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GEOPHYSICS

Possibility of Realization of Contact-Free Electromagnetic Geothermometer

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Estimates of temperature in the Earth's interior are usually obtained on the basis of thermograms from boreholes or data on the thermal flux. However, both approaches have restrictions. For example, in the first case, it is necessary to perform spatial interpolation of thermograms commonly measured in some nonuniformly distributed boreholes, which frequently leads to significant errors. In the second case, the construction of a temperature model is based on the assumption about stationarity of thermal fluxes at lateral boundaries of the model zone and a priori knowledge of the thermal flux (temperature) at its upper and lower boundaries. Since its values (especially at the lower boundary) are usually specified very approximately, the construction of models of temperature distribution on this basis can also lead to significant errors.

In this paper, we suggest a principally new approach to the determination of temperature in the Earth's interior (the so-called contact-free electromagnetic geothermometer). This method allows us to increase significantly the accuracy of the estimates as compared to the known methods.

Researchers frequently use indirect estimates based on geological [1] or geochemical [2] data to refine temperature distribution in the Earth's interior. The use of information about the electrical conductivity of rocks seems to be the most natural approach because this property is a function of temperature [3]. At the same time, the complex nonuniform structure of the Earth's interior and the lack of information about its properties allow this approach to be used only for very rough theoretical models of temperature based on the curves of the global electromagnetic sounding and assumptions about the mechanisms of conductivity [4].

It is possible to suggest a principally new approach to estimation of the spatial distribution of conductivity. It is based on the measurements of magnetotelluric data (MT) at the Earth's surface, construction of vertical profiles of specific electrical conductivity on this basis, and further forecast of temperature based on the artificial neural network calibrated on the basis of the correlation between the calculated values of specific electrical conductivity and known values of temperature at specific points (boreholes). The objective of the present paper is to test this approach using real data on the seismoactive zone of the Northern Tien Shan and to develop methodological recommendations for its application.

METHODS

The Bishkek geodynamic site (BGS), where investigations were carried out, is located in the Chuya Depression in northern Tien Shan (Fig. 1). We used the MT data obtained by the measurements in the frequency range from $5 \cdot 10^{-4}$ to 300 Hz in the vicinity of 13 boreholes with known temperature profiles in the BGS area [5, 6]. Inversion of the MT data at each observation point was carried out using the Bostic transform of the determinant of apparent electrical conductivity. As a result, vertical profiles of apparent electrical conductivity were plotted.

We applied the neural network approach to investigate the possibilities of estimating temperature in the Earth's crust. This method was previously applied for predicting macroparameters of the medium based on MT data [7] and estimating the temperature distribution in the Earth's crust on the basis of geotherm data [8, 9]. The investigations were carried out in three stages: (i) estimation of the influence of the amount of data used for neural network training on the results of the forecast; (ii) study of the influence of the strategy of training; and (iii) estimation of the influence of the local

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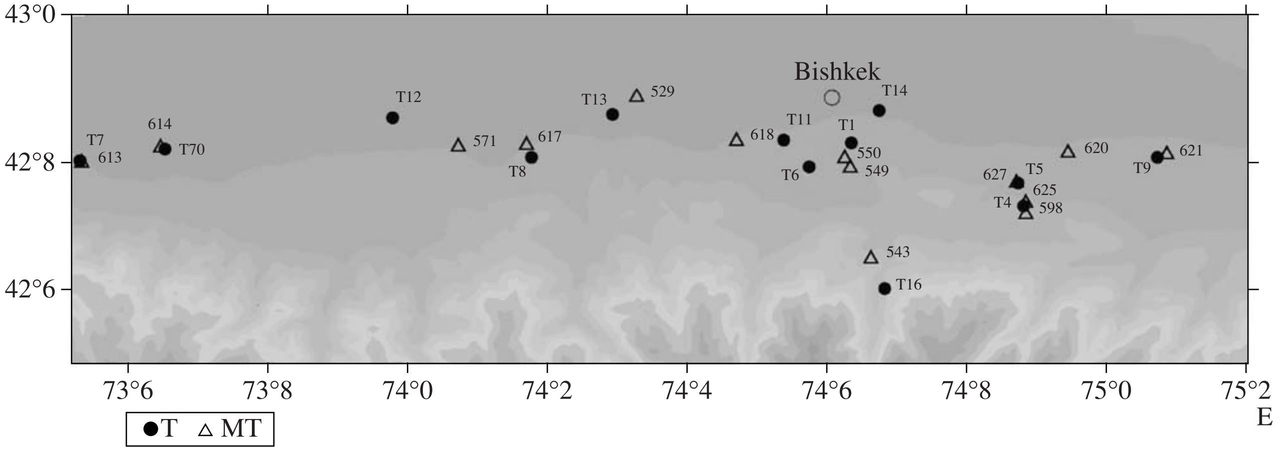

Fig. 1. Location of MT points and boreholes with available temperature data.

geological peculiarities of the environment on the results.

