion people, nearly 8000 Boeing 747 flights will be needed, releasing approximately 8.1 ± 0.30 metric kilotons (kt) of CO₂. As countries secure additional doses, these figures will increase to 14,912 flights and about 15 ± 0.48 kt of CO₂.

According to the variance-based sensitivity analysis, the total number of doses (population), technology, and wealth play a significant role in determining CO₂ emissions across nations. Thus, wealthy nations’ long-term population reduction efforts, technological advancements, and mitigation efforts can benefit the environment as a whole and the CO₂ burdens associated with current COVID-19 and any future disasters’ emergency-supply transportation.

1. Introduction

The environmental impact of natural and unnatural disasters (like pandemics and climate change), particularly the CO₂ emissions associated with disaster relief supplies (henceforth referred to as emergency supplies), is a critical but understudied aspect of disasters. There is compelling evidence that lifesaving emergency supplies have a substantial economic and environmental impact (Ye et al., 2020). Because of the uncertainty surrounding disaster locations and timing, emergency supplies are frequently prepositioned without being consumed, resulting in massive waste both economically and environmentally (Ye et al., 2020). This uncertainty about the location and timing of disaster supplies may be the primary reason for the general lack of environmental studies, specifically the CO₂ emission impact of disaster supplies. Uncertainties concerned with the estimation of transport sector CO₂ release go beyond natural or unnatural disasters whose location and timing are generally uncertain. Even when the locations (starting and ending points) are known, the estimation approaches and thus the results of transportation sector climatic impact estimates during normal times are subject to significant uncertainties. The methodologies used to estimate the transport sector’s GHG releases are subject to significant technical uncertainties (Nocera et al., 2018). Technical uncertainties exist over the precise amount of GHG emitted, or anticipated to be emitted in the case of projections, and the associated variance in atmospheric concentration (Nocera et al., 2018). To make matters worse, uncertainty is increasing as metrics become more relevant to the impacts and damages of climate change (Dessens et al., 2014). Even the “Intergovernmental Panel on Climate Change (IPCC)”, which is a “United Nations” expert on climate change, estimations related to CO₂ and non-CO₂ climate impacts of the aviation sector are being criticized for relatively large uncertainties (Dessens et al., 2014). Based on the above discussion, it can be concluded that the uncertainty of location and timing of disasters has led to a general lack of literature and methodologies for the estimation of any carbon releases expected from the transport of emergency supplies. Second, the currently used methods for the estimation of the transport sector’s climate impacts, including CO₂ emissions, are subject to...
significant uncertainties.

There are four main types of epistemic uncertainties (this type of uncertainty arises from incomplete knowledge about the system) for the transport sector’s GHG emissions estimation. These include (1) current levels, (2) atmospheric concentrations, (3) usage of unique measurement units (like under the IPCC), and simulations (Nocera et al., 2018). Our study’s main uncertainty is somewhat relevant to the first type of epistemic uncertainty that is related to the methods to calculate the current levels of the transport sector’s carbon releases and is general with all categories with widespread and dynamic sources (this issue is resolved by the usage of measuring devices in other stable sectors) (Nocera et al., 2018). In general, a two-step process based on the transport (travel) demand and the related fuel consumption and the carbon releases is adopted to quantify the amount of the transport sector’s carbon releases (Nocera et al., 2018). Our study estimates the expected carbon releases from the air transport of the COVID-19 vaccine by taking into account two-steps the expected demand (consumption) and readily available accounts for air aviation’s carbon releases, such as the per hour carbon releases of a Boeing 747 at cruise speed. It has been shown that the majority of air aviation-related carbon is emitted at cruise levels (Dessens et al., 2014). In contrast, a minor percentage of expected carbon releases from the air transport of the COVID-19 vaccine with no passengers. According to the director of the Northwestern University Transportation Center, “Hani Mahmassani,” COVID-19 vaccines such as Pfizer have a limited usage life once they leave the deep freezers (Schaper, 2020), and in the context of COVID-19 vaccine transportation, the speed of air transport is the only option (“managing director of Cargo in the Americas for United Airlines, Chris Bush” (Schaper, 2020)). When you’re moving vaccines from coast to coast or across the world, there’s one mode of transportation that stands out: air travel (Schaper, 2020). The global aviation industry will play a big part getting COVID-19 vaccines to people in a safe, efficient, timely, and secure way (Federal Aviation Administration, 2021).

