Original article
https://doi.org/10.36233/0372-9311-213

Predicting incidence of Crimean-Congo hemorrhagic fever using satellite monitoring (remote sensing) data in the Stavropol Territory

Vladimir M. Dubyanskiy[1,2], Daria A. Prislegina[1,2✉], Alexander E. Platonov[2]

[1]Stavropol Plague Control Research Institute, Stavropol, Russia;
[2]Central Research Institute of Epidemiology, Moscow, Russia

Abstract

Introduction. With the epidemiological situation for Crimean-Congo hemorrhagic fever (CCHF) remaining tense in many countries worldwide, special attention should be focused on development and improvement of risk-based epidemiological prediction methods.

The **aim** of the study was to build a prediction model for CCHF incidence dynamics (based on the Stavropol Territory) using satellite monitoring (remote sensing) data.

Materials and methods. We analyzed the climate data obtained from the Space Research Institute of the Russian Academy of Sciences as well as the data of public statistics reports on CCHF incidence from 2005 to 2021. The prediction model incorporated the Bayes theorem and Wald sequential analysis. The information content of the factors was assessed using the Kullback method.

Results. Predictions for each of 26 districts were made stepwise (compared to threshold levels) to predict whether there will be at least one case of CCHF, whether the relative incidence per 100,000 population will exceed the median level (0.9 cases) or the average rate (3.5 cases) or the third quartile rate (4.7 cases). The highest values of information coefficients were obtained for soil temperature and moisture content (at depths of 10 and 40 cm), normalized relative vegetation index, relative humidity, maximum and average air temperature, relative air humidity. During the testing of the model in 2021, false-negative (erroneous) prediction was made for 2 districts.

Discussion. The model proved to be most efficient in prediction of occurrence or absence of cases. More accurate quantitative prediction may be difficult due to subjective factors (including misdiagnosing CCHF cases without hemorrhagic manifestations and administering treatment for other conditions with similar symptoms).

Conclusion. The tests of the model demonstrate its potential. The practical application of the prediction will make healthcare workers more alert when screening and detecting CCHF cases.

Keywords: *Crimean-Congo hemorrhagic fever, prediction, prediction model, climatic factors, incidence, remote sensing*

Funding source. This study was carried out with the financial support of the Russian Science Foundation (project No. 19-75-20088 Creation of a methodology, based on remote sensing data of the Earth, for analyzing and forecasting the impact of climatic and environmental factors on the incidence of zoonotic infections).

Conflict of interest. The authors declare no apparent or potential conflicts of interest related to the publication of this article.

For citation: Dubyanskiy V.M., Prislegina D.A., Platonov A.E. Predicting incidence of Crimean-Congo hemorrhagic fever using satellite monitoring (remote sensing) data in the Stavropol Territory. *Journal of microbiology, epidemiology and immunobiology = Zhurnal mikrobiologii, èpidemiologii i immunobiologii.* 2022;99(3):322–335.
DOI: https://doi.org/10.36233/0372-9311-213

Научная статья
https://doi.org/10.36233/0372-9311-213

Прогнозирование заболеваемости Крымской геморрагической лихорадкой на основе данных спутникового мониторинга (дистанционного зондирования Земли из космоса) на примере Ставропольского края

Дубянский В.М.[1,2], Прислегина Д.А.[1,2]✉, Платонов А.Е[2]

[1]Ставропольский научно-исследовательский противочумный институт, Ставрополь, Россия;
[2]Центральный научно-исследовательский институт эпидемиологии, Москва, Россия

Аннотация
Введение. Сохранение напряжённой эпидемиологической ситуации по Крымской геморрагической лихорадке (КГЛ) во многих странах мира требует уделять особое внимание разработке и совершенствованию методов риск-ориентированного эпидемиологического прогнозирования.
Цель исследования — разработка прогнозной модели динамики заболеваемости КГЛ (на примере Ставропольского края) с использованием данных спутникового мониторинга (дистанционного зондирования Земли из космоса).
Материалы и методы. Проанализированы климатические данные Института космических исследований РАН и сведения официальной статистической отчётности по заболеваемости КГЛ с 2005 по 2021 г. Прогнозная модель была разработана на основе теоремы Байеса и последовательного статистического анализа Вальда. Информативность факторов оценивали по методу Кульбака.
Результаты. Прогнозы по каждому из 26 районов были составлены поэтапно (относительно пороговых уровней): будет хотя бы один больной КГЛ, превысит ли относительная заболеваемость на 100 тыс. населения уровень медианы (0,9 заболевших), среднее (3,5 заболевших) и третьего квартиля (4,7 заболевших). Наиболее высокие значения коэффициентов информативности были получены для температуры и влажности почвы (на глубине 10 и 40 см), нормализованного относительного вегетационного индекса, относительной влажности, максимальной и средней температуры воздуха, относительной влажности воздуха. При апробации модели в 2021 г. ложноотрицательный (ошибочный) прогноз был дан для 2 районов.
Обсуждение. Наиболее эффективно модель позволяет прогнозировать наличие или отсутствие больных. Более точное количественное прогнозирование несколько затруднено в связи с наличием субъективных факторов (в том числе постановка больным КГЛ без геморрагических проявлений неверных диагнозов и оказание им помощи по поводу других заболеваний со сходными симптомами).
Заключение. Апробация модели свидетельствует о её перспективности. Внедрение прогноза в практику позволит повысить настороженность медицинских работников для улучшения выявляемости больных КГЛ.

Ключевые слова: *Крымская геморрагическая лихорадка, прогнозирование, прогнозная модель, климатические факторы, заболеваемость, дистанционное зондирование Земли*

Источник финансирования. Исследование выполнено при финансовой поддержке Российского научного фонда (проект № 19-75-20088 «Создание опирающейся на данные дистанционного зондирования Земли методологии анализа и прогнозирования влияния климатических и экологических факторов на заболеваемость природно-очаговыми инфекциями»).

Конфликт интересов. Авторы декларируют отсутствие явных и потенциальных конфликтов интересов, связанных с публикацией настоящей статьи.

