

Task-Oriented Data Synthesis and Control-Rectify Sampling for Remote Sensing Semantic Segmentation

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Abstract

With the rapid progress of controllable generation, training data synthesis has become a promising way to expand labeled datasets and alleviate manual annotation in remote sensing (RS). However, the complexity of semantic mask control and the uncertainty of sampling quality often limit the utility of synthetic data in downstream semantic segmentation tasks. To address these challenges, we propose a task-oriented data synthesis framework (TODSynth), including a Multimodal Diffusion Transformer (MM-DiT) with unified triple attention and a plug-and-play sampling strategy guided by task feedback. Built upon the powerful DiT-based generative foundation model, we systematically evaluate different control schemes, showing that a text-image-mask joint attention scheme combined with full fine-tuning of the image and mask branches significantly enhances the effectiveness of RS semantic segmentation data synthesis, particularly in few-shot and complex-scene scenarios. Furthermore, we propose a control-rectify flow matching (CRFM) method, which dynamically adjusts sampling directions guided by semantic loss during the early high-plasticity stage, mitigating the instability of generated images and bridging the gap between synthetic data and downstream segmentation tasks. Extensive experiments demonstrate that our approach consistently outperforms state-of-the-art controllable generation methods, producing more stable and task-oriented synthetic data for RS semantic segmentation. The code is available at <https://github.com/Yunkai-Yang/crfm>.

1. Introduction

Semantic segmentation in remote sensing (RS) imagery plays a crucial role in land-use classification [21], environmental monitoring [4], and thematic mapping [18]. How-

ever, compared with natural image segmentation, RS semantic segmentation faces substantial challenges due to the complex diversity of land-cover types across spatial resolutions and regions, the difficulty in collecting samples of rare classes, and the requirement for domain-specific expertise. Building large-scale pixel-wise labeled datasets for RS tasks is therefore time-consuming and expensive [8]. Recently, with the rapid advancement of generative models, data synthesis has emerged as a promising alternative to alleviate annotation scarcity and enrich training data for downstream segmentation models [9, 26].

Early progress in text-to-image diffusion models [12, 14, 20, 29, 31] demonstrated remarkable capabilities in generating diverse and realistic samples for classification tasks. Controllable generation has further extended this paradigm to layout-to-image for object detection [35, 46] and mask-to-image for semantic segmentation [28, 36], as exemplified by ControlNet [49] and its variants [19, 30, 53]. The emergence of transformer-based architectures [12, 20, 29] such as Diffusion Transformers (DiTs) has significantly improved generation quality. These powerful pre-trained generation models, such as SDXL [31] and Stable Diffusion 3.5 [33], provide a strong foundation for synthetic data generation and have been widely adapted for natural scene image synthesis.

Despite the maturity of ControlNet-style conditioning mechanisms, effectively controlling DiT-based generative models remains an open challenge [11]. While some studies employ adapter-based modules to inject conditional information, cross-attention control often suffers from inefficient semantic utilization and potential modality conflicts. To mitigate these issues, methods such as CreateLayout [48] introduce siamese multimodal DiTs to decouple modalities and reduce interference. However, for RS imagery, the substantial domain gap between aerial and natural scenes, together with the absence of DiT models pre-trained on RS data, makes it highly uncertain to establish an effective

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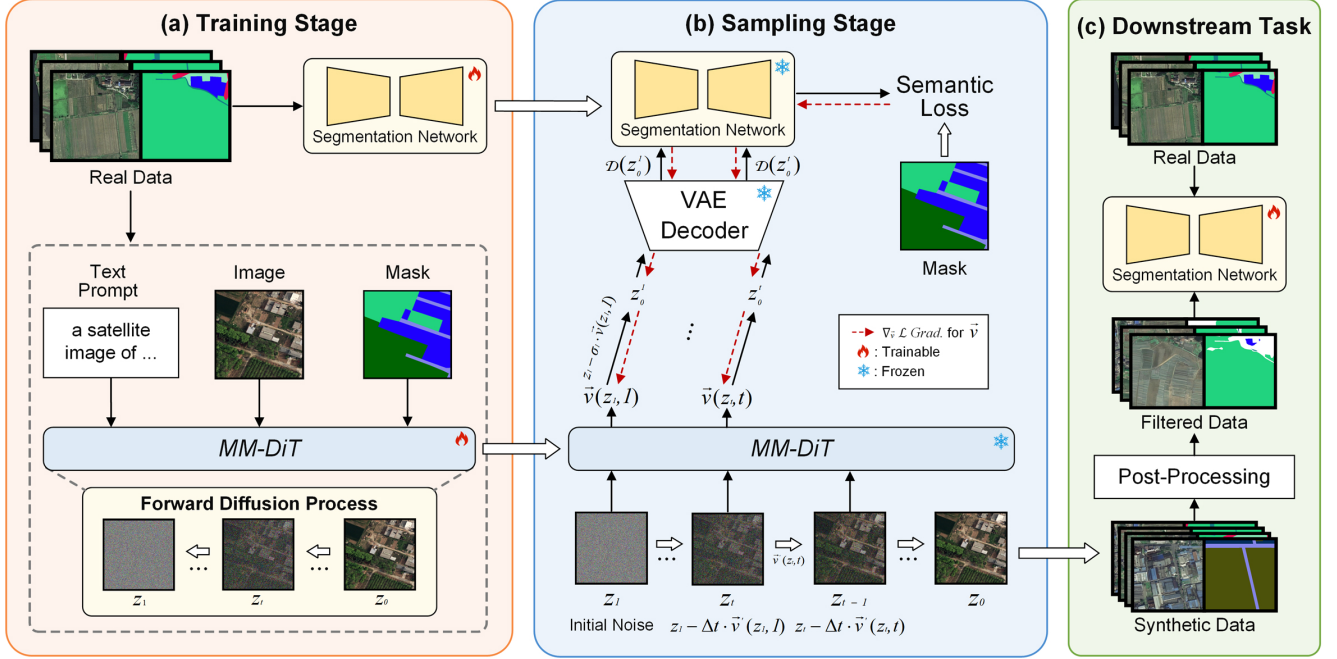


