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Geoscience-aware deep learning: A new paradigm for remote sensing

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ABSTRACT

Information extraction is a key activity for remote sensing images. A common distinction exists between knowledge-driven and data-driven methods. Knowledge-driven methods have advanced reasoning ability and interpretability, but have difficulty in handling complicated tasks since *prior* knowledge is usually limited when facing the highly complex spatial patterns and geoscience phenomena found in reality. Data-driven models, especially those emerging in machine learning (ML) and deep learning (DL), have achieved substantial progress in geoscience and remote sensing applications. Although DL models have powerful feature learning and representation capabilities, traditional DL has inherent problems including working as a black box and generally requiring a large number of labeled training data. The focus of this paper is on methods that integrate domain knowledge, such as geoscience knowledge and geoscience features (GK/GFs), into the design of DL models. The paper introduces the new paradigm of geoscience-aware deep learning (GADL), in which GK/GFs and DL models are combined deeply to extract information from remote sensing data. It first provides a comprehensive summary of GK/GFs used in GADL, which forms the basis for subsequent integration of GK/GFs with DL models. This is followed by a taxonomy of approaches for integrating GK/GFs with DL models. Several approaches are detailed using illustrative examples. Challenges and research prospects in GADL are then discussed. Developing more novel and advanced methods in GADL is expected to become the prevailing trend in advancing remotely sensed information extraction in the future.

1. Introduction

Remotely sensed information extraction techniques derive essential information from remote sensing data for a wide range of Earth system and socio-economic researches and applications (Persello and Stein, 2017; Lian et al., 2020; Zhang et al., 2020; Chen et al., 2021; Liu et al., 2021a; Xia et al., 2021). Since the launch of Landsat-1 in 1972, the continuous development of new sensors has increased the spatial-temporal-spectral resolution of Earth observation data (Vali et al., 2020; Shao et al., 2021; Emilien et al., 2021). In recent years, the accumulation of massive Earth observation datasets, substantial improvements in computing platform performance and the rise of artificial intelligence (AI), are significantly changing the theory and practice of remote sensing information processing (Zhang et al., 2019a). In this regard, and in relation to advances in AI generally, knowledge-driven and data-driven models are the dominant paradigms for spatio-temporal modeling and spatio-temporal decision-making (Bonham-Carter, 1994; Solomatine, 2002; Ge, 2006; Riaz et al., 2018).

Knowledge-driven models rely significantly on *prior* knowledge that is summarized by geoscientific experts or extracted from geoscience data, and these methods extract information usually through knowledge reasoning (Lu and Weng, 2007). In the context of the symbolic school of early AI (Garcez et al., 2019; Futia and Vetrò, 2020), the earlier developed knowledge-driven methods express geoscience knowledge and geoscience features (GK/GFs) from relevant expert experience and geoscience data as a series of clear logical inference rules and other

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formulations through human intervention (Goodfellow et al., 2016; Zhuang et al., 2017), which are readily coded for computer manipulation. Expert systems are the most influential and representative line of research in knowledge-driven methods based on knowledge rule reasoning (Goodenough et al., 1987; Wang et al., 2020a). Subsequently, knowledge-based model reasoning for information extraction was developed by considering the physical processes or physical laws underpinning ground objects and geoscience phenomena (Zhang et al., 2019a). Such physical models combine the interaction mechanism between the remote sensing observations and the targets to extract thematic information or geoscientific parameters related to environmental domains, such as the atmosphere, ocean, vegetation and hydrology (Liang, 2005). However, *prior* knowledge is generally very limited relative to the complicated distributions and patterns of natural phenomena and geographical elements, and the great complexity of underlying physical processes. This greatly hinders the construction of accurate knowledge reasoning models as well as knowledge discovery processes (Goffi et al., 2020; Yuan et al., 2020; Li et al., 2021a). This situation makes it difficult presently to perform large-scale and high-level information extraction tasks using knowledge-driven methods. Nevertheless, knowledge-driven methods are still regarded as one of the most important research directions because of their advanced reasoning ability and interpretability (Arvor et al., 2019; Garcez et al., 2019; Li et al., 2020).

Along another research avenue, more and more research effort has been focused on bottom-up methods, or data-driven methods, with the advent of the era of 'data deluge' in geoscience and remote sensing (Li et al., 2021a). Data-driven methods discover knowledge and extract information via fitting models to a large quantity of data (Sukor et al., 2019; Zhang et al., 2019a), including classic machine learning methods, and deep learning (DL) technologies that have emerged as the cutting-edge AI frameworks in recent years (Wang et al., 2020a; Li et al., 2021a). DL derived from connectionist AI has triggered profound social and industrial changes (Garcez et al., 2019; Futia and Vetrò, 2020), and has brought unprecedented opportunities for the development of geoscience and remote sensing (Zhu et al., 2017; Jiang et al., 2020). First, DL models have powerful feature learning and representation capabilities, able to transform raw inputs into high-level and abstract representations (LeCun et al., 2015). This capability is conducive to revealing the latent characteristics and laws in complex spatial patterns and phenomena through learning mapping or dependences between the inputs and outputs of models. Second, the ever-increasing numbers of spatio-temporal data provide data support for training DL models and developing new algorithms (Reichstein et al., 2019; Li, 2020). By drawing on the successful experience of the computer science community, DL techniques have been demonstrated to have outstanding performance in remote sensing image classification (Bergado et al., 2018; Mullissa et al., 2019), object detection (Hoeser and Kuenzer, 2020), environmental parameter retrieval (Yuan et al., 2020), and other information extraction goals in geoscience and remote sensing (Zhang et al., 2016; Dramsch, 2020; Ma et al., 2019; Bergado et al., 2021), as well as many other complex tasks in other fields (Guo et al., 2016).

Although the rapid progress of DL has exerted a profound impact on various industries and people's lives, the problem of ignoring domain knowledge (e.g., practical engineering theories (Wang et al., 2020b), the experience and theories of remote sensing interpretation (Yao et al., 2020)) and existing scientific laws (e.g., spatial autocorrelation described by Tobler's first law of geography (Li et al., 2021a) and the law of conservation of mass and energy (Reichstein et al., 2019)) is prevalent in the design of its models. This hinders in-depth applications of DL in various fields to a great extent. Different from knowledge-driven methods, although DL models can fit complex nonlinear relationships in real situations, they work as black box models since they are agnostic to the drivers of the underlying real-world phenomena and processes (Castelvecchi, 2016; Paoletti et al., 2019). Therefore, even if the 'black box' performs more accurately, it cannot directly be used as the foundation for subsequent scientific developments (Karpatne et al., 2017a). Besides, the most widely used supervised DL models are extremely limited by the number and representativeness of the labeled data used to train them, resulting in weak generalization and extrapolation ability beyond the training data (Karpatne et al., 2017b; Karniadakis et al., 2021). In terms of remotely sensed information extraction, although data-driven DL methods have achieved a great deal of success, they do not yet deliver many recognized scientific and practical requirements due to the following challenges: First, the internal mechanism of DL-based information extraction methods is elusive, and thus it is difficult for humans to understand how DL produces the final decision. Second, incomplete labeled data used for training in practical situations makes DL models become unreliable and cannot generalize well under new geospatial contexts, especially when the geographic heterogeneity is obvious (Wang et al., 2021a). Third, the training process of DL models relies on data available (Wang et al., 2020b), and does not involve the guidance of GK/GFs, which may lead to unreasonable or incorrect predictions. Therefore, the effectiveness of DL-based methods is still far from the visual interpretation and information processing that can be achieved by domain experts.

Considering the respective merits and faults of knowledge-driven methods and data-driven DL models the combination, especially the in-depth combination, of the two different paradigms to achieve complementary advantages has gained attention recently. There have been several efforts towards this emerging scheme in the research fields of neural-symbolic computing (Garcez et al., 2019; Lamb et al., 2020), physics (Raissi et al., 2019; Karniadakis et al., 2021), hydrology (Jiang et al., 2020), meteorology (Higa et al., 2021) and geospatial science (Janowicz et al., 2020; Li, 2020; Hsu et al., 2021; Li et al., 2021a). For example, in runoff modeling, Jiang et al. (2020) proposed a hybrid physics-AI approach where geosystem dynamics were encoded as a neural network architecture. In two examples of object detection based on geospatial artificial intelligence technology, rim features and spatial autocorrelation were explicitly introduced as *prior* geospatial knowledge into DL models, respectively, for Mars crater detection (Hsu et al., 2021) and weakly supervised terrain detection (Li et al., 2021a). These case studies demonstrated that under the guidance and motivation of domain knowledge, integrated methods are capable of leveraging powerful DL frameworks with increased prediction accuracy, reasoning ability, interpretability, generalization performance and reducing the requirements for labeled data used in training. Accordingly, the symbiotic integration of knowledge-driven and data-driven DL models is considered to be one of the most promising research directions, providing references for remote sensing knowledge discovery and information extraction.

The purpose of this paper is to build the foundations of algorithms and architectures of deeply knowledge-integrated data-driven DL models, with particular attention to how to improve the effectiveness of extracting valuable information from remote sensing data by introducing GK/GFs. To this end, an emerging paradigm called geoscience-aware deep learning (GADL) is proposed in this paper. In GADL, GK/GFs are deeply blended with DL models in several ways which will be reviewed later. The main contributions of this paper include:

(1) We propose a paradigm of GADL aiming at leveraging the value of GK/GFs to improve the performance of DL models in enabling remotely sensed information extraction.
(2) A comprehensive summary of GK/GFs in GADL is introduced.
(3) We provide a taxonomy of approaches in GADL used for integrating GK/GFs with DL models, and five main approaches under this taxonomy are reviewed in detail using typically existing or potential works.

The remainder of the paper is organized as follows. Section 2 elaborates the characteristics of GADL, as well as providing a framework for deep integration of GK/GFs with DL models. Section 3 gives a detailed description and summary of GK/GFs in GADL. Section 4 describes five approaches to integration using illustrative examples. Future challenges and the research prospects for this topic are further analyzed and discussed in Section 5. Finally, Section 6 provides some concluding remarks.

2. Geoscience-aware deep learning (GADL)

2.1. Characteristics

Knowledge-driven and data-driven methods represent the two dominant paradigms to deal with the practical problems of remotely sensed information extraction, depending on GK/GFs or geoscience data. Both knowledge-driven and data-driven DL models have their strengths and weaknesses, and neither knowledge-driven models nor data-driven DL models alone are enough to deal comprehensively with the challenges in remote sensing. Instead, a novel paradigm of symbiotic integration of the two class of methods needs to be further explored and developed. To this end, the paradigm of GADL is introduced in this paper, which attempts to build the foundations of deeply blending GK/GFs in DL models to take full advantage of their complementary advantages and improve the effectiveness of DL models.