Для цитирования: Дубянский В.М., Прислегина Д.А., Платонов А.Е. Прогнозирование заболеваемости Крымской геморрагической лихорадкой на основе данных спутникового мониторинга (дистанционного зондирования Земли из космоса) на примере Ставропольского края. *Журнал микробиологии, эпидемиологии и иммунобиологии.* 2022;99(3):322–335.
DOI: https://doi.org/10.36233/0372-9311-213

Introduction

Crimean-Congo hemorrhagic fever (CCHF) is an especially dangerous arboviral infection; the epidemiological situation has been tense for many years in countries of Central Asia and the Middle East as well as in the Russian Federation [1–12].

As there are currently no specific preventive vaccines against this dangerous infection, risk-based prediction of incidence in a population is given special attention to stabilize the epidemiological situation and to serve as a basis for scientifically grounded planning of non-specific preventive measures.

In Turkey, a multi-agent SIR model was offered for making epidemiological predictions [13]. In Russia, the "maximum stability" estimation method and regression analysis were used to build a short-term prediction model to estimate the expected number of CCHF cases (annual rates) in the current year by the incidence of the "key" month [14].

In the meantime, CCHF is a natural focal, transmissible infection; therefore, when selecting a prediction method, the priority should be given to the methods that address the effect of climatic factors on the population of specific vectors of its pathogen — ixodid ticks and, consequently, on the incidence rates, as is demonstrated by many studies in other countries.

In Iran, the researchers, using the time-series analysis and the seasonal auto-regression integrated moving average (SARIMA) model, found a strong correlation between the number of cases and the monthly average air temperature, monthly maximum relative humidity and accumulated precipitation, and using the Poisson regression analysis together with the McFadden pseudo R-squared – the correlation with the maximum temperature values of the previous month [15, 16]. In Bulgaria, the one-way analysis of variance (ANOVA) showed that the increase in the average air temperature and the normalized difference vegetation index (NDVI) per unit resulted in a 5.5% increase in the CCHF incidence [17].

Earlier, using the correlation analysis, Bayes theorem and Wald sequential analysis, V.M. Dubyanskiy and D.A. Prislegina developed the method for quantitative risk-based prediction of CCHF incidence in each administrative district of the Stavropol Territory [18–20]. The calculations were based on monthly values of five factors of all seasons (air temperature, relative air humidity, precipitation amounts, snow depth and wind speed), which affected different stages in the life cycle of *Hyalomma marginatum* ticks, which are the main vectors and reservoirs of the CCHF virus in Russia [10, 12, 21–25]. The efficiency of the offered method was proved by the fact that the results obtained in 2018 and the actual data had a 87.4% match; the prediction results were used in planning preventive measures.

This study is a continuation of the previous research; its aim is to improve methods used for CCHF incidence prediction and to obtain new data on the relationship between the intensity of epidemic and epizootic processes of this especially dangerous infection and the combined effects of multiple, including previously unaddressed, climatic factors.

Materials and methods

The study incorporated combined methods of epidemiological analysis and mathematical statistics.

The materials included the hydro-meteorological data and NDVI received from the database of the SRI-Monitoring Center for Collective Use of Systems for Archiving, Processing and Analyzing Satellite Data of the RAS Space Research Institute as well as the data of public statistics reports for 2005-2021. To calculate the relative CCHF incidence (per 100,000 population) for administrative districts of the Stavropol Territory, we analyzed the epidemiological survey charts of the infectious disease cluster (Form 357/u), which were provided by the Department of the Federal Service for Surveillance on Consumer Rights Protection and Human Wellbeing (Rospotrebnadzor) for the Stavropol Territory, as well as the archival data from the Department of the Federal Statistics Service for the North Caucasian Federal District and the Federal Statistics Service for each year of the studied period.

The prediction model of the incidence dynamics was based on the Bayes theorem and Wald sequential analysis [26–28]. The Bayes theorem was intentionally used for building the model, as it helped incorporate divergent effects of multiple factors for each administrative district using data on the frequency of the respective values and occurrence/absence of disease cases as well as made it possible to obtain alternative results (one of the two possible prediction outcomes – absence/occurrence of the case, surpassing/non-surpassing of the selected thresholds by the incidence rates).

The threshold level of positive solution probability was set at 99% (the error probability of 1%). We used numeric values of 13 climatic factors (for each month of the studied period and annual means):

- air temperature — average, maximum and minimum (°C);
- soil temperature at depths of 10 and 40 cm (°C);
- soil moisture content at depths of 10 and 40 cm (%);
- snow depth (m);
- area covered by snow (%);
- pressure (Pa);
- relative air humidity (%);
- precipitation (kg/m^2);
- NDVI (relative units).

The information content of 169 parameters was estimated using the Kullback method [26–28]. The factor was deemed as informative, if it demonstrated a larger difference between distributions of two differentiated conditions of the object of study. For example, at the average air temperature of 28°C in June, the probability of at least one case of CCHF within the natural focus of infection is 2 times as high on average as the probability at the temperature of 24°C. This factor can be seen as informative, as the incidence prediction will be true at the ratio of 2:1 at the above temperature. However, the derivative of the information content – the diagnostic coefficient is more convenient to use. It is efficient for estimating the probability of the object being in one of the two studied conditions at certain values of several factors. For example, if the average air temperature in June is 28°C and the average barometric pressure in June is above 103,165.18 Pa, the probability of at least one case of CCHF within the natural focus of infection reaches 0.8.

In addition to using an increased number of factors, the offered model differs fundamentally from the former method of risk-based prediction [18–20] by organization of the data for identification of predictors. Considering a relatively short time series (15 years) and landscape heterogeneity of the Stavropol Territory, the data were organized as follows: The CCHF incidence data broken by administrative districts and years were combined into a cumulative series (a total of 364 values), while the weather and climate variables were distributed according to the incidence.

The incidence was measured in relative numbers of cases per 100,000 population.

Information and prediction coefficients were calculated automatically using the Microsoft Excel 2010-based program developed by the authors.

The step-by-step algorithm for making a prediction using the prediction model:

1. Calculation of information and prediction coefficients of factors with the program.
2. Making an optimized list of factors (with values of the information coefficient ≥ 0.5 in descending order).
3. Predicting the occurrence (absence) of at least 1 case of disease per 100,000 population.
4. Calculating the incidence per 100,000 population compared to the threshold median level (0.9).
5. Calculating the incidence per 100,000 population compared to the average rate (3.5).
6. Calculating the incidence per 100,000 population compared to the third quartile rate (4.7).

