

# Vision-Language Models in Remote Sensing: Current Progress and Future Trends

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**Abstract**—The remarkable achievements of ChatGPT and GPT-4 have sparked a wave of interest and research in the field of large language models for Artificial General Intelligence (AGI). These models provide us with intelligent solutions that are more similar to human thinking, enabling us to use general artificial intelligence to solve problems in various applications. However, in the field of remote sensing, the scientific literature on the implementation of AGI remains relatively scant. Existing AI-related research primarily focuses on visual understanding tasks while neglecting the semantic understanding of the objects and their relationships. This is where vision-language models excel, as they enable reasoning about images and their associated textual descriptions, allowing for a deeper understanding of the underlying semantics. Vision-language models can go beyond recognizing the objects in an image and can infer the relationships between them, as well as generate natural language descriptions of the image. This makes them better suited for tasks that require both visual and textual understanding, such as image captioning, text-based image retrieval, and visual question answering. This paper provides a comprehensive review of the research on vision-language models in remote sensing, summarizing the latest progress, highlighting the current challenges, and identifying potential research opportunities. Specifically, we review the application of vision-language models in several mainstream remote sensing tasks, including image captioning, text-based image generation, text-based image retrieval, visual question answering, scene classification, semantic segmentation, and object detection. For each task, we briefly describe the task background and review some representative works. Finally, we summarize the limitations of existing work and provide some possible directions for future development. This review aims to provide a comprehensive overview of the current state of research in vision-language models for remote sensing and to inspire further research in this exciting and important field.

**Index Terms**—Remote Sensing, Vision-Language Model, AGI, GPT, Transformer

## I. INTRODUCTION

Deep learning has emerged as a powerful tool for various remote sensing (RS) applications. Early works in RS primarily focused on using visual features extracted from images to perform various tasks, such as object detection, semantic segmentation, land cover classification, and change detection.

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As one of the most commonly used deep learning methods, Convolutional neural networks (CNNs) can automatically learn hierarchical representations of remote sensing images, allowing them to capture local and global spatial features and patterns. Moreover, attention mechanisms have been incorporated into deep learning models to improve their performance in RS tasks by allowing the model to focus on specific regions of the input. Thanks to the powerful feature learning abilities of deep neural networks, deep learning models have proven their effectiveness in various RS tasks, achieving state-of-the-art performance compared to traditional machine learning approaches. Nevertheless, existing deep learning-based research mostly focuses on visual understanding tasks while neglecting the semantic understanding of the objects and their relationships. For example, when performing land cover classification, a vision-only model may classify a building rooftop pixel as a highway road if the pixel is visually similar to a highway road. This is because the model lacks the general knowledge that highways can not be inside buildings rooftops.

In recent years, Large language models (LLMs) have emerged as a popular research topic in the fields of natural language processing (NLP) and computer vision. These models build large-scale transformer networks for vision and natural language understanding and have achieved state-of-the-art performance in various language understanding tasks, such as language modeling, text generation, and question answering [115]. Notable, the remarkable achievements of ChatGPT have sparked a wave of interest and research in the field of large language models for artificial general intelligence (AGI). Anticipated to be endowed with further advancements in image comprehension and natural language processing, they are projected to elevate the level of language understanding to an unprecedented level. The great success of large language models has encouraged numerous research in vision-language models (VLMs).

VLMs are generally defined as a family of artificial intelligence models that combines computer vision and natural language processing techniques to generate a comprehensive understanding of both visual and textual information. With the ability to jointly recognize visual and semantic patterns and their relationships, VLMs can go beyond recognizing the objects in an image and can infer the relationships between them, as well as generate natural language descriptions of the image. This makes them better suited for tasks that require both visual and textual understanding, such as image captioning, text-based image retrieval, and visual question answering. More importantly, by combining vision models with LLMs with

general reasoning abilities, VLMs offer a more comprehensive and human-like approach to understanding visual content. In recent years, VLMs have demonstrated impressive results in a variety of computer vision tasks, including image understanding [19], [198], visual question answering [75], [74], text-to-image generation [125], semantic segmentation [20], [187], object detection [183], [99], etc.

In RS, the use of VLMs is a relatively new area of research. With the growing availability of textual metadata associated with RS data, researchers have started exploring the use of vision and language models in this domain [147]. In recent years, some early attempts try to explore VLMs for various RS data analysis tasks, including RS image captioning [133], [100], [185], [188], [186], [48], [83], [132], [155], [82], [190], [60], [202], [160], text-based RS image generation [10], [18], [189], [48], [168], text-based RS image retrieval [1], [48], [118], [48], [178], [4], [25], [177], [176], [119], visual question answering [96], [192], [192], [15], [15], [3], [9], [174], [175], scene classification [72], [136], [113], [150], [86], semantic segmentation [20], [187], object detection [58], [183], [99], etc. With the increasing availability of large-scale RS datasets and advances in deep learning techniques, the use of vision and language models is expected to play a significant role in the future of RS applications.

In this study, we present a comprehensive review of the evolution of models in RS from vision to language and to VLMs. Specifically, we conduct an extensive literature survey on the recent advancements in VLMs in RS. Furthermore, we provide valuable insights and recommendations for potential future research directions in the domain of VLMs for RS applications. Our work contributes to a better understanding of the current state-of-the-art in VLMs and provides instructions for researchers in this field to explore the potential of these models in RS tasks.

## II. FROM VISION TO VISION-LANGUAGE MODEL

### A. Vision Models

The most commonly used vision models are convolutional neural networks (CNNs). CNNs have become one of the most popular and successful vision models due to their ability to extract high-level features by performing convolution operations on input images, followed by pooling and non-linear activation functions. These models are typically trained using backpropagation, a form of gradient descent, to minimize the error between the predicted output and the ground truth label.

CNNs have a long history, dating back to the 1980s. However, it was not until 1998 that CNNs were first used for image classification tasks. In this work, LeCun et al. [71] proposed the LeNet-5 architecture, which consisted of multiple convolutional layers followed by fully connected layers. The LeNet-5 architecture achieved state-of-the-art results on the MNIST dataset, which consists of handwritten digit recognition. Since then, several advancements have been made in CNN architectures. For example, the AlexNet architecture [65], proposed in 2012, achieved state-of-the-art results on the ImageNet [31] dataset, which consists of more than one million images in 1,000 classes. AlexNet used a deeper

network with smaller filters and a larger number of hidden units, which allowed it to capture more complex features in images. In 2014, the VGG architecture [134] achieved similar performance to AlexNet on the ImageNet dataset while using fewer parameters. In 2015, the GoogLeNet architecture [140], also known as Inception, was proposed. This architecture used a module called Inception, which consisted of multiple convolutional filters with different sizes in parallel, allowing the network to capture features at different scales. In 2016, the ResNet architecture [46] was proposed, which introduced residual connections to address the problem of vanishing gradients in deep networks. ResNet used skip connections that allowed the network to learn residual functions instead of directly learning the underlying mapping, which made training deeper networks easier. ResNet achieved state-of-the-art results on the ImageNet dataset with a very deep network of 152 layers. In 2016, DenseNet architecture [52] was proposed to introduce dense connections between layers, where each layer is connected to all subsequent layers in a feed-forward fashion. This approach enables feature reuse and promotes gradient flow, resulting in improved performance with fewer parameters than traditional deep neural networks. In 2017, the ResNeXt architecture [163] was proposed to use a cardinality parameter to increase model capacity without significantly increasing computational complexity. ResNeXt demonstrated the effectiveness of using parallel paths with different filter sizes and numbers of channels to improve the capacity and accuracy of deep convolutional neural networks. In 2019, EfficientNet [143] was proposed to use a combination of compound scaling, efficient block structures, and neural architecture search to achieve state-of-the-art performance on image recognition tasks while maintaining a small number of parameters and computational requirements.

More recently, transformer-based models, initially developed for natural language processing tasks, have been widely explored in numerous computer vision tasks. These models, known as vision transformers, use a self-attention mechanism to extract features from images, allowing them to learn global dependencies between different regions of the image. The self-attention mechanism is formulated as

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

where attention weights are computed by performing a dot-product operation between the query  $Q$  and the key  $K$ , and a scaling factor  $\sqrt{d_k}$  and a softmax operation are applied to convert the weights into a normalized distribution. The resulting weights are multiplied by the corresponding value element  $V$  to generate the final output vector.

The first transformer-based architecture for image classification is ViT [34] proposed. Fig. 1 shows the overview of the ViT model. Several variants of the ViT architecture have been proposed, including DeiT [145], TNT [44], and PVT [156], which further improved performance by incorporating techniques such as distillation, token mixing, and pyramid vision transformer. In addition, considering that the coarse patchify process in ViT neglects the local image information, the Shifted windows (Swin) Transformer [94] was proposed in

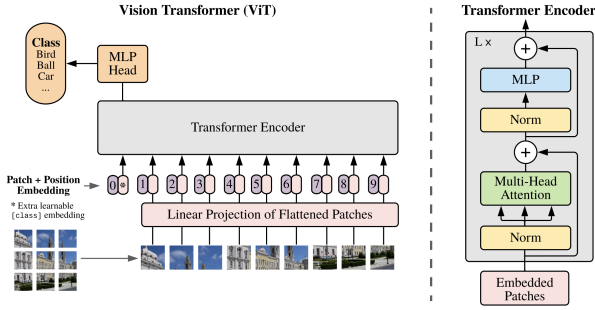


Fig. 1. Architecture overview of ViT model [34]

2021 to utilize a shifted window along the spatial dimension to model the global and boundary features. Twins [27] adopted a spatially separable self-attention mechanism, similar to depth-wise convolution [128], to model the local-global representation. ViL [182] replaced the single class token with a set of local embeddings, which performed inner attention and interaction with their corresponding 2D spatial neighbors. In 2022, VOLO [173] introduced outlook attention, similar to a patch-wise dynamic convolution, to focus on the finer-level features through unfold, linear-wights attention, and refold operations.

## B. Large Language Models

Large language models (LLMs) have emerged as a popular research topic in the fields of natural language processing (NLP) and computer vision in recent years. These models build large-scale transformer networks for vision and natural language understanding and have achieved state-of-the-art performance in various language-related tasks, such as language modeling, text generation, and question answering [115], [32]. In this section, we will provide an overview of some of the critical developments in large language models.