The common problem in remotely sensed information extraction is to represent relationships between remote sensing observations and target outputs such as classes of ground objects or geoscientific parameters. Data-driven methods can learn a model from training samples to extract such relationships automatically. In particular, DL models are usually able to fit observations very well (Reichstein et al., 2019) via end-to-end training, and they bring excellent processing capacity for complex data, as is true for the current deluge of multi-source heterogeneous and high-dimensional remote sensing data. Besides, the powerful capability of feature learning and hidden representation of DL models can endow GADL with the ability to discover potential patterns and laws in complex phenomena and processes. At the same time, knowledge-driven methods deal with information extraction tasks by knowledge reasoning based on explicitly represented relationships between observations and target outputs. This reasoning process encapsulates cause-and-effect relationships, such as those between inputs and outputs, and between parameters and outputs, which are derived from long-term geoscientific practice or proven scientific principles. Therefore, compared with pure data-driven methods, the introduction of GK/GFs makes GADL more interpretable via knowledge-based reasoning, instead of operating as a block box. Simultaneously, it offers the potential for better generalization and extrapolation ability over any unseen observations within or beyond current observed conditions (Reichstein et al., 2019) because of the universality of GK/GFs. It is worth noting that the range of admissible solutions of GADL can be dramatically narrowed by honoring the constraints of GK/GFs in addition to the observations, which is helpful to reduce the dependence on the quality and quantity of labeled data (Wang et al., 2020b; Li et al., 2021b). More importantly, the guidance from GK/GFs can help in producing results of geoscientific consistency by removing scientifically unreasonable or implausible results (Karpatne et al., 2017b). To illustrate this more clearly, the example of spectral confusion in remote sensing image classification is given as follows. In the first case, much hillshade on one side of a mountain is easily confused with water bodies in some land cover products generated by data-driven classifiers (Zhang et al., 2021a). This situation may be improved if topography-related information or features such as from digital elevation models (DEMs) are introduced into the analysis (Lu and Weng, 2007). In the second case, in object-based segmentation and classification of coastal areas using multi-spectral image data as input, it is possible to confuse beach with construction (Qiao et al., 2011). Fortunately, the sea is usually easily identified since it is the largest water body object, and there is an opportunity to improve the classification result by introducing spatial distance knowledge that beaches are closer to the sea than construction. Thus, spatial distance can be used to constrain the classifier to minimize the training error calculated by the multi-dimensional features, and at the same time produce classification results consistent with the spatial relationship of ground objects.

Overall, through the synergistic manner of GK/GFs and DL models, both complementary advantages of knowledge-driven and data-driven DL methods can be integrated into the characteristics of GADL (Fig. 1). First, GADL is primarily committed to increasing the accuracy of information extraction. This benefits from the integrated paradigm having a better chance to reveal hidden features and unknown relationships, as well as to provide the constraints of geoscientific consistency to obtain relationships that are closer to the true relationship between observations and target outputs. Additionally, GADL can be endowed with more enhanced model performance simultaneously, such as reasoning ability, interpretability, generalization ability, powerful feature learning and representation ability, processing and fitting capacity of complex data, and low dependence on labeled data.

2.2. Framework of the deep integrated approaches

The paradigm of GADL aims to achieve deep integration of GK/GFs and DL models through some integrated approaches to extract valuable information from remote sensing data. In the past, many studies have realized the combination of knowledge-driven and data-driven methods through post-processing revision or decision fusion (Lu and Weng, 2007; Jia et al., 2018). Some researchers have applied similar approaches to blend domain knowledge and DL models, such as in research on air pollution prediction (Kabir et al., 2020) and semantic segmentation of remote sensing images (Sun and Wang, 2018). While in this paper, we pay more attention to how to incorporate GK/GFs into the architecture of the DL models themselves in the process of remotely sensed information extraction, instead of the aforementioned one-time post processing or decision fusion. This is what we mean by "deep" in relation to the paradigm of deep integration. In other words, in GADL, GK/GFs are used to guide the design of algorithms and models, or parameter optimization processes of DL, and empower DL models to learn under geoscience awareness.

Fig. 2 demonstrates the framework of deep integrated approaches of GK/GFs and DL models in GADL. On the one hand, useful knowledge/features for solving specific problems should be selected. Generally speaking, GK/GFs can be summarized or extracted from the input geoscience theories (e.g., geoscience principles and laws), expert experience, remote sensing data (e.g., images from active or passive remote sensing) and auxiliary geoscience data (e.g., *in-situ* sensor data (Karpatne et al., 2018), topographic data). For the convenience of subsequent applications, we divide GK/GFs into three types according to the source and nature of GK/GFs, which will be detailed in Section 3. On the other hand, a DL architecture suitable for handling the current task should be designed or determined. Presently, a vast variety of DL models with different characteristics and scope of application have been evolved, which have been summarized in detail by LeCun et al. (2015), Ball et al. (2017), Yuan et al. (2020), Hoeser and Kuenzer (2020). For example, convolutional neural networks (CNNs) are especially suitable for extracting multi-scale information and semantic information from images (Zhu et al., 2017); recurrent neural networks (RNNs) can capture temporal dependencies of time-series data (Qiu et al., 2019; Zhao et al., 2021); graph convolutional networks (GCNs) are able to conduct flexible convolution to extract structural information from irregular non-Euclidean data (Liu et al., 2020; Zhang et al., 2021b). In addition to the above-mentioned commonly used networks, the transformer (Vaswani et al., 2017)-based network has also been developed recently to learn spectrally sequence information for hyperspectral image classification (Hong et al., 2021). The characteristics of different DL models provide a wide range of options and bases for designing fusion strategies in GADL.

In terms of the taxonomy of approaches for integrating GK/GFs with DL models, we consider the representation of knowledge/features as the

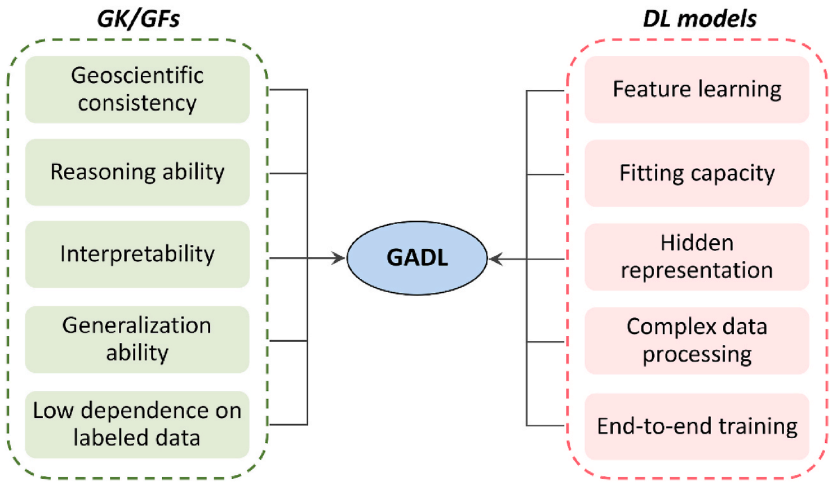

Fig. 1. Characteristics of GADL.

classification basis. In fact, the knowledge or feature representation refers to the means to symbolize and formalize knowledge or features in a computer-useable manner (Baltsavias, 2004). For different problems, how to choose the appropriate representations is a crucial consideration for making decisions and predictions effectively and, thus, is also the cornerstone of building deep integrated approaches to integrate GK/GFs and DL models in GADL. In the light of common representations of GK/GFs, this paper introduces five main approaches for in-depth integration of GK/GFs and DL models, namely: rule-based, semantic network-based, object-based, physical model-based, neural network-based. Different types of GK/GFs and characteristics of varieties of DL models are considered in the specific modeling of each approach, and each approach is elaborated in Section 4 using some emergent or potential examples of GADL research directions. Next, these integrated approaches with enhanced model performance can be applied to land use/land cover (LULC) mapping, object recognition, geoscientific parameter estimation and other problems involving remotely sensed information extraction. Finally, the results are analyzed and model assessment of the deep integrated models in GADL undertaken.

3. Types of GK/GFs

This paper focuses on the GK and GFs that are beneficial for extracting useful information from remote sensing data. They can supplement the limited electromagnetic spectrum information in remote sensing data. GK, which is related to conceptual physical models, often does not require the definition of measurable properties, and it represents the synthesis of cognition and experience accumulated by people in geoscientific practice. Domain experts and scholars have long been aware of the importance of GK for solving geoscience problems, and some different views about GK (or other similar terms, such as geographic knowledge) from different perspectives have been provided. For example, geographic knowledge was described as the product of geographic thinking and reasoning about the world's natural and human phenomena (Golledge, 2002). According to the degree of abstraction, Wang et al. (2021b) hold that GK consists of knowledge related to data, concepts and law. In this paper, we suggest that the scope of GK is potentially extensive, involving an investigator's awareness and understanding of geoscience phenomena, geoscience processes (e.g., hydrological, ecological and atmospheric processes, soil process) and their internal driving mechanisms, and geoscience attributes (e.g., spatial distribution and time variation) of ground objects. In contrast, GFs, which are more related to statistical models, require measurable properties and, thus, exist as data, in the sense that GFs refer to intuitive features that can be extracted directly from remote sensing data or auxiliary data, such as texture features and geometric features. GK and GFs can be formalized and quantified, and further applied in knowledge-driven methods or the paradigm of GADL through some appropriate representations.

Considering the source and nature of GK and GFs, we group them into three types: spatial knowledge/features, physical knowledge/features and regional knowledge/features. On this foundation, for the purpose of illustration, we further subdivide the knowledge/features into nine different forms. More detailed descriptions or examples of each type and form of GK/GFs are listed in Table 1. This division and subdivision of GK/GFs is the basis for deep integration modeling of GK/GFs with DL, because each integrated approach has its own applicability for different types of GK/GFs.

3.1. Spatial knowledge/features

Spatial character is a basic property of geoscience research objects (Zhou et al., 1999), which can be reflected to some extent in remote sensing data. Therefore, spatial knowledge/features are an important type of GK/GFs with which to extract object information efficaciously. This paper further subdivides spatial knowledge/features into four forms: spatial vision features, spatial geometry features, spatial distribution knowledge and spatial relationship knowledge.

Spatial vision features represent the visual perception of ground features reflected directly in remote sensing images. The most representative visual feature is spatial texture; image structure formed by regular spatial changes or the repeated arrangement of tones or fine structures, which form visually identifiable differences. The most widely used quantitative textures methods include the gray level co-occurrence matrix (GLCM) and its derived statistics (Haralick et al., 1973), fractal dimension (Pentland, 1984), and the pixel shape index (Zhang et al., 2006). In fact, since texture alone is insufficient to describe complex Earth surface conditions, the approach of integrating texture with other knowledge/feature forms has attracted increasing attention in practice (Huang et al., 2014).

