AI-Based Geophysical Parameter Inversion Paradigm Theory and Determination Criteria Postprint

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Abstract

Artificial Intelligence (AI) technology has triggered a surge of research in both academic and engineering applications, and has demonstrated strong application potential in the retrieval of geophysical parameters and agricultural meteorological remote sensing parameters. Currently, most AI technology applications in geoscience and agronomy remain as "black boxes," lacking physical meaning, interpretability, and universality. This study proposes a paradigm theory for geophysical parameter retrieval based on AI coupled with physical and statistical methods; specifically, it first conducts physical logical reasoning based on physical energy balance equations to theoretically construct retrieval equation sets, then builds generalized statistical methods based on physical derivation. Representative solutions of the physical method are obtained through physical model simulations, and representative solutions of the statistical method are obtained using multi-source data to serve as training and testing databases for deep learning, and finally employs deep learning for optimized solving. The criteria for establishing a paradigm with universality and physical interpretability include: (1) a causal relationship must exist between input and output variables (parameters); (2) a closed equation set can theoretically be constructed between input and output variables (parameters) (the number of unknowns is less than or equal to the number of equations), such that output parameters can be uniquely determined from input parameters. If a strong causal relationship exists between input parameters (variables) and output parameters (variables), deep learning may be directly employed for retrieval. If a weak correlation exists between input parameters and output parameters, the addition of prior knowledge is required to improve the retrieval accuracy of output parameters. Furthermore, this study validates the theory through a case study of the joint

retrieval of key parameters in agricultural remote sensing—land surface temperature, emissivity, near-surface air temperature, and atmospheric water vapor content. Analysis results demonstrate that the theory is feasible and can assist in optimizing the design of satellite sensor band combinations. The proposal of this theory and its determination conditions marks a milestone in the history of geophysical parameter retrieval.

Full Text

The Paradigm Theory and Judgment Conditions of Geophysical Parameter Retrieval Based on Artificial Intelligence

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Abstract: Deep learning is one of the most important technologies in the field of artificial intelligence, which has sparked a research boom in academic and engineering applications. It also shows strong application potential in remote sensing retrieval of geophysical parameters. The cross-disciplinary research is just beginning, and most deep learning applications in geosciences are still "black boxes", with most applications lacking physical significance, interpretability, and universality. A paradigm theory for geophysical parameter retrieval based on artificial intelligence coupled physics and statistical methods was proposed in this research. Firstly, physical logic deduction was performed based on the physical energy balance equation, and the inversion equation system was constructed theoretically. Then, a fuzzy statistical method was constructed based on physical deduction. Representative solutions of physical methods were obtained through physical model simulation, and other representative solutions as the training and testing database for deep learning were obtained using multi-source data. Finally, the solution using deep learning was optimized. The conditions for determining the formation of a universal and physically interpretable paradigm are: (1) There must be a causal relationship between input and output variables (parameters); (2) In theory, a closed system of equations (with unknowns less than or equal to the number of equations) can be constructed between input and output variables (parameters), which means that the output parameters can be uniquely determined by the input parameters. If there is a strong causal relationship between input parameters (variables) and output parameters (variables), deep learning can be directly used for inversion. If there is a weak correlation between the input and output parameters, prior knowledge needs to be added to improve the inversion accuracy of the output parameters. Thermal infrared remote sensing data were used to retrieve land surface temperature, emissivity, near surface air temperature and atmospheric water vapor content as a case to prove the theory. The analysis results show that the proposed theory and conditions are feasible, and the accuracy and applicability are better than traditional methods. The theory and judgment conditions of geophysical parameter retrieval paradigms are also applicable for target recognition such as remote sensing classification, but it needs to be interpreted from a different perspective. For example, the feature information extracted by different convolutional kernels must be able to uniquely determine the target. Under satisfying with the conditions of paradigm theory, the inversion of geophysical parameters based on artificial intelligence is the best choice. The proposal of this theory is of milestone significance in the history of geophysical parameter retrieval.

Keywords: artificial intelligence; deep learning; retrieval paradigm; physical logic derivation; explainable; ChatGPT

2 Theory and Judgment Conditions for Geophysical Parameter Retrieval Paradigm

Deep learning is currently one of the most important technologies in the field of artificial intelligence, sparking a research boom in both academic and engineering applications. It has achieved remarkable results in natural language generation models, computer vision, speech recognition, and other domains. Given the application potential and importance of deep learning in geoscience and agricultural science, it is essential to accelerate the deep integration of artificial intelligence with remote sensing technology to provide key technical support for weather forecasting, crop monitoring, and agricultural disaster prediction, serving global disaster monitoring and national food security.

