

UP-Diff: Latent Diffusion Model for Remote Sensing Urban Prediction

Zeyu Wang, *Student Member, IEEE*, Zecheng Hao, Jingyu Lin, Yuchao Feng, and Yufei Guo

Abstract—This study introduces a novel Remote Sensing (RS) Urban Prediction (UP) task focused on future urban planning, which aims to forecast urban layouts by utilizing information from existing urban layouts and planned change maps. To address the proposed RS UP task, we propose UP-Diff, which leverages a Latent Diffusion Model (LDM) to capture position-aware embeddings of pre-change urban layouts and planned change maps. In specific, the trainable cross-attention layers within UP-Diff’s iterative diffusion modules enable the model to dynamically highlight crucial regions for targeted modifications. By utilizing our UP-Diff, designers can effectively refine and adjust future urban city plans by making modifications to the change maps in a dynamic and adaptive manner. Compared with conventional RS Change Detection (CD) methods, the proposed UP-Diff for the RS UP task avoids the requirement of paired pre-change and post-change images, which enhances the practical usage in city development. Experimental results on LEVIR-CD and SYSU-CD datasets show UP-Diff’s ability to accurately predict future urban layouts with high fidelity, demonstrating its potential for urban planning. Code and model weights are available at <https://github.com/zeyuwang-zju/UP-Diff>.

Index Terms—Remote Sensing (RS), Urban Prediction (UP), UP-Diff, Latent Diffusion Model (LDM), cross-attention.

I. INTRODUCTION

URBAN Prediction (UP) is a crucial field in city development, which forecasts and analyzes future trends in urban growth [40], [32], [1]. It helps researchers address the challenges arising from population growth [5], transportation congestion [37], and climate changes [21], [18]. Currently, Remote Sensing (RS) technology plays a critical role in city development by capturing RS images about detailed urban landscapes [28], [6], which are essential for monitoring the urban growth. By leveraging the RS technology, researchers can significantly improve the accuracy and efficiency of urban layout prediction, enabling them to make well-informed decisions to optimize the urban development strategies.

Despite the advancements in RS technology for city development, current works normally focus on the RS Change Detection (CD) task. As illustrated in Fig. 1 (a), RS CD aims to identify the differences between two images captured at

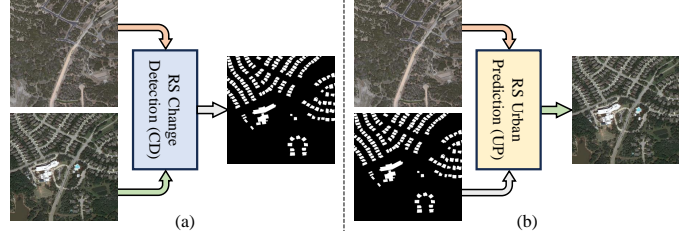


Fig. 1. Illustration of the difference between (a) conventional RS Change Detection (CD) and (b) our proposed RS Urban Prediction (UP).

different time points of the same geographic area from the aerial view [30], [3]. However, in practical urban planning, our goal is to forecast future urban layouts based on existing urban layouts and proposed modifications [19]. Current methods for RS CD primarily focus on detecting the layout changes rather than predicting future urban developments. In addition, the requirement for paired pre-change and post-change images poses a challenge for RS data collection. Collection of paired RS images must be guaranteed at long intervals, and the position and orientation of the probe must be accurate. Therefore, it not only increases the cost of data acquisition and image alignment but also impedes effective urban planning.