Spatial geometry features are another commonly used fundamental form for analyzing remote sensing objects, where shape is a main form that is conducive to identifying ground information. In the long-term remote sensing interpretation work of geoscientists, it is often used as additional information to make up for the limitations of spectral information (Arvor et al., 2013; Jawak et al., 2015). Shape expresses the outline of targets on the two-dimensional image plane, and it can be characterized by some basic descriptors (e.g., area, length, width), shape indices, moments and so on (see Table 1). In image analysis, the

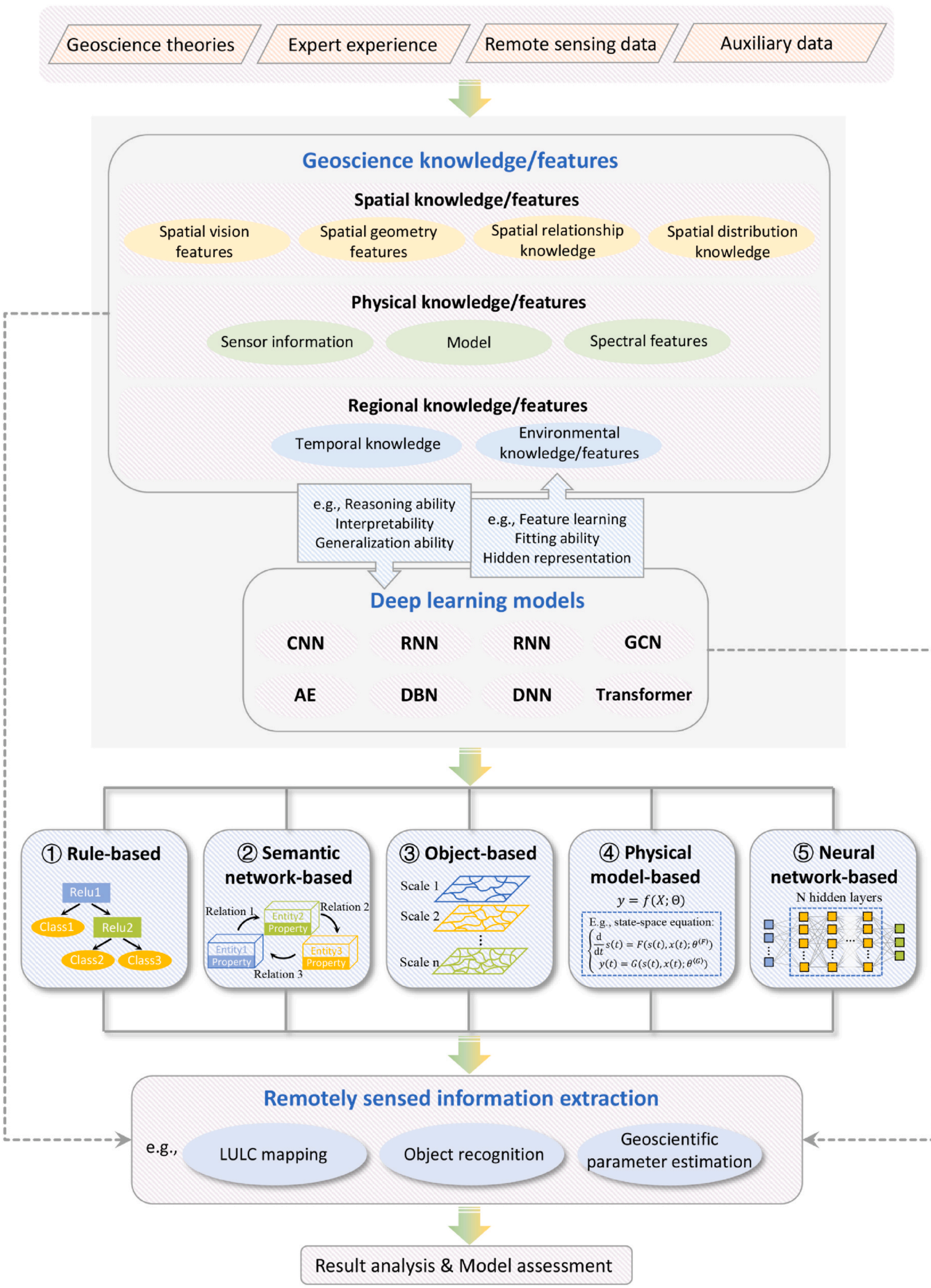

Fig. 2. Framework of approaches for deep integration of GK/GFs and DL models in GADL. Different types of GK/GFs and varieties of DL models can be deeply integrated based on the different representations of GK/GFs. Under this taxonomy, five main integrated approaches of GK/GFs and DL models are provided for solving various problems of remotely sensed information extraction. Note that only GK/GFs-based models and only DL models are capable of solving these problems (see 2 Gy dotted lines), but GADL offers an opportunity to fully combine the strengths of both models.

Table 1
Types, forms, and descriptions or examples of GK/GFs used in remotely sensed information extraction.

Types	Forms	Specific forms	Specific items	Descriptions or examples	References
Spatial knowledge/ features	Spatial vision features	Texture	Statistics based on GLCM	GLCM is the frequency of pixel pairs with gray values i and j respectively in a certain direction and distance. Some textural statistics are obtained from GLCM, e.g., Correlation, contrast, entropy.	Haralick et al. (1973)
			Random field model	Random field models use probability models to describe the random process of texture, including Markov random field (MRF) model, Gibbs model, simultaneous autoregressive random (SAR) model.	Hassner and Sklansky (1981); Liao et al. (1992); Elfadel and Picard (1994)
			Wavelet transform	Wavelet transform can analyze image texture details at multiple scales, and its successful development branches include tree-structured wavelet transform.	Mallat (1989); Chang and Kuo (1993)
			Fractal Dimension	Fractal dimension can be used as a measure of image roughness that is not sensitive to scale.	Pentland (1984)
			Morphological texture	Mathematical Morphology uses structuring elements with certain shape and size to detect the corresponding textures in the image.	Aptoula and Lefèvre (2011)
	Spatial geometry features	Shape	Basic descriptor	E.g., area, length, width, length/area, density, main direction, centroid, convexity.	Zhang and Lu (2004); Sun (2014)
			Shape index	E.g., $0.25E/\sqrt{A}$, $E/2\sqrt{\pi A}$, where E and A represent perimeter and area respectively.	Song and Civco (2004); Wu (2007); Du et al. (2019)
			Minimum bounding rectangle	It is the smallest rectangle that contains every point in the shape.	Yang et al. (2008)
			Moments	E.g., boundary moments, invariant moments, Zernike moments.	Zhang and Lu (2004); Ma et al. (2011)
	Spatial distribution knowledge	Spatial position	Geographic position	Geographic position refers to the absolute position of targets in a geographic coordinate system.	Zhou et al. (1999); "Geographic coordinate system", 2021
		Spatial structure	Structural characteristics	This refers to the geometric structure and its characteristics of the spatial distribution of ground objects. For example, connectivity of linear features such as rivers and roads.	Atkinson (2009); Ge (2013); Ge et al. (2019)
		Spatial pattern	Landscape pattern	This refers to the spatial arrangement and combination of landscape elements with different sizes and shapes. It can be divided into random, dispersed and clustered distribution, or point, linear and areal distribution.	Wu (2007); Ge et al. (2016); Ge et al. (2019)
	Spatial relationship knowledge	Orientation relation	Distance relation	It is used to specify how far the object is away from the reference object in a certain metric space (e.g., Euclidean space).	Chen and Zhao (1999); Qiao et al. (2011)
			Directional relation	It refers to the direction of one object relative to another.	
		Non-orientation relation	Topological relation	The disjoint, meet, overlap, inside, contains relations between any two spatial objects represented by points, lines, or polygonal areas.	Clementini et al. (1994)
Physical knowledge/ features	Sensor information	Imaging mode	Imaging parameter	Parameters related to imaging mode in remote sensing image metadata, e.g., imaging time, attitude, height.	Baltsavias (2004); Olsen (2007)
		Sensor performance	SNR	Signal-to-noise ratio (SNR) is the ratio of a signal level to a noise level, it reflects the image quality and radiometric performance of a remote sensing imaging system.	Fiete and Tantalo (2001)
			Spectral resolution	This refers to the bandwidth and the sampling rate over which the sensor gathers information.	Schowengerdt (2006); Pradham et al., 2008
			Spatial resolution	This refers to the smallest features in the scene that can be separated.	
			Radiometric resolution	This refers to range of discrete signals that the sensor can record.	
			Temporal Resolution	This refers to the time elapsed between consecutive images of the same ground location taken by the sensor.	
	Model	Physical model	Imaging geometric model	The imaging geometric model describes the relationship between the position of ground points in geospatial space and image points on remote sensing images. For example, the central projection model, rigorous sensor model, and affine projection model in optical imaging system.	Hattori et al. (2000); Robertson (2003)
			Quantitative remote sensing model	Quantitative remote sensing models are based on physical processes and mechanisms to characterize the interaction between remote sensing signals and ground features. For example, radiation transfer models, geometric-optical models, and dynamic models that characterize plant growth, carbon cycle, and water cycle.	Zhang et al. (2019a)
	Spectral features	Spectral index	Vegetation index	The indicators are designed to evaluate vegetation growth and biomass, including NDVI, enhanced vegetation index (EVI), ratio vegetation index (RVI), difference vegetation index (DVI), soil-adjusted vegetation index (SAVI).	Bannari et al. (1995); Xue and Su (2017)
			Water index	The indicators are designed to delineate open water features and enhance water information, e.g., normalized	McFeeters (1996); Xu (2006)

(continued on next page)

Table 1 (*continued*)

Types	Forms	Specific forms	Specific items	Descriptions or examples	References
				difference water index (NDWI), modified normalized difference water index (MNDWI).	
			Built-up index	The indicators are designed to map built-up areas quickly and objectively, e.g., normalized difference built-up index (NDBI).	Zha et al. (2003)
			Soil index	The indicators are designed to enhance soil covers, e.g., normalized difference soil index (NDSI).	Deng et al. (2015)
			Burn index	The indicators are designed to highlight burnt areas in large fire zones, e.g., normalized burn ratio (NBR), differenced normalized burn ratio (dNBR).	García and Caselles (1991); Cocke et al. (2005)
			Other indices	Other indices are used to enhance corresponding information. For example, the cloud index (CI) and cloud shadow index (CSI) are proposed to indicate the potential clouds and cloud shadows.	Zhai et al. (2018)
		Spectral characteristic	Spectrum library	The spectrum library is a collection of reflection spectrum data of various ground objects. It can be measured by spectrometers or obtained by hyperspectral images.	Zomer et al. (2009)
			Spectral reflectance curve	The relationship curve between the reflectivity of the ground object and the wavelength.	Singh and Sirohi (1994); Kim et al. (2018)
		Band combination	False-color composite	This is a synthesis method of any non-red, green, and blue real bands, which can be used to display richer information or highlight certain information.	Yin et al. (2012); Lu et al. (2020)
Regional knowledge/ features	Temporal knowledge	LULC change	Land use transfer matrix	The matrix describes the structural characteristics of regional land use change and the change direction of each land use type.	Liu et al. (2018b)
		Phenological change	Seasonal rhythm	For example, the growth of plants (including crops) changes regularly with the seasonal change of climate.	Zeng et al. (2020b)
	Environmental knowledge/features	Topographical features	DEM	DEM is a 3D representation of the terrain elevation of the bare Earth surface.	"Digital elevation model", 2021
			DSM	DSM refers to the ground elevation model including the height of surface buildings, bridges and trees.	
			Slope	Slope is the rise or fall of the land surface, and it refers to the elevation difference between two points of a unit distance.	Brouwer et al. (1985)
			Aspect	Aspect is the compass direction that a topographic slope faces.	Chang and Tsai (1991); "Aspect", 2013
		Historical knowledge	Physical regionalization	Physical regionalization refers to the regional division based on regional differentiation, including the division of landforms, climate, hydrology, soil, organisms and other physical geographical elements.	Lu and Weng (2007); Macias et al. (2020)
			Map products	Historical classification products and other socioeconomic zoning products related to regions such as historical LULC maps, vegetation type maps, soil maps. They are highly condensed expert knowledge.	Lu and Weng (2007); Wu et al. (2015); Zhu et al. (2021)

Note: The specific items in each knowledge/feature form mentioned in the table are limited, and only the items commonly used in remotely sensed information extraction are listed.

quantitative representation of shape is usually based on smaller meaningful objects into which the image is segmented (Lande et al., 2014). Also, shape usually provides explicit geometric constraints for the detection of buildings, roads and other objects (Cheng and Han, 2016; Lian et al., 2020).

