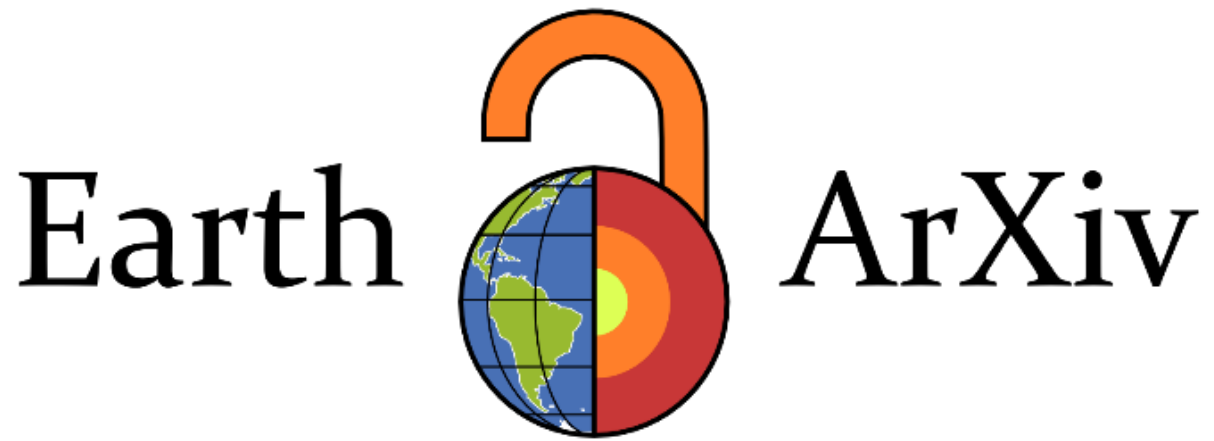




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S²AM-Net: Structure-semantic SAM-guided Network for Few-Shot Segmentation in Mining Areas

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Abstract

Precise mining land-cover classification is essential for monitoring environmental degradation and ecological restoration. Few-Shot Segmentation (FSS) offers a promising solution under limited annotations, but it still faces common challenges such as ambiguous foreground features and overfitting to the small support set. Moreover, mining landscapes are characterized by highly detailed structures, which are often lost during standard downsampling. To address these issues, we propose a Structure-semantic Adaptive Matching Network (S²AM-Net). It employs adaptive prior enhancement module to suppress background noise, selective edge attention with multi-scale learnable Sobel convolutions to preserve fine-grained structural details, and mask semantic alignment using SAM-generated masks for texture-invariant alignment. We also construct a dedicated benchmark, DLRSD-mining-6ⁱ, for complex mining categories. Extensive experiments on this dataset and iSAID-5ⁱ demonstrate that our method consistently outperforms existing approaches. The source code is available at: <https://github.com/cowqer/S2AMNet>.

Keywords: Mining area segmentation, Few shot, Adaptive prior enhancement, Selective edge attention, Segment anything model.

1. Introduction

Driven by the acceleration of global industrialization, intensive open-pit mining and subsequent ecological restoration have fundamentally reshaped regional land cover patterns. Although these activities supply essential resources for socioeconomic development, they simultaneously precipitate severe environmental consequences such as land degradation, landscape fragmentation, and geohazard risks (Zhou et al., 2023; Chen et al., 2018; Liu et al., 2025). While contemporary restoration initiatives aim to mitigate these adverse impacts, their efficacy is frequently compromised by suboptimal topographic reconfiguration and incomplete vegetation re-establishment. Within this context, accurate land cover classification has emerged as a fundamental prerequisite for monitoring ecological dynamics and evaluating the long-term success of reclamation strategies (Chen et al., 2020).

High-resolution remote sensing (RS) imagery, which

captures fine-grained surface characteristics, has become an indispensable data source for analyzing complex mining landscapes. Traditional classification methods based on manual interpretation and field surveys can achieve high accuracy, but they are labor-intensive and slow, making them impractical for large-scale or rapid monitoring tasks. In recent years, deep learning has shown remarkable performance in semantic segmentation for RS applications (Fan et al., 2026; Li et al., 2025). Nevertheless, fully supervised approaches depend heavily on large-scale pixel-level annotations, the acquisition of which is prohibitively expensive. This reliance severely limits their scalability. In addition, fully supervised models struggle to recognize unseen categories, reducing their adaptability in dynamic mining environments where land cover types frequently change (Gidaris and Komodakis, 2018). Although our preliminary studies explored transfer learning (Pan and Yang, 2009) strategies on small-scale datasets, segmentation accuracy and visual quality remain constrained by the limited availability of annotated samples.

Few-Shot Semantic Segmentation (FSS) (Shaban et al., 2017) addresses these limitations by enabling the

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segmentation of novel classes with only a few annotated samples (support set). FSS learns transferable and generalizable representations, exploiting category similarity or shared generic features to quickly adapt to unseen classes in query images. This capability makes FSS particularly suitable for remote sensing applications, where annotation costs are high and land cover categories change frequently. Recently, FSS has been extended to the remote sensing domain as RS-FSS (Yao et al., 2021; Wang et al., 2023; Tian et al., 2020; Li et al., 2024). For instance, Yao et al. (2021) employed a scale-aware focal loss to manage extreme object scale variations, while Wang et al. (2023) integrated self-correlation and spectral branches to mitigate overfitting. Despite these advances, existing RS-FSS methods struggle in complex mining environments due to three primary factors, as illustrated in Fig. 1.

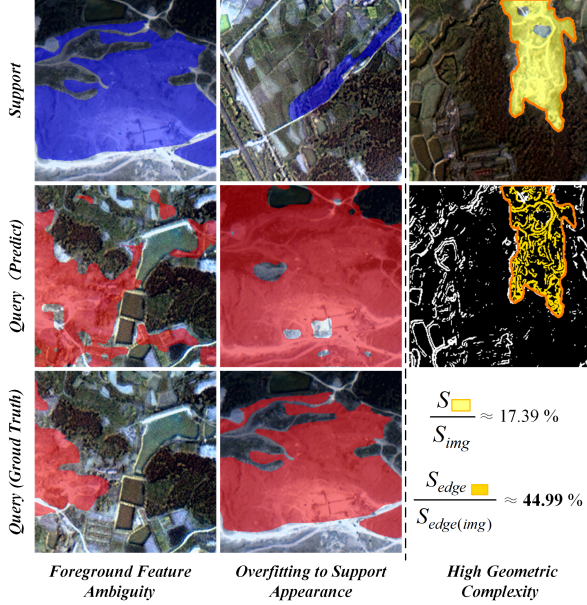


Figure 1: Core challenges in mining FSS: (Left) foreground ambiguity from cluttered backgrounds; (Middle) appearance gap causing overfitting; (Right) high geometric complexity with disproportionate edge information.

First, the inability to suppress cluttered background interference leads to severe foreground feature ambiguity. Representative approaches such as PFENet (Tian et al., 2020) employ high-level priors to emphasize foreground regions but often fail to inhibit irrelevant noise from mining-specific backgrounds. Consequently, standard convolutions inevitably assimilate background clutter into foreground features, resulting in false activations in query images (Fig. 1, left).

Second, over-reliance on support features triggers

texture overfitting, which prevents the model from bridging the visual gap during significant appearance variations. By overlooking generic objectness priors, this paradigm struggles to recognize query targets that look different from the support (Fig. 1, middle). As a result, the model focuses on superficial visual signatures rather than capturing the underlying semantic essence of the target.

Third, mining targets occupy only a small portion of the image, yet contain a disproportionately high amount of edge information, which is easily lost during feature extraction. Mining targets are characterized by a critical spatial-semantic imbalance where targets occupy only 17.39% of the image area but encapsulate 44.99% of the total edge information (Fig. 1, right). Existing architectures rely on repeated downsampling, which tends to smooth out these complex geometric details. Without explicit exploitation of edge cues, these methods fail to preserve discriminative boundaries, leading to fragmented segmentation results in structurally complex mining scenes.

To address these challenges, a novel framework for mining FSS, Structure-semantic Adaptive Matching Network (S²AM-Net), is proposed, as illustrated in Fig. 2. The backbone first extracts multi-level feature maps. To mitigate feature ambiguity, the Adaptive Prior Enhancement (APE) module leverages high-level feature priors to generate a pseudo-foreground prototype for the query, which is fused with the support foreground prototype to refine the original features. This process explicitly enhances foreground activations while suppressing background clutter before the correlation encoding stage. In the decoding stage, two key components are employed: Mask Semantic Alignment (MSA) and Selective Edge Attention (SEA). Existing SAM-based FSS methods (Li et al., 2024; Ao et al., 2024) mainly exploit SAM-generated masks for foreground enhancement, consistency regularization, or mask classification. Different from existing SAM-based paradigms that primarily exploit SAM masks for foreground enhancement or mask-level supervision, the proposed MSA leverages SAM-generated masks as structure-aware semantic cues to guide foreground semantic alignment between support and query features. The SEA module captures high geometric complexity through multi-scale learnable Sobel edge attention, dynamically emphasizing boundary information across scales to preserve intricate spatial structures of mining targets.

To facilitate evaluation in complex scenarios, the DLRSD-mining-6ⁱ dataset is constructed, integrating the LCMA dataset (Zhou et al., 2023) with standard RS-FSS protocols from DLRSD (Shao et al., 2018). Ex-

tensive experiments on both the public iSAID-5i (Yao et al., 2021) and DLRSD-mining-6ⁱ demonstrate the effectiveness and superiority of S²AM-Net.

The primary contributions of this work are summarized as follows:

1. We develop S²AM-Net, an FSS framework specifically designed to mitigate the feature ambiguity and structural degradation prevalent in complex mining scenes.
2. We introduce the Adaptive Prior Enhancement module, which rectifies high-level semantic representations by guiding pseudo-prototype generation, effectively suppressing cluttered background noise while explicitly enhancing foreground activations.
3. We introduce Mask Semantic Alignment and Selective Edge Attention to enhance correlation in representations from semantic and structural perspectives. MSA incorporates SAM-generated masks as structure-aware priors to guide semantic alignment between support and query features, while SEA captures multi-scale boundary cues via learnable edge filtering to preserve geometric details.
4. We establish DLRSD-mining-6ⁱ, a benchmark for few-shot segmentation in remote sensing, providing a standardized platform for evaluating mining area segmentation. Extensive experiments on both iSAID-5i (Yao et al., 2021) and the new dataset demonstrate the effectiveness of S²AM-Net.

2. Related Work

Few-Shot Segmentation (FSS) has attracted significant attention for its ability to generalize to novel categories with limited annotations, in contrast to fully supervised semantic segmentation. In remote sensing, FSS methods can be broadly categorized into prototype-based approaches and cross-guidance mechanisms, with recent studies leveraging foundation models (e.g., SAM, CLIP) to provide additional priors rather than forming an independent methodological branch.

