Global Analysis of SARS-COV-2 Mitigation Impact Reveals an Arabian Peninsula Cluster with High Infection Rates and Shared Indicators

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Abstract

Background

SARS-CoV-2 is a novel virus that appeared in China in November 2019 and spread rapidly. With no vaccine or effective treatment, countries have adopted different mitigation measures to reduce SARS-COV-2 spread with different efficacy.

Methods

We mapped the impact of mitigation measures across different countries. We compared regional SARS-COV-2 population burden via Kruskal-Wallis statistical testing. We analyzed time of adoption of mitigation measures and the impact of PCR testing on mitigation impact. We analyzed the association of climate, health, demographic and economic indicators with mitigation impact via non-parametric correlation tests. We performed mechanistic modelling of to predict short-term SARS-COV-2 case numbers in selected countries.

Results

Many countries showed a reduction of infection rates within one month of implementing mitigation measures. However, we identified a geographic cluster of countries centered on the Arabian Peninsula (AP) that show a high SARS-COV-2 population burden despite early adoption of mitigation measures. We find that higher air pollution levels ($p=0.01$), higher CO2 emissions ($p=0.03$) and younger population ($p=0.02$) were associated with reduced mitigation impact in AP countries. We also show that mechanistic modelling can closely predict confirmed case numbers in the short term.

Conclusions

The impact of mitigation measures varies greatly between countries. Countries with similar profiles as AP countries should adopt more stringent mitigation measures to more rapidly reduce SARS-CoV-2 spread. Specific interventions targeting young people may also be effective in reducing SARS-COV-2 spread.

Keywords

SARS-COV-2**;** Arabian Peninsula; mitigation impact; infection rates; mechanistic modelling

Background

On March 11, 2020 the World Health Organization declared an outbreak of a novel coronavirus [1] as a pandemic [2] due to a rising case number of 118,000 infections and 4291 deaths in 114 countries. As of writing, cases continue to rise in numerous countries. No vaccine is yet available, and no antiviral drugs have been found to be specifically effective against COVID-19, although there are ongoing clinical trials. Vaccines and antiviral therapy can take several months to many years until they are discovered, tested, and made available broadly.

However, non-pharmaceutical interventions such as isolation of infectious patients, school closures, and bans on public gatherings have been widely adopted in order to slow the spread of SARS-CoV-2. A successful mitigation strategy will reduce the virus' basic reproduction number R_0, [3,4] thus reducing the number of patients requiring Intensive Care Unit (ICU) admission and preventing saturation of local healthcare systems. Such interventions have shown some effectiveness in past pandemics and simulation-based models.

During the 1918 Spanish flu, which infected 30% of the world's population and killed 50-100 million people, [5] non pharmaceutical interventions were effective. [6,7] Cities that implemented distancing strategies including isolation, quarantine, and school closures had much lower progression and lower overall scope of death. School closure and public gathering bans were the two measures implemented most frequently for a median duration of 4 weeks in the United States, and this combination was significantly

associated with reductions in weekly excess death rate (EDR). Furthermore, cities that implemented nonpharmaceutical interventions earlier had greater delays in reaching peak mortality and lower overall mortality. [8] However, the majority of these bans were transitory in nature, with most lasting only a few weeks. When bans were relaxed, mortality rates rose. [7] These results are especially significant as the 1918 Spanish flu was estimated to have a R_0 of 1.2-3.0 in community settings. [9]

In contrast to the largely uncontrolled 1918 influenza pandemic, the recent SARS pandemic in 2002, which claimed approximately 8000 lives in 29 countries, was successfully contained. SARS was contained as most spread occurred in hospital settings and asymptomatic people were less likely to spread the virus, thereby making it much easier to detect and isolate infectious persons. [10]

Simulation-based data on pandemics show that while school closures are minimally effective, social distancing among healthy people and isolation of patients are effective at reducing rates of illness. [11] Simulation-based data on a novel strain of influenza virus suggest that increasing the number of mitigation measures reduces the attack rate of the virus, by a percentage dependent on the delay between the detection of the first case and the introduction of measures. [12]

These established non-pharmaceutical interventions might not be successful at containing COVID-19, as studies show that SARS-COV-2 spreads as efficiently in non-symptomatic as symptomatic people. [13] Asymptomatic or presymptomatic people are

113 likely the ones that spread the virus the most, [14] which does not occur in influenza and
114 SARS infections. [10] Talking, singing, breathing has been shown to generate viable
115 SARS-COV-2 aerosols. [15] Viral aerosols could remain suspended in the air for several
116 hours. [16] SARS-COV2 is highly contagious with a median R_0 of 3.28 (Range 2-6) [17]
117 which leads to rapid spread than influenza (R_0 of 1.3) [18] and SARS (R_0 2-4). [19]
118 The case fatality rate (CFR) of SARS-CoV-2 is currently not well established but ranges
119 from 0.06% in Singapore to greater than 15 % in Belgium (as of July 13, 2020). In all
120 estimates however, it is higher than influenza, which has a case fatality rate of 0.1%.
121 For COVID-19, there exists no consensus about which measure (or combination of
122 measures) should be taken. Different countries implement different measures at
123 different times with different enforcement methods. There is no epidemiological
124 threshold at which measures are known to carry maximal public health impact. [20]
125 Because the mitigation measures carry severe disruption and a high cost to economic
126 and community life, their effect must be examined in the case of COVID-19 specifically.
127
128 In this study, we analyze the efficacy and impact of mitigation measures implemented
129 by different countries worldwide during the first months of the pandemic (from Jan. 22,
130 2020 to June 22, 2020). We find a geographical cluster centered on the Arabian
131 Peninsula (AP) with sustained exponential increase in cases in April and May. This
132 sustained exponential increase was not seen in neighboring Arab countries and resulted
133 in a relatively large percent of the population becoming infected. It was also not due to
134 late implementation of social distancing efforts or to testing artifacts. Further correlation
135 analysis showed that lower age and air quality likely contributed to the sustained

exponential increase. Our global and comparative study helps reveal how the impact of similar social distancing measures vary across countries and how additional factors need to be considered in designing COVID19 mitigation approaches.

