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# Modeling and predicting the spread of COVID-19: a continental analysis

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## 1. Introduction

The outbreak of coronavirus disease 2019 (COVID-19) infectious disease that started in the Hebei capital city, Wuhan, China, in November 2019 and spread like a wildfire to every continent in the world is unfolding from a global health crisis to an economic emergency posing a major threat to sustaining the world economy. According to the May 18, 2020, report from Worldometers, there are 4,819,102 confirmed cases of infected people and 316,959 deaths worldwide. On March 11, 2020, COVID-19 was declared as a pandemic by the WHO owing to its global spread, that is, approximately 4 months after the first case on November 17, 2019.

COVID-19 belongs to the family of coronavirus that can cause severe illness to humans and eventually lead to the death of the infected person. The first known case of viral attack from the family of coronavirus is the severe acute respiratory syndrome (SARS) that occurred in 2003 [1–3]. The second case is the 2012 Middle East respiratory syndrome (MERS) outbreak in Saudi Arabia [4,5]. COVID-19 is the third viral attack from the family of coronavirus that is currently ravaging the lives of many globally. The rapid spread and growth pattern of COVID-19 is very alarming, spreading across the world within 3 months. The entire world is shaking and trying to catch its breath owing to the shocking impact of the new and rising COVID-19 pandemic. After the reported first set of cases, human-to-human transmission has been singled out as the most significant reason responsible for the explosive rapid spread of the virus throughout the world. The situation is similar in this vein all over the world where both incidence and prevalence

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rates are simultaneously on the rise in the past 6 months. The government of different continents have implemented containment strategies, which include nationwide lockdowns, screening at key places, and quarantine of suspected people in specified isolation centers, among others, to limit the spread of this disease. Nevertheless, the cumulative incidence of COVID-19 keeps growing every day in most countries while the discharge rate is comparatively insignificant. The world wonders what the exact spread pattern of the epidemic is, how long it takes for a carrier of the virus to be able to infect others with it, and when it will begin to subside. Recently, many research and developmental studies have been put in place toward drug development for the treatment of COVID-19 patients as well as vaccine formulation for prevention of the spread. Contrarily, modeling the available epidemiologic data about COVID-19 cases has remained a unique research focus in different parts of the world. While dynamics of human mobility and interactions have limited the outcome, output documented from recent studies show that effective data logging and predictive modeling could enhance public health planning and assist policymakers to make better differentiated decisions that could be useful in different parts of the world [88].

Epidemiologic data collection, modeling, and predicting trends are important for providing effective public intervention strategies [60,61,82]. Currently, researchers are making concerted efforts to understand the spread pattern and predict the growth rate in different communities and countries. Among these efforts, the ones in Asia appear more prominent; the reason is not far-fetched as the outbreak of the disease emanated from there. Many of the other studies outside Asia also rely on the Asian data of the epidemic for modeling and predicting their own spread of cases and future outbreak projection [78]. Different models ranging from statistical modeling techniques [6–10] like susceptible-exposed-infectious-removed (SEIR) model, susceptible-infectious-removed (SIR) model, susceptible-infectious-quarantine-recovered (SIQR) model, logistic growth model (LGM), susceptible-infectious-recovered/death (SIRD), GIS-based spatial model (SLM), spatial error model (SEM), multiscale geographically weighted regression (MGWR) [51], simplified model [55], and Bayesian LGM [56] have been applied with success. Others include sentiment analysis [42], deep learning [46], and machine learning methods [49] that have proved very useful in epidemiologic and clinical research for data analysis, forecasting, and decision-making on COVID-19 and have been adopted across different continents of the world. The most prominent of these models for infectious disease forecasting are the compartmental epidemic models, such as SEIR [11], SIR [12], SIQR [13], LGM [14], and SIRD [15], which were used to simulate the COVID-19 epidemic situation in Asian studies [28,33,35,40,44,47,51,57], Africa [66], South America [62], Europe [72,77,82], and Australia [84,85,86,87], respectively. Also, another widely used model is the Cox regression models, which were used for modeling COVID-19 epidemic situations in Rwanda [20] and China [21]. Variants of SIR have been used across all the continental studies. They, however, found predominant use in Asia and North America. Logistic models have also found wide use in North America [56,58,59] and Europe [72,82].

Despite the potentials of statistical models for epidemiologic research, especially in forecasting the spread patterns of infectious diseases like COVID-19, the accuracy of such predictions have raised several concerns among many researchers [22–24], and machine learning algorithms have been suggested as a better alternative to statistical models for a more accurate prediction of spread patterns of infectious diseases [25–27]. In addition to the predicting power of the model adopted, the availability of sufficient and reliable data has been found to be paramount to accurate modeling and prediction.