In this paper, we propose a novel RS-based task focusing on urban planning, called RS Urban Prediction (UP). As illustrated in Fig. 1 (b), the main objective of the proposed RS UP task is to forecast future urban layouts by leveraging information from existing urban layouts and planned change maps. To address the challenge of the proposed task, we present UP-Diff, which is a novel Latent Diffusion Model (LDM) building upon the Stable Diffusion (SD) [25]. Firstly, UP-Diff incorporates a trainable ConvNeXt model [20] to encode the pre-change urban layouts and planned change maps into position-aware embeddings. Subsequently, these embeddings are fed into the trainable cross-attention layers within the iterative diffusion modules of UP-Diff. It enables the model to dynamically focus on the specific regions crucial for urban planning. Meanwhile, we transfer the pre-trained SD model weights to mitigate the challenge of limited annotated RS image pairs. Our main contributions are as follows:

- We propose the RS Urban Prediction (UP) task to forecast future urban layouts based on existing urban RS layouts and planned change maps. To our knowledge, this is the first work on RS-based urban prediction.
- We also propose UP-Diff, which is a latent diffusion model with iterative layout-aware attention mechanism to dynamically enhance the critical urban regions.

This work is supported by grants from the National Natural Science Foundation of China under contracts No.12202412 and No.12202413.

Zeyu Wang, Jingyu Lin, and Yufei Guo are with Intelligent Science & Technology Academy of CASIC, China (e-mail: wangzeyu2020@zju.edu.cn, jingyu.lin@monash.edu, yfguo@pku.edu.cn). Zeyu Wang is also with College of Information Science & Electronic Engineering, Zhejiang University, China.

Zecheng Hao is with School of Computer Science, Peking University, China (e-mail: haozecheng@pku.edu.cn).

Yuchao Feng is with College of Engineering, Westlake University, China (e-mail: fengyuchao@wioe.westlake.edu.cn).

Corresponding author: Yufei Guo.

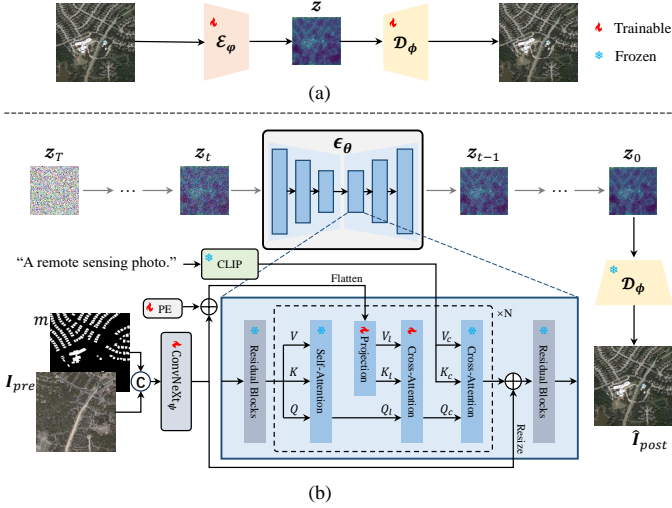


Fig. 2. Illustration of our proposed UP-Diff for Remote Sensing Urban Prediction. (a) Training of the autoencoder for reconstruction. (b) Training of UP-UNet for latent diffusion and denoising. C denotes the concatenation.

- Extensive experiments on LEVIR-CD [8] and SYSU-CD [29] datasets demonstrate that UP-Diff can accurately predict the future urban layouts with high fidelity.

II. RELATED WORKS

A. Remote Sensing Change Detection

Current research on RS CD normally adopts deep learning-based models. Convolutional Neural Networks (CNNs) have been widely applied on this task [38], [9], [35]. Later, Transformer-based models have also shown the ability to capture long-range context and relationships between different positions [7], [11]. Recently, the advanced diffusion models, known for their effectiveness in capturing complex patterns in RS images, have also shown promise in RS CD [4], [36].

B. Diffusion Models

Diffusion models have emerged as the leading choice for image generation, which originate from Denoising Diffusion Probabilistic Models (DDPMs) [31], [14]. Building upon this foundation, the Latent Diffusion Model (LDM) [25] has pushed the boundaries by using a low-dimensional latent space [10]. Current works on diffusion models normally guide the generation given text conditional information [24], [27], [25]. Moreover, recent advancements have been made in the field of layout-to-image diffusion models, where the spatial controls serve as the input conditions [2], [41], [16], [17].