Methods

Data collection and processing

Several different publicly available data sources were used in this study. The data on case numbers and fatalities per country covering the period of Jan. 22-Jun. 22 2020 were downloaded from the John Hopkins-maintained server (https://github.com/CSSEGISandData/COVID-19). [21] Data from different regions within the same country were added together. Data on mitigation dates were obtained from publicly available news sources as shown in Table S1. Data on SARS-COV2 testing were also obtained from publicly available sources as shown in Table S2. Indicator data were downloaded from the World Bank Open Data portal (https://data.worldbank.org/indicator) [22] as EXCEL files and batch processed with custom Matlab scripts. Hourly weather data was obtained from Synoptic (https://download.synopticdata.com) [23] from the main airport weather station for selected cities for the period Jan.1, 2020 to April 30, 2020. Weather data were binned into months by calculating the median for that month (Month 1=Jan, Month 2=Feb, Month 3=March, Month 4=April).

Normalized RMSE

We employed a phenomenological approach that utilizes curve fitting to generate inferences and describe the evolution of the pandemic and the impact of interventions. An exponential curve was fit through the confirmed case number data for each country starting from the date of the first detected case up to different dates. The normalized root mean square error (nRMSE) was then calculated as:

$$nRSME = \frac{Root\ Mean\ Square\ Error}{Max\ (confirmed\ cases) - Min\ (confirmed\ cases)}.$$

All data analysis and graphs were generated using Matlab.

Indicator correlations

Kendall-tau correlation coefficients and p-values were calculated from nRSME data vs. indicator value. Indicator values were available from multiple years; we used the latest year for which data was available. NRSME data were calculated for every country with at least 500 cases from the date of the first case to different end dates.

Predictive Modeling

The model consists of the following system of ordinary differential equations:

$$\begin{cases} S'(t) = -\tau(t)S(t)[I(t) + U(t)], \\ I'(t) = \tau(t)S(t)[I(t) + U(t)] - \nu I(t) \\ R'(t) = \nu_1 I(t) - \eta R(t), \\ U'(t) = \nu_2 I(t) - \eta U(t). \end{cases} \quad (1)$$

This system is supplemented by initial data

$$S(t_0) = S_0 > 0,\ I(t_0) = I_0 > 0,\ R(t_0) = 0 \text{ and } U(t_0) = U_0 \geq 0. \quad (2)$$

Here $t \geq t_0$ is time in days, t_0 is the beginning date in the model of the epidemic, $S(t)$ is the number of individuals susceptible to infection at time t, $I(t)$ is the number of asymptomatic infectious individuals at time t, $R(t)$ is the number of reported symptomatic infectious individuals at time t, and $U(t)$ is the number of unreported symptomatic infectious individuals at time t.

The fraction f of asymptomatic infectious become reported symptomatic infectious, and the fraction $1 - f$ become unreported symptomatic infectious. The rate asymptomatic infectious become reported symptomatic is $v_1 = f\,v$, the rate asymptomatic infectious become unreported symptomatic is $v_2 = (1-f)v$, where $v_1 + v_2 = v$. The cumulative number of reported cases at time t is given by the formula

$$CR(t) = \nu_1 \int_{t_0}^{t} I(\sigma) d\sigma, \text{ for } t \geq t_0, \tag{3}$$

and the cumulative number of unreported at time t is given by the formula

$$CU(t) = \nu_2 \int_{t_0}^{t} I(\sigma) d\sigma, \text{ for } t \geq t_0. \tag{4}$$

To estimate the parameters, we assume that $(100 \times f)$% of symptomatic infectious cases go unreported. The actual value of f is unknown and varies from country to country. We assume $\eta = 1/7$, which means that the average period of infectiousness of both unreported symptomatic infectious individuals and reported symptomatic infectious individuals is 7 days. We assume $v = 1/7$, which means that the average period of infectiousness of asymptomatic infectious individuals is 7 days. These values can be modified as further epidemiological information becomes known.

We assume that in Phase II of a COVID-19 epidemic, the cumulative number of reported cases $CR(t)$ grows approximately exponentially, according to the formula:

$$CR(t) = \chi_1 \exp(\chi_2 t) - \chi_3, \; t \geq t_0. \tag{5}$$

We fix the value $\chi_3 = 1$. The values of χ_1 and χ_2 are fitted to cumulative reported case data in the early phase of the epidemic, when it is recognized that $CR(t)$ is growing exponentially (*i.e.*, we use an exponential fit $\chi_1 \exp(\chi_2 t)$ to fit the data $CR(t) + 1$). We assume the initial value S_0, corresponds to the population of the region of the reported case data. The value of the susceptible population $S(t)$ is assumed to be only slightly changed by removal of the number of people infected in the beginning of the second phase. The other initial conditions are

$$I_0 = \frac{\chi_2 \chi_3}{f\nu}, \;\; U_0 = \left(\frac{\nu_2}{\eta + \chi_2}\right) I_0, \;\; R_0 = \left(\frac{\nu_1}{\eta + \chi_2}\right) I_0. \tag{6}$$

The value of the transmission rate $\tau(t)$, during Phase II of the epidemic, when the cumulative number of reported cases grows approximately exponential, is the constant value

$$\tau_0 = \left(\frac{\chi_2 + \nu_1 + \nu_2}{S_0}\right)\left(\frac{\eta + \chi_2}{\nu_2 + \eta + \chi_2}\right). \tag{7}$$

The initial time for the beginning of the second phase is

$$t_0 = \frac{1}{\chi_2}\Big(\log(\chi_3) - \log(\chi_1)\Big). \tag{8}$$

The value of the basic reproductive number is

$$\mathcal{R}_0 = \left(\frac{\tau_0 S_0}{\nu_1 + \nu_2}\right)\left(1 + \frac{\nu_2}{\eta}\right). \tag{9}$$

These formulas for I_0, U_0, t_0, τ_0, and R_0 were derived in [eq 1]. Their numerical values, which are technically theoretic, are essential for identification of the exponential growth rate of $CR(t)$ in Phase II of the pandemic.

During Phase II of the pandemic, $\tau(t) \equiv \tau_0$ is constant. When strong government measures such as isolation, quarantine, and public closings are implemented, Phase III begins. The actual effects of these measures are complex, and we use an exponential decrease for a time-dependent decreasing transmission rate $\tau(t)$ in the third phase to incorporate these effects. The formula for $\tau(t)$ during the third phase is:

$$\begin{aligned} \tau(t) &= \tau_0,\ 0 \le t \le N, \\ \tau(t) &= \tau_0 \exp(-\mu(t - N)),\ N < t. \end{aligned} \tag{10}$$

The date N and the value μ are chosen so that the cumulative reported cases in the numerical simulation of the epidemic aligns with the cumulative reported case data after day N, when the public measures take effect. In this way we are able to project forward the time-path of the epidemic after the government imposed public restrictions take effect. The daily number of reported cases from the model can be obtained by computing the solution of the following equation:

$$DR'(t) = v_1\, I(t) - DR(t), \text{ for } t \ge t_0 \text{ and } DR(t_0) = DR_0. \tag{11}$$

Results

Global Mitigation Impact

To examine the effect of COVID19 mitigation measures implemented by different countries worldwide we first parameterized the cumulative confirmed case number curves for each country. We calculated the max-min normalized root mean square error (nRMSE) of an exponential fit through the cumulative confirmed case number data of each country with at least 500 cases. Countries with sustained exponentially rising cases show a low nRMSE while countries with sustained low case show a high nRMSE. The nRMSE captures well the degree of mitigation in the early part of COVID19 spread (Fig 1A and additional file 1).