Figure 1. The overall workflow of the task-oriented data synthesis framework (TODSynth) consists of three stages: (a) Training stage using an MM-DiT generative model conditioned on text and mask. (b) Sampling stage with the proposed control-rectify flow matching (CRFM). (c) Downstream tasks trained on a combination of real and synthetic data.

mask-to-image control scheme.

In addition, the inherent stochasticity of the sampling process often leads to semantic drift and control deviation, resulting in unstable mask-conditioned generation and reduced effectiveness of synthetic data in downstream tasks. Recent studies typically adopt sample filtering strategies to directly select [37] or selectively utilize high-quality synthetic data [27]. For instance, FreeMask [45] introduces adaptive filtering and re-sampling to suppress noisy labels caused by inconsistencies between generated images and masks, while promoting the synthesis of more complex scenes. Such post-generation strategies practically retain the effective regions of synthetic data for downstream training. Similarly, EarthSynth [28] employs a rule-based CLIP scoring mechanism [2, 13] to evaluate image-object-background triplets and filter more informative samples for downstream tasks. Although these methods help reduce noise in synthetic datasets, they are inherently post-generation solutions and cannot fully resolve the intrinsic uncertainty of generation quality. In complex or few-shot scenarios, strict filtering may remove useful annotations and significantly degrade the performance of downstream tasks.

To address these limitations, we propose a task-oriented data synthesis framework that systematically examines mask-control strategies and introduces a control-rectify sampling method for RS semantic segmentation. We first compare different mask-to-image control schemes and ob-

serve that an appropriate DiT-based control design can markedly improve the effectiveness of synthetic data. In RS scenarios where fine-grained text descriptions are scarce, the text-image-mask joint attention scheme consistently outperforms both mask-adaptor and siamese MM-attention approaches.

Second, to mitigate the inherent uncertainty in sampling, we propose a control-rectify flow matching method, a plug-and-play sampling strategy guided by downstream task feedback. By leveraging the semantic loss signals from a pre-trained segmentation model, the sampler dynamically adjusts the sampling trajectory during the early high-plasticity stage, enabling in-process quality optimization. This improves the relevance and stability of synthetic data in complex and few-shot scenarios, rather than relying solely on post-processing filtering.

We conduct extensive experiments demonstrating that the proposed task-oriented data synthesis approach achieves OA/mIoU/mAcc improvements of 1.39%/4.14%/6.83% on FUSU-4k [47] and 1.60%/2.08%/2.22% on LoveDA-5k [40] compared to baseline. Our main contributions are summarized as follows:

- We introduce TODSynth, a task-oriented data synthesis framework that integrates architecture-level and sampling-level control to enhance the effectiveness of synthetic data for RS semantic segmentation.
- We propose a control-rectify flow matching (CRFM) method to mitigate generation uncertainty and enhance

the performance in complex and few-shot RS scenes. It is a task-feedback-guided sampling optimization strategy that leverages a pre-trained task network to refine generation without retraining the diffusion model.

- We conduct extensive experiments on two representative remote sensing semantic segmentation tasks, showing that the proposed TODSynth outperforms existing SOTA generation methods.

2. Related Work

2.1. Conditional Image Generation

Conditional image generation [25, 39, 43, 48, 49] aims to generate images under specific constraints such as layouts, masks, or text prompts. In this work, we mainly introduce layout-to-image and mask-to-image generation. ControlNet [49] achieves effective control by combining a frozen pre-trained diffusion backbone with a trainable copy through “zero convolution” layers, enabling guidance of the decoder under single or multiple conditions, such as depth maps, edges, or segmentation masks. Beyond this, adapter-based variants such as UniControl [43] enable flexible multi-condition fusion. Recent MM-DiT [12, 34, 42] explore different control strategies based on DiT architecture. For example, CreateLayout [48] introduces a siamese MM-DiT to decouple text and layout modalities, while EasyControl [50] and UniCombine [39] employ lightweight condition injection and use LoRA modules to improve training efficiency.