III. METHODS

A. Overview

Our proposed UP-Diff is illustrated in Fig. 2. To enhance the modeling efficiency, UP-Diff follows LDM [25], which adopts an autoencoder to encode the input image into the latent space z and learn the representation through a reconstruction process. The autoencoder comprises the encoder \mathcal{E}_ϕ and the decoder \mathcal{D}_ϕ . In order to augment the model’s comprehension

of the RS layout and target alterations, we incorporate the embedded conditions through iterative attention-based blocks within the UP-UNet in the latent space. It enables our UP-Diff model to dynamically prioritize specific target urban regions. To our knowledge, UP-Diff is the first diffusion model for the proposed RS UP task, where the iterative diffusion process generates high-fidelity post-change RS images.

B. Condition Embedding

Condition embedding is critical in our proposed UP-Diff. Firstly, the text condition c is obtained by embedding “A remote sensing photo.” via the CLIP text encoder [23]. Utilizing the cross-attention layer from the SD model by incorporating c greatly enhances the awareness of RS features.

Meanwhile, the layout condition l is obtained by embedding the concatenated pre-change image I_{pre} and change map m by a trainable ConvNeXt model [20] with parameters ψ :

$$l = \text{ConvNeXt}_\psi(\text{Concat}[I_{pre}, m]), \quad (1)$$

where the semantic layout feature l is added after the iterative attention-based blocks. The ConvNeXt model has been pre-trained on large-scale natural image datasets. In addition, the tokenized layout condition l^* is derived by flattening l :

$$l^* = \text{Flatten}(l) + \text{PE}, \quad (2)$$

where PE denotes a trainable position embedding to enhance the position-aware information. The tokenized l^* serves as a suitable form for the gated cross-attention mechanism.

C. UP-UNet

Our proposed UP-UNet, denoted as ϵ_θ , serves as the core component for the latent denoising iterations. UP-UNet inherits the spatial structure of UNet [26], where the basic module consists of the residual convolutional blocks [12] and iterative attention-based layers [34]. We keep the original layers from SD model [25] and frozen the model weights to fully utilize the generative model pre-trained on large-scale natural images. As illustrated in Fig. 2, the UP-UNet is mainly composed of cascaded self-attention and cross-attention layers, which can be formulated as below:

$$\text{Attn}(Q, K, V) = \text{softmax}\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) \cdot V, \quad (3)$$

where the matrices Q , K , and V are derived from linear projection of the input features. The token dimension of the matrix K is denoted by d_k . In self-attention mechanism, the matrices Q , K , and V are derived from the same input feature. In cross-attention mechanism, Q is derived from one modality, while K and V are obtained from another modality. The cross-attention layer is followed by the feed-forward layer to increase the representation ability, which is omitted in Fig. 2.

In specific, the trainable cross-attention layer in the middle of UP-UNet block incorporates a gated mechanism, which focuses on the target RS layout regions. The gated cross-attention layer can be formulated as:

$$Q_c = Q_l + \lambda \cdot \tanh(\gamma)(\text{Attn}(Q_l, K_l, V_l)), \quad (4)$$