We plotted the color-coded nRMSE for each country on the world map over different time frames separated by 30 days. We observed that while many countries had initially low mitigation and close to exponential increase in cases, the rate of increase was reduced within one month. However, we observed one cluster centered in the Arabian Peninsula (AP) which showed exponential increase after two months (Fig 1B and additional file 2). The AP countries consist of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates, and Yemen.

To further examine this cluster, we compared the confirmed case numbers in the AP countries to those in other Arab countries and selected countries with early COVID19 infections (Fig 1C, upper panel). We see that AP countries registered their first cases later than some other countries and had a slower rise in cases. However, exponential

increase was sustained for a longer time. This sustained exponential increase resulted in a relatively larger percent of the population becoming infected (Fig 1C, lower panel). As a group, these countries also have significantly greater numbers of confirmed cases relative to the population size, compared to other Arab and non-Arab countries (Fig 1D).

Mitigation Timeline and Testing

To further examine this cluster's behavior, we compared testing parameters and social distancing measures dates between AP countries and neighboring countries (Fig 2A). Since the number of confirmed cases reported by a given country is affected by its testing capacity, we took into consideration the factor of PCR testing rates in the different Arab countries. We calculated the correlation between the mitigation effects observed and the different testing parameters (the total number of tests performed, testing rate per capita, and the percentage of positive tests). Our results show that higher testing does not correlate with the observed mitigation levels. For example, while the UAE conducted more than 150,000 tests per million, of which less than 5% were positive, Qatar performed around 70,000 tests per million, of which more than 20% were positive (Fig 2B). However, both countries showed low mitigation levels.

We then explored how the timing of the social distancing measures varied across different Arab countries. We plotted the time of implementation of measures in the AP and in neighboring Arab countries showing high and moderate mitigation (Fig 2C and additional file 3). Most of the AP countries implemented many of the mitigation measures fewer than 20 days after the first reported case in that country, a timeline that

287 is comparable to the other neighboring countries like Lebanon (Fig 2C). Despite these
288 early measures, the mitigation levels in the GCC countries remained lower. Our analysis
289 shows that the lower rate of mitigation in the AP countries is not likely to be due to the
290 date of implementation of the mitigation measures. In fact, most Arab countries set up
291 quite early and strict measures such as complete curfew in certain cases, school
292 shutdowns, closure of all public institutions, and border closures.
293

294 **Indicators**

295 Since mitigation rates and testing parameters do not explain the lack of mitigation in AP
296 countries, we attempted to examine the role of any environmental, demographic or
297 economic factors in explaining these observations. To do this we made use of open
298 indicator data available from the World Bank and weather data available from Synoptic.
299 We calculated correlations between the nRMSE and indicator data for countries with at
300 least 500 cases for the period from the first case up to May 22, 2020. The nRMSE
301 represents how close to exponential the increase in cases over the examined timeframe
302 while the indicator is a specific measure of a country at a specific year. We found that
303 several indicators significantly correlate with the nRMSE in many Arab countries,
304 especially the Arabian Peninsula countries showing relatively unmitigated infections (Fig
305 3A). Specifically, country-level indices of energy use, land use and the environment
306 factors showed significant ($p \leq 0.05$) positive and negative associations with the
307 effectiveness of mitigation measures (Fig 3B and 3C). Our analysis shows that higher
308 mean annual PM2.5 air pollution ($p=0.01$) and higher CO_2 emissions per capita ($p=0.03$)
309 were associated with poor mitigation in the Arab countries (Fig 3B).

In addition, countries with higher energy use per capita (p=0.04), higher electric power consumption per capita (p=0.05), lower renewable energy consumption (p=0.01), and lower energy imports (p=0.04) showed worse mitigation levels (Fig 3B). This is consistent with the correlation observed between poor mitigation and high CO_2 emissions, as it is evident that energy consumption generates more CO2 emissions while renewable energy consumption decreases CO2 emissions.

Countries with higher annual freshwater withdrawals were significantly more likely to show poor mitigation compared to countries with lower withdrawals (p=0.0028), as were countries with smaller forest and agricultural lands (p=0.01 and p=0.05, respectively) (Fig 3B). Countries with higher annual population growth (p=0.02) were significantly more likely to show poor mitigation.

In addition, countries with a younger population were significantly correlated with worse mitigation (p=0.02) (Fig 3B). A relatively younger population in the GCC countries relative to the other Arab countries (as defined by the percentage of the population younger than 65 years of age) partially explains the degree of mitigation with a correlation value of 0.43. As younger patients are more likely to have mild symptoms, they are at increased likelihood of spreading the virus unknowingly in case they fail to follow strict quarantine and stay-at-home orders.

333 **Predictive Modeling**

334 We also carried out one-month SEIR-based projections for infected patient numbers in
335 nine Arab countries as cumulative cases and as daily cases (Fig 4 and additional file 5,
336 respectively) using data from the first cases to April 22, 2020. These projections are
337 largely consistent with the observed data; however, Algeria and Egypt have a higher
338 case number than projected while Qatar's and Saudi Arabia's numbers are slightly
339 lower than projected. This analysis highlights that appropriate modelling can be used to
340 project cases within these countries for at least one month and that exponential growth
341 fitting countries will have very high case numbers within a single month even with
342 mitigation measures in place.

343

Discussion

We have performed a comparative global analysis of mitigation impact and found a geographic cluster of countries centered on the Arabian Peninsula, which showed reduced responsiveness to mitigation measures and high infection rates. While infection rates were reported among Arabian Peninsula countries at different time frames, [24–26] these studies did not compare infection rates to other worldwide countries.