According to the spatial range from small to large involved in the distribution of ground objects, spatial distribution knowledge generally includes the spatial absolute position, spatial structural characteristics and spatial distribution pattern of ground objects. First, objects distributed in different spatial locations often exhibit certain regional characteristics. For example, both horizontal zonality and vertical zonality associated with horizontal position and elevation, respectively, should be considered when distinguishing vegetation types (Yao et al., 2020). At the same time, spatial absolute location can also be used for geographic registration of images and historical data (Zhong et al., 2020; Li et al., 2021b), which is the key to the integration of multi-source knowledge/feature forms. Second, some ground objects often present obvious spatial structural characteristics which are conductive to information extraction. For example, farmland and fishponds are usually regular, while roads and rivers are linear features with connectivity. Multiple-point simulation is an effective way to capture complex geometric structural information (Atkinson, 2009). It first recognizes the structural characteristics of ground objects from training data, and then reproduces the spatial distribution structures. For example, Ge (2013) successfully introduced the spatial structural information of ground objects acquired by multi-point simulation into the soft classification results to reduce the uncertainty of soft classification. Third, spatial distribution pattern as *prior* knowledge has been applied to differentiate the distribution structure of ground objects in existing research (Xu et al., 2013; Ge et al., 2016, 2019), so as to guide the selection of information extraction strategies under different distribution patterns. Super-resolution land cover mapping is a technique that reconstructs the spatial distribution of land cover objects at the subpixel scale. In this regard, Ge et al. (2016) developed divide-and-conquer super-resolution mapping strategies for different types of ground objects (i.e., areal, linear and point objects classified according to the planar shape of the spatial distribution).

There are mutual restrictions and interdependencies amongst the various elements of the geographical environment. Therefore, target objects are often closely related to their surroundings and other objects. This kind of spatial connection or association is summarized as spatial relationship knowledge, which is a high-level knowledge/feature form represented through the relative positions of ground objects. Spatial relationship knowledge is a popular knowledge/feature form for remote sensing image classification and object detection and extraction (Baltsavias, 2004). Distance relation is the most fundamental spatial relation, and an example of its application is the image classification of the city and offshore area (Qiao et al., 2011). In this study, the spatial relationship related to spatial distance and spatial adjacency helped to modify and improve the preliminary classification results, discriminating water and shadows effectively, as well as beach and construction. In another example, the urban buffer defined around population center coordinates and the nearest distance from river formed a spatial model for knowledge-based land cover classification, leading to increased accuracy (Daniels, 2006). The directional relation is less widely used, but a representative example is the use of shadow, which is a common cue for building detection (Cheng and Han, 2016). In this respect, Ok (2013) modeled the directional spatial relationship between buildings and their shadows to automatically detect buildings from single very-fine-resolution images. The topological relation is a type of spatial relationship knowledge for spatial analysis of geoscience data or ground objects expressed by points, lines and polygonal areas. In applications, the topological relation is especially suitable for the extraction of linear features such as roads, to ensure their intersection and connectivity (Lian et al., 2020). It is worth noting that although the introduction of spatial relationships can compensate for spectral confusion (Qiao et al., 2011), how to appropriately transform the invisible relationships between targets into explicit knowledge representations has always been an important topic for information extraction (Cheng and Han, 2016).

3.2. Physical knowledge/features

Physical knowledge/features are related mainly to the imaging principle and process of the sensor, as well as the mechanism of electromagnetic waves reflected and radiated by ground objects. Here, the physical knowledge/features that can be used in extraction information from remote sensing data is grouped into three forms: sensor information, model, and spectral features.

Sensor information is the mastery of the sensor imaging mode and imaging performance. This knowledge/feature form can provide the necessary parameters and information for methods of target information extraction and quantitative estimation of geoscience variables, as well as guide the selection of remote sensing images and the design of information extraction algorithms. First, some parameters in remote sensing image metadata are generally available. The elevation and azimuth angles of the satellite and Sun can be used for shadow-based building height inversion (Li et al., 2014), while these angular parameters on the geometric properties of satellite imaging are also indispensable input parameters for vegetation canopy reflectance models (Hilker et al., 2017). Furthermore, in the "remotely sensed big data era" (Zhang et al., 2019a), more and more research focuses on the fusion of images from different sensors with various spatial, temporal and spectral resolutions, including some street view images and geo-tagged photos. In this way, the complementarity of multi-source sensor data in the spatial, temporal and spectral dimensions can, for example, be brought into fuller play to obtain more accurate results for subpixel mapping (He et al., 2019), LULC mapping and change detection (Cao et al., 2018; Xi et al., 2019), and impervious surface extraction (Powell et al., 2008; Zhang et al., 2017a; Shao et al., 2021).

Model refers to knowledge of the parametric models associated with the remotely sensed information extraction process, including the imaging geometric models used for image geometry rectification when necessary, and the physical models that are of greater concern here. Physical models mainly refer to quantitative remote sensing models in remotely sensed information extraction. Quantitative remote sensing physical models transform electromagnetic wave information into useful knowledge by establishing physically meaningful equations and models (Zhou et al., 1999), which are utilized to retrieve the geoscientific information needed for operations and research. In plant growth, the terrestrial water cycle, carbon and nitrogen cycles, land surface radiation, and other geoscientific processes, such physical models express the mechanisms of action between geoscience variables and remote sensing observations and transmission media through clear formulae (Zhang et al., 2019a; Yuan et al., 2020; Jiang et al., 2020).

Spectral features are based on the spectral reflectance characteristics of ground objects. One of the most widely used knowledge/feature forms in spectral features is the spectral index. In contrast to imaging geometric models and quantitative remote sensing models, spectral indices, which are abstract constructs obtained by mathematical operation on multi-spectral remote sensing data, more empirical-based than physical-based, but we include them here because of their wide application. They are developed by experts to extract and quantify thematic information related to the indices. For example, required biophysical or environmental parameters, such as biomass, chlorophyll content and vegetation coverage can usually be estimated by establishing the relationship between them and vegetation indices (Li et al., 2012; Tong and He, 2017; Yue et al., 2019). Adamo et al. (2020) incorporated normalized difference vegetation index (NDVI), green/red ratio, blue/NIR ratio and brightness for effective implementation of knowledge-driven grassland ecosystem classification; Zhai et al. (2018) proposed a cloud index and cloud shadow index, and both spectral indices were applied in a unified cloud/shadow detection algorithm. Besides, when synthesizing multi-band images, false color composites are often used to highlight some ground object information. There was a successful application case, where Lu et al. (2020) found that false color red-green-blue composite images from multi-band sensors helped to discriminate water-in-oil and oil-in-water emulsions in the ocean.

3.3. Regional knowledge/features

Regional knowledge/features are related to the temporal evolution of ground objects, the physical geographical environment, regional differentiation and the socio-economic conditions within a region. Here, we subdivide regional knowledge/features into temporal knowledge and environmental knowledge/features, as shown in Table 1.

Temporal knowledge reflects primarily the changes in ground objects over time. The most typical temporal knowledge used in remotely sensed information extraction is the seasonal variation of plant growth (i.e., seasonal rhythm). First, this phenological rhythm is beneficial for extracting vegetation information itself (Almeida et al., 2013). One prime example is that different temporal images are often selected to distinguish vegetation areas according to the biomass differences of different types of vegetation, such as herbaceous and woody classes, evergreen and winter-deciduous classes (Adamo et al., 2020). Second, the extraction of non-vegetation objects can be facilitated by maximizing the spectral signature differences between vegetation and non-vegetation objects such as residential areas (Zhou et al., 1999) and impervious surfaces (Weng et al., 2009).

Environmental knowledge/features refer to the surrounding environmental conditions of the ground objects and knowledge of the spatial dependence from a rather macroscopic perspective. Among the various factors affecting the formation of the land surface environment, topography is undoubtedly a dominant factor. In previous studies, DEMs, digital surface models (DSMs), slope, aspect and related terrain indices were used frequently as *prior* information and combined with remote sensing data and other georeferenced GIS data to establish classification and analysis models, demonstrated to significantly increase the mapping accuracy of LULC (Daniels, 2006), vegetation type (Yao et al., 2020), soil type (Dornik et al., 2016) and landslide susceptibility (Senouci et al., 2021) in mountainous regions (Lu and Weng, 2007). Another type of environmental knowledge/features is embedded in historical products related to physical regionalization, classification of ground objects and other zoning. These products, such as land use thematic maps, geomorphologic thematic maps and ecological zoning maps within a certain area are all the result of the regional cognition of geoscientists from a professional perspective. Thus, this type of knowledge can be extremely valuable (Wu et al., 2015; Wang et al., 2021b). The following applications have shown that the integration of this type of knowledge can overcome the problem of spectral confusion to a large extent and improve information extraction. With the effective support of the mountain altitudinal belts, Yao et al. (2020) produced a vegetation type map with medium and large scales in mountain areas. Based on the urban ecoregion scheme proposed by Schneider et al. (2010), Liu et al. (2018a) first stratified the global area, then calculated the normalized urban areas composite Index (NUACI) (Liu et al., 2015) and set region-specific thresholds for multi-temporal global urban land mapping. Additionally, pre-interpreted thematic maps can be regarded as *prior* knowledge to guide automatic collection of object samples for object-based remote sensing classification (Wu et al., 2015). More importantly, regional knowledge/features have also been demonstrated to be valuable in large-scale land cover mapping. The reliable GlobeLand30 global land cover mapping product (Chen et al., 2015) were produced after implementing natural knowledge, cultural knowledge and temporal constraints knowledge-based interactive testing, for example.