One of the pioneering and well-known large language models is the GPT (Generative Pre-trained Transformer) [115] model developed by OpenAI. The GPT model was trained on a massive corpus of web text and achieved impressive performance on a wide range of language modeling and text generation tasks. Fig. 2 gives an overview of the GPT method. Given a sequence of tokens  $t = \{t_1, \dots, t_N\}$ , GPT maximizes the following likelihood:

$$\mathcal{L}(t) = \mathbb{E}_{t_i} [\log P(t_i | t_{i-k}, \dots, t_{i-1}; \theta)] \quad (2)$$

where  $k$  denotes the length of the context window, and  $\theta$  denotes the network parameters.

Since the GPT model, the GPT series has undergone several iterations. GPT-2 [116] with 1.5 billion parameters, achieved remarkable performance on numerous language tasks, including language translation, summarization, question answering, and text completion, and has gained widespread attention for its ability to generate high-quality, coherent, and fluent text that looks indistinguishable from text written by humans. GPT-3 [12] shows that pretrained large language models can be zero-shot learners and ignited research enthusiasm in in-context learning. InstructGPT [111], one of the key

techniques used in ChatGPT, introduced a promising approach for improving the control and flexibility of large language models. It works by adding high-level instructions in the form of natural language phrases or templates. These instructions can be used to guide the generation process and ensure that the output text satisfies specific constraints or requirements. The latest version, GPT-4 [110] demonstrated the enormous potential of large-scale language models for advancing AI and has paved the way for a new era of intelligent machines that can understand and communicate with us in a more natural way.

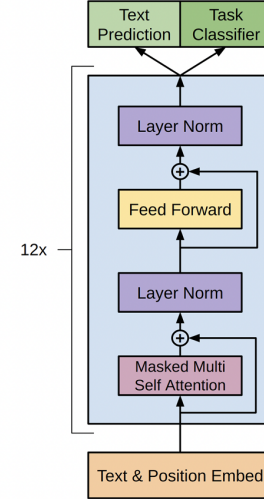


Fig. 2. Network architecture and training objectives of the GPT model [115].

Another popular large language model is BERT [32], developed by Google. Unlike the GPT models, BERT was pre-trained on a bidirectional task, meaning that it can take into account both the left and right contexts of a word during pre-training. This enables BERT to capture more nuanced relationships between words and achieve state-of-the-art results on various NLP tasks. Specifically, the pre-training objectives of BERT contain two unsupervised tasks: 1) masked LM, which tries to predict several masked tokens given nearby tokens; 2) Next Sentence Prediction, which tries to predict the next sentence given the previous sentence, as shown in Fig. 3. Given a sequence of tokens  $t = \{t_1, \dots, t_N\}$ , the training objective of masked LM is defined as:

$$\mathcal{L}(t) = \mathbb{E}_{\mathcal{M}} [\sum_{i \in \mathcal{M}} \log P(t_i | x^{\mathcal{M}}; \theta)] \quad (3)$$

where  $\mathcal{M}$  denotes randomly masked positions,  $t^{\mathcal{M}} = \{t_i : i \notin \mathcal{M}\}_{i=1}^N$  represents the corrupted sequence that is masked according to  $\mathcal{M}$ , and  $\theta$  denotes the network parameters.

There are numerous variants of the BERT model. For example, RoBERTa [93], developed by Facebook AI, improved BERT by using more iterations and data augmentation techniques, including dynamic masking and noising. ALBERT [69] proposed three techniques, including factorized embedding parameterization, cross-layer parameter sharing, and sentence order prediction task, to reduce the model size of BERT and improve model training speed. MacBERT [29]

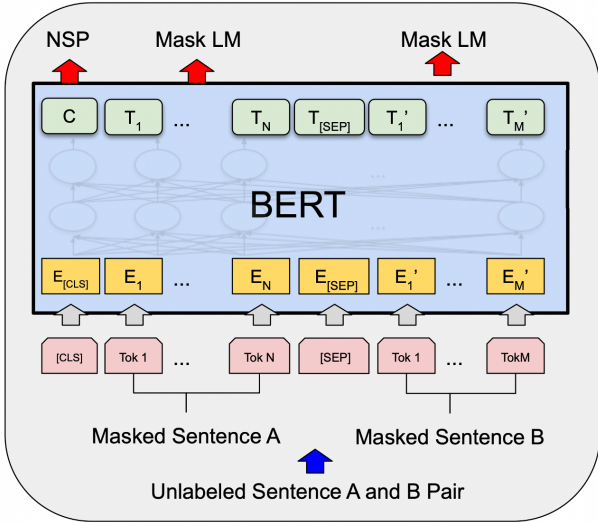


Fig. 3. Pre-training objectives of the BERT model [93].

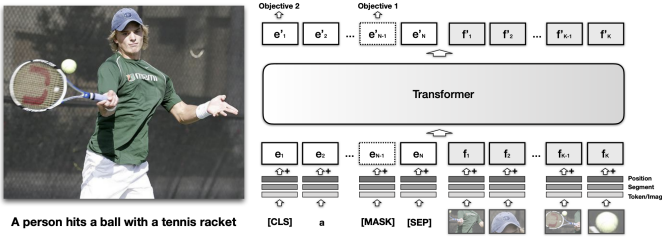


Fig. 4. Illustration of the architecture of VisualBERT [78]

proposed to replace the [MASK] token with another synonym at mask locations instead of using the [MASK] tag.

In addition to GPT and BERT, several other large language models have emerged in recent years. T5 [117] applied a single unified architecture to a wide range of NLP tasks by task-agnostic pre-training on a massive corpus of diverse text data with the goal of creating a general-purpose language model. CoT [159] proposed a useful technique called chain-of-thought prompting that enables intermediate reasoning in large language models.

### C. Vision-Language Models

Given the success of pre-trained models in computer vision and natural language processing (NLP), researchers have attempted to pre-train large-scale models that incorporate both modalities, which are called Vision-Language Models (VLMs). These VLMs can be categorized into two model architectures: fusion-encoder and dual-encoder models. Fusion-encoder models use a multi-layer cross-modal Transformer encoder to jointly encode image and text pairs and fuse their visual and textual representations. Meanwhile, dual-encoder models encode images and text separately and use either a dot product or MLP to capture the interactions between the modalities.

1) *Fusion Encoder*: The fusion encoder accepts visual features and text embeddings as input and employs multiple

fusion techniques to capture the interaction between visual and text modalities. The latent features of the final layer are regarded as the fused representation of the distinct modalities after either a self-attention or cross-attention operation. VisualBERT [78] is a pioneering work that implicitly aligned elements of an input text with regions in an associated input image using self-attention. It combined BERT [32] for processing natural language and pretrained Faster-RCNN [123] for generating object proposals. The original text, along with the image features extracted from object proposals, were treated as unordered input tokens and fed into VisualBERT to capture the intricate associations by jointly processing them with multiple Transformer layers (See Fig. 4). Subsequently, several VLM models, including Uniter [21], OSCAR [81], InterBert [88], utilized BERT as a text encoder and Faster-RCNN as an object proposal generator to model vision-language interaction.

In contrast to self-attention operations utilized in single-stream architectures, dual-stream architectures utilize a cross-attention mechanism to capture the interaction between visual and language modalities. The cross-attention layer usually consists of two unidirectional sub-layers, with one processing language-to-vision and the other processing vision-to-language. These sub-layers facilitate information exchange and semantic alignment between the two modalities. One prominent example is ViLBERT [98], which processed visual and textual inputs separately and employed co-attentional transformer layers to enable information exchange between modalities. Fig. 5 illustrates how each stream is composed of transformer layers (TRM) and novel co-attention transformer blocks (Co-TRM). In addition, recent works such as LXMERT [142], Visual Parsing [170], ALBEF [76] and WenLan [54] also employed separate transformers before cross-attention to decouple intra-modal and cross-modal interaction. Chen et al. [19] proposed VisualGPT that adapts pre-trained language models to small quantities of in-domain image-text data by utilizing a novel self-resurrecting encoder-decoder attention mechanism.

2) *Dual Encoder*: A dual encoder uses two separate encoders for each modality to encode visual and textual information independently. The image and text embeddings encoded from the corresponding encoder are then projected onto the shared semantic latent space via operations such as attention layers or dot products, which are used to calculate similarity scores between Vision and Language. Compared to the fusion encoder, the dual encoder does not use the complex cross-attention in the transformer, because it pre-computes and stores the image and text embeddings, making Vision-Language interaction modeling more efficient. For example, Contrastive Language-Image Pre-training (CLIP) [114], as illustrated in Fig. 6, utilizes a text encoder and an image encoder jointly to accurately match pairings of (image, text) samples. Let  $(x_i^I, x_i^T)$  be a batch of  $N$  image-text pairs, where  $x_i^I$  and  $x_i^T$  represent the image and text of the  $i_{th}$  pair, and  $z_i^I$  and  $z_j^T$  denote the normalized embeddings of the  $i_{th}$  image and  $j_{th}$  text, respectively. CLIP employs InfoNCE loss [109] to calculate the loss for the image encoder, as shown in Eq. 4.

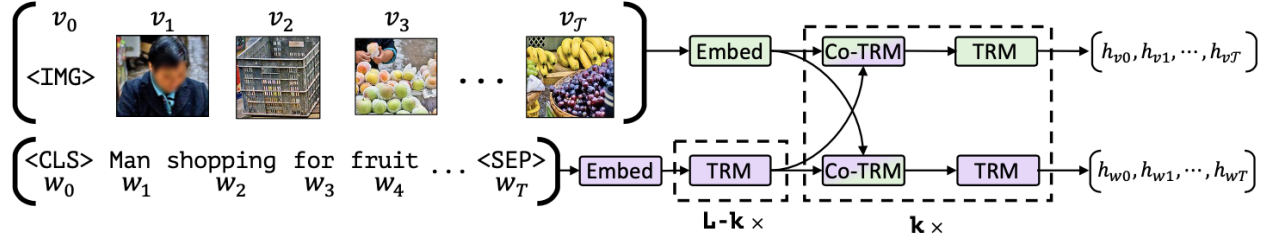


Fig. 5. Illustration of the architecture of ViLBERT [98].