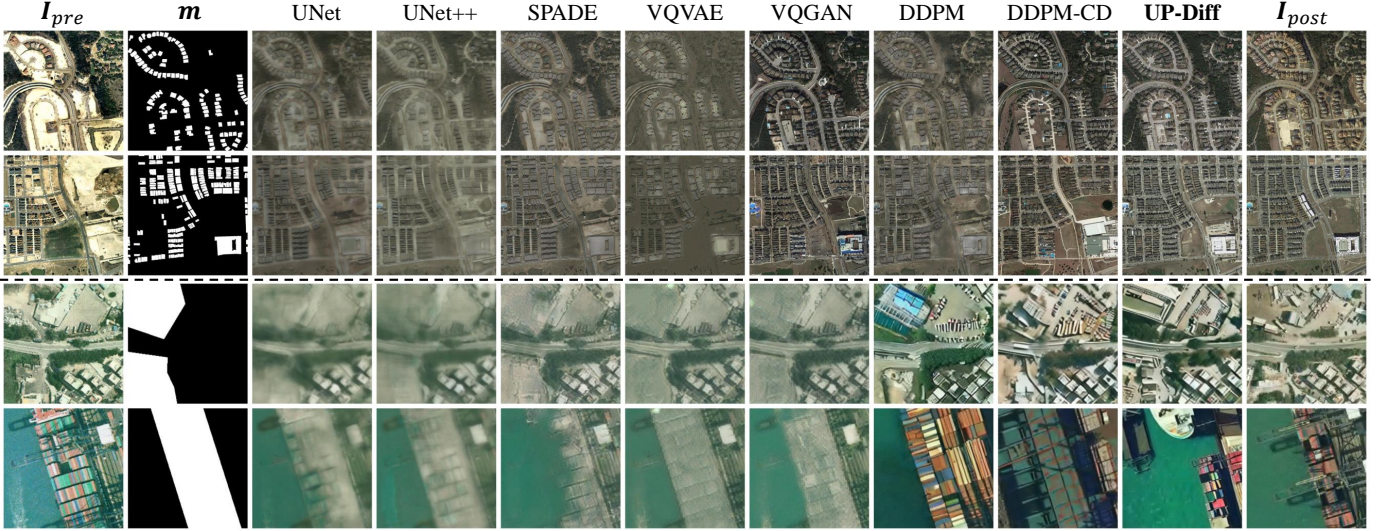


Fig. 3. Qualitative results of the baseline methods and our UP-Diff on LEVIR-CD and SYSU-CD datasets for the proposed RS UP task.

where λ is a hyperparameter and γ is a learnable parameter initialized as 0. The tokens K_l and V_l are obtained by the linear projection from l^* . Inside the iterative diffusion blocks of UP-UNet, a trainable cross-attention layer is introduced between the fixed self-attention and cross-attention layers, enabling the model to anticipate the layout of change area. Through the implementation of a gated mechanism, the model can dynamically adjust the attention weights to enhance its perception on the target urban layout.

D. Training & Sampling Formulation

We first fine-tune the autoencoder for reconstruction on the RS image datasets. During the diffusion training process, the model weights of the autoencoder are frozen, and the latent z_0 is obtained by encoding the post-change image I_{post} through \mathcal{E}_ϕ . After that, the noise-contaminated latent features z_1, z_2, \dots, z_T are achieved via a Markov chain:

$$q(z_t | z_{t-1}) = \mathcal{N}(z_t; \sqrt{1 - \beta_t} z_{t-1}, \beta_t \mathbf{I}), \quad (5)$$

where the hyperparameter β_t corresponds to the variance of the Gaussian distribution, and it undergoes a linear increase as t . Meanwhile, we can directly obtain z_t based on z_0 and β_t via the reparameterization [15]:

$$z_t = \sqrt{\bar{\alpha}_t} z_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, \quad (6)$$

where $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ denotes the randomly sampled Gaussian noise. Meanwhile, $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$. Therefore, z_T converges to standard normal distribution $\mathcal{N}(\mathbf{0}, \mathbf{I})$ when $T \rightarrow \infty$. The training objective of our proposed UP-UNet, denoted as \mathcal{E}_θ , can be represented as:

$$\min_{\theta} \mathcal{L}_{\text{UP-Diff}} = \mathbb{E}_{z_t, \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), t, c} \left[\|\epsilon - \epsilon_\theta(z_t, t, l, c)\|_2^2 \right], \quad (7)$$

where $t \sim \text{Uniform}(\{1, \dots, T\})$ is a random time step. l and c denote the layout condition and text condition, respectively.