2.1. Prototype-based Few-Shot Segmentation

Prototype-based methods embed support features into a metric space to generate class-representative prototypes, which are then used to segment query images via distance metrics such as Euclidean distance or cosine similarity. PANet (Wang et al., 2019) pioneered

this direction by introducing prototype alignment regularization to enforce consistent embeddings across support and query images. Following this, Nguyen and Todorovic (2019) leveraged gradient information from the support set during inference to fine-tune query features. To improve prototype robustness, Siam et al. (2019) proposed generating masked proxies and accumulating historical features to form multi-prototypes, providing more stable category representations.

Early approaches often relied solely on high-level features, suffering from spatial coarseness and bias toward seen classes, as highlighted by (Tian et al., 2020). PFENet (Tian et al., 2020) addressed this by generating training-free prior masks and concatenating spatial priors with query features. PFENet++ (Luo et al., 2023) further refined these priors using a Noise Suppression Module (NSM), while Xu et al. (2024) employed an ambiguity eliminator to improve foreground-foreground matching in cross-attention mechanisms.

To handle extreme intra-class variance, Li et al. (2021) used superpixel clustering to produce multiple prototypes adaptable to object deformation and scale changes, and DPNet (Chen et al., 2025) optimized dual prototypes for crack detection. In remote sensing scenarios with significant scale variation, SDM (Yao et al., 2021) proposed scale-aware detailed matching for local boundaries, DMMLNet (Wang et al., 2021) extracted multi-scale prototypes for diverse geospatial objects, while TBRNet (Wang et al., 2025) fused multi-scale semantic dependencies to highlight discriminative subregions.

Although most prototype-based methods focus on foreground priors, they often neglect background clutter, which is critical in mining scenes with complex environments.

2.2. Cross-Guidance Methods

Cross-guidance approaches model pixel-to-pixel or region-to-region interactions between support and query images to constrain feature matching. HSNet (Min et al., 2021) constructs 4D hypercorrelation tensors to capture multi-level semantic correspondences, improving foreground localization. MS2A2Net (Li et al., 2023) enhances this with bidirectional guidance between support and query sets. HDMNet (Peng et al., 2023) uses a hierarchically decoupled Transformer for pixel-level alignment, mitigating category bias and overfitting.

In remote sensing, SCCNet (Wang et al., 2023) adds a frequency-domain branch alongside self- and cross-correlation to generate auxiliary masks. MGCL (Li et al., 2024) incorporates SAM-generated masks to enforce intra-class consistency, and HRL (He et al., 2025)

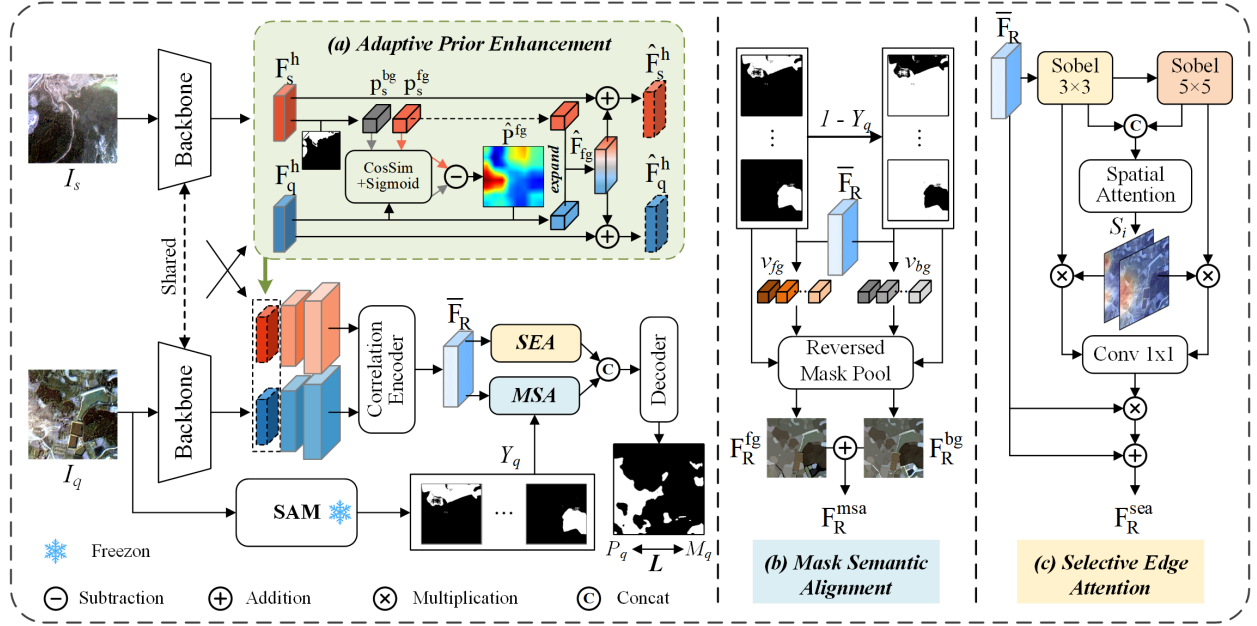


Figure 2: Overview of the proposed S²AM-Net. The framework uses a shared backbone, an Adaptive Prior Enhancement (APE) module for foreground enhancement and background noise suppression, and a Correlation Encoder-Decoder incorporating Mask Semantic Alignment (MSA) for texture-invariant alignment and Selective Edge Attention (SEA) for preserving fine-grained structural boundaries.

captures cross-image consistency across multiple feature levels.

While these cross-guidance methods improve regional semantic matching, fine-grained structural details are often lost due to the reliance on downsampled features.

2.3. Foundation Model-Assisted FSS

Vision Foundation Models (VFMs), such as SAM (Kirillov et al., 2023) and CLIP (Radford et al., 2021), provide robust priors and cross-modal semantic consistency, helping to overcome data scarcity in FSS. SAM-based methods primarily exploit structural priors for correlation learning and mask generation. For instance, MGCL (Li et al., 2024) uses frozen SAM weights to generate high-quality masks and integrates them into correlation learning to reduce foreground-background confusion. GRPN (Peng et al., 2025) employs graph prompt reasoning to optimize mask generation, SEMPNet (Ao et al., 2024) reformulates segmentation as SAM-based mask classification, and FSSAM (Xu et al., 2025) leverages SAM2’s spatiotemporal memory for sequential consistency. CLIP-derived semantic priors are used in DPNet (Chen et al., 2025) and PI-CLIP (Wang et al., 2024) to enhance feature discriminability, while ICPD-Net (Jiang et al., 2025) and MVLPNet (Yang et al., 2025) integrate ranking

and support set aggregation mechanisms for consistent foreground matching in remote sensing.

Despite their effectiveness, existing SAM-based FSS methods mainly leverage SAM priors for foreground-oriented tasks, such as mask generation, consistency regularization, or mask-based classification. However, the structural information encoded in SAM masks is often underutilized in support-query correlation modeling, and background context is not explicitly incorporated into semantic alignment.

3. Methodology

3.1. Problem Definition

FSS aims to segment target objects in query images from novel categories, given only a few annotated support samples. Formally, the dataset is divided into a training set $\mathcal{D}_{\text{train}}$ and a testing set $\mathcal{D}_{\text{test}}$, containing object categories $\mathcal{C}_{\text{train}}$ and $\mathcal{C}_{\text{test}}$ respectively, where $\mathcal{C}_{\text{train}} \cap \mathcal{C}_{\text{test}} = \emptyset$. This disjoint setting ensures the evaluation of the model’s generalization capability to unseen classes.

Following the standard episodic training paradigm, for a k -shot task, each episode consists of a support set $\mathcal{S} = \{(I_s^n, M_s^n)\}_{n=1}^k$ containing k image-mask pairs, and a query set $\mathcal{Q} = \{(I_q, M_q)\}$. All samples in an episode belong to the same specific category. The model is trained

on C_{train} to learn the mapping from support guidance to query segmentation and is expected to generalize this capability to C_{test} without further optimization.

3.2. Method Overview

The overall architecture of S²AM-Net is illustrated in Fig. 2. Given a query image I_q and support images I_s , a shared pretrained backbone (e.g., ResNet (He et al., 2016)) is employed to extract hierarchical features. Specifically, a Feature Pyramid Network (FPN) (Lin et al., 2017) structure is integrated to derive multi-scale representations $\{F_{s,l}, F_{q,l}\}_{l=1}^L$ across $L = 3$ scales, which capture rich spatial-semantic information. Simultaneously, high-level semantic features $\{F_q^h, F_s^h\}$ are preserved to provide the global context required for the subsequent prior enhancement module.

To address the inherent class-specific bias and background clutter in mining scenes, the APE module is introduced to rectify high-level semantic features by guiding pseudo-prototype generation, effectively suppressing background noise while enhancing foreground activations for more discriminative support-query matching.

Subsequently, multi-scale 4D correlation tensors are constructed between the refined support and query features. These correlations are further enhanced from both semantic and structural perspectives. Specifically, the MSA module leverages class-agnostic priors from a frozen SAM to map both foreground and background regions onto query features, achieving texture-invariant semantic alignment. In addition, Selective Edge Attention multi-scale high-frequency spatial gradients via learnable Sobel convolutions, preserving fine-grained geometric structures that are often lost during downsampling. The enhanced correlation representations from both semantic and structural branches are fused and fed into a correlation decoder to predict the final segmentation mask.

3.3. Adaptive Prior Enhancement

In few-shot segmentation, the limited availability of support samples necessitates accurate target localization within the query image. However, high-level features, unlike mid-level features that capture generic object parts, are inherently class-specific to the training categories (C_{train}). This specificity introduces a bias towards seen classes, limiting the generalization of high-level features to unseen testing classes (C_{test}).

Recent methods (Tian et al., 2020; Xu et al., 2024; Yang et al., 2025; Jia et al., 2023) mitigate this issue by deriving prior masks from high-level features to guide

segmentation. While effective, this strategy primarily treats high-level features as fixed priors and may underutilize their potential, especially in cluttered scenes where background activations dominate.

To address this, we propose the Adaptive Prior Enhancement module. APE constructs a query-adaptive pseudo-prototype from the generated priors, which is then used to rectify the original high-level features. This process enhances foreground activations, suppresses background noise, and provides a more discriminative representation for support-query matching.

Formally, given the high-level support feature map $F_s^h \in \mathbb{R}^{C \times H \times W}$ and its corresponding binary mask M_s , we first construct foreground and background prototypes from the high-level support features F_s^h and the corresponding binary mask M_s :

$$p_s^{fg} = \text{MAP}(F_s^h, M_s), \quad p_s^{bg} = \text{MAP}(F_s^h, 1 - M_s), \quad (1)$$

where MAP denotes masked average pooling. These prototypes summarize global statistics of the support object and background, providing class-specific priors for guiding query segmentation.

