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Assessing the future progression of COVID-19 in Iran and its neighbors using Bayesian models

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A R T I C L E I N F O

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A B S T R A C T

Background: The short term forecasts regarding different parameters of the COVID-19 are very important to make informed decisions. However, majority of the earlier contributions have used classical time series models, such as auto regressive integrated moving average (ARIMA) models, to obtain the said forecasts for Iran and its neighbors. In addition, the impacts of lifting the lockdowns in the said countries have not been studied. The aim of this paper is to propose more flexible Bayesian structural time series (BSTS) models for forecasting the future trends of the COVID-19 in Iran and its neighbors, and to compare the predictive power of the BSTS models with frequently used ARIMA models. The paper also aims to investigate the casual impacts of lifting the lockdown in the targeted countries using proposed models.

Methods: We have proposed BSTS models to forecast the patterns of this pandemic in Iran and its neighbors. The predictive power of the proposed models has been compared with ARIMA models using different forecast accuracy criteria. We have also studied the causal impacts of resuming commercial/social activities in these countries using intervention analysis under BSTS models. The forecasts for next thirty days were obtained by using the data from March 16 to July 22, 2020. These data have been obtained from Our World in Data and Humanitarian Data Exchange (HDX). All the numerical results have been obtained using R software.

Results: Different measures of forecast accuracy advocated that forecasts under BSTS models were better than those under ARIMA models. Our forecasts suggested that the active numbers of cases are expected to decrease in Iran and its neighbors, except Afghanistan. However, the death toll is expected to increase at more pace in majority of these countries. The resuming of commercial/social activities in these countries has accelerated the surges in number of positive cases.

Conclusions: The serious efforts would be needed to make sure that these expected figures regarding active number of cases come true. Iran and its neighbors need to improve their extensive healthcare infrastructure to cut down the higher expected death toll. Finally, these countries should develop and implement the strict SOPs for the commercial activities in order to prevent the expected second wave of the pandemic.

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Introduction

The novel coronavirus disease (COVID-19) started in Wuhan, China during December 2019 and declared as pandemic by the World Health Organization (WHO) on March 11, 2020 (World Health Organization, 2020). This virus transmits through respiratory droplets and contact with infected surfaces (Al-qaness et al., 2020). The pace of transmission is very fast for this disease, due to which, it was able to infect almost all the countries around the globe in a short span of time (Tomar & Gupta, 2020). After China, Iran became the hub of this disease in Asia (Muniz-Rodriguez et al., 2020). Though, the real time data show that the country has been able to slow down the trajectory of outbreak, the number of positive cases is still soaring at almost constant pace. Iran shares border with Afghanistan, Armenia, Azerbaijan, Iraq, Pakistan and Turkey. It is important to investigate the current and future trends of the pandemic in Iran and its neighbors in order to (i) compare the patterns of the outbreak in Iran and its neighbors (ii) know the expected surges in number of cases, and (iii) assess the required healthcare facilities to tackle the expected figures.

The researchers are continuously observing the future trends of the pandemic in Iran. Different models have already been applied to study the future behavior of the outbreak in the country. To be more specific, the currently used models include Neural Network and ARIMA model (Moftakhar et al., 2020), SIR model (Zareie et al., 2020), Gumpertz differential equations (Ahmadi et al., 2020) and SEIR Model (Perc et al., 2020; Zhan et al., 2020). Although these are valuable contributions, but results of these contributions are based on quite small datasets, which can affect the reliability of the corresponding forecasts (Moftakhar et al., 2020). Secondly, all of these contributions utilized the classical models which consider the model parameters as fixed quantities, which may not be suitable for dynamic systems such as this pandemic (McQuire et al., 2019; Scott & Varian, 2013). A careful review of literature suggests that no study has involved the evolving behavior of the COVID-19 patterns.