Understanding the spread pattern of COVID-19 that has shown to exhibit some differences compared to other recent outbreaks would be of great assistance to epidemiologists and other personnel in the public health sector in providing an efficient way of alleviating the effects of the pandemic. This information will be useful for the governments and other relevant agencies to carry out essential activities and effective policy-making that could help in the situation of future occurrence of related situations [28]. The pattern and projection of the spread across different countries of the world have varied as can be seen from different studies. In particular, the pandemic has exhibited a nonlinear and complex nature [29]. In addition, different methods have been adopted by the existing studies for modeling and prediction. Furthermore, COVID-19 cases are still emerging and reemerging across countries and continents. Hence this chapter is aimed at presenting a review of the various studies geared toward modeling and predicting COVID-19 spread patterns in a continent by continent form. It also presents a current situation report based on the general outcome of this analysis.

## 2. A continental review of modeling and prediction studies

This section presents an analysis of the current confirmed and death cases in the world, as depicted in Fig. 16.1. Also, it shows the analyses of the studies that have been carried out on the spread of COVID-19 from different continents, with nations represented as bubbles, sized relative to the number of cases in the respective continents and colored according to the continents. As shown in Fig. 16.1, Europe has more countries with high COVID-19 case numbers and deaths compared with other continents.

Tables 16.1–16.6 present an analysis of the model types considered in this study per country along with the deduction inferred from the aggregation of studies in Asia, North America, South America, Africa, Europe, and Australia, respectively.

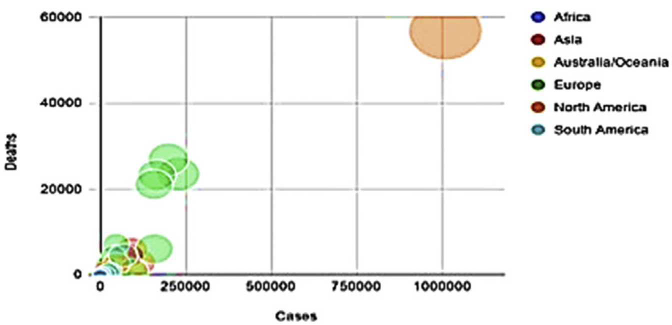


**FIGURE 16.1** Bubble chart of confirmed cases and deaths of coronavirus disease 2019 (COVID-19).

**Table 16.1** Asian studies.

| Country/models | Publication inference |
|---|---|
| **China**<br>SEIR, LSTM-RNN [16,28], modified stacked auto encoder [29], Spatial Moran index, space-time Cube (STC) [30], Moran index [31], sentiment analysis [42], 3D deep learning [46], machine learning methods [49] | Artificial intelligence approach predicts better than statistical measures and aids in public health planning and policy-making. Machine learning is a veritable tool for studying genomics in COVID-19. Implementing control measures on stipulated date reduced eventual COVID-19 epidemic size. Prediction shows that the epidemics will end in the middle of April. Forecasting improves when the data are reliable and the training time is long. There is a positive correlation of the confirmed cases in the regions under study via the spatial distribution. The spatiotemporal distribution of cases is uneven. Population-based neighborhood formation showed a strong spatial association. Infected person numbers in densely populated regions may likely increase. Results provided some consistency with the actual situation. Deep learning distinguished COVID-19 from community-acquired pneumonia and other nonpneumonic lung diseases by using chest CT The number of confirmed cases is expected to exceed 76,000. COVID-19 is still an unclear infectious disease. |
| **India and multiple countries with India**<br>Tree-based models [32,34], SEIR and regression model [35], fixed compartmental SEIR, Stochastic model [36] | A close match between analytical results and the available results shows the actual trend of the derived model. Lockdown and social distancing had been effective in preventing disease spread. An approximate estimation of new cases can be performed easily. Lockdown policies in India played an important role in eradicating the COVID-19 spread. Likelihood of increase in the number of cases. India's healthcare resources may be overwhelmed by the end of May. |
| **South Korea**<br>Variants of SEIR model [33,51] | Aging, time delay for control action and susceptibility of the recovered cases were considered in setting up the model due to early growth rate among the elderly. Model was able to predict the number of isolated patients over time identifying the exact number of beds required in advance and establish a response strategy for a pandemic characterized by large-scale cluster outbreaks. |
| **Iran with Bahrain, Iraq, Kuwait, Oman, Afghanistan, Pakistan**<br>Gompertz, von Bertalanffy, LSE models [37], linear regression, and LSTM model [38], binomial-distribution likelihood framework, chi-square [39] | The trend of COVID-19 that had been increasing was expected to flatten from the end of April 2020 if appropriate public behavior and government intervention are put in place. Predictions are helpful for a base idea to build accurate models from more aggregation of data. Underreporting occurred largely at an early stage of COVID-19 outbreak. Model estimates were consistent with previous research. Continuous spread of epidemic from Iran to neighboring countries is fragile to the public health systems of the Middle East. |
| **Japan**<br>Stochastic model extension to SEIR [40], cumulative density function, likelihood function, and Weibull distribution [41] | The number of infected and removed cases are expected to increase rapidly with no reduction of the time spent in crowded zone. 4 h spent showed stagnant growth of spread. Infection and spread are meant to reduce if hours spent is cut to 2 h. Most infections occurred before the quarantine commenced. |
| **Malaysia**<br>Curve fitting model, SIR, System dynamics [43] | Forecasts from each of the models suggested the epidemic may peak between the middle of April to the end of May 2020. |

