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

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Abstract

[Purpose/Significance] Artificial Intelligence (AI) technology has sparked a research surge in academic and engineering applications, demonstrating powerful application potential in the retrieval of geophysical parameters and agricultural meteorological remote sensing parameters. Currently, most AI applications in geoscience and agronomy remain "black boxes," lacking physical meaning or interpretability and universality. To promote the application of AI in geoscience and agronomy and cultivate interdisciplinary talents, this study proposes a paradigm theory for geophysical parameter retrieval based on AI coupled with physical and statistical methods.

[Method] First, physics-based logical reasoning is conducted based on the physical energy balance equation to theoretically construct the retrieval equation system, followed by building 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, finally utilizing deep learning for optimized solution.

[Results and Discussion] The conditions for forming a paradigm with universality and physical interpretability include: (1) a causal relationship must exist between input and output variables (parameters); (2) a closed equation system can theoretically be constructed between input and output variables (parameters) (the number of unknowns is less than or equal to the number of equations), meaning that output parameters can be uniquely determined by input parameters. If a strong causal relationship exists between input parameters (variables) and output parameters (variables), deep learning can be directly used for retrieval. If a weak correlation exists between input parameters and output pa-

rameters, prior knowledge needs to be added to improve the retrieval accuracy of output parameters. Furthermore, this study uses the joint retrieval of key parameters in agricultural meteorological remote sensing—land surface temperature, emissivity, near-surface air temperature, and atmospheric water vapor content—as a case study to demonstrate the theory. Analysis results indicate that the theory is feasible and can assist in optimizing the design of satellite sensor band combinations.

[Conclusion] The proposal of this theory and its determining conditions holds milestone significance 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: [**Objective**] Artificial intelligence (AI) technology has sparked a research boom in academic and engineering applications, demonstrating strong potential for retrieving geophysical and agrometeorological remote sensing parameters. However, most current AI applications in geoscience and agronomy remain "black boxes" lacking physical meaning, interpretability, and universality. To promote AI applications in geoscience and agronomy and cultivate interdisciplinary talent, this study proposes a paradigm theory for geophysical parameter retrieval that couples physical and statistical methods. [**Methods**] The construction of this retrieval paradigm theory includes three main components: First, physical logic deduction based on the physical energy balance equation is used to theoretically construct the inversion equation system, eliminating the ill-conditioned problem of insufficient equations. Second, a generalized statistical method is built upon physical deduction. Representative solutions of physical methods are obtained through physical model simulation, while representative solutions from statistical methods using multi-source data serve as training and testing databases for deep learning. Finally, deep learning is employed for optimized solution. [**Results and Discussions**] The conditions for forming a universal and physically interpretable paradigm are: (1) A causal relationship must exist between input and output variables (parameters); (2) A closed system of equations can theoretically be constructed between input and output variables (parameters) (where the number of unknowns is less than or equal to the number of equations), meaning output parameters can be uniquely determined by input parameters. If a strong causal relationship exists between input and output parameters, deep learning can be directly used for inversion. If the correlation is weak, prior knowledge must be added to improve retrieval accuracy. This study demonstrates the theory using the joint retrieval of key agrometeorological remote sensing parameters—land surface temperature, emissivity, near-surface air temperature, and atmospheric water vapor content—as a case study. The analysis results confirm the feasibility of the theory and show it can assist in optimizing satellite sensor band combination design. [**Conclusions**] The proposed theory and judgment conditions represent a milestone in the history of geophysical parameter retrieval.

Keywords: artificial intelligence; deep learning; retrieval paradigm; physical logic derivation; interpretable; agrometeorological remote sensing

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The emergence and advancement of generative AI represented by ChatGPT have drawn widespread attention, establishing AI as a core driver of a new round of industrial transformation that will further unleash tremendous energy in scientific innovation and create powerful new engines. The integration of AI with specific industries will spawn new technologies, products, and industries, profoundly transforming human thinking and production models and enabling overall productivity leaps across society and industries. Deep learning is currently one of the most important AI technologies, sparking research booms in both academic and engineering applications and achieving remarkable results in natural language generation models, computer vision, speech recognition, and other fields. Given the application potential and importance of deep learning in geoscience and agronomy, it is essential to accelerate the deep integration of AI and remote sensing technology to provide key technical support for weather forecasting, crop monitoring, and agricultural disaster prediction, thereby serving global disaster monitoring and national food security.