Next, we compute cosine similarities between the high-level query features F_q^h and the support prototypes to produce coarse foreground and background similarity maps. For each spatial location x , the foreground and background similarity maps $S^{fg}(x), S^{bg}(x)$ are calculated as:

$$S^{fg}(x) = \langle \hat{F}_q(x), \hat{p}_s^{fg} \rangle, \quad S^{bg}(x) = \langle \hat{F}_q(x), \hat{p}_s^{bg} \rangle, \quad (2)$$

where $\hat{F}_q(x)$ represents the L_2 normalized query feature vector at position x ; $\hat{p}_s^{fg}$ and $\hat{p}_s^{bg}$ are the normalized foreground and background support prototypes, respectively; $\langle \cdot \rangle$ represents cosine similarity.

Based on these similarity maps, a Softmax operation with a temperature factor τ (empirically set to 1.1) is applied to generate the foreground probability prior P^{fg} and the background probability prior P^{bg} .

$$P^*(x) = \frac{\exp(S^*(x)/\tau)}{\exp(S^{fg}(x)/\tau) + \exp(S^{bg}(x)/\tau)}, \quad * \in \{fg, bg\}, \quad (3)$$

We then compute a rectified activation map to emphasize confident foreground regions while suppressing background noise (Fig. 2(a)).

$$\hat{p}^{fg} = P^{fg} - P^{bg}. \quad (4)$$

Although $\hat{p}^{fg}$ is a linear transformation of P^{fg} , it introduces an explicit contrastive mechanism by producing signed responses, which enhances discriminative

capability by suppressing background activations and highlighting foreground-consistent regions. The final query-adaptive prototype p_q^{fg} is then generated through a weighted global pooling operation.

$$p_q^{fg} = \frac{\sum_x (F_q^h(x) \odot \hat{P}^{fg}(x))}{\sum_x P^{fg}(x) + \epsilon} \quad (5)$$

where $\odot$ represents element-wise multiplication, and ϵ is a small constant introduced to ensure numerical stability.

We then linearly fuse the support and query prototypes to balance category generality with instance specificity.

$$\hat{p}^{fg} = \alpha p_q^{fg} + (1 - \alpha) p_s^{fg}, \quad (6)$$

where α is a balancing coefficient (set to 0.5) that controls the fusion ratio between the query-adaptive prototype and the support prototype.

Finally, the fused prototype $\hat{p}^{fg}$ is spatially expanded to match the dimensions of the high-level feature maps. This process, denoted as the expansion operation $E(\cdot)$ (labeled as ‘‘Expand’’ in Fig. 2), injects explicit foreground semantics into the feature space through an additive residual connection.

$$\hat{F}_q^h = F_q^h + E(\hat{p}^{fg}), \quad \hat{F}_s^h = F_s^h + E(\hat{p}^{fg}), \quad (7)$$

where $E(\cdot)$ broadcasts the C -dimensional prototype vector across the spatial height and width. The resulting rectified features, $\hat{F}_q^h$ and $\hat{F}_s^h$, exhibit enhanced foreground responses and significantly reduced background ambiguity, providing a robust foundation for the subsequent relationship encoding stage.

3.4. Mask Semantic Alignment

To establish a stable class-agnostic prior and enhance the reliability of pixel-level matching in complex mining environments, we first employ a Correlation Encoder to transform the rectified features into a multi-scale similarity space. Following Li et al. (2024); Wang et al. (2023), the encoder computes 4D correlation volumes R_l at each scale l by concatenating foreground and background cosine similarities.

$$R_l = \sigma(\text{Concat}(\cos(\hat{F}_q, \hat{F}_s^{fg}), \cos(\hat{F}_q, \hat{F}_s^{bg}))), \quad (8)$$

$$\hat{F}_s^{fg} = \hat{F}_s \odot M_s, \quad \hat{F}_s^{bg} = \hat{F}_s \odot (1 - M_s), \quad (9)$$

where σ denotes the sigmoid function.

To obtain the multi-scale correlation map F_R , R_l is processed via 4D convolutions (Conv4D_l) and pooled across the support spatial dimensions.

$$F_{R_l} = \text{AvgPool}_{3,4}(\text{Conv4D}_l(R_l)), \quad \hat{F}_R = \{F_{R_l}\}_{l=1}^3. \quad (10)$$

However, these correlation features are still sensitive to appearance variations, especially in complex mining scenes. To address this issue, we introduce a Mask Semantic Alignment (MSA) module that incorporates structural priors into F_R . We adopt SAM as the mask generator due to its class-agnostic design and strong generalization to unseen categories, making it well-suited for few-shot segmentation.

Specifically, given M class-agnostic mask priors $\{Y_q^{(i)}\}_{i=1}^M$, we extract regional prototypes for both foreground and background via Masked Average Pooling (MAP):

$$v_{fg}^{(i)} = \text{MAP}(F_R, Y_q^{(i)}), \quad v_{bg}^{(i)} = \text{MAP}(F_R, 1 - Y_q^{(i)}). \quad (11)$$

These prototypes are projected back to pixel space via Reversed Masked Average Pooling (RMAP) (Li et al., 2024), and fused to produce the final enhanced feature.

$$F_R^{fg} = \sum_{i=1}^M Y_q^{(i)} \cdot v_{fg}^{(i)}, \quad F_R^{bg} = \sum_{i=1}^M (1 - Y_q^{(i)}) \cdot v_{bg}^{(i)}, \quad (12)$$

Different from previous SAM-guided approaches (Li et al., 2024), which performs RMAP on foreground prototypes only, we propose a dual-path alignment that jointly models foreground and background correlations. This is crucial in mining scenarios where foreground and background regions often share similar spectral and textural characteristics.

We therefore introduce a background alignment path F_R^{bg} to complement the foreground path F_R^{fg} , and fuse them as:

$$F_R^{\text{msa}} = F_R^{fg} + F_R^{bg}. \quad (13)$$

While F_R^{fg} captures object-specific responses, F_R^{bg} suppresses background-induced false activations, resulting in more discriminative and robust alignment.

3.5. Selective Edge Attention

Inspired by the large-kernel selective aggregation mechanism in LSKNet and SKnet (Li et al., 2019, 2025), we develop a Selective Edge Attention (SEA) module tailored for few-shot mining segmentation. Unlike Li et al. (2019, 2025), which enhances contextual representation in fully supervised settings, SEA is designed to strengthen geometry-aware edge refinement

under limited supervision. Specifically, we incorporate Sobel-initialized convolutions to provide an explicit structural prior and introduce residual modulation to reinforce boundary preservation within the correlation space.

In parallel with the semantic alignment branch, SEA aims to preserve the intricate structural details and irregular boundaries of mining targets. To this end, multi-scale edge features are extracted from the correlation map $\bar{F}_R$ through a cascaded pathway of learnable Sobel convolutions.

$$E_1 = \text{Sobel}_{3 \times 3}(\bar{F}_R), \quad E_2 = \text{Sobel}_{5 \times 5}(E_1), \quad (14)$$

where the kernels are initialized as Sobel operators to provide a geometry-aware starting point for edge detection. The filters are kept learnable to allow adaptive refinement of edge patterns, enabling the model to capture diverse structural variations beyond fixed gradient operators. Each edge map E_i is then compressed into a channel-mixed feature U_i through a 1×1 convolution. To adaptively integrate these multi-scale cues, a spatial attention block (Fig. 2(c)) generates scale-specific attention maps S_i .

$$[S_1, S_2] = \sigma(\text{Conv}_{7 \times 7}(\text{Concat}(U_1, U_2))), \quad (15)$$

where σ denotes the sigmoid function. These attention maps are used to selectively weight the corresponding edge features U_i , enabling SEA to capture both fine edges from smaller targets and broader structural outlines from larger targets. The final edge-enhanced feature is obtained via residual modulation.

$$F_R^{\text{sea}} = F_R \odot \left(1 + \text{Conv}_{1 \times 1}\left(\sum_{i=1}^2 U_i \odot S_i\right)\right). \quad (16)$$

By incorporating gradient-based structural priors and adaptive feature modulation, SEA encourages the network to focus on geometry-consistent regions and improves the preservation of object structures. It is worth noting that such structural awareness is implicitly encoded in the feature space rather than explicitly forming pixel-level edge responses.

3.6. Mask Prediction and Training Criteria

The final query mask is predicted by aggregating the original correlation map $\bar{F}_R$ with the semantic-aligned features F_R^{msa} and the edge-enhanced features F_R^{sea} through a lightweight convolutional decoder. Specifically, these three representations are concatenated and processed by two consecutive 3×3 convolution layers:

$$P_q = \text{Conv}_{3 \times 3}^{(2)}(\text{Concat}(\bar{F}_R, F_R^{\text{msa}}, F_R^{\text{sea}})), \quad (17)$$

which enables complementary integration of global semantic alignment and fine-grained structural refinement.

Under the standard 1-shot setting, the prediction P_q is supervised using the Binary Cross-Entropy (BCE) loss with respect to the ground-truth query mask M_q .

$$\mathcal{L}_{1\text{-shot}} = \text{BCE}(P_q, M_q). \quad (18)$$

For the K -shot setting ($K > 1$), an ensemble strategy is adopted: each support sample k generates a prediction $P_q^{(k)}$, and the training loss is averaged over all K support predictions.

$$\mathcal{L}_{K\text{-shot}} = \frac{1}{K} \sum_{k=1}^K \text{BCE}(P_q^{(k)}, M_q). \quad (19)$$

During inference, the K predictions are fused via majority voting, improving robustness against outlier support samples while preserving the individual decision boundaries.

4. Experiments

4.1. Datasets

To evaluate the proposed method in mining-area scenarios, we construct a few-shot semantic segmentation dataset, termed DLRSD-mining-6ⁱ, by integrating the DLRSD dataset (Shao et al., 2018) with the LCMA dataset (Zhou et al., 2023). Seventeen densely annotated common land-cover categories are selected from DLRSD, and mining-specific targets from LCMA (e.g., spoil heaps and mining pits in Fig 3) are merged into a single *mining* category, resulting in a total of 18 semantic classes. To reduce domain discrepancies, only 77 LCMA images containing mining regions are introduced as the additional class, without using non-mining regions to supplement other categories. Following a standard few-shot protocol similar to that used in DLRSD-5ⁱ (Wang et al., 2023), the categories are evenly divided into three mutually exclusive folds, with 12 base classes for training and six novel classes for testing in each fold. The detailed class splits are reported in Table 1. All images are resized into 256×256 patches, and evaluation is conducted under an episodic support-query setting.

To further assess generalization across diverse remote sensing scenes, we additionally conduct experiments on the iSAID-5ⁱ dataset. iSAID-5ⁱ is derived

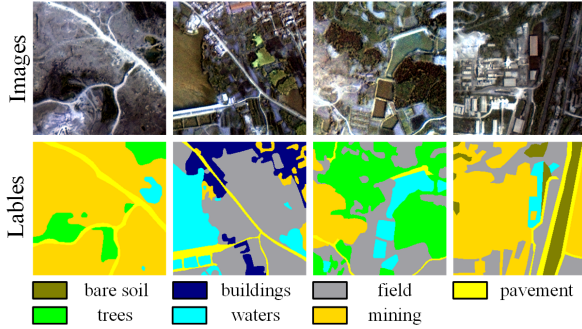


Figure 3: Representative image patches and semantic labels from the DLRSD-mining-6¹ dataset, featuring diverse land-cover categories and the specialized *mining* class.