Synthesizing training data for remote sensing (RS) semantic segmentation [6, 9, 27] has gained increasing attention due to the scarcity of labeled data. SatSynth [38] explores joint generation of images and corresponding masks for satellite segmentation by training diffusion models from scratch. However, training diffusion models on small RS datasets often yields suboptimal results. To overcome this limitation, several RS generative foundation models have been developed, including DiffusionSat [15], EarthSynth [28], and TerraGen [36], which build upon Stable Diffusion (SD) v1.5 [1] and are trained on large RS datasets to enable controllable generation. Similarly, TISynth [9] introduces additional reference guidance to achieve transferable RS semantic segmentation data synthesis via joint reference-semantic fusion, also based on SD v1.5.

Despite these advances, major challenges remain due to the domain gap between natural and RS imagery, the limited availability of RS-specific DiT pre-trained models, and the uncertainty in effective DiT control strategies. In this work, we systematically explore mask-to-image control schemes for RS semantic segmentation and adopt MM-DiT with unified triple attention.

2.2. Training Data Synthesis for Downstream Tasks

Synthetic data has been widely employed to augment training datasets for downstream tasks such as semantic segmentation. Existing works [27] generally adopt uncertainty-aware segmentation approaches or sample filtering methods, e.g., adaptive filtering [45] and CLIP-based selection [28, 37]. While these methods are effective in reducing noise, they rely on post-processing and cannot resolve the intrinsic uncertainty of generation quality, particularly in complex or few-shot scenarios.

In related areas such as dataset distillation [7, 32, 41] and layout-to-image (L2I) generation [48, 54], some works attempt to improve synthetic data via distribution matching [16, 17] or trajectory matching [3, 10]. The training-free L2I method [5] apply marginal attention constraints to optimize latent features, enhancing spatial controllability and reducing semantic failures. However, these strategies are misaligned with semantic segmentation objectives, limiting their direct applicability.

Different from these approaches, we propose a control-rectify flow matching method to mitigate generation uncertainty and enhance the effectiveness of synthetic data for downstream tasks. Our method leverages semantic loss to dynamically adjust the sampling directions during the early, high-plasticity stage of generation. This strategy improves the effectiveness of generated data without directly modifying feature maps or constraining the distribution of synthetic samples, providing a task-oriented solution for robust data synthesis in RS semantic segmentation.

3. Methodology

3.1. Preliminary

Flow-based generative models formulate data synthesis as a continuous transport from a base distribution to the target distribution. The evolution of a sample along a trajectory $\mathbf{y}_t$ parameterized by $t \in [0, 1]$ is described by an ordinary differential equation (ODE):

$$\frac{d\mathbf{y}_t}{dt} = \mathbf{v}_\theta(\mathbf{y}_t, t), \quad (1)$$

where $\mathbf{v}_\theta$ denotes a learnable velocity field. Flow Matching (FM) [22] supervises the model with ideal transport velocities constructed between paired samples, enabling stable training without stochastic score matching. Rectified Flow (RF) [23] further simplifies this by assuming a linear trajectory between the endpoints:

$$\mathbf{z}_t = (1 - t)\mathbf{z}_0 + t\mathbf{z}_1, \quad (2)$$

with constant velocity $\mathbf{v}_\theta = \mathbf{z}_1 - \mathbf{z}_0$, allowing deterministic and efficient generation.

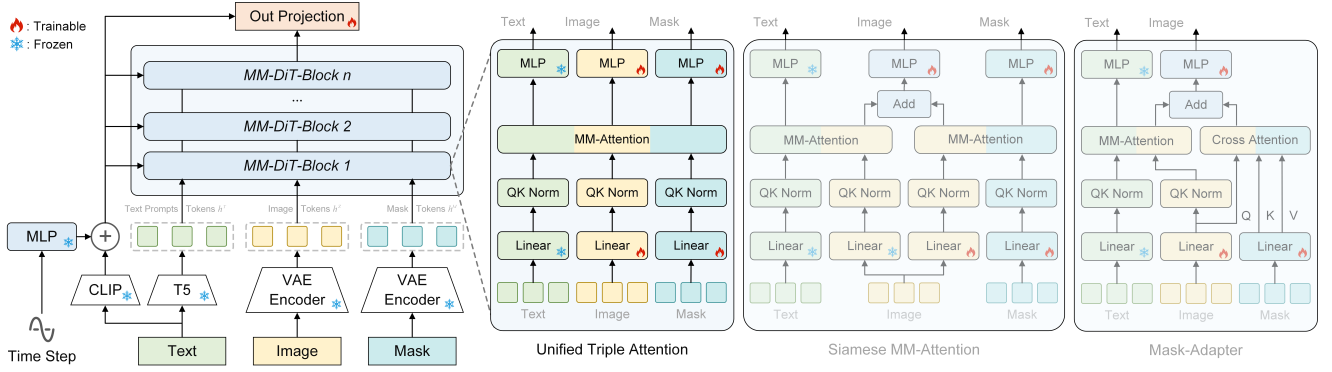


Figure 2. The architecture of MM-DiT with unified triple attention. For comparison, the mask-adaptor and siamese MM-attention schemes are also illustrated.