According to the 2022 National Statistical Yearbook, the average annual area affected by agricultural meteorological disasters in China reaches 12.0716 million hectares, with direct economic losses from meteorological disasters alone reaching 238.6 billion RMB in 2022. Therefore, rapid and accurate acquisition of key agricultural meteorological parameters is crucial for scientifically guiding agricultural meteorological disaster prevention and mitigation, crop yield estimation, and ensuring national food security. The United States, Japan, and the European Union have successively developed key parameter retrieval systems for meteorological satellites. Although China began researching meteorological satellite parameter retrieval technology in the 1990s and has made significant progress, it still encounters bottlenecks such as more unknowns than equations, variations in relative incidence angles, and mixed pixel problems. In recent years, with the rapid development of computer hardware technology and artificial intelligence, AI has demonstrated powerful advantages. Therefore, studying how to integrate artificial intelligence technology with traditional physical and statistical methods for geophysical and agricultural meteorological remote sensing parameter retrieval, and developing physically meaningful and interpretable AI algorithms, is of great significance for improving remote sensing parameter retrieval accuracy and perfecting the paradigm theory of geophysical parameter retrieval, while providing key monitoring parameters for smart agriculture and smart Earth.

The establishment of disciplinary knowledge generally follows three steps: first, observing phenomena from a physical perspective; second, describing physical phenomena using mathematical methods; and third, solving mathematical problems from an engineering perspective. The "Artificial Intelligence Geophysical Parameter Retrieval Paradigm Theory" can be stated as follows: If target information (problems) can be described mathematically in theory or physical logic (i.e., a unique solution curve can be formed in space), then artificial intelligence methods can solve the equation solutions through big data learning and optimization calculations, coupling physical and statistical methods. This makes the coupled method not only possess the respective advantages of physical and statistical methods but also fully utilizes the optimization computing power of deep learning, maximizing the retrieval accuracy of geophysical parameters. This ensures that the retrieval paradigm is not only universal but also physically meaningful and interpretable.

Specifically, the geophysical parameter retrieval paradigm theory proposed in this study enables deep learning to construct a complete closed system of equations between input parameters (variables) and output parameters (variables). If there is a strong causal relationship between input parameters (variables) and output parameters (variables), deep learning can be directly used for inversion to obtain high-precision results. If there is a weak correlation between input and output parameters, it is necessary to add strongly correlated prior knowledge to improve the inversion accuracy of output parameters. In fact, deep learning networks better conform to real-world situations from the perspective of information flow transmission than statistical and physical methods, and these methods are essentially consistent, all being means for people to understand the world and interpret and solve real-world problems at different cognitive levels.

The conditions for determining whether deep learning-based geophysical parameter retrieval forms a universal and physically interpretable paradigm are twofold: (1) There must be a causal relationship between the input and output variables (parameters) of deep learning, meaning that when other conditions remain unchanged, changing any input variable will cause the output variable to change. Let the deep learning input variables be x_i and output variables be y_j, then the causal relationship is expressed as formula (1): $y_j = f(x_i)$, where $i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, m$; and f represents some causal relationship function. (2) In theory, a closed system of equations can be constructed between input and output variables (parameters) (with the number of unknowns less than or equal to the number of equations), meaning that output parameters can be uniquely determined by input parameters. This can be expressed mathematically as formula (2): $F(x, y) = 0$, where $x = x_1, x_2, \ldots, x_n$; $y = y_1, y_2, \ldots, y_m$; and F represents a vector function composed of k equations.

To ensure that output parameters can be uniquely determined by input parameters, the condition $k \geq m$ must be satisfied. To demonstrate that the use of deep learning has physical significance, physical logic deduction must be performed during research. When there is a causal relationship between input and output variables and enough equations can theoretically be constructed, if there is a strong correlation between input and output variables, direct inversion calculation can be performed with high accuracy maintained. However, if the relationship is weak, strongly correlated variables must be used as prior knowledge to ensure high accuracy.