INFLUENCE OF THE DATA CONTENT

The neural network was sequentially trained on 2, 4, 6, 8, 10, and 12 pairs of temperature and electrical conductivity (henceforth, T–MT) profiles randomly selected from the total dataset to estimate the influence of the training data content. These data were tested on the data from MT points most closely located to the boreholes, for which thermograms were available. Simultaneously, training of neural networks was carried out using only the thermograms.

Figure 2 demonstrates the variation in the relative root-mean-square error of temperature forecast in the borehole (ε) for the case of using only the temperature data (triangles) and electromagnetic data together with thermograms (dots). Comparison of the graphs shows the following regularity: when both temperature and electromagnetic data (instead of only thermograms) are used for temperature forecast, the relative error decreases faster with the increase in the training data content. In addition, the error of forecast becomes practically minimal already when we use a sample of only six pairs of T–MT data, whereas the estimate based only on the thermograms reaches this level when data of 8–10 boreholes are used. This fact suggests the following important conclusion: when the number of borehole temperature measurements is limited, the estimate of its forecast can be decreased strongly (almost by a factor of 2) by using not only temperature but also MT data measured at the surface.

INFLUENCE OF THE STRATEGY ON NEURAL NETWORK TRAINING

Two strategies were used to study the influence of local peculiarities of the Earth's crust between the borehole and MT point on the error of temperature forecast in the borehole based on electromagnetic data. The first neural network was trained on five sets of randomly selected 12 pairs of T–MT data with further temperature forecast in three boreholes based on the data of electrical conductivity from the nearest MT points. The data from these boreholes were not used for training. In this case, two versions were considered for temperature forecast in boreholes T5 and T6: (i) using electrical conductivity profiles from points 627 and 618; (ii) using electrical conductivity profiles from points 620 and 549. On the other hand, electromagnetic data from MT points 618 and 550 were analyzed together with thermograms measured not only in boreholes T6 and T1, but also in boreholes T11 and T14, respectively. Within the second strategy, the neural network was trained blindfolded using all available MT data. Later, forecast of electrical conductivity was performed at the depths of temperature measurements in the boreholes. Finally,

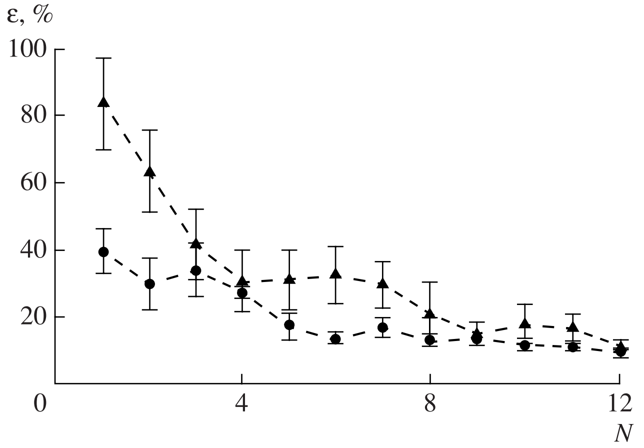

Fig. 2. Mean relative error of temperature forecast (ε) based on the electrical conductivity data (dots) and thermograms (triangles) as function of the number of pairs of temperature–electrical conductivity profiles (or only thermograms) used in neural network training.