During the inference process, we can reverse the diffusion process into the denoising process. Starting from a Gaussian

noise z_T , our proposed UP-UNet gradually generates less noisy $z_{T-1}, z_{T-2}, \dots, z_0$ by the following iteration:

$$z_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(z_t - \frac{1 - \alpha_t}{\sqrt{1 - \alpha_t}} \epsilon_\theta(z_t, t, l, c) \right) + \beta_t \epsilon. \quad (8)$$

Finally, we obtain the denoised z_0 , which is then decoded by \mathcal{D}_ϕ into the generated post-change image \hat{I}_{post} .

IV. EXPERIMENTS

A. Implementations

We implement UP-Diff using PyTorch 1.13.1 on Intel(R) Xeon(R) Platinum 8255C CPU@2.50GHz and two NVIDIA Tesla V100 GPUs with CUDA 12.2. AdamW optimizer is adopted with the learning rate of 5e-5 and 10,000 warmup training iterations. The batch sizes per GPU are set to 2 and 4 for training the autoencoder and the UP-Diff, respectively. Additionally, we employ random flips and crops on the RS images for data augmentation.

B. Datasets

We conduct experiments on two datasets with different RS scenes and resolutions to demonstrate the generalizability:

- Learning, Vision, and Remote sensing Dataset (LEVIR-CD) [8] contains 445, 64, and 128 RS image pairs for training, validation, and testing, respectively, captured in Texas, USA. We conduct the experiments on the dataset with the large resolution of 512×512 .
- Sun Yat-Sen University Dataset (SYSU-CD) [29] is a large-scale RS image dataset gathered in Hong Kong, China, containing 12,000/4,000/4,000 samples for training/validation/testing, respectively. We adopt the official resolution of 256×256 for experiments.

C. Baselines

We compare our UP-Diff with the following baselines listed in Table I. For the conventional deep learning models, we

TABLE I
QUANTITATIVE COMPARISON ON THE GENERATED IMAGE QUALITY.

Model	LEVIR-CD		SYSU-CD	
	LPIPS↓	FID↓	LPIPS↓	FID↓
UNet [26]	0.504	196.28	0.521	139.59
UNet++ [42]	0.497	185.48	0.523	120.05
SPADE [22]	0.423	142.58	0.436	66.28
VQVAE [33]	0.406	185.45	0.477	73.20
VQGAN [10]	0.402	179.22	0.478	60.56
DDPM [14]	0.420	134.63	0.430	61.03
DDPM-CD [4]	0.418	144.38	0.414	49.80
UP-Diff	0.342	117.79	0.400	34.57

↓ denotes that lower values are better.

concatenate I_{pre} and m as input for end-to-end training. For the diffusion-based models, we implement them by replacing the original I_{post} with m as the input conditions.

D. Qualitative Comparison

The qualitative results of the baseline methods and our UP-Diff on LEVIR-CD and SYSU-CD datasets are shown in Fig. 3. It can be seen that pre-change images I_{pre} (the first column) are typically captured on barren land, while the post-change images I_{post} (the last column) display neatly arranged buildings. The baseline models employing end-to-end training, including UNet, UNet++, SPADE, and VQVAE, can generate the post-change images with general building outlines but lack fidelity and diversity. The advanced VQGAN, DDPM, and DDPM-CD models produce high-fidelity images, but some texture details do not accurately align with the actual transformations depicted in the change maps. In contrast, our proposed UP-Diff model can produce high-quality post-change images that faithfully capture target urban modifications, such as the specific buildings, main roads, and vessels on the water.

E. Quantitative Comparison

We evaluate the models from two quantitative aspects. On one hand, we evaluate the quality of the generated images using Learned Perceptual Image Patch Similarity (LPIPS) [39] and Fréchet Inception Distance (FID) [13]. On the other hand, inspired by the assessment in semantic image synthesis [22], we utilize a pre-trained RS CD model (DMINet [11]) to test the RS CD metrics based on original input I_{pre} and output \hat{I}_{post} . The metrics include Precision (Pre.), Recall (Rec.), F1-score (F1), and Intersection over Union (IoU).