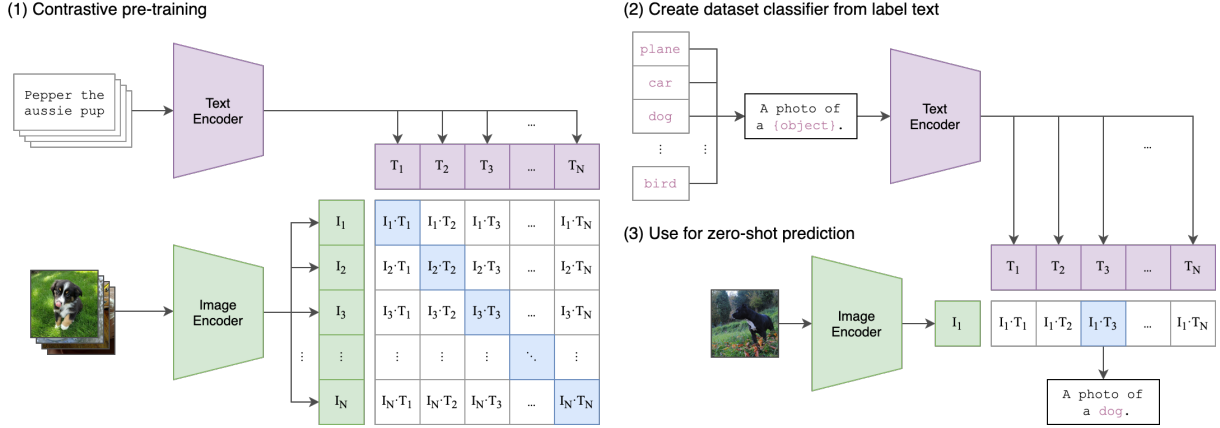


Fig. 6. Illustration of the architecture of CLIP [114].

$$L_I = -\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(\text{sim}(z_i^I, z_i^T)/\tau)}{\sum_{j=1}^N \exp(\text{sim}(z_i^I, z_j^T)/\tau)},$$

$$L_T = -\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(\text{sim}(z_i^T, z_i^I)/\tau)}{\sum_{j=1}^N \exp(\text{sim}(z_i^T, z_j^I)/\tau)},$$
(4)

where  $\text{sim}(\cdot)$  is the similarity function calculated using dot product, and  $\tau$  is a temperature variable used to scale the logits. The loss function is symmetrical for both the image and text encoder, which results in the final loss which is the average of the image encoder loss and the text encoder loss.

Furthermore, ALIGN [57] introduced a dual-encoder architecture with a contrastive loss to align image and text representations before cross-modal attention. This loss pulled together matched image-text pairs and pushes apart non-matched pairs. To overcome the limitations of CLIP, Li et al. [84] proposed a novel training paradigm called data-efficient CLIP, which improves the efficiency of learning generic visual features. This approach incorporates both intra-modality self-supervision as well as inter-modality multi-view supervision, and further introduces a new kind of supervision strategy based on finding similar texts via their embeddings. Alayrac et al. [5] introduced Flamingo, a model trained on only a few input/output examples that can accept interleaved visual data and text as input and generate text in an open-ended manner. Specifically, Flamingo used spatiotemporal features from the vision encoder and initialized cross-attention layers to interleave these visual tokens between the pretrained

language model layers. Similarly, Li et al. [74] proposed a generic and efficient pretraining strategy, BLIP-2, which bootstrapped vision-language pretraining from off-the-shelf frozen pre-trained image encoders and frozen large language models. They first bootstrapped vision-language representation learning from a frozen image encoder and then bootstrapped vision-to-language generative learning from a frozen language model. Recently, Kirillov et al. [62] built a foundation segmentation model (SAM) that can be applied to a range of image understanding tasks, such as semantic segmentation, edge detection, panoptic segmentation, and instance segmentation, in a zero-shot setting. The SAM adopted a heavyweight image encoder to obtain image embeddings and then used a prompt encoder to generate queries from input prompts to produce multiple object masks and confidence scores. Zhu et al. [199] proposed MiniGPT-4 that trained a single linear projection layer to align the visual features encoded from a pretrained ViT with a pretrained large language model. This simplified model with only 13B parameters shows fantastic performance on various cross-modality tasks, such as image captioning, writing poems/stories from images, and building websites from draft images.

### III. VISION-LANGUAGE MODELS IN REMOTE SENSING

#### A. Foundation Models

Foundation models refer to large pre-trained deep learning neural networks trained in a task-agnostic manner on massive amounts of data. These models can be applied to various downstream tasks using fine-tuning, few-shot, or zero-shot

Method	Year	Task	Visual Encoder	Text Encoder	Datasets
RingMo [137]	2022	FM	ViT [34], Swin Transformer [94]	-	two million RS images collected from multiple public datasets and GF-2
Wang et al. [153]	2022	FM	ViT [34], ViTAE [169]	-	MillionAID [97]
GFM [106]	2023	FM	Swin-B [94]	-	GeoPile [106]
Cha et al.	2023	FM	ViT [34]	-	MillionAID [97]
Shi et al. [133]	2017	RSIC	VGG-f [17]	-	Google Earth, GF-2
Lu et al. [100]	2017	RSIC	AlexNet [65], VGG [134], GoogLeNet [140]	LSTM [48]	RSICD [100]
Zhang et al. [185]	2017	RSIC	CaffeNet [65]	RNN [49]	UCM [171]
VAA [188]	2019	RSIC	VGG16 [134]	LSTM [48]	UCM-Captions [171], Sydney-Captions [181]
Zhang et al. [186]	2019	RSIC	VGG16 [134]	LSTM [48]	UCM-Captions [171], Sydney-Captions [181], RSICD [100]
Li et al. [83]	2020	RSIC	ResNet-101 [46]	LSTM [48]	UCM-Captions [171], Sydney-Captions [181], RSICD [100]
VRTMM [132]	2020	RSIC	VGG16 [134]	Transformer [149]	NWPU-RESISC45 [22]
Wang et al. [155]	2020	RSIC	AlexNet [65], VGG [134], ResNet [46]	Transformer [149]	UCM-Captions [171], Sydney-Captions [181], RSICD [100]
Li et al. [82]	2020	RSIC	AlexNet [65], VGG [134], ResNet [46], GoogLeNet [140]	LSTM [48]	UCM-Captions [171], Sydney-Captions [181], RSICD [100]
Zhao et al. [190]	2021	RSIC	ResNet-50 [46]	LSTM [48]	UCM-Captions [171], Sydney-Captions [181], RSICD [100]
Zia et al. [202]	2022	RSIC	ResNet [46]	Transformer [149]	UCM-Captions [171], Sydney-Captions [181], RSICD [100]
VLCA. [160]	2023	RSIC	CLIP [114]	GPT-2 [116]	DIOR-Captions [160]
Bejiga et al. [10]	2019	T2IG	GAN [28]	-	MODIS
BTD-sGAN [18]	2021	T2IG	D-sGAN [103]	-	Oxford-102, GF
StrucGAN [189]	2021	T2IG	AttnGAN [167]	LSTM [48]	RSICD [100]
Txt2Img-MHN [168]	2022	T2IG	VQVAE [148], VQGAN [36]	BPE [131]	RSICD [100]
DBTN [1]	2020	T2IR	VGG [134], Inception V3 [141], ResNet-50 [46], EfficientNet [143]	LSTM [48]	TextRS [1]
Rahhal et al. [118]	2020	T2IR	BiT [64]	Bi-LSTM [41]	TextRS [1], UCM [171]
SAM [25]	2021	T2IR	Inception V3 [141]	Bi-GRU [130]	UCM-Captions [171], Sydney-Captions [181], RSICD [100], NWPU-RESISC45-Captions
GalR [178]	2022	T2IR	CNN [178]	GRU [26]	RSICD [100], RSITMD [176]
Rahhal et al. [4]	2022	T2IR	ViT [34]	Transformer [149]	RSICD [100], RSITMD [176], UCM [171]
LW-MCR [177]	2021	T2IR	SqueezeNet [56]	Group CNN	Sydney [181], UCM [171], RSITMD [176], RSICD [100]
AMFMN [176]	2022	T2IR	ResNet-18 [46]	GRU [26]	Sydney [181], UCM [171], RSITMD [176], RSICD [100]
Rahhal et al. [119]	2023	T2IR	Transformer [149]	Transformer [149]	TextRS [1], UCM [171], Sydney [181], RSICD [100]
Lobry et al. [96]	2020	VQA	ResNet-152 [46]	LSTM [48]	RSVQA [96]
Zheng et al. [192]	2021	VQA	VGG-16 [134]	GRU [26]	RSIVQA [192]
Chappuis et al. [15]	2022	VQA	ResNet-152 [46]	BERT [32]	RSVQA [96]
Al et al. [3]	2022	VQA	Vision Transformer	Transformer [149]	VQA-TextRS [3]
Bazi et al. [9]	2022	VQA	ViT [34]	CLIP [114]	Sentinel-2 and aerial images
Yuan et al. [174]	2022	VQA	CNN [174]	RNN [49]	RSVQA [96], RSIVQA [192]
Yuan et al. [175]	2022	VQA	ViT [34]	RNN [49]	CDVQA [175]
Sun et al. [139]	2022	VG	Darknetz[37]	BERT [32]	RSVG [139]
Zhan et al. [180]	2023	VG	CNN	BERT [32]	RSVGD [180]
Li et al. [72]	2017	SC	GoogLeNet [135]	Word2vec [107]	UCM [172], RSSCN7 [203], Sydney 900 [72].
Sumbul et al. [136]	2017	SC	CNN [136]	Word2vec [107]	self collected
Quan et al. [113]	2018	SC	GoogLeNet [135]	Word2vec [107]	UCM [172], AID [161].
Wang et al. [150]	2021	SC	ResNet-152 [46]	Word2vec [107]	UCM [172], AID [161], NWPU-45 [22]
Li et al. [86]	2022	SC	ResNet-101 [46]	Word2vec [151], Fasttest [59], [11], Glove [162], BERT [32]	UCM [172], AID-30 [161], NWPU-45 [22]
Zhang et al. [183]	2023	OD	Faster RCNN [123]	Glove [162]	NWPU VHR-10 [23], DIOR [77]
Lu et al. [99]	2023	OD	Faster RCNN [123]	GRU [26]	NWPU VHR-10 [23], DIOR [77], FAIRIM [138]
Jiang et al. [58]	2021	SS	ResNet [46]	-	ISPRS Vaihingen [126]
Chen et al. [20]	2019	SS	ResNet [20]	-	Vaihingen [126], the Zurich Summer dataset *
Zheng et al. [187]	2023	SS	3D-CNN [187]	GPT-2 [116]	Houston [30], [70], Pavia [38], GID [144]

TABLE I

SUMMARY OF WELL-KNOWN VISION-LANGUAGE MODELS IN REMOTE SENSING. “-” MEANS NOT APPLICABLE. “FM” DENOTES FOUNDATION MODEL, “RSIC” DENOTES REMOTE SENSING IMAGE CAPTIONING, “T2IG” DENOTES TEXT-BASED IMAGE GENERATION, “VQA” DENOTES VISUAL QUESTION ANSWERING, “VG” DENOTES VISUAL GROUNDING, “SC” DENOTES SCENE CLASSIFICATION, “OD” DENOTES OBJECT DETECTION, AND “SS” DENOTES SEMANTIC SEGMENTATION.