We have also analyzed potential factors that could be correlated with mitigation impact. We found highly significant negative correlations between air pollution and CO_2 emissions and mitigation impact. The higher the air pollution and CO_2 emissions, the higher the infection rates and the lower the mitigation impact.

The role of air pollution in partially explaining the degree of mitigation with a correlation value of -0.5 is supported by emerging research on the diffusion dynamics of COVID-19 and small studies conducted on air quality in China, Italy, and California, USA. [27–31] Pansini et al. (2020) and Baron (2020) have found that levels of PM2.5 in the air of cities are correlated with increased SARS-CoV-2 mortality, [32,33] but our study does not support this finding as mortality levels in the GCC countries remain low, further discussed below. To our knowledge, our study is the first to report a correlation between infection rates and the specific metric of CO_2 emissions per capita. One previous study reported significant correlation between weather, humidity and SARS-COV-2 daily case and fatality numbers among Arabian Peninsula [34] but without comparing this to other

366 countries as we have done. We found no significant correlations between mean
367 temperatures, humidity or visibility and mitigation impact among Arab countries.
368
369 The AP countries have been experiencing rapid socio-economic growth and
370 industrialization, leading to high energy and water demands. The demand patterns in
371 the region, in both residential and industrial sectors are determined by the geophysical
372 conditions and resources, the rapid population growth, the resultant urbanization, and
373 rising living standards. [35–37] In these countries, the energy production and
374 consumption result in the bulk of CO_2-equivalent emissions, with the power and water
375 sectors producing on average 43% of emissions. [38] The mechanisms connecting
376 these factors with COVID-19 infection require further study but may be related to the
377 level of growth and industrialization within the country. Thus, indices of land and energy
378 use correspond to the factors of air pollution and carbon dioxide emissions, which are
379 increased in rapidly developing countries.
380
381 Moreover, consistent with a recent study showing that the spread rate increases with
382 temperature and young age,[39] our analysis shows a correlation between low
383 mitigation impact and the relatively young population of the GCC countries. The
384 correlation between the degree of mitigation and population age can be explained by
385 behavioral, health, mental, social, and psychological factors that differ between the age
386 groups. This factor of population age could also explain why the CFR values remain
387 extremely low in the AP countries despite the less effective mitigation measures. The
388 CFR values as of May 22, 2020 range from 0·046% in Qatar to 0.86% in the UAE, with

389 a mean CFR of 0·457% among the AP countries. These CFR rates are among the
390 lowest globally, a finding that can be explained by three trends. [40] First, the younger
391 age of the patients infected [41] decreases the likelihood of patient co-morbidities and/or
392 the development of complications during the course of illness. Second, the AP countries
393 have had wide and accessible testing in place, thus allowing for the detection of mild
394 cases of infection, which are more likely to resolve without complication (Fig 2B). Third,
395 the GDP per capita of the AP countries, while not significant in reducing the spread of
396 COVID-19, could translate into faster allocation of resources to hospital rooms, ICUs
397 and protective equipment, thereby allowing healthcare systems to provide standard-of-
398 care treatment to all patients admitted with SARS-CoV-2 throughout the duration of the
399 pandemic.
400 Interestingly, certain demographic factors that were expected to be strongly correlated
401 with mitigation levels, such as population density, were not found to be statistically
402 significant among the AP countries or at the global level. This is discordant with the
403 limited literature, which suggests that density is a significant factor in non-mitigation. [42]
404 Other variables like GDP per capita, researchers per capita, literacy levels, and the
405 prevalence of diabetes in the population were significantly correlated with mitigation
406 levels on the global scale, but not so within the cluster of the AP countries (Fig 3B and
407 additional file 4).
408
409 While our analysis has uncovered interesting trends and correlations between delayed
410 impact of mitigation and certain indicators, these correlations are not necessarily
411 causative or exhaustive. However, some of these indicators could be used to better

strategize mitigation strategy and social distancing measures. They could be useful in the context of a second wave or another pandemic to determine the potential impact at a population level. For example, the observation that younger populations have decreased SARS-COV-2 mitigation could suggest that strategies targeting younger people through awareness campaigns or mandatory work from home could increase the effectiveness of mitigation measures.

Furthermore, there are many features within these countries that have not been measured but that may play an important role in the spread of the disease. For example, there could be a difference in the compliance to mitigation measures between different countries. Additional data, if shared across countries, is important to enable further analysis and a unified effort against what is likely to be a long-lasting pandemic.

Conclusion

Our study shows that environmental and demographic factors might explain the lesser degree of COVID-19 mitigation observed among the GCC countries. The significant correlation ($r = 0.5$, $p = 0.01$) between poor mitigation and elevated air pollution suggests the important role of environmental policies and regulatory bodies in reducing environmental pollutants and CO_2 emissions levels. The significant correlation between poor mitigation and a younger population ($r = 0.43$, $p = 0.02$) additionally highlights the need for implementing mitigation measures even in mild and asymptomatic patients. The indicators with significant correlation to mitigation levels are certainly difficult to reform within a short period of time. Instead, these correlations are useful in helping government authorities decide on the duration and strictness of the social distancing rules. Although the Arabian Peninsula cluster of countries has implemented social distancing protocols early on, the mitigation has been delayed and complicated by the additional factors of demography, environment, and energy use. Countries with similar profiles as Arabian Peninsula countries should carry out more stringent distancing measures.

List of abbreviations

AP: Arabian Peninsula

ICU: Intensive Care Unit

EDR: excess death rate

CFR: case fatality rate

nRMSE: normalized root mean square error

449 Arab-nonAP: non-Arabian Peninsula

450

451 ## Declarations

452 **Ethics approval and consent to participate**

453 Not applicable

454

455 **Consent for publication**

456 Not applicable

457

458 **Availability of data and materials**

459 The datasets supporting the conclusions of this article are available on John Hopkins,

460 the World Bank, Synoptic and Worldometer,

461 https://github.com/CSSEGISandData/COVID-19 [21],

462 https://data.worldbank.org/indicator [22], and https://download.synopticdata.com [23]

463

464 **Competing interests**

465 The authors declare that they have no competing interests

466

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471

Authors' contributions

NH did data management, collection analysis, interpretation, and figures with inputs from JT. RC contributed to the data collection. QG and PM developed the predictive modelling. MR and RC did the literature search and prepared the first draft of the manuscript. NH, JT, RC, and MR revised the manuscript with inputs from RM and LC. All authors have read and approved the manuscript.

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Fig 1. Geographic distribution of mitigation effectiveness for countries with at least 500 confirmed cases.