Deep learning applications cannot be separated from specific problems or objects. As shown in Figure 1 [Figure 1: see original paper], when solving an application problem, we must first perform physical logic deduction on the problem object, theoretically construct equations, and determine the causal relationship between input and output variables. Second, we determine the number of equations from the number of unknowns in the equations, i.e., determine how many input parameters can uniquely determine the output variables. Third, we analyze whether representative solutions of all physical methods can be obtained through physical model simulation; if not, we construct a generalized statistical method based on physical logic deduction and use multi-source data to supplement representative solutions. Then, we use big data technology and deep learning to optimize and solve the spatial curve function of physical and statistical method solutions. Finally, we perform verification and repeated iterations until the accuracy is achieved and optimization calculation stops. If the above two conditions cannot be proven when applying deep learning, the application is generally considered a "black box". If it can be proven that there is definitely no closed relationship between input and output parameters (number of unknowns greater than number of equations), then such applications are only suitable for local areas, cannot be universal, and are difficult to transplant, thus cannot be called a paradigm.

3.1 Physical Logic Deduction

Agricultural meteorological remote sensing key parameters are important components of geophysical parameters. This study uses agricultural meteorological remote sensing key parameters as an example to demonstrate the geophysical parameter retrieval paradigm theory. First, physical logic deduction is performed. During the process of surface thermal radiation reaching satellite sensors through the atmosphere, it is mainly affected by surface type and soil moisture (SM), land surface temperature (LST), near-surface air temperature (NSAT), and atmospheric water vapor content (WVC). Land surface temperature and soil moisture retrieval are based on the physical process of surface thermal radiation conduction and its transmission through the atmosphere to the sensor. The inversion equation can usually be described by formula (3), as shown in Figure 2 [Figure 2: see original paper].

In formula (3), $B_\lambda(T_\lambda)$ (known) is the radiation received by the satellite, $(1 - \tau_\lambda(\theta))B_\lambda(T_a)$ is the atmospheric radiation contribution, and $B_\lambda(T_s)\tau_\lambda(\theta)\varepsilon_\lambda$ is the surface radiation. Here, $\tau_\lambda(\theta)$ is atmospheric transmittance (unknown), T_s is land surface temperature (unknown), T_a is near-surface air temperature (unknown), and ε_λ is surface emissivity (unknown), meaning one equation has at least four unknowns. It should be noted that the observation angle is actually also an unknown, as the combination of different surface features in each pixel leads to large variations in relative incidence angles that are difficult to accurately determine. Due to the intrinsic constraints among geophysical parameters, the mutual constraints among satellite parameters can be used to reduce one unknown. As shown in Figure 2, different parameters influence and entangle with each other. Nitrogen, phosphorus, and potassium dissolve in soil moisture; changes in soil moisture affect dielectric constant, thereby changing emissivity; emissivity changes affect surface radiation efficiency; and land surface temperature changes determine soil moisture evaporation rate, thus affecting energy exchange with near-surface air and changing near-surface air temperature and atmospheric profile temperature. Theoretically, soil moisture changes also affect thermal infrared band emissivity, but traditional algorithms do not consider this, generally assuming thermal infrared band emissivity is relatively constant, though it actually changes with soil and vegetation water content. Therefore, in areas with more rainfall, the accuracy of traditional thermal infrared remote sensing methods for retrieving land surface temperature fluctuates relatively greatly, but artificial intelligence methods can overcome this difficulty. Changes in near-surface air temperature affect the atmospheric profile, thereby affecting the mean atmospheric operating temperature. When surface thermal radiation passes through the atmosphere, it is absorbed by atmospheric water vapor before reaching the satellite sensor. Therefore, from physical logic deduction, there are four unknowns in a single equation. Without prior knowledge, at least four thermal infrared window bands are theoretically needed to construct the retrieval equation system; if atmospheric water vapor is available as prior knowledge, only three thermal infrared bands may be needed. Most previous studies mainly focused on retrieving individual parameters. Since different parameters are entangled with each other, using artificial intelligence methods for joint retrieval and cross-iteration can improve retrieval accuracy. After physical logic deduction determines the theoretical construction of physical methods, practical application research reveals that methods based solely on physical models are not entirely reliable in accuracy, as physical models simplify the real world and many geoscience models are only suitable for partial conditions. Therefore, to satisfy as many situations as possible, generalized statistical methods must also be established based on physical logic deduction to ensure method completeness and reliability of accuracy.