Table 1: Testing Classes for Each Fold of DLRSD-Mining-6ⁱ

Dataset	Test Classes
DLRSD-Mining-6 ⁰	airplane, bare soil, buildings, cars, chaparral, court
DLRSD-Mining-6 ¹	dock, field, grass, mobile home, pavement, sand
DLRSD-Mining-6 ²	sea, ship, tanks, tree, water, mining

from the iSAID benchmark, which contains 2,806 high-resolution aerial images annotated with 15 semantic categories and 655,451 object instances. Following the protocol of Yao et al. (2021), the categories are evenly partitioned into three mutually exclusive folds, each serving as unseen classes in turn, with class splits summarized in Table 3. All images are resized to 256×256 , and a 3-fold cross-validation strategy is adopted, where the model is trained on two folds and evaluated on the remaining one.

4.2. Implementation Details

To obtain category-agnostic candidate regions, we adopt the Segment Anything Model with frozen parameters as a mask generator, using the ViT-H variant as the image encoder. Importantly, SAM is only used in an offline manner to pre-generate masks, which are subsequently used as inputs for the APE module. Therefore, SAM is not involved during training or inference and does not introduce additional computational overhead.

During mask generation, input images are resized to 1024×1024 , and 32 sampling points are uniformly placed along each image edge. Masks with a stability score below 0.5 are discarded. The remaining masks are ranked by area, with up to 128 masks retained; when

the number of valid masks exceeds this limit, only the top-ranked masks are preserved, whereas zero-valued dummy masks are padded when fewer than 128 masks are available, to maintain a fixed input size for subsequent modules.

For fair comparison, ImageNet-pretrained CNN backbones (VGG16 (Simonyan and Zisserman, 2014), ResNet50, and ResNet101 (He et al., 2016)) are employed as feature extractors, from which multi-scale features at three levels are obtained. All images are resized to 256×256 before being fed into the segmentation network.

The model is trained using SGD with a momentum of 0.9 and a weight decay of 5×10^{-4} . The backbone is jointly optimized with other modules, while its learning rate is set to be 10^3 times smaller to preserve pretrained representations. Training is conducted for 50 epochs on iSAID-5ⁱ and 100 epochs on DLRSD-mining-6ⁱ, with initial learning rates of $1 \times 10^{-2}/1 \times 10^{-3}$ and $1 \times 10^{-2}/1 \times 10^{-3}$ for weights/biases, respectively. Each batch contains 16 support-query pairs, and all experiments are performed on a single NVIDIA RTX 4090 GPU.

In terms of computational complexity, our model requires 11.51 GFLOPs under the 1-shot setting with an input size of 256×256 , demonstrating favorable efficiency.

By default, the hyperparameter α in Eq. 3.3 is set to 0.5. In the Selective Edge Attention module, Sobel convolution kernels with sizes of 3×3 and 5×5 are employed to capture multi-scale edge information, as illustrated in Fig. 2.

4.3. Comparison of results

Comparison on the DLRSD-mining-6ⁱ. To verify the effectiveness of the proposed framework, we conduct comparative experiments on the proposed DLRSD-mining-6ⁱ dataset. Performance is evaluated using the mean Intersection over Union (mIoU) under both 1-shot and 5-shot settings across multiple backbone networks, including ResNet-50, ResNet-101, and VGG-16. The results of our method are reported in the ‘‘Ours’’ column of the corresponding tables.

As shown in Table 2, the proposed method consistently achieves the highest average mIoU across the three folds under all backbone configurations. Taking ResNet-50 as an example, our method attains a mean mIoU of 45.20% in the 1-shot setting, outperforming the recent MGCL (2024) by 4.77%. When increasing the number of support samples to five, the performance is further improved to 49.31%, indicating the

Table 2: Quantitative comparison on DLRSD-mining-6ⁱ dataset under 1-shot and 5-shot settings. Params denote the number of parameters excluding the backbone network for fair comparison. Methods marked with * use frozen backbones.

Backbone	Network	1-shot (%)				5-shot (%)				Params
		Fold1	Fold2	Fold3	Mean	Fold1	Fold2	Fold3	Mean	w/o backbone
VGG-16	HSNet* (Min et al., 2021)	30.59	36.59	41.06	36.08	33.87	40.25	44.44	40.40	2.57 M
	SCCNet (Wang et al., 2023)	31.03	38.58	34.71	34.77	34.91	43.30	44.61	40.94	5.15 M
	SEMPNet* (Ao et al., 2024)	29.50	40.25	41.22	36.99	30.27	41.31	43.01	38.20	0.37 M
	HRL* (He et al., 2025)	26.63	29.88	30.97	29.16	29.26	37.25	39.12	35.21	10.97 M
	MGCL (Li et al., 2024)	29.46	42.63	42.92	38.34	32.10	42.63	42.18	38.97	0.70 M
	Ours	31.44	40.04	48.21	39.90	35.76	47.66	53.21	45.54	0.75 M
ResNet-50	HSNet* (Min et al., 2021)	33.40	40.44	44.44	39.43	38.49	44.21	51.30	44.67	2.57 M
	SCCNet (Wang et al., 2023)	28.67	38.40	38.28	35.12	32.01	42.92	48.01	40.98	5.15 M
	SEMPNet* (Ao et al., 2024)	34.14	41.43	46.14	40.57	35.55	42.22	42.67	40.15	0.37 M
	HRL* (He et al., 2025)	26.33	33.00	31.60	30.31	29.73	39.33	34.72	34.59	10.97 M
	MGCL (Li et al., 2024)	32.48	38.39	50.42	40.43	37.09	46.42	58.38	47.30	0.70 M
	Ours	36.65	45.49	53.45	45.20	41.27	50.35	56.38	49.31	0.75 M
ResNet-101	HSNet* (Min et al., 2021)	32.83	39.01	48.57	40.14	38.08	43.00	55.49	45.52	2.57 M
	SCCNet (Wang et al., 2023)	23.43	40.90	50.51	38.28	27.58	44.97	53.12	41.89	5.15 M
	SEMPNet* (Ao et al., 2024)	33.53	41.58	46.94	40.68	33.66	42.80	49.30	41.92	0.37 M
	HRL* (He et al., 2025)	22.72	34.08	35.42	30.74	22.95	37.04	36.59	32.19	10.97 M
	MGCL (Li et al., 2024)	30.06	38.44	52.37	40.29	31.39	46.42	58.31	45.37	0.70 M
	Ours	35.49	38.73	51.59	41.94	39.62	44.41	57.85	47.29	0.75 M

effectiveness of the proposed framework in exploiting additional support information. Moreover, as the backbone is deepened from ResNet-50 to ResNet-101, the proposed method maintains a stable performance advantage. Notably, on the classical VGG-16 backbone, our approach achieves 45.54% mIoU in the 5-shot setting, surpassing SCCNet by 4.6%. It is worth noting that MGCL and SCCNet are trained without freezing the backbone, while several other compared methods adopt frozen backbone settings, following their original implementations. Even under these mixed training protocols, these improvements are achieved with only 0.75M parameters, remaining comparable to MGCL and significantly more lightweight than most existing methods. These consistent gains across different architectures suggest that the performance improvements mainly stem from the proposed APE, SEA, and MSA modules rather than from a specific backbone choice, which is further validated by the ablation studies in the following section.

Comparison on the iSAID-5i. To further evaluate the generalization capability of the proposed method, ex-

periments are conducted on the iSAID-5i benchmark. As summarized in Table 3, the proposed approach achieves the highest *cross-fold mean* mIoU among all compared methods under the 1-shot setting, demonstrating strong robustness in few-shot remote sensing scenarios.

Table 3 further reports quantitative comparisons under both 1-shot and 5-shot settings with different backbone networks. With the VGG-16 backbone, our method achieves mean mIoU scores of 35.53% and 39.24% under the 1-shot and 5-shot settings, respectively. Compared with the recent MGCL method, the proposed approach improves the 1-shot performance by 1.80% while achieving comparable 5-shot results. Notably, our method obtains the best performance on Fold1 and Fold3 in the 1-shot setting, and consistently outperforms earlier approaches such as HSNet and SCCNet.

Consistent performance gains are observed with deeper backbones. Under the ResNet-50 backbone, the proposed method achieves 38.87% mIoU in the 1-shot setting and 45.40% in the 5-shot setting, outperforming most recent methods and showing particularly strong

Table 3: Quantitative comparison on iSAID-5¹ dataset under 1-shot and 5-shot settings. Params denote the number of parameters excluding the backbone network for fair comparison. Methods marked with * use frozen backbones.

Backbone	Networks	1-shot(%)				5-shot(%)				Params
		Fold1	Fold2	Fold3	Mean	Fold1	Fold2	Fold3	Mean	w/o backbone
VGG-16	HSNet* (Min et al., 2021)	22.74	23.05	25.76	23.85	27.20	28.86	28.82	28.29	2.57 M
	SDM (Yao et al., 2021)	29.24	20.80	34.73	28.26	36.33	27.98	42.39	35.57	8.73 M
	SCCNet (Wang et al., 2023)	30.00	27.41	32.43	29.95	36.52	31.40	37.53	35.15	5.15 M
	HMRE* (Jia et al., 2023)	36.48	28.28	35.36	33.37	37.33	29.28	43.36	36.66	-
	MGCL (Li et al., 2024)	37.54	25.79	37.86	33.73	44.57	32.54	44.66	40.59	0.70 M
	HSE (Jia et al., 2025)	37.18	29.79	36.04	34.34	47.03	36.75	45.66	43.15	-
	DSMF-Net (Qi et al., 2025)	31.25	24.35	31.04	28.88	40.73	26.92	38.05	35.23	-
	Ours	38.32	27.85	40.41	35.53	42.25	30.84	44.63	39.24	0.75 M
ResNet-50	HSNet* (Min et al., 2021)	30.76	24.35	38.20	31.10	38.08	30.56	45.28	37.79	2.57 M
	SDM (Yao et al., 2021)	34.29	22.25	35.62	30.72	39.88	30.59	45.70	38.72	11.08 M
	SCCNet (Wang et al., 2023)	36.21	27.42	43.37	35.67	42.58	30.30	50.26	41.05	5.15 M
	HMRE* (Jia et al., 2023)	40.88	32.88	37.22	36.99	42.41	34.69	41.06	39.39	-
	MGCL (Li et al., 2024)	42.35	28.87	43.61	38.28	51.50	32.57	50.40	44.82	0.70 M
	HSE (Jia et al., 2025)	44.03	35.87	39.26	39.72	47.03	36.75	45.66	43.15	-
	DSMF-Net (Qi et al., 2025)	39.03	25.92	40.57	35.17	43.69	30.81	42.32	38.94	-
-	Ours	44.23	28.29	44.08	38.87	49.31	33.96	52.92	45.40	0.75 M
ResNet-101	HSNet* (Min et al., 2021)	34.91	26.51	40.84	34.09	41.71	31.08	48.54	40.44	2.57 M
	SCCNet (Wang et al., 2023)	37.65	29.19	42.99	36.61	41.87	32.12	49.63	41.21	5.15 M
	MGCL (Li et al., 2024)	42.35	28.87	43.61	38.28	51.50	32.57	50.40	44.82	0.70 M
	Ours	43.94	31.88	44.29	40.03	51.36	33.14	51.60	45.37	0.75 M

performance in the 5-shot scenario. Although HSE achieves a higher 1-shot result of 39.72%, its performance drops to 43.15% in the 5-shot setting, whereas our method maintains superior multi-shot generalization capability. In comparison, DSMFNet achieves only 35.17% and 38.94% under the same settings, both significantly lower than our approach.