4. Deep integrated approaches in GADL

In recent years, some advanced approaches for integrating domain knowledge into DL models have been developed. Based on the representation of GK/GFs, a taxonomy of these approaches applied for remotely sensed information extraction is provided in this section. Five main approaches are summarized in Table 2 under this criterion. A review of each category is detailed in the following subsections.

4.1. Rule-based integration

Rule-based knowledge/feature representation, which mainly expresses knowledge/features by structured “if-then” forms that are consistent with human logical reasoning, is one of the simplest machine-understandable expressions and the focus of early AI research (Wang et al., 2020a). Both expert systems (Goodenough et al., 1987) and the widely used decision tree in machine learning (Friedl and Brodley, 1997) are developed based on this kind of representation (Wang et al., 2020a). Since rule-based representation is highly explanatory and operable, it has flexible applications in many Earth system science problems (Xu et al., 2005; El Hajj et al., 2009; Schneider et al., 2010; Lu et al., 2020; Singh et al., 2020). In these cases, a large number of spectral features (e.g., spectral indices) and environmental knowledge/features (e.g., topographical features, phenological stages, cropping systems, socioeconomic statistics) listed in Table 1 can be transformed into rules to be used in the process of information extraction. In this context, it is desirable to incorporate these logic rules into DL models, so as to introduce GK/GFs and increase interpretability.

Integrating rule-based knowledge/features into neural networks has been explored in some contexts. Neural-symbolic computing aims at integrating symbolic AI based on knowledge representations and connectionist AI based on neural networks in a principled way to construct an explainable AI system (Samek et al., 2017; Garcez et al., 2019). The knowledge-based artificial neural network (KBANN) (Towell and Shavlik, 1994) is one of the most influential models in the early development of neural-symbolic systems that combines logical reasoning and neural learning. In KBANN, a rules-to-network translator is responsible for establishing a mapping between a rule set used by experts and a neural network first. Then the newly-built initial network is refined using a learning algorithm (e.g., the backpropagation algorithm) and a set of training examples. Subsequently, Wu (2001) discussed the conceptual steps of an interpreting system for remotely sensed imagery based on the approach for constructing KBANN. Specifically, Wang (2018) designed a rule-embedded neural network and validated it with a time-series electrocardiograph signal detection problem. In this design, a rule modulating block was used to generate the rule-modulated map, which brought knowledge from human teachers to contribute to the global-based inference. For DL models, a general iterative distillation method was proposed by Hu et al. (2016), which had the ability to introduce logic rules expressing structured information into DL models and guide the learning process. Fig. 3 depicts the architecture of rule knowledge distillation, where a student network is projected to a rule-regularized subspace to construct a teacher network at each iteration, and simultaneously this student network is updated to form a trade-off between imitating the soft predictions from the teacher network and predicting the true labels. Experiments on both CNNs and RNNs, respectively, for sentiment analysis and named entity recognition have demonstrated that this algorithm is able to integrate knowledge encoded as rules to DL models.

Generally, since static rule-based representation is brittle and lacks learnability, simultaneously neural networks lack interpretability and have high learning costs, the combination of these two aspects can overcome their respective deficiencies. However, there are few studies on the rule-based integration of GK/GFs and DL models due to many challenges. For example, the algorithm of embedding rules into neural network is relatively more complex; the rule-based approach is probably

Table 2
A taxonomy of approaches for integrating GK/GFs with DL models.

Categories	Applicable GK/GFs	Characteristics	Typical references
Rule-based integration	Spectral features (e.g., spectral indices), and environmental knowledge/features (e.g., precipitation, temperature, topographical features, phenological stages)	The representation of rule-based knowledge/features is flexible, but it is relatively difficult to embed it into neural networks.	Towell and Shavlik (1994); Wu (2001); Hu et al. (2016); Wang (2018)
Semantic network-based integration	Spatial distribution knowledge and spatial relationship knowledge	It is suitable for expressing relational knowledge, but the construction process of semantic network itself is relatively complicated. It is also not very easy to embed the semantic network into neural networks.	Alirezaie et al. (2019); Li et al., 2020a
Object-based integration	Spectral features, spatial knowledge such as texture, geometry, spatial distribution, and spatial relationship	Image objects are suitable for flexible expressions of more GK/GFs. The integration models based on GCN, which are more conducive to representing the long-range spatial relations, deserve further attention.	Zhao et al. (2017); Zhao et al. (2019); Hong and Zhang (2020)
Physical model-based integration	Mechanisms and processes that can be expressed in explicitly mathematical formulas	It is one of the popular approaches to introduce domain knowledge into DL models recently. Some complex constraints from the physical models may lead to more time consumption.	Reichstein et al. (2019); Raissi et al. (2019); Jiang et al. (2020); Wang et al. (2020b); Wang et al. (2020c); Karniadakis et al. (2021); Teisberg et al. (2021)
Neural network-based integration	Spatial features, spectral features, temporal knowledge, and environmental knowledge/features	It is another popular approach to integrate GK/GFs into DL models. This category has more plentiful and flexible forms. How to effectively strengthen the auxiliary geoscience data/features that are conducive to improving the performance of DL models, and enhance the interpretability of results remains to be further investigated.	Li et al. (2017); Audebert et al. (2018); Kim et al. (2018); Wu et al. (2021); Li et al. (2021b); Yang et al. (2021); Mañas et al. (2021); Ayush et al. (2021)

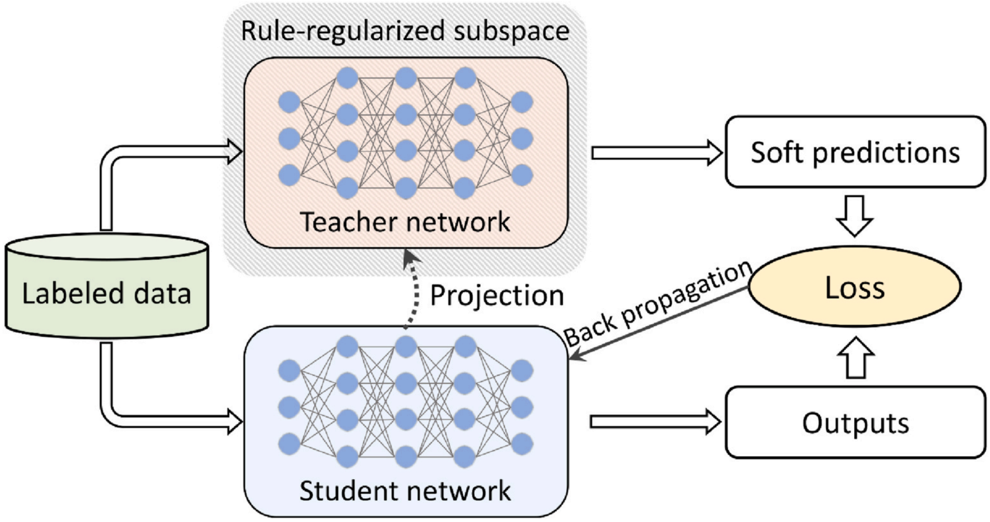

Fig. 3. Flowchart of an iterative rule knowledge distillation.

not suitable for scaling up. Still, the existing research has opened a door for subsequent remotely sensed information extraction.

4.2. Semantic network-based integration

The semantic network is one of the most common formalisms for knowledge representation in symbolic AI. It is a way to express knowledge in the form of a directed graph. A semantic network is composed of nodes representing entities or concepts and directed arcs representing relationships between nodes. Compared with rule-based knowledge representation, a semantic network is good at constructing the organic relationship between various complex things, especially suitable for expressing relational knowledge (Zhou et al., 1999; Hao et al., 2021). Thus, it is highly appropriate for characterizing the spatial distribution knowledge and spatial relationship knowledge in GK/GFs. Ontologies and knowledge graphs (KGs) are two representative modern implementations of semantic networks (Futia and Vetrò, 2020).

An ontology semantically describes fundamental concepts and their relations by different levels of abstraction, and has strong capabilities for knowledge representation, inference and sharing (Arvor et al., 2013; Réjichi et al., 2015; Li et al., 2020). In the domain of remote sensing analysis, ontologies were investigated as conceptual support for topological representations to provide formal semantic relationships for remote sensing data (Oliva-Santos et al., 2014). At the same time, ontological knowledge representing different spatial and hierarchical levels was recommended to be exploited in a joint DL manner to address the complex land cover and land use classification task (Zhang et al., 2019b). In particular, ontology-based methods were suggested to apply in remote sensing interpretation because of their explicit representation of symbolic knowledge (Réjichi et al., 2015; Andrés et al., 2017; Arvor et al., 2019). In this sense, ontologies have played a positive role in the unification of GK/GFs and DL models. As a first attempt in this direction, Alirezaie et al. (2019) proposed a semantic image segmentation method in which an ontological reasoner can interact with the DL model. More specifically, as Fig. 4 shows, features of misclassified regions are conceptualized by an ontological reasoner in terms of their spatial relations with the surroundings; then the reasoner gives feedback to the convolutional auto-encoder (AE) classifier in the form of additional channels. Li et al. (2020) further presented a collaborative framework to combine knowledge-guided ontological reasoning and DL in an iterative manner for semantic segmentation of remote sensing images. In this method, it is worth emphasizing that the ontological reasoning consists of two reasoning modules: the intra-taxonomy reasoning refining the classification result of DL model through ontological reasoning rules, and the extra-taxonomy reasoning generating the inferred channels used as input to the DL model. In doing so, it promotes both interpretability and classification accuracy.

KGs, which are essentially large-scale semantic networks, are a new

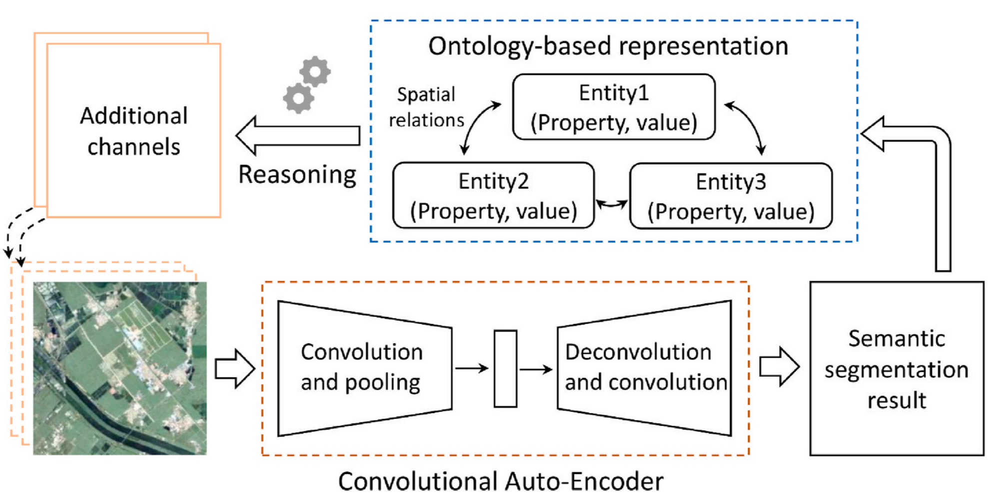

Fig. 4. Flowchart of remote sensing image semantic segmentation based on the synergy of ontological reasoning and a DL model.

method of knowledge representation (Hao et al., 2021). Thanks to the native reasoning mechanism, KGs have performed well in personalized recommendation, intelligent search, question answering, etc. (Lu et al., 2019). Given that KGs and their underlying semantic technology can provide human-understandable insights for DL techniques, Futia and Vetrò (2020) suggested incorporating KGs into DL models focusing on three future research directions: knowledge matching, cross-disciplinary explanations and interactive explanations.