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

2. Geophysical Parameter Retrieval Paradigm Theory and Judgment Conditions

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 "AI-based 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 AI methods can solve equations by coupling physical and statistical methods through big data learning and optimization calculations. This makes the coupled method possess not only the respective advantages of physical and statistical methods but also fully utilizes the optimization computing power of deep learning to maximize geophysical parameter retrieval accuracy. This ensures the retrieval paradigm is not only universal but also physically meaningful and interpretable.

Specifically, the geophysical parameter retrieval paradigm theory proposed in this study requires that a complete closed system of equations can be constructed between deep learning input parameters (variables) and output parameters (variables). If a strong causal relationship exists between input parameters (variables) and output parameters (variables), deep learning can be directly used for inversion to obtain high-precision results. If the correlation is weak, strongly correlated prior knowledge needs to be added to improve retrieval accuracy. Additionally, a large number of representative solutions from physical methods can be obtained through physical model simulation, and deep learning can then acquire the curve function of solutions through training. Therefore, deep learning through big data patterns can replicate physical methods. Meanwhile, many physical methods cannot describe all situations. To overcome the limitations of physical methods, generalized statistical methods are further constructed based on physical logic deduction, and multi-source data are used to obtain representative solutions of statistical methods to supplement the shortcomings of physical methods. In fact, from the perspective of information flow transmission, deep learning networks better conform to reality, and physical and statistical methods are merely partial manifestations of them. These methods are essentially consistent—they are all means for people to understand the world and interpret and solve real-world problems at different cognitive levels.

There are two conditions for determining whether deep learning-based geophysical parameter retrieval forms a universal and physically interpretable paradigm: (1) A causal relationship must exist between deep learning input and output variables (parameters), meaning that when other conditions remain unchanged, changing any input variable will cause the output variable to change. If deep learning input variables are denoted as xi and output variables as yj, the causal relationship is expressed as Equation (1): yj = f(xi), where i = 1, 2, …, n; j = 1, 2, …, 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) (where the number of unknowns is less than or equal to the number of equations), meaning output parameters can be uniquely determined by input parameters. This can be expressed mathematically as Equation (2): F(x, y) = 0, where x = x1, x2, …, xn; y = y1, y2, …, ym; and F represents a vector function composed of k equations.

To ensure output parameters can be uniquely determined by input parameters, the condition $k \geq m$ must be satisfied. To demonstrate that deep learning applications have physical meaning, physical logic deduction must be conducted during research. When input variables and output variables have a causal relationship and can theoretically construct sufficient equations, if representative solutions can be obtained through physical model simulation, deep learning can directly perform inversion calculations while maintaining high precision when the correlation is strong. However, if the relationship between input and output variables 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, physical logic deduction must first be performed on the problem object to theoretically construct equations and determine the causal relationship between input and output variables. Second, the number of equations is determined by the number of unknowns in the equations, i.e., determining how many input parameters can uniquely determine the output variables. Third, it is determined whether representative solutions can be obtained through physical model simulation. If not, generalized statistical methods based on physical logic deduction are constructed, and multi-source data are used to supplement representative solutions. Finally, deep learning is used to optimize and solve for the spatial curve function of solutions from physical and statistical methods, followed by verification and iterative optimization until the desired accuracy is achieved. 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 a closed relationship definitely does not exist between input and output parameters (where unknowns outnumber equations), such applications are only suitable for local areas, cannot be universal, and are difficult to transplant, and therefore cannot be called paradigms.

3. Case Analysis of Geophysical Parameter Retrieval Paradigm Theory

3.1 Physical Logic Deduction

Key agrometeorological remote sensing parameters are important components of geophysical parameters. This study uses key agrometeorological remote sensing parameters as examples 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 primarily affected by surface types and soil moisture (SM), land surface temperature (LST), near-surface air temperature (NSAT), and atmospheric water vapor content (WVC). The retrieval of land surface temperature and soil moisture is based on the physical process of surface thermal radiation conduction and its transmission through the atmosphere to the sensor, and the retrieval equation can generally be described by Equation (3), as shown in Figure 2 [Figure 2: see original paper].