Therefore, air transport can be regarded as one of the most important modes of safely and timely dispatch of much-needed COVID-19 vaccines globally. Fig. 1 presents a simple presentation of different sections of a COVID-19 vaccine’s transportation journey and highlights the scope of our study. The nature of natural and unnatural disasters makes it almost impossible to know the exact locations, and hence the distances can’t be exactly measured. However, the consumption (demand) quantity, emissions accounts (per hour carbon releases), and demand-based number of journeys (e.g., flights) can be estimated prior to or in the early stages of a disaster like the COVID-19 pandemics. Using the concept of consumption-based emissions accounting approach (CBA),¹ our ESEEM methodology allocates emissions primarily based on total population or expected volume of consumption (i.e., the requirement for COVID-19 vaccine doses) while using average flight hours (or in other words, average distance) rather than exact distances between emergency supply dispatch and final consumption locations. Although the knowledge about the exact dispatch and destination location could provide much more accurate estimates, the usage of average distance can also provide somewhat reliable findings. Because the average distance between nations is constant for all locations/countries, the use of the average distance logically implies that any change in the location of the COVID-19 vaccination production or consumption will not significantly affect the consumption-based emissions estimations. Furthermore, even when using different procedures for the distance data estimations, the average distance between countries and major destinations does not vary significantly. The robustness of our model is tested using the conventional and MCM-based one sample t-test to prove statistically significant similarities between sample CO₂ emissions estimations (estimated based on our minimum direct distance dataset (MDD) of 243 locations) with a larger population (derived from several datasets including MDD, “Center d’Etudes Prospectives et d’Informations Internationales (CEPII)’ distance data between important cities/agglomerations and capitals (Mayer and Zignago, 2011)). Finally, there are uncertainties associated with disasters such as the currently evolving COVID-19 pandemic (with the passage of time, numerous new COVID-19 variants like Alpha, Beta, Gamma, Delta, and Omicron have emerged) and with transportation sector CO₂ emissions estimates; thus, there is a need to evaluate the uncertainties associated with COVID-19 vaccine air transport-related CO₂ emissions estimates. It is well accepted that estimating measurement uncertainty is critical for the validity of any measurement and is an important quality assurance parameter (Singh et al., 2021). The GUM (“Guide to the Expression of Uncertainty in Measurement”) gives general criteria for evaluating and expressing uncertainty in measurement (Farrance and Frenkel, 2012). The most widely used methods for estimating uncertainty are the “Expression of Uncertainty in Measurement” (GUM, as defined by the “Joint Committee on Guides in Metrology” (Joint Committee for Guides in Metrology, 2008a)) and Monte Carlo Simulation (MCM, as defined in GUM supplements 1 (Joint Committee for Guides in Metrology, 2008b) and 2 (Joint Committee for Guides in Metrology, 2011)) (Mahmoud and Hegazy, 2017). Therefore, we have also used the GUM and MCM, the two most accepted methods, to estimate the uncertainty related to the results of our study. Aside from air transport, our study’s robustness tested and validated ESEEM model has the potential to estimate CO₂ (or pollutant) emissions from transport of emergency supplies via any other mode of transport, such as road, rail, and water, where we have demand estimates or demand can be predicted without the not easily available location estimates. The remainder of the paper is organized as follows: Section 2 provides a detailed literature review on the general environmental and transportation-related impacts of COVID-19. Section 3 presents data sources. Section 4 details the methods. Section 5 represents the results. Finally, sections 5 and 6 discuss results and present conclusions.

2. Literature review

Generally, different aspects of COVID-19’s impact on the environment and carbon emissions have been studied. In terms of the

¹ Under CBA, the consuming nation, not the producing nation, is held accountable for the carbon releases from industrial production and transport sectors (Sajid et al., 2021).
environment in general, the impact of the COIVD-19 pandemic on aerosols and air pollution (Shan et al., 2021), solid and plastic waste management (Vanapalliat al., 2021), circular economy (Ibn-Mohammed et al., 2021), water consumption (Kalbusch et al., 2020), sustainability (Barbier and Burgess, 2020), the climate (Forster et al., 2020), and public awareness (Rousseau and Deschacht, 2020) has been studied. Specifically for CO2 emissions, the impact of COVID-19’s economic and carbon policy on CO2 emissions (Shan et al., 2020), real-time (daily) CO2 emissions (Le Quéré et al., 2020), energy use and CO2 emissions (Sajid and Gonzalez, 2021; Naderipouret al., 2020), and renewable energy (Naderipouret al., 2020) has been studied in detail. Specifically, several COVID-19-related logistics and transport studies have considered the negative effects of the current COVID-19 pandemic on the disruption of transportation activities during the current COVID-19 pandemic. Table 1 summarizes some of the literature on this subject.

There is a general lack of literature on methodologies related to the environmental impacts of disaster-related emergency supplies. Due to uniqueness and data availability issues, many COVID-19-related transport and logistics operations management research studies have resorted to the development of new methods and/or the modification of existing techniques. However, no reference methodology has been developed for pandemic emergency supplies-related CO2 emissions, particularly for the COVID-19 vaccine’s global air transport-related CO2 emissions. Furthermore, few studies, in general, take into account the CO2 emissions associated with pandemic emergency supplies. In particular, a few studies have estimated the carbon emissions expected from the global distribution of the COVID-19 vaccine. Furthermore, the socio-economic drivers of political decisions, economic choices, and social structure, all of which play a role in the occurrence of disasters (Revet, 2020), have not been extensively studied in relation to CO2 emissions for emergency supplies in the related literature.

