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A new model for the spread of COVID-19 and the improvement of safety

Costas A. Varotsos[a,*], Vladimir F. Krapivin[b]

[a] Department of Environmental Physics and Meteorology, National and Kapodistrian University of Athens, Panepistimioupolis, Bldg PHYS-V, GR-157 84 Athens, Greece
[b] Kotelnikov's Institute of Radioengineering and Electronics, Russian Academy of Sciences Mokhovaya Str., 11, Bldg 7, 125009 Moscow, Russia

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ABSTRACT

COVID-19 has been spreading rapidly around the world since December 2019. The main goal of this study is to develop a more effective method for diagnosing and predicting the COVID-19 spread and to evaluate the effectiveness of control measures to reduce and stop the virus spread. To this end, the COVID-19 Decision-Making System (CDMS) was developed to study disease transmission. CDMS divides the population into groups as susceptible, infected, cured and dead. The trends of the people's number in these groups have deterministic and stochastic components. The deterministic components are described by a differential equations system with parameters determined by the data reported. The stochastic components are represented as an indicator of instability that characterizes the tendency of COVID-19 spread. The simulation experiments have shown a good agreement between the CDMS estimates and the data reported in Russia and Greece. The analysis performed showed that the newly-introduced instability indicator may be the precursor to the pandemic dynamics. In this context, our results showed three potential candidates for a second wave of COVID-19 disease: USA, Russia and Brazil. Although the proportion of infected individuals in countries with high temperatures is lower than in European countries and Russia, temperature and humidity are slowly affecting the effects of the pandemic. Finally, the results presented may contribute to the urgent need to reduce the risks associated with the second wave of the COVID-19, to improve public health intervention and safety measures to be taken by various countries.

1. Introduction

The mathematical tools of epidemiology, the biological models of the population, and the statistical methods allow the study of different processes of spread of the various viruses both in a restricted area and on a global scale (Brauer and Castillo-Chavez, 2012, Brauer et al., 2019, Freedman, 2012, Krapivin et al., 2015, Varotsos et al., 2013, 2016, 2020). Specifically, mathematical methods are used in microbiology and virology to detect important factors that control the spread of the virus. Traditionally, a mathematical model has been able to predict the evolution of the virus between different regions, which is the focus of the World Health Organization (WHO), mainly for some West African countries. For example, a forecasting of the progression of the epidemic with a deadly human disease was made for the Ebola virus disease discovered in 1976 in Central Africa. In this case, the spread of the Ebola virus was limited to two areas including Zaire and Sudan, which did not require global efforts to reduce its spread to other areas. Understanding the pathways of any virus transmission is usually achieved by using different mathematical models adapted to the epidemiological parameters of the specific virus.

The situation with coronavirus differs significantly from other events in recent decades. Global panic erupted in early December 2019 when the first victim of COVID-19 was diagnosed in Wuhan, China. After that, the number of infected people in many countries increased rapidly. Most governments have begun to introduce restrictions on human mobility inside and outside their countries in order to reduce the spread of the virus. In particular, these restrictions, which were intended to reduce and eliminate the spread of the coronavirus, include, among others things:

- restrictions of international and domestic flights,
- prohibition of population concentration in groups,
- defining different marketing processes,
- transition to remote working regime,
- establishment a self-isolation regime for many groups of the human population (social distancing),
- use quarantine regime and isolate individuals or their groups considered to be suspected carriers of the virus, and
- introduction of financial support measures for various sectors of the national economy.

* Corresponding author.
E-mail address: covar@phys.uoa.gr (C.A. Varotsos).

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However, the situation with COVID-19 differs significantly from the pandemic cases in the past, both in the very high rate of global spread and in the dramatic increase in infected and diseased people and in the absence of a vaccine against this virus. Therefore, epidemic models developed in time helped to understand the role of different quarantine parameters. The existing mathematical models that were able to adapt to the short-term forecasts of stochastic processes that govern the COVID-19 pandemic (Chen et al., 2020, Karako et al., 2020, Plank et al., 2020, Tiwari, 2020) offered great help in this. Most of these models use differential equations systems, some parameters of which reflect the characteristics of the COVID-19 pandemic process.

He et al. (2020) developed a discrete-time stochastic epidemic model from which relevant parameters were estimated using statistical data from January 11 to February13, 2020 in China. Plank et al. (2020) based on a continuous-time branching process model, considered different scenarios to isolate the cases and assessed the effects of restrictive control on the population of New Zealand. Tiwary (2020) evaluated the effectiveness of the Susceptible-Infected-Removed (SIR) and Susceptible-Infectious-Quarantined-Recovered (SIQR) models for reducing COVID-19 spread using personal isolation and has defined parameters and indicators that quantify the COVID-19 spread in India. Karako et al. (2020) using the stochastic transmission model, assessed the effectiveness of the strategies for controlling the spread of COVID-19 in Japan. Analyzing the cases in China, Chen et al. (2020) proposed a time-independent susceptible-infected-recovered model that can be used to predict the number of infected and dead. This model is based on two time-invariant variables that reflect an individual's average contacts with others per unit time and the recovery rate.