**Table 16.1** Asian studies.—cont'd

| Country/models | Publication inference |
|---|---|
| **Philippines**<br>SEI model [44] | Results from model estimation show that the exposure time is a significant factor in spreading the disease. Attendees of social gatherings should stay for less than 9 h. |
| **Saudi Arabia**<br>Naïve Bayes [45] | There is visible support and positive attitude toward the infection control measures to combat COVID-19 from Saudi's tweets using sentiment analysis. |
| **Armenia, Kazakhstan, Kyrgyzstan, Moldova, Uzbekistan, Azerbaijan, Georgia, Russia, Ukraine, and Belarus**<br>SEIR model [47] | Model complies with strict preventive measures to substantially reduce the spread of COVID-19. The untimely loosening of these measures, in the worst-case scenario, could lead to a dramatic increase in the number of active cases and a possible prolongation of the epidemic. |
| **Singapore**<br>FluTE, agent-based influenza epidemic simulation model [48] | A combined approach of interventions (e.g., quarantine, school closure, and workplace distancing) is more effective prevent infections. |

*COVID-19*, coronavirus disease 2019; *CT*, computed tomography; *SEIR*, susceptible-exposed-infectious-removed; *SIR*, susceptible-infectious-removed.

The review includes 69 articles. Articles focused on Asia (34.8%) and Europe (23.2%) were dominant. North America and South America contributed to 14.5% and 8.7% of the articles, respectively. About 6.8% were each from Africa and Australia. An additional 7.2% focused on multiple continents (Fig. 16.2).

Table 16.7 shows that the articles used diverse modeling techniques to explore the current patterns of the pandemic, predict its dynamics, and assess how effective the different public health policies were. Most of the articles (42.3%) used compartmental epidemiologic models (SIR, SEIR, SIRD, SIQR, moving-in-move-out SEIR, SEIRS). LGMs were also used in 8.5% of the articles. Advanced machine learning techniques such artificial neural network (ANN), deep learning, and decision trees were used in 10.16% of the articles. Time series-based models were also used in 5.08% of the articles. Other models used include exponential growth model, graph-plot-based comparative analysis, Gompertz model, Richards growth model, sentiment analysis, solvable delay model, and Australian census-based epidemic model.

# 3. Discussion

A few studies have been carried out in Africa, of which four focused exclusively on African countries and two considered Africa with other continents (namely, Asia and Europe). Studies suggest the risk is still very high in less urbanized countries, and hence the countries that are least connected to the world are more likely to record lower and slower transmissions at the early stages of an epidemic [8]. However, it was predicted that by June 30, 2020, around 16.3 million people in Africa would have contracted

**Table 16.2** North American studies.

| Country/models | Publication inference |
|---|---|
| **Canada**<br>Age-structured compartmental model [50] | Active social distancing helps in maintaining health system capacity and also allows periodic emotional and economic recess for the masses. |
| **United States**<br>GIS-based spatial model (SLM), SEM, MGWR [51], logistic models, variants of SEIR model [53], simplified model [55], Bayesian logistic growth model [56] | Geographic modeling of COVID-19 is a predictive tool useful for measuring future disease outbreak. Mitigating the contact rate plays a role in regulating the widespread of disease at an early phase, and staying long in quarantine would decline the scale of cases after the peak.<br>The trajectory path of COVID-19 can be measured in highly populated metropolitan areas by simply fine-tuning two control factors related to (1) populated areas and (2) initiative response from an organization/public to epidemics. |
| **United States and Canada**<br>Dynamic multimodel [52] | Preliminary data evidence from the author shows that the infection tracks in both countries keep on changing. |
| **United States and other countries**<br>SEIR model and machine learning [57], hierarchical logistic model [59] | COVID-19 outbreak is controllable in the foreseeable future if comprehensive and stringent control measures are taken.<br>Data of anticipated cases and the shape and pace of the long-term course of the epidemic can be shown. |
| **Mexico**<br>Discrete and time-dependent Markov chain, modified SIR model [54], SEIARD model [6] | The probability distribution of COVID19 is envisaged in every state in Mexico if there is no precautionary measure of constraint.<br>It is significant to consider the symptom-free infected persons, as they represent the major percentage of the infected people and could play a critical role in the spread of the virus without their knowledge. |
| **Honduras, Ecuador, Costa Rica, United States**<br>Logistic model, SIR model [58] | The study forecasts the spread of COVID-19 in Honduras and the model prediction fitted well when tested in predicting the spread for other countries. |

*COVID-19*, coronavirus disease 2019; *MGWR*, multiscale geographically weighted regression; *SEIR*, susceptible-exposed-infectious-removed; *SEM*, spatial error model; *SIR*, susceptible-infectious-removed.