This study fills the critical knowledge gaps outlined in the preceding paragraph. This study developed a methodology called “emergency supply estimation methodology” (ESEEM) that is tailored to fuzzy data on the location and timing of disasters. Furthermore, this study also estimated the country-specific and aggregate CO2 emissions expected from the global air transport of the COVID-19 vaccine. This includes the emissions from air transport of one dose per capita for 7.8 billion people (ODCV) and the air transport emissions of more than one dose per capita secured by certain countries, i.e., required doses per capita (RDCV). In addition, the socio-economic drivers of political decisions (population and number of doses), economic choices (technology), and forms of social structure (prosperity) are estimated across nations using IPAT (Environmental Impact = Population × Affluence × Technology) and variance-based sensitivity analysis (VBSA). Our study integrates the IPAT with VBSA to estimate the sensitivity (importance) of these three factors to the expected carbon releases from the global air dispatch of the COVID-19 vaccine. The IPAT and its various extensions (ImPACT, IPBAT, and STRIPAT) (York et al., 2003) currently use variance (Chontanawat, 2019), regression (Hwang et al., 2020), and some hybrid approaches (Xia et al., 2020) to estimate the effects of different factors on the environment. Few studies integrate sensitivity analysis using the IPAT method.

The development of the novel ESEEM methodology could aid in the estimation of previously overlooked CO2 emissions from the transport of disaster-related emergency supplies. The novel methodology can be used or modified by other studies to estimate the various disaster relief supplies-related environmental impacts when the exact location and timing of the disaster are unknown or imprecise. Furthermore, estimating the impact of key socio-economic factors can aid in the development of long-term policies that can help reduce the environmental impact of disaster-related emergency supplies in general. The presentation of expected CO2 emissions from the global air transport of ODCV and RDCV, as well as the estimation of the impact of key factors, can help mitigate the COVID-19 vaccine’s global air transport emissions. Finally, the IPAT analysis of the COVID-19 vaccine air dispatch-related CO2 emissions policymakers to reduce the CO2 emissions expected from the COVID-19 vaccine’s global air transport. Supplementary figure 1 depicts a graphical overview of our study’s ESEEM methodology.

2 Adaptation of technology has been considered a key economic choice, that has various macro and micro-economic implications across countries (Foster and Rosenzweig, 2010).
Previous research on the impact of COVID-19 on the transportation industry.

| Reference      | Study                                                                 | Main methodology                                                                 |
|----------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Choi (2020)    | This study developed analytical models to investigate how logistics and technology may turn “static service operations” into “bring-service-near-your-home” mobile service operations. | Several analytical models.                                                       |
| Mirticga and Choi (2020) | This study used a multi-method approach to investigate how small and medium-sized transportation companies manage asymmetric client relationships in the face of the COVID-19 epidemic. | Quantitative survey-based statistical methods and qualitative interviews.          |
| Amankwah-Amoah (2020) | This study presented the global airline industry’s response to the COVID-19 pandemic’s environmental shocks. | A firm’s response conceptual framework.                                            |
| Govindan et al. (2020) | The purpose of this study was to assist in demand management in the healthcare supply chain, to alleviate community stress, to disrupt the COVID-19 propagation cycle, and, more broadly, to minimize epidemic outbreaks due to interruptions in the healthcare supply chain. | “Practical decision support system and fuzzy inference system”                   |
| Ivanov (2020)   | A simulation study that raised fresh research concerns about COVID-19’s impact on global supply networks. | Simulations.                                                                      |
| Dai et al. (2021) | This article focused on COVID-19 vaccine transport in a supply chain model with one distributor and one retailer, where the distributor obtains the manufacturer’s COVID-19 vaccines and then resells them to the retailer. | Time-delayed difference equations model.                                         |
| Cuiet al. (2021) | This study examined the effects of COVID-19 shocks on China’s transportation sector. | Computable General Equilibrium modeling (CGE) with decomposition analysis.        |
| Hensher et al. (2021) | The authors investigated the effects of working from home on strategic transportation modeling. | A novel methodology was developed to identify the impact of homework on transportation. |
| Kim and Kwan (2021) | The authors undertook a longitudinal study to determine how the COVID-19 epidemic affected people’s movement. | Various methods for studying longitudinal data.                                   |
| Zhang et al. (2021) | This study analyzed the effects of six developed countries’ COVID-19 transportation policy measures. | Comparison of transport and health-related COVID-19 policies using the PASS approach. |
| Warnock-Smith et al. (2021) | The authors examined the effects of the COVID-19 epidemic on the Chinese passenger air transport sector. | Various empirical statistical analysis methods.                                  |
| Hasselwander et al. (2021) | This study examined the transportation policy implications of COVID-19 in the megacity of Manila. | Analysis of pooled Google and Apple cell phone and GPS data.                     | Map-based analysis.                                                           |

Table 1 (continued)

| Reference      | Study                                                                 | Main methodology                                                                 |
|----------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Tiikkaja and Virti (2021) | The authors studied the impact of the COVID-19 pandemic on public transportation usage and frequency in Finland’s Tampere region. | Causal Bayesian Network (CBN).                                                   |
| Zhu et al. (2021) | This study looked at how COVID-19 recovery preparedness influenced the global air transport industry. |                                                     |