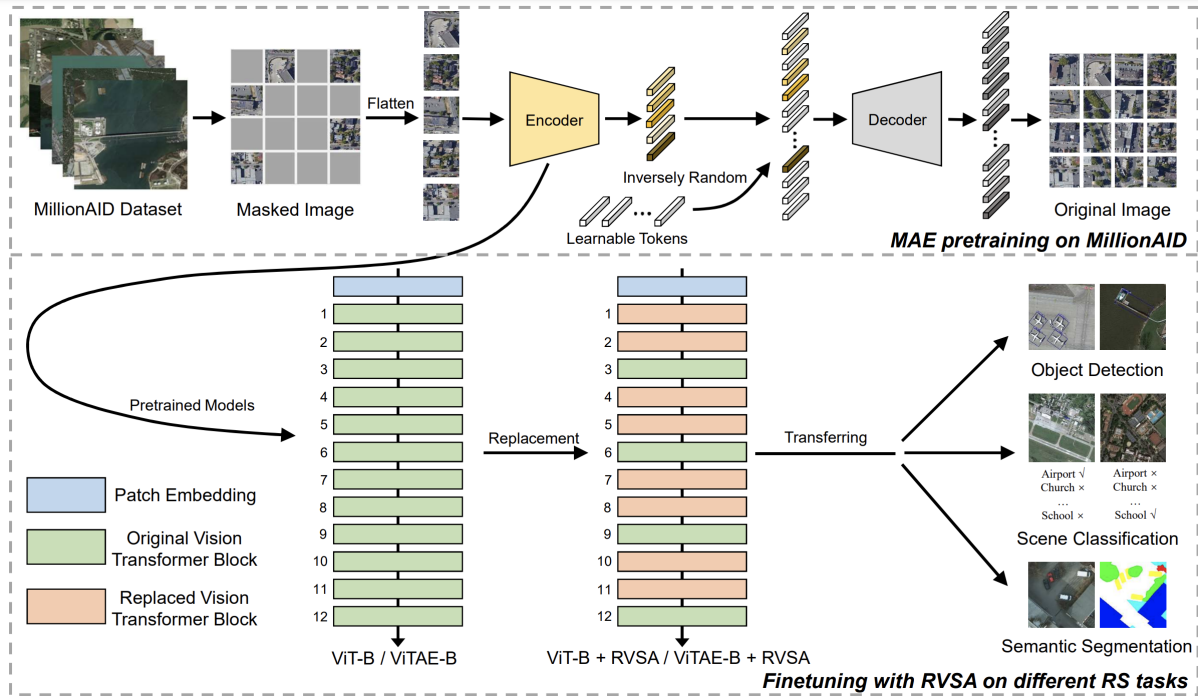


Fig. 7. Method overview of the remote sensing vision transformer network in [153].

learning. Examples of foundation models include GPT-3 [12], BERT [32], and T5 [117]. These models have been pre-trained on large amounts of text data and are able to be finetuned for a wide range of NLP tasks, such as language translation, question answering, and text classification. In remote sensing (RS), pretraining is critical for enhancing the performance on classification, detection, and segmentation tasks [165]. Previous approaches have predominantly leveraged the ImageNet dataset for pretraining. However, transferring the ImageNet pretrained model to RS tasks suffers from huge domain gaps due to the significant difference between natural images and RS images. Thus designing a foundation model tailored for RS data is necessary. Researchers have pursued this goal using two approaches: supervised learning and self-supervised learning. In supervised learning, [152] pre-trained deep neural networks on the MillionAID dataset, a large-scale RS dataset, and improved the performance of these models on RS datasets. However, the need for a significant amount of labeled data remains a hurdle, as it can impede the training of larger models. Therefore, self-supervised techniques gradually become the primary methods used to develop foundation models for remote sensing, as they can leverage a substantial amount of unlabeled data [157]. Some works [2], [79], [6], [105], [47] resorted to contrastive learning for the foundation model training, incorporating RS-specific information, such as geographic data, time-series data, audio data, and so on. Recently, masked image modeling (MIM) has recently gained increasing attention in computer vision, such as BEiT [8], MAE [45], SimMIM [164], as it eliminated the need for additional information, data augmentation, and selection of positive and negative pairs. Thus it is easier to leverage vast amounts of data. Some works applied MIM to develop RS

foundation models. For example, [137] collected two million RS images from satellite and aerial platforms to create a large-scale RS dataset. Based on the dataset, they designed the first generative self-supervised RS foundation model, RingMo. RingMo achieved state-of-the-art on eight datasets across four downstream tasks, including change detection, scene recognition, object detection, and semantic segmentation. [153] made the first attempt to build a plain vision transformer with about 100 million parameters for a large vision foundation model tailored to RS tasks. The method overview is shown in Fig. 7. They also introduced a rotated varied-size window attention mechanism to enhance the ability of the vision transformer to adapt to RS images. [106] discovered that models pretrained on diverse datasets, such as ImageNet-22k, should not be disregarded when constructing geospatial foundation models, as their representations remain effective. Consequently, they built a geospatial foundation model for geospatial applications in a sustainable manner. [14] developed the first billion-scale foundation model in the RS field and proved the effect of increasing the size of the model from million-scale to billion-scale.

### B. Image Captioning

Remote sensing image captioning (RSIC) is a complex task that requires the machine to understand the content of a remote sensing (RS) image and describe it in natural language. This is a challenging task as the generated description must capture not only the ground elements of different scales, but also their attributes and manners in which they interrelate. Unlike other tasks that aim to predict individual tags or words, RSIC aims to generate comprehensive sentences. To generate concise and meaningful sentence descriptions, it is important

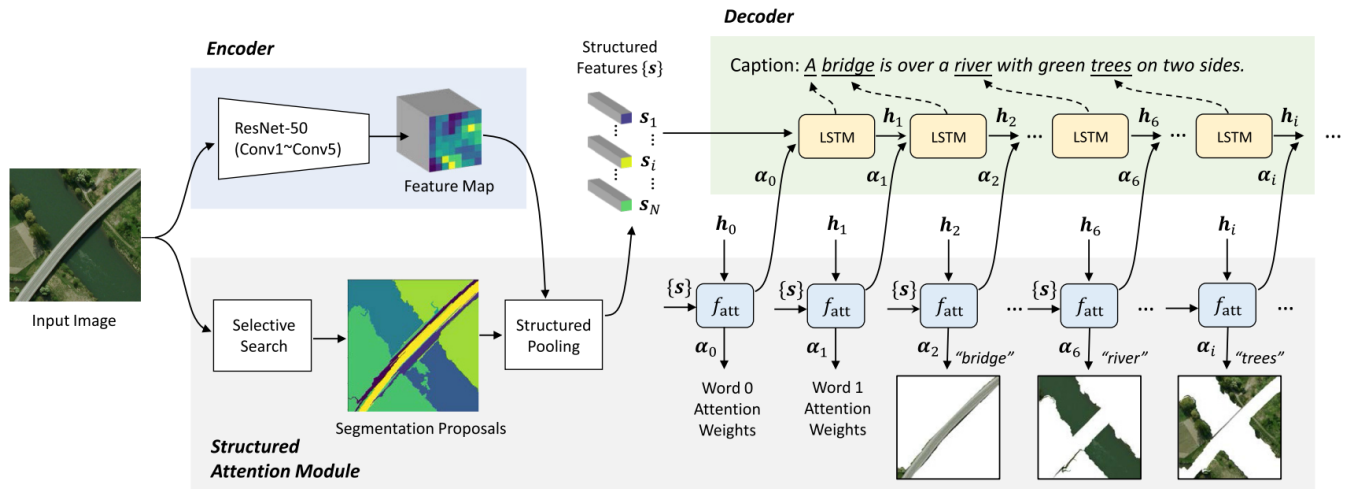


Fig. 8. Overview of a remote sensing image captioning method proposed in [190]. The model consists of an image encoder, a structured attention module, and a text decoder.

to identify and recognize ground elements at different levels, analyze their attributes, and utilize class dependence and spatial relationships from a high-level perspective.

Shi et al. [133] proposed a solution to address the challenge of different semantics of the same ground elements in RS images under different geographical scales. They introduced a fully convolutional network (FCN) to generate comprehensive and robust sentences for RS images obtained from Google Earth and GF-2, while ensuring desirable speed performance. They first tackled three subtasks, including key instance detection, environment analysis, and landscape analysis, and then integrated the results from each of these stages to generate language descriptions. Similarly, Lu et al. [100] provided instructions on how to comprehensively describe RS images, taking into account the scale ambiguity, category ambiguity, and rotation ambiguity, and created a large-scale image dataset for RS captioning by collecting more than ten thousand RS images. In contrast, Zhang et al. [185] employed a convolutional neural network to detect the primary objects in RS images, and a recurrent neural network language model to generate natural language descriptions of the detected objects.