MODIS satellite sensor is currently one of the best sensors in terms of thermal infrared band quantity and quality. This study will conduct simulation and demonstration analysis for MODIS thermal infrared bands. MODIS bands 27/28/29/31/32/33 (6.5–13.5 m) were selected, where bands 27, 28, and 29 are in the water vapor absorption region of thermal infrared bands, bands 31 and 32 are in the window region of thermal infrared bands, and band 33 is at the edge of the thermal infrared window region. Emissivity curves of surface features measured by JPL (http://speclib.jpl.nasa.gov) were used as input parameters for MODTRAN4, with land surface temperature ranging from 273–325 K and near-surface air temperature ranging from 273–320 K. Atmospheric water vapor content ranged from 0.1–4.0 g/cm^2, and the simulation observation angle was 0–45°. When the angle was too large, atmospheric transmittance on the slant path was too low, so this portion of simulation data was removed. The simulated data were randomly divided into two parts: 45,650 groups for training data and 16,550 groups for testing data. Based on the amount of information about different parameters obtained by the sensor, different parameter retrievals were divided into three groups to demonstrate the geophysical parameter theory and judgment conditions. The first group retrieved land surface temperature and emissivity, mainly analyzing and demonstrating the impact of the number of equations and causal relationships between input and output variables on retrieval accuracy. The second group retrieved near-surface air temperature, mainly analyzing and demonstrating the use of strongly correlated variables between input and output as prior knowledge to improve the accuracy of weakly correlated variable retrieval. The third group retrieved atmospheric water vapor content, mainly analyzing and demonstrating that when there is strong correlation between input and output variables, adding prior knowledge can improve retrieval stability but has little effect on accuracy improvement.

3.2 Land Surface Temperature and Emissivity Retrieval

As known from the physical logic deduction in Section 3.1, retrieving land surface temperature requires at least four thermal infrared bands to form a radiative transfer equation system, meaning that when fewer than four thermal infrared bands are input, retrieval accuracy will not be high. Table 1 shows the theoretical retrieval accuracy of land surface temperature for the band 29-31-32 combination under given conditions. Table 1 indicates that when the hidden layer is 9 layers with 700 nodes per layer, the highest average theoretical accuracy is 1.13 K, with a standard deviation of 1.17 K and a correlation coefficient of 0.988.

Table 2 shows the retrieval error information for the band 28-29-31-32 combination. It can be seen that the highest retrieval accuracy occurs when the hidden layer is 9 and each layer has 800 nodes. The highest average accuracy is 0.45 K, with a standard deviation of 0.53 K and a correlation coefficient of 0.998. Comparing Tables 1 and 2, when four thermal infrared bands are used, the average accuracy improves by 0.68 K. MODIS band 28 is a water vapor absorption band, and adding thermal infrared water vapor absorption bands can improve retrieval accuracy. When only two thermal infrared bands (bands 31 and 32) are used for retrieval, the error is close to 2 K, so traditional split-window algorithms must obtain atmospheric water vapor and surface emissivity as prior knowledge. To achieve retrieval accuracy within 1 K, at least four thermal infrared bands are needed, or two thermal infrared bands plus high-precision surface emissivity and water vapor as prior knowledge, thus proving that high-precision land surface temperature retrieval from thermal infrared remote sensing based on artificial intelligence theoretically requires satisfying the condition of closed equations.

Table 3 shows the land surface temperature retrieval error information for the MODIS band 27-28-29-31-32 combination. Table 3 indicates that when the number of hidden layers is 9 and each hidden layer has 900 nodes, the retrieval accuracy is highest. The highest average accuracy is 0.44 K, with a standard deviation of 0.52 and a correlation coefficient of 0.999. MODIS band 27 is also a water vapor band, and theoretically, adding water vapor absorption bands can improve water vapor accuracy and overall retrieval accuracy. The improvement is not obvious here, mainly because ground radiation in band 27 is very difficult to penetrate to the sensor, meaning transmittance is very low, and the brightness temperature on the satellite mainly contains high-altitude atmospheric water vapor information, thus contributing not significantly to land surface temperature retrieval accuracy but increasing retrieval stability.

