

DGMA²-Net: A Difference-Guided Multiscale Aggregation Attention Network for Remote Sensing Change Detection

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Abstract—Remote sensing change detection (RSCD) focuses on identifying regions that have undergone changes between two remote sensing images captured at different times. Recently, convolutional neural networks (CNNs) have shown promising results in the challenging task of RSCD. However, these methods do not efficiently fuse bitemporal features and extract useful information that is beneficial to subsequent RSCD tasks. In addition, they did not consider multilevel feature interactions in feature aggregation and ignore relationships between difference features and bitemporal features, which thus affects the RSCD results. To address the above problems, a difference-guided multiscale aggregation attention network, DGMA²-Net, is developed. Bitemporal features at different levels are extracted through a Siamese convolutional network and a multiscale difference fusion module (MDFM) is then created to fuse bitemporal features and extract, in a multiscale manner, difference features containing rich contextual information. After the MDFM treatment, two difference aggregation modules (DAMs) are used to aggregate difference features at different levels for multilevel feature interactions. The features through DAMs are sent to the difference-enhanced attention modules (DEAMs) to strengthen the connections between bitemporal features and difference features and further refine change features. Finally, refined change features are superimposed from deep to shallow and a change map is produced. In validating the effectiveness of DGMA²-Net, a series of experiments are conducted on three public RSCD benchmark datasets (LEVIR-CD, BCDD, and SYSU-CD). The experimental results demonstrate that DGMA²-Net surpasses the current eight state-of-the-art methods in RSCD. Our code is released at <https://github.com/yikuizhai/DGMA2-Net>.

Index Terms—Remote sensing change detection (RSCD), mul-

This study was funded by Guangdong Basic and Applied Basic Research Foundation (No.2021A1515011576), Guangdong Science and Technology Planning Project (No.2021A0505030080, No.2021A0505060011), Guangdong Higher Education Innovation and Strengthening School Project (No.2020ZDZX3031, No.2022ZDZX1032, No.2023ZDZX1029), Wuyi University Hong Kong and Macao Joint Research and Development Fund (No.2022WGALH19), Guangdong Jiangmen Science and Technology Research Project (No.2220002000246, No.2023760300070008390). (*Corresponding author: Yikui Zhai and Xudong Jia.*)

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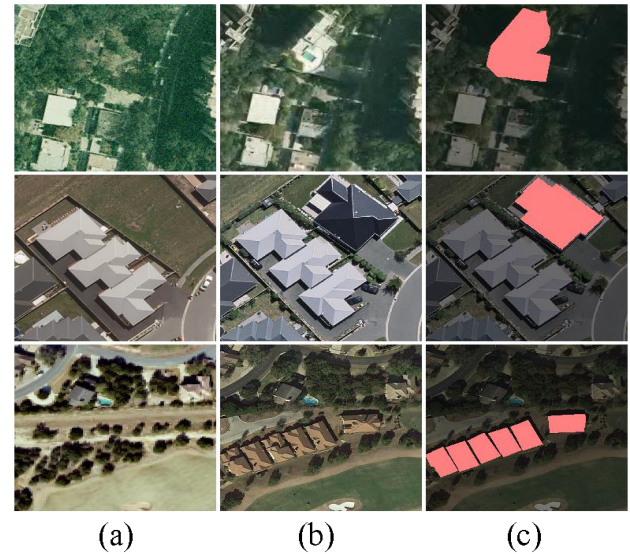


Fig. 1. RSCD examples. (a) T1 images, (b) T2 images, (c) Changes marked in red.

tiscale difference fusion module (MDFM), difference aggregation module (DAM), difference-enhanced attention module (DEAM).

I. INTRODUCTION

REMOTE sensing change detection (RSCD) is an important task to identify any changes occurring on the Earth's surface by analyzing bitemporal or multitemporal images acquired at the same geographic location. This task is playing an increasingly important role in disaster assessment [1], [2], environmental monitoring [3], land management [4], and urban transformation analysis [5]. Some samples of the RSCD task are shown in Fig. 1. Over the past few decades, researchers have done many studies on RSCD.

There are two main categories of traditional RSCD methods, pixel-based and object-based methods. The pixel-based methods calculate, transform, and compare each pixel of synchronized bitemporal or multitemporal images, and generate a change map through an appropriate threshold or a clustering algorithm. Commonly used methods include change vector analysis (CVA) [6], principal component analysis (PCA) [7],

and slow feature analysis (SFA) [8]. However, these pixel-based methods only focus on a single pixel, ignoring embedded relationships between contexts in bitemporal or multitemporal images, resulting in many noises in change maps. To address this issue, scholars began to switch the research direction from pixels to objects. The object-based methods, such as KL divergence [9] and image correlation analysis [10], focus on specific and low-level semantic objects and detect changes in bitemporal or multitemporal images. However, the low-level features in these methods are artificially created. They are inadequate in handling the complexity of real-world environments.

In recent years, deep learning has demonstrated remarkable performance in computer vision and has attracted great attention in various fields [11]. Convolutional neural networks (CNNs), thanks to their strong feature extraction abilities, have developed extensive applications in computer vision [12]. Example applications include but are not limited to image classification [13], [14], object detection [15], [16], and semantic segmentation [17], [18]. In the field of RSCD, CNNs have also emerged as a prominent research method for change detection and surpassed traditional RSCD methods. Weight-sharing Siamese CNNs are widely employed in deep learning-based RSCD methods [20] to extract features from bitemporal images. These methods are further categorized into metric-based methods [21]–[26] and classification-based methods [27]–[39]. Metric-based methods determine changes by computing parametric distances of bitemporal images in an embedding space where ‘pull in’ distances are for changed pixels and ‘pull away’ distances are for non-changed pixels. Classification-based methods classify each pixel in the embedding space to get a set of changed regions.

Despite the favorable outcomes attained thus far in RSCD by current deep learning methods, significant challenges in feature fusion and aggregation persist in these methods. Feature fusion at each stage of the methods is limited to local feature interactions. Additionally, most deep learning-based RSCD methods follow simple fusion operations, such as feature concatenation and feature subtraction [35], [40], [41]. Moreover, few studies have been concentrated on using multiscale feature learning mechanisms in bitemporal feature fusion, although multiscale feature learning mechanisms have been proven to be effective in deep learning [54]. As a result, fused features often contain many noises, which adversely affect RSCD results.

Feature aggregation is also of great significance in RSCD. Features at different levels contain different pieces of semantic information. Shallow features contain low-level visual information, such as image texture, object edges and other similar characteristics. With the network layers becoming deeper, these low-level features undergo a transition towards a higher level of abstraction, and deep features thus contain richer semantic information, such as image content, object location, etc. U-Net models [42]–[46] are widely used in RSCD for feature aggregation. Within a U-Net network, deep features are superimposed with skip connections over shallow features to produce a change map. Furthermore, many RSCD works embed attention mechanisms into these methods to

obtain more discriminative features [27]–[31]. These methods accomplish feature aggregation through feature concatenation, skip connections, and stepwise upsampling operations. However, these methods do not consider the multilevel feature interaction which plays a key role in RSCD [58]. Moreover, these methods ignore the relationships between difference features and bitemporal features, thus affecting the RSCD results.

To address the above-mentioned issues, a novel difference-guided multiscale aggregation attention network, DGMA²-Net, is proposed. This network uses a multiscale feature learning mechanism to fuse bitemporal features and generate difference features. In detail, bitemporal features at different levels are extracted through a Siamese convolutional network and multiscale difference fusion modules (MDFMs) are then created to fuse bitemporal features. After the MDFM treatment, two difference aggregation modules (DAMs) are used to aggregate information at different depths and perform multilevel feature interactions. The features after the DAMs and the bitemporal features are sent into the difference-enhanced attention modules (DEAMs) to further enhance the change areas and refine difference features. A change map is produced by superimposing the refined difference features. The primary contributions of this work are outlined as follows:

- 1) A multiscale difference fusion module (MDFM) is proposed to fuse bitemporal features in multiscale manner. To our knowledge, MDFM is the first bitemporal feature module to take advantage of multiscale feature learning mechanism to generate difference features and thus reduces noises in difference features.
- 2) A difference aggregation module (DAM) is introduced to effectively aggregate difference features. Different from previous works that only focused on interactions within features, DAM explores the interactions in multilevel features for the aggregation of semantic information and makes full use of contexts at different levels.
- 3) A difference-enhanced attention module (DEAM) is proposed to further enhance change areas and refine difference features by revamping the self-attention mechanism. It is our knowledge that DEAM is the first one developed to investigate interactions between difference features and bitemporal features based on self-attention mechanism.
- 4) The integration of the MDFM, DAM and DEAM in the DGMA²-Net creates a new approach for RSCD. Quantitative and qualitative experimental results on three public datasets demonstrate that DGMA²-Net achieves superior performance and exceeds state-of-the-art RSCD methods.

II. RELATE WORK

A. Traditional RSCD Method

There have been many traditional RSCD methods. Among them, algebraic and clustering methods are representative methods. Algebraic methods include image difference, image ratio, and image regression [47], [48]. Combined with CVA [6] and SFA [8], algebraic methods are used to obtain different

characteristics of bitemporal images and delineate change areas. Since these methods largely depend on the selection of a threshold, some transformation techniques such as PCA [7] and tasseled cap transformation [49] are introduced to help determine the threshold and conduct RSCD. These threshold-based methods are subjective. In recognizing this limitation, clustering-based methods are brought in for RSCD [50]–[52]. However, these methods cannot understand the semantic meaning of changed regions, which leads to false positive errors. In addressing the above issues, object-based methods including KL divergence [9] and image correlation analysis [10] are developed to explore semantic interactions of changed objects.