Zhang et al. [188] propose a Visual Aligning Attention model that employs a well-crafted visual aligning loss. This loss is determined by explicitly evaluating the feature similarity between the attended image features and corresponding word embedding vectors. To address the effect of non-visual words in training the attention layer, they introduced a visual vocab that eliminates such words in sentences during the computation of the visual aligning loss. Additionally, to bridge the semantic gap between low-level features and high-level semantics in RS images, Zhang et al. [186] utilized the Fully Convolutional Network (FCN) to generate image features and the attention mechanism to obtain intermediate vectors, which are then used as inputs to the LSTM decoder to produce descriptions of RS images. Following this work, Li et al. [83] proposed a multi-level attention model that contains three attention structures: attention to different areas of the

image, attention to different words, and attention to vision and semantics. Moreover, they also corrected inaccuracies in existing datasets, including word errors, grammatical errors, and inappropriate captions. In another study, Shen et al. [132] proposed a Two-stage Multi-task Learning Model based on Variational Autoencoder (VAE) and Reinforcement Learning for RSIC. They first fine-tuned the CNN jointly with the VAE in the first stage and then utilized Transformer and Reinforcement Learning to both spatial and semantic features to generate the text description. Similarly, Kandala et al. [60] employed a Transformer-based encoder–decoder network for RSIC. In particular, to deal with the limited training data, an auxiliary decoder, trained for multilabel scene classification, has been used to assist the encoder in the training process by leveraging its conceptual similarity to image captioning and its ability to highlight semantic classes. Instead of using the encoder–decoder architecture with a lack of explainability, Wang et al. [155] proposed an explainable word–sentence framework for RSIC, which consisted of two networks, a word extractor, and a sentence generator. The first network extracted the valuable words in the given RS image, and the second network organized these words into a coherent sentence. Besides, Li et al. [82] proposed a novel truncation cross-entropy loss to solve the overfitting problem caused by a cross-entropy loss in RSIC.

To address the issue of disregarding domain knowledge in previous methods, Zhao et al. [190] proposed a fine-grained and structured attention-based model to utilize the structural characteristics of semantic contents in high-resolution RS images. Fig. 8 gives an overview of the method. In addition, Zia et al. [202] first employed the multi-scale visual feature encoder to extract detailed information from RS images and subsequently utilized the adaptive multi-head attention decoder to refine the description generation based on the extracted multi-scale features. Besides, they incorporated topic-sensitive word embedding to produce more human-like and innovative descriptions. More recently, Wei et al. [160] introduced a



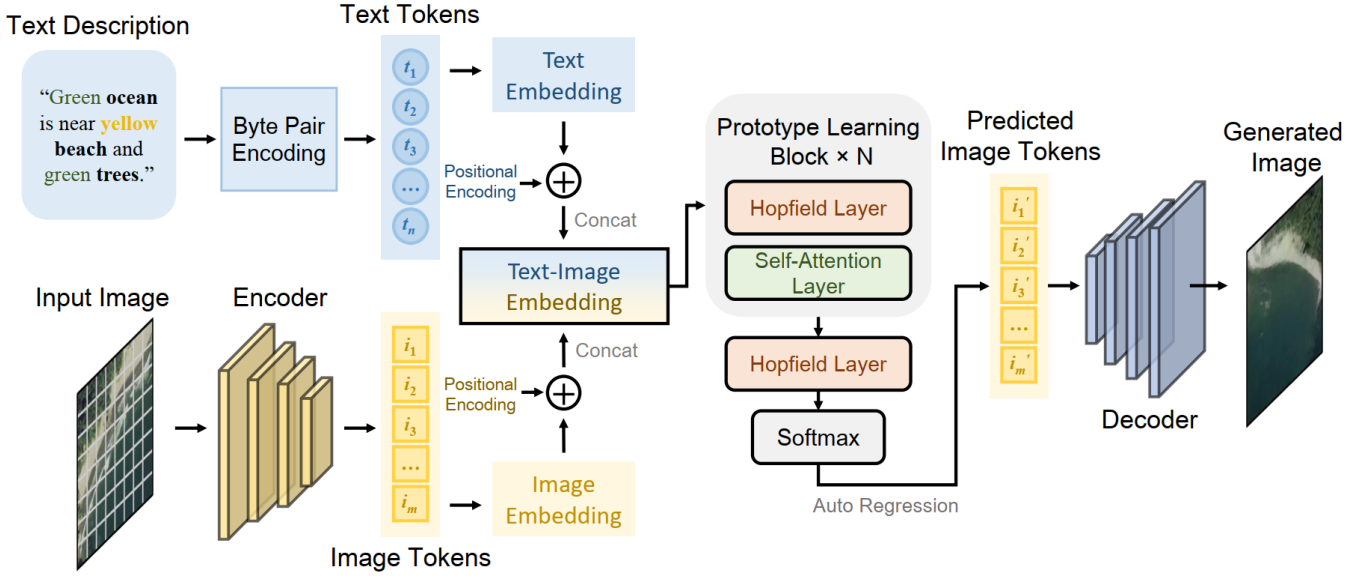


Fig. 9. Illustration of the proposed method in [168] for text-based remote sensing image generation.

vision-language aligning network that jointly represents both vision and language for RSIC. This work was conducted on the DIOR-Captions dataset, a newly created dataset for enriching object detection in optical RS images dataset with manually annotated Chinese and English contents.

### C. Text-based Image Generation

Text-based image generation is an emerging field of research that combines natural language processing and computer vision to create realistic images from textual descriptions. The application of this technology to remote sensing (RS) images holds significant potential in real-world applications. One area where it could be beneficial is in assisting urban planners by generating realistic RS images based on their text descriptions. This would enable them to evaluate the feasibility of their designs and make better-informed decisions. Another potential use case is in generating high-quality labeled datasets of RS images, which is often a challenging and time-consuming process. Text-based image generation techniques could be used to create synthetic RS datasets from text descriptions, alleviating the shortage of labeled samples.

Several research studies have investigated text-based RS image generation using generative adversarial networks (GANs). For example, Bejiga et al. [10] conducted a pioneering investigation into the synthesis of RS images using text descriptions by utilizing GANs. They generated RS images based on ancient text descriptions of geographical areas by transforming text representation into pixel values that captured image characteristics such as size and color. Besides, Chen et al. [18] proposed an enhanced GAN, called Text-based Deeply-supervised GAN (BTD-sGAN), to address the low quantity and poor quality of RS images. BTD-sGAN employed a two-layer Unet++ framework and took Perlin Noise, image segmentation graph, and encoded text vector as input to generate RS images. Moreover, Zhao et al. [189]

introduced a structured GAN, i.e., StrucGAN, to generate RS images based on textual descriptions while considering structural information. The proposed StrucGAN utilized a bidirectional long short-term memory (LSTM [48]) as the text encoder to capture semantic features and adopted the StackGANs to generate images gradually from small to large scales. The model also included a branch consisting of a region proposal module (RPM) and a discriminator to ensure the generation of structurally reasonable images. Furthermore, Xu et al. [168] presented a novel approach, Txt2Img-MHN, to generate RS images from text descriptions using a modern Hopfield network. As illustrated in Fig. 9, unlike the previous work focused on learning joint text-image representations, the Txt2Img-MHN applied the Hopfield network to the text-image embeddings and performed prototype learning hierarchically, which guarantees better coarseness and finesse in the learning steps along with richer semantic encoding.

### D. Text-based Image Retrieval

The efficient organization and management of vast amounts of remote sensing (RS) data has long posed a significant challenge to the RS community. To address this challenge, text-based image retrieval (TBIR) has emerged as a prominent research topic, aiming to provide an effective solution for RS data management. The primary objective of image retrieval is to extract a specific image from a large dataset, and it has gained considerable attention recently. The fundamental idea is to narrow down the search for the targeted image and retrieve the image that matches a particular query. This task is valuable in practical applications such as deforestation detection, visual navigation, and urban planning.

To achieve this, Abdullah et al. [1] constructed a new dataset, named TextRS, for text-based image retrieval tasks. The dataset comprised images from four distinct scene datasets, each annotated with five corresponding sentences.

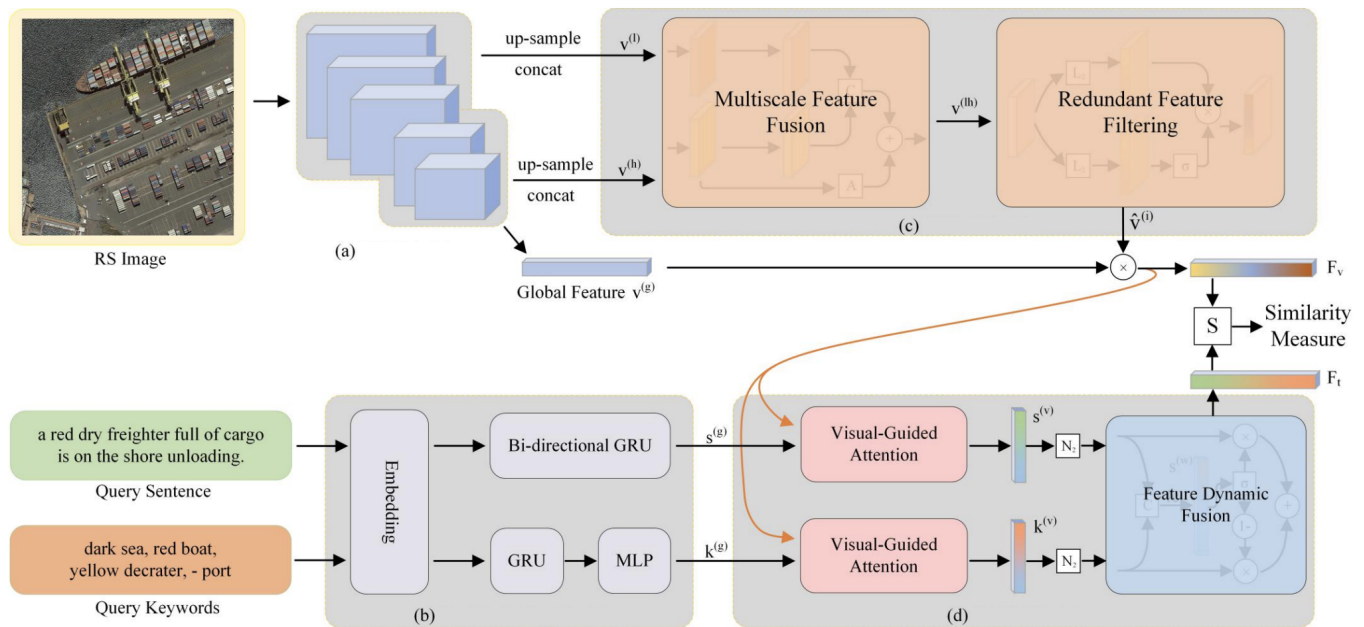


Fig. 10. Illustration of the proposed method in [176] for text-based remote sensing image retrieval.