3.2. The Overall Workflow of TODSynth

Due to the high cost of expanding RS datasets, we propose TODSynth, a training data synthesis framework designed to enhance the performance of downstream RS semantic segmentation models. Considering the challenges of fine-grained semantic control, we integrate architecture-level and sampling-level control strategies to improve the effectiveness of synthetic data. The overall workflow is illustrated in Fig. 1.

At the architecture level, to enhance mask-to-image control, we adopt the MM-DiT architecture combined with the pre-trained SD v3.5 model (Fig. 1(a)). To address semantic imbalance, global semantic information is embedded into the text prompt, which is combined with pixel-level mask guidance. A text-image-mask unified attention mechanism is employed to strengthen the model’s ability to generate complex scenes and few-shot categories. We further compare different DiT-based control strategies (Fig. 2), demonstrating that the text-image-mask joint attention scheme consistently outperforms both mask-adaptor and siamese MM-attention approaches on this task.

Despite improvements at the architecture level, the stochastic nature of the generation trajectory can still cause deviations from the semantic mask constraints in certain regions, reducing the effectiveness of the synthesized data. To address this, we propose a sampling-level control strategy, namely Control-Rectify Flow Matching (CRFM) (Fig. 1(b)). During the high-plasticity early sampling stage, CRFM adjusts the trajectory by applying a rectification vector $\mathbf{v}'_{\text{rec}}$ to the predicted velocity field. This vector is computed from the cross-entropy loss between early predictions and the ground-truth mask, enhancing the alignment of the generated samples with the semantic constraints and mitigating uncertainty in data synthesis.

Finally, the refined synthetic data is combined with real samples and used to train downstream semantic segmentation models (Fig. 1(c)).

3.3. Unified Triple Attention

Our work builds upon the SOTA MM-DiT architecture adopted by the SD v3.5 family. We focus on effectively incorporating semantic masks $\mathbf{C}^m$ to achieve precise spatial control during image generation. MM-DiT performs multimodal fusion using a Unified Attention mechanism that processes the text sequence $\mathbf{h}^t$ and image latent sequence $\mathbf{h}^z$ jointly by concatenating their tokens:

$$\mathbf{h}_o^t, \mathbf{h}_o^z = \text{Attn}([\mathbf{h}^t, \mathbf{h}^z]), \quad (3)$$

where $[\cdot, \cdot]$ denotes length-wise concatenation. Each modality uses its own projection matrices ($\mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_v$) to map features into the query, key, and value spaces. On this basis, we examine three mask-conditioning strategies: unified triple attention, siamese MM-attention, and mask-adaptor.

Unified triple attention (Tri-attention) extends MM-DiT by adding a third modality stream for the mask sequence $\mathbf{h}^m$. Following the unified fusion principle, attention is computed over all three token sequences:

$$\begin{aligned} \mathbf{h}_o^t, \mathbf{h}_o^z, \mathbf{h}_o^m &= \text{Attn}([\mathbf{h}^t \mathbf{W}_q^t, \mathbf{h}^z \mathbf{W}_q^z, \mathbf{h}^m \mathbf{W}_q^m], \\ &[\mathbf{h}^t \mathbf{W}_k^t, \mathbf{h}^z \mathbf{W}_k^z, \mathbf{h}^m \mathbf{W}_k^m], \\ &[\mathbf{h}^t \mathbf{W}_v^t, \mathbf{h}^z \mathbf{W}_v^z, \mathbf{h}^m \mathbf{W}_v^m]). \end{aligned} \quad (4)$$

Tri-attention integrates the mask stream directly, enabling crucial cross-modal interaction between the textual and mask modalities during the fusion process, allowing the semantic information encoded in the text to enhance the model’s understanding of the required spatial and semantic distribution.

We also evaluate the siamese MM-attention in L2I [48]. It processes text-image and mask-image interactions through two separate MM-attention blocks. Unlike L2I generation, the pure segmentation mask in M2I lacks localized textual descriptions, reducing semantic richness. Although the siamese design originally intended to mitigate token-length imbalance across modalities, this issue is less pro-

nounced in M2I due to the natural tokenization of the mask, diminishing the benefit of decoupled attention.

Mask-Adapter injects mask features into the image branch using a lightweight cross-attention module while keeping the MM-DiT backbone unchanged. Although computationally efficient, the mask information suffers from two limitations: 1) it is not directly fused with text embeddings, weakening the learning of global semantic information, especially in fine-grained and few-shot scenarios. 2) The mechanism only allows $\mathbf{h}^z$ to query $\mathbf{h}^m$, meaning the mask representation remains static throughout the denoising process, restricting its adaptive refinement. These constraints limit the precision and controllability of the generated results.