COVID-19 [8]. As of May 19, 2020, the total number of cases in Africa is 84,521. The prediction of Achoki et al. [8] then suggests an increase of more than 16 million cases in the next 1 month (to June), which is very unrealistic. Mbuvha and Marwala [17] suggested that the combination of prompt preventive and control measures, demographics, and social factors has resulted in reducing the spread of COVID-19 in South Africa. Similar mitigating measures are in force in many African countries, and based on this, it is unlikely that the prediction by Achoki et al. [8] will be realistic. However, it is also true that there may be a strong underdetection due to limited tests, which might lead to underestimation of the actual cases in national reports. But even in those cases, a prediction of an increase of more than 16 million cases in the next 1 month might not be realistic. It has been claimed that the virus will spread more slowly in Africa, particularly in sub-Saharan Africa, due to the warm climatic conditions, but this hypothesis was disproved by Ayebare et al. [68]. However, Ayebare et al. [68] further stated that a rapid

**Table 16.3** South American studies.

| Country/models | Publication inference |
|---|---|
| **Peru**<br>SIR model [60], predictive Bayesian nonlinear model [61] | Imprecise data collection and reporting existed at the early stages of the pandemic. Epidemiologic modeling and prediction helps authorities to monitor and implement strategies in order to manage the COVID-19 pandemic. |
| **Brazil**<br>SIQR model [62], SIR model [9], data-driven age-structured census-based SIRD-like epidemiologic model [64] | The number of quarantined individuals grew exponentially, stabilized, and afterward decayed to zero. The long-term simulations forecast the optimal date to end the policy. It is important to adopt measures to test the population.<br>In Brazil, there was the need for more intensive care units to avoid future overloading. There was the proposal of an urgent intense quarantine in order to minimize the number of severe cases and deaths. The need to delay the relaxation of the isolation measures in order to reduce spread was also recommended. |
| **Brazil, China, Italy, Spain, Iran, Germany**<br>RGM [63] | The fatality curves of Italy, which were in the middle and China in the late stage of the COVID-19 pandemic were well presented. The possibility of adopting effective countermeasures only existed with a narrow window of opportunity. |
| **Chile**<br>Cubic adjustment model, exponential total case model [18] | The exponential total case model revealed the daily effort to reduce a high initial daily growth rate. |

*COVID-19*, coronavirus disease 2019; *RGM*, Richards growth model; *SIQR*, susceptible-infectious-quarantine-recovered; *SIR*, susceptible-infectious-removed; *SIRD*, susceptible-infectious-recovered/death.

acceleration in the number of cases will likely overpower the existing weak health infrastructure. Hence swift action to control the spread in West Africa is required. Considering the measures that have been taken in most of these countries, a rapid acceleration in the number of cases is unlikely, unless compliance to those measures are low. Current statistics in Africa are rather suggesting that the pandemic spread is low. The governments of almost all African nations have implemented containment strategies that include nationwide lockdowns, screening at key places, and quarantine of suspected people in specified isolation centers [8]. However, the situation report of the past 3 months shows a simultaneous and gradual rise in both incidence and prevalence rates (of COVID-19). As the world battles with the search for drugs/vaccines that can alleviate the effect of the pandemic, efforts are also being directed at finding out the exact spread pattern of the epidemic, how long it takes for a carrier of the virus to be able to infect others with it, and when it will begin to subside. Currently, modeling of spread patterns as well as prediction of spread rates seem to be the major tools being used by most researchers. Aggregation and analysis of relevant data by researchers, modelers, health organizations, governments, and policymakers is definitely the way forward. Indeed, large-scale collection of real-time data could help curb the COVID-19 pandemic.