The present study develops the method of predicting the spread of COVID-19 by examining various scenarios depending on the range of people movements and interactions (Chen et al., 2020, Krapivin, 1970, Krapivin and Mkrtchyan, 2019). The COVID-19 decision-making system (CDMS) is designed to assess epidemic parameters and predict the epidemic consequences.

2. Method

The epidemic situation in many countries at the beginning of COVID-19 infection was shaped by different social restrictions and medical events which, as a rule, were determined on the basis of specialized solutions, the effectiveness of which depends significantly on the use of technology for big data processing and management (Cracknell and Varotsos, 2007, 2011, Varotsos et al., 2019, Kwon et al., 2020, Varotsos et al., 2017). Modeling technology and constructive algorithm help to evaluate the effect of such solutions as the introduction of quarantine, social distancing, and individual protective means. A variety of symptomatic conditions have arisen due to the COVID-19 pandemic, such as the examination of the deterministic and stochastic processes of the population moving around a given area, taking into account specific individual interactions of people infected with the virus.

The schematic diagram of COVID-19 infection and its prevention includes a series of functional processes such as infection, disease, recovery and death. The rates and trends of the medical incomes are a function of the decisions taken by governments to minimize the effects of the COVID-19 pandemic. Indeed, many countries do not have structures for functional and reliable big data clouds that could help introduce very effective tools for quick solution and rapid response to the spread of coronavirus. The main scheme of the COVID-19 Decision-Making System (CDMS) is shown in Fig. 1.

This figure focuses on the existing information analysis and evaluation of possible trends in the pandemic with recommendations to governments to choose a more effective scenario for managing the spread of coronavirus in region. Table 1 lists the main blocks with CDMS functions.

CDMS divides the population into groups of individuals as susceptible (S (t)), infected (P(t)), recovered (R(t)), and dead (D(t)). The overall size of the population is N. The interactions between groups are described by the following equations that reflect the dependence of individuals' health on different management parameters, such as quarantine establishment and traffic restrictions.

$$\begin{cases} S(t+\Delta t) = S(t) - [\xi\beta(t)S(t)P(t)/N]\Delta t \\ P(t+\Delta t) = P(t)\{1+\beta(t)S(t)/N - \eta(t)\}I(t)\Delta t \\ R(t+\Delta t) = R(t) + \eta(t)q(t)P(t)\Delta t \\ D(t+\Delta t) = D(t) + \gamma(t)[1-q(t)]P(t)\Delta t \end{cases} \tag{1}$$

where t is the running time, Δt is the operational time interval, $\beta(t)$ is the probability of transition in time t, ξ is the immune indicator, $\eta(t)$ is the recovering rate in time t, $\gamma(t)$ is the death rate caused by the disease, $q(t)$ is the indicator of medical support, $I(t)$ is the instability indicator of stochastic component.

The numerical evaluations of the parameters in (1) are carried out by the SARD block using statistical reports on the status of the effects of COVID-19 disease. Using the reported data, the following parameters can be calculated (Chen et al., 2020b, Chen et al., 2020a):

$$\beta(t) = [\Delta P(t) + \Delta R(t)]/P(t),\ \eta(t) = \Delta R(t)/P(t) \tag{2}$$

All processes caused by COVID-19 have a stochastic component, the stability of which characterizes the level of uncertainty in the observed data and helps to forecast the epidemic characteristics more accurately. The indicator instability ($I(t)$) indicates the phase state of the components $Y(t) = \{S(t), P(t), R(t), D(t)\}$(Sukov et al., 2008; Krapivin et al., 2012; Varotsos and Mazei, 2020):

$$I(t) = \frac{1}{ns}\sum_{j=m}^{m+n}\sum_{i=1}^{s} b_i u_i(t_j) \tag{3}$$

where n is the time interval for the mean of the parameters, m is the start time for data input, s is the number of characteristics registered, $b_i \in [0.1]$ is the update value of the i-th characteristic,

$$u_i(t_j) = \begin{cases} 1 \text{ when } \Delta Y_i(t_j)\cdot\Delta Y_i(t_{j-1}) \leqslant 0; \\ 0 \text{ when } \Delta Y_i(t_j)\cdot\Delta Y_i(t_{j-1}) > 0 \end{cases} \tag{4}$$

$$\Delta Y_i = \bar{Y}_i - Y_i;\ \bar{Y}_i(n) = \frac{1}{n}\sum_{j=1}^{n} Y_i(t_j),\ t_i - t_{j-1} = \Delta t \tag{5}$$

An indicator $I(t)$ defined by Eqs. (3)–(5) characterizes the variability of the current mean value of the vector $Y(t)$ components. Indeed, the $I(t)$ indicator indicates the probability of the individual's transition over time ν between the phases of the COVID-19 pandemic that satisfies Wald's distribution:

$$P(\nu < y) = W_c(y) = \int_0^y w_c(z)dz, \tag{6}$$

where

$$w_c(z) = \sqrt{\frac{c}{2\pi}}z^{-\frac{3}{2}}\exp\left[-\frac{c}{2}(z+z^{-1}-2)\right], \tag{7}$$

$c = (E\nu)^2(D\nu)^{-1}$ $E\nu$ is the average time interval of the individual's transition until the change of his phase state, $D\nu$ is the dispersion of the time interval ν.