Through the above analysis, we adopt the Tri-attention scheme and fully fine-tune both the image and mask branches, given the lack of DiT-based generative models pre-trained on diverse RS imagery.

3.4. Control-Rectify Flow Matching

Upon training a conditional generative flow model [22, 23], the inherent stochasticity of the trajectory and the imperfections in model prediction inevitably lead to generated images that, in certain regions, deviate from the semantic mask constraints during the inference process. Such conditional deviations often manifest in the early stages of the model’s generation, where small errors are rapidly amplified. Therefore, we propose the Control-Rectify Flow Matching (CRFM) mechanism, enabling the timely correction of the velocity vector early in the flow trajectory, thereby ensuring the synthesized results adhere more faithfully to the target semantic distribution.

The original RF model predicts a constant vector field, defined simply as $\mathbf{v} = \mathbf{z}_1 - \mathbf{z}_0$. When incorporating the conditional controls $\mathbf{C}^t$ and $\mathbf{C}^m$ (text and semantic mask), the ideal vector field $\mathbf{v}_\Theta$ for the conditional flow trajectory retains this straight-line property. It can be formally expressed as:

$$\mathbf{v}_\Theta(\mathbf{z}_t, t, \mathbf{C}^t, \mathbf{C}^m) = \mathbf{z}_1 - \mathbf{z}_0. \quad (5)$$

This formulation implies that, ideally, at every time step t along the probabilistic path, the model’s predicted vector field remains the deterministic constant difference between the terminal data point $\mathbf{z}_0$ and the initial noise point $\mathbf{z}_1$, irrespective of the current state $\mathbf{z}_t$.

Therefore, the generation process, which maps the initial noise sample $\mathbf{z}_1$ to the final data sample $\mathbf{z}_0$, is described by solving the ODE via integration from $t = 1$ to $t = 0$:

$$\mathbf{z}_0 = \mathbf{z}_1 + \int_1^0 \mathbf{v}_\Theta(\mathbf{z}_t, t, \mathbf{C}^t, \mathbf{C}^m) dt. \quad (6)$$

In practical implementation, this continuous integration is typically approximated using numerical solvers, such as the

Euler method, which discretizes the process into N time steps. The iterative generation is then described by the following update rule:

$$\mathbf{z}_{t_{i-1}} = \mathbf{z}_{t_i} + \mathbf{v}_\Theta(\mathbf{z}_{t_i}, t_i, \mathbf{C}^t, \mathbf{C}^m) \cdot \Delta t, \quad (7)$$

where $\mathbf{z}_{t_N} = \mathbf{z}_1$ is the starting noise, and the final generated sample is $\mathbf{z}_{t_0} \approx \mathbf{z}_0$.

Assuming $\mathbf{v}_\Theta^T$ is the target velocity field that guides samples toward the data distribution, and $\mathbf{v}_\Theta^P$ is the learned velocity field predicted by the flow model, the residual vector $\mathbf{v}_{\text{res}}$ can be calculated as the difference between the true and predicted fields:

$$\mathbf{v}_{\text{res}} = \mathbf{v}_\Theta^T - \mathbf{v}_\Theta^P. \quad (8)$$

We utilize this residual vector as the rectified vector field $\mathbf{v}_{\text{rec}}$. Consequently, the target velocity field can be decomposed and represented as:

$$\mathbf{v}_\Theta = \mathbf{v}_\Theta^P + \mathbf{v}_{\text{rec}}. \quad (9)$$

Theoretically, if we can accurately compute $\mathbf{v}_{\text{rec}}$ at every step along the flow trajectory, then regardless of any inherent drift or deviation in the learned field, the final synthesized result will align well with the target data distribution.

Unlike standard data distributions, the conditional data distribution $q(\mathbf{z}_0 | (\mathbf{C}^t, \mathbf{C}^m))$ represents the mapping from the initial latent noise $\mathbf{z}_1 \sim p(\mathbf{z})$ to the target latent state $\mathbf{z}_0$, conditioned on textual prompts $\mathbf{C}^t$ and semantic masks $\mathbf{C}^m$. Generating samples from this conditional distribution requires the flow model to produce a velocity field that strictly respects the specified conditions, particularly the spatial constraints imposed by $\mathbf{C}^m$. Although the unified triple attention scheme is designed to produce an appropriate conditional vector field based on the input modalities, the stochasticity inherent in the initial latent noise and the complexity of the mask constraints inevitably lead to deviations in the generated semantics. This motivates the need for an early, targeted trajectory correction mechanism to enforce strict adherence to the conditions throughout the flow.