A) The cumulative confirmed cases and exponential fit for countries from the best to the worst mitigation up to June 22, 2020. B) Mitigation quantification (nrmse) for the indicated months. Every country with at least 500 cases is indicated by a colored circle with the color representing the mitigation measure (nRMSE). Interestingly, while many countries have shown improvement during a one month period there's a cluster of countries in and around the Arabian peninsula that is showing relatively unmitigated infections (dashed circle). Maps were created with Matlab 2019a (https://www.mathworks.com/products/matlab.html) C) Confirmed cases for different country groups up to June 22, 2020. Arab countries are divided into Arabian Peninsula

606 (AP) and non-Arabian Peninsula (Arab-nonAP). Selected countries in red are France,
607 Spain, Italy, South Korea, New Zealand and Germany. The upper panel shows the
608 confirmed cases normalized to the maximum number to show the profiles of different
609 countries. The lower panel shows the confirmed cases as a percent of the population.
610 D) Boxplots showing the percent of a population infected across different country
611 groups up to June 22, 2020. Other is all countries not including Arab countries. Arab-
612 nonAP are Arab countries excluding Arabian peninsula and Arab-AP are Arabian
613 peninsula countries. The boxplot shows the 25-75 interquantile range with the line in the
614 middle showing the median. The whiskers extend to non-outliers. The outliers are
615 shown as a +. The inset box shows the kruskal-wallis calculated p-values between each
616 group.
617
618 **Fig 2. Arab country mitigation measures and infection projection.**
619 A) Zoom to Arab countries. Maps were created with Matlab 2019a
620 (https://www.mathworks.com/products/matlab.html). B) Correlations of Testing
621 Parameters to the normalized root mean square error (nrmse). The scatterplot, Kendall
622 Tau correlation coefficient and pValue are shown for different testing parameters. C)
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624 various mitigation measures. The date of first infection is shown as FirstCase and the
625 number of elapsed days until the indicated mitigation is show as number of days.
626 Despite most GCC countries implementing measures comparable to other countries,
627 their mitigation was not as successful as other countries.
628

Fig 3. Correlations between nRMSE and multiple indicators for Arab countries with at least 500 cases.

A) Indicators were grouped together based on World Bank categories and the p-value (x-axis) was plotted against correlation coefficient (y-axis) for every indicator. Some indicators occur in more than one category. The vertical line was set at p-value <= 0.05. Correlations with p-value <= 0.05 are highlighted in blue. The numbers within the plots refer to the indicator number shown in panel B. B) The indicator, correlation coefficient and p-value for every indicator. The significant correlations (p<=0.05) are highlighted in blue. C) A scatterplot of indicator value vs. nrmse for every indicator with available data. Indicators are sorted by the lowest p-value to the highest p-value. The number in the title is the indicator number shown in panel B. The letters are country codes as shown in the legend below. Indicators were extracted from the World Bank Open Data portal and Synoptic and processed as described in the Methods. Kendall rank correlations were calculated between each measure and nRMSE.

Fig 4. Projections of nine Arab countries as cumulative cases.

Black points represent the actual cases, blue lines represent projections assuming the confirmed cases are the true case numbers and gray lines represent projections assuming a 40% uncounted case numbers. The red dot shows the actual confirmed cases on May 22 2020

Additional files

Additional file 1: Validating the mitigation measure.

To quantify the degree that a country was slowing down the infection we calculated a mitigation measure as the min-max normalized root mean square (rmese/max-min) of an exponential fit through all the data. The gray line is the fit and the red points are the data. The normalized rmse (in the title) captures well the fit to an exponential for all these countries.

Additional file 2: Mapping of nRSME onto countries with at least 500 cases at 30 day intervals from 23-Feb to 22-Jun.

Maps were created with Matlab 2019a (https://www.mathworks.com/products/matlab.html).

Additional file 3: Mitigation Measure Time.

Here we show the times that different countries applied various mitigation measures. The date of first infection is shown as FirstCase and the number of elapsed days until the indicated mitigation is show as number of days.

Additional file 4: Correlations between nRMSE and multiple indicators for all countries with at least 500 cases.

A) Indicators were grouped together based on World Bank categories and the p-value (x-axis) was plotted against correlation coefficient (y-axis) for every indicator. Some indicators occur in more than one category. The vertical line was set at p-value <= 0.05. Correlations with p-value <= 0.05 are highlighted in blue. The numbers within the plots refer to the indicator number shown in panel B. B) The indicator, correlation coefficient

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Additional file 5: Projections of nine Arab countries as daily cases.

Black points represent the actual cases while blue lines represent projections.