It is noted that these methods can be easily implemented, however they overlook the semantic and spatial information embedded in bitemporal images and are highly sensitive to noises. In addition, these methods require manual annotation of objects or features and rely on the arbitrary setting of a threshold. These methods are not suitable for RSCD in complex scenes.

B. Deep Learning-Based RSCD Method

Recently the advancement in deep learning has led to a great success of developing many methods which use CNNs for RSCD. The deep learning-based methods can be categorized into metric-based methods [21]–[26] and classification-based methods [27]–[39].

1) Metric-based methods: These methods learn features and determine change regions or areas by using parameterized embedding distances of pixels in bitemporal images. These methods use contrastive loss [23], [25] or triplet loss [24] to optimize parameters of their models through training. Chen et al. [22] introduced a spatiotemporal attention mechanism to catch features in bitemporal images and developed a new loss function to optimize the entire metric-based learning model. Liu et al. [25] used a denoising self-encoder and a probability model to eliminate noises, calculate distances between features in heterogeneous images, screen features by a preset threshold, and generate change maps.

2) Classification-based method: These methods fuse features in bitemporal images and group fused features into a feature space for classification. Li et al. [19] developed a temporal feature interaction module and used the module for refining and improving the detection quality of different remote sensing images. As a result, the efficiency of RSCD is achieved. Lei et al. [34] constructed a reverse attention mechanism and a multi-part feature fusion strategy for RSCD. Fang et al. [35] constructed a densely connected Siamese network to reduce the information loss of a neural network through the transmission between an encoder and a decoder. Lei et al. [38] introduced a new RSCD network with a difference enhancement module and constructed an attention mechanism through spatial multiscale smooth pooling techniques, which effectively enhances edge integrity and internal compactness of changed regions.

It is noted that the effectiveness of the deep learning-based RSCD methods is strongly dependent on the quality of their

acquired feature representations. Significant endeavors therefore should be dedicated to acquiring discriminative feature representations that optimize the performance of RSCD.

C. Bitemporal Feature Fusion

Bitemporal feature fusion is an essential process in RSCD models. The purpose of bitemporal feature fusion is to fuse or compare bitemporal features and capture their differences so that the model can better understand the change trends and extract difference features. Feature concatenation, feature subtraction, feature addition, and a series of attention mechanisms are used in feature fusion for RSCD. Fang [35] et al. fused bitemporal features through feature concatenation. Lei et al. [38] proposed a difference enhancement module in feature fusion operations, while Song et al. [39] introduced a context change enhancement module to leverage the quality of change detection from bitemporal images. Raza et al. [42] had a fusion operation through a parallel attention mechanism. All these studies constructed a channel attention mechanism through a set of global average pooling, maximum pooling, and feature subtraction operations for better feature fusion. It is important to point out that these RSCD methods focus on differences in bitemporal features. Using difference features to guide bitemporal feature fusion can achieved better results. As a RSCD example with difference features, Li et al. [19] constructed a temporal feature interaction module which uses difference features and a series of arithmetic operations for bitemporal feature fusion. It is noted that although these methods have achieved satisfactory results, most of them use simple fusion operations or rely on existing attention mechanisms to achieve bitemporal feature fusion.

D. Feature Aggregation

Existing RSCD methods have successfully adopted U-Net, an encoder-decoder U-shape architecture with skip connections, for feature aggregation. An example method developed by Daudt et al. [22] used three distinct U-Net-based modules for feature aggregation. However, these simple feature-based methods are difficult in performing multilevel feature interactions, thus affecting the RSCD results. Considering this issue, recent works have begun to introduce attention mechanisms for feature aggregation. Zhao et al. [36] built a triple-stream network which uses a self-attention mechanism along with skip connections and upsampling operations for feature aggregation. Zhang et al. [37] built a decoder with self-attention and channel-attention mechanisms and aggregated difference features and bitemporal features through concatenation and upsampling operations. Eftekhari et al. [27] also used a self-attention mechanism to construct channel and spatial attentions and performed feature aggregation on bitemporal features through concatenation and upsampling operations. Lei et al. [30] constructed an attention mechanism through a Gaussian kernel, progressively up-sampled difference features, and used skip connections to complete feature aggregation. It is noted that these methods with skip connections lack capabilities of interacting multilevel features. As a result, they do not efficiently aggregate difference features with complementary

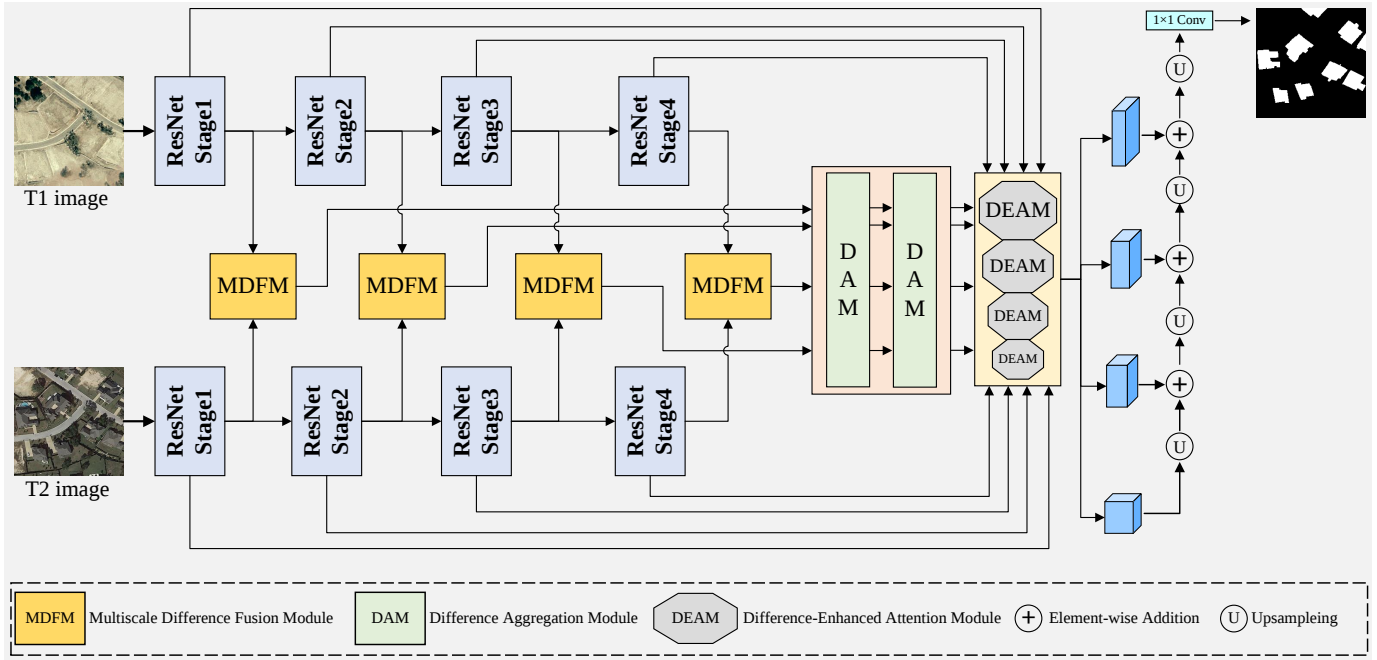


Fig. 2. Architecture of the DGMA²-Net. Bitemporal images pass through a Siamese convolutional network to generate multilevel bitemporal features. These features are entered into the MDFMs to create difference features. Difference features are generated and refined through two DAMs and four DEAMs, and the resulting features are up-sampled to create a change map.

information of contexts in bitemporal features. It is also noted that self-attention mechanisms have been applied on bitemporal features or difference features in RSCD. However, these self-attention mechanisms do not consider the coupling interactions of bitemporal features and difference features, thus affecting the RSCD results.

III. METHOD

A. DGMA²-Net Architecture

This section describes the DGMA²-Net architecture. As shown in Fig. 2, DGMA²-Net comprises an encoder and a decoder for RSCD. The encoder first uses the pretrained Siamese weight-sharing ResNet-18 [53] to extract multilevel bitemporal features from a pair of registered and synchronized bitemporal images (T1 and T2), and then utilizes the multiscale difference fusion modules (MDFMs) to fuse the extracted features. After the MDFM operations, difference features along with their context information are further fed to the difference aggregation modules (DAMs) for feature aggregation and interaction. The refined features are then sent to the difference-enhanced attention modules (DEAMs) to further enhance the changes. A change map is produced by superimposing the feature from deep to shallow.

B. Multiscale Difference Fusion Module (MDFM)

In DGMA²-Net, the MDFM fuses features obtained from bitemporal images and generates difference features with valuable context information. In Fig. 3, bitemporal features coming from two paired images are denoted as F_i^1 and F_i^2 , where $i \in \{1, 2, 3, 4\}$, represents the ResNet-18 stage index. F_i^1 and F_i^2 , extracted by the weight-sharing ResNet-18, go through a

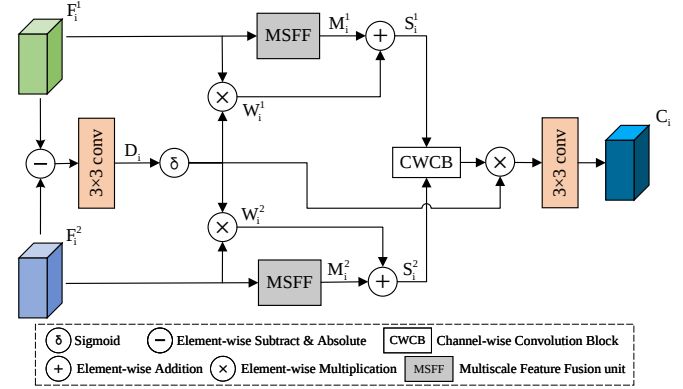


Fig. 3. MDFM structure.

series of pixel-by-pixel subtraction, absolute value operation, and 3×3 convolution operation. The initial difference feature D_i is then generated. This process can be expressed as:

$$D_i = \text{Conv}_{3 \times 3}(|F_i^1 - F_i^2|) \quad (1)$$

where $|\cdot|$ represents an absolute operation, $\text{Conv}_{3 \times 3}(\cdot)$ represents a 3×3 convolutional layer, a batch normalization layer, and a ReLU activation function.