Bayesian models are efficiently used for the estimation of dynamic systems (Roda, 2020). The Bayes estimates often have smaller mean square errors, as compared to their classical counterparts (Gelman et al., 2004). These models provide reliable results even in case of correlated estimates (MacLehose et al., 2007; Wakefield et al., 2010). In case of temporal data, the recently introduced Bayesian structural time series (BSTS) models are used (Scott & Varian, 2013). These models have some appealing advantages as compared to conventional time series models. These models consider the model parameters as random variables, which is more suitable for an evolving system, such as COVID-19. In addition, these models include the prior information and are capable to reflect the stochastic nature of temporal data more accurately (McQuire et al., 2019). Using these models, the trend, seasonality and regression components of the series can be modeled separately. The usual Bayesian dynamic linear models require variables to be Gaussian; however, the BSTS models have the capacity to incorporate the non-Gaussian variables 16. The BSTS models are very promising alternative to the classical time series models. These models allow the model parameters to evolve over time and are capable to include the prior information 10,17. These models have already been used to forecast the health harms due to drinking alcohol 18, crime rate due to alcohol licensing policies 11 and consumer sentiments 10. On the other hand, very large number of models, including all ARIMA and vector autoregressive models, can be expressed in the state space form 19. The intervention analysis for the dynamic time series can also be studied using BSTS models 20. Despites these features, the Bayesian models have not yet replaced the conventional models in forecasting the future behavior of this pandemic.

The main remedial measure for COVID-19 is the social distancing. The social distancing have already slow down the outbreak of pandemic in different countries (Anderson et al., 2020; Li et al., 2020). However, a careful review of the literature suggests that the impact of resuming the commercial/social activities (by lifting lockdown) have yet to be explored. The BSTS models can also be used to investigate such impacts using intervention analysis. However, unlike conventional models, these models measure the evolving impacts in terms of dynamic confidence interval for the difference between inherent and counterfactual observations (Scott & Varian, 2014).

The study has three main aims. The first aim of the study is to propose the BSTS models for investigating the future trends of COVID-19 and compare the predictive power of the proposed models with most frequently used ARIMA models. Secondly, the study has been designed to investigate the current and future progression in outbreak of COVID-19 in Iran and its neighbors, namely Afghanistan, Armenia, Azerbaijan, Iraq, Pakistan and Turkey, using BSTS models. Finally, thus study attempts to discuss the impacts of relaxing the social distancing strategies in countries (under study) using intervention analysis under BSTS models. We observed the better predictive power for BSTS models, as compared to ARIMA models, for predicting the future trends regarding different parameters of the COVID-19 in Iran and its neighbors.

Methodology

The data regarding cumulative number of confirmed cases, cumulative number of deaths, cumulative number of recoveries, number of active cases and cumulative number of tests conducted, have been obtained from Our World in Data (Our World in Data, 2020) and HDX (Novel, 2020). These agencies update and publish these data for all the counties on daily basis. Since, the published datasets have been considered for the analysis; we do not require ethical approval for the study.

ARIMA models

The ARIMA model is based on three parameters 'p', 'd' and 'q', where 'p' defines the autoregressive component, 'q' represents the moving average process and 'd' denotes the number of differencing. The mathematically form the ARIMA (p, d, q) model can be written as

$$W_t = \theta_1 w_{t-1} + \theta_2 w_{t-2} + \ldots + \theta_p w_{t-p} + \omega_1 - \lambda_1 \omega_{t-1} - \omega_2 - \lambda_2 \omega_{t-2} - \ldots - \omega_q - \lambda_q \omega_{t-q} \tag{1}$$

where, θ_p represents the terms of autoregressive process, $\omega_q$are the coefficients of the error terms, $\lambda_q$are the values of moving average operator and $W_t$is d-order differenced time series.

Bayesian structural time series models

The structural time series models (STSM) or state space models analyze the different components of the time series separately. This feature facilitates the interpretation of the individual components of the series. These models are also capable of enhancing predictive power of the model by incorporating explanatory variables and utilizing prior information regarding the model parameters. Additionally, the other layers including the cycles and interventions can also be incorporated in the model if required (Brodersen & Hauser, 2020).