Calculations for item 2 were made against the selected minimum threshold value (the value of 0.000009, which is lower than the rate of 1 case per 100,000 population). The calculations for the prediction were made by summing up the values of prediction coefficients of the informative factors in accordance with their values for each administrative district until the numeric value of +20 or -20 was received to indicate the occurrence/absence of disease cases with a probability of 99%. Then, when the districts with positive results were identified, the prediction for them was made against other selected threshold levels of incidence.

Results

The prediction model was built for making prediction for CCHF epidemiological situation for each district using the climate data of the previous year. To date, there have been no similar studies in predicting CCHF incidence by using satellite monitoring (remote sensing) data and the identical algorithm.

The model is built for alternative-based predictions: Whether there will be or will not be at least 1 CCHF case in the district, whether the relative incidence (per 100,000 population) will exceed the median level (0.9 cases), the average rate (3.5), the third quartile rate (4.7). The informative predictors for each threshold are presented in **Table 1**.

A total of 57 predictors were used for the threshold "whether there will be or will not be at least one case of CCHF in the district"; 62 predictors were used for the threshold "whether the relative incidence will exceed the median level (0.9 cases per 100,000 population)"; 56 predictors were used for the threshold "whether the relative incidence will exceed the average rate (3.5 cases)"; 55 predictors were used for the threshold "whether the relative incidence will exceed the third quartile rate (4.7 cases)".

The assessment of the information content of factors showed the highest values of information coefficients for soil temperature and moisture content (at depths of 10 cm and 40 cm), NDVI, relative humidity, maximum and average air temperature (in June), relative air humidity and NDVI (in August). During the above months, these climatic factors (according to the literature data) have a strong impact on embryogenesis, survival rate and preimaginal phases and development of *H. marginatum*, the population of feeders of preimaginal phases, thus having a significant effect on the size of imago tick population in the next year (the year of prediction) [22, 24, 25].

The prediction model for CCHF incidence dynamics was checked using the historical data for 2018–2020 (**Table 2**).

The model-based erroneous predictions were divided into 4 types:

- false-positive — the predicted result is positive; however, no cases have been reported;
- false-negative — the predicted result is negative; however, cases of disease have been detected;
- overestimated — the actual incidence rate is lower than the predicted rate against the threshold level;
- underestimated — the actual incidence rate is higher than the predicted rate against the threshold level.

In 2020, the epidemiological prediction for 2021 was prepared (**Table 3**).

Table 1. Climatic and environmental indicators used as predictors of the forecast model

Predictor	Indicator	Will there be at least one sick	Indicator	Above/below the median	Indicator	Above/below average	Indicator	Above/below the third quartile
1	2	3	4	5	6	7	8	9
1	Soil temperature at a depth of 40 cm in June	1,59	Soil temperature at a depth of 40 cm in June	1,89	NDVI in June	1,85	Humidity in June	1,83
2	Humidity in June	1,51	Humidity in June	1,79	Humidity in June	1,84	NDVI in June	1,65
3	Soil temperature at a depth of 40 cm in August	1,31	Soil temperature at a depth of 40 cm in August	1,64	Soil temperature at a depth of 40 cm in June	1,74	Soil temperature at a depth of 40 cm in June	1,62
4	Soil moisture at a depth of 10 cm in June	1,30	Soil moisture at a depth 10 cm in June	1,51	Maximum air temperature in June	1,38	Average annual air humidity	1,52
5	Average annual air humidity	1,29	Average annual air humidity	1,48	NDVI in August	1,35	Soil moisture at a depth of 10 cm in June	1,36
6	NDVI in June	1,18	NDVI in June	1,38	Soil moisture at a depth of 10 cm in June	1,32	Maximum air temperature in June	1,29
7	Soil temperature at a depth of 10 cm in June	1,15	Soil temperature at a depth of 10 cm in June	1,33	Soil temperature at a depth of 40 cm in August	1,32	Soil temperature at a depth of 10 cm in June	1,24
8	Soil moisture at a depth of 40 cm in June	1,13	NDVI in August	1,33	Soil temperature at a depth of 10 cm in June	1,26	Air humidity in May	1,23
9	NDVI in August	1,06	Humidity in August	1,24	Average annual air humidity	1,26	Humidity in August	1,20
10	Humidity in August	1,06	Soil moisture at a depth of 40 cm in June	1,23	Air temperature in June	1,24	Soil temperature at a depth of 40 cm in August	1,20
11	Soil temperature at a depth of 40 cm in July	1,04	Soil temperature at a depth of 40 cm in July	1,22	Pressure in May	1,20	Air temperature in June	1,11
12	Maximum air temperature in June	1,01	Maximum air temperature in June	1,18	Pressure in April	1,20	Давление в мае Pressure in May	1,11
13	Humidity in July	0,97	Pressure in February	1,17	Pressure in March	1,18	Pressure in April	1,10
14	Pressure in January	0,97	Pressure in January	1,16	Pressure in June	1,14	Pressure in March	1,07
15	Pressure in October	0,96	Pressure in March	1,15	Pressure in October	1,13	Pressure in June	1,07
16	NDVI in July	0,95	Pressure in June	1,14	NDVI in July	1,13	NDVI in August	1,07
17	Pressure in March	0,95	Pressure in May	1,14	Pressure in August	1,13	Soil moisture at a depth of 10 cm in May	1,05
18	Pressure in August	0,94	NDVI in July	1,13	Pressure in February	1,07	Pressure in February	1,05
19	Air humidity in May	0,94	Pressure in April	1,13	Pressure in January	1,05	Pressure in October	1,04