3. Materials and methods

3.1. Data handling

We developed a MDD dataset from a given country (i.e., the United States) to 243 other countries and major autonomous regions using online distance calculators (MapCrow, 2021; DistanceFromTo, 2021). These data were used to estimate the total flight hours needed by a Boeing 747 to fly from the US to the 243 destinations. Using this data, the average (mean) flight hours required to travel from one country to another was estimated (Boeing 747 average (cruise) speed in miles per hour is available at several sources (Badic, 2010; Hopkins, 2020)). Furthermore, two other methods and datasets available from “CEPII” for the estimation of bilateral distances between countries were used. These include two data sets based on simple bilateral distances between (1) important cities/agglomerations (2) and the capitals of countries. Although two weighted bilateral distances between the biggest cities and capitals are weighted using the population contribution of the city to the country’s total population (Mayer and Zipagno, 2011) are also available under the “CEPII,” but the weighted datasets have several missing values and hence not considered in this study. The purpose of using different distance datasets for the estimation of CO2 emissions is to test for robustness and validate our ESEEM methodology. We estimated the total expected emissions from the global air distribution of the COVID-19 vaccine using average flight hours, the total number of Boeing 747 flights required to deliver ODCV to 7.8 billion people (Lei, 2020; Wenqian, 2020; Carbon Independent and “Avia, 2019), and the per-hour carbon emissions released by a Boeing 747 at cruise speed (Carbon Independent and “Avia, 2019). Additionally, using the country-specific worldwide population data from the United Nations “World Population Prospects 2019” (United Nations, 2019) and COVID-19 vaccines secured per capita from Nature’s news article (Mullard, 2020) allowed the estimation of the countrywide consumption-based carbon emissions from the dispatch of ODCV and the aggregated and country-specific carbon emissions from the RDCV.

3.2. Methodology

This section only provides the estimations related to the ESEEM methodology. The estimations related to all other methodologies, including GUM, MCM, IPAT, and “Fourier Amplitude Sensitivity Test (FAST)” analyses, are provided as supplementary methods. The study developed and used the ESEEM methodology to estimate the CO2 emissions from the global air transport of ODCV. In order to estimate the CO2 emissions related to the dispatch of ODCV to all of the world’s population, in the first step, a single dispatch location country k is considered. Afterward, the distances of almost all other countries and major autonomous and semi-autonomous regions from this country k (in miles) are estimated. This will, in theory, help us indicate the total distance needed by a Boeing 747 cargo aircraft to fly at least once from a given dispatch location to all other major COVID-19 vaccine delivery locations around the globe, thus covering the entire world population.
\[ TD^k = \sum_{i=1}^{n} D_i^k \]  

(1)

Where \( TD^k \) represents the total distance needed to be traveled at least once from country \( k \) to all other countries. \( D_i^k \) represents the distance to be covered from country \( k \) to a particular country \( t \). The total \( TD \) in miles is then divided by the Boeing 747 average miles per hour speed (mph) to estimate total flight hours needed to travel from a given country \( k \) to all other countries and major autonomous/semi-autonomous regions of the world.

\[ TFH^k_{747} = \frac{TD^k}{AS} \]  

(2)

where \( TFH^k_{747} \) represents the total flight hours needed for a Boeing 747 aircraft to travel to all other worldwide destinations. \( AS^h_{747} \) represents the average flight speed (cruising speed) of a Boeing 747 aircraft in miles per hour. By simply multiplying the per hour carbon emissions released during a Boeing 747 flight by the total flight hours required to dispatch the necessary ODCV to all other nations across the globe, the total carbon emissions can be obtained.

\[ C^k_{747} = c^k_{747} \times TFH^k_{747} \]  

(3)

where \( C^k_{747} \) represents the total carbon emissions released during a single flight from a given destination \( k \) to all other nations by a Boeing 747 aircraft. \( c^k_{747} \) represents the per hour CO2 emissions produced by a Boeing 747 at cruising speed. This covers all 243 destinations, totaling 243 Boeing 747 flights. However, we know that dispatching at ODCV to all of the world’s population will require at least 8000 Boeing 747 flights (Lei, 2020; Wenqian, 2020; Carbon Independent and ‘Avia, 2019).

\[ TC^k_{747} = \frac{c^k_{747}}{TFH^k_{747}} \times TFH^k_{747} \]  

(4)

\[ TC^k_{747} = \frac{c^k_{747}}{TFH^k_{747}} \times AFH^k_{747} \times TFH^k_{747} \]  

(5)

where \( TC^k_{747} \) represents the total CO2 emissions released in order to dispatch ODCV to all of the world’s population. \( AFH^k_{747} = \frac{TFH^k_{747}}{TFH^747} \) represents the average flight hours needed for a Boeing 747 to travel from a given country \( k \) to another country or autonomous/semi-autonomous region. \( TFH^747 \) represents the total number of destinations. \( TFH^747 \) represents the total number of flights required by a Boeing 747 cargo aircraft to deliver ODCV to all of the world’s population. The global dispatch of the COVID-19 vaccine’s contribution to the total emissions based on the consumption (demand) of ODCV by different nations can be estimated using the following equation:

\[ TC^k_{747} = TC^k_{747} \times CWP \]  

(6)

Where \( TC^k_{747} \) represents the country-specific share of the total carbon emissions expected from the air dispatch of the COVID-19 vaccine. \( CWP \) (\( r = 1, 2, 3, \ldots, n \)) presents the percentage contribution of country \( r \) in total world population.

\[ CWP = \left( \frac{P_r}{TWP} \right) \times 100 \]  