These models can be given as pair of equations

$$W_t = Y_t \varphi_t + \omega_t; \cdot \omega_t \tilde{} N(0, \Phi_t) \tag{2}$$

$$\varphi_{t+1} = Z_t \varphi_t + H_t \mu_t; \cdot \mu_t \tilde{} N(0, \Omega_t) \tag{3}$$

Since Equation (2) relates the experimental data W_t to the unobserved latent variableφ_t, it is named observation equation. Here, W_t is $l \times 1$ vector of observations, Y_t is a $l \times m$ matrix of known observations, φ_t is unobserved $l \times 1$ state vector and ω_t are the randomly and independently distributed Gaussian error terms with zero mean and varianceΦ_t. Equation (3) represents the latent state over time and is named transition equation. It is simply an autoregressive model ofφ_t, defined by the unobservable Markov Chain process observed byW_t. TheZ_t is $l \times l$ transition matrix, H_t is $l \times m$ error control matrix, and μ_t another Gaussian random error term with mean zero and varianceΩ_t. The Bayesian version of the STSM is called the Bayesian structural time series (BSTS) models.

The BSTS models can be used to conduct the intervention analysis for a time series. These models can estimate the post-intervention difference between the observed series and a simulated time series that would have occurred had the intervention not took place. These computations help to assess the causal impacts of lifting lockdowns using the following steps. In the first step the BSTS model is estimated using data up to target date (date of lifting the lockdown). The next step uses estimated model to predict the post-lockdown period in the absence of the intervention (lifting the lockdown). In the last step, the difference between predicted and true series is computed, in the post-lockdown period, to estimate the causal impact of lifting the lockdown.

The forecasts for different parameters of the pandemic have been obtained using BSTS models. These models include the features of the Bayes approach. Using these models the prior information (in the form of expert opinion) is combined with the likelihood function (data at hand) to update the current information and to produce the final Bayesian models, called posterior distributions. These models employ the Bayesian model averaging and Kalman filtering to produce more precise forecasts (Scott, 2020). However, using these models, the closed form estimators for model parameters are not available, due to complexity of these models. We have used Markov Chain Monte Carlo (MCMC) method to estimate the model parameters numerically using R language. The MCMC methods draw the random samples for the model parameters using conditional distributions and average the results to produce the final estimates. The diagnostic checking for the models has been carried out using Ljung Box test. The comparison between the forecast accuracy of BSTS models and most commonly used ARIMA models has been reported based on different measures of forecast accuracy, such as, root mean square error (RMSE), mean absolute percentage error (MAPE) and Root Mean Square Percentage Error (RMSPE). Since the improved forecast accuracy under BSTS models were observed, we have reported the forecasts for different parameters of the pandemic under BSTS models only. Further, the impacts of resuming the commercial/social activities have also been investigated. To this end, we considered the lifting of lockdowns (in the said countries) as intervention and carried out the intervention analysis under BSTS models.

Results and discussions

On July 22, 2020 Iran had 278827 confirmed cases, Pakistan had 267428 cases, Turkey had 221500 cases, Iraq had 7159 cases, Afghanistan had 35727 cases, Azerbaijan had 28242 cases and Armenia had 35693 cases. On the other hand, on the same date, there were 19353 active cases in Iran, 48576 active cases in Pakistan, 10760 active cases in Turkey, 26062 active cases in Iraq, 10613 active cases in Afghanistan, 7423 active cases in Azerbaijan and 10249 active cases in Armenia. The maximum proportion of recoveries was observed in Turkey with 92.65% recoveries. Iran had 87.81% recoveries and Pakistan had 79.71% recoveries. The rest of the countries had approximately 70% recoveries. The mortality rate per 100 cases was 5.25 in Iran, 4.06 in Iraq, 3.33 in Afghanistan, 2.49 in Turkey, 2.12 in Pakistan, 1.90 in Armenia and 1.33 in Azerbaijan. Using these data, we compared the performance of proposed BSTS models with most frequently used ARIMA models. The comparison was based on different forecast accuracy criteria, namely, such as, RMSE, MAPE and RMSPE. The results have been placed in Table 1. These results advocate the superior performance of the proposed models as compared to ARIMA models, with few exceptions. The results for MAPE and RMSPE are less than 0.1 for all models, which indicate sufficient forecast capabilities of the proposed models (Hyndman & Koehler, 2006). Further, the diagnostic checking for the proposed models has been considered using Ljung Box test. These results have also been reported in Table 1. For a parsimonious model, the residuals from the concerned model should be white noise. We have tested this assumption at lag-10 and lag-20 respectively. At both lags, the residuals from the proposed models were found to be white noise. Hence, all the proposals can be efficiently used to produce the respective forecasts.