DOI: https://doi.org/10.36233/0372-9311-213

Continuation of the Table 1

1	2	3	4	5	6	7	8	9
20	Pressure in February	0,94	Humidity in July	1,12	Pressure in September	1,05	Pressure in August	1,03
21	Pressure in April	0,93	Pressure in October	1,12	Average annual pressure	1,04	Soil moisture at a depth of 40 cm in June	1,02
22	Air temperature in June	0,93	Pressure in August	1,11	Humidity in July	1,03	Humidity in July	0,97
23	Pressure in June	0,92	Air temperature in June	1,11	Air humidity in May	1,01	NDVI in July	0,96
24	Pressure in May	0,91	Pressure in September	1,09	NDVI annual average	1,01	Pressure in September	0,96
25	Pressure in September	0,89	Average annual pressure	1,08	Soil temperature at a depth of 40 cm in July	0,98	Average annual pressure	0,95
26	Average annual pressure	0,88	Air humidity in May	1,07	Humidity in August	0,98	Pressure in January	0,94
27	Average annual soil temperature at a depth of 40 cm	0,86	Average annual soil temperature at a depth of 40 cm	1,06	Minimum air temperature in June	0,97	Soil temperature at a depth of 40 cm in July	0,85
28	Soil temperature at a depth of 10 cm in August	0,84	Soil temperature at a depth of 10 cm in August	1,04	Soil moisture at a depth of 40 cm in June	0,96	Minimum air temperature in June	0,80
29	Soil moisture at a depth of 10 cm in July	0,78	Soil moisture at a depth of 10 cm in July	0,97	Average annual soil temperature at a depth of 40 cm	0,86	Pressure in July	0,76
30	Minimum air temperature in June	0,78	NDVI in September	0,97	Soil moisture at a depth of 10 cm in May	0,86	Soil temperature at a depth of 10 cm in August	0,75
31	Soil temperature at a depth of 40 cm in September	0,77	Soil temperature at a depth of 40 cm in September	0,96	Pressure in July	0,84	Soil moisture at a depth of 40 cm in May	0,73
32	Soil moisture at a depth of 10 cm in May	0,75	Pressure in July	0,95	Soil temperature at a depth of 10 cm in August	0,84	Rainfall in May	0,73
33	Average annual soil temperature at a depth of 10 cm	0,73	Soil moisture at a depth of 10 cm in May	0,92	NDVI in September	0,80	Average annual precipitation	0,72
34	Soil temperature at a depth of 10 cm in July	0,73	Minimum air temperature in June	0,91	Soil moisture at a depth of 10 cm in July	0,79	Average annual soil temperature at a depth of 40 cm	0,72
35	NDVI annual average	0,72	NDVI annual average	0,89	Air temperature in July	0,76	Soil moisture at a depth of 10 cm in July	0,70
36	Pressure in July	0,72	Average annual soil temperature at a depth of 10 cm	0,88	Maximum air temperature in July	0,73	Rainfall in June	0,69
37	Minimum air temperature in August	0,71	Air temperature in August	0,88	Air temperature in August	0,73	Air temperature in August	0,67

Continuation of the Table 1

1	2	3	4	5	6	7	8	9
38	Air temperature in August	0,70	Soil temperature at a depth of 10 cm in July	0,84	Minimum air temperature in August	0,71	NDVI average annual	0,66
39	Minimum average annual air temperature	0,70	Minimum average annual air temperature	0,83	Soil temperature at a depth of 10 cm in July	0,68	Soil moisture at a depth of 10 cm in August	0,63
40	Average annual air temperature	0,68	Minimum air temperature in August	0,81	Soil temperature at a depth of 40 cm in September	0,68	Average air temperature	0,61
41	Minimum air temperature in September	0,66	Minimum air temperature in September	0,80	Average air temperature	0,67	NDVI in September	0,60
42	Soil moisture at a depth of 10 cm in August	0,65	Maximum air temperature in July	0,76	Rainfall in June	0,65	Soil temperature at a depth of 10 cm in July	0,60
43	Minimum air temperature in May	0,64	Air temperature in July	0,74	NDVI in May	0,63	Air temperature in July	0,59
44	NDVI in September	0,63	Average annual air temperature	0,69	Minimum average annual air temperature	0,63	Maximum air temperature in July	0,57
45	Air temperature in July	0,62	Rainfall in June	0,69	Rainfall in May	0,60	Soil moisture at a depth of 40 cm in August	0,56
46	Soil temperature at a depth of 10 cm in September	0,59	Maximum air temperature in August	0,69	Minimum air temperature in July	0,59	NDVI in May	0,55
47	Maximum air temperature in August	0,58	Rainfall in May	0,68	Average annual soil temperature at a depth of 10 cm	0,58	Air humidity in September	0,54
48	Maximum air temperature in July	0,57	Soil moisture at a depth of 10 cm in August	0,68	Soil moisture at a depth of 40 cm in May	0,56	Minimum air temperature in August	0,53
49	Soil moisture at a depth of 40 cm in August	0,57	Soil moisture at a depth of 40 cm in July	0,68	Maximum air temperature in August	0,56	Humidity in April	0,53
50	Maximum air temperature average annual	0,57	Soil moisture at a depth of 40 cm in August	0,67	Soil moisture at a depth of 40 cm in July	0,55	Soil temperature at a depth of 40 cm in May	0,53
51	Soil moisture at a depth of 40 cm in July	0,55	Minimum air temperature in May	0,66	Average annual precipitation	0,54	Air temperature in May	0,52
52	Maximum air temperature in May	0,54	Minimum air temperature in July	0,66	Soil temperature at a depth of 40 cm in May	0,54	Average annual soil temperature at a depth of 10 cm	0,52
53	Proportion of snow covered area in January	0,54	Soil moisture at a depth of 40 cm in May	0,66	Minimum air temperature in September	0,53	Soil temperature at a depth of 40 cm in September	0,51

End of the Table 1

1	2	3	4	5	6	7	8	9
54	Minimum air temperature in July	0,53	Soil temperature at a depth of 10 cm in September	0,63	Minimum air temperature in May	0,52	Maximum air temperature in May	0,51
55	Soil moisture at a depth of 40 cm in May	0,52	Maximum air temperature average annual	0,58	Maximum air temperature in May	0,51	Minimum air temperature average annual	0,50
56	Rainfall in June	0,52	Maximum air temperature in May	0,58	Maximum air temperature average annual	0,51		
57	Rainfall in May	0,51	Air temperature in September	0,56				
58			Average annual precipitation	0,56				
59			NDVI in May	0,55				
60			Air humidity in September	0,52				
61			Soil temperature at a depth of 10 cm in May	0,52				
62			Air temperature in May	0,50				

Table 2. The results of checking the forecast model of the CCHF morbidity dynamics using retrospective data for 2018–2020

Results	Year					
	2018		2019		2020	
	abs.	%	abs.	%	abs.	%
Correct	16	61,5	12	46,2	7	26,9
False positive	3	11,5	7	26,9	14	53,8
False negative	1	3,8	2	7,7	1	3,8
Overestimated	4	15,4	5	19,2	4	15,4
Underestimated	2	7,7	0	–	0	–

Before we move on to the discussion of the efficiency of prediction, we would like to point out the following aspects. CCHF patients frequently do not develop hemorrhagic syndrome; they can have ARVI-like symptoms [8, 9, 19]; some patients are diagnosed with other conditions; some cases are not reported [8, 9, 19]. Therefore, the number of reported cases depends not only on objective environmental factors, but also on subjective factors, including the severity of the disease, the qualification of medical and laboratory personnel at some healthcare facilities [19]. The above subjective factors are not addressed during the prediction. Consequently, the occurrence or absence of disease cases in general can be predicted most efficiently. The more accurate data on incidence rates are more dependent on subjective factors and are less predictable.