Methods marked with “-” indicate that the corresponding implementations are not publicly available, and thus their parameter statistics cannot be obtained. Despite the strong segmentation performance, the proposed method requires only 0.75M parameters (excluding the backbone network), which is comparable to MGCL and substantially fewer than most existing methods, demonstrating a favorable trade-off between segmentation accuracy and model complexity.

4.4. Ablation Study

To comprehensively analyze the effectiveness of the proposed modules for mining-area and remote sensing

object segmentation, as well as the impact of their associated design choices, we conduct a series of ablation experiments on the DLRSD-mining-6¹ dataset under the 1-shot setting, using ResNet-50 as the backbone network.

Effectiveness of Individual Modules. Table 4 presents an ablation study evaluating the contributions of the APE module, SEA, and MSA modules. The baseline model, which excludes all proposed components, achieves a mean mIoU of 38.23%, with particularly limited performance on the mining category (16.70%), indicating insufficient capability in modeling complex mining-area semantics.

Introducing the APE module alone leads to a noticeable improvement, raising the mean mIoU to 41.65% and increasing the mining-class mIoU by more than 11%. This improvement indicates that adaptive prior enhancement can enhance foreground representations by leveraging category-agnostic semantic priors. When the SEA module is further incorporated, the mining-

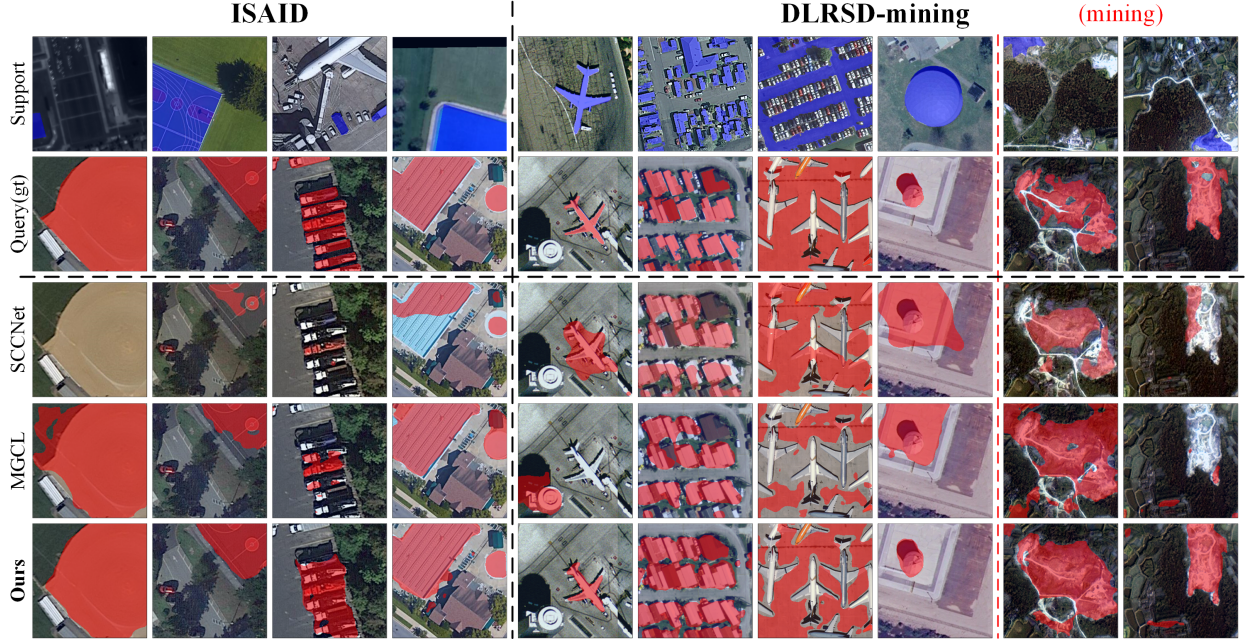


Figure 4: Visual comparison of few-shot segmentation results on iSAID-5i and DLRSD-mining-6i.

Table 4: Ablation study on the effects of APE, SEA, and MSA modules.

APE	SEA	MSA	Fold0	Fold1	Fold2	Mean	Mining
×	×	×	32.62	36.80	45.27	38.23	16.70
✓	×	×	32.47	43.85	48.64	41.65	28.09
✓	✓	×	35.61	44.10	46.21	41.97	35.20
×	✓	✓	35.98	41.92	51.19	43.03	28.35
✓	×	✓	35.14	41.41	51.11	42.55	31.18
✓	✓	✓	36.65	45.49	53.45	45.20	36.98

class performance is substantially improved (from 28.09% to 35.20%), suggesting that selective edge attention plays a crucial role in preserving fine-grained structural information, which is essential for accurately delineating irregular mining boundaries.

The integration of MSA with either APE or SEA consistently enhances overall performance, particularly on Fold2 which contains the mining class, implying that mask-based semantic aggregation improves robustness under challenging class distributions. Among the partial configurations, the combination of SEA and MSA achieves the highest mean mIoU of 43.03%, highlighting the complementary nature of boundary-aware feature refinement and region-level semantic aggregation.

Finally, the full model incorporating all three modules achieves the best performance across all folds,

reaching a mean mIoU of 45.20% and a mining-class mIoU of 36.98%. Compared with the baseline, this corresponds to improvements of 6.97% in mean mIoU and 20.28% in mining-class performance, respectively. These results confirm that APE, SEA, and MSA jointly contribute to more accurate and robust few-shot segmentation in complex mining-area scenarios.

Ablation Study of Kernel Size in the Selective Edge Attention. Table 5 evaluates the impact of different successive kernel size configurations in the SEA module. Without SEA, the model achieves a mean mIoU of 42.55%, indicating limited capability in modeling boundary-sensitive features, particularly for the mining category.

Table 5: Ablation study on the combination of successive kernel sizes in SEA.

(k_1, k_2)	Fold0	Fold1	Fold2	Mean	Mining
w/o SEA	35.14	41.41	51.11	42.55	31.18
$(3 \times 3, 3 \times 3)$	35.17	37.63	52.73	41.84	35.97
$(3 \times 3, 5 \times 5)$	36.65	45.49	53.45	45.20	36.98
$(3 \times 3, 7 \times 7)$	36.10	43.28	50.44	43.27	31.78
$(5 \times 5, 7 \times 7)$	34.58	41.75	49.95	42.09	25.36

The design of SEA follows the selective multi-kernel paradigm in SKNet and LSKNet, where combining two kernels with moderate receptive field expansion pro-

vides an effective trade-off between representation capacity and efficiency. As shown in Table 5, small kernels such as $(3 \times 3, 3 \times 3)$ offer insufficient contextual modeling, whereas excessively large combinations (e.g., $(3 \times 3, 7 \times 7)$ and $(5 \times 5, 7 \times 7)$) tend to reduce local boundary sensitivity. This indicates that overly enlarged receptive fields may dilute the spatial cues that SEA aims to enhance.

Among all configurations, $(3 \times 3, 5 \times 5)$ consistently achieves the best performance across all folds, obtaining a mean mIoU of 45.20% and a mining mIoU of 36.98%. The 3×3 kernel maintains local edge structures, while the 5×5 kernel moderately expands contextual perception, which is beneficial for irregular mining regions. Therefore, $(3 \times 3, 5 \times 5)$ is adopted as the default configuration of the SEA module.

Ablation Study of Fusion Parameter α . Table 6 analyzes the influence of the fusion parameter α , which balances query-adaptive and support-based foreground prototypes. As our study primarily targets performance under the 1-shot setting, with 5-shot serving as supplementary evaluation, maintaining a balanced contribution from support-derived semantic priors and query-adaptive structural cues is expected to favor stable generalization.

Table 6: Ablation Study on the Fusion Parameter α

α	Fold0	Fold1	Fold2	Mean	Mining
0	34.34	40.88	38.99	38.07	22.67
0.3	35.99	43.20	51.27	43.49	28.39
0.5	36.65	45.49	53.45	45.20	36.98
0.7	35.09	39.09	54.22	42.80	36.31
0.9	36.28	45.19	50.19	43.89	35.88

When $\alpha = 0$, performance degrades substantially across all folds, indicating that relying solely on support-derived prototypes fails to capture query-specific variations. Introducing query adaptation ($\alpha = 0.3$) yields consistent improvements, confirming the necessity of instance-level refinement. The best overall performance is achieved at $\alpha = 0.5$, reaching a mean mIoU of 45.20% and the highest mining mIoU of 36.98%, demonstrating that balanced fusion provides the most reliable representation under limited supervision.

Although Fold2 achieves its highest performance at $\alpha=0.7$, this behavior appears to be fold-specific rather than indicative of a consistent trend. A closer inspection of the performance variation reveals that Fold2 is

relatively insensitive to changes in α , showing only a marginal improvement of +0.77% from $\alpha=0.5$ to $\alpha=0.7$. In contrast, Fold0 and Fold1 exhibit substantially higher sensitivity to this coefficient. For instance, the performance of Fold1 drops sharply from 45.49% to 39.09% when α increases to 0.7, corresponding to a decrease of 6.40%.

This discrepancy suggests that Fold2 is less sensitive to the fusion ratio, likely due to higher intra-class diversity and more complex scene composition, where stronger query adaptation remains beneficial. In contrast, Fold0 and Fold1 exhibit relatively lower intra-class variation, and over-emphasizing query-specific cues introduces instability and degrades performance. Therefore, $\alpha = 0.5$ provides a better trade-off between support-based stability and query-driven adaptability, leading to the most consistent performance across all folds.