Dependence of the errors of temperature forecast in the borehole on the strategy of neural network training and geological peculiarities of the environment

Borehole and MT point no.	Relative errors of temperature forecast (%)			Local peculiarities of the Earth's crust between the borehole and MT point
	1	2	3	
T1-MT550	24.3	31.3	24.9	Fracture of upthrust type
T4-MT625	12.5	26.1	5.9	No
T5-MT620	7.7	12.4	16.7	Fracture of upthrust type
T5-MT627	0.7	23.8	16.7	No
T6-MT549	8.8	3.9	14.9	″
T6-MT618	16.0	10.5	14.9	″
T7-MT613	0.7	8.9	17.2	″
T8-MT617	1.0	24.4	13.2	″
T9-MT621	8.9	48.1	14.8	″
T10-MT614	1.4	16.1	5.9	″
T11-MT618	29.1	31.7	16.5	″
T12-MT571	9.0	15.6	17.9	″
T13-MT529	9.6	32.1	135.2	Cold water flows
T14-MT550	10.2	26.5	27.0	No
T16-MT543	26.9	136.8	101.2	Deep fracture
Mean error	11.9 ± 2.3	29.9 ± 8.1	29.5 ± 9.2	
Mean error without the consideration of anomalous zones	8.9 ± 2.5	21.0 ± 3.6	15.0 ± 1.7	

the neural network trained for the correlation between electrical conductivity and temperature for 14 pairs of T–MT data was used for temperature forecast in the borehole, the data from which was not used for training. In order to compare the results of temperature forecast based on electromagnetic and geothermal data with the results obtained using the neural network trained only on the temperature data, we trained the neural networks using the same thermograms, which were used previously (and using only these thermograms), and performed the forecast in the same boreholes.

The forecast results are presented in the table and Fig. 3. The errors of temperature forecast using the first method (based on the electrical conductivity data from the nearest MT point) are presented in the table (column 1). The errors of forecast using the second method (blindfolded application of all available MT data) are presented in column 2. Finally, the errors of forecasts based only on the thermograms are presented in column 3.

The mean relative error of the temperature forecast based on the first method is 11.89%, which appeared unexpectedly high for this region because it is characterized by a complex geological structure and large scatter of temperature distribution. The mean relative error based on the second method is 22.9%. In the case of forecast based only on the samplings of thermograms, it was 31.35%. Despite the fact that errors in the forecast based on the second and third methods appeared smaller in three cases than that based on the first method, the results of forecast based on the first method appeared better in 80% of cases. In other words, the best results of the forecast are obtained on the basis of deliberate choice of the location of MT points closest to the points of temperature forecast. At the same time, the distance between the T–MT pair used for the forecast and MT points and other boreholes, data from which were used to train the neural network, has no determining importance. This is demonstrated by the comparison of forecast results in the case of extrapolation, which we observe in boreholes T7, T9, and T16 located in the periphery of the study region. It is seen from the table that this error exceeds the mean value for borehole T16 more than two times and is much smaller than the mean value for boreholes T7 and T9. Hence, the geographical factor is secondary for the temperature forecast. This fact confirms the conclusion in [8].

INFLUENCE OF LOCAL GEOLOGICAL INHOMOGENEITIES

It is seen from the table that estimation of the forecast is influenced significantly by the existence or absence of local geological inhomogeneities between the point of temperature forecast and the MT point, the data from which are used for the forecast. For example, when the borehole and MT point were located on different sides of the tectonic distortion of the upthrust type (T1–MT550, T5–MT620, and T16–MT543), the error in the temperature forecast in the borehole increased several times. The same increase in the forecast error was observed in the presence of a local region with a thick (~200 m) layer of the Earth's crust into which cold water flowed to create an anomalous negative temperature gradient with depth (T13–MT529). In this connection, it is interesting to compare the results of the forecast for pairs T1–MT550 and T14–MT550. In the first pair characterized by the presence of a fracture between them, the distance between the borehole and MT point is 2.17 km. In the second pair, the distance is 4.97 km, but the error in the temperature forecast is inversely proportional to the distance. The same effect is observed for the pair T5–MT620 (existence of a fracture) and T5–MT627. In both cases, the errors in the forecast based on the second method (blindfold data are used) are not related to the distance in the pair T–MT or to the presence (or absence) of geological peculiarities. The forecast based on the neural network trained only on temperature data performed for the boreholes located in special zones yields greater errors. This is clearly seen in the graphs for pairs T13–MT529 and T16–MT543 (Fig. 3).

Thus, we can make the following conclusion: the forecast error depends on the presence of geological peculiarities of the environment (e.g., upthrust folding when disjunctive distortions are traced to the Earth's surface) between the point of temperature forecast and MT point, data from which are used for the forecast (although much smaller than in the case of application of the two other approaches). A priori knowledge of the geological peculiarities in the study region can assist in the correct location of the point of MT measurements relative to the point for which the forecast is performed. Thus, the error can be decreased strongly. The exclusion of forecast estimates for T–MT pairs, where the Earth's crust is characterized by the existence of certain geological inhomogeneities, decreases the mean relative error of the forecast from 11.89 to 8.9%. Thus, 6–8 thermograms used for the calibration of electromagnetic data are sufficient for providing a 12% accuracy of the temperature forecast. If geological information about the study region is available a priori, a 9% accuracy is provided.