The proposed CRFM mechanism introduces an innovative, targeted gradient-based correction at the early stages of the generation trajectory. Specifically, CRFM first generates a pre-synthesized prediction of the final sample, $\mathbf{x}_0^t$, using the current state, $\mathbf{z}_0$ and the predicted velocity field $\mathbf{v}^P$:

$$\mathbf{z}_0^t = \mathbf{z}_t - \sigma_t \mathbf{v}^P(\mathbf{z}_t, t, \mathbf{C}^t, \mathbf{C}^m), \quad (10)$$

$$\mathbf{x}_0^t = \mathcal{D}(\mathbf{z}_0^t), \quad (11)$$

where $\mathcal{D}$ denotes the VAE decoder that maps the latent space to the image space. Here, $\mathbf{z}_0^t$ is the predicted latent representation of the final sample, and $\mathbf{x}_0^t$ serves as the input to a pre-trained segmentation network $\mathcal{S}$. The output of this network is then used to compute a Cross-Entropy loss against the ground-truth semantic mask $\mathbf{C}^m$:

$$\mathbf{v}'_{\text{rec}} = -\nabla_{\mathbf{v}_t} \mathcal{L}_{CE}(\mathcal{S}(\mathbf{x}_0^t), \mathbf{C}^m). \quad (12)$$

The resulting gradient is back-propagated to produce the predicted rectified vector field, denoted as $\mathbf{v}'_{\text{rec}}$, which estimates the theoretically required residual vector $\mathbf{v}_{\text{rec}}$. This correction is incorporated to update the predicted velocity field:

$$\mathbf{v}'(\mathbf{z}_t, t, \mathbf{C}^t, \mathbf{C}^m) = \mathbf{v}^P(\mathbf{z}_t, t, \mathbf{C}^t, \mathbf{C}^m) + \alpha \mathbf{v}'_{\text{rec}}, \quad (13)$$

where α is a tunable scalar that controls the strength of the correction applied at each step. This process effectively adjusts the predicted velocity vector $\mathbf{v}^P$ during the critical early steps, ensuring stricter adherence to the specified conditions throughout the generation. The proposed CRFM differs fundamentally from previous methods in its optimization target. Instead of performing gradient optimization directly on the latent state $\mathbf{z}_t$ [5], we focus on rectifying the underlying velocity vector field $\mathbf{v}_{\Theta}$, which indirectly updates $\mathbf{z}_t$ through ODE integration.

Based on the above theoretical analysis, we also validated this intuition experimentally. We found that direct optimization of $\mathbf{z}_t$ using the gradient of downstream tasks leads to mode collapse, where the generative model fails to capture the full diversity of the target distribution and instead converges to a limited subset of samples, resulting in ineffective synthetic data. By contrast, optimizing the underlying velocity field provides stable, continuous corrections along the trajectory, thereby effectively mitigating mode collapse.

Moreover, it is important to note that we apply this task-guided loss gradient only during the early stages of sampling. On one hand, the early stage exhibits high stochasticity, making it more amenable to trajectory adjustment. On the other hand, pre-trained segmentation models inherently contain prediction errors. These errors, although present, can still provide useful guidance for coarse adjustments at early steps. Applying corrections too late in the trajectory, however, could amplify these errors, making the sampling process overly dependent on the segmentation model. This may generate adversarial-like perturbations that deviate from the normal image distribution and degrade synthetic quality. Therefore, the proposed CRFM adjusts the directions of velocity field only in the early step, effectively reducing uncertainty in data synthesis and ensuring that the generated results adhere more faithfully to the target semantic distribution.

3.5. Implementation Details

Our TODSynth model leverages the MM-DiT [12] architecture, building upon the foundational SD v3.5 [33] framework. The model is trained at a 512×512 resolution. Optimization is performed using the AdamW optimizer, setting the learning rate to $\eta = 1 \times 10^{-5}$ and the weight decay to 0.01. For post-processing, image synthesis for each semantic mask involves redefining and fixing a sequence of

random seeds. A subsequent filtering step ensured that the synthesized images either resulted in a minimum of three distinct classes or preserved those classes containing only a few samples. Our models are trained for 200,000 steps on 8 NVIDIA RTX 4090 GPUs.

Our semantic segmentation approach is implemented using the MMSegmentation framework [24]. For fair comparison and robust training, we adopt the standard data augmentation techniques integrated within MMSegmentation. These techniques include basic transformations (random crop and random flip) and the comprehensive PhotoMetricDistortion, which sequentially applies a range of photometric adjustments, such as random brightness, random contrast, random saturation, and random hue.

4. Experiment

4.1. Datasets and Evaluation

FUSU. FUSU [47] is a high-resolution aerial land-cover dataset originally developed for change detection research. The imagery is sourced from Google Earth with a spatial resolution of approximately 0.2–0.5 m. FUSU provides fine-grained annotations covering 17 land-cover categories (e.g., residential, industrial, cropland, inland water, wetland, park, commercial land, greenbelt, service land, etc.). Following the setting in TISynth [9], we use a 4,000-sample subset of FUSU (denoted as FUSU-4k) and adopt the T1 image-mask pairs cropped to 512×512 pixels for training and evaluation.