3. Results and discussion

The migration processes of any virus have probabilistic and deterministic components that determine the rate of loss of income due to the virus pandemic. CDMS describes the transient processes that occurred in 2020 in many parts of the world. Epidemiology theory provides an interdisciplinary approach to disease transmission processes (Anderson, 1979, Diekmann et al., 2012, Oldstone, 2009, Omran, 2005). The methodological approach to the COVID-19 spread

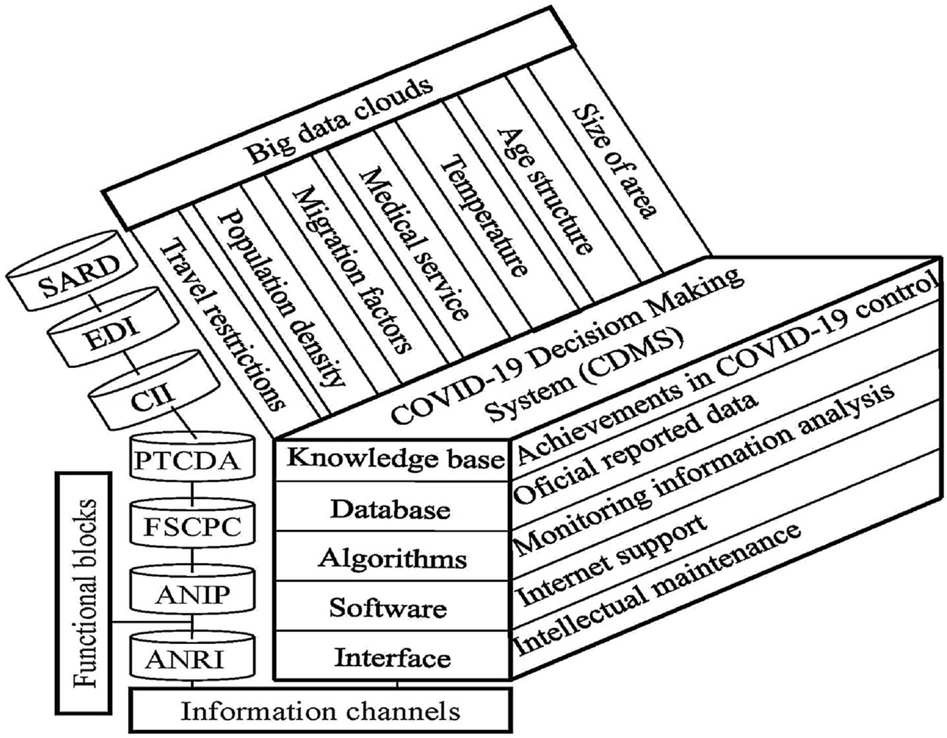

Fig. 1. Main structure of the COVID-19 decision-making system (CDMS).

Table 1
CDMS functional blocks and their characteristics.

Block	Block function
SARD	Statistical analysis of the reported data
CII	Calculation of the instability indicator
ANIP	Assessment of the number of infected people
ANRI	Assessment of the number of recovered individuals
EDI	Estimate of dead individuals
PTCDA	Prognosis of trends in COVID-19 pandemic aftereffects
FSCPC	Formation of scenarios for COVID-19 pandemic control

conducted at CDMS is based on the use of differential equations and stochastic methods to simulate transition processes between population phase states, such as susceptible, exposed, infected, hospitalized, recovered, and died (He et al., 2020). The transition of an individual between his states is considered a stochastic process with the Wald distribution (Krapivin, 1970, Wald, 1947). The movement of the population within the given area is controlled by the restrictions introduced by the administration and is followed by reported and simulated data, and then the consequences of COVID-19 disease depend mainly on these restrictions. Different countries use almost identical set of restrictions such as self-isolation, quarantine, testing, social distancing, hospitalization (ICAO, 2020), which are characterized by various parameters.

Table 2 demonstrates these varieties in the coronavirus epidemic management parameters. Many authors discuss the dependence of the expected effects of the COVID-19 pandemic on climate (Fuentes et al., 2020, Wang et al., 2020). The analysis of global pandemic data allows the preliminary conclusion that temperature and humidity slowly affect the effects of pandemic. The rate of infected people in countries with high temperatures is lower than in European countries and Russia.