The future patterns for different parameters of the pandemic in Iran and its neighbors have been given in Fig. 1 and in Table 2 (given in the appendix). In Fig. 1, the logarithmic scale has been considered for the Y-axis; hence straight lines show the exponential trends. The different line colors for 110th day represent the comparison of true versus fitted values from the BSTS models. It is encouraging to observe that fitted values from the BSTS models are very close to the true values, as the lines for the fitted values have overlapped the lines for the true values. Fig. 1(A) represents the future patterns of cumulative number of cases in the said countries. These forecasts suggest that the current pace of growth in the cumulative number of cases is expected to continue in the next thirty days. According to these forecasts, Iran is expected to have 25.23% increase in total number of cases. We expect these numbers to increase in Pakistan by 15.90%, in Turkey by 12.12%, in Iraq by 68.17%, in Afghanistan by 11.10%, in Azerbaijan by 45.37% and in Armenia by 34.79%. Unfortunately, the death toll is expected to increase at more paces for all the countries except Turkey, Fig. 1(B). Our forecasts suggested that the death figures can soar by 41.40% in Iran, 20.64% in Pakistan, 8.88% in Turkey, 64.66% in Iraq, 47.23% in Afghanistan, 63.83% in Azerbaijan and 59.44% in Armenia. Hence these countries should embitter their expensive care infrastructure to avoid these expected figures. The encouraging aspect of these forecasts was that the healthy pace of recoveries is expected in these countries. These forecasts have been reported in Fig. 1(C). We expect 29% increase in recoveries for Iran, 38.15% for Pakistan, 14.64% for Turkey, 94.77% for Iraq, 14.65% for Afghanistan, 75.46% for Azerbaijan and 55.89% for Armenia. Fig. 1(D) elucidates that the number of active cases are expected to stay at current state for Iraq and Afghanistan, while for other countries the active number of cases are expected to reduce in the next thirty days. In particular, the active numbers of cases are expected to decrease by 34.73% in Iran, by 82.31% in Pakistan, by 34.20% in Turkey, by −0.12% in Iraq, by 0.95% in Afghanistan, by 38.46% in Azerbaijan and by 17.82% in Armenia. So, Iraq and Afghanistan need to mobilize all their resources to cut down the active number of cases. All other countries need to make sure that the expected decrease in number of active cases should come true.

Iran resumed the comercial/social activities on April 20, 2020, Pakistan on May 9, Turkey on April 27, Iraq on April 11, Azerbaijan on April 20 and Armenia on May 4, 2020 (Wikipedia. 2020; https://, 2020). These dates have been considered as intervention for each of the countries. The impacts of remuning the comercial/social activities in theses countries have been presented in Fig. 2 and in Table 3 (given in appendix). The results for cumulative number cases have only been reported, because the patters for other parameters of the pandemic were similar. Further, such results were not reported for Afghanistan, as the country did not imposed the lockdown. Fig. 2 and Table 3 reveal that lifting the lockdowns has resulted in substantially more positive cases (black lines) in all countries, as compared to the figures expected under lockdowns (grey shades). To be more specific, due to liftine of lockdown, Iran experienced absolute increase of 95000 positive with 95%

Table 1
Results regarding diagnostic checking and forecast accuracy for the proposed models.

Country	Model	RMSE	MAPE	RMSPE	Lag-10		Lag-20	
					Statistic	P-value	Statistic	P-value
Iran	BSTS	427.5731	0.0029	0.0091	0.9222	0.9999	2.1092	0.9856
	ARIMA	480.1059	0.0038	0.0092				
Pakistan	BSTS	479.0241	0.0194	0.0368	7.9655	0.6322	22.8040	0.2985
	ARIMA	472.2850	0.0281	0.0841				
Turkey	BSTS	211.7206	0.0086	0.0220	10.5560	0.3931	19.8360	0.4683
	ARIMA	274.8335	0.0135	0.0431				
Iraq	BSTS	287.2881	0.0182	0.0273	3.2500	0.9749	20.0730	0.4534
	ARIMA	292.7497	0.0183	0.0292				
Afghanistan	BSTS	120.4284	0.0193	0.0324	4.7489	0.9073	18.6580	0.5441
	ARIMA	119.5267	0.0247	0.0544				
Azerbaijan	BSTS	70.9547	0.0166	0.0298	2.3563	0.9928	8.7475	0.9857
	ARIMA	73.6370	0.0180	0.0407				
Armenia	BSTS	1.3305	0.0225	0.0404	10.5990	0.3896	19.8640	0.4665
	ARIMA	1.3972	0.0265	0.0440				