Overall, the current research on integrating ontologies or KGs into DL models, especially in terms of remotely sensed information extraction, is in its infancy focusing mainly on envisioning or preliminary experiments. This is mainly because the construction process of ontologies and KGs is relatively complicated, and it is not very easy to embed them into the optimization process of neural networks at present. However, with the introduction and development of new concepts such as geographic KGs (Wang et al., 2021b), this will still likely be a promising approach to explainable AI in the field of geoscience and remote sensing.

4.3. Object-based integration

Object-based image analysis, or to be precise geographic object-based image analysis (GEOBIA), is devoted to analyzing remote sensing imagery automatically by means of meaningful image objects (typically derived from segmentation) rather than individual pixels (Hay and Castilla, 2008; Blaschke et al., 2014). During the process, not only spectral information, but also spatial knowledge such as texture, geometry, the location distribution of ground objects and contextual information introduced by multi-scale segmentation are quantified as the characteristics of the image objects (Chen et al., 2018). Thus, compared with single pixels that express only spectral information and limited contextual relations, the image object has become a crucial carrier of knowledge (Blaschke et al., 2014). In GEOBIA, object-based analysis is often combined with rule sets to make full use of GK/GFs, and this approach has been popularized in remotely sensed information extraction, including object detection (Cheng and Han, 2016), change detection (Zhang et al., 2017b; Toure et al., 2018), (super-resolution) land cover mapping (Wu et al., 2015; Chen et al., 2017; Du et al., 2019) and agricultural landscape mapping (Garcia-Pedrero et al., 2015).

Although most DL methods, especially those based on CNN architectures for remote sensing image analysis are pixel-based, some research showed that DL models could benefit from the strengths of object-based methods. In this regard, in the majority of methods integrating GEOBIA and CNN, remote sensing images are partitioned into image objects to generate patches as the inputs to a CNN, and the classes of the image objects are then determined through pixel classification using the CNN. These methods are mostly different in patch generation and segmentation methods. For example, to accurately predict the land use classes of image objects with different shapes, Zhang et al. (2018) designed two object-based CNN models with either a range of small input windows or a large input window to deal with linearly shaped objects and other general objects. Fu et al. (2018) extracted image patches as inputs to a CNN according to fixed window sizes and the center of gravity of the segmentation objects generated by a multi-resolution segmentation algorithm. Moreover, in a change detection method for geographical areas (Liu et al., 2021b), the bounding boxes of segmented objects were used to generate image patches that fed in the CNN. Different from the aforementioned patch-based CNNs integrated with GEOBIA, Zheng et al. (2021) proposed a deep object-based semantic change detection framework for end-to-end building damage assessment, where a deep object localization network was adopted to generate accurate building objects, in place of conventionally non-differentiable image segmentation.

Some studies have introduced more object-based GK/GFs into object-based CNN frameworks and achieved satisfactory results. For example, Zhao et al. (2017) combined highly abstracted deep features from CNNs with object-based features (i.e., the mean brightness of each band and the NDVI) under the constraint of boundary information of image objects, and then leveraged a two-layer neural network classifier and optimal statistics to achieve more precise fine-resolution image classification. Afterwards, this object-based CNN was utilized for identifying complex ground objects by inputting semantic elements derived from open street map data, which is a pivotal step for further urban scene classification (Zhao et al., 2019). In addition, Hong and Zhang (2020) devoted a CNN to extracting deep features of ground objects from multiscale low-level features such as texture, shape and spectral features of image objects, and these multiscale deep features were stacked for hyperspectral image classification.

Besides CNNs, in recent few years, GCNs have also attracted mounting attention, because its information propagation based on graph structures are suitable to exploit spatial contextual information in image analysis (Liu et al., 2020; Zhang et al., 2021b). To reduce the computational burden of GCNs in remote sensing image classification, Hong et al. (2020a) proposed a minibatch training fashion, which uses minibatch GCNs generated by random sampling from a full graph to train large-scale GCNs. In addition, the segmented superpixel, which is a homogeneous region composed of raw pixels similar to an image object, is usually selected as the nodes of the graph in some GCNs-based methods to circumvent high storage and computational cost. By using superpixels, there is no need for extra shape constraints or post-processing in remote sensing image classification. Meanwhile, it is convenient to integrate spatial relations between superpixels into network structures (Zeng et al., 2020a). For example, Wan et al. (2019) and Wan et al. (2020) introduced multi-scale spatial structural information by building different graph structures, and captured the changes of spatial dependence and similarity between nodes through dynamic updating of edge weights.

In summary, the effectiveness of integration of object-based knowledge/feature representations and DL models has been confirmed in recent research when maintaining the integrity of distribution patterns of ground objects and guaranteeing semantic consistency within each image object. However, research in this area is still in early development, and many object-based knowledge and features (e.g., long-range spatial relations) are expected to be incorporated into object-based DL architectures. In particular, GCNs and other graph neural networks are naturally compatible with object-based methods, and their potential in this area remains to be further investigated. Here, a schematic implementation of a potential object-based GCN method for image classification is shown in Fig. 5, where the segmented objects and their corresponding features (e.g., texture, shape and spectral features) can be regarded as graph nodes and node attributes, respectively. The multiscale and long-range spatial relations between nodes can be introduced for constructing graph that will be used by GCNs to learn node representations and obtain classification results.

4.4. Physical model-based integration

Many geoscientific problems rely on physical theories and representations. Physical models are explicitly mathematical formulas designed by human experts to better analyze and understand processes or phenomena in the real-world system. Such physical models, whose structures are often described by complex forms (e.g., a series of nonlinear differential equations (DEs) (Todorovski and Džeroski, 2006; Karpatne et al., 2017b; Raissi et al., 2019)), encapsulate rich domain-specific knowledge (e.g., cause-effect relationships between variables) involved in geoscience processes and phenomena. As a cornerstone of geosciences, physical model-based approaches have always been the basis for the development of research fields such as geoscientific parameter retrieval and dynamic systems modeling. However, there is a lack of sound physical models since real physical processes are generally highly complex (Zhang et al., 2019a). At the same time, high computational cost is often needed to estimate the

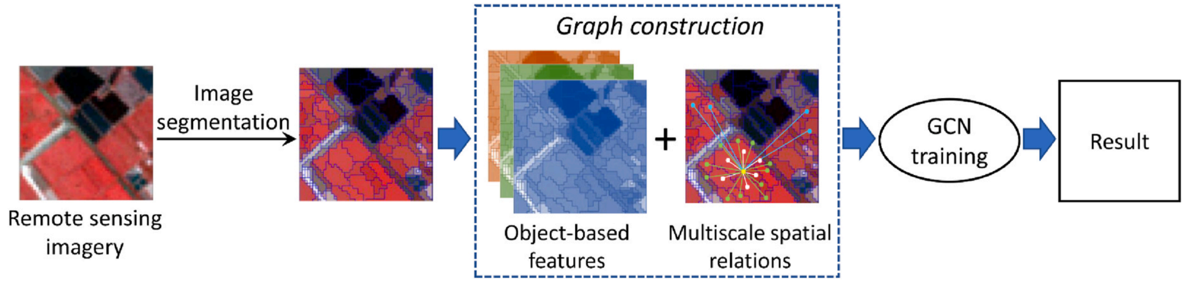

Fig. 5. A schematic implementation of an object-based GCN. Multiscale spatial relations can be introduced for graph construction, where the white nodes and green nodes denote the first-order neighbors and second-order neighbors of the yellow center node. Besides, graph structures also help to build long-range spatial relations. For example, the long-range similarity between the blue nodes and the center node. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

parameters of physical models (Yuan et al., 2020). Given this, DL models have been exploited to provide a feasible and alternative scheme for approximating complex physical processes. DL-based methods have achieved remarkable successes for the retrieval of land surface temperature (Tan et al., 2019), spatiotemporal estimation of air pollutants (Li and Wu, 2021), and many other applications requiring environmental parameter estimation and process simulation. Nevertheless, limitations still exist in DL model-based applications due to a lack of labeled instances and lack of guidance from scientific principles or laws, as well as the sensitivity of DL models to noise in training data (Wang et al., 2020b).

To overcome the above challenges, current research is pointing to the need for a new paradigm which aims to actualize the synergy of DL and physical models (Reichstein et al., 2019; Gil et al., 2019). For example, theory-guided data science (TGDS) was recommended as a schema (Karpatne et al., 2017b), where scientific theories and data science models were systematically combined through several strategies. One of the most effective avenues to deeply integrate physical models with DL is modeling physical regularization-constrained DL architectures to ensure physical consistency and interpretability (Karpatne et al., 2017b; De Bézenac et al., 2019). The architecture of this strategy is demonstrated in Fig. 6. In fact, embedding physical constraints into neural networks has appeared for a long time. For example, super-resolution mapping using a Hopfield neural network (HNN) adopted a similar strategy. In this method, the proportion constraint was injected into the energy function of the HNN to retain the class proportions determined from soft classification (Tatem et al., 2001, 2002). In recent years, this approach has been continuously adapted. Karpatne et al. (2017a) established a physics-guided neural network (PGNN) model for modeling lake temperature. The physics-based loss function of this neural network was designed according to the physical relationships between physical quantities. Similar work was studied by Jia et al. (2019), where a physics-guided recurrent neural network (PGRNN) was presented to model lake water temperature. This model integrates a special energy conservation flow into the standard recurrent process and captures the variation of energy balance over time by introducing the loss function term for energy conservation. Subsequently, a more general framework, the theory-guided neural network (TgNN), was developed to deal with the problem of subsurface flow (Wang et al., 2020b). This framework simultaneously imports practical experience (i.e., expert knowledge, engineering controls) and physics principles (i.e., those expressed by partial differential equations (PDEs) and boundary conditions) as penalty terms of the loss function of a deep neural network (DNN). More motivating examples concern physics-informed neural networks (PINNs) (Raissi et al., 2019; Karniadakis et al., 2021), in which PDEs were embedded into the loss function of neural networks using automatic differentiation. In this way, the loss function of PINNs seamlessly integrates the supervised loss of measurements and the unsupervised loss of PDEs. The powerful capability of this physics-informed learning is reflected in its diverse application. For example, Teisberg et al. (2021) applied PINNs to interpolate mass-conserving ice thickness in combination with loss of radar data fit, velocity data fit and mass conservation loss. Also, Wang et al. (2020c) investigated the performance of PINNs constrained by the