Sensitivity Analysis of the MSA Module. To further investigate the proposed MSA module, we conduct additional sensitivity analyses on the SAM stability threshold, mask number, and SAM backbone scale. As shown in Table 8, the best overall performance is achieved when the stability threshold is set to 0.5, whereas overly loose or strict thresholds slightly degrade segmentation accuracy due to noisy or insufficient mask priors. Furthermore, the segmentation performance generally improves as the number of generated masks increases, particularly for the mining category, indicating that richer structural priors are beneficial for sparse target localization. Although comparable performance can still be achieved with fewer masks (e.g., 32 or 64), the overall mIoU obtained with 128 masks remains the highest. Considering that the SAM automatic mask generator typically produces more than 100 masks per image on average, we empirically set the maximum number of masks to 128 in order to sufficiently exploit the structural information provided by the generated masks. In addition, replacing SAM ViT-H with lighter variants such as ViT-L and ViT-B results in only moderate performance degradation. Since the SAM masks are generated in an offline preprocessing manner, the choice of SAM backbone does not affect the actual training or inference efficiency of the segmentation framework. Therefore, SAM ViT-H is adopted as the default configuration due to its superior overall performance.

4.5. Discussion

4.5.1. Per-Class Performance Analysis

Table 2 presents a per-class mIoU comparison on the DLRSD-mining-6ⁱ dataset across 18 categories.

Table 7: Quantitative comparison (mIoU, %) on the DLRSD-mining-6^l dataset under 1-shot and 5-shot settings.

Networks	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	Mean
1-shot																			
HSNet (Min et al., 2021)	30.55	30.56	28.70	11.99	42.97	55.64	25.63	97.56	29.10	44.12	23.78	22.47	58.71	50.29	32.60	38.28	55.89	36.98	39.77
SCCNet (Wang et al., 2023)	16.59	29.56	21.20	7.37	42.28	55.00	24.82	98.43	28.93	34.72	24.20	19.28	58.51	38.36	28.31	33.98	42.92	27.58	35.11
PCFNet (Ao et al., 2023)	30.36	33.64	33.09	15.38	43.09	57.78	22.42	95.87	34.85	48.95	33.13	27.29	68.24	50.60	41.72	36.85	52.02	29.61	41.94
SEMPNet (Ao et al., 2024)	31.90	26.43	33.06	15.24	46.06	52.12	20.79	96.85	32.39	45.04	33.65	19.87	65.88	60.38	39.40	36.33	52.79	22.07	40.57
HRL (He et al., 2025)	16.40	28.69	35.78	8.96	38.31	29.86	18.79	63.96	24.24	51.10	22.60	17.33	44.03	29.43	17.99	32.14	37.19	28.79	30.31
MGCL (Li et al., 2024)	25.13	25.30	38.18	10.00	40.37	55.87	22.02	77.98	29.18	46.31	31.04	23.78	90.01	46.48	47.35	36.28	57.07	25.34	40.43
Ours	40.51	33.58	36.44	9.84	42.86	56.66	24.25	96.60	33.35	52.83	38.01	27.89	91.01	48.55	45.89	40.20	58.04	36.98	45.19
5-shot																			
HSNet (Min et al., 2021)	40.30	32.58	31.03	16.92	43.22	66.90	27.44	98.11	34.54	46.11	28.85	30.22	64.55	49.54	44.56	45.78	63.32	40.05	44.67
SCCNet (Wang et al., 2023)	18.53	31.39	28.42	9.04	42.10	62.58	24.85	98.67	36.37	38.98	32.71	25.93	66.30	45.99	41.95	45.40	54.51	33.95	40.98
PCFNet (Ao et al., 2023)	34.49	39.20	42.88	19.27	43.12	67.20	23.15	97.36	43.57	51.21	36.99	36.36	82.45	52.31	49.50	40.70	62.27	37.51	47.75
SEMPNet (Ao et al., 2024)	32.45	29.60	36.92	17.14	44.63	52.57	20.83	96.85	32.32	45.29	34.74	23.31	69.78	60.32	34.97	35.83	58.97	23.24	40.00
HRL (He et al., 2025)	32.21	22.64	37.04	12.54	32.91	41.04	20.90	79.42	33.61	51.76	32.00	18.27	37.33	26.42	25.87	39.21	50.57	28.94	34.59
MGCL (Li et al., 2024)	28.52	35.10	47.89	11.46	42.53	57.02	23.52	87.55	37.49	50.80	41.59	37.58	93.84	53.56	54.51	45.05	64.41	38.92	47.30
Ours	46.63	36.14	45.82	11.50	42.66	64.86	25.78	97.41	39.39	54.43	44.85	40.23	93.34	56.27	44.41	44.40	58.10	41.29	49.31

Table 8: Sensitivity analysis of the proposed MSA module under different stability thresholds, SAM backbone scales, and mask numbers. Results are reported in terms of mIoU (%).

Setting	Variant	Fold0	Fold1	Fold2	Mean	Mining
Threshold	0.3	34.95	41.88	49.87	42.23	29.92
	0.5	36.65	45.49	53.45	45.20	36.98
	0.7	33.22	43.33	51.24	42.60	30.14
	0.9	34.49	44.02	49.60	42.70	31.52
SAM Scale	ViT-H	36.65	45.49	53.45	45.20	36.98
	ViT-L	36.69	45.75	52.32	44.92	33.04
	ViT-B	35.79	42.42	49.29	42.50	33.81
Mask Number	4	35.03	44.18	39.59	39.60	21.94
	8	34.58	42.34	43.48	40.13	27.23
	16	34.75	43.67	49.86	42.76	25.60
	32	34.89	43.66	53.12	43.89	36.41
	64	35.12	44.02	52.59	43.91	35.79
	128	36.65	45.49	53.45	45.20	36.98

Overall, the proposed method achieves the highest mean mIoU of 45.19%, outperforming all competing approaches, which demonstrates strong generalization performance. Notably, our method shows consistent improvements on structurally complex and semantically ambiguous categories, such as C10, C11, C12, C16, and C17. In particular, the mining category (C18) benefits significantly from the proposed framework, achieving the best mIoU of 36.98% under the 1-shot setting. Compared with MGCL (25.34% in C18), our framework exhibits a substantial performance lead. As indicated by the ablation results in Table 4, even the partial configuration comprising only APE and MSA (achieving 42.55% mean mIoU and 31.18% mining mIoU) already outperforms the full MGCL model (40.43% mean mIoU and 25.34% mining mIoU). This confirms that our MSA module, by introducing a background align-

ment path during the decoding stage, provides superior semantic alignment compared to the unidirectional foreground enhancement used in MGCL. This dual-path design is particularly effective at resolving the ambiguity between mining targets and look-alike background clutter.

These gains reflect an enhanced capability in capturing irregular boundaries and heterogeneous appearances commonly observed in mining areas. When increasing the number of support samples to 5-shot, the proposed method further boosts the mining-class performance to 41.29%, ranking first among all compared methods. These gains further demonstrate the effectiveness of the proposed adaptive prior enhancement and boundary-aware modeling in challenging remote sensing scenarios.

4.5.2. Visualization analysis of APE

As shown in Fig. 5, removing APE leads to incomplete object activation and fragmented predictions in complex mining scenes, particularly around thin structures and irregular boundaries. In contrast, the proposed APE module generates a spatial prior that is approximately aligned with the target regions, providing reliable coarse localization that effectively guides subsequent segmentation. This results in more complete region coverage and improved boundary continuity, while simultaneously enhancing foreground responses and suppressing background interference. Such behavior suggests that APE improves the discriminative structure of the feature space by amplifying foreground-consistent responses and attenuating background ambiguity. The consistent improvement observed across different samples further provides strong evidence that the

APE module enhances the robustness of segmentation in mining environments.

4.5.3. Visualization analysis of SEA

We further analyze the behavior of the SEA module through visualization in Fig. 6, which presents the intermediate responses (E_1 , E_2), the SEA activation map, and the final prediction alongside the query image and ground truth.

It is important to note that SEA operates on high-level correlation features rather than raw pixel intensities. The Sobel-initialized convolutions therefore encode structural information implicitly within the correlation space, meaning the intermediate maps reflect geometry-sensitive feature responses rather than explicit pixel-level edge maps.

As shown in Fig. 6, E_1 and E_2 respond to regions at different scales, capturing complementary structural cues. E_1 (3×3) captures fine-grained local boundary responses, such as the circular contour of the storage tank in row 2 and the diagonal structural patterns of the dock in row 3, while E_2 (5×5) consolidates these into smoother and spatially coherent representations by suppressing high-frequency noise. Through the spatial attention mechanism, these multi-scale responses are selectively fused, producing the SEA activation that concentrates more consistently on foreground target regions compared to either intermediate map alone. In rows 4-5, where targets exhibit irregular or low-contrast appearances, the intermediate responses are relatively diffuse. Nevertheless, the SEA activation still achieves moderate foreground concentration. Notably, even in cases where the final predictions still show noticeable discrepancies with the ground truth, the SEA activation maps consistently reveal structural outlines that closely resemble the target boundaries, further confirming that SEA provides effective geometric guidance within the correlation feature space.

4.5.4. Comparison with Fully Supervised Mining Segmentation

Previous studies have shown that even fully supervised state-of-the-art models exhibit limited performance in open-pit mining scenarios. For instance, EGUNet (Zhou et al., 2023), a representative fully supervised segmentation network specifically designed for mining-area extraction, reports a mining-area mIoU of 42.32% for the open-pit category on the LCMA dataset. In contrast, the proposed method achieves a mining mIoU of 36.98% under the 1-shot setting and further improves to 41.29% with 5-shot supervision.

Despite relying on significantly fewer annotated samples, our approach attains performance that is highly competitive with a task-specific fully supervised model. Although the evaluation protocols are not strictly identical, this comparison still provides a meaningful reference for assessing practical effectiveness. The results suggest that few-shot segmentation can approach the performance level of dedicated fully supervised mining models, highlighting its potential for mining-area analysis in scenarios where dense annotations are expensive or difficult to obtain.

5. Conclusion

This paper investigates few-shot semantic segmentation in complex mining scenes, where severe background clutter, large intra-class appearance variation, and intricate object geometry significantly challenge existing RS-FSS methods. To address these issues, we propose a Structure–Semantic Adaptive Matching Network that enhances both semantic robustness and structural fidelity under extremely limited annotation conditions.

To mitigate background clutter and class-specific bias in mining scenes, we introduce an adaptive prior enhancement module to strengthen foreground representations before correlation matching. Built upon this, the proposed framework enhances multi-scale 4D correlation tensors from complementary semantic and structural perspectives. Specifically, the mask semantic alignment module improves semantic consistency by incorporating class-agnostic regional priors from a frozen Segment Anything Model, while the selective edge attention module preserves fine-grained geometric structures and irregular object boundaries through multi-scale spatial gradient modeling.

Extensive experiments on both the proposed DLRSD-mining-6ⁱ dataset and the public iSAID-5ⁱ benchmark demonstrate that S²AM-Net consistently outperforms other methods under 1-shot and 5-shot settings across different backbone networks. These results demonstrate the effectiveness and robustness of the proposed structure–semantic adaptive matching network, highlighting its potential for practical mining-area monitoring and ecological restoration assessment in remote sensing applications.