The results in Table I demonstrate that our UP-Diff model achieves the best LPIPS and FID scores across both datasets, with scores of 0.342 LPIPS and 117.79 FID on the LEVIR-CD dataset, and 0.400 LPIPS and 34.57 FID on the SYSU-CD dataset, respectively. The diffusion-based model DDPM-CD also exhibits commendable performance, achieving LPIPS scores of 0.418 and 0.414 on the two datasets, respectively. Meanwhile, from Table II, we can see that when we use the generated post-change images \hat{I}_{post} for evaluation on the RS CD task, the evaluation scores all demonstrate our excellent performance. For example, UP-Diff achieves the Pre. score of 92.23% and F1 score of 82.41% on LEVIR-CD dataset,

TABLE II
QUANTITATIVE COMPARISON ON THE GENERATED IMAGE FOR RS CD TASK. THE RESULTS ARE RECORDED IN (%).

	Model	Pre.↑	Rec.↑	F1↑	IoU↑
LEVIR-CD	UNet [26]	55.54	50.41	49.70	47.90
	UNet++ [42]	64.39	55.79	59.19	53.51
	SPADE [22]	80.33	64.52	71.46	62.32
	VQVAE [33]	70.00	59.82	64.96	57.43
	VQGAN [10]	84.56	69.63	74.79	65.43
	DDPM [14]	74.58	68.13	77.23	69.74
	DDPM-CD [4]	86.54	72.15	77.37	67.93
	UP-Diff	92.23	76.55	82.41	73.35
SYSU-CD	UNet [26]	77.23	84.63	79.10	66.26
	UNet++ [42]	77.71	85.29	79.62	66.94
	SPADE [22]	79.58	84.52	80.33	68.71
	VQVAE [33]	77.43	84.97	78.62	66.89
	VQGAN [10]	81.02	85.26	80.05	67.48
	DDPM [14]	80.14	83.29	81.48	69.74
	DDPM-CD [4]	84.11	85.43	84.74	74.33
	UP-Diff	86.82	86.10	86.45	76.86

↑ denotes that higher values are better.

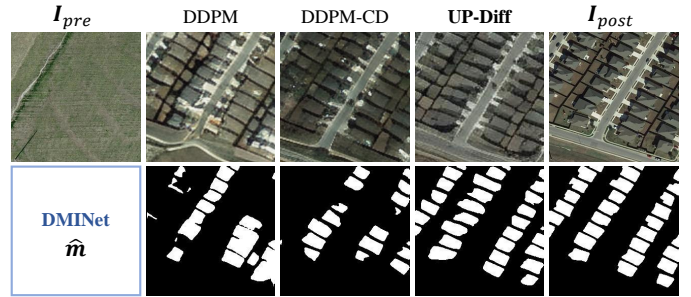


Fig. 4. Qualitative comparison on the generated images for RS CD task.

respectively. However, these baseline methods exhibit obvious inferior performance when contrasted with our method. We also show an example of the generated change maps through DDPM, DDPM-CD, and our UP-Diff in Fig. 4. It can be seen that the result of our UP-Diff aligns well with the ground-truth I_{post} , while the results from baseline methods exhibit differing degrees of deviation from I_{post} .

V. CONCLUSION

In this work, we introduce a novel task called Remote Sensing (RS) Urban Prediction (UP) for forecasting future urban layouts. Meanwhile, we propose the latent UP-Diff model tailored for the RS UP task, utilizing iterative layout-based gated cross-attention layers to focus on critical regions. Our qualitative and quantitative results on two datasets illustrate the superiority of UP-Diff over baseline methods in the RS UP task, including conventional deep learning and diffusion-based approaches. The post-change images generated by UP-Diff align well with ground-truth images during migration to the RS Change Detection (CD) task with a pre-trained model. In the future, we aim to develop more efficient methods with mobility for the proposed RS UP task. Furthermore, we plan to introduce a novel pluralistic RS UP task, where the generated post-change images can exhibit great diversity, contributing to flexible urban planning initiatives.