Additional file 6: Data on testing rate

Additional file 7: Data on mitigation measures

Figures

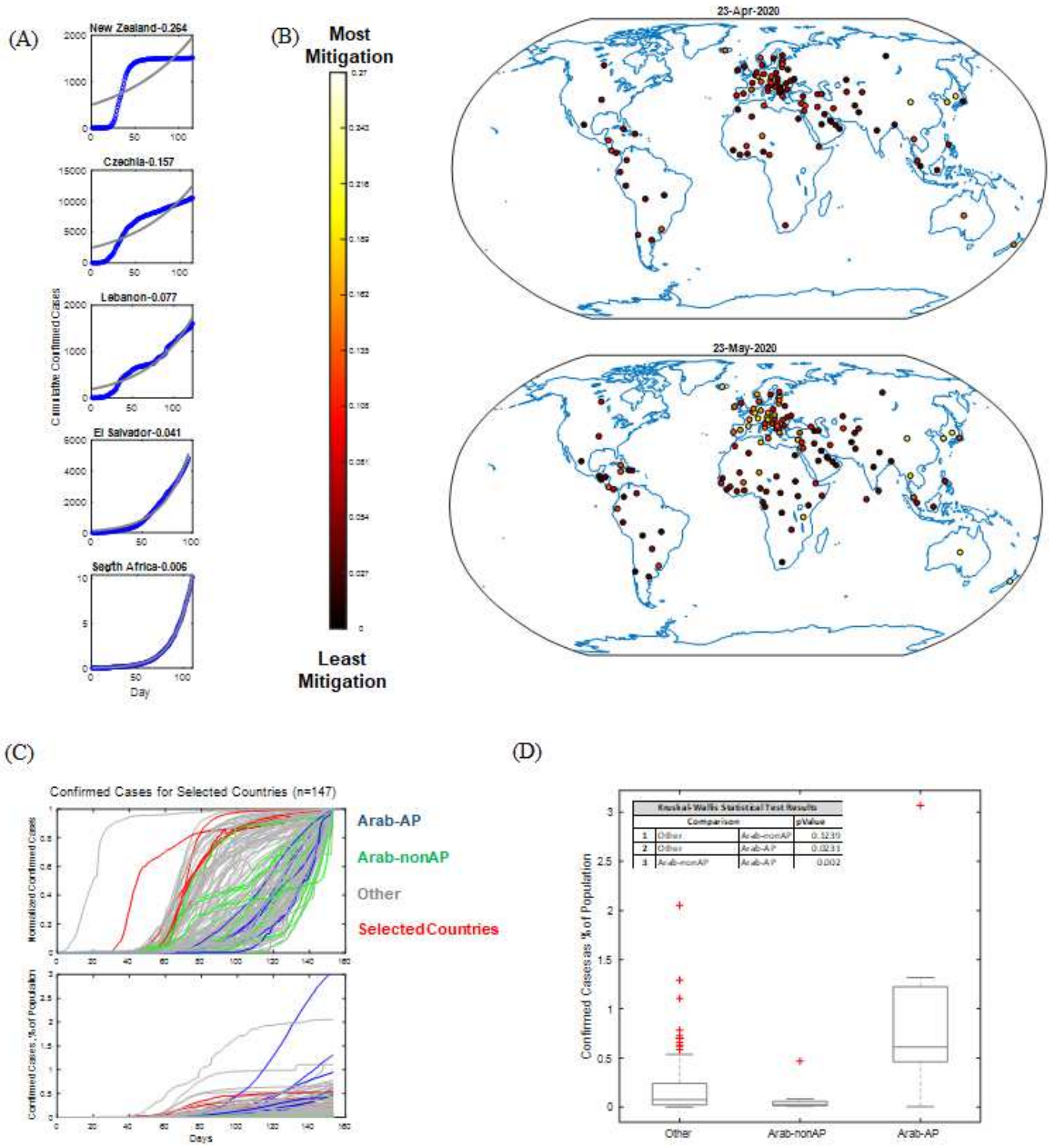

Figure 1

Geographic distribution of mitigation effectiveness for countries with at least 500 confirmed cases. A) The cumulative confirmed cases and exponential fit for countries from the best to the worst mitigation up to June 22, 2020. B) Mitigation quantification (nrmse) for the indicated months. Every country with at

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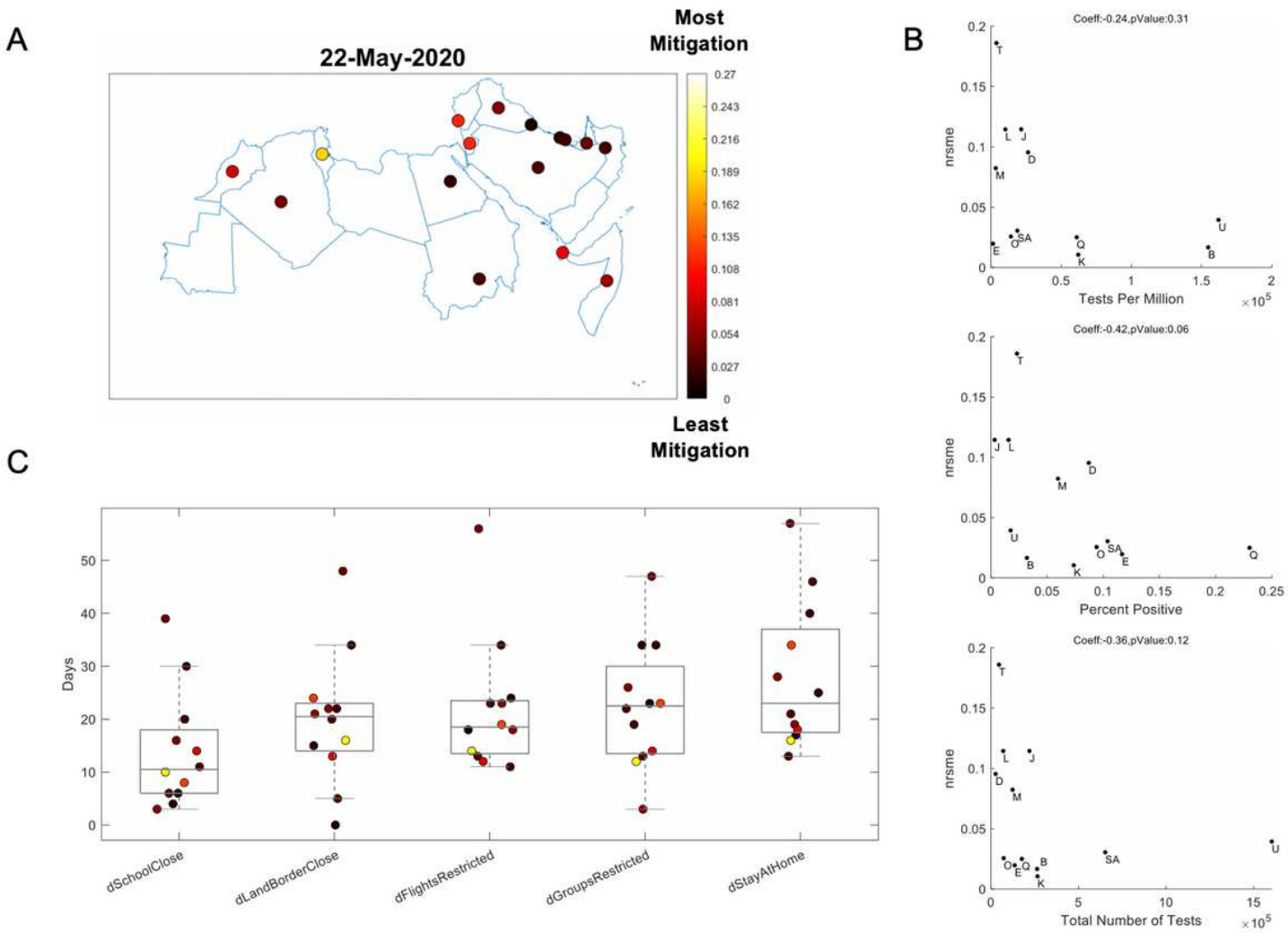
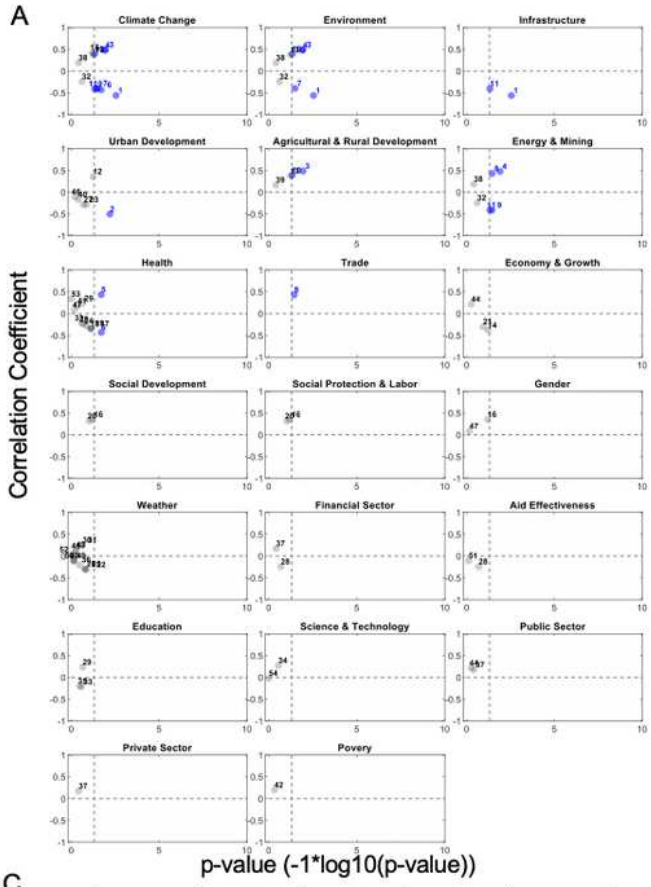


