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スタッキング法を使用した中国全域の熱流量分布予測

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Modeling of Terrestrial Heat Flow Distribution throughout China Using Stacking Method

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1． Introduction

Geothermal energy is recognized as a valuable renewable resource in various fields, including electricity generation, agriculture, and aquaculture. Although the utilization of geothermal energy as a heat source in China accounts for the largest proportion worldwide, the usage of geothermal electricity is still under development. As committed in the 13th and 14th Five-Year Plans, China is moving forward in utilizing geothermal energy as an alternative energy source, especially in the middle-to-deep geothermal and hot dry rock categories.

Although it is essential to clarify the subsurface temperature distribution throughout China to specify preferable sites for geothermal electricity generation, the data points containing such information are limited. Thus, a stacking method is utilized to predict the distribution of heat flow, which is strongly related to temperature, and its effectiveness is discussed.

2． Methods

2.1 Stacking Method

The stacking method is a machine learning technique that integrates the outputs from variable machine learning methods, termed base models. The outputs of

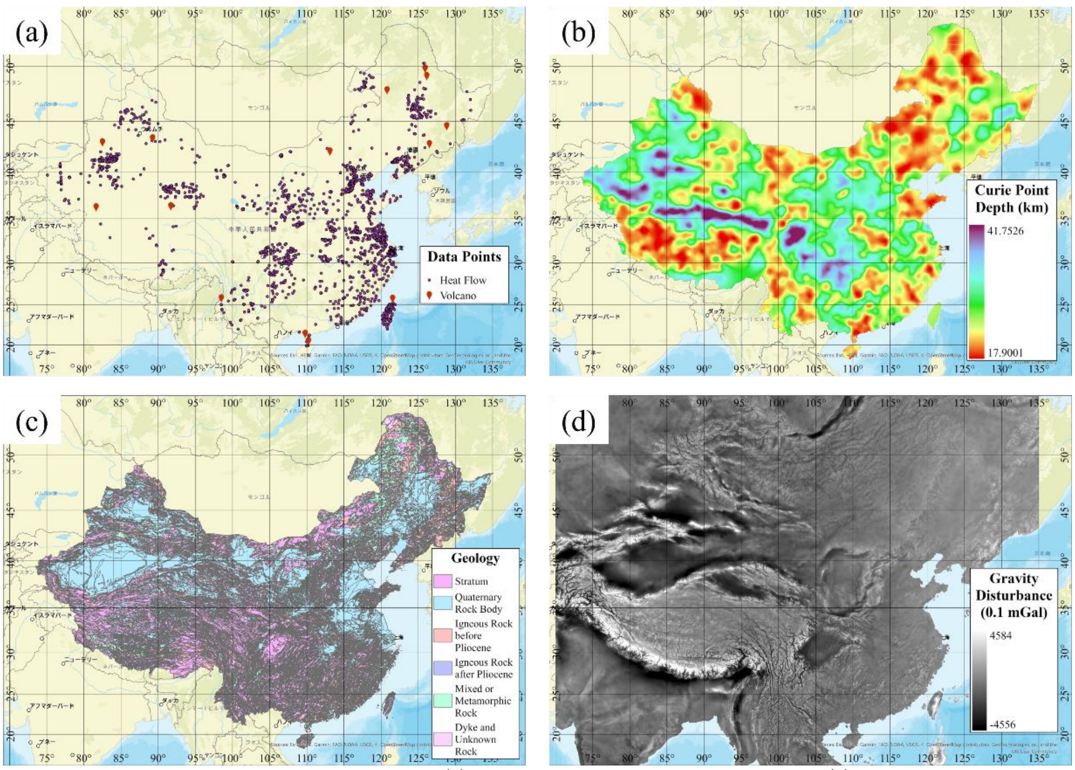

Fig. 1 Datasets used for machine learning: (a) heat flow and volcano data points, (b) Curie point depth, (c) rock type, and (d) gravity disturbance.

base models are used as the input of the metamodel to predict the target value. This method is known to be beneficial for improving the versatility of machine learning models and preventing overfitting. In this study, XGBoost, LightGBM, and Random Forest are chosen as the base models of the stacking model, and Linear Regressor is utilized as a metamodel following Ieki et al. (2025).