It is important to point out that after the initial difference feature D_i is generated, the multiscale feature learning mechanism created by [54] is enhanced in this study for fusing bitemporal features. Using the convolutions of different kernel sizes, the MDFM constructs a multiscale fusion process. As shown in Fig. 4, the MDFM employs a pair of multiscale feature fusion (MSFF) units to enhance the fusing operations. The MSFF unit includes four branches of convolutional op-

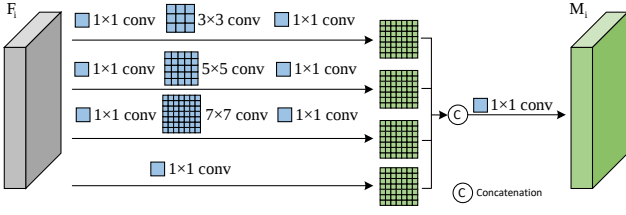


Fig. 4. MSFF unit structure.

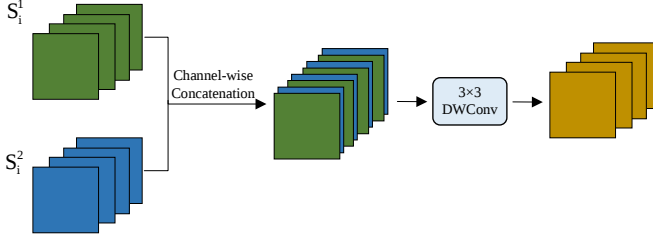


Fig. 5. CWCB structure.

erations with different kernel sizes, three of which contain $[1 \times 1, 3 \times 3, 1 \times 1]$, $[1 \times 1, 5 \times 5, 1 \times 1]$, and $[1 \times 1, 7 \times 7, 1 \times 1]$ convolutional fusing operations. The fourth branch only contains a 1×1 convolution operation. The MSFF process can be described as follows:

$$M_i = \text{Conv}_{1 \times 1}(\text{Cat}(\text{Conv}_{1 \times 1}(F_i), \text{Conv}_{1 \times 1}(\text{Conv}_{3 \times 3}(\text{Conv}_{1 \times 1}(F_i))), \text{Conv}_{1 \times 1}(\text{Conv}_{5 \times 5}(\text{Conv}_{1 \times 1}(F_i))), \text{Conv}_{1 \times 1}(\text{Conv}_{7 \times 7}(\text{Conv}_{1 \times 1}(F_i)))))) \quad (2)$$

where $\text{Cat}(\cdot)$ is a concatenation operation, M_i is the concatenated features of the four branches.

An element-wise channel weight W_i is introduced in DGMA²-Net. Following the idea of residual, S_i , which simultaneously incorporate multiscale information, is generated by adding W_i and M_i . This process can be expressed below:

$$W_i = F_i \times \sigma(\text{Conv}_{3 \times 3}(D_i)) \quad (3)$$

$$S_i = W_i + M_i \quad (4)$$

The channel-wise convolution block (CWCB) is employed in DGMA²-Net to perform the bitemporal feature fusion operation. As shown in Fig. 5, S_i^1 and S_i^2 are concatenated channel-by-channel and the concatenated features are operated through a 3×3 depth-wise convolution operation. The fused features through CWCB are multiplied by W_i . The final fused difference feature C_i is obtained after the 3×3 convolution operation is completed. C_i can be expressed as:

$$C_i = \text{Conv}_{3 \times 3}(\text{DWConv}_{3 \times 3}(\text{Stack}(S_i^1, S_i^2)) \times W_i) \quad (5)$$

where $\text{DWConv}(\cdot)$ represents a depth-wise convolution operation, the $\text{Stack}(\cdot)$ represents the channel-wise feature concatenation operation.

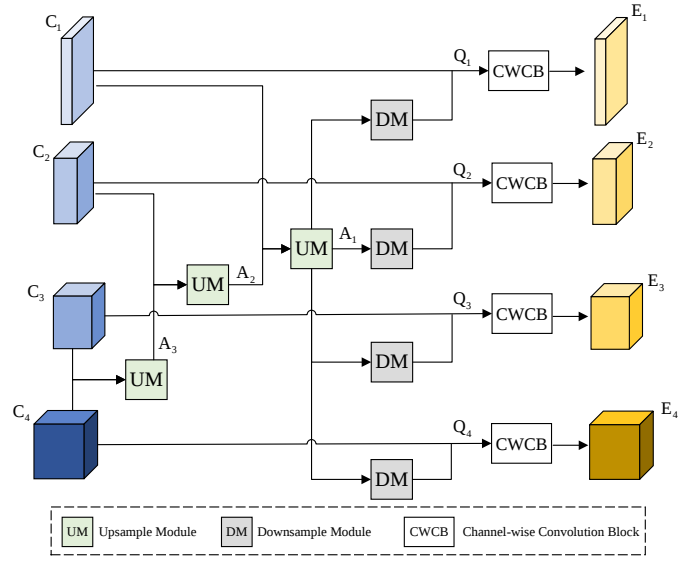


Fig. 6. DAM Structure.

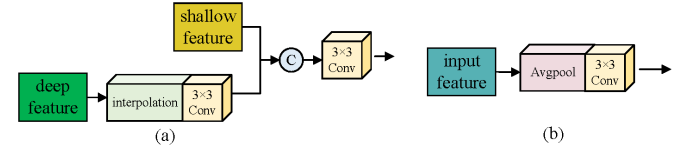


Fig. 7. UM and DM structure. (a) UM, (b) DM.

C. Difference Aggregation Module (DAM)

The difference aggregation module (DAM) is developed in this study to take advantage of feature differences and effectively aggregate features by considering multilevel interactions of difference features. As shown in Fig. 6, the upsample modules (UM) are used to fuse deep features with shallow features, that is, deep features from their previous ResNet-18 stage are transformed to be the same size as shallow features (or the fused features from the previous ResNet-18 stage). After the transformation, a 3×3 convolution operation is applied on deep features (see Fig. 7(a)).

The deep features are further concatenated with the shallow features and a 3×3 convolution operation is conducted again. The aggregation process can be mathematically expressed as follows:

$$A_{i-1} = \text{Conv}_{3 \times 3}(\text{Cat}(\text{shallow}, \text{Conv}_{3 \times 3}(\text{UP}(\text{deep})))) \quad (6)$$

where shallow represents the shallow feature, deep represents the deep feature, $\text{UP}(\cdot)$ represents the interpolation operation.

After all the features are aggregated, the final aggregated feature A_1 needs to be reverted to the same size as C_i , and it is sent into the down sample module (DM) (see Fig. 7(b)). Specifically, A_1 is reverted by the average pooling at different scales, after a 3×3 convolution operation is executed. The refined feature Q_i is obtained through the following calculation:

$$Q_i = \begin{cases} \text{Conv}_{3 \times 3}(A_1) & i = 1 \\ \text{Conv}_{3 \times 3}(\text{Avgpool}(\text{Conv}_{3 \times 3}(A_1))) & \text{other} \end{cases} \quad (7)$$

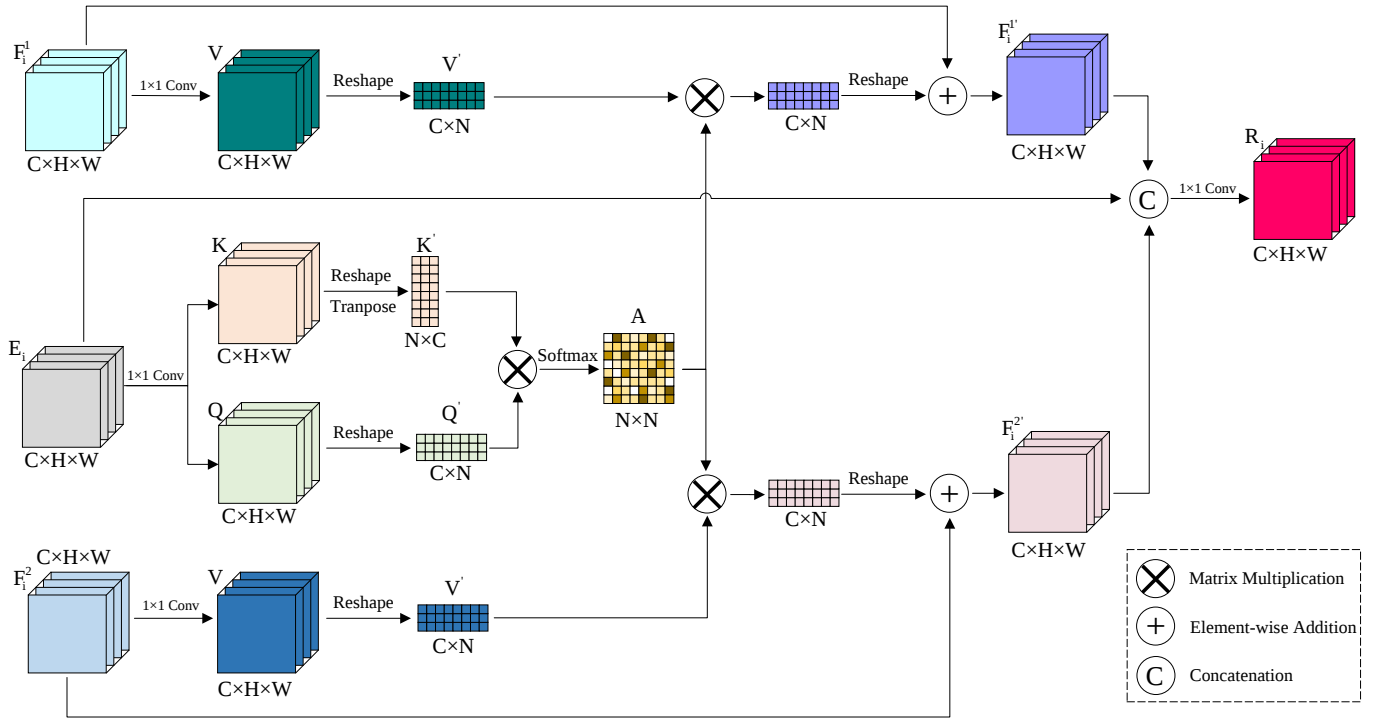


Fig. 8. DEAM Structure.

where $\text{Avgpool}(\cdot)$ represents an average pooling operation.