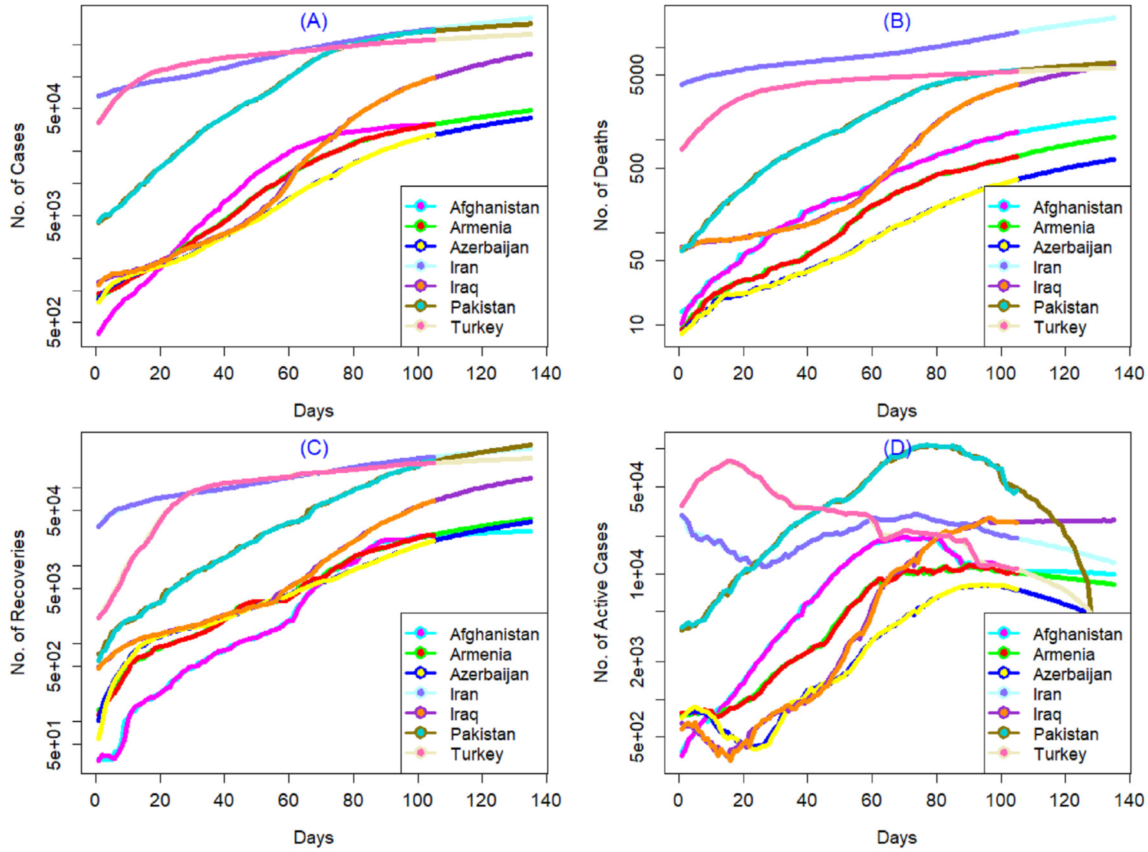

Fig. 1. True versus fitted values and forecasts for different paramaters of the pandemic in Iran and its neighbors.

prediction interval {85000, 108000}. Similarly, the absolute increase for Pakistan has been 56425{48076, 63712} for Turkey 101000 {90000, 120000}, for Iraq 16611 {14152, 18933}, for Azerbaijan 4882 {4113, 5583} and for Armenia 3523 {868, 5062}, respectively. However, the percentage increase in number of positive cases was 51.67%, 26.74%, 83.81%, 20.62%, 20.90% and 10.95% for Iran, Pakistan, Turkey, Iraq, Azerbaijan and Armenia, respectively. Fortunately, the fast trajectory of recoveries in these countries have subsided the impacts of resuming commercial activities to a great extend. However, these countries still need to have a close look at the SOPs developed to maintain the social distances while carrying the commercial activities so that the possible second wave of the pandemic can be prohibited.