LoveDA. LoveDA [40] is a domain-adaptive semantic segmentation benchmark consisting of 5,987 images with 0.3 m resolution and a spatial size of $1,024 \times 1,024$ pixels. It includes six semantic classes: building, road, water, barren, forest, and agriculture. In this work, we consider the rural-to-urban setting, using 3,274 rural images for training and 2,713 urban images for testing.

Evaluation metrics. Semantic segmentation performance is measured using Overall Accuracy (OA), Mean Intersection over Union (mIoU), and Mean Accuracy (mAcc). Image synthesis quality is evaluated using Frechet Inception Distance (FID).

4.2. Comparison Results

We compare TODSynth with SOTA training data synthesis methods on two RS semantic segmentation datasets. The comparison methods include four UNet-based controllable generators (i.e., Freestyle [44], FreeMask [45], ControlNet [49], and SynthEarth [28]) and a MM-DiT-based controllable generation method (i.e., SD v3.5 with Tri-attention).

For a fair comparison, all methods except SynthEarth are fine-tuned on the same RS datasets. SynthEarth, as a large-scale generative foundation model trained on extensive RS

Table 1. Quantitative comparison with different training data synthesis methods (%). We report segmentation performance, the use of post-processing filters, and the ratio of synthetic to real training data for each method.

Method	Post-processing	Syn/Real volume	FUSU-4k			LOVEDA-5k		
			OA	mIoU	mAcc	OA	mIoU	mAcc
Baseline [52]	-	-	74.27	45.27	56.44	78.22	64.04	78.71
Freestyle [44]	×	×10	73.49	44.99	57.75	78.59	64.10	78.77
Controlnet [51] (SD v1.5)	×	×10	73.85	45.13	56.77	78.24	63.89	79.42
FreeMask [45]	FM	×5	74.23	45.83	56.29	79.26	64.93	79.06
SynthEarth* [28]	CLIP Score	×5	75.35	47.53	58.91	78.87	64.07	78.00
SD v3.5 [33]	FM	×3	75.41	48.57	61.67	79.72	65.45	79.91
Ours	FM	×3	75.66	49.41	63.27	79.82	66.12	80.93

*SynthEarth is a unified generative model that can be directly used for inference.

Table 2. Comparison of different control strategies on FUSU-4k.

Method	FUSU-4k		
	OA	mIoU	mAcc
Controlnet [51] (SD v1.5)	73.85	45.13	56.77
Mask-adapter	74.94	47.41	59.62
Siamese MM-attention	74.94	48.46	61.44
Tri-Attention	75.41	48.57	61.67

imagery and supporting training-free controllable generation, is directly used to synthesize RS segmentation data without additional tuning. All downstream semantic segmentation experiments use the same model architecture.

To isolate the contribution of the proposed CRFM, we evaluate SD v3.5 using the same architecture and post-processing filter as TODSynth. Therefore, the presence or absence of CRFM is the only difference. Table 1 summarizes distinctions among all methods, including post-processing strategies, the ratio of synthetic to real training samples, and segmentation performance on FUSU-4k and LoveDA. Fully supervised training on real data is used as the baseline.

Across both datasets, TODSynth consistently achieves the best performance. Compared to the supervised baseline trained on real data, TODSynth improves OA/mIoU/mAcc by 1.39%/4.14%/6.83% on FUSU-4k and 1.60%/2.08%/2.22% on LoveDA. Moreover, MM-DiT-based models exhibit stronger controllability compared with UNet-based generators, even when the SynthEarth is a RS generative foundation model. This advantage is particularly evident on FUSU, which contains 17 diverse land-cover categories.

Comparing TODSynth with SD v3.5 under identical architecture and post-processing settings, our CRFM achieves an improvement of 0.84%/1.6% mIoU/mAcc on FUSU-4k and 0.67%/1.02% mIoU/mAcc on LoveDA by dynamically adjusting the sampling trajectory. This demonstrates the ef-

fectiveness of the proposed sampling-level control.

Furthermore, TODSynth achieve superior performance with fewer synthetic samples compared to methods requiring larger synthetic datasets, highlighting its practicality.

4.3. Ablation Study

We conduct the ablation study on the FUSU dataset. All experiments use the same post-processing strategy and downstream semantic segmentation implementation.

For DiT-based controllable generation, we compare three control strategies: Unified Triple Attention (Tri-Attention), Siamese MM-Attention, and Mask-Adapter, using ControlNet (SD v1.5) as the baseline. As shown in Table 2, Tri-Attention consistently outperforms both Siamese MM-Attention and Mask-Adapter. The Mask-Adapter, while efficient, provides limited control because it does not fuse text and mask embeddings and keeps mask features static, restricting precision and adaptability. In contrast, MM-DiT-based methods achieve better performance, and Tri-Attention achieves the best results with a concise implementation. We therefore adopt Tri-Attention in this work.