The data presented in Table 3 prove the above. Out of 26 administrative districts of the Stavropol Territory, the erroneous prediction was made only for two of them: Grachevsky and Shpakovsky districts; thus, the prediction for the threshold "whether there will be or will not be at least one case of CCHF in the district" was erroneous by 7.7%. The above districts were expected not to have any cases, though, in fact, there were reported cases.

The overestimated number of cases was predicted for 11 districts. Here, it is unlikely that we deal with a serious mistake, as we cannot exclude poor diagnostics (misdiagnosis) or the probability that the case of infection was reported in another district (at the place of the patient's residence).

Table 3. The results of approbation of the forecast model of the CCHF morbidity dynamics for 2021

Administrative region	Forecast result	Factual morbidity (per 100,000 population)
Alexandrovsky	≤ 0,000009	0
Andropovsky	≤ 0,000009	0
Apanasenkovsky	> 4,7	10,1
Arzgirsky	> 4,7	8,3
Blagodarnensky	> 4,7	5,2
Budennovsky	> 4,7	0
Georgievsky	> 0,9	0
Grachevsky	≤ 0,000009	2,7
Izobilnensky	> 4,7	0
Ipatovsky	> 4,7	5,4
Kirovsky	≤ 0,000009	0
Kochubeevsky	≤ 0,000009	0
Krasnogvardeisky	> 4,7	5,4
Kursky	> 4,7	0
Levokumsky	> 4,7	0
Mineralovodsky	≤ 0,000009	0
Neftekumsky	> 4,7	1,6
Novoaleksandrovsky	> 4,7	0
Novoselytsky	> 4,7	0
Petrovsky	> 4,7	1,4
Predgornyy	≤ 0,000009	0
Soviet	> 4,7	0
Stepnovsky	> 4,7	0
Trunovsky	> 4,7	3,4
Turkmensky	> 4,7	0
Shpakovsky	≤ 0,000009	1,3

Conclusion

The application of the prediction model in 2021 demonstrated its potential. Based on the studied literature, no country has achieved better results in predicting CCHF incidence [24].

In the meantime, the model incorporates primarily weather variables serving as predictors. Although the information used for building the model is completely consistent with the literature data on indirect combined effects of climatic factors on the epidemiological situation of CCHF, the model should include biotic predictors [24, 25, 30].

The practical application of the prediction will increase the alertness of healthcare workers in the at-risk regions, will improve the detectability of CCHF cases and implementation of non-specific preventive measures.

Focusing on this area, we are planning to test the prediction model in other CCHF-endemic regions (the Rostov Region and the Republic of Kalmykia).