As the input data, deduplicated dataset from the China Heat Flow Database and International Heat Flow Commission (2024) in the form of heat flow value were linked to the related data point coordinates. For the estimation, the target area was divided into 1km × 1km cells and the center of each cell was targeted for the calculation.

2.2 Feature Engineering

Along with the input data, feature data composed of Curie point depth (Xiong et al., 2016), rock type (Pang et al., 2017), surface temperature, volcano location, gravity acceleration, and gravity disturbance were added at the input data and estimation points. For volcano location data, the Euclidean distance from the closest volcano was used, and for the other data in raster form, data extracted at the data points was used directly. Part of the datasets are shown in Fig. 1.

2.3 Accuracy Evaluation

For accuracy evaluation, K-fold cross-validation was utilized. In the process, input data are split into training and test data, and the accuracy is evaluated by the difference between the observed values in the test data and output values from the learned model using the training data. For the loss function, the root mean squared error (RMSE) by Equation (1) was used.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (1)$$

where y_i is an observed value, $\hat{y}_i$ is a predicted value, and n is the number of observations. The benchmark for the stacking method is shown in Fig. 2, and the RMSE for each base model included in the stacking model is also plotted for comparison. It can be concluded from the result that the combination of multiple machine-learning methods can reduce the estimation error.

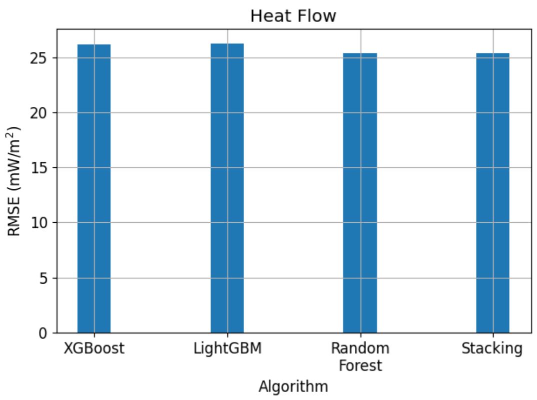

Fig. 2 RMSE benchmark of Stacking method with comparison of three base models.

3. Results

The predicted heat flow map by the stacking method is shown in Fig. 3. The result reveals high heat flow values in Tibet and the Eastern Coast of Taiwan, where the orogenic belts are distributed nearby, whereas low values in Sinkiang and Northeastern China. These regional trends may be verified partly from the geothermal utilization in China including the Yangbajain geothermal site in which the only geothermal electric powerplant in China is under operation. However, the stacking result show unrealistic large-scale circle patterns and straight-banded distributions that are closely related to the original dataset feature, particularly the Curie point depth. This implies that the stacking method is insufficient to capture promising geothermal resource sites with high spatial resolution.

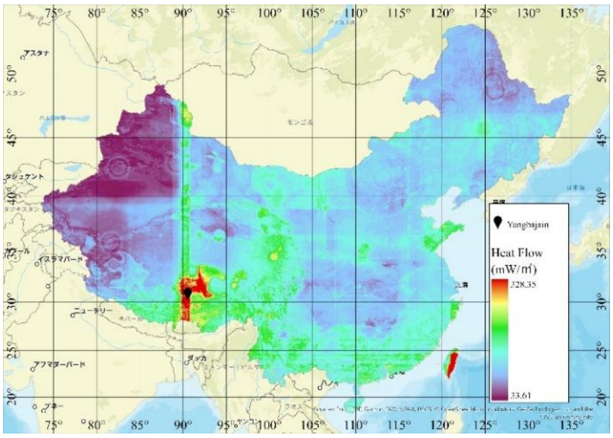

Fig. 3 Produced heat flow map by the stacking method.

4. Discussion and Conclusion

In this study, a stacking method considering several geological features was used to produce a heat flow map from point-measurement data in continental China. The result showed a general agreement with the high heat zones in China but was not sufficient to accurately specify promising geothermal resource sites.

As our next step, a prediction of heat flow values through a deep neural network (DNN) is in progress. Furthermore, the result by DNN will be used to simulate the temperature-at-depth distribution by a physics-informed neural network that sets the surface temperature and Curie point depth as boundary conditions, which is expected to clarify a 3D subsurface temperature distribution to great depths throughout China and estimate geothermal power generation.

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