The stages of spread and the rate of loss of income due to the pandemic COVID-19 2020 have different overwhelming results essentially not depending on the region, but as shown in Fig. 2, there is a correlation between infected and dead people. With the increase in infected people, the number of dead income has stabilized regardless of time.

Table 2
Average assessments of COVID-19 transition parameters by different regions.

Region	β	η	ξ	γ	q
Australia	0.062	0.056	0.37	0.0139	0.77
Belarus	0.093	0.007	0.72	0.0057	0.82
Brasil	0.087	0.044	0,34	0.0312	0.58
China	0.078	0.020	0.63	0.0548	0.75
France	0.093	0.026	0.39	0.1921	0.79
Germany	0.094	0.021	0.42	0.0471	0.81
Greece	0.089	0.111	0.54	0.0701	0.76
Italy	0.097	0.130	0.44	0.1441	0.72
Japan	0.088	0.014	0.45	0.0529	0.79
Russia	0.077	0.017	0.68	0.0132	0.74
South Africa	0.086	0.013	0.41	0.0211	0. 57
USA	0.096	0.019	0.31	0.0559	0.72
World	0.095	0.008	0.45	0.0027	0.68

The analysis of the official data in Russia and Greece shows that the effects of hygiene and infectivity conditions of the hospitalized individuals have reached the expected results and practically could not be improved. Nevertheless, there are management parameters that could improve the results of the COVID-19 pandemic.

The immediate risk of infection and mortality according to Fig. 3 increases with increasing population density. The simulation results show that the processes describing the COVID-19 infection and the subsequent results are accompanied by the function $I(t)$ which allows the conclusion regarding the increase in $I(t)$ to correspond to the increase of the components of $Y(t)$ and vice versa. This result is confirmed by the behavioral effects of the instability indicator for the atmosphere/ocean system (Varotsos et al., 2019).

A variety of conditions for the spread of pandemic in a population divided into categories are synthesized by the SARD block and are analyzed by PTCDA and FSCPC blocks to formulate possible scenarios for the implementation of CDMS to evaluate the effectiveness of restriction procedures (Atkeson et al., 2020). Based on this idea, two scenarios are introduced that are used for two countries – Russia and

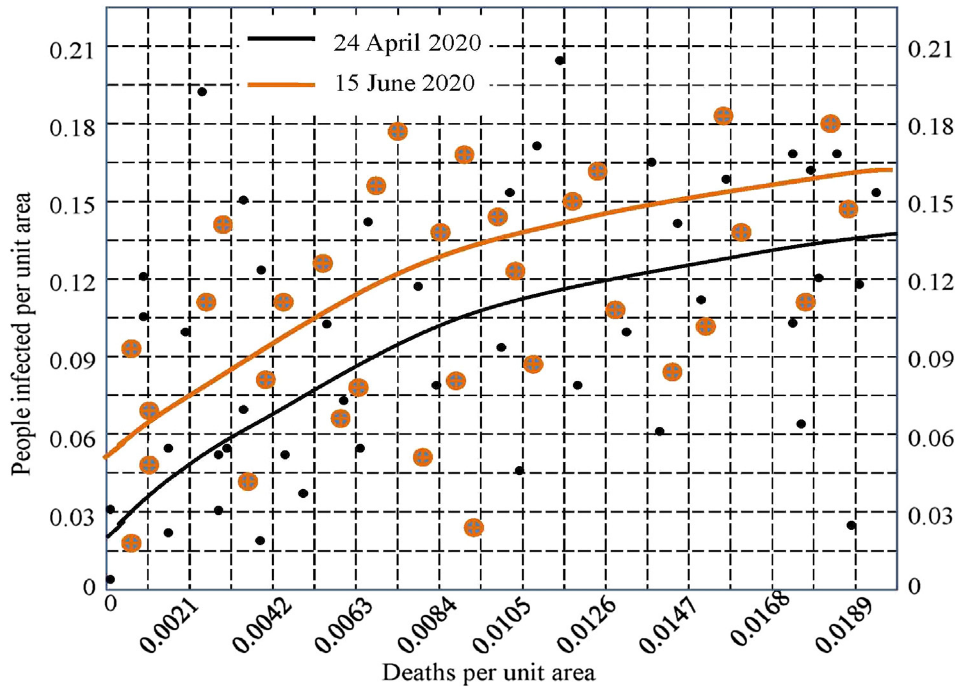

Fig. 2. The correlation between the number of infected and dead people reported on 24 April and 15 June 2020.

Greece. Each of these countries is characterized by the size of its area and population. Russia has an area of 17.1 million km^2 and a population density 8.45 per km^2. The area of Greece is 131957 km^2 and a population density of 81.24 per km^2. These characteristics have largely determined strategic solutions to eliminate the spread of COVID-19 by taking into account existing resources to prevent coronavirus.