(7)

\[ TWP = \sum_{i=1}^{n} P \]  

(8)

Where \( TWP \) represents the total world population, and \( P \) represents the population of country \( r \). The above Eq. (6) presents the countrywide contribution to CO2 emissions from the necessary air dispatch of ODCV to the global population. However, some nations have pre-ordered a certain quantity of COVID-19 vaccines, which is sufficient to vaccinate their entire population several times. Thus, the total amount of expected CO2 emissions from the global air dispatch of RDCV can be estimated using the following equations:

\[ RTC_{747} = PTC_{747} \times RWP \]  

(9)

\[ RTC_{747} = RWP \times RCWP \]  

(10)

Where \( RTC_{747} \) represents the total amount of revised CO2 emissions after adjusting for the additional vaccines (i.e., more than one per capita delivery of vaccine doses to certain nations). \( RWP \) represents the newly revised contribution by country \( r \) to the expected carbon emissions from the global dispatch of the COVID-19 vaccine after adjusting the number (quantity) of pre-orders per nation. \( PTC_{747} \) represents carbon emissions from the dispatch of ODCV per unit of the world’s population. \( RWP \) represents the revised world population (total dose requirement after adjusting for the additional doses secured). And \( RCWP \) represents the revised percentage contribution of each country to the global population after the adjustment of their pre-ordered COVID-19 vaccine quantities. The procedure for the estimation of \( RWP, PTC_{747}, \) and \( RCWP \) is described below.

\[ PTC_{747} = \frac{TC_{747}}{TWP} \]  

(11)

\[ RWP = \sum_{i=1}^{n} P \times PCDr \]  

(12)

\[ RCWP = \left( \frac{RP}{RWP} \right) \times 100 \]  

(13)

\[ RP = P \times PCDr \]  

(14)

Where \( PCDr \) represents the per capita RDCV by country \( r \). This includes the necessary one dose per capita and additional ensured (secured) per capita COVID-19 vaccine doses. The increased number of Boeing 747 cargo aircrafts necessary to cover this hypothetically increased world population based on the per capita delivery of COVID-19 vaccine doses is estimated through the following equation:

\[ RTFL_{747} = \frac{RTC_{747}}{\left( \frac{P_{747}}{TFH_{747}} \times AFH_{747} \right)} \]  

(15)

Where \( RTFL_{747} \) represents the revised number of total Boeing 747 cargo flights required to deliver the COVID-19 vaccine doses to the revised total population of the world (RWP).

4. Results

4.1. Robustness of the model

Robust models can consistently predict outcomes and projections even when uncertain events significantly alter one or more of the input variables or assumptions (Kenton, 2020). The t-test can be used to check the robustness of the ESEEM model estimates. For the testing the robustness of the model one sample t-test where the population mean value derived from a population presenting a total of 618 observations based on the (1) MDD (2) distance between important cities/agglomera-

\[ (Bullen, 2021) \] population size 10000 and the maximum sample size at 10% of the population, i.e., 1000. The Skewness values (0.25 and 0.003) were within, while Kurtosis values were very near (−1.3 and −1.2) to the acceptable range of ±1 for normality (Sajid et al., 2021), i.e., our
sample is approximately normal. At $P = 0.274$ (95% CI = $-42.02, 11.95$), and $P = 0.610$ (95% CI = $-64.70, 38.00$) the MCM-based t-test’s null hypothesis of similar means was not rejected for both the CO$_2$ emissions from ODCV and RDCV. Furthermore, with the values of $P = 0.712$ (95% CI = $-16.99, 24.85$), and $P = 0.756$ (95% CI = $-37.64, 51.77$) the original data based t-test also failed to reject the null hypotheses for these two estimates (see supplementary Table 1). This demonstrates that there is no statistically significant difference between the results obtained based on our distance data and the average of results generated using different distance data procedures. Table 2 presents the results from the one-sample t-test performed on the simulated data. While Fig. 2 presents the results of the outlier analysis.

4.2. Validation of the model

Before elaborating the emission estimations, it’s important to validate the model or, in other words, the results. Model validation is the process of determining the degree to which a model accurately represents the true real-world value (Whiting et al., 2019). The results of a model validation study can be used to either figure out how much uncertainty there is in the model or to improve or calibrate the model itself (Kerr et al., 2014). The certainty there is in the model or to improve or calibrate the model itself and combined standard uncertainties (SD) under the MCM and GUM approaches were almost similar. However, there were some differences and Frenkel, 2012; Shen et al., 2021). As evident from Table 3, the individual uncertainties. This is because, due to their inherent complexity, researchers have historically preferred MCM to more traditional uncertainty estimation techniques such as the GUM (Farance and Frenkel, 2012; Shen et al., 2021). As evident from Table 3, the mean and combined standard uncertainties (SD) under the MCM and GUM approaches were almost similar. However, there were some differences under the MCM and GUM in % sensitivity contributions and values for individual input quantities. Supplementary tables S2 and S3 present the results of sensitivity analyses for CO$_2$ emissions from air dispatch of ODCV and RDCV. Furthermore, Fig. 3 depicts the estimated PDF of the output quantity (solid blue line) and the PDF of a Gaussian (normal) distribution with the same mean and standard deviation as the output quantity (dotted red line). In our instance, the Gaussian approximation is also very accurate for estimating both the uncertainty of carbon emissions from the air transport of ODCV and RDCV.