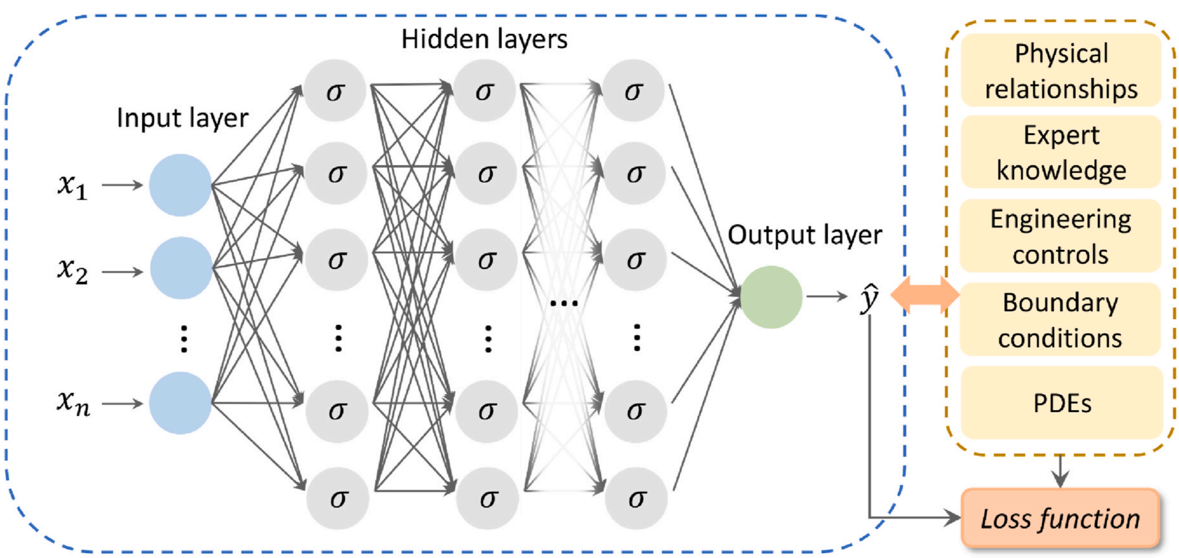

Fig. 6. Physical regularization-constrained DL architectures.

advection-diffusion equations of atmospheric pollution plumes for image super-resolution with missing values. Another effective strategy to deeply implant physical representations into DL is to wrap physical models into the neural network layers. As presented by Jiang et al. (2020), a physical process-wrapped recurrent neural network (P-RNN) layer with physically meaningful parameters was designed, and it was utilized to incorporate geosystem dynamical ordinary differential equations into DL models.

Overall, the introduction of physical models can provide constraints for the optimization process of DL models. Although the above methods are applied mainly in physics related disciplines at present, the research can provide profound inspiration for the quantitative extraction of information from remote sensing data. Meanwhile, similar methods can be used for geospatial statistical characteristics, such as spatial autocorrelation (e.g., Moran's I (Moran, 1950) and LISA (Anselin, 1995)), and spatial heterogeneity (e.g., q statistics (Wang et al., 2016)). Through in-depth integration of physical models into DL, it should be possible to obtain more accurate, reliable and understandable results of geoscientific parameter estimation, simulation and interpolation (including downscaling) involving geoscientific processes and phenomena governed by physical laws or natural laws.

4.5. Neural network-based integration

Neural networks themselves are capable of effective knowledge/feature representation. In particular, unlike conventional machine learning needing labor-intensive feature engineering, DL is a powerful representation-learning technology because it allows automatic learning of features with multiple levels of abstraction from raw data through multiple processing layers (LeCun et al., 2015). For the issue of remotely sensed information extraction, rich auxiliary geoscience data and shallow GFs provide a driving factor for DL-based knowledge discovery, and the deep or latent GK/GFs can be excavated by DL models and will be hidden in the trainable parameters of neural networks (Wu, 2001; Wang et al., 2020a). Therefore, the following two strategies are worthy of attention. First, the integration of different types of GK/GFs extracted from remote sensing data by DL models. Second, simultaneous feed-in of geoscience-related data, formalized information or shallow features into DL models together with remote sensing data, and then use of deep GK/GFs extracted by neural network layers to assist or guide information extraction from remote sensing data. Currently, benefiting from the flexible architectural design of DL model, the above approach can be attempted via the following six main means.

(1) Introducing auxiliary geoscience data/features as input into DL models through individual neural network processing stream. This architecture stacks directly geoscience auxiliary data converted into raster format and remote sensing data or converts information into feature representations, such as those formalized as geographical laws, as its input. For example, DSM and normalized DSM can be fed into a CNN as additional channels stacked with image data (Paisitkriangkrai et al., 2015) to improve semantic pixel labelling. Kim et al. (2018) transformed two seasons of multispectral images into 2-D spectral reflectance curve graphs, taken as the input of CNNs for land cover classification. In their work, the multitemporal images endow 2-D spectral curves with phenological characteristics of land covers. To estimate ground-level $PM_{2.5}$ in China, Li et al. (2017) developed a deep belief network (DBN) model taking spatial-temporal autocorrelation of $PM_{2.5}$ as two input variables, and these two terms were computed, respectively, based on inverse spatial and temporal distance weightings.

(2) Designing DL models with two neural network branches to learn deep features separately from input auxiliary geoscience data/features and remote sensing images and then fuse them. Those deep features are generally fused through summation or concatenation in the middle or at the end of the two streams. FuseNet (Hazirbas et al., 2016) is one of the most influential two-branch CNN architectures based on heterogeneous data fusion, which is developed to improve semantic image segmentation results by incorporating depth information. Subsequently, Audebert et al. (2018) further investigated the usefulness of FuseNet for semantic labeling of remote sensing imagery. In this architecture, NDSM/DSM/NDVI and remote sensing imagery were input as the auxiliary branch and main branch, respectively, and the auxiliary features were fused into the main branch though element-wise summation at multiple levels (See Fig. 7). Many other studies suggested that topographical data can benefit semantic segmentation (Sherrah, 2016; Marmanis et al., 2016, 2018), in which color images and NDSM/DSM data are processed in two parallel networks since DSM and images have different statistics (Sun and Wang, 2018). Among them, Marmanis et al. (2018) appended a special boundary-detection network before the segmentation network, and this special block also contained a DSM stream to help extract explicit boundary information for the purpose of improving semantic image segmentation. Different from frameworks relying solely on image data, Wu et al. (2021) proposed a novel framework for remote sensing cloud/snow detection, in which geographic information (i.e., altitude, latitude and longitude) was introduced by encoding it to a string of auxiliary maps and feeding it into the branch network. Finally, the deep features were concatenated with dense features from image data for more accurate prediction. Similar dual-branch architectures were also used for deeply joint spectral-spatial features of imagery (Yang et al., 2016) or heterogeneous features from aerial and street view images (Cao et al., 2018; Hoffmann et al., 2019), as well as fusing multimodal data for remotely sensed image classification via several different fusion strategies under a general multimodal DL framework (Hong et al., 2020b).

(3) Leveraging attention modules to achieve feature enhancement or feature selection when fusing features. Although the above two approaches are relatively more common to integrate GK/GFs into DL models, the current fusion strategies cannot strengthen the features that are conducive to improving the performance of DL models. An attention module is a special structure that can be embedded into DL models (Yang and Qi, 2021). It is capable of automatically learning and computing feature weights utilized to highlight critical information, in other words, suppress the interference of useless information (Yang et al., 2021). Combining spatial attention (Woo et al., 2018) and channel attention (Hu et al., 2018) has exhibited impressive capabilities in scene semantic segmentation (Fu et al., 2019) and building outline extraction (Zhao et al., 2021), etc., which can capture feature weights and help obtain key features in both spatial and channel dimensions. Lately, two kinds of attention mechanisms have been used to incorporate GFs into DL models for semantic segmentation of remote sensing imagery. In this vein, Yang et al. (2021) designed a novel attention-fused CNN architecture which contains a multipath encoder structure with dual branches to process heterogeneous input data. More importantly, two spatial and channel attention-fused block modules were also introduced into this architecture to overcome difficulties in fusing not only multipath features, but also multilevel features. Similarly, Mou et al. (2019) introduced both spatial and channel relation modules into DL models through serial or parallel integration, which enabled spatial and channel relational reasoning and explicitly modeled global relations.

(4) Transferring the GK/GFs that pretrained networks contain to downstream tasks of remotely sensed information extraction. Years of practice have shown that DL, which serves as a general-purpose representation-learning procedure (Bengio et al., 2013), is highly suited to discover knowledge from inputs that is helpful

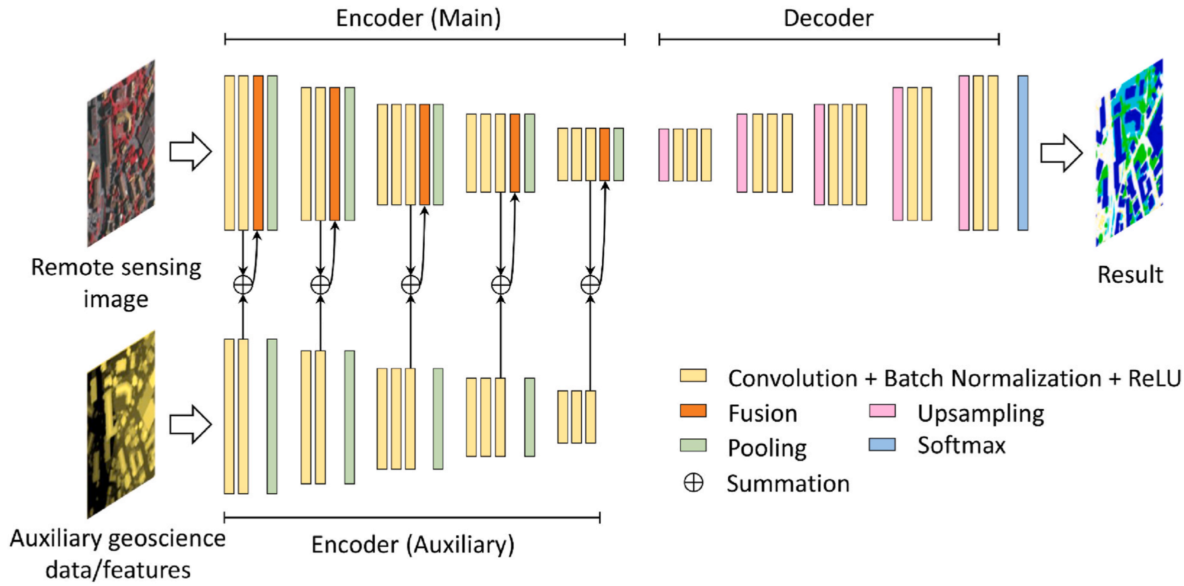

Fig. 7. Diagram of FuseNet architecture for semantic segmentation of remote sensing imagery.

for downstream classification or other prediction tasks (Wang et al., 2020a). For example, a feasible way to deeply integrate GK/GFs and DL is using GK/GFs as supervised information to guide the pretraining of DL models. Then, GK/GFs can be encapsulated indirectly in the well-trained model parameters to act on specific downstream tasks. In recent work, Li et al. (2021b) leveraged the geographical location of remote sensing images and their correspondingly preexisting global land cover products as GK to pretrain the network. The pretrained model was then fine-tuned for specific information extraction tasks such as semantic segmentation and object detection, which achieved encouraging accuracy. In two recent studies (Mañas et al., 2021; Ayush et al., 2021), geolocation and seasonal contrast of remote sensing images provided effective supervision for network pretraining and were conductive to increasing the accuracy of downstream predictions.