R E F E R E N C E S

1. Shahhosseini N., Wong G., Babuadze G., Camp J.V., Ergonul O., Kobinger G.P., et al. Crimean-Congo hemorrhagic fever virus in Asia, Africa and Europe. *Microorganisms.* 2021; 9(9): 1907. https://doi.org/10.3390/microorganisms9091907
2. Obaidat M.M., Graziano J.C., Morales-Betoulle M., Brown S.M., Chiang C.F., Klena J.D. Rift Valley fever and Crimean-Congo hemorrhagic fever viruses in ruminants, Jordan. *Emerg. Infect. Dis.* 2021; 27(2): 653–55. https://doi.org/10.3201/eid2702.203713
3. Temur A.I., Kuhn J.H., Pecor D.B., Apanaskevich D.A., Keshtkar-Jahromi M. Epidemiology of Crimean-Congo hemorrhagic fever (CCHF) in Africa-underestimated for decades. *Am. J. Trop. Med. Hyg*. 2021; 104(6): 1978–90. https://doi.org/10.4269/ajtmh.20-1413
4. Dieng I., Barry M.A., Diagne M.M., Diop B., Ndiaye M., Faye M., et al. Detection of Crimean Congo haemorrhagic fever virus in North-eastern Senegal, Bokidiawé 2019. *Emerg. Microbes Infect.* 2020; 9(1): 2485–87. https://doi.org/10.1080/22221751.2020.1847605
5. Schulz A., Barry Y., Stoek F., Pickin M.J., Ba A., Chitimia-Dobler L., et al. Detection of Crimean-Congo hemorrhagic fever virus in blood-fed Hyalomma ticks collected from Mauritanian livestock. *Parasit. Vectors*. 2021; 14(1): 342. https://doi.org/10.1186/s13071-021-04819-x
6. Balinandi S., von Brömssen C., Tumusiime A., Kyondo J., Kwon H., Monteil V.M., et al. Serological and molecular study of Crimean-Congo hemorrhagic fever virus in cattle from selected districts in Uganda. *J. Virol. Methods*. 2021; 290: 114075. https://doi.org/10.1016/j.jviromet.2021.114075
7. Negredo A., Sánchez-Ledesma M., Llorente F., Pérez-Olmeda M., Belhassen-García M., González-Calle D., et al. Retrospective identification of early autochthonous case of Crimean-Congo hemorrhagic fever, Spain, 2013. *Emerg. Infect. Dis.* 2021; 27(6): 1754–6. https://doi.org/10.3201/eid2706.204643
8. Kulichenko A.N., Maletskaya O.V., Prislegina D.A., Vasilenko N.F., Semenko O.V., Gazieva A.Yu., et al. *Epidemiological Situation on Natural Focal Infectious Diseases in the Southern and North Caucasian federal districts in 2019. Analytical Review [Epidemiologicheskaya obstanovka po prirodno-ochagovym infektsionnym boleznyam v Yuzhnom i Severo-Kavkazskom federal'nykh okrugakh v 2019 g]*. Stavropol'; 2020. Available at: https://www.snipchi.ru/updoc/2020/An-Obzor%20po%20prirodno-oschagovim%202020.pdf (in Russian)
9. Maletskaya O.V., Taran T.V., Prislegina D.A., Dubyanskiy V.M., Volynkina A.S., Semenko O.V., et al. Natural-focal viral fevers in the South of the European part of Russia. Crimean-Congo hemorrhagic fever. *Problemy osobo opasnykh infektsiy.* 2020; (4): 75–80. https://doi.org/10.21055/0370-1069-2020-4-75-80 (in Russian)
10. Onishchenko G.G., Efremenko V.I., Beyer A.P. *Crimean-Congo hemorrhagic fever [Krymskaya gemorragicheskaya likhoradka]*. Moscow; 2005. (in Russian)
11. Platonov A.E., Avksent'ev N.A., Avksent'eva M.V., Derkach E.V., Platonova O.V., Titkov A.V., et al. Social and economic burden of five natural focal infections in the Russian Federation. *Farmakoekonomika. Sovremennaya farmakoekonomika i farmakoepidemiologiya.* 2015; 8(1): 47–56. https://doi.org/10.17749/2070-4909.2015.8.1.047-056 (in Russian)
12. Smirnova S.E. *Crimean-Congo Hemorrhagic Fever (Etiology, Epidemiology, Laboratory Diagnostics) [Krymskaya-Kongo gemorragicheskaya likhoradka (etiologiya, epidemiologiya, laboratornaya diagnostika)].* Moscow: ATiSO; 2007. (in Russian)
13. Estrada-Peña A., Zatansever Z., Gargili A., Aktas M., Uzun R., Ergonul O., et al. Modeling the spatial distribution of Crimean-Congo hemorrhagic fever outbreaks in Turkey. *Vector Borne Zoonotic Dis*. 2007; 7(4): 667–78. https://doi.org/10.1089/vbz.2007.0134
14. Kharchenko T.V. *Modern epidemiological features of the Crimean-Congo hemorrhagic fever in the Russian Federation:* Diss. Stavropol'; 2011 (in Russian)
15. Ansari H., Shahbaz B., Izadi S., Zeinali M., Tabatabaee S.M., Mahmoodi M., et al. Crimean-Congo hemorrhagic fever and its relationship with climate factors in southeast Iran: a 13-year experience. *J. Infect. Dev. Ctries*. 2014; 8(6): 749–57. https://doi.org/10.3855/jidc.4020
16. Mostafavi E., Chinikar S., Bokaei S., Haghdoost A. Temporal modeling of Crimean-Congo hemorrhagic fever in eastern Iran. *Int. J. Infect. Dis*. 2013; 17(7): 524–8. https://doi.org/10.1016/j.ijid.2013.01.010
17. Vescio F.M., Busani L., Mughini-Gras L., Khoury C., Avellis L., Taseva E., et al. Environmental correlates of Crimean-Congo haemorrhagic fever incidence in Bulgaria. *BMC Public Health*. 2012; 12: 1116. https://doi.org/10.1186/1471-2458-12-1116
18. Dubyanskiy V.M., Prislegina D.A., Kulichenko A.N. Risk-oriented model for predicting epidemiological situation with Crimean-Congo hemorrhagic fever (on the example of Stavropol region). *Analiz riska zdorov'yu.* 2018; (1): 13–21. https://doi.org/10.21668/health.risk/2018.1.02 (in Russian)
19. Prislegina D.A., Dubyanskiy V.M., Maletskaya O.V., Kulichenko A.N., Vasilenko N.F., Manin E.A., et al. Crimean-Congo hemorrhagic fever in the Stavropol Region: contemporary clinical and epidemiological aspects and new approach to forecasting of morbidity. *Infektsionnye bolezni: novosti, mneniya, obuchenie.* 2018; 7(3): 49–56. https://doi.org/10.24411/2305-3496-2018-13007 (in Russian)
20. Prislegina D.A., Dubyanskiy V.M., Kulichenko A.N. Particular dangerous arbovirus fevers in the south of Russia: improvement of monitoring with modern information technology application. *Meditsina truda i ekologiya cheloveka.* 2019; (4): 50–8. https://doi.org/10.24411/2411-3794-2019-10047 in Russian)
21. Tokhov Yu.M., Degtyarev D.Yu., Dubyanskiy V.M. *Ixodid Ticks (Morphology, Medical Significance, Population Regulation) [Iksodovye kleshchi (morfologiya, meditsinskoe znachenie, regulyatsiya chislennosti)].* Stavropol'; 2015. (in Russian)
22. Trukhachev V.I., Tokhov Yu.M., Lutsuk S.N., Dylev A.A., Tolokonnikov V.P., D'yachenko Yu.V. Distribution and ecological characteristics of Hyalomma ixodid ticks in the ecosystems of the Stavropol Region. *Yug Rossii: ekologiya, razvitie.* 2016; 11(2): 59–69. https://doi.org/10.18470/1992-1098-2016-2-59-69 (in Russian)
23. Tokhov Yu.M., Chumakova I.V., Lutsuk S.N., D'yachenko Yu.V., Kotenev E.S., Zaytsev A.A. Ticks as the reservoir of contagious diseases in the Stavropol territory. *Vestnik veterinarii.* 2013; (2): 19–21. (in Russian)
24. Prislegina D.A., Dubyanskiy V.M., Platonov A.E., Maletskaya O.V. Effect of the natural and climatic factors on epidemiological situation related to natural focal infections. *Infektsiya i immunitet.* 2021; 11(5): 820–36. https://doi.org/10.15789/2220-7619-EOT-1631 (in Russian)
25. Kulichenko A.N., Prislegina D.A. Climatic prerequisites for changing activity in the natural Crimean-Congo hemorrhagic fever focus in the South of the Russian Federation. *Infektsiya i*