To retrieve the image that matches a particular query, they also proposed a novel Deep Bidirectional Triplet Network composed of LSTM [48] and CNNs for RS retrieval by matching text to image representations. Similarly, Rahhal et al. [118] proposed an unsupervised text-image retrieval model for RS images by utilizing a visual Big Transfer Model to learn image representation and a bidirectional LSTM [48] network to encode textual descriptions. The model was optimized using an unsupervised embedding loss to ensure that an image's features are closest to its corresponding textual description, and vice versa, while being dissimilar to other image features.

Yuan et al. [178] proposed a novel remote sensing text-image retrieval framework that integrated local and global information, using a dynamic fusion module to effectively integrate features from different levels. In response to the problem of existing methods that were limited to processing queries formulated in English, Rahhal et al. [4] proposed a multi-language framework composed of a language encoder for generating language representation features from the textual description and a vision encoder for extracting visual features from the corresponding image. The authors trained the model on text descriptions from four different languages, including English, Arabic, French, and Italian. In addition, Chen et al. [25] introduced a novel cross-modal image-text retrieval network based on a designed semantic alignment module, which was used to obtain more discriminative feature representations by using attention and gate mechanisms to establish the direct relationship between RS images and their paired text data.

Yuan et al. [177] proposed a concise but effective cross-modal model for RS image retrieval to address the challenges posed by the multi-scale and target redundancy characteristics of RS data. The proposed model incorporated multi-scale information and dynamically filtered out redundant features

during RS image encoding, while text features were obtained via lightweight group convolution. Furthermore, to improve retrieval performance, they developed a novel hidden supervised optimization method based on knowledge distillation. This method enabled the proposed model to acquire dark knowledge of the multi-level layers and representation layers in the teacher network, which significantly improved the accuracy of our lightweight model. In a similar vein, Yuan et al. [176] employed a multi-scale self-attention module to obtain the salient features of RS images to filter redundant features dynamically, which is illustrated in Fig. 10. The authors also constructed a fine-grained RS Image-Text Match dataset, which enabled RS image retrieval based on keywords and sentences both independently. Recently, Rahhal et al. [119] proposed an efficient text-image retrieval approach that utilized vision and language transformers to align the visual representations of RS images to their corresponding textual representations using two contrastive losses for image-to-text and text-to-image classification.

### E. Visual Question Answering

Visual question answering (VQA) is a task that seeks to provide answers to image-related questions. While it has gained popularity in the field of computer vision, it is still in its early stages in the remote sensing (RS) community. The remote sensing VQA system enables non-expert users to interact with RS images using natural language questions as queries, thus enabling a user-friendly and high-level understanding of the images. Pioneering work [96] built the first large-scale VQA benchmark dataset for RS images. Both low- and high-resolution RS images were collected data from OpenStreetMap, with human-generated questions and answers relevant to the image. In [96], the authors provided a benchmark method that uses Convolutional neural networks (CNNs)

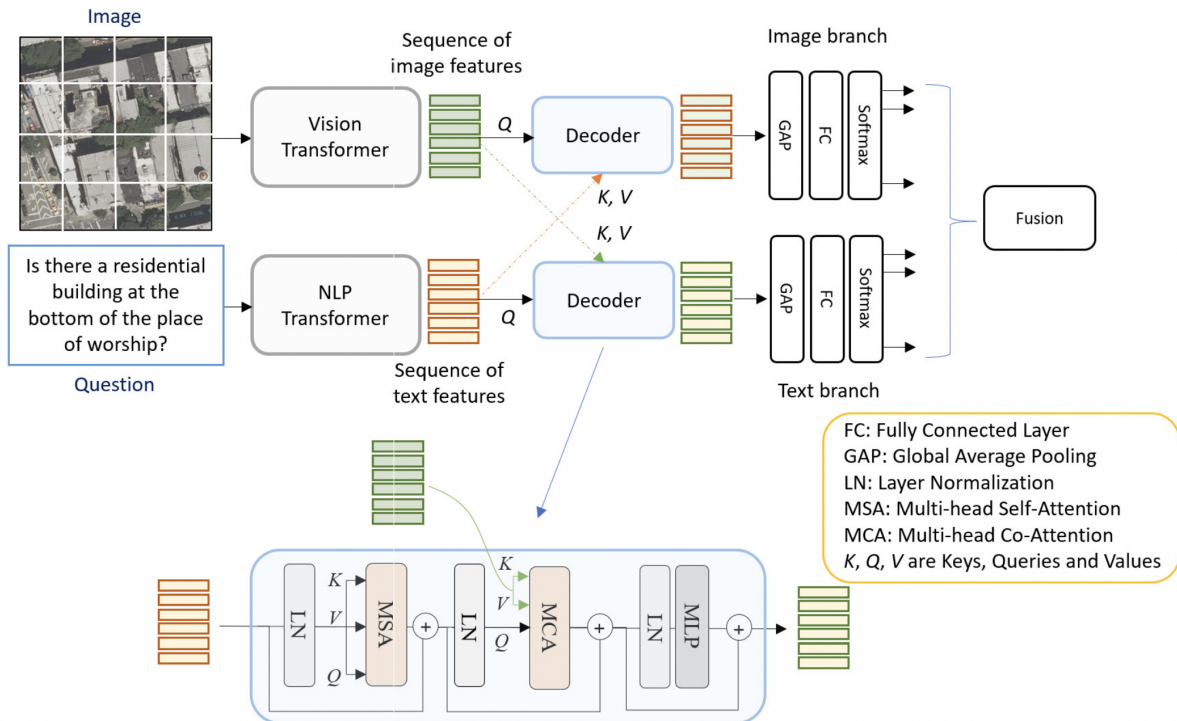


Fig. 11. Framework of a remote sensing visual question answering method proposed in [9]. The method uses a vision-language transformer to encode image and question pairs into textual and visual feature representations.

for visual feature learning, and LSTM [48] networks were adopted for text embedding extraction. Mutual attention was further designed to enhance the alignment between visual and textual features. In [95], the authors built a large-scale remote sensing VQA dataset by referring to the existence of land use classes in each RS image. Zheng et al. [192] introduced a mutual attention network to exploit semantic correspondence between visual and textual features, with a bilinear module to conduct feature fusion. Chappuis et al. [15] proposed to use large language transformers, e.g. BERT [32] for textural feature learning and demonstrated better performance than recurrent neural networks.

Unlike previous methods that mainly focus on solving remote sensing VQA in a closed-ended scenario, Al et al. [3] introduced a novel dataset, VQA-TextRS, which was created through human annotation. It incorporates a diverse range of open-ended question-answer pairs. In order to address the task of open-ended VQA, they utilized vision and language transformer networks to extract visual and textual features from both the image and the accompanying question, followed by a transformer decoder that leverages a cross-attention mechanism to integrate the two modalities. As a result, the proposed method achieved an accuracy of 84.01% in relation to queries about the presence of objects within the image. A similar idea was proposed in [9] where the authors proposed to use the CLIP [114] model to embed images and questions as visual and textual representations, followed by an attention mechanism to learn correlations between these representations. Fig. 11 gives an overview of the proposed method for remote sensing VQA. In contrast to traditional approaches that utilize

visual encoder networks for feature learning, Chappuis et al. [16] introduced a novel method that converts context information from images into text prompts that a language model can process. This enables the processing of both questions and visual contexts within a unified language model. Yuan et al. [174] introduced a self-paced curriculum learning (SPCL)-based training technique to train the RSVQA model in an easy-to-hard way. Recently, an interesting idea was proposed in [175]. The authors leveraged a VQA system for change detection on multitemporal aerial images. They built a change detection-based visual question-answering (CDVQA) dataset that contains multitemporal images and question-answer pairs using an automatic question-answer generation method. Furthermore, they developed a baseline method for the CDVQA task which contains four parts: multitemporal feature encoding, multitemporal fusion, multimodal fusion, and answer prediction.

#### F. Visual Grounding

Visual grounding for remote sensing data (RSVG) is a novel topic recently, and research on this task remains limited. Specifically, RSVG involves utilizing a remote sensing image and an associated query expression to provide the bounding box for the particular object of interest [180]. Through the process of localizing objects in remote sensing scenes using natural language guidance, RSVG offers object-level understanding and facilitates accessibility for end users. The potential applications of RSVG include target object detection and recognition, search and rescue tasks, urban planning, and so on.

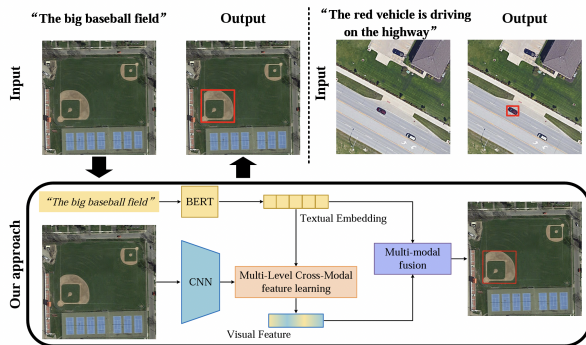


Fig. 12. Illustration of remote sensing visual grounding method proposed in [180].

Compared with query expressions in natural images, expressions in RSVG often involve complicated geospatial relations, and the objects of interest are often not visually salient. Despite the extensive research on visual grounding in natural images, this task remains under-explored in the field of remote sensing. RSVG was first introduced in [139], which not only introduced a novel dataset but also proposed a new method for achieving visual grounding in remote sensing scenes. The model proposed in this work consists of three components, namely, the language encoder, image encoder, and fusion module. The language encoder is used to create a geospatial relation graph, where nodes represent ground objects and edges characterize their geospatial relationships. As for the image encoder, an adaptive region attention module is leveraged to extract visual features from a large-scale remote sensing scene. In the end, a fusion module is utilized to integrate the geospatial relation graph into visual features. Another recent work was proposed by Zhan et al. [180], in which they built a new dataset and developed a novel transformer-based module, shown in Fig. [139]. On one hand, the proposed module addresses the scale variation problem by utilizing multi-scale visual features and multi-granularity language features to learn discriminative representations. On the other hand, to deal with cluttered backgrounds, the module dynamically filters out irrelevant noise and strengthens salient features. Besides, this work also benchmarked the performance of several state-of-the-art visual grounding methods designed for natural images on remote sensing data.