4.3. CO$_2$ emissions from ODCV

The MDD dataset developed in this study is considered for the estimation of total direct and consumption-based emissions. Supplementary tables S6 and S7 present the CO$_2$ emissions estimated under CEPI’s different locations/distances datasets. The expected CO$_2$ emissions from the global air transport of the COVID-19 vaccine by roughly 8000 Boeing 747 cargo aircraft flights to 7.8 billion people were estimated to be approximately 8.1 ± 0.30 metric kilotons (kt). The average flight hours for a Boeing 747 cargo aircraft to travel from one country to another was estimated at 10 h per flight. Keeping this in view, countries with the largest total populations will be responsible for the largest emissions of carbon. For example, China, India, the European Union, the United States, and Indonesia, emitting approximately 1494 ± 57.44 metric tons (t), 1432 ± 52.50 t, 462 ± 5.50 t, 343 ± 2.90 t, and 284 ± 2.09 t respective metric tons (t), comprise nearly 50% of the 206 nations’ total emissions.

4.4. CO$_2$ emissions from RDCV

After adjusting for the additional per capita secured doses by certain countries, the total number of required doses increases from 7.8 billion to 14.3 billion, which is approximately 1.8 doses per capita of the world’s current population. The total number of Boeing 747 flights required to dispatch these doses will be approximately 14,912 flights. As such, the total CO$_2$ emissions increase from 8.1 ± 0.30 kt to 15 ± 0.48 kt, which represents an increase of almost 85% in total carbon emissions compared to the one dose-per-capita dispatch.

Countries like Canada (1800%), the United States (1600%), the United Kingdom (1500%), Australia (1500%), and the European Union (1400%), proportional to their secured doses, may have the largest increase in consumption-based carbon emissions compared to one dose per capita. This adjustment of required (secured) per-capita COVID-19 vaccine doses by different nations also restructures the leader board of carbon emissions, surpassing China as the largest producer. India, the United States, and the European Union, with emissions of 2864 ± 122.15, 2404 ± 85.34, and 2310 ± 78.75 respective metric tons (t), account for almost 19%, 16%, and 15% of total emissions from air transport of globally required COVID-19 vaccines, respectively. After the adjustment of secured doses per capita, China, with a ~10% contribution, drops to fourth place. In comparison, Indonesia and Brazil, emitting 568 ± 4.79 t and 441 ± 2.97 t, respectively, become the fifth and sixth largest contributors after the adjustment of secured doses per capita by certain nations.

4.5. Sensitivity of population (P), affluence (A), and technology (T) to the carbon emissions

The purpose of the Global Sensitivity Analysis (GSA) is to measure the relative significance of input variables (factors) in the value assessment of the specified output variable (Saltelli, 2002). Carbon emissions from the global air transport of the COVID-19 vaccine are the output variable, and I, P, and T are the input variables. P is equal to the total number of required doses, which expresses the number of doses to be carried to the world’s entire population (i.e., one per capita plus any additional secured doses). As a result, A represents the GDP per dose, and T expresses emitted CO$_2$ per unit of GDP. Out of 206 nations, 180 nations were considered for the IPAT analysis. This is mainly due to the lack of or old age of GDP data for some countries.

Fig. 4 details the results obtained via the FAST VBSA. The success of the FAST analysis is determined by the sum of the main Effect Sensitivity Index (SM) values; if the value is greater than the 0.6 benchmark, then the analysis is successful (Saltelli et al., 2012). A sum of 0.6 indicates that the indices have explained more than 60% of the variance in the model output (Saltelli et al., 2012). The sum of the SM values of P, A, and T was 0.9, well above the benchmark. For individual input indices, P, which shows the total number of required COVID-19 vaccine doses and has a sensitivity index value of 0.52, is the most influential factor regarding CO$_2$ release from the global air dispatch of COVID-19.
vaccines. T (CO\textsubscript{2} intensity/GDP = 0.27) is the second most important factor, and A (GDP/Capita = 0.12) is relatively the least important factor for CO\textsubscript{2} emissions. One of the important elements of the GSA study is the robustness of the model, i.e., the estimated sensitivity indices do not change substantially when computed using a different model simulation sample (Pianosi et al., 2015). Convergence of sensitivity indices denotes stability of the values, ranking means order stability, and screening means that the division between sensitive and non-sensitive variables is stable (Sarrazin et al., 2016). During the convergence analysis of the FAST results, sensitivity, ranking, and order did not change when the number of model samples increased from 105 to 1105. In other words, any simulated sample size greater than 105 will produce stable results, and thus our simulated sample size of 1105 is more than enough to produce robust results under the FAST analysis. This shows that our IPAT with FAST analysis is robust. Fig. 5 displays the country-specific population after adjusting for the total number of required doses, affluence (GDP/dose), and technological level (CO\textsubscript{2}/GDP) used to estimate the sensitivity indices for this study.