There are, however, a number of teething challenges/bottlenecks to COVID-19-related modeling and prediction in Africa and other low-income settings. *First*, the

**Table 16.4** African studies.

| Country/models | Publication inference |
|---|---|
| **Nigeria**<br>Exponential growth model [65] | Epidemiologic statistics relating to COVID-19 epidemic in Nigeria at the initial stage were scanty, yet the probability of future threats and numerous asymptomatic cases in Nigeria is high. |
| **South Africa**<br>SIR compartmental model [66] | COVID-19 in South Africa was at its early stage then, but the study reported the possible effectiveness of mitigating procedures, demographics, and societal issues in decreasing the spread rate of the pandemic. |
| **Uganda**<br>Modified COVID-19 screening/triage algorithm [67], co-variate-based instrumental variable regression model [17] | A screening algorithm for COVID-19 that could be adopted for training health personnel on effective triage of patients, especially in low-income settings in Sub-Saharan Africa, was produced. It could also serve as a rapid and simple tool providing decision support on patients who needed to be isolated or directly tested for SARS-CoV-2 |
| **Ghana**<br>Graph-plot-based comparative analysis of COVID-19 data in Johns Hopkins Center for Systems Science and Engineering [68] | Comparative analysis does not support the hypothesis that the spread will be slower in warmer climates. A rapid acceleration in the number of cases will likely overpower the existing weak health infrastructure. Hence, swift action to control the spread in West Africa is required. |
| **Rwanda**<br>Cox regression, K-means clustering [8] | Nations having general, demographic, and prior health weaknesses to serious COVID-related ailment and death are less expected to report cases. Even if they do, they report with little or no information made available to the public. |
| **Senegal**<br>WHO report monitoring and assessment charter, IDV index clustering [69] | African nations imported COVID-19, and many of them were getting prepared to combat the associated challenges. Improvement of surveillance strategies and large-scale capacity building were required to prevent onward spread. |

*COVID-19*, coronavirus disease 2019; *SARS-CoV-2*, severe acute respiratory syndrome coronavirus 2; *SIR*, susceptible-infectious-removed.

General Data Protection Rules/Policies (GDPR) across nations could prevent the release of personal data of citizens without their consent, and this is a great challenge to modeling and prediction. Governments of nations may have to carefully override some of these rules for the greater good of combating the dreaded COVID-19. Alternatively, as a matter of urgency, governments should enact policies/strategies for sharing data with minimal privacy issues for analysis/predictive research. *Second* is the problem of data availability or even the challenge of "missing data." Currently, limited data are available on the early growth trajectory, and there is lack of transparency in data sharing protocols of most African countries [68]. Furthermore, scarce data (epidemiologic) on COVID-19 adds uncertainty to models of how COVID-19 will spread. This lack of data could also be the reason why several predictions exist for diverse models in the literature. This is especially true, as assumptions are still being made by different scientists/modelers on the behavior of COVID-19. While some believe COVID-19 behaves like influenza (therefore use influenza data), others believe it behaves like SARS-CoV (hence use SARS data). These different assumptions are likely to lead to very different COVID-19 model

**Table 16.5** European studies.

| Country/model | Publication inference |
|---|---|
| **Italy**<br>Generalized linear model [20], Gauss error function and Monte Carlo simulation [70], SEIRD model [71], solvable delay model [10], logistic growth model [72], stochastic SIR model [73], ARIMA [74,81], artificial neural network (modified auto encoder) and SEIR model [83] | Strict control measures by the government can efficiently limit the spread of the virus to nearby areas. Model provides good forecasts of the number of COVID-19 infections at local level and peak date of the number of daily positive cases and declaration of cases. Models could be easily adapted to monitor other infected areas that have varying restriction policies. If containment measures are implemented by the government, the spread of COVID-19 virus can be mitigated. Predictions tend to improve as new cases are confirmed daily, which can assist the government to make decisions. The SEIR model produced a better prediction of active cases. Continuation of restrictive measures and strict compliance with rules on gatherings, travel restrictions, and closure of commercial activities may reduce the size of the epidemic. |
| **Belgium**<br>Semimechanistic Bayesian hierarchical model [75] | There will be reduced growth in the number of daily reported cases if control interventions are enforced and implemented early enough. Bayesian models ensured that the modeled deaths can reproduce observed deaths as closely as possible. |
| **France**<br>Individual SEIR (iSEIR) model and turning phase concept [76], SIRD model [77] | Turning phase is vital to emergency planning during an outbreak. Model provides a timeline for effective actions that help fight the pandemic. Public health officials are provided with estimates that are more realistic (in terms of time, magnitude, and maximum number of infected people). |
| **Ukraine**<br>SIR model and Statistics-based method [78] | Prediction accuracy increases as the number of daily observations increases. Prediction also reduces if control measures are relaxed or newly infected people come into the country. |
| **Spain**<br>Support vector regression and random forest [19] | Possibility of supplying information about the behavior of variables of interest on the virus spread on a short-term basis. Ensemble model predicts outbreak 7 days ahead for hospitalized and ICU patients. |
| **United Kingdom**<br>ARIMA model [79], nonlinear autoregressive artificial neural network (ANN) [80] | The challenge of exponential growth should be combated with aggressive interventions. To control the pandemic and its infection at the hospital level, there is the need to adopt rapid control measures. Model predicts a huge number of confirmed cases in Austria, Belgium, Norway, Switzerland, the United Kingdom, and Netherlands but with negligible number of recovery and death cases. The larger the data (confirmed cases), the higher the prediction rate. AI is efficient in forecasting future cases and deaths of coronavirus outbreak by using historical data. |
| **Germany**<br>Logistic growth model and SEIR model [82] | Epidemiologic data collection, modeling, and predicting trends are important for providing effective public intervention strategies. |