In Equation (3), $B\lambda(T\lambda)$ (known) is the radiation received by the satellite, (1-$\tau\lambda($ $))B\lambda(Ta)$ represents atmospheric radiation contribution, and $B\lambda(Ts)\tau\lambda($ $)$ λ is surface radiation. Here, $\tau\lambda($ $)$ is atmospheric transmittance (unknown), Ts is land surface temperature (unknown), Ta is near-surface air temperature (unknown), and λ is surface emissivity (unknown). A single equation contains four unknowns. Without prior knowledge, at least four thermal infrared window bands are theoretically required to construct the retrieval equation system. With atmospheric water vapor as prior knowledge, only three thermal infrared bands may be needed. Most previous studies focused on retrieving individual parameters. Since different parameters are interrelated and entangled, using AI methods for joint retrieval and cross-iteration can improve retrieval accuracy.

Soil moisture changes affect dielectric constant variations, thereby altering emissivity. Emissivity changes affect surface radiation efficiency, while land surface temperature changes determine soil moisture evaporation rates, thereby 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 variations, but traditional algorithms do not consider this, generally assuming thermal infrared band emissivity is relatively constant. In fact, emissivity also changes with soil and vegetation water content. Therefore, in areas with abundant rainfall, the accuracy of traditional thermal infrared remote sensing methods for retrieving land surface temperature fluctuates relatively significantly, but AI methods can overcome this difficulty. Changes in near-surface air temperature affect atmospheric profiles, thereby influencing the mean atmospheric effective temperature. When surface thermal radiation passes through the atmosphere, it is absorbed by atmospheric water vapor before reaching satellite sensors. Therefore, from physical logic deduction, it is known that a single equation contains four unknowns. Without prior knowledge, at least four thermal infrared window bands are theoretically required to construct the retrieval equation system. With atmospheric water vapor as prior knowledge, only three thermal infrared bands may be needed. Most previous studies focused on retrieving individual parameters. Since different parameters are interrelated and entangled, using AI 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 because physical models simplify the real world, and many geoscience models are only suitable for partial conditions. Therefore, to accommodate as many situations as possible, generalized statistical methods must be further established based on physical logic deduction to ensure method completeness and reliability of accuracy.

The MODIS satellite sensor is currently one of the best sensors in terms of thermal infrared band quantity and quality. This study conducts simulation and demonstration analysis for MODIS thermal infrared bands. MODIS bands 27/28/29/31/32/33 (6.5–13.5 m) are selected, where bands 27, 28, and 29 are in the water vapor absorption region of thermal infrared bands, and bands 31 and 32 are in the window region, with band 33 at the edge of the thermal infrared window region. JPL-measured surface spectral curves (http://speclib.jpl.nasa.gov) are used as input parameters for MODTRAN4, with land surface temperature ranging from 273–325 K, near-surface air temperature from 273–320 K, atmospheric water vapor content from 0.1–4.0 g/cm^2, and simulated observation angles from 0–45°. When the simulated observation angle is too large, transmittance becomes too low due to excessive water vapor along the slant path, so this portion of simulated data was removed. The simulated data were randomly divided into two parts: 45,650 training datasets and 16,550 testing datasets. Based on the amount of information for different parameters obtained by the sensor, parameter retrievals are divided into three groups to demonstrate the theory and judgment conditions. The first group retrieves land surface temperature and emissivity, primarily analyzing and demonstrating how the number of equations and causal relationships between input variables and output variables affect retrieval accuracy. The second group retrieves near-surface air temperature, mainly analyzing and demonstrating how using strongly correlated variables between input and output variables as prior knowledge can improve the accuracy of weakly correlated variable retrieval. The third group retrieves atmospheric water vapor content, primarily analyzing and demonstrating that when strong correlation exists between input and output variables, adding prior knowledge can improve retrieval stability but has minimal impact 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 retrieval accuracy will be low when fewer than four thermal infrared bands are used as input. Table 1 shows the theoretical retrieval accuracy for the MODIS band 29, 31, and 32 combination under given conditions. 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 MODIS band 28-29-31-32 combination. When the hidden layer is 9 layers with 800 nodes per layer, the retrieval accuracy is highest, with an average accuracy of 0.45 K, standard deviation of 0.53 K, and correlation coefficient of 0.998. Comparing Tables 1 and 2 shows that when using four thermal infrared bands, the average accuracy improves by 0.68 K. MODIS band 28 is a water vapor absorption band, and adding water vapor absorption bands can improve water vapor accuracy, theoretically improving overall retrieval accuracy.