For post-processing of synthetic data, current approaches can be grouped into image-level filtering, e.g., CLIP-based methods like Earthsynth [28] and SDS [37], and pixel-level filtering, e.g., Freemask [45] and TISynth [9]. We compare these two types of post-processing filters, as well as the combination with our proposed CRFM. As shown in Table 3, pixel-level filtering significantly improves downstream performance, particularly in mIoU and mAcc, due to its finer-grained region selection. Incorporating CRFM into the pixel-level filter further boosts performance (0.84%/1.60% mIoU/mAcc on FUSU), demonstrating its effectiveness in complex and few-shot scenarios.

4.4. Discussion

We further analyze the effectiveness and sensitivity of CRFM. We conduct extensive experiments using different sampling steps and CRFM steps to test its sensitivity to the

Table 3. Comparison of different post-processing strategies on FUSU-4k.

Experiment	FreeMask Filter [45]	CLIP Score Filter [28]	CRFM	OA	mIoU	mAcc
Exp1	×	✓	×	74.78	46.69	58.08
Exp2	✓	×	×	75.41	48.57	61.67
Exp3 (Ours)	✓	×	✓	75.66	49.41	63.27

Table 4. Performance of CRFM with different sampling steps and CRFM steps on FUSU-4k.

Method	OA	mIoU	mAcc	FID
step=23, CRFM=0	75.41	48.57	61.67	35.85
step=23, CRFM=2	75.79	48.80	61.05	34.86
step=23, CRFM=4	75.66	49.41	63.27	38.65
step=23, CRFM=6	75.71	48.74	61.30	66.95
step=18, CRFM=0	75.53	47.81	59.32	40.23
step=18, CRFM=2	75.86	47.99	59.46	38.94
step=18, CRFM=4	76.24	48.93	60.54	57.01
step=18, CRFM=6	76.02	49.57	62.19	86.69
step=13, CRFM=0	75.02	46.86	59.44	49.53
step=13, CRFM=2	75.73	48.29	59.99	48.61
step=13, CRFM=4	76.08	49.04	62.05	81.90
step=13, CRFM=6	76.19	49.09	62.50	132.92

sampling step and empirical usage.

As discussed in the Methodology section, early adjustment of the sampling trajectory helps reduce the gap between synthetic data and downstream tasks, mitigating the uncertainty in synthetic data. First, with the standard sampling step of 23, we apply CRFM starting from the first step, using 2, 4, and 6 CRFM steps. CRFM=0 represents the baseline without CRFM. As shown in Table 4, we observe that the effectiveness of synthetic data for downstream tasks and its quality initially improve and then decline as CRFM steps increase. This is because early-stage randomness allows easier trajectory adjustment, but excessive adjustment becomes constrained by the capabilities of the pre-trained segmentation model. Over-adjustment also generates adversarial-like samples that deviate from the natural image distribution, causing a deterioration in FID. Therefore, CRFM is sensitive to the number of adjustment steps and the pre-trained segmentation model. In practice, applying CRFM for about the first four steps balances downstream performance and synthetic data quality.

Next, we test shorter sampling steps with 18 and 13 steps, again starting CRFM from the first step with 2, 4, and 6 adjustment steps. We observe the same trend: synthetic data quality initially improves with more CRFM steps but declines if over-adjusted, particularly at 6 steps, where downstream performance may still increase but FID drops significantly due to adversarial-like artifacts. Thus, when

reducing the number of sampling steps, we also reduce the number of CRFM steps. Additional sensitivity analyses regarding the pre-trained segmentation model appear in the supplementary material.

Based on these analyses, we summarize the limitations and future directions of this study:

The first issue is CRFM sensitivity. CRFM is sensitive to the sampling step and the pre-trained segmentation model. Applying it for a small number of early steps is the most stable approach. It also requires a sufficiently capable pre-trained segmentation model; with very limited data, the model does not provide effective guidance, reducing CRFM’s effectiveness. We will explore more robust pre-trained models, such as RS foundation models, to improve the effective of evaluation and sampling stability.

The second issue is synthetic data diversity and cross-domain performance. Currently, we do not leverage a strong RS generative foundation model or external RS reference data, which limits the diversity of synthetic samples. Future work explores incorporating additional information to enhance the effectiveness of synthetic data for downstream tasks.

5. Conclusion

In this paper, we propose a training data synthesis framework for RS semantic segmentation that integrates an MM-DiT architecture with task-guided sampling. We systematically evaluate different mask-to-image control schemes for this task. To enhance control over mask boundaries and semantics in the synthesized data, we adopt a unified triple attention mechanism within MM-DiT control blocks, improving the interaction between text, image, and mask. Furthermore, we introduce the control-rectify flow matching method, guided by semantic loss, to dynamically adjust sampling directions during the early, high-plasticity stage. This approach mitigates the intrinsic uncertainty of generation quality, thereby improving the utility of synthesized data for downstream semantic segmentation tasks. Extensive experiments demonstrate the strong control capabilities of our framework in mask-guided synthesis and task-guided sampling, surpassing SOTA approaches for semantic segmentation data synthesis. This work shows that task-oriented data synthesis can substantially enhance the effectiveness of synthetic data for downstream applications.

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