It is pointed out that skip connections are applied in each DAM to prevent the loss of semantic information. Moreover, CWCB is also used to utilize the multilevel difference features C_i and the refined features Q_i to obtain the refined difference features E_i . To achieve the best result, two DAMs are applied in DGMA2-Net and the ablation experiments described in Section IV confirm the necessity of two DAMs.

D. Difference-Enhanced Attention Module (DEAM)

In DGMA2-Net, a set of difference-enhanced attention modules (DEAMs) are used for linking difference features to bitemporal features (see Fig 2). Each DEAM expands the structure of a self-attention mechanism by building query (Q), key (K), and value (V). This module demonstrates an innovative approach to establishing the relationships between difference features and bitemporal features. In detail, four DEAMs are embedded in DGMA2-Net to receive difference features E_i from the two DAMs and mine the relationships between difference features and bitemporal features (F_i^1 and F_i^2). For each DEAM, a set of attention operations are conducted (see Fig. 8).

A 1×1 convolution is conducted on the refined difference feature $E_i \in \mathbb{R}^{C \times H \times W}$ and E_i is split into two feature vectors, key ($K \in \mathbb{R}^{\frac{C}{8} \times H \times W}$) and query ($Q \in \mathbb{R}^{\frac{C}{8} \times H \times W}$). After K and Q are transformed, matrix multiplication is performed to obtain attention matrix $A \in \mathbb{R}^{N \times N}$.

A 1×1 convolution is also applied to $F_i^1 \in \mathbb{R}^{C \times H \times W}$ and $F_i^2 \in \mathbb{R}^{C \times H \times W}$, respectively. The result of the convolution is noted as the value vector $V \in \mathbb{R}^{C \times H \times W}$ for the two

bitemporal features (F_i^1 and F_i^2), respectively. The value vector V is further reshaped to be V' for bitemporal features.

To further integrate difference features and bitemporal features, the DEAM multiplies the attention matrix A by the V' vector. The result of the multiplication is reshaped and summed with F_i^1 and F_i^2 , respectively, to obtain the difference-enhanced features $F_i^{1'}$ and $F_i^{2'}$. This process can be expressed as:

$$F_i^{1'} = V' \otimes A + F_i^1 \quad (8)$$

$$F_i^{2'} = V' \otimes A + F_i^2 \quad (9)$$

where $\otimes$ represents the matrix multiplication.

$F_i^{1'}$, $F_i^{2'}$ and E_i are further concatenated and processed by a 1×1 convolution kernel to get a difference-enhanced feature R_i , which can be formulated as:

$$R_i = \text{Conv}_{1 \times 1}(\text{Cat}(F_i^{1'}, F_i^{2'}, E_i)) \quad (10)$$

The difference-enhanced features are superimposed from shallow to deep, step by step, to create the final feature, and a change map is obtained by applying a 1×1 convolution layer on the final feature.

E. Hybrid Loss Function

In recognizing that unchanged areas prevail in bitemporal images [35], the DGMA2-Net employs a hybrid loss function to optimize the training process. The hybrid loss function combines the cross-entropy loss function and the dice loss function. The cross-entropy loss function is formulated as:

$$L_{BCE} = \frac{1}{H \times W} \sum_{k=1}^{H \times W} y_k \log(\hat{y}_k) + (1 - y_k) \log(1 - \hat{y}_k) \quad (11)$$

where H and W represent the height and width of bitemporal images, $\hat{y}_k$ represents the prediction result of the k^{th} pixel in bitemporal images, and y_k represents the ground-truth associated with the k^{th} pixel. The dice loss function can be formulated as:

$$L_{DICE} = 1 - \frac{2 \sum_{k=1}^{H \times W} y_k \hat{y}_k}{\sum_{k=1}^{H \times W} (y_k + \hat{y}_k)} \quad (12)$$

The hybrid loss function can be formulated as:

$$L_{TOTAL} = L_{BCE} + L_{DICE} \quad (13)$$

IV. EXPERIMENT

A. Experimental Setup

In this study a set of experiments were conducted to verify the effectiveness of DGMA²-Net.

1) *Dataset*: Three public RSCD datasets, namely LEVIR-CD [22], WHU-BCDD (BCDD) [41], and SYSU-CD [21] were used in the experiments.

The LEVIR-CD dataset consists of 637 pairs of images obtained from the Google Earth application programming interface (API). Each image has a size of 1024×1024 pixels and a resolution of 0.5m. This dataset primarily focuses on changes in physical buildings. The dataset is randomly partitioned into training, testing, and validation sets by a ratio of 7:1:2. All images were cropped to be 256×256 pixels. A total of 7120 pairs of images were available for training, 1024 pairs for validation, and 2048 pairs for testing.

The BCDD dataset consists of a pair of aerial images with 32507×15354 pixels. The resolution of the images is 0.075 m. Following the guidance from BIT [55], we cropped the aerial images into 7620 pairs of 256×256 blocks without overlapping and randomly made the training set with 6096 pairs, the validation set with 692 pairs, and the test set with 692 pairs.

The SYSU-CD dataset consists of 20,000 pairs of images with a size of 256×256 pixels and a resolution of 0.5 m. It encompasses diverse and intricate change scenes such as expanded roads, new urban buildings, vegetation changes, and enlarged suburban areas. The dataset is randomly partitioned in this study into 12000 pairs of images for training, 4000 pairs for validation, and 4000 pairs for testing.

2) *Evaluation metrics*: Five widely used metrics, namely overall accuracy (OA), precision (Pre), recall (Rec), F1 score (F1), and intersection over union (IoU), were adopted in this study for evaluating the performance of DGMA²-Net. These metrics are defined as follows:

$$OA = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \quad (14)$$

$$precision = \frac{T_p}{T_p + F_p} \quad (15)$$

$$recall = \frac{T_p}{T_p + T_n} \quad (16)$$

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (17)$$

$$IoU = \frac{T_p}{T_p + F_p + F_n} \quad (18)$$

where T_p represents the sum of accurately classified changed pixels, F_p represents the sum of truly unchanged pixels misclassified as changed, T_n represents the sum of accurately classified unchanged pixels, and F_n represents the sum of unchanged pixels falsely detected as changed. OA denotes the proportion of accurately classified pixels to the total pixels. The precision measures the false positive rate of the DGMA²-Net, while recall reflects the false negative rate. F1, which considers both precision and recall, provides a comprehensive measure of the model performance. IoU quantifies the degree of overlapping changes on the detection map and the ground-truth map, making it a crucial metric for evaluating the accuracy of the DGMA²-Net.

3) *Implementation details*: PyTorch framework was adopted in this study for all experiments and a single GeForce RTX 2080ti was used for accelerating the model training process. Random flipping and cropping techniques were employed to augment images from the three datasets. The DGMA²-Net was trained using the Adam optimizer with the momentum of 0.9 and a weight decay of 0.0001. Additionally, β_1 and β_2 of Adam optimizer were set to be 0.9 and 0.99, respectively. During training, the batch size was set to be 16 and the learning rate was set to be 0.0001. In addition, a poly learning rate decay strategy [19], that is $(1 - cur_iteration / max_iteration)^{power} \times lr$, was followed, where *power* and *max_iteration* were set to be 0.9 and 80000, respectively.

B. Comparative Models

Three traditional methods, CVA [6], SFA [8], PCA-Kmeans [50], and eight state-of-the-art deep learning-based methods, FC-Conc [20], FC-Diff [20], SNUNet [35], BIT [55], GeSAnet [56], DMINet [29], ICIF-Net [57], and USSFC-Net [30], were used to be the baseline models for comparing with DGMA²-Net on the three datasets (see Section IV-A). These eight methods are briefly described with the following highlights:

1) CVA. It calculates the change vector of each pixel in bitemporal images, and obtains the change areas through threshold filtering.

2) SFA. It learns transformations to extract slow features from bitemporal images. The learned slow features can be used to represent changes in each pixel position.

3) PCA-Kmeans. It applies PCA and K-means clustering on difference images for change detection. Each pixel pair, corresponding to identical positions in distinct images, is transformed into a feature vector.

4) FC-Conc. It employs a Siamese neural network and a feature-level fusion approach to extract multilevel concatenated features.

5) FC-Diff. Like FC-Conc, it employs a feature fusion method to leverage the absolute difference between feature pairs in the fusion operations of bitemporal images.