5. Discussion

Natural and unnatural disasters are difficult to predict in terms of location and timing, which raises the environmental and economic cost of emergency supplies (disaster relief supplies) (Ye et al., 2020). At the same time, man-made climate change is causing natural disasters. CO\textsubscript{2} emissions are a major contributor to climate change. As a result, there is an urgent need to estimate the CO\textsubscript{2} emissions associated with emergency supplies. The current COVID-19, in particular, is a massive disaster that humanity is dealing with. Keeping in mind the novelty of the situation, many studies have developed novel methodologies to estimate the various environmental and economic impacts. “Susceptible-Exposed-Infectious-Removed” (Kumar et al., 2021), “sense-and-respond” (Choi, 2021), “airline responses to environmental shocks” (Amanikwah-Amoah, 2020), and “working from home” (Hensher et al., 2021) are examples of these COVID-19 motivated novel methodologies. However, due to the uncertainty of the location and timing of natural and unnatural disasters, literature in general, and specifically the COVID-19 related literature, has largely ignored emergency-supply transport-related CO\textsubscript{2} releases. This study filled a critical research gap by developing a novel methodology called ESEEM, which can estimate CO\textsubscript{2} emissions without knowing the exact location. The methodology’s robustness was demonstrated by estimating the results using different locations/distances data and comparing the results using a one-sample t-test. The t-test failed to reject the null hypothesis, indicating that there is no statistically significant difference in the results obtained when different locations/distances data were used under our proposed ESEEM methodology. Furthermore, the ESSEM was validated using the

![Fig. 2. Outlier analysis for MCM-based simulated sample (N = 1000). a, CO\textsubscript{2} emission from ODCV. b, CO\textsubscript{2} emissions from RDCV. As there are no circles or asterisks outside the boxplot indicates that there are no outliers in the sample data.]

![Fig. 3. The estimated PDF of the output quantity (solid blue line) and the PDF of a Gaussian (normal) distribution with the same mean and standard deviation as the output quantity (dotted red line). a, ODCV. b, RDCV.]

| Item | ODCV | RDCV |
|------|------|------|
| MCM |      |      |
| Mean | 7.2704 | 13.725 |
| SD   | 0.299  | 0.479  |
| Mean absolute deviation (MAD) | 0.32 | 0.493 |
| GUM’s Linear Approximation (Gauss’s Formula) | | |
| Mean | 7.2704 | 13.725 |
| SD   | 0.299  | 0.479  |
GUM and MCM uncertainty estimations techniques. The ESEEM methodology allocates emissions primarily based on total population or expected volume of consumption (i.e. requirement for COVID-19 vaccine doses), while using average rather than exact distances between emergency supply dispatch and final consumption locations.

The current COVID-19 pandemic has compelled governments to impose restrictions not only on people’s travel but also on commercial activity (Amankwah-Amoah, 2020). Having said that, most related studies have focused on the reduction of environmental pressures (such as CO\(_2\) emissions and pollution) and economic activities because of the COVID-19-mandated reduction in economic and non-economic activities. However, few studies have taken into account the CO\(_2\) emissions associated with the global distribution of the COVID-19 vaccine. Our study provides the first estimates of CO\(_2\) emissions associated with the global air dispatch of a single dose of COVID-19 vaccine and subsequent vaccine doses secured. The study estimated the CO\(_2\) emissions from the global air dispatch of COVID-19 doses and allocated these emissions to different nations based on their demand for the COVID-19 vaccines. Furthermore, the study using the IPAT and VBSA analyses estimated the impact of key factors like the total doses requirement (demand), technology, and affluence on the CO\(_2\) expected from the global transport of COVID-19 vaccine to different countries.

The necessary evil, i.e., the carbon emissions from the dispatch of at least one dose of the COVID-19 vaccine to 7.8 billion people, is unavoidable but can be minimized by ordering only the necessary doses. Our results showed that, compared to the air dispatch of one dose of COVID-19 vaccine to the world’s 7.8 billion people, the adjustment of additional secured doses by some countries would cause the CO\(_2\) emissions due to air transport to increase by 85%. China may not be the highest contributor; countries with smaller populations, such as India, the United States, and the European Union, could have greater consumption-based emissions.

The IPAT method’s VBSA (variance-based sensitivity analysis) revealed that all three factors, namely population (total number of doses), technology, and affluence, are sensitive to carbon emissions from the global air dispatch of required COVID-19 vaccine doses. Notably, the most sensitive factor to these emissions was the number of doses (population). That is, demand for the COVID-19 vaccine is the primary driver of the CO\(_2\) emissions expected from global air dispatch of the COVID-19 vaccine. As a result, governments should reconsider reducing the total number of secured doses to a bare minimum in order to reduce both the humanitarian and environmental risks associated with additional COVID-19 vaccine doses. Furthermore, the world population should be controlled in order to reduce the emergency-supply-related emissions from any future disasters and the driving impact of CO\(_2\) emissions on the occurrence of natural disasters. International organizations and national...
governments should play a role in population control so that future disasters such as the COVID-19 pandemic can be avoided. Controlling the population may be the key to reducing the frequency and severity of future disasters, including pandemics because population growth not only increases the likelihood of pandemics through habitat loss but also increases the subsequent disaster’s emergency-supplies-related CO₂ release, which contributes to climate change and thus the occurrence of natural disasters.