Thus, we justified the principal possibility of realizing a contact-free electromagnetic geothermometer and developed optimal methods of its application with account for the a priori geological information and available thermograms, which allows us to decrease the errors of remote estimates of temperature to a minimal level.

The practical application of contact-free electromagnetic geothermometer can provide the following facilities: (1) more precise temperature forecast in the cases when the available number of thermograms is insufficient; (2) more exact temperature forecast in the extrapolation regime; (3) monitoring of temperature in

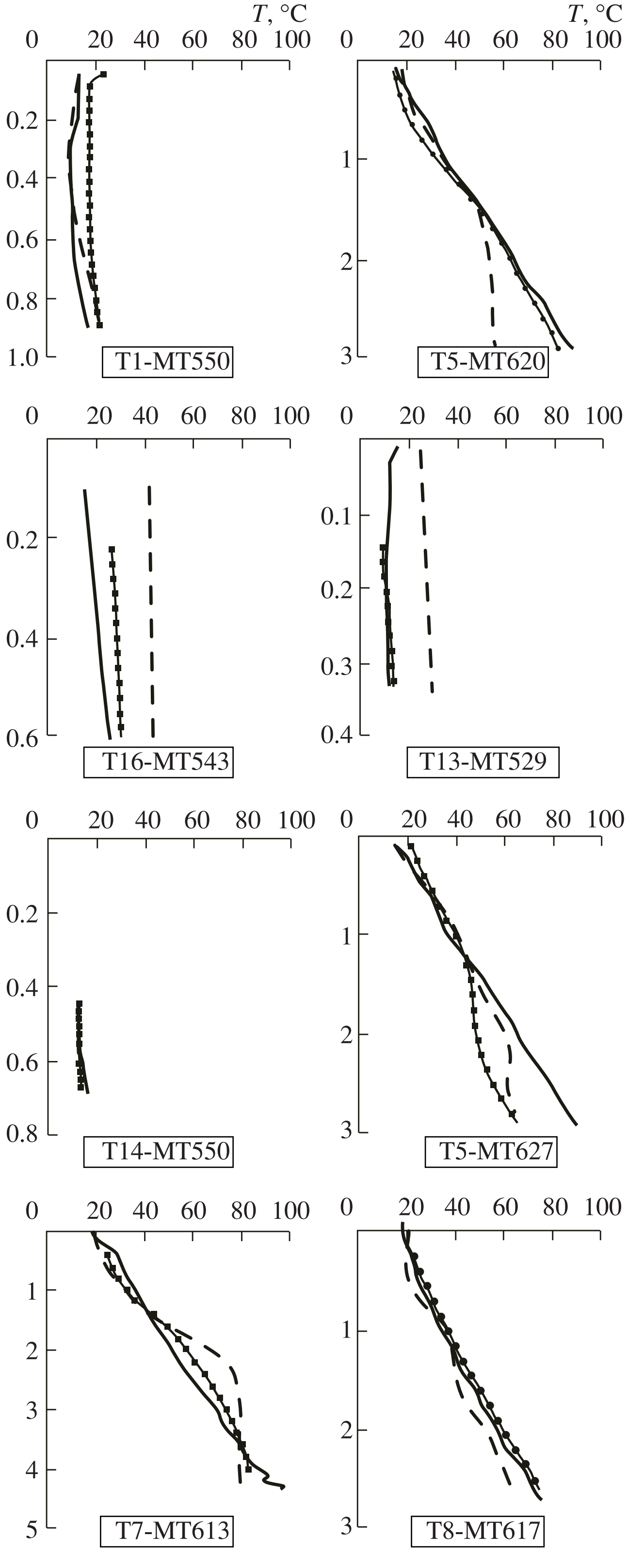

Fig. 3. Measured and model temperature distributions in boreholes. Solid line shows measured temperature; dashed line, temperature model based only on temperature data; and dotted line, temperature model based on temperature and MT data.

boreholes based on the observations of the MT field at the surface; and (4) contact-free remote temperature estimates in the boreholes in areas characterized by extreme conditions for conventional geothermometers.

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