6) SNUNet. It takes advantage of the Siamese network and the Nested-UNet architecture and adopts a multilevel feature connection method. It applies a channel attention mechanism to each layer of decoded features and employs a deep supervision mechanism to enhance the ability of discriminating features.

7) BIT. It employs a transformer encoder to capture contextual information within a condensed tokenized space-time framework by representing bitemporal images as multiple label tokens. Subsequently, the extracted tokens, enriched with global information, are reintroduced into the embedding space. In doing so, original features are enhanced through the transformer decoder.

8) GeSANet. It is a model based on deformable convolution and the CANDECAMP/PARAFAC decomposition theory. It uses deformable convolution to conduct the pixel-level adaptive matching of multitemporal images and uses CANDECAMP/PARAFAC decomposition theory to reconstruct tensors to filter pseudo-change information.

9) DMINet. It unifies a self-attention mechanism and an across-attention mechanism in a single module to steer the global feature distribution. It uses subtraction and concatenation as well as multilevel difference aggregation for detecting changes.

10) ICIF-Net. It integrates CNN and transformer to facilitate the interactions of global and local features. In addition, an attention mechanism is constructed through convolutions to integrate information from features of different resolutions.

11) USFFC-Net. It is a lightweight model which implements a new multiscale feature extraction method and constructs an attention mechanism through the Gaussian kernel. It relies on spatial-spectral dependences of extracting richer features.

All training parameters except the batch size were set to be the default parameters of the above models. Due to the limitation of memory size, the batch size of SNUNet and USFFC-Net was adjusted to be 16 in the study.

C. Comparisons of DGMA²-Net with Baseline RSCD Models

In this study, DGMA²-Net was compared with the eleven baseline models. It is noted that F1 and IoU are the metrics in RSCD that best reflect model performance, so that the quality of a model is ultimately judged through F1 and IoU. The quantitative analysis of the models on the three datasets is shown in Table I and the below are our findings:

1) Analysis of traditional methods

The results from Table I clearly indicate that the performance metrics of traditional methods are significantly lower than those of deep learning-based methods on the three datasets. For instance, on the LEVIR-CD dataset, the highest F1 achieved by any of the three traditional methods is only 10.45, whereas the lowest F1 achieved by the deep learning-based method is 71.55. Visual results of each method are also demonstrated in Fig. 9 to 11. It can be observed from columns (d), (e), and (f) that the detection results of traditional methods exhibit considerable noise, far inferior to those achieved by deep learning methods. These findings indicate the challenges faced by traditional methods in complex environments and

underscore the superior performance of deep learning in RSCD.

2) Analysis of deep learning-based methods

1) *Experiments on LEVIR-CD*: The RSCD models' performances in predicting changes in bitemporal images from the LEVIR-CD dataset are shown in Fig. 9. In these models, it is obvious that DGMA²-Net, compared with the baseline models, is effective in RSCD. As shown in Table I, although DGMA²-Net is not the best model in terms of recall, it is the best from the view of other metrics (precision (0.9213), F1 (0.9121), IoU (0.8384), and OA (0.9914)). In contrast, the DMINet model has the highest recall (0.9275) among the RSCD models, slightly higher than DGMA²-Net (0.9031). However, the precision of the DMINet model is relatively low (0.8774), which indicates that the DMINet model has more false positives.

II) *Experiments on BCDD*: The RSCD models' performances in predicting changes in bitemporal images from the BCDD dataset are shown in Fig. 10. It is noted that DGM2A-Net has fewer missed detections and less false positive errors than the baseline models, when it deals with detections of physical buildings in a relatively large area. For physical buildings with small areas, DGMA²-Net is successful in extracting the buildings completely and identifying the edges of the buildings, while the baseline models have noticeable false and missed detections. Moreover, it can be seen in Table I that the DGMA²-Net is superior to the baseline models in precision (0.9626), F1 (0.9448), IoU (0.8954), and OA (0.9956). The USFFC-Net model has the highest recall (0.9575), higher than DGMA²-Net (0.9277). However, the precision of the DMINet model is low (0.8758), which implies many false positives.

III) *Experiments on SYSU-CD*: It is noteworthy that all metrics of the models in the SYSU-CD dataset are lower than those in the LEVIR-CD and BCDD datasets (See Table I), because the change objects in the SYSU dataset are more complex, and the detection results are more susceptible to noise, which leads to more false detections. Among the models, DGMA²-Net showcases its superior performance in all metrics. It has its precision, recall, F1, IoU, and OA to be 0.8432, 0.8324, 0.8378, 0.7208, and 0.9240, respectively. The RSCD models' performances in predicting changes in bitemporal images from the SYSU-CD dataset are shown in Fig. 11. It is observed that DGMA²-Net is better in detecting change areas with fewer false and missed detections, while the baseline models have more false and missed detections.

In summary, the experiments on the three datasets confirmed the effectiveness of DGMA²-Net, which can be attributed to DGMA²-Net's capabilities of multiscale feature learning capabilities and multilevel feature interaction, as well as adequate operations of bitemporal features and difference features.

IV) *Analysis of model efficiency*: Table II shows the number of parameters (Params), floating-point operations (Flops) of the deep learning-based models, as well as the time needed to run an epoch and FPS on LEVIR-CD dataset. It is noted that although the Params of DGMA²-Net is higher than the baseline models, the Flops and training efficiency are not much different from the baseline models. Unfortunately, the FPS is relatively low among all the models, which indicates

TABLE I
QUANTITATIVE ANALYSIS OF RSCD MODELS (PRECISION, RECALL, F1, IOU AND OA) ON THREE DATASETS. THE BEST VALUES ARE IN BOLD. ALL RESULTS ARE DESCRIBE AS PERCENTAGES (%)

Dataset		LEVIR-CD					BCCD					SYSU-CD				
		Pre	Rec	F1	IoU	OA	Pre	Rec	F1	IoU	OA	Pre	Rec	F1	IoU	OA
Traditional Methods	CVA [6]	5.040	61.36	9.320	4.890	39.19	4.130	62.96	7.750	4.030	38.85	24.28	62.13	34.92	21.15	45.39
	SFA [8]	6.110	36.32	10.45	5.510	68.28	5.910	44.18	10.43	5.500	69.03	31.83	41.61	36.06	22.00	65.21
	PCA-Kmeans [50]	5.160	37.07	9.050	4.740	62.06	6.410	48.53	11.32	6.000	69.08	43.18	46.80	44.92	28.96	72.93
Deep Learning Methods	FC-Conc [20]	82.03	63.44	71.55	55.70	97.43	71.81	64.23	67.81	51.29	97.51	76.99	61.88	68.61	52.22	86.65
	FC-Diff [20]	88.22	68.31	77.00	62.60	97.92	66.25	62.99	64.58	47.69	97.18	78.55	45.72	57.80	40.65	84.25
	SNUNet [35]	91.06	87.74	89.37	80.78	98.94	87.75	73.52	80.01	66.68	98.50	81.60	81.61	81.60	68.93	91.32
	BIT [55]	90.69	88.45	89.56	81.09	98.95	94.98	92.05	93.49	87.78	99.48	81.69	77.82	79.71	66.26	90.66
	GeSAnet [56]	91.31	88.94	90.11	82.00	99.01	86.59	71.97	78.61	64.75	98.40	75.11	82.57	78.66	64.83	89.44
	DMINet [29]	87.74	92.75	90.18	82.11	98.97	90.18	78.55	83.97	72.36	98.78	80.05	82.89	81.44	68.70	91.09
	ICIF-Net [57]	86.08	92.23	89.05	80.26	98.84	90.90	82.41	86.45	76.13	98.95	76.69	80.69	78.64	64.80	89.66
	USFFC-Net [30]	89.37	91.53	90.44	82.54	99.04	87.58	95.75	91.48	84.30	99.33	80.41	78.72	79.56	66.05	90.25
	DGMA ² -Net	92.13	90.31	91.21	83.84	99.14	96.26	92.77	94.48	89.54	99.56	84.32	83.24	83.78	72.08	92.40

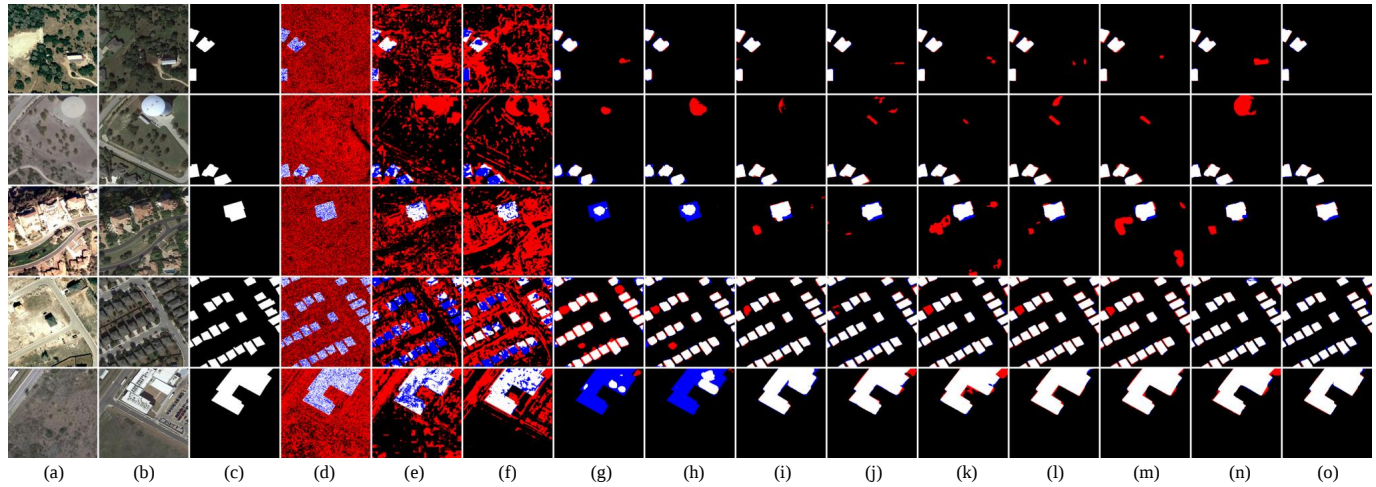


Fig. 9. Visual comparisons of DGMA²-Net and the baseline RSCD models on LEVIR-CD dataset. (a) T1 images, (b) T2 images, (c) Ground-truth, (d) CVA, (e) SFA, (f) PCA-Kmeans, (g) FC-Conc, (h) FC-Diff, (i) SNUNet, (j) BIT, (k) GeSAnet, (l) DMINet, (m) ICIF-Net, (n) USFFC-Net, (o) DGMA²-Net.

that exploring the potential for acceleration and investigating certain lightweight architectures is still necessary.