(5) Combining different DL models to excavate various GK/GFs for more accurate prediction. As mentioned in Section 2, different DL models are good at processing different datasets and excavating different deep GK/GFs. These knowledge/features generally have complementary advantages that are instrumental in performance gains of information extraction. There are several examples to illustrate this. To achieve the precise delineation of boundaries in building segmentation, Shi et al. (2020) proposed a gated GCN which combined the GCN and the RNN with gated recurrent units and they were, respectively, responsible for capturing short-range and long-range spatial information. A unitized framework for urban land cover classification was designed by Qiu et al. (2019), in which a residual CNN was capable of learning spectral-spatial features whereas an RNN was used for capturing temporal dependencies from sequential images. In work on hyperspectral image classification, Liu et al. (2020) blended CNN and GCN branches to generate a joint spectral-spatial feature representation, where the former and the latter can learn deep features at the pixel scale and superpixel scale, respectively. Tao et al. (2019) proposed a novel spatial information inference structure which can be embedded into CNN-based road extraction architectures. This structure regards several 3-D convolutional RNNs as information processing units and enables useful topology information to be transmitted to identify roads under occlusions, which provides complementary global spatial information for general visual features.

(6) Normalizing the loss function of the DL models by the constraints of various GK/GFs extracted from DL models to characterize geoscience features. Normalization provides a flexible spatially explicit way for the DL models to embed geoscience characteristics in optimization to keep invariant GK/GFs (Janowicz et al., 2020). In addition to the physical model mentioned in 4.4, the deep representation learned from DL models can also be embedded into the loss function of DL models as a regularizer. For example, Mosinska et al. (2018) obtained topologically linear knowledge using a pretrained VGG network (Simonyan and Zisserman, 2014), and imported it to the loss function of a DL model by a newly designed penalty term that is sensitive to linear structures. In another example, the latent shape representation of the buildings was used to constrain the semantic segmentation of the buildings, thus reducing over-fitting (Wang and Li, 2020).

Obviously, neural network-based approaches are able to integrate GK/GFs into DL models by more plentiful and flexible means, and they have obtained some impressive achievements in some complex tasks. Therefore, this kind of approach has become one of the popular approaches to introduce GK/GFs into DL models recently. With the further exploration of many outstanding problems, such as how to effectively strengthen the auxiliary geoscience data/features that are conducive to accurate results, these approaches will bring advantages in more tasks.

5. Challenges and future research

The rapid development of AI, big data and cloud computing has projected geoscience research into the era of big knowledge (Lu et al., 2018). Currently, researchers generally use AI and big data to solve problems of information extraction from remote sensing data while ignoring the importance of knowledge. In this context, an emerging paradigm of GADL is proposed in this paper to solve practical problems in the field of remotely sensed information extraction by means of integrating GK/GFs with the most popular AI frameworks, namely DL models. Although some progress has been made with this paradigm, how to effectively realize, choose and assess the deep integrated methods in GADL is still an open research direction. In this context, the main challenges and future opportunities for research are considered in this section.

5.1. Performance evaluation

In-depth integration of GK/GFs into DL models can theoretically bring performance gains, which has been preliminarily demonstrated in a small number of studies so far. However, there is still a lot of research to be done in the evaluation of deep integrated models and methods, especially in quantitative evaluation. First, in terms of the accuracy of the results, it is necessary to analyze quantitatively the contribution of GK/GFs to accuracy gains, and at the same time confront and tackle the possible negative effects of the introduction of GK/GFs. For example, importing physics-based penalty terms into the loss function of DL models may affect the convergence and optimization speed of the model (Karpatne et al., 2017a); incorporating formalized GK/GFs into DL for remote sensing image classification can boost the overall accuracy, but may reduce the accuracy of specific classes (Audebert et al., 2018). Additionally, the complexity of deep integrated models, including time consumption and the number of parameters, needs to be further investigated and analyzed to ensure that it is within an acceptable range, because the extraction and fusion of GK/GFs may bring additional calculations. Lastly, other performance issues in deep integration in GADL, such as interpretability, generalization ability, robustness and the impact of the quantity and quality of trainable data on the properties of deep integrated models, need to be evaluated on a large number of datasets and information extraction instances in the remote sensing community.

5.2. Uncertainty estimation

Another direction for deep integrated model in GADL would be to introduce uncertainty estimation in their architectures. In the paradigm of GADL, there are many sources of uncertainty, including knowledge such as experience and common sense, input data (e.g., remote sensing data suffering from various degradation, noise effects, or spectral variabilities caused by various factors (Hong et al. (2018)) in the process of imaging) and the deep integrated models themselves. Therefore, it is necessary to estimate the uncertainty related to model outputs (Raissi et al., 2019). In terms of DL models, although they have been used widely in the fields of computer vision, remote sensing and geoscience, and have made excellent achievements in tasks such as semantic image segmentation and target recognition, the vast majority of current DL models do not provide uncertainty measures associated with their predictions (Dechesne et al., 2021). In recent years, Bayesian/probabilistic inference has been recommended to measure the confidence and credibility of DL models (Reichstein et al., 2019). For example, a Bayesian DL method based on Monte Carlo Dropout was proposed by Dechesne et al. (2021), which was able to estimate prediction uncertainty and provide uncertainty maps for qualitative evaluation of the segmentation results of remote sensing images. Due to the difficulty of specifying meaningful priors over millions of parameters, it is challenging to adapt the mainstream general DL methods to Bayesian DL (Baan, 2021). Considering no assumption of the normal noise and linear data, the non-parametric bootstrapping method can be a good method of ensemble learning to obtain uncertainty evaluation for the general integrated DL model in GADL (Kumar and Srivastava, 2012). Similarly, for deep integrated models in GADL, it is worth studying how to represent and assess their uncertainty based on the above methods.

5.3. Insufficient labeled data

The complex and deep structure of DL models requires a large number of labeled data for training (Yuan et al., 2020). Although the idea of introducing GK/GFs to DL architectures can reduce the demand for labeled data to a certain extent, which may ameliorate the common problem of lack of labeled data (Wang et al., 2020b; Li et al., 2021b), the current quantity and quality of labeled data required for remotely sensed information extraction is still very limited. This dilemma greatly limits the scope of applications of the paradigm of deep integration such as application across large areas (Wang et al., 2020a). Therefore, much research effort is needed in this regard. First, it would be worthwhile to further enrich and standardize the labeled data library, and build a sample library based on knowledge that contains diversified attributes (e.g., geoscientific attributes, physical attributes, social attributes and semantic attributes) of each labeled example. More importantly, more effort should be focused on developing the effective combination of GK/GFs with deep transfer learning (Huang et al., 2018; Tong et al., 2020), self-supervised learning (Mañas et al., 2021; Ayush et al., 2021) for representation extraction, and semi-supervised learning (Papandreou et al., 2015; Kang et al., 2019), etc. With the support of GK/GFs, we can learn powerful representations from a large amount of remote sensing data, and effectively combine them with limited labeled training samples to obtain high generalization ability in an unsupervised way or a semi-supervised way (Wang and Gao, 2014; Wu and Prasad, 2017; Ren et al., 2019). These learning strategies can alleviate the existing problems to a great extent due to their small demand for manual annotation and, therefore deserve to be further promoted in the remote sensing community.

5.4. Selection and development of integrated approaches

GADL aims to effectively learn from available data while complying with the constraints from GK/GFs through deep integration of GK/GFs and DL models. In this respect, this paper provides and discusses five representative knowledge/feature representations and the corresponding approaches in which they are embedded in DL models. In practical terms, how to select the appropriate representation of knowledge/features and its deep integrated approach with DL models is vital for specific tasks of remotely sensed information extraction. Therefore, different representations and in-depth integration approaches need to be analyzed carefully and compared extensively in the future. Additionally, the research on these deep integrated approaches is still immature, and the representations of GK/GFs discussed in this paper are not exhaustive. For example, when representing spatial knowledge/features, the distinction between spatial continua and spatial objects is critical, which fundamentally determines the choice of different spatial statistical models. For example, in air photo interpretation the representation of many features (tone, brightness, texture, etc.) relies on spatial continua, but the representation of spatial pattern relies on spatial objects being defined first. So, the classes of ground features defined and extracted are predicated explicitly on whether the spatial continua or object-based data models are invoked first. Besides, more endeavors are needed to explore in-depth combinations of other knowledge/features expressed in various forms (Gil et al., 2019) such as geo-texts, questionnaires and map symbols with DL models to further develop the paradigm of GADL. At the same time, it is necessary to tap deeply the potential of DL technologies and the internal mechanisms of complex phenomena and processes to achieve more deep-level integration.

6. Conclusion

In this paper, we proposed an emerging paradigm called GADL of deep integration of GK/GFs and DL models for extracting information from remote sensing data. This paradigm aims to leverage the value of GK/GFs to improve the performance of DL models. On the basis of a comprehensive investigation of existing research, we first provided a comprehensive summary of GK/GFs, laying the foundation for knowledge/feature representations and their further introduction into DL models. Then, we provided a taxonomy of approaches in which GK/GFs are integrated systematically with DL models based on five representations of GK/GFs: rule-based, semantic network-based, object-based, physical model-based and neural network-based. For each integrated approach, some prototypical examples of methods and applications were reviewed, and we also highlighted some promising avenues for deeply symbiotic integration. Finally, some insights into potential future directions for in-depth combination were provided. For example, the computational complexity and the performance gains of the integrated models deserve further investigation; uncertainty estimation of the integrated models in GADL combined with Bayesian/probabilistic inference is a potential direction; the incorporation of GK/GFs with deep transfer learning, self-supervised or semi-supervised learning is a promising way to make models work well with insufficient labeled data. The methods discussed in this paper are not exhaustive. We anticipate that more novel methods of deep integration of GK/GFs and DL models will be explored in the future, which will contribute to the discovery and understanding of more complex or underlying geoscience phenomena and processes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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