Figure 2

Arab country mitigation measures and infection projection. A) Zoom to Arab countries. Maps were created with Matlab 2019a (https://www.mathworks.com/products/matlab.html). B) Correlations of Testing Parameters to the normalized root mean square error (nrmse). The scatterplot, Kendall Tau correlation coefficient and pValue are shown for different testing parameters. C) Mitigation Measure Time. Here we show the times that different countries applied various mitigation measures. The date of first infection is shown as FirstCase and the number of elapsed days until the indicated mitigation is show as number of days. Despite most GCC countries implementing measures comparable to other countries, their mitigation was not as successful as other countries.



B

#	Indicator	Corr Value	Corr pValue
1	Annual freshwater withdrawals, total (% of internal resources)	-0.56	0.00
2	PM2.5 air pollution, mean annual exposure (micrograms per cubic meter)	-0.50	0.01
3	Forest area (% of land area)	0.49	0.01
4	Renewable energy consumption (% of total final energy consumption)	0.48	0.01
5	Population ages 65 and above (% of total population)	0.43	0.02
6	Population growth (annual %)	-0.43	0.02
7	CO2 emissions (metric tons per capita)	-0.40	0.03
8	Energy imports, net (% of energy use)	0.43	0.04
9	Energy use (kg of oil equivalent per capita)	-0.41	0.04
10	Agricultural land (% of land area)	0.39	0.05
11	Electric power consumption (kWh per capita)	-0.41	0.05
12	Mortality caused by road traffic injury (per 100,000 people)	0.36	0.06
13	Arable land (% of land area)	0.37	0.06
14	Gross savings (% of GDP)	-0.38	0.06
15	Droughts, floods, extreme temperatures (% of population, average 1990-2009)	0.42	0.06
16	Vulnerable employment, male (% of male employment) (modeled ILO estimate)	0.35	0.06
17	Immunization, DPT (% of children ages 12-23 months)	-0.35	0.07
18	Immunization, measles (% of children ages 12-23 months)	-0.35	0.08
19	Diabetes prevalence (% of population ages 20 to 79)	-0.34	0.08
20	Vulnerable employment, female (% of female employment) (modeled ILO estimate)	0.32	0.10
21	GDP per capita (current US$)	-0.30	0.12
22	air_temp_set_1_(month2)	-0.31	0.14
23	Population in the largest city (% of urban population)	-0.28	0.14
24	International migrant stock (% of population)	-0.28	0.14
25	air_temp_set_1_(month1)	-0.30	0.17
26	air_temp_set_1_(month3)	-0.29	0.17
27	Population in urban agglomerations of more than 1 million (% of total population)	-0.28	0.20
28	Net migration	-0.24	0.21
29	Population ages 0-14 (% of total population)	0.23	0.23
30	relative_humidity_set_1_(month1)	0.25	0.23
31	relative_humidity_set_1_(month3)	0.25	0.23
32	Electricity production from natural gas sources (% of total)	-0.24	0.25
33	Population ages 15-64 (% of total population)	-0.22	0.27
34	Researchers in R&D (per million people)	0.27	0.28
35	Literacy rate, adult total (% of people ages 15 and above)	-0.20	0.33
36	air_temp_set_1_(month4)	-0.20	0.35
37	air_temp_set_1_(month4)	-0.20	0.35
38	Strength of legal rights index (0=weak to 12=strong)	0.17	0.39
39	Electricity production from oil sources (% of total)	0.19	0.39
40	Rural population (% of total population)	0.17	0.40
41	Urban population (% of total population)	-0.17	0.40
42	Prevalence of undernourishment (% of population)	0.18	0.44
43	GINI index (World Bank estimate)	0.20	0.48
44	relative_humidity_set_1_(month2)	0.14	0.52
45	Central government debt, total (% of GDP)	0.21	0.55
46	relative_humidity_set_1_(month4)	0.12	0.59
47	relative_humidity_set_1_(month4)	0.12	0.59
48	Population density (people per sq. km of land area)	-0.10	0.63
49	Fertility rate, total (births per woman)	0.08	0.69
50	visibility_set_1_(month1)	-0.10	0.72
51	visibility_set_1_(month3)	-0.10	0.72
52	visibility_set_1_(month4)	-0.10	0.72
53	visibility_set_1_(month4)	-0.10	0.72
54	Prevalence of HIV, total (% of population ages 15-49)	-0.11	0.76
55	visibility_set_1_(month2)	0.03	0.94
56	Community health workers (per 1,000 people)	0.33	1.00
57	Technicians in R&D (per million people)	-0.02	1.00
58	PM2.5 air pollution, population exposed to levels exceeding WHO guideline value (% of total)		