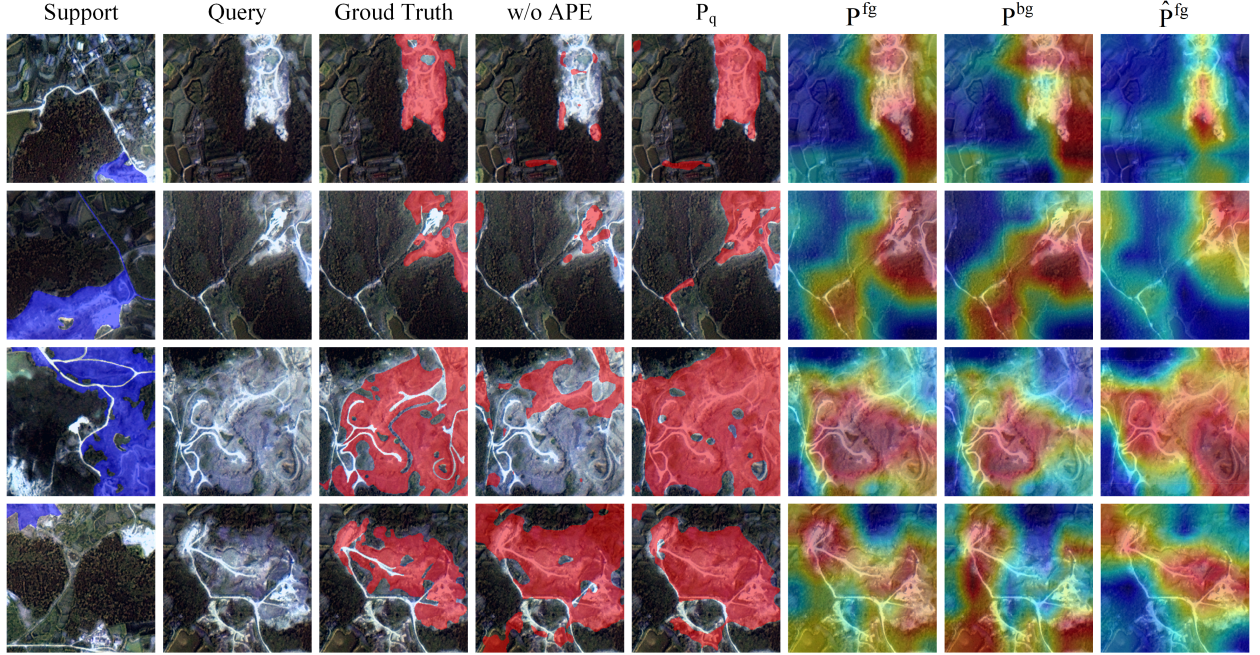


Figure 5: Visualization of the proposed APE module in mining scenes. From left to right: support image, query image, ground truth, prediction without APE, adaptive prior generated by APE ($\hat{P}_{fg}$), and final prediction with APE (P_q).

Appendix A. Additional Experiments

Appendix A.1. Ablation: APE Prior as a Direct SAM Prompt

We evaluate a baseline that directly uses the APE-generated prior as a binary prompt for SAM, bypassing the proposed pipeline. Since SAM produces multiple candidate masks, we adopt an oracle selection strategy based on the highest mIoU.

As shown in Table A.9, the proposed model significantly outperforms this baseline (45.20 vs. 23.17 mean mIoU). This indicates that APE alone cannot provide sufficiently structured prompts for SAM, and that direct prompting is inadequate for complex remote sensing scenes. Qualitative results in Fig. A.7 further show that SAM performs well on objects with regular shapes, but degrades in categories with large intra-class variation. This is mainly because APE-generated masks provide limited structural diversity when used as prompts for SAM. In contrast, our method integrates SAM-derived structural priors within the correlation space and refines them via explicit alignment, leading to more robust and consistent predictions across complex scenes.

Table A.9: Comparison between our full model and the APE Prompt + SAM (Oracle) baseline across three folds.

Method	Fold 0	Fold 1	Fold 2	Mean
APE Prompt + SAM (Oracle)	20.15	27.27	22.10	23.17
Ours	36.65	45.49	53.45	45.20

Appendix A.2. Ablation: Sequential vs. Parallel Design of MSA and SEA

We investigate the architectural choice of using a parallel rather than sequential design for MSA and SEA. The parallel structure allows both modules to operate on the same correlation maps independently, leveraging their complementary semantic and geometric cues.

As shown in Table A.10, the parallel design achieves the best performance (mean 45.20), outperforming both MSA→SEA (39.78) and SEA→MSA (39.48). The degradation of sequential designs can be attributed to interference between semantic smoothing and gradient-sensitive representations.

Overall, the parallel design better preserves complementary information from both branches, leading to more stable performance in complex remote sensing scenes.

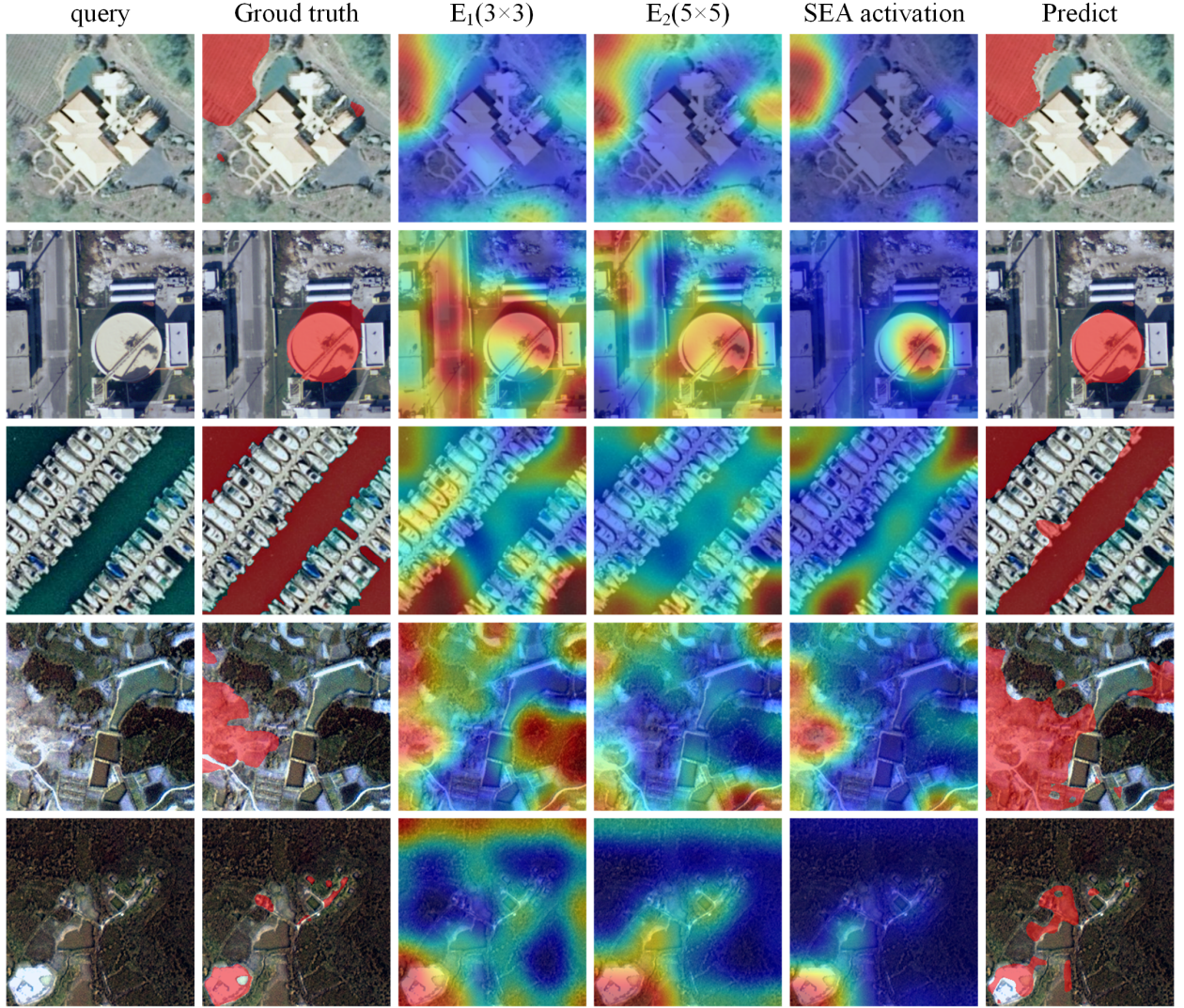


Figure 6: Visualization of the SEA module. From left to right: query image, ground truth, intermediate responses (E_1 , E_2), SEA activation, and final prediction.

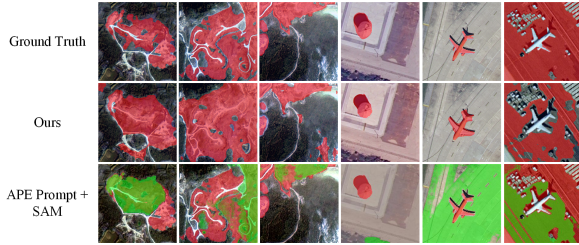


Figure A.7: Qualitative comparison between our method and the APE Prompt + SAM (Oracle) strategy. From top to bottom: query images, our segmentation results (red), and the results of the prompting-based approach (green).

Table A.10: Ablation study on the interaction order of MSA and SEA modules.

Architecture	Fold 0	Fold 1	Fold 2	Mean
Sequential (MSA→SEA)	33.49	38.78	47.06	39.78
Sequential (SEA→MSA)	32.49	39.65	46.30	39.48
Parallel (ours)	36.65	45.49	53.45	45.20

Appendix A.3. Ablation: Effect of Background Rectification in the Prior Estimation

In Eq. 4, the rectified prior is defined as $\hat{P}^{fg} = P^{fg} - P^{bg}$ rather than directly using P^{fg} . This formulation introduces an explicit contrastive mechanism

that suppresses background responses while enhancing foreground-consistent activations.

As shown in Figure 5, the rectified prior produces more concentrated spatial responses compared to P^{fg} , which tends to generate diffuse activations across both foreground and background regions.

As reported in Table A.11, replacing $\hat{P}^{fg}$ with P^{fg} leads to a consistent performance drop (42.74 vs. 45.20 mean mIoU), demonstrating the effectiveness of background rectification in improving foreground prior quality.

Table A.11: Ablation study on the effect of background rectification in the prior estimation (Eq. 4).

Method	Fold 0	Fold 1	Fold 2	Mean
Only P^{fg}	34.55	43.34	50.32	42.74
Ours ($P^{fg} - P^{bg}$)	36.65	45.49	53.45	45.20

Analysis of Learned Sobel Kernels in SEA

The learnable Sobel kernels in SEA are initialized from canonical Sobel filters as geometry-aware priors, but remain fully trainable during optimization. We also evaluate a structurally constrained variant, where symmetry priors are enforced by learning only half of the kernel parameters while fixing the remaining weights through mirrored sign inversion.