Table 4 shows the retrieval error information when MODIS bands 27-28-29-31-32-33 are used as input parameters. The highest accuracy occurs when the hidden layer is 8 and each hidden layer has 900 nodes, with the highest average accuracy of 0.44 K, standard deviation of 0.53 K, and correlation coefficient of 0.998. Comparing Tables 3 and 4, adding band 33 does not improve retrieval accuracy. The main reason is that thermal infrared band 33 is greatly affected by CO_2 and is not very suitable for retrieving land surface temperature. Therefore, adding thermal infrared bands does not necessarily increase retrieval accuracy and may sometimes reduce it. The analysis in Tables 3 and 4 shows that when the added band has a strong correlation with output parameters, accuracy can be improved; Table 4 demonstrates that when the added band has a weak relationship with output parameters or adds noise, retrieval accuracy will be reduced.

Emissivity can also be retrieved simultaneously. Tables 5 and 6 show the emissivity errors for bands 31 and 32 when using the band 27-28-29-31-32 combination, with retrieval errors below 0.01. Emissivity in thermal infrared bands is less affected by soil moisture changes than in passive microwave bands and can be used to characterize surface types. In microwave bands, emissivity is greatly affected by soil moisture changes, and land surface temperature and soil moisture are entangled through emissivity.

3.3 Near-Surface Air Temperature Retrieval

Near-surface air temperature is a key parameter in weather forecasting and agricultural drought models, traditionally obtained mainly through meteorological station interpolation. Some studies have retrieved near-surface air temperature from remote sensing data using statistical methods or neural networks, but these usually lack interpretability and physical meaning, and have limited accuracy. This study uses deep learning and physical logic deduction to retrieve near-surface air temperature, with detailed reasoning and analysis processes referred to in references [9] and [15]. In thermal infrared remote sensing window bands, thermal infrared sensors mainly obtain information from the surface, with relatively less information about near-surface air temperature, thus limiting retrieval accuracy. Table 7 shows the error information for directly retrieving near-surface air temperature using the MODIS band 27-28-29-31-32 combination, with the highest accuracy achieved when the hidden layer is 10 and each layer has 700 nodes. The highest theoretical average accuracy is 1.42 K, with a standard deviation of 1.46 K and a correlation coefficient of 0.975.

Table 8 shows the retrieval error for near-surface air temperature using the band 27-28-29-31-32+LST+LSE31+LSE32 combination (where LSE31 is band 31 emissivity and LSE32 is band 32 emissivity). The highest accuracy occurs when the hidden layer is 10 and each layer has 800 nodes, with the highest average accuracy of 0.81 K, standard deviation of 0.91 K, and correlation coefficient of 0.984. When land surface temperature and emissivity are used as prior knowledge, the accuracy of near-surface air temperature is significantly improved, and the retrieval becomes more stable. This is mainly because using land surface temperature as prior knowledge amplifies the signal of near-surface air temperature, and emissivity provides surface type information, thus greatly improving retrieval accuracy and making the algorithm more transplantable. Therefore, for parameter retrieval where input variables and output variables are weakly correlated, adding strongly correlated variables as prior knowledge can improve the retrieval accuracy and stability of weakly correlated parameters.

3.4 Atmospheric Water Vapor Content Retrieval

Atmospheric water vapor content is an important parameter for weather forecasting and agricultural drought monitoring. Based on the above analysis, Table 9 shows the retrieval error of atmospheric water vapor content using the band 27-28-29-31-32 combination. The highest accuracy occurs when the number of hidden layers is 9 and each hidden layer has 800 nodes, with the highest average accuracy of 0.09 g/cm^2, standard deviation of 0.11 g/cm^2, and correlation coefficient of 0.989.

Table 10 shows the retrieval error of atmospheric water vapor content using the band 27-28-29-31-32+LST+LSE combination. The highest accuracy occurs when the hidden layer is 9 and each hidden layer has 900 nodes, with the highest average accuracy of 0.08 g/cm^2, standard deviation of 0.09 g/cm^2, and correlation coefficient of 0.992. Comparing Tables 9 and 10, when LST and LSE are used as prior knowledge, the accuracy is slightly improved and the error is relatively stable. If the prior knowledge LST and LSE have certain errors, the accuracy may not be significantly improved. Therefore, when there are two input bands in the input parameters that are relatively sensitive to output parameter water vapor, prior knowledge may not need to be added.