The number of infected people in Russia includes 10% of those infected in Moscow. An analysis of traffic restrictions introduced during the pandemic, which began in Russia more than 2 months after the Moscow shutdown, shows that the problem of returning tourists to Russia has been solved by a non-optimal method. Travelers arriving in Moscow from other countries are tested and if some are diagnosed with coronavirus are self-isolated at home or hospitalized if they have severe symptoms. The tactics of self-isolation at home of confirmed individuals with coronavirus is not optimal. Fig. 4 shows the modeling results when 50% of travelers arriving in Moscow could be isolated immediately in two weeks (Scenario 1_{rus}). The 2 $_{rus}$ scenario corresponds to 100% isolation of travelers.

The coronavirus pandemic situation in Greece is linked to traditional events aimed at minimizing the consequences. International flights were restricted and passengers arriving in Athens and other cities were tested for coronavirus or quarantined when infected. A critical analysis of the restrictions introduced in Greece due to the COVID-19 pandemic shows that there are indicators whose improvement could reduce losses.

The tested passengers could all be isolated during 14 days (Scenario

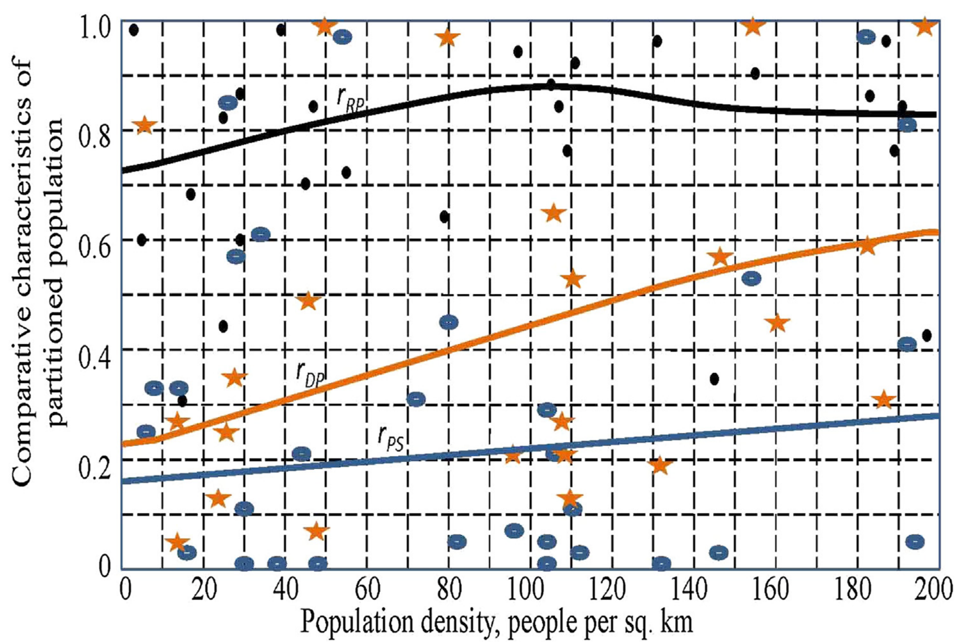

Fig. 3. Dependence of the ratios $r_{PS} = P/S$, $r_{RP} = R/P$, and $r_{DP} = D/P$ on the population density.

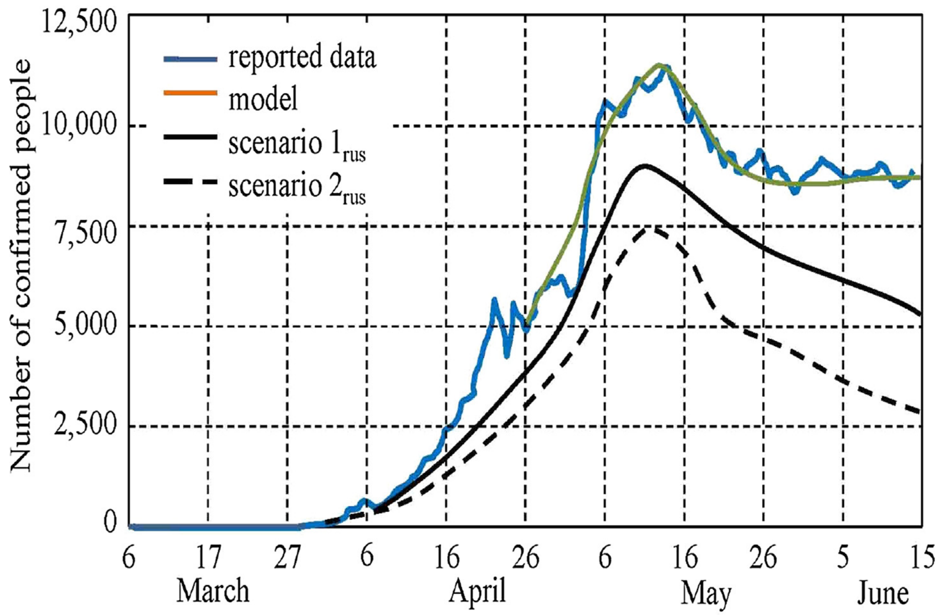

Fig. 4. Model estimate of the spread of COVID-19 in Russia during 2020.