### G. Zero-Shot Scene Classification.

Zero-shot remote sensing scene classification (RSSC) aims to recognize unseen scene concepts by referring to both visual features and semantic relationships between semantic classes. Li et al. [72] proposed the first zero-shot learning-based approach for remote sensing (RS) scene classification, which employed a pretrained word2vec model on the Wikipedia corpus to derive semantic embeddings for category names, followed by the construction of a semantic graph to capture the inter-class relationships. Quan et al. [113] enhanced this method by incorporating a semi-supervised Sammon embedding algorithm [127] to align the semantic and visual prototypes.

Additionally, Sumbul et al. [136] presented a zero-shot learning technique for fine-grained RS image classification, which trained a compatibility function to establish the association between image features and semantic embeddings, enabling knowledge transfer from seen to unseen classes. Building upon the work of Kodirov et al. [63], Wang et al. [150] proposed a distance-constrained semantic autoencoder to align the visual features and semantic representations for the zero-shot RSSC. In [85], Li et al. employed transformer-based large language models, such as BERT, to extract semantic embeddings from expert-defined text descriptions for each class. Fig. 13 shows the method overview of the proposed method for zero-shot RSSC. Li et al. [86] introduced a generative adversarial network (GAN)-based approach for zero-shot RSSC, where a generator network was trained to synthesize image features from class semantics. In addition, the authors investigated different language processing models, i.e., Word2vec [151], Fasttext [59], [11], Glove [162], and BERT [32], for semantic embedding extraction. In contrast to natural images, RS scenes exhibit substantial structural and background variations, posing a significant challenge for models to learn robust visual features for scene understanding. Furthermore, the semantic correlations among diverse scene classes in RS images are comparatively weaker than those in natural images, rendering the semantic-reasoning-based zero-shot learning task even more challenging.

### H. Few-Shot Object Detection.

Object detection is a prominent task in remote sensing (RS) that involves detecting object instances by identifying their bounding boxes and class labels. This field has undergone significant advancements due to extensive research efforts in recent years, including two-stage detectors, such as Fast R-CNN [40] and Faster R-CNN [123], and one-stage detectors, such as SSD [92], YOLO [122], and RetinaNet [89], and recently proposed DETR variants [13], [200].

Few-shot object detection (FSOD) in RS images is a relatively new research area that has gained significant attention in recent years. This task aims to detect objects of interest in RS images using only a few annotated examples. Recent FSOD methods can be roughly divided into two families: 1) meta-learning-based [80], [24], [197] and finetuning-based [191], [53], [184]. Meta-learning-based methods contain a meta-learner to learn task-agnostic knowledge from a large number of sampled tasks, each task (also called episode) includes a support set and a query set and uses a task-specific learner to perform detection on specific tasks. Finetuning-based methods first train a detection model on base classes and then finetune network weights on novel classes. A comprehensive literature review of few-shot object detection in RS images can be found in [91]. Only a few attempts exploit VLMs for FSOD in RS images. Zhang et al. [183] proposed to build a corpus that contains language descriptions for each region, such as object attributes and relations, to encode the corresponding common sense embeddings. Lu et al. [99] proposed to use text descriptions for all object categories as additional features to mitigate classification confusion in FSOD. Fig. 14 shows the

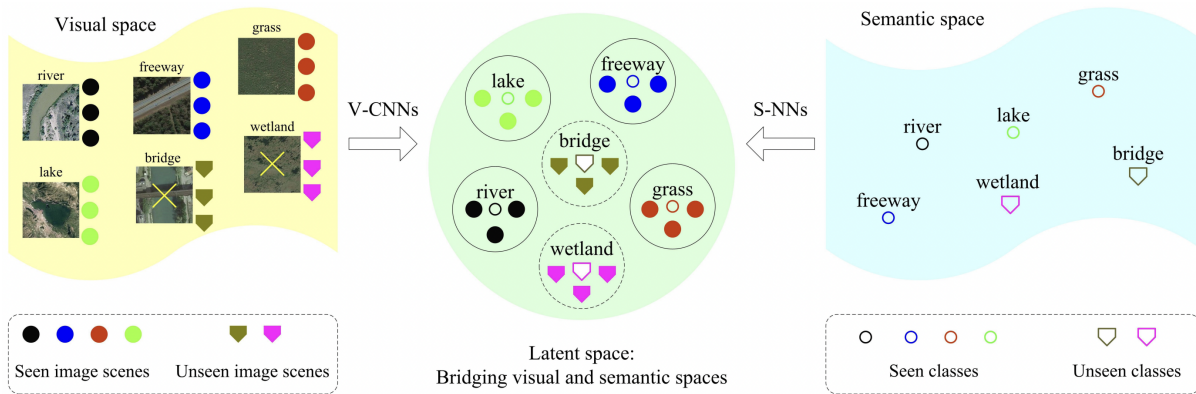


Fig. 13. Flowchart of the proposed Zero-shot remote sensing scene classification [85]. Visual features from remote sensing images and semantic features from class names are aligned in the latent space.

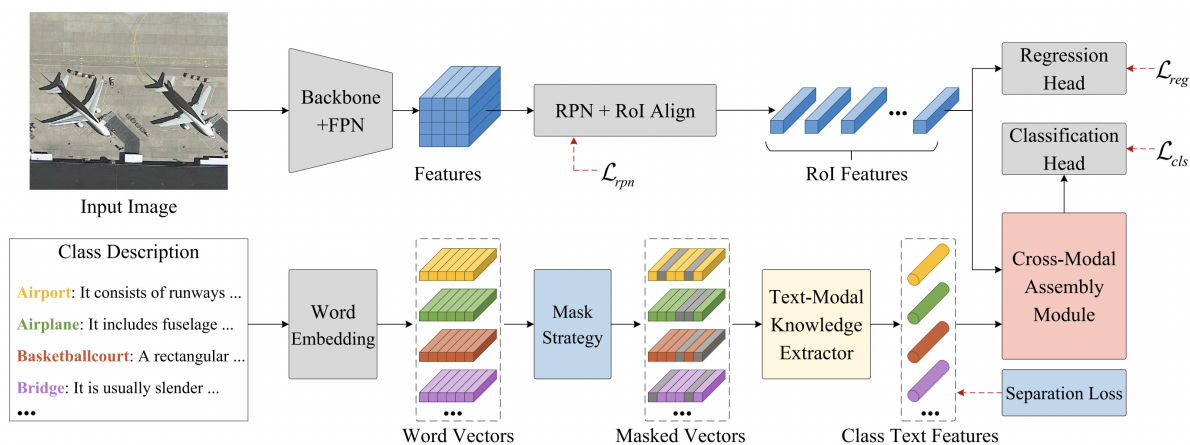


Fig. 14. The architecture of the few-shot object detection method proposed in [99]. Class descriptions are used for object classification.

method overview of the proposed method for few-shot object detection in RS images. These methods show the potential of combing visual and language features for better representation learning and thus enhance the performance of FSOD in RS images.

In computer vision, VLMs have shown great potential in few- / zero-shot object detection. The utilization of multi-modal vision-language pre-training models has made Open-Vocabulary Object Detection (OVOD) an active research area, as it allows for more realistic scenarios to be considered. In contrast to traditional object detection methods that are trained and evaluated on fixed and predefined classes, OVOD involves training on annotated datasets and generalizing the trained models to previously unseen novel classes. To enable Open-Vocabulary (zero-shot) detection, a common strategy is to modify existing object detection heads by matching object features and class embeddings. Usually, the class text embedding is generated by feeding prompts to the text encoder of a pre-trained VLM. The embedding is subsequently utilized as the region classifier to supervise the training of a detector.

Various techniques have been proposed in ViLD [42], BLC [193], PL [120], DSES [7] to improve detection performance, such as using pretrained VLMs like CLIP [114], enhance word embeddings for “foreground” and “background”

in RPN networks, and exploring better ways to integrating semantic and visual information. For example, Kim et al. [61] proposed to apply prior knowledge from text descriptions to guide the few-shot detection model. Specifically, they constructed a knowledge graph to extract semantic relationships between object categories by calculating similarities between word embeddings from a pretrained GloVe [112] text model. RegionCLIP [194] performed regional vision-language pre-training using generated pseudo region-text pairs and then transferred the backbone network to the OVOD task. VILD [43] adopted a two-stage open-vocabulary detector that distills embeddings from a teacher model, such as CLIP [114] or ALIGN [57]. Inspired by the CoOp approach [196], DetPro [35] introduced a technique that learns a continuous detection prompt, boosting the performance of VILD. OWL-ViT [108] added detection heads on a pre-trained image-text model and then fine-tuned the model on object detection datasets. Notably, Kuo et al. [68] introduced an open-vocabulary (zero-shot) object detection method, named F-VLM, built upon frozen vision and language models. This work demonstrates that frozen VLMs have the ability to preserve locality-sensitive features that are crucial for object detection and exhibit robust performance as a region proposal

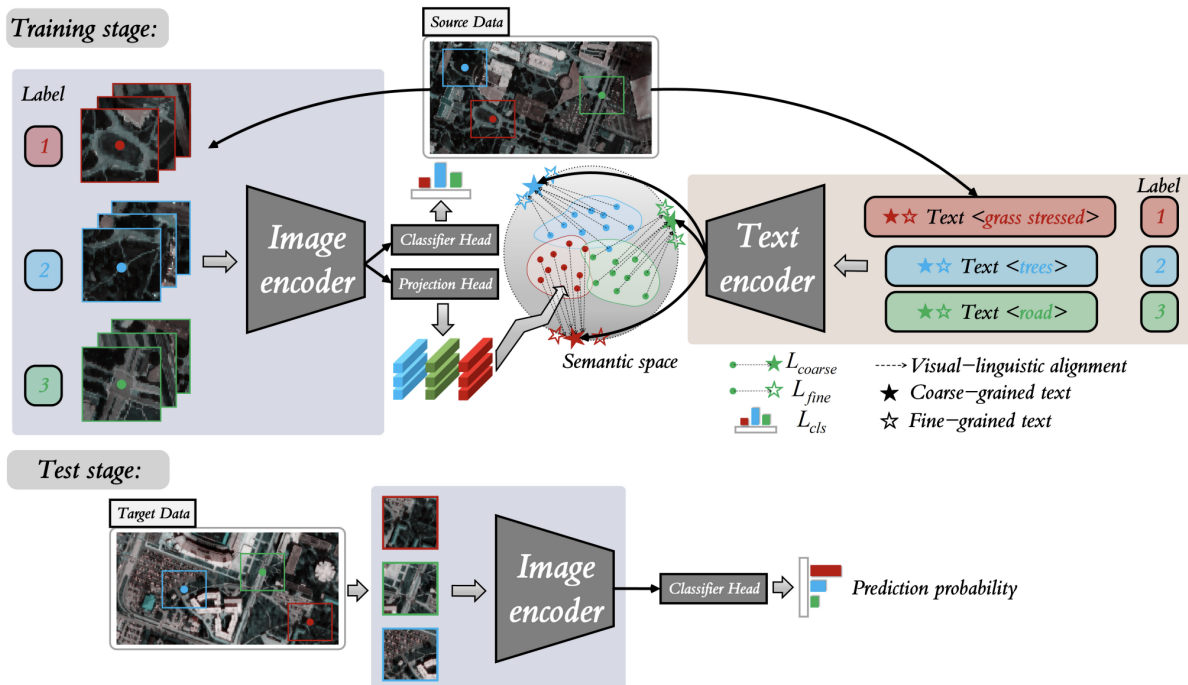


Fig. 15. Overview of cross-scene hyperspectral image classification method proposed in [187]. Visual features and text features are aligned in the semantic space.

classifier. F-VLM demonstrated remarkable performance on several zero-shot detection benchmarks. These works show the potential capabilities of vision-languages models in few- / zero-shot object detection in RS images.