As reported in Table A.12, the constrained variant consistently underperforms the fully learnable kernels (42.46 vs. 45.20 mean mIoU), suggesting that strict preservation of Sobel structure is unnecessary for optimal performance.

Figure A.8 visualizes the learned filters before and after training. The trained kernels exhibit clear adaptation while still preserving gradient-sensitive characteristics, with several filters retaining evident symmetry patterns similar to classical gradient operators.

The deviation of the 5×5 kernels from canonical Sobel filters is expected due to the cascaded design. Since the preceding 3×3 Sobel layer already captures first-order gradients, the larger kernels mainly refine higher-order structural information, leading to more diverse yet task-adaptive patterns.

Table A.12: Ablation study on kernel constraints in SEA.

Method	Fold 0	Fold 1	Fold 2	Mean
Structural constraints	34.49	41.62	51.28	42.46
Learnable kernels (ours)	36.65	45.49	53.45	45.20

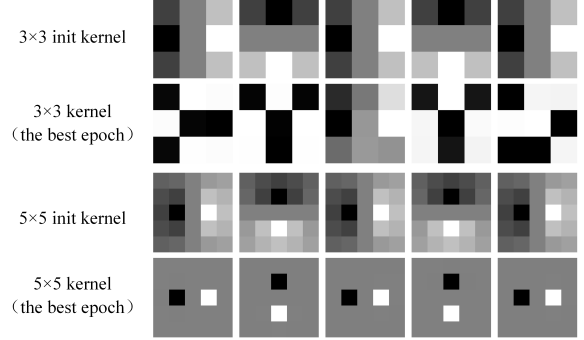


Figure A.8: Comparison of filter responses before and after training.

To further analyse kernel behaviour, we visualise filters before and after training in Figure 6. The learned kernels exhibit noticeable adaptation while still preserving clear gradient-sensitive patterns, rather than degenerating into arbitrary structures; some filters also retain evident symmetry consistent with classical gradient operators. The deviation of the 5×5 kernels from canonical Sobel form is expected due to the cascaded design: as the 3×3 Sobel filter already captures first-order gradients, the 5×5 kernels act as higher-order structural refiners rather than standalone edge detectors, leading to more diverse but task-adaptive patterns.

Statistical Stability of the Mining Category and Spatial Independence of Support–Query Pairs.

The mining category is only available in Fold 2 of the LCMA dataset. Nevertheless, all competing methods are evaluated under identical episode sampling and random seed settings, ensuring fair comparison. Following the reviewer’s suggestion, we report mean $\pm$ std results over three random seeds (0, 123, 321) in Table A.13, confirming consistent performance with small variance. We acknowledge that the limited scale of this subset is an inherent constraint, and plan to expand the mining-category data in future work to reduce split-sensitivity.

Regarding spatial correlation: patch overlap occurs only at boundary margins, which contain virtually no mining targets, as mining sites are geographically discrete and concentrated in isolated inland areas. Spatial visualisation confirms no overlapping mining regions across any support–query pair, and reported performance is not inflated by spatial leakage.

Backbone Training and Parameter Counting.

The backbone network is jointly optimized during training with a reduced learning rate rather than being frozen.

Table A.13: Comparison of different methods under three random seeds. Results are reported as mean $\pm$ std (%).

Method	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	mIoU
1-shot																			
HSNet (Min et al., 2021)	31.99	29.04	28.11	12.17	42.93	58.65	25.67	97.91	27.76	41.86	23.01	22.59	58.57	48.07	36.17	39.54	56.92	33.59	39.70
	± 1.40	± 1.84	± 0.96	± 1.03	± 0.15	± 3.28	± 0.25	± 0.36	± 1.30	± 1.96	± 1.18	± 0.73	± 1.85	± 2.84	± 0.60	± 0.75	± 2.12	± 2.36	± 0.24
SCCNet (Wang et al., 2023)	17.97	29.39	20.56	7.45	42.39	55.67	25.08	98.46	27.55	32.80	24.10	21.51	57.23	38.76	31.83	33.63	43.96	27.52	35.33
	± 1.52	± 0.55	± 0.69	± 0.48	± 0.10	± 0.81	± 0.30	± 0.15	± 1.20	± 1.68	± 0.15	± 2.06	± 1.55	± 0.35	± 3.25	± 0.32	± 1.25	± 3.34	± 0.34
PCFNet (Ao et al., 2023)	33.61	32.87	31.42	15.14	43.45	61.35	23.33	96.09	34.39	48.22	31.81	28.65	66.45	46.47	42.86	39.29	53.74	30.06	42.18
	± 2.91	± 0.76	± 1.46	± 0.25	± 0.36	± 3.09	± 0.79	± 0.21	± 0.58	± 0.80	± 1.33	± 1.34	± 3.33	± 3.59	± 0.99	± 2.19	± 1.67	± 1.84	± 0.22
SEMPNet (Ao et al., 2024)	31.65	27.16	32.69	15.26	45.17	51.53	20.81	96.85	32.12	45.14	33.08	21.87	63.25	60.33	40.13	36.01	53.37	21.98	40.46
	± 0.25	± 0.69	± 0.54	± 0.09	± 1.04	± 1.15	± 0.05	± 0.01	± 0.51	± 0.19	± 0.57	± 1.73	± 2.68	± 0.44	± 2.06	± 0.29	± 0.56	± 0.16	± 0.30
MGCL (Li et al., 2024)	26.72	29.88	37.21	9.30	40.35	55.45	22.48	79.54	28.41	46.40	31.48	25.92	90.09	45.91	50.09	34.81	59.42	26.75	41.12
	± 1.72	± 6.76	± 0.95	± 0.62	± 0.22	± 2.27	± 0.40	± 1.69	± 0.94	± 0.29	± 0.97	± 2.15	± 0.39	± 0.57	± 2.80	± 1.29	± 2.05	± 1.52	± 0.60
Ours	40.95	33.90	37.65	9.62	42.51	58.27	23.82	96.30	32.13	52.97	37.28	30.53	90.25	47.14	47.29	39.89	59.66	35.53	45.32
	± 1.01	± 0.28	± 1.07	± 0.45	± 0.33	± 1.61	± 0.50	± 0.69	± 1.08	± 0.53	± 0.64	± 2.33	± 2.08	± 1.37	± 2.30	± 0.34	± 1.54	± 1.27	± 0.30
5-shot																			
HSNet (Min et al., 2021)	35.24	29.72	28.88	13.82	43.01	62.07	26.28	98.09	29.57	42.52	24.70	25.17	60.94	49.61	38.80	41.90	59.67	35.69	41.43
	± 4.43	± 2.79	± 2.03	± 2.87	± 0.23	± 4.87	± 1.04	± 0.19	± 4.34	± 3.11	± 3.72	± 4.43	± 3.50	± 0.82	± 5.01	± 3.37	± 3.46	± 4.45	± 2.81
SCCNet (Wang et al., 2023)	18.59	31.31	28.91	9.14	42.18	61.52	24.69	98.76	36.11	38.88	32.69	26.34	66.97	45.82	42.45	46.45	54.45	36.04	41.18
	± 0.08	± 0.16	± 0.78	± 0.47	± 0.10	± 0.93	± 0.14	± 0.14	± 0.23	± 0.42	± 0.14	± 0.43	± 1.55	± 0.45	± 1.72	± 0.93	± 0.37	± 2.62	± 0.23
PCFNet (Ao et al., 2023)	37.29	38.67	41.37	18.16	43.68	68.60	23.79	97.73	42.43	51.45	38.53	33.86	80.77	46.42	49.28	41.37	61.90	37.05	47.35
	± 2.47	± 0.54	± 1.39	± 0.96	± 0.49	± 1.26	± 0.56	± 0.33	± 0.99	± 0.34	± 1.33	± 2.16	± 2.73	± 5.11	± 1.47	± 0.58	± 0.71	± 0.72	± 0.35
SEMPNet (Ao et al., 2024)	32.45	29.54	37.06	17.20	44.95	52.40	20.84	96.85	32.38	45.13	34.85	23.20	68.95	60.27	34.68	35.65	59.34	23.72	41.10
	± 0.27	± 0.12	± 0.33	± 0.06	± 0.74	± 0.52	± 0.02	± 0.00	± 0.06	± 0.32	± 0.10	± 0.13	± 1.50	± 0.31	± 1.48	± 0.20	± 0.34	± 0.59	± 0.95
MGCL (Li et al., 2024)	29.29	34.70	48.27	11.48	42.64	56.78	23.38	87.39	37.72	50.27	41.48	35.64	93.28	53.51	57.29	45.96	64.62	39.19	46.62
	± 1.12	± 0.45	± 1.02	± 0.34	± 0.09	± 0.83	± 0.26	± 0.23	± 0.24	± 0.49	± 0.16	± 1.68	± 0.61	± 0.30	± 3.22	± 0.86	± 0.41	± 2.45	± 1.25
Ours	47.98	36.02	45.95	11.29	42.80	62.30	25.22	97.21	39.71	54.48	44.94	38.36	93.46	57.26	49.48	44.50	57.68	40.70	49.41
	± 1.29	± 0.31	± 0.36	± 0.32	± 0.19	± 2.39	± 0.55	± 0.17	± 0.38	± 0.11	± 0.16	± 1.63	± 0.66	± 0.53	± 0.21	± 0.14	± 0.56	± 0.91	± 0.18

C1–C18: airplane, bare soil, buildings, cars, chaparral, court, dock, field, grass, mobile home, pavement, sand, sea, ship, tanks, tree, water, mining region

For parameter counting, we follow the common practice of reporting only task-specific modules excluding the backbone network. Accordingly, all compared methods are unified under the same setting in the revised table, and methods using frozen backbones are marked with “*”. Since total parameter counts vary substantially across different backbone choices, we additionally report total parameters (including the backbone) under the ResNet-50 setting in Table A.14.

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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Datavailability

Data will be made available on request.

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Table A.14: Quantitative comparison on DLRS-mining-6ⁱ dataset under 1-shot and 5-shot settings. Params denote the number of parameters excluding the backbone network for fair comparison. Methods marked with * use frozen backbones.

Backbone	Network	1-shot (%)				5-shot (%)				Total Params
		Fold1	Fold2	Fold3	Mean	Fold1	Fold2	Fold3	Mean	
ResNet-50	HSNet* (Min et al., 2021)	33.40	40.44	44.44	39.43	38.49	44.21	51.30	44.67	26.13 M
	SCCNet (Wang et al., 2023)	28.67	38.40	38.28	35.12	32.01	42.92	48.01	40.98	28.71 M
	SEMPNet* (Ao et al., 2024)	34.14	41.43	46.14	40.57	35.55	42.22	42.67	40.15	23.93 M
	HRL* (He et al., 2025)	26.33	33.00	31.60	30.31	29.73	39.33	34.72	34.59	61.03 M
	MGCL (Li et al., 2024)	32.48	38.39	50.42	40.43	37.09	46.42	58.38	47.30	24.20 M
	Ours	36.65	45.49	53.45	45.20	41.27	50.35	56.38	49.31	24.25 M

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