The results from the study are in close agreement with the earlier studies conducted to forecast the patterns of COVID-19 in different countries such as; China (Fanelli & Piazza, 2020; Li et al., 2020), France (Fanelli & Piazza, 2020), Germany (Perc et al., 2020), India (Tomar & Gupta, 2020), Iran (Moftakhar et al., 2020; Perc et al., 2020), Itly (Fanelli & Piazza, 2020), Nigeria (Abdulmajeed et al., 2020), Pakistan (Yousaf et al., 2020), Slonenia (Perc et al., 2020), United States (Perc et al., 2020). However, the said studies have employed the classical time series models, while we have proposed the BSTS models. In addition, the causal impacts of lifting the lockdowns were not investigated in the said contribution. Our study has also investigated the causal impacts of lifting the lockdowns in the countries under study.

Conclusion

The study has been planned to assess the future behaviors of different parameters of the COVID-19 in Iran and its neighbors. We have proposed a more flexible approach, using BSTS models, to obtain the said forecasts. The proposed models are capable to include the prior information and allow the coefficients to vary with time in order to detect the data generation process more accurately. The proposed Bayesian models provided improved forecasts as compared to the most commonly used ARIMA models. The impacts of resuming the commercial/social activities in the said countries have also been investigated using the proposed models. Our forecasts suggest that in terms of percentage increase in the number of positive cases the countries under the study are expected to have following ranks Iraq > Azerbaijan > Armenia > Iran > Pakistan > Turkey > Afghanistan. On the other hand the expected death figures will be reasonable for Turkey, moderate for Pakistan and high in rest of the countries. So, the countries expecting high death figure should improve their crucial care infrastructure to avoid the harmful expected figures.