1_{gr}), regardless of test results. The first case in Greece was confirmed on February 26, 2020 but the restrictions were delayed: cafes, bars, museums, shopping malls, sports facilities and restaurants closed only on March 13. Restrictions on all unnecessary travel across the country were imposed on March 22. The 2_{gr} scenario considers that restrictions in different parts of Greece could be imposed immediately or even earlier on February 26.

Figs. 4 and 5 characterize the possible expected medical consequences from the implementation of the above scenarios. The trend of coronavirus pandemic consequences for the Russian population could be significantly optimized due to the stronger quarantine at Moscow airports. The $I(t)$ instability indicator calculated for Russia shows that the number of infected people is slowly declining, which is not in line with the trends in the countries listed in Table 2.

4. Conclusions

This paper presented an analysis of a COVID-19 decision-making system with numerical results that showed the possibility of a combined use of a model and statistical data analysis to assess the pandemic effects on the population. This study used data reported from 11 January to 30 June 2020. The newly-introduced instability indicator $I(t)$ describes trends in the number of susceptible $S(t)$, infected $P(t)$, recovered $R(t)$ and dead $D(t)$ individuals. The maximum value of $I(t)$ corresponds to the maximum of these functions. Preliminary analysis of simulation experiments using CDMS shows that the arrival situation when $I(t)$ begins to increase after reduction can be interpreted as the beginning of the second wave of COVID-19.

Unfortunately, there is not enough data to make this study reliable. The data in Table 3 can only be indicative of the possible presence of a

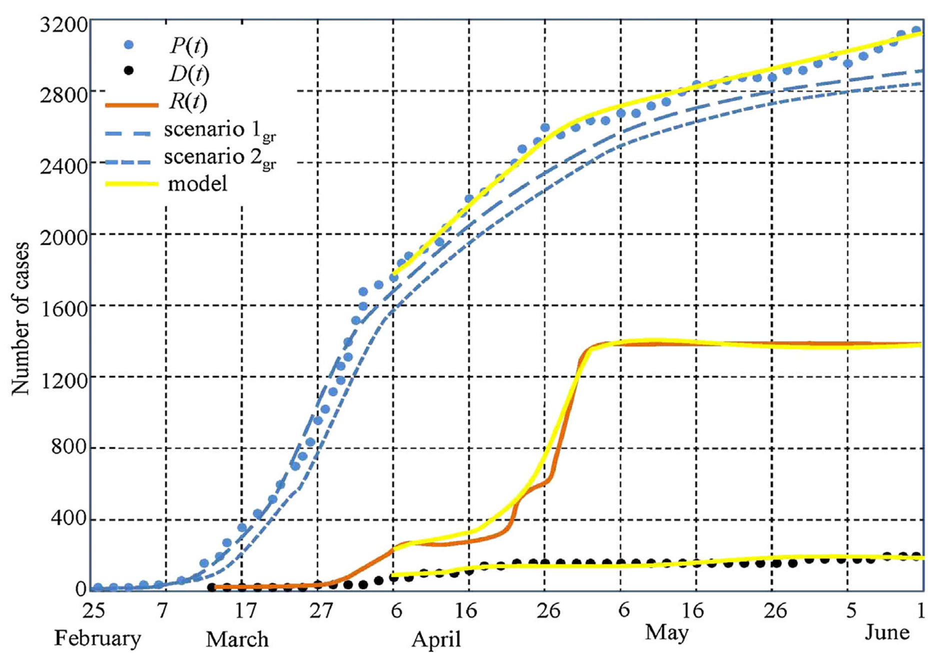

Fig. 5. Dynamics of COVID-19 disease in Greece.

Table 3
Evaluation of the trends of the pandemic instability indicator from various counties.

Region	Date					
	15 March	15 April	15 May	5 June	15 June	30 June
Australia	0.571	0.884	0.369	0.203	0.201	0.132
Belarus	0.097	0.487	0.978	0.356	0.243	0.188
Brasil	0.566	0.792	0.441	0.291	0.303	0.426
China	0.896	0.253	0.093	0.085	0.102	0.152
France	0.436	0.654	0.721	0.343	0.338	0.289
Germany	0.334	0.846	0.706	0.477	0.272	0.199
Greece	0.404	0.786	0.912	0.404	0.237	0.178
Italy	0.189	0.523	0.798	0.407	0.203	0.254
Japan	0.299	0.763	0.903	0.461	0.322	0.164
Russia	0.096	0.553	0.887	0.445	0.367	0.371
South Africa	0.454	0.784	0.437	0.279	0.195	0.089
USA	0.426	0.652	0.794	0.369	0.278	0.351
World	0.537	0.654	0.703	0.485	0.566	0.496

coronavirus outbreak in another phase, which is interpreted as a "second wave". The results of Table 3 allow the separation of three candidates for the second wave – the USA, Russia and Brazil. The probability of the coronavirus pandemic to pass into a negative phase is equal to 0.46 ± 0.08 for USA, 0.37 ± 0.06 for Russia and 0.42 ± 0.07 for Brazil. In particular, the calculation of $I(t)$ for the reported data on the pandemic income recorded during a week helps to estimate this probability for all countries or other restricted areas.