*AI*, artificial intelligence; *ARIMA*, autoregressive integrated moving average; *COVID-19*, coronavirus disease 2019; *ICU*, intensive-care unit; *SEIR*, susceptible-exposed-infectious-removed; *SEIRD*, susceptible-exposed-infectious-removed-dead; *SIR*, susceptible-infectious-removed; *SIRD*, susceptible-infectious-recovered/death.

**Table 16.6** Australian studies.

| Country/model | Publication inference |
|---|---|
| Australia<br>Australian census-based epidemic model (ACE-Mod) [84], individual-based (UK-based) Simulation model and compartmental model [85], risk stratified transmission model [86], SARIMA model [87] | Government should enforce strict compliance with laid down strategies to curtail the spread of the virus, as low compliance leads to an increase in the spread of the virus. Isolation alone is not sufficient to curtail the spread. A combination of measures is needed to strengthen overall decrease in cases. Also, records of travel patterns of residents and foreign travelers will assist in implementation of new COVID travel restrictions. |

*SARIMA*, seasonal autoregressive integrated moving average.

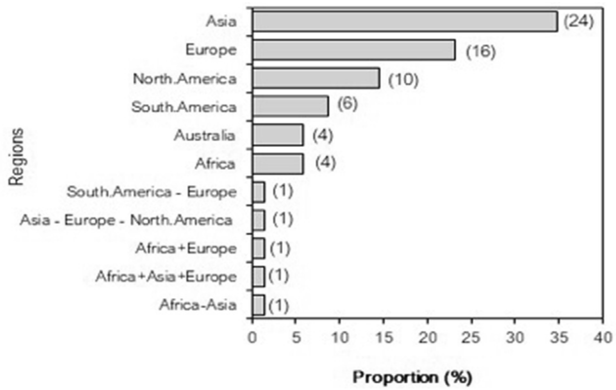


**FIGURE 16.2** By-continent distribution of the 69 articles included in this review.

predictions. Besides, the problem of missing data is huge. The actual number of infected persons, for instance, may differ from the number of reported cases, thus making even the scarce data not a true reflection of reality. Missing or inaccurate data in Africa can be attributed to weaker surveillance systems, poor contact tracing and active case detection, slow testing and clinical diagnosis, and the challenge of asymptomatic patients or carriers of the COVID-19 virus [8,68,69]. *Third* is the fact that although a number of statistical models exist for the prediction of disease spread, a lot of them are not suitable for the prevailing circumstances in Africa, as some of the parameters for effective working of such models are lacking or completely unavailable in some low-income settings like sub-Saharan Africa [8,17].

For South America, we came across seven articles mainly from Peru, Brazil, and Chile. In Peru, the number of cases is expected to peak at around 13,000 infected people around April 22 [62]. In addition, assuming an intervention level similar to the one used in China, the total number of deaths in Peru is expected to be 612 [63]. As of April 29, the number of cases is 31,190, which is more than two times the predicted peak. In addition,

**Table 16.7** By-model distribution of the 69 articles included in this review.

| Model type | Qty | % |
|---|---|---|
| Compartmental model (SIR, SEIR, SIRD, SIQR, moving-in-move-out models) | 35 | 42.37 |
| Logistic growth model | 5 | 8.47 |
| Regression model | 5 | 8.47 |
| ANN | 3 | 5.08 |
| Predictive Bayesian nonlinear model | 3 | 5.08 |
| Time series models | 3 | 5.08 |
| Deep learning | 2 | 3.39 |
| Exponential growth model | 2 | 3.39 |
| Graph-plot-based comparative analysis | 2 | 3.39 |
| Simulation model | 2 | 3.39 |
| Spatial Moran index | 2 | 3.39 |
| Australian census-based epidemic model (ACE-Mod) | 1 | 1.69 |
| Binomial-distribution likelihood framework | 1 | 1.69 |
| Cox regression | 1 | 1.69 |
| Cubic adjustment model | 1 | 1.69 |
| Gauss error function | 1 | 1.69 |
| Gompertz model | 1 | 1.69 |
| K-means clustering | 1 | 1.69 |
| Richards growth model (RGM) | 1 | 1.69 |
| Risk stratified transmission model | 1 | 1.69 |
| Screening/triage algorithm | 1 | 1.69 |
| Sentiment analysis | 1 | 1.69 |
| Solvable delay model | 1 | 1.69 |
| Space-time cube (STC) | 1 | 1.69 |
| Tree-based model | 1 | 1.69 |
| von Bertalanffy growth model | 1 | 1.69 |
| Weibull distribution | 1 | 1.69 |