REFERENCES

- [1] M. M. Aburas, Y. M. Ho, M. F. Ramli, and Z. H. Ash'aari, "The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: A review," *International Journal of Applied Earth Observation and Geoinformation*, vol. 52, pp. 380–389, 2016.
- [2] O. Avrahami, T. Hayes, O. Gafni, S. Gupta, Y. Taigman, D. Parikh, D. Lischinski, O. Fried, and X. Yin, "Spatext: Spatio-textual representation for controllable image generation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 18 370–18 380.
- [3] T. Bai, L. Wang, D. Yin, K. Sun, Y. Chen, W. Li, and D. Li, "Deep learning for change detection in remote sensing: a review," *Geo-spatial Information Science*, vol. 26, no. 3, pp. 262–288, 2023.
- [4] W. G. C. Bandara, N. G. Nair, and V. M. Patel, "Ddpm-cd: Remote sensing change detection using denoising diffusion probabilistic models," *arXiv preprint arXiv:2206.11892*, 2022.
- [5] J. Bolorinos, N. K. Ajami, and R. Rajagopal, "Consumption change detection for urban planning: monitoring and segmenting water customers during drought," *Water Resources Research*, vol. 56, no. 3, p. e2019WR025812, 2020.
- [6] J. B. Campbell and R. H. Wynne, *Introduction to remote sensing*. Guilford press, 2011.
- [7] H. Chen, Z. Qi, and Z. Shi, "Remote sensing image change detection with transformers," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–14, 2021.
- [8] H. Chen and Z. Shi, "A spatial-temporal attention-based method and a new dataset for remote sensing image change detection," *Remote Sensing*, vol. 12, no. 10, p. 1662, 2020.
- [9] J. Chen, Z. Yuan, J. Peng, L. Chen, H. Huang, J. Zhu, Y. Liu, and H. Li, "Dasnet: Dual attentive fully convolutional siamese networks for change detection in high-resolution satellite images," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 1194–1206, 2020.
- [10] P. Esser, R. Rombach, and B. Ommer, "Taming transformers for high-resolution image synthesis," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2021, pp. 12 873–12 883.
- [11] Y. Feng, J. Jiang, H. Xu, and J. Zheng, "Change detection on remote sensing images using dual-branch multilevel intertemporal network," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–15, 2023.
- [12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.
- [13] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, and S. Hochreiter, "Gans trained by a two time-scale update rule converge to a local nash equilibrium," *Advances in neural information processing systems*, vol. 30, 2017.
- [14] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," *Advances in neural information processing systems*, vol. 33, pp. 6840–6851, 2020.
- [15] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," *arXiv preprint arXiv:1312.6114*, 2013.
- [16] Y. Li, H. Liu, Q. Wu, F. Mu, J. Yang, J. Gao, C. Li, and Y. J. Lee, "Gligen: Open-set grounded text-to-image generation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 22 511–22 521.
- [17] Y. Lin, X. Xian, Y. Shi, and L. Lin, "Mirrorediffusion: stabilizing diffusion process in zero-shot image translation by prompts redescription and beyond," *IEEE Signal Processing Letters*, 2024.
- [18] Q. Liu, S. Wan, and B. Gu, "A review of the detection methods for climate regime shifts," *Discrete Dynamics in Nature and Society*, vol. 2016, no. 1, p. 3536183, 2016.
- [19] Y. Liu, J. Yue, S. Xia, P. Ghamisi, W. Xie, and L. Fang, "Diffusion models meet remote sensing: Principles, methods, and perspectives," *arXiv preprint arXiv:2404.08926*, 2024.
- [20] Z. Liu, H. Mao, C.-Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, "A convnet for the 2020s," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2022, pp. 11 976–11 986.
- [21] X. Pan, F. Xie, Z. Jiang, and J. Yin, "Haze removal for a single remote sensing image based on deformed haze imaging model," *IEEE Signal Processing Letters*, vol. 22, no. 10, pp. 1806–1810, 2015.