D. Ablation Experiment

The DGMA²-Net is composed of three key components: MDFM, DAM, and DEAM. The ablation experiment in this study therefore is aimed at assessing the marginal impacts of these three components on DGMA²-Net. Findings from the ablation study are as follows:

1) *MDFM ablation experiment*: In DGMA²-Net, the MDFM is critical to fusing bitemporal features and embedding useful semantic information into difference features in a multiscale manner. This study used two standard fusing operations (concatenation and subtraction), DEM [31], and TFIM [21] as the ablation baseline modules to compare with the MDFM. The concatenation operation directly concatenates bitemporal features, while the subtraction operation gets the difference of bitemporal features and performs absolute value operations.

Table III presents the ablation experimental results. It is noted when MDFM is removed and replaced by concatenation or subtraction, the model performance decreases significantly. In comparison with concatenation and subtraction, DEM and TFIM have better performance, the performance is still not as good as MDFM. Specifically, while the MDFM is the best in F1, IoU, and OA on the three datasets. In the LEVIR-CD dataset, the recall of the MDFM is 0.9031, only second to the DEM (0.9041). In the BCDD dataset, the MDFM achieves the best in all metrics. In the SYSU-CD dataset, the MDFM is the best in terms of recall, F1, IoU, and OA.

The visual results are shown in Fig. 12. When concatenation, subtraction, DEM and TFIM are employed to conduct temporal feature fusion, the change results are degraded by the background noises, while our MDFM performs well in reducing mistaken and missed predictions. This confirms that the use of the concurrent convolution operations with different kernel sizes in the multiscale feature learning mechanism

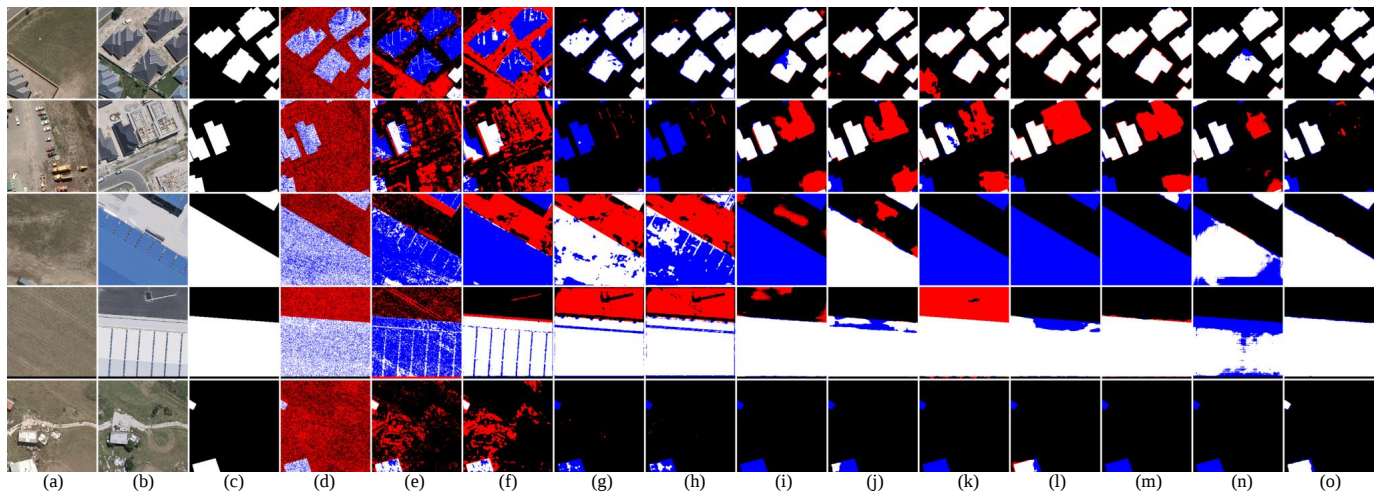


Fig. 10. Visual comparisons of DGMA²-Net and the baseline models on the BCDD dataset. (a) T1 images, (b) T2 images, (c) Ground-truth, (d) CVA, (e) SFA, (f) PCA-Kmeans, (g) FC-Conc, (h) FC-Diff, (i) SNUNet, (j) BIT, (k) GeSAnet, (l) DMInet, (m) ICIF-Net, (n) USFFC-Net, (o) DGMA²-Net.

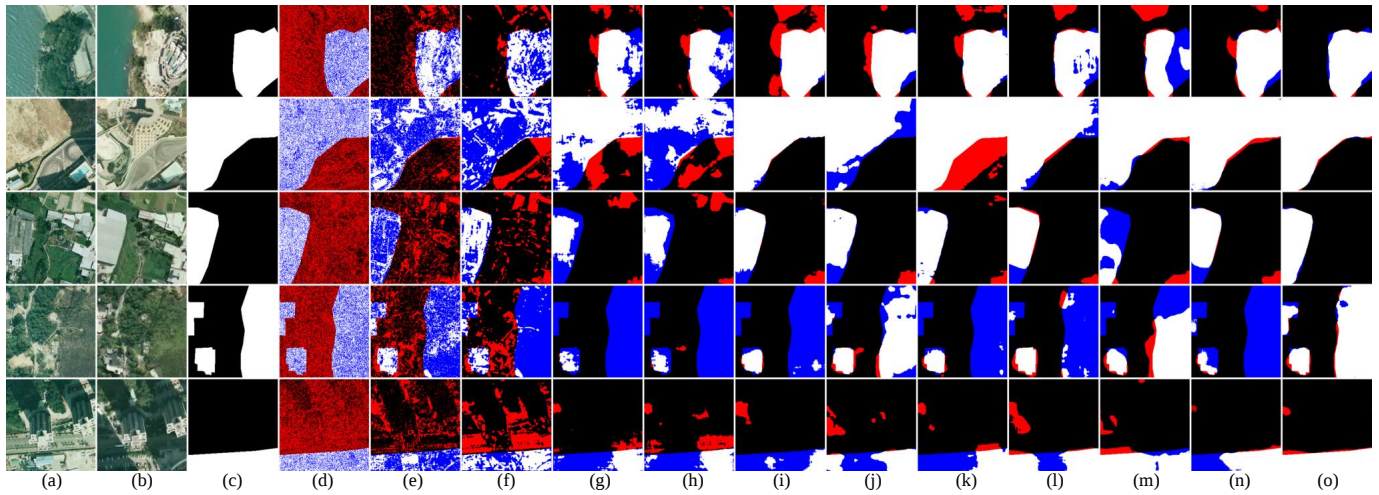


Fig. 11. Visual comparisons of DGMA²-Net and the baseline models on SYSU-CD dataset. (a) T1 images, (b) T2 images, (c) Ground-truth, (d) CVA, (e) SFA, (f) PCA-Kmeans, (g) FC-Conc, (h) FC-Diff, (i) SNUNet, (j) BIT, (k) GeSAnet, (l) DMInet, (m) ICIF-Net, (n) USFFC-Net, (o) DGMA²-Net.

TABLE II

QUANTITATIVE ANALYSIS OF MODELS ON PARAMS, FLOPS, TRAIN TIME FOR ONE EPOCH ON LEVIR-CD DATASET AND FPS ON LEVIR-CD DATASET. THE BEST VALUES ARE IN BOLD

Method	Params(M)	Flops(G)	Epoch time(min)	FPS
FC-Conc [20]	1.55	5.32	1.0	52
FC-Diff [20]	1.35	4.72	1.0	56
SNUNet [35]	12.03	54.82	9.2	37
BIT [55]	3.01	8.48	1.5	40
GeSAnet [56]	36.50	8.61	2.3	10
DMInet [29]	6.24	14.48	3.1	61
ICIF-Net [57]	25.30	23.84	7.0	16
USFFC-Net [30]	1.52	4.86	2.0	16
DGMA ² -Net	37.10	18.10	2.9	22

effectively alleviates the fusion of semantic information of bitemporal features into difference features and thus reduces

noises.

2) *DAM ablation experiment*: The DAM is developed to aggregate features and perform multilevel feature interactions after the MDFM operations. Table IV lists the ablation experimental results. It is interesting to note that using one DAM is not the optimal configuration since the ability of one DAM in guiding the learning of features is limited. The optimal configuration is with two DAMs. When zero to four DAMs are considered in DGMA²-Net, the resulting metrics (F1, IoU, and OA) indicate that DGMA²-Net with two DAMs is the best choice. After two DAMs are embedded in DGMA²-Net, the performance (in terms of F1, IoU, and OA) decreases gradually, which indicates that too many DAMs may overfit DGMA²-Net in model training.

Fig. 13 visually shows the impacts of DAMs in DGMA²-Net. It is noted that as more DAMs are employed in DGMA²-Net (from zero to two DAMs), change areas are obviously detected with clear boundaries. This observation indicates that noises in the difference features are significantly reduced.