It is clear that protection measures in different countries are not effective enough and could be more effective in the future to analyze more data using different models, such as the stochastic model SEIR (Susceptible, Exposed, Infectious, Recovered) and the susceptible-infected-deceased (SID) model (He et al., 2020, Islam et al., 2020). The existence of reserves in social and economic measures is followed by the comparison of relations $P(t)/S(t)$, $R(t)/P(t)$, and $D(t)/P(t)$ for different countries where the dynamic variations of these indicators can achieve more than 50%.

In practice, it was impossible to coordinate measures to curb the pandemic of COVID-19 in conditions of high uncertainty. Therefore, in this study the decision-making system can be modernized to take into account the results of COVID-19 pandemic, taking into account the overall social, medical and administrative resources that can be used to minimize economic and population losses.

The issue of validating the CDMS is resolved by data shown in Figs. 4 and 5, where the deviation of the model results from the reported data is evaluated by 8.5% for Russia and 1.6% for Greece. The rate of a dramatic increase in the reported cases in many countries depends on the big data generated by a complex task of modernized CDMS validation, taking into account the uncertainty levels in the data provided by administration of countries and the World Health Organization (Ivorra, 2020, Park et al., 2020). In this area the results of the present study mentioned above clearly provide the potential for improved safety.

References

Anderson, M., 1979. Population biology of infectious diseases: Part 1. Nature 280, 361–367.

Atkeson, A., Kopecky, K., Zha, T., 2020. Estimating and forecasting disease scenarios for COVID-19 with an SIR model. NBER Working Paper Series, Paper No. 27335, 148 pp.

Brauer, F., Castillo-Chavez, C., 2012. Mathematical Models in Population Biology and Epidemiology. Springer, New York, 510 pp.

Brauer, F., Castillo-Chavez, C., Feng, Z., 2019. Mathematical Models in Epidemiology. Springer-Verlag, New York, 619 pp.

Chen, Y.C., Luy, P.E., Changz, C.S., Liux, T.H., 2020. A Time-dependent SIR model for COVID-19 with undetectable infected persons, 28 pp. http://gibbs1.ee.nthu.edu.tw/ A TIME DEPENDENT SIR MODEL FOR COVID 19.

Chen, S., Yang, J., Yang, W., Barnighausen, T., 2020a. COVID-19 control in China during mass population movements at New Year. The Lancet 395 (10226), 764–766.

Cracknell, A.P., Varotsos, C.A., 2007. Editorial and cover: Fifty years after the first artificial satellite: from Sputnik 1 to Envisat. Int. J. Remote Sens. 28 (10), 2071–2072.

Cracknell, A.P., Varotsos, C.A., 2011. New aspects of global climate-dynamics research and remote sensing. Int. J. Remote Sens. 32 (3), 579–600.

Diekmann, O., Heesterbeek, H., Britton, T., 2012. Mathematical tools for understanding infectious disease dynamics. Princeton Series in Theoretical and Computational Biology, Princeton University Press, 517 pp.

Freedman, D.A., 2012. Statistical models: Theory and practice. Cambridge University Press, 240 pp.

Fuentes, R., Galeotti, M., Lanza, A., Manzano, B., 2020. Covid-19 and Climate Change: A Tale of two global problems, pp. 1-24. https://globalnews.ca/news/6816250/coronavirus-Covid-19-oil-gas-sector-federal-bailout.

He, S., Tang, S., Rong, L., 2020. A discrete stochastic model of the COVID-19 outbreak: Forecast and control. Math. Biosci. Engin. 17 (4), 2792–2804.

ICAO, 2020. Effects of novel coronavirus (COVID-19) on civil aviation: economic impact analysis, Montréal, Canada, 2020. https://www.icao.int.

Islam, S., Kabir, K.M.A., Kamrujjaman, M., 2020. COVID-19 Epidemic compartments model and Bangladesh. Preprint, DOI: 10.20944/preprints202004.0193.v1, https://www.researchgate.net › publication › 340604406_COVID-19_Epid.

Ivorra, B., 2020. Validation of the forecasts for the international spread of the coronavirus disease 2019 (COVID-19) done with the Be-CoDiS mathematical model. Technical Report, DOI: 10.13140/RG.2.2.33677.69609/1 https://www.researchgate.net/publication/339314163.