- [22] T. Park, M.-Y. Liu, T.-C. Wang, and J.-Y. Zhu, "Semantic image synthesis with spatially-adaptive normalization," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp. 2337–2346.
- [23] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark *et al.*, "Learning transferable visual models from natural language supervision," in *International conference on machine learning*. PMLR, 2021, pp. 8748–8763.
- [24] A. Ramesh, P. Dhariwal, A. Nichol, C. Chu, and M. Chen, "Hierarchical text-conditional image generation with clip latents," *arXiv preprint arXiv:2204.06125*, vol. 1, no. 2, p. 3, 2022.
- [25] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2022, pp. 10 684–10 695.
- [26] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical image computing and computer-assisted intervention—MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18*. Springer, 2015, pp. 234–241.
- [27] C. Saharia, W. Chan, S. Saxena, L. Li, J. Whang, E. L. Denton, K. Ghasemipour, R. Gontijo Lopes, B. Karagol Ayan, T. Salimans *et al.*, "Photorealistic text-to-image diffusion models with deep language understanding," *Advances in neural information processing systems*, vol. 35, pp. 36 479–36 494, 2022.
- [28] R. A. Schowengerdt, *Remote sensing: models and methods for image processing*. elsevier, 2006.
- [29] Q. Shi, M. Liu, S. Li, X. Liu, F. Wang, and L. Zhang, "A deeply supervised attention metric-based network and an open aerial image dataset for remote sensing change detection," *IEEE transactions on geoscience and remote sensing*, vol. 60, pp. 1–16, 2021.
- [30] A. Singh, "Review article digital change detection techniques using remotely-sensed data," *International journal of remote sensing*, vol. 10, no. 6, pp. 989–1003, 1989.
- [31] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan, and S. Ganguli, "Deep unsupervised learning using nonequilibrium thermodynamics," in *International conference on machine learning*. PMLR, 2015, pp. 2256–2265.
- [32] D. Triantakonstantis and G. Mountrakis, "Urban growth prediction: a review of computational models and human perceptions," 2012.
- [33] A. Van Den Oord, O. Vinyals *et al.*, "Neural discrete representation learning," *Advances in neural information processing systems*, vol. 30, 2017.
- [34] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
- [35] D. Wang, X. Chen, M. Jiang, S. Du, B. Xu, and J. Wang, "Ads-net: An attention-based deeply supervised network for remote sensing image change detection," *International Journal of Applied Earth Observation and Geoinformation*, vol. 101, p. 102348, 2021.
- [36] Y. Wen, X. Ma, X. Zhang, and M.-O. Pun, "Gcd-ddpm: A generative change detection model based on difference-feature guided ddpm," *IEEE Transactions on Geoscience and Remote Sensing*, 2024.
- [37] R. A. Williamson, S. Morain, A. Budge, and G. Hepner, *Remote sensing for transportation security*. National Consortia on Remote Sensing in Transportation, 2002.
- [38] C. Zhang, P. Yue, D. Tapete, L. Jiang, B. Shangguan, L. Huang, and G. Liu, "A deeply supervised image fusion network for change detection in high resolution bi-temporal remote sensing images," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 166, pp. 183–200, 2020.
- [39] R. Zhang, P. Isola, A. A. Efros, E. Shechtman, and O. Wang, "The unreasonable effectiveness of deep features as a perceptual metric," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 586–595.
- [40] Y. Zhang and Y. Liu, "Data imputation using least squares support vector machines in urban arterial streets," *IEEE Signal Processing Letters*, vol. 16, no. 5, pp. 414–417, 2009.
- [41] G. Zheng, X. Zhou, X. Li, Z. Qi, Y. Shan, and X. Li, "Layoutdiffusion: Controllable diffusion model for layout-to-image generation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 22 490–22 499.
- [42] Z. Zhou, M. M. Rahman Siddiquee, N. Tajbakhsh, and J. Liang, "Unet++: A nested u-net architecture for medical image segmentation," in *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 20, 2018, Proceedings 4*. Springer, 2018, pp. 3–11.