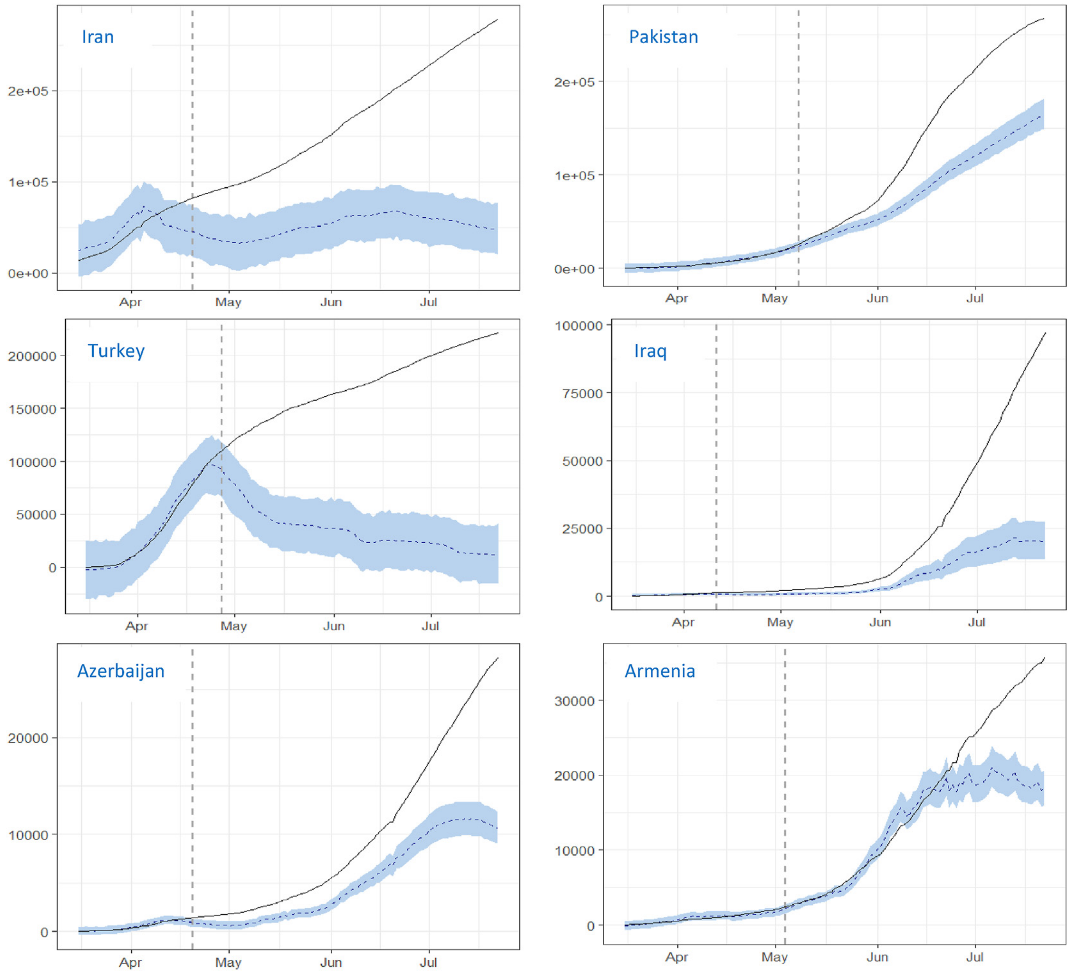

Fig. 2. Impacts of resuming the social activities in Iran and its neighbors.

In Iraq and Afghanistan the active numbers of cases are expected to stay at the current state, while for other countries these numbers are expected to decrease significantly.

So, Iraq and Afghanistan need to strictly adhere the social distance strategies to cut down the active number of cases. As resuming the commercial/social activities in these countries has already increased the outbreak of the pandemic, the development and implementation of the strict social distance SOPs are mandatory to prevent the expected second wave of the outbreak in these countries.

The study has few limitations. Although, the proposed models have produced gains in the forecast accuracy, the underlying uncertainty of the data my affect the forecasts. In addition, we assumed that obtained data is correct and no intervention will took place during the next month. The violation of these assumptions can result in inefficient forecasts.

Authors' contribution

The study was carried out by one author.

Conflict of interest disclosures

The author declares that there are no competing interests.

Ethical statement

Since we have used the published data, no ethical approval is needed.

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

Table 2
Forecasts for different parameters of the pandemic for next thirty days

Country	Expected Positive Cases	Expected Deaths	Expected Recoveries	Expected Active Cases
Iran	349169 (307685, 394185)	20706 (19218, 22135)	315832 (267984, 359838)	12631 (679, 41721)
Pakistan	309941 (247856, 367370)	6849 (5614, 7981)	294502 (269793, 306569)	8591 (2449, 52820)
Turkey	248355 (198797, 295987)	6017 (4747, 7250)	235258 (163133, 304483)	7080 (3865, 63698)
Iraq	163379 (143212, 183864)	6504 (5688, 7295)	130783 (113266, 149452)	26092 (5832, 52817)
Afghanistan	39693 (31602, 47147)	1752 (1422, 2056)	27429 (5033, 48121)	10512 (5147, 33896)
Azerbaijan	41055 (36152, 45881)	616 (553, 688)	35870 (31638, 40057)	4568 (199, 8242)
Armenia	48112 (41948, 54983)	1081 (877, 1324)	38608 (29392, 48495)	8423 (897, 16149)

Table 3
Impacts of resuming the social/commercial activities in Iran and its neighbors

Country	Actual Figures	Expected Figure under Lockdown	Absolute Impact of Resuming Social/Commercial Activities	Posterior probabilities	Probabilities of causal Impact
Iran	278827	183827 (170827, 193827)	95000 (85000, 108000)	0.0011	0.9989
Pakistan	267428	211003 (203716, 219352)	56425 (48076, 63712)	0.0010	0.9990
Turkey	221500	120500 (101500, 131500)	101000 (90000, 120000)	0.0010	0.9990
Iraq	97159	80548 (78226, 83007)	16611 (14152, 18933)	0.0010	0.9990
Azerbaijan	28242	23360 (22659, 24129)	4882 (4113, 5583)	0.0011	0.9989
Armenia	35693	32170 (30631, 33825)	3523 (1868, 5062)	0.0011	0.9989

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