Karako, K., Song, P., Chen, Y., Tang, W., 2020. Analysis of COVID-19 infection speed in Japan based on stochastic transition model. Bioscience Trends 14 (2), 134–138.

Krapivin, V.F., 1970. Control of random walks of a point in the plane. Math. Stat. Prob. 8, 167–173.

Krapivin, V.F., Varotsos, C.A., Soldatov, V.Yu., 2015. New Ecoinformatics Tools in Environmental Science: Applications and Decision-making. Springer, London, U.K., 903 pp.

Krapivin, V.F., Soldatov, V.Y., Varotsos, C.A., Cracknell, A.P., 2012. An adaptive information technology for the operative diagnostics of the tropical cyclones; solar–terrestrial coupling mechanisms. J. Atmos. Sol. Terr. Phys. 89, 83–89.

Krapivin, V.F., Mkrtchyan, F.A., 2019. Nature-society system survivability indicators. J. Sci. Techn. Binh Duong University 1, 1–10.

Kwon, O., Kim, J., Kim, N., Lee, N. (Eds), 2020. Special Issue "Big Data Analytics amid COVID-19: Toward sustainable society". Sustainability, 2020, 12 https://www.mdpi.com›journal›Big_Data_Analytics_to_Fight_COVID-19.

Oldstone, M.B.A., 2009. Viruses, Plagues, and History: Past. Oxford University Press, Present and Future, pp. 390.

Omran, A.R., 2005. The Epidemiologic transition: a theory of the epidemiology of population change. The Milbank Quarterly 83 (4), 731–757.

Park, S., Bolker, B., Champredon, D., Earn, D., Li, M., Weitz, J., Grenfell, B.T., Dusho J., 2020. Reconciling early-outbreak estimates of the basic reproductive number and its uncertainty: framework and applications to the novel coronavirus (2019-nCoV) outbreak, medRxiv. https://www.researchgate.net › publication › 338988729_Reconciling_earl.

Plank, M.J., Binny, R.N., Hendy, S.C., Lustig, A., James,1.A., Steyn, N., 2020. A stochastic model for COVID-19 spread and the effects of Alert Level 4 in Aotearoa New Zealand. MedRxiv Preprint. https://doi.org/10.1101/2020.04.08.20058743, 23 pp.

Sukov, A.I., Soldatov, V.Y., Krapivin, V.F., Cracknell, A.P., Varotsos, C.A., 2008. A sequential analysis method for the prediction of tropical hurricanes. Int. J. Remote Sens. 29 (9), 2787–2798.

Tiwari, A., 2020. Modelling and analysis of COVID-19 epidemic in India. MedRxiv Preprint, doi: https://doi.org/10.1101/2020.04.12.20062794, 6 pp.

Varotsos, C.A., Krapivin, V.F., 2017. A new big data approach based on geoecological information-modeling system. Big Earth Data 1 (1–2), 47–63.

Varotsos, C.A., Efstathiou, M.N., Cracknell, A.P., 2013. On the scaling effect in global surface air temperature anomalies. Atmos. Chem. Phys. 13, 5243–5253. https://doi.org/10.5194/acp-13-5243-2013.

Varotsos, C.A., Mazei, Y.A., Burkovsky, I., Efstathiou, M.N., Tzanis, C.G., 2016. Climate scaling behaviour in the dynamics of the marine interstitial ciliate community. Theor. Appl. Climatol. 125 (3-4), 439–447.

Varotsos, C., Mazei, Y., Novenko, E., Tsyganov, A.N., Olchev, A., Pampura, T., et al., 2020. A new climate nowcasting tool based on paleoclimatic data. Sustainability 12 (14), 5546. https://doi.org/10.3390/su12145546.

Varotsos, C.A., Mazei, Y.A., 2020. Erratum: Future temperature extremes will be more Harmful: a new critical factor for improved forecasts. Int. J. Environ. Res. Public Health 17 (9), 3288.

Varotsos, C.A., Krapivin, V.F., Soldatov, V.Yu., 2019. Monitoring and forecasting of tropical cyclones: a new information-modeling tool to reduce the risk. Int. J. Dis. Risk Red. 36, 1–7.

Varotsos, C.A., Krapivin, V.F., Mkrtchyan, F.A., 2019. New optical tools for water quality diagnostics. Water Air Soil Pollut. 230 (8), 177.

Wald, A., 1947. Sequential Analysis. John Wiley & Sons Inc, New York, pp. 212.

Wang, M., Jiang, A. , Gong, L. , Lu, L. , Guo, W., Li, C., Zheng, J., Li, Ch., Yang, B., Zeng, J., Chen, Y., Zheng, K., Li, H., 2020. Temperature significantly Change COVID-19 transmission in 429 cities. MedRxiv Preprint. https://doi.org/10.1101/2020.02.22.20025791.