The theory and judgment conditions of geophysical parameter retrieval paradigms are also applicable to remote sensing classification and other target recognition tasks, but they need to be interpreted from a different perspective. Currently, Convolutional Neural Networks (CNN) are considered one of the better methods for classification and target recognition. In fact, CNN further utilizes different convolution kernels to extract target information at different scales based on traditional neural networks, with the purpose of uniquely determining the target through information from different dimensions to improve classification (target recognition) accuracy. Theoretically, if the information extracted from different dimensions (different convolution kernels) can also construct mathematical equations to uniquely determine output parameters, a paradigm can also be formed; otherwise, there will also be uncertainty.

In recent years, breakthroughs in artificial intelligence in many fields have spawned many new technologies, products, and industries that will profoundly affect and change human production, lifestyle, and thinking patterns, achieving an overall leap in productivity. To promote the application of artificial intelligence in geoscience and agricultural science and cultivate interdisciplinary talents, this study proposes a paradigm theory and judgment conditions for geophysical parameter retrieval based on artificial intelligence. Through physical logic deduction, target information (problems) can be described mathematically in theory or physical logic, and solutions of physical methods can be obtained through physical model simulation. To overcome the shortcomings of physical methods, generalized statistical methods are constructed based on physical logic deduction, and solutions of statistical methods are obtained through multi-source data. On this basis, the solutions of physical and statistical methods constitute the training and testing data for deep learning, achieving the goal of coupling physical and statistical methods through deep learning. Deep learning combines physical and statistical methods through big data learning and optimization calculations, ensuring that the proposed paradigm is not only physically meaningful and interpretable but also universal.

Whether artificial intelligence methods for geophysical parameter retrieval form a paradigm—that is, a deep learning paradigm with physical mechanisms and interpretability—has two basic conditions: (1) There must be a causal relationship between input and output variables (parameters); (2) In theory, a closed system of equations can be constructed between input and output variables (parameters) (with the number of unknowns less than or equal to the number of equations), meaning that output parameters can be uniquely determined by input variables. If the above two conditions cannot be proven or demonstrated when using deep learning, we generally consider it a "black box". If it can be proven that there is definitely no closed relationship between input and output parameters (number of unknowns greater than number of equations), then such applications may only be suitable for local areas, cannot be universal, and are difficult to transplant, thus cannot be called a paradigm.

The application of artificial intelligence methods cannot be separated from specific problems. When solving an application problem, we must first perform physical logic deduction on the problem object, theoretically construct equations, and determine the causal relationship between input and output variables. Then, we determine the number of equations from the number of unknowns in the equations, i.e., determine how many input parameters can uniquely determine the output variables, and finally use deep learning for optimization solutions. The physical logic deduction performed first in this paper is the key to making deep learning physically meaningful and interpretable. Using MODIS remote sensing data to retrieve land surface temperature, emissivity, near-surface air temperature, and atmospheric water vapor content demonstrates the paradigm theory: when output parameters (LST and LSE) have strong correlation with input variables (BTi), using deep learning to couple physical and statistical methods can achieve very high accuracy; when output parameters (NSAT) have weak correlation with input variables (BTi), adding prior knowledge (LST and LSE) can improve the retrieval accuracy and stability of output parameters (NSAT); when there is partial strong correlation (WVC and BTi), adding prior knowledge (LST and LSE) can slightly improve accuracy and stability, but errors in prior knowledge (LST and LSE) may introduce uncertainty, so prior knowledge may also be omitted. The analysis of MODIS sensor thermal infrared band geophysical parameter retrieval shows that bands 27, 28, 29, and 31 are more suitable for retrieving atmospheric water vapor content, while bands 28, 29, 31, and 32 are more suitable for retrieving land surface temperature, emissivity, and near-surface air temperature. To obtain the highest accuracy for four parameters, instrument design with five bands (27, 28, 29, 31, 32) is recommended. If only four thermal infrared bands can be designed, priority should be given to 27, 28, 31, and 32. The analysis results of this study demonstrate that the geophysical parameter retrieval paradigm theory and judgment conditions are reliable, and their proposal is of milestone significance for using artificial intelligence methods to retrieve surface physical parameters.

Conflict of Interest Statement: This study has no conflicts of interest between researchers and publicly available research results.

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Note: Figure translations are in progress. See original paper for figures.