*ANN*, artificial neural network; *SEIR*, susceptible-exposed-infectious-removed; *SIR*, susceptible-infectious-removed; *SIQR*, susceptible-infectious-quarantine-recovered; *SIRD*, susceptible-infectious-recovered/death.

the number of deaths is 854 as of April 29, 2020. These statistics indicate that the current observed values greatly differ from the predicted ones. The higher number of current deaths compared to the 612 predicted might be due to the fact that the measures taken in the country are not similar to those of China. In this line, Canabarro et al. [66], in their Brazilian study, concluded that there are inadequate measures put in place to combat the pandemic and proposed an urgent intense quarantine to avoid the situation of overwhelming their health systems with cases invariably. Also, the study proposed a delay in the relaxation of the undergoing isolation measures in order to avoid an increase in the spread of the infections in a short period. Other studies in the region also suggest that there is a narrow chance, after the onset of the epidemic, during which the government can execute effective countermeasures [18]. Moreover, Gilbert et al. [70] suggest that the current policies should be prolonged, if not, they will only be able to shift the peak of infection into the future, keeping the value of the peak in almost the same value. Also, authors suggested the importance of testing the population as a means to combat the pandemic.

In North America, emphasis related to modeling found in the literature focuses more on the United States, Mexico, and Canada [52,53,55], while other countries in the region with a growing intention and spread of the epidemic are yet to be considered. Also, limited data are available on the early growth trajectory and lack of transparency in data sharing protocols of most countries in the continents under consideration [54]. There are few studies on modeling and prediction that have leveraged on the available COVID-19 data in the North American region. Most authors still use China and Italy datasets to predict the spread in other countries, which may be uncertain [6,56,61]. Therefore disease models are built on assumptions and historical data collected from other diseases. Furthermore, studies have shown that there are different preventive measures carried out in curbing the spread of COVID-19 in North America, and the effectiveness of these measures can be subject to the policymaker's informed decision in specific countries of the studies [55–57].

Asia is one of the continents that has been active on COVID-19 research. Combining AI with classical compartmental models provides a better prediction of the disease spread [16,46]. Using AI, Rabajante [46] predicts the epidemics will end in China by the middle of April. The number of daily cases in China has considerably dropped down, although the risk of a second wave of the pandemic is still permanent. As could be expected, Kang et al. [33] found that the number of infected persons in densely populated regions may likely increase and the need to further prevent the transmission, possibly to avoid a second wave. In particular, the number of confirmed cases in China is expected to exceed 76,000 [43], and current statistics (82,858 cases as of April 29, 2020) are in line with this prediction. The authors, however, reported COVID-19 as still an unclear infectious disease. In India the lockdown and social distancing measures were found to be effective in preventing the disease spread [34,36]. Using linear regression, Pandey et al. [37] found overfitting as a major problem with disease spread time series data and that shortage of training data needs to be addressed. As found in South America, Chatterjee et al. [38] also reported that healthcare resources may be overwhelmed, specifically by the end of May 2020, in India. In Iran, the epidemic is predicted to flatten as from April 28, 2020, if appropriate public behavior and government intervention are in place [39]. Large underreporting at an early stage of the COVID-19 outbreak has also been highlighted in many countries including Iran, Bahrain, Iraq, Kuwait, Oman, Afghanistan, and Pakistan [41]. In Japan, Karako et al. [42] found that infections and spread are meant to reduce if hours spent in crowded zones are cut to 2 h. Many of the restriction policies put in place as a result of the outcome of various research carried out using data-driven AI and epidemiologic models have proven to yield a considerably positive effect on reducing the spread, as many Asian countries are currently not experiencing any additional new cases. Exceptions are countries like Indonesia, Singapore, Philippines, and Vietnam, recording high new cases of 529, 465, 214, and 314, respectively, as at May 16, 2020, with 17 and 6 new cases in Malaysia and China, respectively. These countries may need to adopt additional measures to quicken the lessening of the cases as low as possible to curtail the pandemic. New measures such as contact tracing apps, compulsory wearing of face masks in outside engagement, social responsibility, and collaborative open source repository are underway, which are believed to use AI analytics to provide better predictive solutions.