According to our findings, technology was the second most influential factor. As a result, investment in technology, in general, can help reduce CO₂ emissions and thus the frequency and severity of future disasters. Ideally, the airline industry should invest more in short-term projects such as biofuels, carbon-neutral synthetic fuels, and green operations, among others. In the long run, projects such as technological innovations and sustainable infrastructure will not only reduce the expected emissions from the global air dispatch of the COVID-19 vaccine but will also reduce emissions from their regular flight operations. However, the airline industry has suffered greatly as a result of COVID-19-related domestic and international flight disruptions. As a result, governments should provide subsidies to the aviation industry for the adoption of long-term and short-term green technologies and operations. Choi has proposed various subsidy schemes such as operations-cost-subsidy, safety-technology-support, and fixed-cost-subsidy to support logistics service providers providing “mobile service operations” in Hong Kong during the COVID-19 pandemic (Choi, 2020). Similarly, these schemes, particularly the operations-cost-subsidy and safety-technology-support schemes that have been shown to have a greater impact, can be considered for the air industry adopting green logistics during COVID-19 vaccine dispatch.

Besides the number of doses and technology, financial prosperity (affluence) is also sensitive to CO₂ emissions from global air dispatch (Fig. 6). This means richer nations tend to influence more emissions than comparatively less-rich nations. Richer nations, with sufficient funds, can concentrate on resolving the problem, first, by reducing the number of secured doses and greening their own air transport and second, by providing financial support to developing nations, enabling them to afford relatively greener air dispatch of COVID-19 vaccines. This is also the general case in the literature, where it is argued that the richer nations should take more responsibility for the mitigation of global carbon releases [74, 75].

6. Conclusions

CO₂ emissions contribute significantly to the occurrence of natural and unnatural disasters. Emergency supplies for disasters have a significant environmental impact, including CO₂ emissions from transportation. The uncertainty surrounding the location and timing of disaster supplies may be the main reason for the general lack of environmental studies, specifically the impact of disaster supplies on CO₂ emissions. This study addressed this critical research gap by developing an ESEEM methodology. The ESEEM methodology assigned emissions primarily based on total population or anticipated volume of consumption, average flight hours (or in other words, average distance), and CO₂ emissions per hour. The total direct and national consumption-based COVID-19 vaccine air transport-related CO₂ emissions were calculated in this study by constructing two scenarios: (1) one vaccine dose is air dispatched to 7.8 billion people (ODCV) (2) and adjusting for any additional doses secured (RDCV). The methodology’s robustness was demonstrated by comparing the results obtained with data from different locations, where the MCM based t-test for carbon emissions from both the ODVC and RDCV at \( \text{P} = 0.274 \) (95% CI = -42.02, 11.95), and \( \text{P} = 0.610 \) (95% CI = -64.70, 38.00) revealed no statistically significant difference. Furthermore, the methodology was validated via GUM and MCM-based uncertainty estimations.

According to the findings, nearly 8000 Boeing 747 flights will be required to deliver at least one dose of the COVID-19 vaccine to 7.8 billion people, resulting in an estimated 8.1 ± 0.30 kt of CO₂ emissions. As countries secure additional doses, these figures will rise to 14,912

![Population (doses), Affluence (GDP per dose), Technology (CO₂/GDP)](image-url)

**Fig. 6. Spatial maps presenting the adjusted population (doses), affluence, and technology of selected countries.** Here, countries belonging to European Union (EU) are taken as a single unit. The Population (green) shows the total number of doses required, including one dose per capita and any additional secured doses. The GDP per dose is represented by Affluence (red), and the CO₂ emissions per unit of GDP are represented by Technology (purple) in grams per USD.
flights and approximately 15.53 ± 0.53 kt of CO₂. According to the variance-based sensitivity analysis, the total number of vaccine doses (population), technology, and wealth, with sensitivity indices of 0.52, 0.27, and 0.12, respectively, played a significant role in determining CO₂ emissions across nations. Specifically, the number of vaccine doses should be reduced to a bare minimum, while greener alternative fuels and financial assistance should be provided to reduce the current expected COVID-19 vaccine global air dispatch emissions. Long-term efforts such as population reduction, investment in green infrastructure and technology, and financial assistance from wealthy nations can help reduce CO₂ emissions from future disaster-related emergency supplies, lowering the risk of future disasters.

6.1. Limitations

Estimating the disaster’s emergency supply-related CO₂ or pollutant releases using precise location/distance data is beyond the scope of this study. Furthermore, only the commonly used Boeing 747-400 carrier was considered (Lei, 2020; Wenqian, 2020; Carbon Independent and ‘Avia, 2019). The study did not consider the issue of a first-last mile, other cargo/payload carried, and the intermodality. Therefore, as more data becomes available in the coming years, future research can concentrate on precise COVID-19 production location, first-last mile, cargo/payload, and intermodality to accurately estimate the overall carbon footprint of the COVID-19 vaccines’ global and local transport.

CRediT authorship contribution statement

Muhammad Jawad Sajid: Conceptualization, Formal analysis, writing. Ghaffar Ali: Writing, Writing – review & editing, submission. Ernesto D.R. Santibanez Gonzalez: Writing – review & editing, Supervision.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2022.130716.

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