TABLE III
ABLATION EXPERIMENT ON MDFM. THE BEST VALUES ARE IN BOLD

Dataset	Feature Fusion	Pre	Rec	F1	IoU	OA
LEVIR-CD	Concatenation	91.12	89.12	90.11	82.00	99.00
	Subtraction	91.00	89.05	90.01	81.84	98.99
	DEM	90.63	90.41	90.52	82.68	99.04
	TFIM	91.34	89.84	90.59	82.79	99.05
	MDFM	92.13	90.31	91.21	83.84	99.14
BCDD	Concatenation	94.79	88.85	91.72	84.71	99.35
	Subtraction	92.44	90.66	91.54	84.40	99.32
	DEM	95.53	90.44	92.92	86.77	99.44
	TFIM	95.16	91.65	93.37	87.57	99.47
	MDFM	96.26	92.77	94.48	89.54	99.56
SYSU-CD	Concatenation	81.86	82.67	82.26	69.87	91.59
	Subtraction	85.93	79.92	82.82	70.68	92.18
	DEM	86.24	80.23	83.13	71.13	92.32
	TFIM	86.46	79.94	83.07	71.04	92.32
	MDFM	84.32	83.24	83.78	72.08	92.40

TABLE IV
ABLATION EXPERIMENT ON DAM. THE BEST VALUES ARE IN BOLD

Dataset	Number of DAM	Pre	Rec	F1	IoU	OA
LEVIR-CD	0	91.67	88.16	89.88	81.62	98.66
	1	92.42	88.66	90.50	82.65	99.05
	2	92.13	90.31	91.21	83.84	99.29
	3	90.67	89.92	90.29	82.30	99.01
	4	90.08	88.71	89.39	80.81	98.93
BCDD	0	93.13	91.44	92.28	85.66	99.38
	1	95.40	90.96	93.13	87.14	99.45
	2	96.26	92.77	94.48	89.54	99.56
	3	95.05	88.04	91.41	84.18	99.32
	4	89.84	91.49	90.66	82.92	98.23
SYSU-CD	0	81.67	82.19	81.93	69.39	91.45
	1	85.30	80.17	82.66	70.44	92.07
	2	84.32	83.24	83.78	72.08	92.40
	3	80.18	83.52	81.82	69.23	91.24
	4	84.98	76.25	80.38	67.19	91.22

When three or four DAMs are configured in DGMA²-Net, changed areas are getting blurred and missed and false detections are being noticed.

To further demonstrate the advantages of DAMs, skip connections and GRM [21] are considered in the ablation experiments to compare with DAMs. Skip connections are used to replace the DAMs to aggregate bitemporal features and difference features from the MDFM, while the GRM conducts the same aggregation through concatenation and channel attention operations. Quantitative results are shown in Table V. It is observed that when DEMs are removed and skipconnections are used, the metrics of the model downgrade. When GRM is

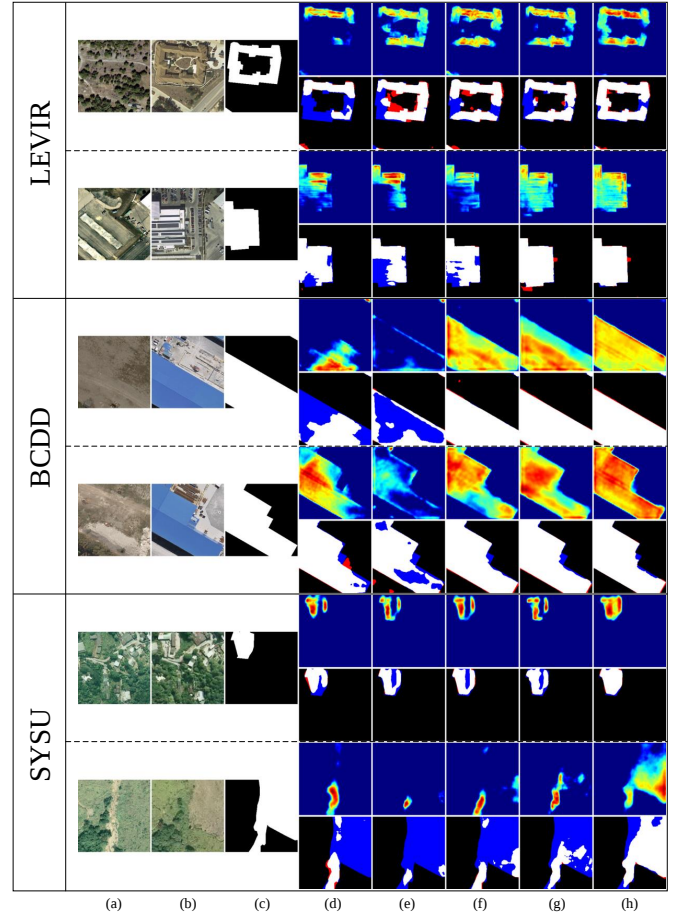


Fig. 12. Visual comparisons of the MDFM and the ablation baseline modules. (a) T1 images, (b) T2 images, (c) Ground-truth, (d) Visualize and predicted results of concatenation, (e) Visualize and predicted results of subtraction, (f) Visualize and predicted results of DEM, (g) Visualize and predicted results of TFIM, (h) Visualize and predicted results of MDFM.

TABLE V
ABLATION EXPERIMENT ON DAM. THE BEST VALUES ARE IN BOLD

Dataset	Feature Aggregation	Pre	Rec	F1	IoU	OA
LEVIR-CD	Skip Connections	91.86	87.79	89.78	81.46	98.98
	GRM	90.58	90.53	90.55	82.74	99.04
	DAM	92.13	90.31	91.21	83.84	99.14
BCDD	Skip Connections	94.83	88.29	91.45	84.24	99.33
	GRM	96.04	90.87	93.38	87.58	99.47
	DAM	96.26	92.77	94.48	89.54	99.56
SYSU-CD	Skip Connections	83.58	78.39	80.90	67.92	91.27
	GRM	821.6	82.67	82.41	70.08	91.68
	DAM	84.32	83.24	83.78	72.08	92.40

used for feature aggregation, its recall in LEVIR-CD is slightly higher than those of DAM, however its other metrics are lower than that of DAM, showing that the DAMs are superior to skip connections and GRM in feature aggregation.

Fig. 14 presents the predicted results of the DAMs, skip connections, and GRM. It can be found that when using skipconnections and GRM, the model still has certain missed

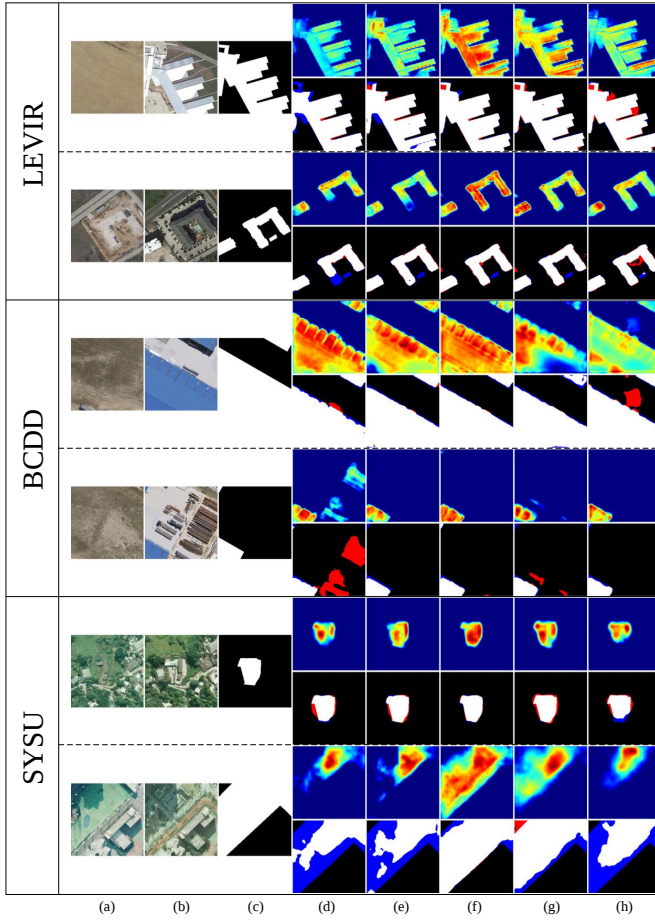


Fig. 13. Visual comparisons of the DAMs on three datasets. (a) T1 images, (b) T2 images, (c) Ground-truth, (d) Visualize and predicted results of zero DAM, (e) Visualize and predicted results of one DAM, (f) Visualize and predicted results of two DAMs, (g) Visualize and predicted results of three DAMs, (h) Visualize and predicted results of four DAMs.

and false detections. When DAMs are used, these phenomena reduces, confirming the importance of multilevel feature interaction in RSCD feature aggregation.

3) *DEAM ablation experiment*: The DEAM is developed to explore the interactions between bitemporal features and difference features, enhance the change areas, and refine difference features. Table VI lists the ablation experimental results of the DEAMs. When the DEAMs are removed, most metrics decrease. When DEAMs are added, the performance improves. Specifically, F1 has been improved by 0.56%, 1.38%, and 0.81%, while IoU has been improved by 0.92%, 2.44%, 1.18% on the three datasets, respectively. This reflects that our DEAM can promote learning from bitemporal features and difference features.

The visual results of the DEAM ablation experiments are shown in Fig. 15. It is observed that the emergence of the DEAMs makes the model go deeper into changing areas, and reduces the false detections and missed detections. Additionally, it shows that DEAM can effectively refine features, enhance the changing areas, and also yields excellent performance.