Table 3 shows the land surface temperature retrieval error information for the MODIS band 27-28-29-31-32 combination. When the hidden layer is 9 layers with 900 nodes per layer, the retrieval accuracy is highest, with an average accuracy of 0.44 K, standard deviation of 0.52 K, and correlation coefficient of 0.999. MODIS band 27 is also a water vapor band, and adding water vapor absorption bands can theoretically improve water vapor accuracy and overall retrieval accuracy. The accuracy improvement is not significant here mainly because ground radiation in band 27 is almost impossible to penetrate to the sensor (i.e., transmittance is very low), and the brightness temperature at the top of the atmosphere mainly contains high-altitude atmospheric water vapor information, thus contributing little 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. When the hidden layer is 8 layers with 900 nodes per layer, the accuracy is highest, with an average accuracy of 0.51 K, standard deviation of 0.55 K, and correlation coefficient of 0.997. Comparing Tables 3 and 4 shows that adding band 33 does not improve retrieval accuracy when water vapor bands are already included. The main reason is that thermal infrared band 33 is significantly affected by CO_2 and is not very suitable for retrieving land surface temperature. Therefore, adding thermal infrared bands does not necessarily improve retrieval accuracy and may sometimes reduce it. Table 3 demonstrates that when added bands have strong correlation with output parameters, accuracy can be improved. Table 4 shows that when added bands have weak correlation with output parameters or increase noise, retrieval accuracy will be reduced.

Emissivity can also be retrieved simultaneously. Tables 5 and 6 show the emissivity retrieval errors for bands 31 and 32 when using the band 27-28-29-31-32 combination, with retrieval errors below 0.01. In thermal infrared bands, emissivity is less affected by soil moisture changes compared to 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 become entangled through emissivity.

3.3 Near-Surface Air Temperature Retrieval

Near-surface air temperature is a key parameter for 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 typically lack interpretability and physical meaning, with limited accuracy. This study uses deep learning and physical logic deduction to retrieve near-surface air temperature, with the reasoning and analysis process detailed in references [9] and [15].

In thermal infrared window bands, thermal infrared sensors mainly obtain information from the surface, with relatively less information content for near-surface air temperature, so retrieval accuracy is limited. Table 7 shows the error information for directly retrieving near-surface air temperature using the MODIS band 27-28-29-31-32 combination. The highest accuracy occurs when the hidden layer is 10 layers with 700 nodes per layer, achieving a theoretical average accuracy of 1.42 K, standard deviation of 1.46 K, and 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 layers with 800 nodes per layer, achieving an 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 retrieving weakly correlated parameters, adding strongly correlated variables as prior knowledge can improve the accuracy and stability of weakly correlated parameter retrieval.

3.4 Atmospheric Water Vapor Content Retrieval

Atmospheric water vapor content is an important parameter for weather forecasting and agricultural drought monitoring models. Based on the above analysis, Table 9 shows the retrieval error for atmospheric water vapor content using the band 27-28-29-31-32 combination. The highest accuracy occurs when the hidden layer is 9 layers with 800 nodes per layer, achieving an 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 for 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 layers with 900 nodes per layer, achieving an 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 shows that when LST and LSE are used as prior knowledge, accuracy improves slightly and errors become relatively more stable. However, if prior knowledge LST and LSE contain certain errors, the improvement may not be significant. Therefore, when two input bands are relatively sensitive to the output parameter water vapor, prior knowledge may not need to be added.