immunitet. 2019; 9(1): 162–72. https://doi.org/10.15789/2220-7619-2019-1-162-172 (in Russian)
26. Gubler E.V. *Computational Methods for Analysis and Identification of Pathological Processes [Vychislitel'nye metody analiza i raspoznavaniya patologicheskikh protsessov].* Leningrad: Meditsina; 1978. (in Russian)
27. Gubler E.V., Genkin A.A. *Application of Statistical Non-Parametric Criteria in Medico-Biological Investigations [Primeneniye neparametricheskikh kriteriyev statistiki v mediko-biologicheskikh issledovaniyakh]*. Leningrad: Meditsina; 1973. (in Russian)
28. Dubyanskiy M.A., Kenzhebaev A., Stepanov V.M., Asenov G.A., Dubyanskaya L.D. *Prognostication of Plague Epizootic Activity in Sub-Aral and Kyzylkum Areas [Prognozirovanie epizooticheskoy aktivnosti chumy v Priaral'e i Kyzylkumakh]*. Nukus: Karakalpakstan; 1992. (in Russian)
29. Yigit G.K. An example of tick-Crimean Congo hemorrhagic fever (CCHF) in Eflani district, Karabuk, Turkey. *Sci. Res. Essays.* 2011; 6(11): 2395–402. https://doi.org/10.5897/SRE11.574
30. Cherkasskiy B.L. *Risk in Epidemiology [Risk v epidemiologii]*. Moscow: Prakticheskaya meditsina; 2007. (in Russian)

СПИСОК ИСТОЧНИКОВ

1. Shahhosseini N., Wong G., Babuadze G., Camp J.V., Ergonul O., Kobinger G.P., et al. Crimean-Congo hemorrhagic fever virus in Asia, Africa and Europe. *Microorganisms.* 2021; 9(9): 1907. https://doi.org/10.3390/microorganisms9091907
2. Obaidat M.M., Graziano J.C., Morales-Betoulle M., Brown S.M., Chiang C.F., Klena J.D. Rift Valley fever and Crimean-Congo hemorrhagic fever viruses in ruminants, Jordan. *Emerg. Infect. Dis.* 2021; 27(2): 653–55. https://doi.org/10.3201/eid2702.203713
3. Temur A.I., Kuhn J.H., Pecor D.B., Apanaskevich D.A., Keshtkar-Jahromi M. Epidemiology of Crimean-Congo hemorrhagic fever (CCHF) in Africa-underestimated for decades. *Am. J. Trop. Med. Hyg*. 2021; 104(6): 1978–90. https://doi.org/10.4269/ajtmh.20-1413
4. Dieng I., Barry M.A., Diagne M.M., Diop B., Ndiaye M., Faye M., et al. Detection of Crimean Congo haemorrhagic fever virus in North-eastern Senegal, Bokidiawé 2019. *Emerg. Microbes Infect.* 2020; 9(1): 2485–87. https://doi.org/10.1080/22221751.2020.1847605
5. Schulz A., Barry Y., Stoek F., Pickin M.J., Ba A., Chitimia-Dobler L., et al. Detection of Crimean-Congo hemorrhagic fever virus in blood-fed Hyalomma ticks collected from Mauritanian livestock. *Parasit. Vectors*. 2021; 14(1): 342. https://doi.org/10.1186/s13071-021-04819-x
6. Balinandi S., von Brömssen C., Tumusiime A., Kyondo J., Kwon H., Monteil V.M., et al. Serological and molecular study of Crimean-Congo hemorrhagic fever virus in cattle from selected districts in Uganda. *J. Virol. Methods*. 2021; 290: 114075. https://doi.org/10.1016/j.jviromet.2021.114075
7. Negredo A., Sánchez-Ledesma M., Llorente F., Pérez-Olmeda M., Belhassen-García M., González-Calle D., et al. Retrospective identification of early autochthonous case of Crimean-Congo hemorrhagic fever, Spain, 2013. *Emerg. Infect. Dis.* 2021; 27(6): 1754–6. https://doi.org/10.3201/eid2706.204643
8. Куличенко А.Н., Малецкая О.В., Прислегина Д.А., Василенко Н.Ф., Семенко О.В., Газиева А.Ю. и др. *Эпидемиологическая обстановка по природно-очаговым инфекционным болезням в Южном и Северо-Кавказском федеральных округах в 2019 г. Аналитический обзор.* Ставрополь; 2020. Available at: https://www.snipchi.ru/updoc/2020/An-Obzor%20po%20prirodno-oschagovim%202020.pdf
9. Малецкая О.В., Таран Т.В., Прислегина Д.А., Дубянский В.М., Волынкина А.С., Семенко О.В. и др. Природно-очаговые вирусные лихорадки на юге европейской части России. Крымская геморрагическая лихорадка. *Проблемы особо опасных инфекций*. 2020; (4): 75–80. https://doi.org/10.21055/0370-1069-2020-4-75-80
10. Онищенко Г.Г., Ефременко В.И., Бейер А.П. *Крымская геморрагическая лихорадка*. М.; 2005.
11. Платонов А.Е., Авксентьев Н.А., Авксентьева М.В., Деркач Е.В., Платонова О.В., Титков А.В. и др. Социально-экономическое бремя пяти природно-очаговых инфекций в Российской Федерации. *Фармакоэкономика. Современная фармакоэкономика и фармакоэпидемиология*. 2015; 8(1): 47–56. https://doi.org/10.17749/2070-4909.2015.8.1.047-056
12. Смирнова С.Е. *Крымская-Конго геморрагическая лихорадка (этиология, эпидемиология, лабораторная диагностика)*. М.: АТиСО; 2007.
13. Estrada-Peña A., Zatansever Z., Gargili A., Aktas M., Uzun R., Ergonul O., et al. Modeling the spatial distribution of Crimean-Congo hemorrhagic fever outbreaks in Turkey. *Vector Borne Zoonotic Dis*. 2007; 7(4): 667–78. https://doi.org/10.1089/vbz.2007.0134
14. Харченко Т.В. *Современные эпидемиологические особенности Крымской геморрагической лихорадки в Российской Федерации*: Автореф. дисс. … канд. мед. наук. Ставрополь; 2011
15. Ansari H., Shahbaz B., Izadi S., Zeinali M., Tabatabaee S.M., Mahmoodi M., et al. Crimean-Congo hemorrhagic fever and its relationship with climate factors in southeast Iran: a 13-year experience. *J. Infect. Dev. Ctries*. 2014; 8(6): 749–57. https://doi.org/10.3855/jidc.4020
16. Mostafavi E., Chinikar S., Bokaei S., Haghdoost A. Temporal modeling of Crimean-Congo hemorrhagic fever in eastern Iran. *Int. J. Infect. Dis*. 2013; 17(7): 524–8. https://doi.org/10.1016/j.ijid.2013.01.010
17. Vescio F.M., Busani L., Mughini-Gras L., Khoury C., Avellis L., Taseva E., et al. Environmental correlates of Crimean-Congo haemorrhagic fever incidence in Bulgaria. *BMC Public Health*. 2012; 12: 1116. https://doi.org/10.1186/1471-2458-12-1116
18. Дубянский В.М., Прислегина Д.А., Куличенко А.Н. Риск-ориентированная модель прогнозирования эпидемиологической ситуации по Крымской геморрагической лихорадке (на примере Ставропольского края). *Анализ риска здоровью*. 2018; (1): 13–21. https://doi.org/10.21668/health.risk/2018.1.02
19. Прислегина Д.А., Дубянский В.М., Малецкая О.В., Куличенко А.Н., Василенко Н.Ф., Манин Е.А. и др. Крымская геморрагическая лихорадка в Ставропольском крае: современные клинико-эпидемиологические аспекты и новый подход к прогнозированию заболеваемости. *Инфекционные болезни: новости, мнения, обучение*. 2018; 7(3): 49–56. https://doi.org/10.24411/2305-3496-2018-13007
20. Прислегина Д.А., Дубянский В.М., Куличенко А.Н. Особо опасные арбовирусные лихорадки на юге России: совершенствование мониторинга с применением современных информационных технологий. *Медицина труда и экология человека*. 2019; (4): 50–8. https://doi.org/10.24411/2411-3794-2019-10047
21. Тохов Ю.М., Дегтярев Д.Ю., Дубянский В.М. *Иксодовые клещи (морфология, медицинское значение, регуляция численности)*. Ставрополь; 2015.
22. Трухачев В.И., Тохов Ю.М., Луцук С.Н., Дылев А.А., Толоконников В.П., Дьяченко Ю.В. Распространение и экологическая характеристика иксодовых клещей рода Hyalomma в экосистемах Ставропольского края. *Юг России: экология, развитие*. 2016; 11(2): 59–69. https://doi.org/10.18470/1992-1098-2016-2-59-69
23. Тохов Ю.М., Чумакова И.В., Луцук С.Н., Дьяченко Ю.В., Котенев Е.С., Зайцев А.А. Иксодовые клещи – резервуар возбудителей инфекционных и инвазионных болезней на территории Ставропольского края. *Вестник ветеринарии*. 2013; (2): 19–21.
24. Прислегина Д.А., Дубянский В.М., Платонов А.Е., Малецкая О.В Влияние природно-климатических факторов на эпидемиологическую ситуацию по природно-очаговым инфекциям. *Инфекция и иммунитет*. 2021; 11(5): 820–36. https://doi.org/10.15789/2220-7619-EOT-1631
25. Куличенко А.Н., Прислегина Д.А. Крымская геморрагическая лихорадка: климатические предпосылки изменений активности природного очага на юге Российской Федера-