### I. Few-/ Zero-shot Semantic Segmentation

In the realm of semantic segmentation, few-shot learning approaches enable the segmentation of novel classes with a limited number of annotated images. Recent efforts have focused on two categories, namely parameter matching-based and prototype-based methods. Notably, the Pioneering work PANet [154] achieved a breakthrough in few-shot segmentation by introducing a prototype alignment module that produces highly representative prototypes for each semantic class and segments query objects based on feature matching. Jiang et al. [58] proposed a few-shot learning method for remote sensing (RS) image segmentation, but the adoption of few-shot learning in RS image segmentation remains in its infancy. To overcome the data reliance on deep learning-based segmentation methods, recent studies [20], [187] have explored self-/semi-supervised learning and weakly supervised learning to reduce the need for dense annotation. Chen et al. [20] introduced a semi-supervised method for few-shot segmentation of RS images based on contrastive learning. Zhang et al. [187] introduced a network for cross-scene hyperspectral image classification, which utilizes language guidance to achieve domain generalization. Fig. 15 gives an overview of the proposed method.

In computer vision, pre-trained VLMs have been extensively explored for open-vocabulary semantic segmentation, thanks to their remarkable success in open-vocabulary image

classification, in which the model can classify any category without the need for additional annotated images of that category. Inspired by CLIP, DenseCLIP [121] solved the dense prediction problem by matching each pixel with the text. MaskCLIP [195] employed pseudo per-pixel labels created from CLIP and self-training to achieve annotation-free segmentation. Similarly, [179] used pixel-level pseudo-labels for dense supervision. ZegFormer [33] first grouped pixels into segments and then classified the segments with CLIP. OpenSeg [39] involved proposal generation and segment classification similar to ZegFormer, but it necessitated training with class-agnostic mask annotations to generate mask proposals. CLIPSeg [101] built upon the CLIP model and produced image segmentations based on arbitrary prompts. ZSSeg [166] first generated mask proposals and then utilized CLIP to classify the generated proposals in a two-stage manner. LSeg [73] utilized an image encoder to match pixel embeddings with text embeddings and a text encoder to offer a flexible class representation. OVSeg [87] proposed to finetune the CLIP model on masked image regions and corresponding texts from the COCO Captions dataset and obtained better open vocabulary segmentation performance. Fusioner [104] combined different vision and language models using a cross-modality fusion module to achieve open-vocabulary semantic segmentation. SegCLIP [102] gathered patches with learnable centers to semantic regions through text-image pair training, which can dynamically capture semantic groups and generate segmentation results.

#### IV. CONCLUSION AND FUTURE TRENDS

Computer vision and natural language processing have traditionally been studied as distinct fields, each with its own unique challenges and applications. However, the extraordinary success of ChatGPT has recently generated significant attention from researchers in the field of large language models for AGI. These models combine the strengths of computer vision and natural language processing, facilitating the development of more human-like intelligent systems built upon VLMs. Several studies in remote sensing (RS) have demonstrated the superiority of VLMs over purely visual models in various RS tasks, including image captioning, text-based image generation, text-based image retrieval, visual question answering, scene classification, semantic segmentation, and object detection. While these early attempts have shown the success of applying VLMs to remote sensing, it is still an emerging field for most researchers. Hence, this paper aims to present a comprehensive review of the application of visual language models in remote sensing, providing other researchers with a rapid understanding of the field's background and recent advances. It also seeks to encourage further investigations in this exciting and consequential field.

After reviewing the literature on VLMs in remote sensing, we identified several limitations in the current research. Firstly, the number of RS datasets used for training VLMs is limited, and the sample size is much smaller than the billions of image datasets in the computer vision field. Secondly, most of the existing RS VLMs still use classical CNN and RNN as image and language encoders, with only a handful of works exploring pre-trained visual transformers and large language models in computer vision, such as GPT, BERT, and Flan-T5. This can limit the feature learning abilities of these models. Additionally, training these VLMs from scratch requires a substantial computational burden, particularly for large networks with billions of parameters. There calls for effective model finetuning techniques for large VLMs in RS. Moreover, RS data can exhibit high variability due to factors such as lighting conditions, atmospheric interference, and sensor noise. This variability can make it difficult for VLMs to capture the relationships between visual and textual information accurately, but little existing work has taken this into account. Furthermore, VLMs may struggle to handle the large spatial and temporal scales of RS data, which can cover large areas and span long periods, making it challenging to capture the relationships between visual and textual information over space and time.

Given the limitations of existing VLMs research in RS. We list several promising research directions in the following.

- **Large-scale dataset.** It is well-known that the accuracy of AI-based systems is heavily reliant on the scale and diversity of training datasets. However, in RS, the existing largest datasets, including the Million-AID, fall short in terms of scale compared to web-scale datasets employed in the computer vision community that encompass billions of images. For instance, the LAION-5B [129] dataset is an open-source collection that comprises over 5 billion image-text pairs. To address the pressing need for

more rich datasets that can facilitate the training of large RS VLMs at scale, concerted efforts must be made to create data collection and sharing mechanisms. Therefore, it is essential for the research community to collaborate toward building datasets that are sufficiently diverse and paired with language descriptions.

- **Vision-language foundation models.** In RS, existing foundation models only focus on the vision models, which neglect the semantic understanding of the objects and their relationships. In contrast, vision-language foundation models can leverage their language understanding capabilities to reason about the relationship between objects, attributes, and their surrounding context, allowing for obtaining more representative features from RS images. These features can then be applied to various downstream tasks such as scene understanding, object detection, semantic segmentation, etc.
- **Text-based image generation using diffusion models.** Existing neural networks usually require a considerable volume of data to be trained for convergence, however, the collection of data sets requires a large amount of human and material resources. The diffusion model [125], on the other hand, has recently attracted a great deal of attention due to its ability to generate high-quality images with greater detail and fidelity. By using diffusion models to generate new images based on existing text descriptions, we can create synthetic data and effectively expand the size of our datasets to improve the robustness and generalization of deep learning models. Additionally, by incorporating techniques such as style transfer or domain adaptation, we can generate synthetic images that are more diverse and representative of real-world scenarios, further enhancing the effectiveness of data augmentation through diffusion models.
- **Few-/zero-shot learning.** Benefiting from powerful reasoning abilities from LLMs, VLMs show great potential for data-efficient learning by recognizing unseen objects or patterns based on the relationships between words and concepts in vision data. This makes them particularly useful in few-/zero-shot learning scenarios, where there is limited labeled data available for training. While previous attempts have explored the understanding of RS images in few-/zero-shot settings using smaller vision and language models, they lack the reasoning abilities necessary to comprehend and identify unseen objects or patterns. As we move towards the era of AGI, new techniques must be designed to better integrate LLMs into RS image understanding tasks, such as object detection, semantic segmentation, and change detection, particularly in few-/zero-shot settings.
- **Efficient finetuning on RS data.** Existing large language models usually contain billions of parameters (e.g., GPT-3 has 175B parameters), making it impractical to finetune the whole model to fit RS data. Therefore, there calls for efficient model finetuning techniques that can adapt LLMs (such as LLaMA [146]) for RS image analysis tasks. There are three potential solutions: 1) prompt fine-tuning [12] that designs learnable prompts that are

finetuned in new domains; 2) adapter networks [50], [90] that insert adapter layers between existing layers in deep neural networks; 3) low-rank adaption that injects trainable rank decomposition matrices into each layer of Transformer architectures. For instance, recently proposed LoRA [51] can reduce the number of trainable parameters by 10,000 times and reduce the GPU memory by three times.

- **Integrate RS expert knowledge into LLMs.** To better utilize LLMs for RS data analysis, an important step is to integrate RS expert knowledge into LLMs properly—this calls for empowering large language models with domain-specific knowledge about RS images, such as sensor imaging theory, spatial correlation, and spectral characteristics of ground objects. Recent work developed a new technique, called instruction tuning [158], to enhance the performance of LLMs under instructions. The instruction is finetuned on several full-shot tasks and then evaluated for its zero-shot generalization ability on specific tasks. In remote sensing, we can adopt a similar idea to enable knowledge-based instructions to generate and understand RS images.
- **Linking text-based information with RS via geolocation.** LLMs can be exploited to analyze text data associated with geolocation such as social media text messages [201], newspapers, etc., to extract linguistic features or even geoinformation, which can then be further fused with remote sensing data. This opens up new perspectives for a wide range of applications, such as semantic understanding of buildings [55], disaster response [67], and geo-aware social dynamics [66], [124], and offer new possibilities to utilize unconventional geodata sources that are complementary to remote sensing data.

Finally, exploring VLMs in RS can bring new insights and opportunities for advancing the field and is an exciting research topic for future investigations. By leveraging the power of language understanding capabilities, VLMs can facilitate a wide range of remote sensing tasks, such as land use/cover classification, object detection, and change detection, in a more efficient and accurate manner. Further research in this direction could lead to the development of novel approaches for remote sensing data analysis, which could have practical applications in fields such as agriculture, forestry, urban planning, and environmental monitoring, among others.

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