Humans understand the world through observation (sampling), then abstractly construct patterns in their brains based on observation and reflection to maximize knowledge formation for rapid world understanding or target recognition. This can essentially be 归结为 defining rules to understand the world. The goal is singular—maximizing recognition (cognitive) accuracy—so there is no need to overly consider the specific form of methods (statistical, physical, or AI methods), as these are all means of cognition. According to the authors' years of research experience, statistical methods, physical methods, and machine learning methods are essentially consistent—they are methods or means defined by people to understand the laws of things according to different situations, especially the currently widely used deep learning neural network algorithms, which are actually more advanced statistical optimization calculation methods. The accuracy and general applicability of these methods depend on whether the rules followed when constructing sample databases (representativeness and accuracy of training and testing data) better conform to real-world conditions.

Traditional remote sensing geophysical parameter retrieval methods are mainly suitable for flat terrain and pure pixels with single surface types. As shown in Figure 3 [Figure 3: see original paper], for geophysical remote sensing parameter retrieval, traditional physical methods cannot solve the pixel relative incident angle problem and struggle with mixed pixel problems, leading to bottlenecks in traditional method retrieval accuracy. In recent years, AI breakthroughs in many fields have spawned numerous new technologies, products, and industries that will profoundly influence and change human production, lifestyles, and thinking patterns, achieving overall productivity leaps. To promote AI applications in geoscience and agronomy and cultivate interdisciplinary talent, this study proposes an AI-based geophysical parameter retrieval paradigm theory and judgment conditions. Through physical logic deduction, target information (problems) can be described using mathematical expressions in theory or physical logic, and physical model simulation can obtain solutions for physical methods. To overcome physical method limitations, generalized statistical methods are constructed based on physical logic deduction, and multi-source data are used to obtain statistical method solutions. On this basis, solutions from physical and statistical methods constitute deep learning training and testing data, 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 the proposed paradigm is not only physically meaningful and interpretable but also universal.

Whether AI methods for retrieving geophysical parameters form a paradigm—that is, form a deep learning paradigm with physical mechanisms and interpretability—has two basic conditions: (1) A causal relationship must exist between input and output variables (parameters); (2) A closed system of equations can theoretically be constructed between input and output variables (parameters) (where the number of unknowns is less than or equal to the number of equations), meaning output parameters can be uniquely determined by input variables. If the above two conditions cannot be proven when using deep learning, the application is generally considered a "black box." If it can be proven that a closed relationship definitely does not exist between input and output parameters (unknowns exceed equations), such applications may be mainly suitable for local areas, cannot be universal, are difficult to transplant, and cannot be called paradigms.

AI method applications cannot be separated from specific problems. When solving an application problem, physical logic deduction must first be performed on the problem object to theoretically construct equations and determine causal relationships between input and output variables. Then, the number of equations is determined by the number of unknowns in the equations, i.e., determining how many input parameters are needed, and finally deep learning is used for optimized solution. Conducting physical logic deduction is 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 coupled with 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 partial strong correlation exists (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 can also be omitted. Through analysis of geophysical parameter retrieval from MODIS sensor thermal infrared bands, 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 achieve the highest accuracy for all four parameters, instrument design with five bands (27, 28, 29, 31, 32) is most appropriate. If only four thermal infrared bands can be designed, bands 27, 28, 31, and 32 should be prioritized. The analysis results demonstrate that the geophysical parameter retrieval paradigm theory and judgment conditions are reliable, and their proposal is of great significance for using AI methods to retrieve surface physical parameters.

The geophysical parameter retrieval paradigm theory and judgment conditions are also applicable to remote sensing classification and other target recognition tasks, but require interpretation from a different perspective. For example, feature information extracted by different convolutional kernels must be able to uniquely determine the target. Under paradigm conditions, AI-based geophysical parameter retrieval is the best choice. Therefore, it is recommended that the Ministry of Science and Technology and the National Natural Science Foundation of China provide support to create China's "ChatGPT" for geophysical parameter retrieval paradigms based on AI.

Conflict of Interest Statement: This study has no conflicts of interest among researchers or with publicly disclosed research results.

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