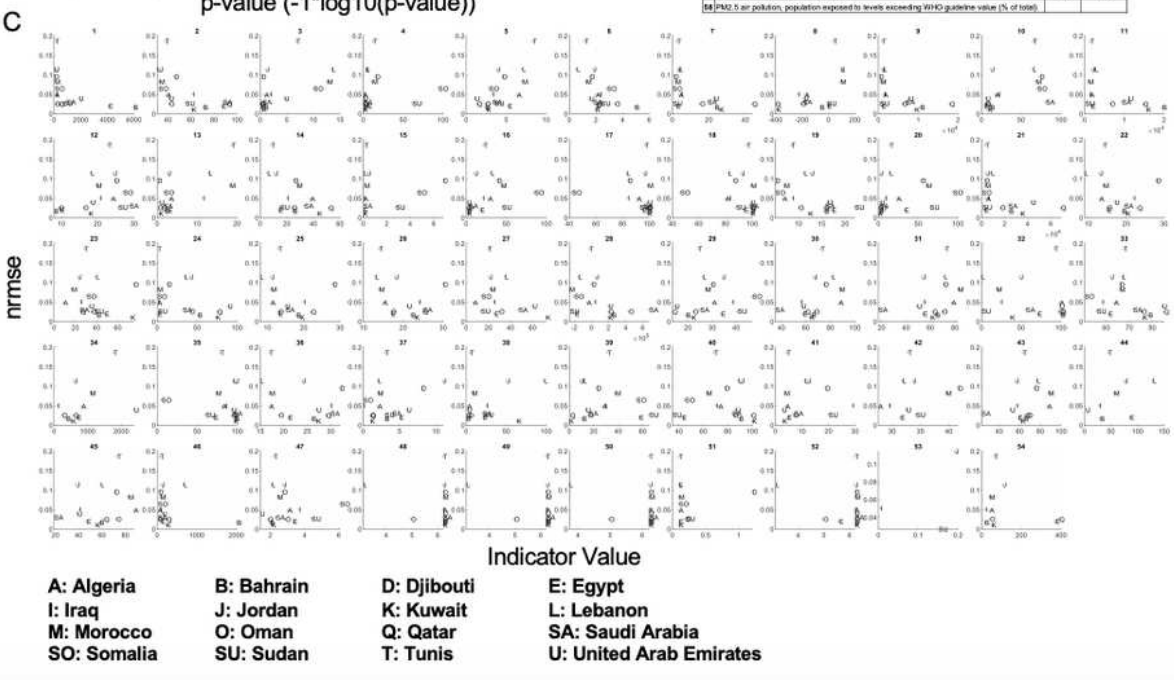


Figure 3

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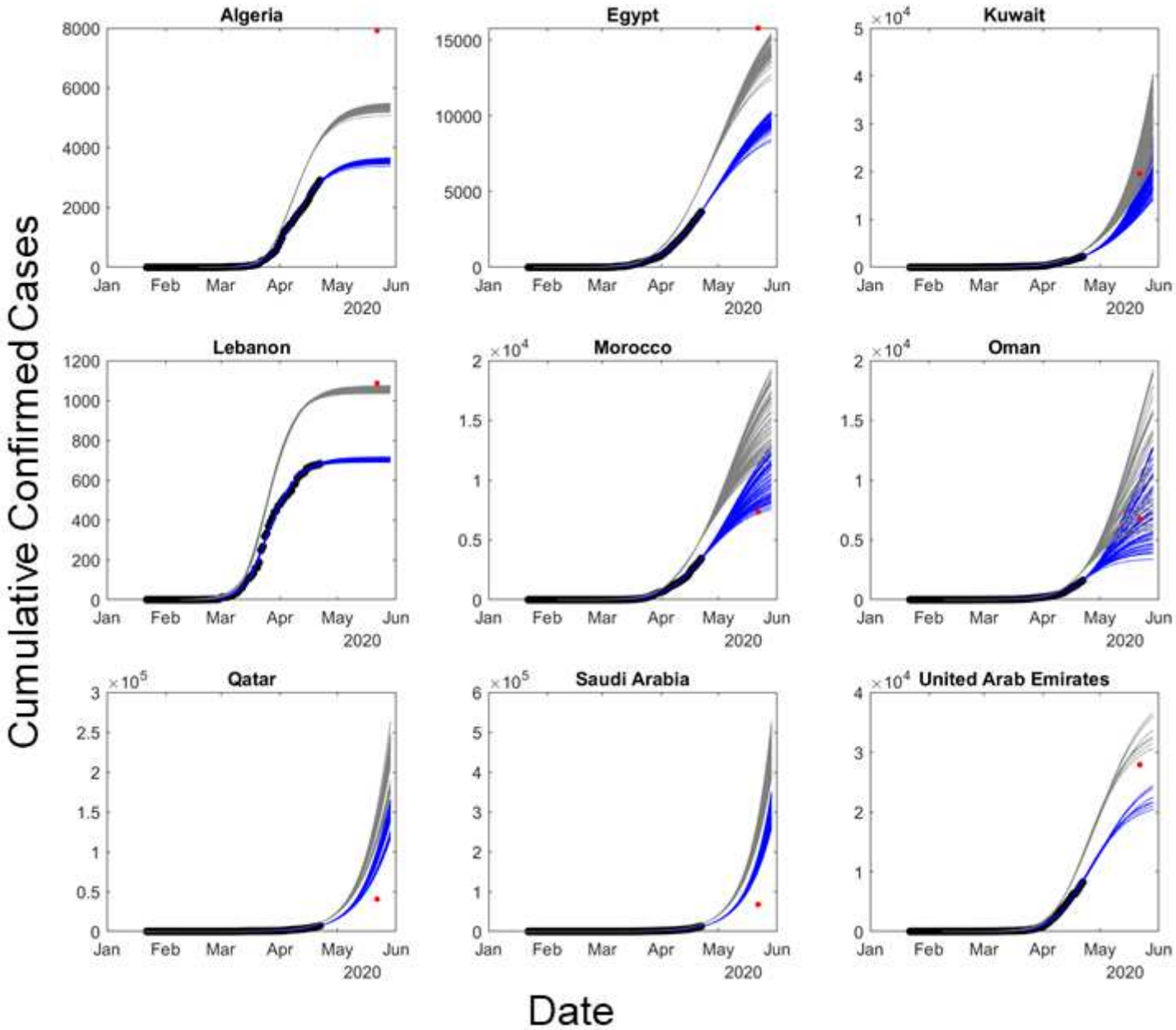

Figure 4

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Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Additionalfile67.pdf
- S5Fig.pptx
- S4Fig.pptx
- S3Fig.pptx
- S2Fig.pptx
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