Studies carried out on European countries show that forecast models can be developed with AI technologies to predict COVID-19 outbreaks. For instance, the model developed by Vattay [74] shows that COVID-19 pandemic will end in Italy by May 8, 2020. In reality, the weekly surveillance report from the WHO shows that as of 16th May, there has been a drastic reduction in the number of cases by 53%. This reduction in the number of cases started from the 14th epidemiologic week (April 6 to April 12, 2020), which has made the government of Italy to relax some of its lockdown rules from 4th May. The works of Perone [76], Nesteruk [79], and Ghazaly et al. [82] involving Italy, France, Spain, and Russia reveal that predictions improve as new cases are confirmed daily. This implies that "the larger the data (number of confirmed cases), the higher the prediction rate." This has brought up the need for collection of larger volumes of data (big data) made available in a timely and accurate manner. A similar study by Zhou et al. [6] on eight high-risk countries including Italy, Germany, France, Spain, and some Asian countries using LGM and SEIR model also shows that collection of epidemiologic data is essential to achieve accurate forecast models. In addition, there might be an increased number of cases in Europe, if control measures are relaxed and if there is nonenforcement or strict compliance with government rules [76,77,79]. Enforcement of rules, including closure of public gatherings and schools and travel restrictions, may help curb the spread of the epidemic.

In the case of Australia, to the best of our knowledge, as of the time of writing this report, a few studies on modeling and prediction of COVID-19 have been reported in the literature. This includes the work of Zhang et al. [84] that used the Australian census-based epidemic model (ACE-Mod) and showed that low compliance with intervention strategies such as lockdown, social distancing, and the use of face mask could lead to an exponential rise of the pandemic in Australia and that high compliance with these intervention strategies will lead to a strong control of the spread of the virus in under 15 weeks. In the study by Fox et al. [85], a simulation and compartmental model was used to model the impact of the outbreak of COVID-19 on intensive-care units in New South Wales, and results from this study show that as the number of infected people increases, the intensive-care units would be overwhelmed if the intervention strategies provided by the government are not accompanied by an effective and substantial increase in critical care services. The risk stratified model employed by Moss et al. [86] shows that measures such as isolation and quarantine are not sufficient to curtail the spread of the virus. Also, the model forecasts that if the pandemic is prolonged, it will exceed the capacity of the Australian healthcare system. Results from the seasonal autoregressive integrated moving average (SARIMA) model used in the study by Liebig et al. [87] suggest an exponential growth in the epidemic curve, but records of travel patterns of residents and foreign travelers could help the government to implement travel policies that could flatten the curve.

As of May 18, 2020, Antarctica is the only continent left in the world without a reported case of COVID-19. There has not been any scientific evidence reported in the literature for this exemption, but researchers are making efforts to unravel the reasons behind the current immunity in this region.

# 4. Conclusion

The chapter provides insight into the spread of COVID-19 across the continents of the world. It presents an analysis of the current confirmed and death cases in the different continents. It also analyzes the current studies that have been carried out on this topic on a continent-by-continent basis. Our review showed a strong commitment of researchers to understand the spread of COVID-19, possibly due to the fact that it is a pandemic that has affected all the countries in the globe. Nevertheless, our study reveals that literature in this area was dominated by research from Asia and Europe, followed by North America. Very few contributions emanated from other continents including Africa while no study was reported in Antarctica. Most of the models and predictions were based on compartmental epidemiologic models and a few used advanced machine learning techniques, despite being a promising modeling approach to address uncertainties in estimation, especially for long-term prediction. Combining AI with classical compartmental models actually provides a better prediction of the disease spread. While some models have accurately predicted the end of the epidemic in some countries, other predictions strongly depart from the reality. Different assumptions were often made in parameterizing the models (for instance, assumptions and historical data collected from other diseases or other countries), and these assumptions might be wrong and might not fit the local contexts, leading predictions to significantly deviate from actual observations. Careful attention should be paid to this aspect in the future research. Furthermore, free access for researchers to some key data such as age, gender, comorbidity, historical medical data of cases, and deaths is currently an important limitation that future research dealing with relevant aspects of the disease transmission and caused-death should address. Nonpharmaceutical interventions such as lockdown, social distancing, face mask use, among others, were the measures put in place to control the disease in all continents, although some countries were reluctant about these. Many of these restriction policies have proven to yield considerably positive effects on reducing the spread in many continents. Nevertheless, the virus is still not fully known. Therefore consistent commitment from scholars is needed to provide timely reliable information that could guide decision-makers, especially because there are increasing alerts on the risk of a second wave of the pandemic in many places if appropriate measures are not taken until an effective drug or a vaccine is developed. The statistics provided in this study was based on the realities of COVID-19 pandamic in the world and the associated computational models developed by researchers for modeling and predicting the spread of the virus between the period of November 2019 and June 2020.

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