ции. *Инфекция и иммунитет*. 2019; 9(1): 162–72. https://doi.org/10.15789/2220-7619-2019-1-162-172

26. Гублер Е.В. *Вычислительные методы анализа и распознавания патологических процессов*. Ленинград: Медицина; 1978.
27. Гублер Е.В., Генкин А.А. *Применение непараметрических критериев статистики в медико-биологических исследованиях*. Ленинград: Медицина; 1973.
28. Дубянский М.А., Кенжебаев А., Степанов В.М., Асенов Г.А., Дубянская Л.Д. *Прогнозирование эпизоотической активности чумы в Приаралье и Кызылкумах.* Нукус: Каракалпакстан; 1992.
29. Yigit G.K. An example of tick-Crimean Congo hemorrhagic fever (CCHF) in Eflani district, Karabuk, Turkey. *Sci. Res. Essays.* 2011; 6(11): 2395–402. https://doi.org/10.5897/SRE11.574
30. Черкасский Б.Л. *Риск в эпидемиологии*. М.: Практическая медицина; 2007.

Information about the authors

Vladimir M. Dubyanskiy — D. Sci. (Biol.), Head, Department of epizootological monitorning and prognostication, Stavropol Plague Control Research Institute, Stavropol, Russia; member of the temporary research team for the implementation of the grant of the Russian Science Foundation, Central Research Institute of Epidemiology, Moscow, Russia, https://orcid.org/0000-0003-3817-2513

Daria A. Prislegina[✉] — Cand. Sci. (Med.), senior researcher, Laboratory of epidemiology, Stavropol Plague Control Research Institute, Stavropol, Russia; member of the temporary research team for the implementation of the grant of the Russian Science Foundation, Central Research Institute of Epidemiology, Moscow, Russia, daria775@rambler.ru, https://orcid.org/0000-0002-9522-129X

Alexander E. Platonov — D. Sci (Biol.), Prof., chief researcher, Laboratory of zoonoses, Central Research Institute of Epidemiology, Moscow, Russia, https://orcid.org/0000-0001-7450-0081

Author contribution. All authors made a substantial contribution to the conception of the work, acquisition, analysis, interpretation of data for the work, drafting and revising the work, final approval of the version to be published.

The article was submitted 28.0.2022;
accepted for publication 20.06.2022;
published 30.06.2022

Информация об авторах

Дубянский Владимир Маркович — д.б.н., зав. отделом эпизоотологического мониторинга и прогнозирования Ставропольского противочумного института, Ставрополь, Россия; член временного научного коллектива по выполнению гранта РНФ ЦНИИ Эпидемиологии, Москва, Россия, https://orcid.org/0000-0003-3817-2513

Прислегина Дарья Александровна[✉] — к.м.н., с.н.с. лаб. эпидемиологии Ставропольского противочумного института, Ставрополь, Россия; член временного научного коллектива по выполнению гранта РНФ ЦНИИ Эпидемиологии, Москва, Россия, daria775@rambler.ru, https://orcid.org/0000-0002-9522-129X

Платонов Александр Евгеньевич — д.б.н., проф., г.н.с. лаб. эпидемиологии природно-очаговых инфекций ЦНИИ Эпидемиологии, Москва, Россия, https://orcid.org/0000-0001-7450-0081

Участие авторов. Все авторы внесли существенный вклад в проведение поисково-аналитической работы и подготовку статьи, прочли и одобрили финальную версию до публикации.

Статья поступила в редакцию 28.03.2022;
принята к публикации 20.06.2022;
опубликована 30.06.2022