4) *Module efficiency analysis*: It is noted that in the absence of MDFM, we substitute subtraction. Table VII shows the

TABLE VI
ABLATION EXPERIMENT ON DEAM. THE BEST VALUES ARE IN BOLD.
O/W REPRESENTS THE DGMA²-NET WITHOUT/WITH DEAM

Dataset	o/w DEAM	Pre	Rec	F1	IoU	OA
LEVIR-CD	without DEAM	90.49	90.81	90.65	82.89	99.05
	with DEAM	92.13	90.31	91.21	83.84	99.14
BCDD	without DEAM	94.69	91.56	93.10	87.10	99.45
	with DEAM	96.26	92.77	94.48	89.54	99.56
SYSU-CD	without DEAM	87.89	78.58	82.97	70.90	92.39
	with DEAM	84.32	83.24	83.78	72.08	92.40

TABLE VII
QUANTITATIVE ANALYSIS OF MODELS ON PARAMS, FLOPS, AS WELL AS
F1, TRAIN TIME FOR ONE EPOCH AND FPS ON LEVIR-CD DATASET.
THE BEST VALUES ARE IN BOLD

Method	F1	Params(M)	Flops(G)	Epoch time(min)	FPS
DGMA ² -Net without MDFM	90.01	24.55	10.35	1.9	35
DGMA ² -Net without DAM	89.88	29.24	13.58	2.4	25
DGMA ² -Net without DEAM	90.65	36.67	18.10	2.8	25
DGMA ² -Net	91.21	37.10	18.10	2.9	22

efficiency analysis of the three proposed modules (MDFM, DAM and DEAM). It is noted that subtraction is used to conduct bitemporal feature fusion. It can be observed from the table that without MDFM, the model's Params, Flops, training efficiency, and FPS are better. In addition, it is observed that MDFM has the greatest impact on the efficiency of the model. For example, FPS dropped from 35 to 22, and the training time for one epoch increased from 1.9 minutes to 2.9 minutes. Compared with MDFM, DAM and DEAM have less impact on the efficiency of the model and can also improve the performance of the model. Notably, the multiscale convolution kernel and DAM consume more computing resources, and lightweight bitemporal feature fusion methods and feature aggregation methods need to be studied.

V. CONCLUSION

In this work, a difference-guided multiscale multilevel aggregation network, DGMA²-Net, is developed for RSCD. DGMA²-Net comprises three main components: MDFM, DAM, and DEAM. Initially, a ResNet-18 architecture is employed to extract multilevel features from the bitemporal images. The MDFMs are then used to fuse semantic information from bitemporal features into difference features through a series of convolutional operations with various kernel sizes. The MDFM is proven to be a new approach in fusing semantic information of bitemporal features in difference features. Additionally, the DAMs are instrumental in effectively aggregating multilevel difference features and facilitating multilevel feature interactions. Lastly, the DEAMs further enhance the

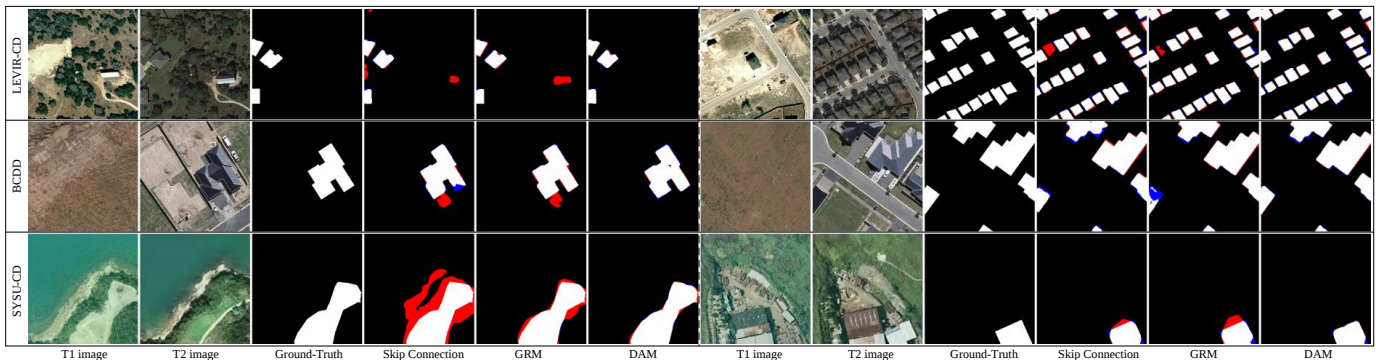


Fig. 14. Visual comparisons of DAMs, skip connections, and GRM on three datasets.

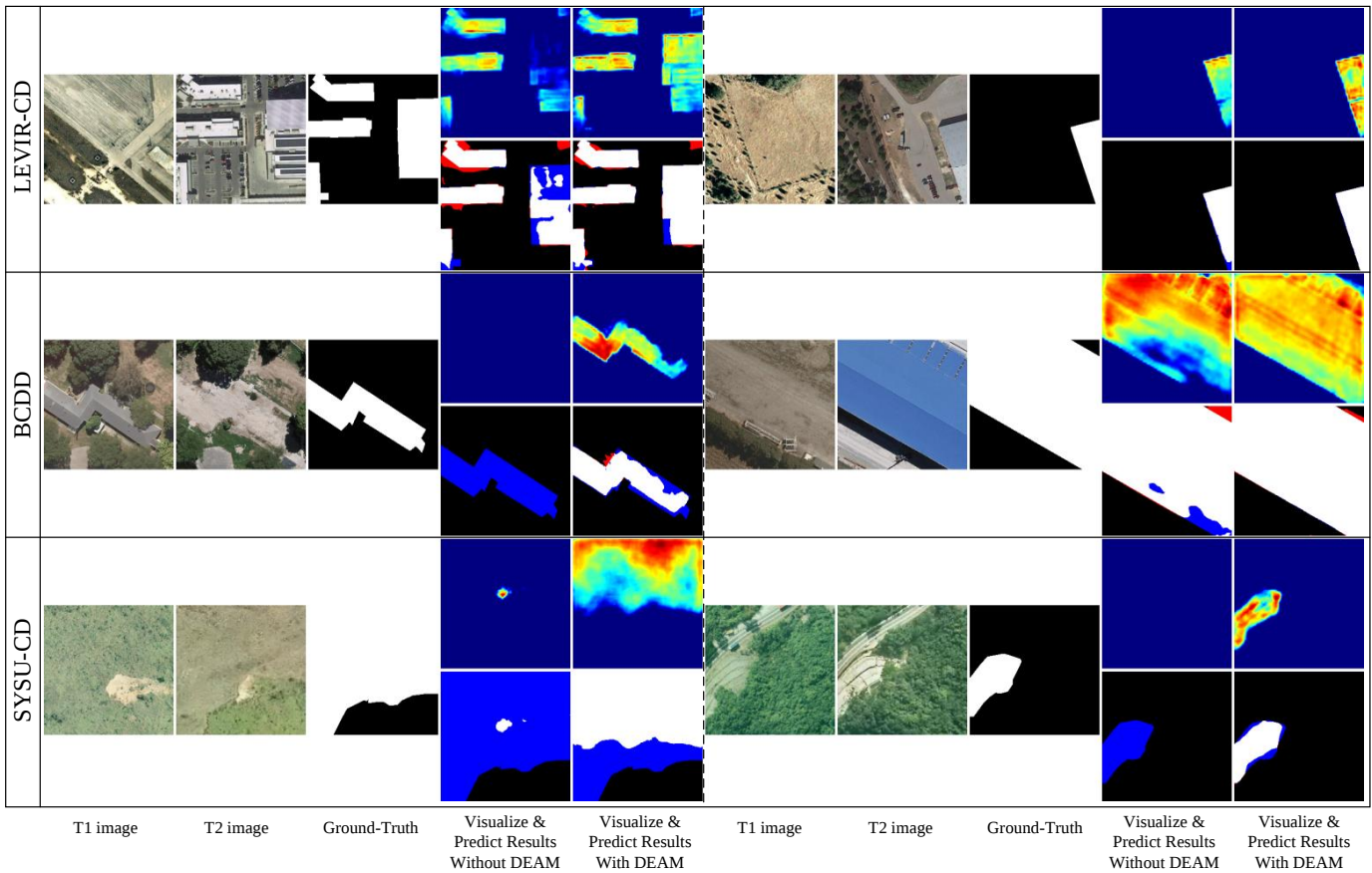


Fig. 15. Visual comparisons of the DGMA²-Net with and without DEAMs.

detection of change areas through the interactions between difference features and bitemporal features.

The experimental results on three popular RSCD datasets (LEVIR-CD, BCDD, SYSU-CD) demonstrate that DGMA²-Net has exceptional performances in RSCD and surpasses the state-of-the-art baseline models. In addition, the ablation tests provide results that indicate that the MDFM, DAM, and DEAM are effective in fusing bitemporal features, refining difference features, and detecting change areas. The incorporation of MDFM, DAM, and DEAM within the framework of DGMA²-Net introduces an innovative approach to RSCD that unequivocally outperforms the baseline RSCD models.

The DGMA²-Net still requires more computing resources

for RSCD, especially MDFM. With the continuous advancement of RSCD technologies, bitemporal feature fusion can be conducted by more lightweight and novel methods. Secondly, the multilevel feature aggregation in this article employed two DAMs. Therefore, future exploration could focus on investigating multilevel feature aggregation methods that only incorporate a single feature aggregation module. Furthermore, a new model is planned to incorporate semi-supervised, unsupervised, and self-supervised methods in RSCD since DGMA²-Net requires a large amount of annotated labels.

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