# Is synthetic data from generative models ready for image recognition?

## GISLab Short-Term Course 2025 Summer

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# Outline

- 1. Introduction to Image Classification using Deep Learning
- 2. Traditional Data Augmentation Methods
- 3. Generative Models for Data Augmentation
- 4. Remote Sensing Dataset for Diaster Events: xBD
- Project - **Explore whether generated images can benefit image classification**

# Image Classification: Overview


Figure: Overview of image classification.

# Background: Image Classification with Deep Learning

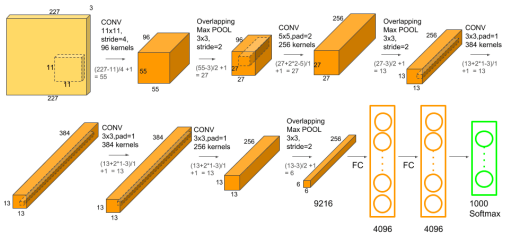
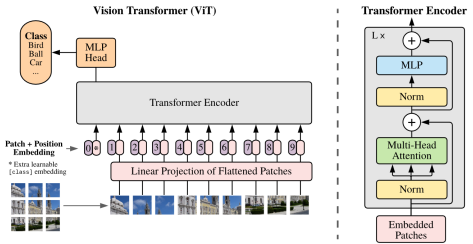




Figure: Left: AlexNet on ILSVRC-2010 (Berg, Deng, and Fei-Fei, 2010) Right: Architecture of AlexNet (Krizhevsky, Sutskever, and Hinton, 2012).


Berg, et al. Large Scale Visual Recognition Challenge 2010, 2010.
Krizhevsky, et al. ImageNet Classification with Deep Convolutional Neural Networks, NeurIPS, 2012.

# Architecture Evolution of Image Classification

- **2012: AlexNet**, **2016: ResNet**
- **2021: ViT**
- **2021: Swin Transformer**
  (Liu et al., 2021) (Dosovitskiy et al., 2021)
- **2021: CLIP-ViT**
  (Radford et al., 2021)
- **2022: MAE-ViT**
  (He et al., 2022)
- **2022: CoCa-ViT**
  (Yu et al., 2022)




Overview of Vision Transformer (Dosovitskiy et al., 2021).


Liu, et al. Swin Transformer: Hierarchical Vision Transformer Using Shifted Windows, ICCV, 2021.
Dosovitskiy, et al. An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale, ICLR, 2021.
Radford, et al. Learning Transferable Visual Models From Natural Language Supervision, ICML, 2021.
He, et al. Masked Autoencoders Are Scalable Vision Learners, CVPR, 2022.
Yu, et al. CoCa: Contrastive Captioners Are Image-Text Foundation Models. TMLR. 2022.

# RemoteCLIP: Vision-Language Foundation Model for Remote Sensing

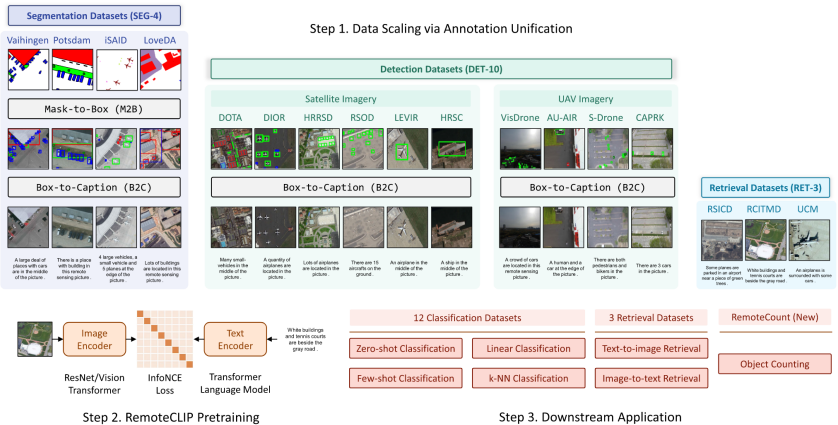



Figure: RemoteCLIP (Liu et al., 2024): A Vision-Language Foundation Model for Remote Sensing.

Liu, et al. RemoteCLIP: A Vision Language Foundation Model for Remote Sensing. TGRS. 2024.

# Traditional Data Augmentation Methods

- **Geometric Transformations: Rotation**, **Flipping** (horizontal/vertical), **Scaling**, **Translation**, **Cropping**
- **Color Jittering:** Adjusting brightness, contrast, saturation, and hue
- **Noise Injection:** Adding random noise to images
- **Cutout** (DeVries and Taylor, 2017)
- **CutMix** (Yun et al., 2019)
- **Copy-Paste** (Ghiasi et al., 2021)

There is also a comprehensive study entitled 'How to train your ViT? Data, Augmentation, and Regularization in Vision Transformers' (Steiner et al., 2022).

DeVries, et al. Improved Regularization of Convolutional Neural Networks with Cutout, arXiv, 2017.
Yun, et al. CutMix: Regularization Strategy to Train Strong Classifiers With Localizable Features, ICCV, 2019.
Ghiasi, et al. Simple copy-paste is a strong data augmentation method for instance segmentation, CVPR, 2021.
Steiner, et al. How to Train Your ViT? Data, Augmentation, and Regularization in Vision Transformers. TMLR. 2022.

# Generative Models for Data Augmentation

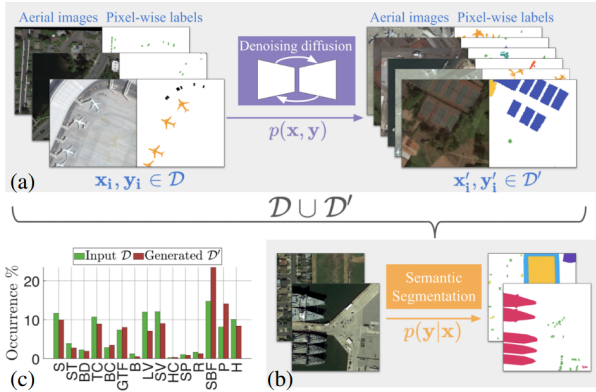



Figure: SatSyn (Toker et al., 2024) proposes a generative model (diffusion model) to generate both images and corresponding masks for satellite segmentation. The synthetic dataset is used for data augmentation, yielding significant quantitative improvements in satellite semantic segmentation compared to other data augmentation methods.

Toker, et al. SatSynth: Augmenting Image-Mask Pairs through Diffusion Models for Aerial Semantic Segmentation, CVPR, 2024.

# Generated Text-Image Dataset Improving Image Classification

| Dataset | Task | CLIP-RN50 | CLIP-RN50+SYN | CLIP-ViT-B/16 | CLIP-ViT-B/16+SYN |
|---|---|---|---|---|---|
| CIFAR-10 | o | 70.31 | 80.06 (+9.75) | 90.80 | 92.37 (+1.57) |
| CIFAR-100 | o | 35.35 | 45.69 (+10.34) | 68.22 | 70.71 (+2.49) |
| Caltech101 | o | 86.09 | 87.74 (+1.65) | 92.98 | 94.16 (+1.18) |
| Caltech256 | o | 73.36 | 75.74 (+2.38) | 80.14 | 81.43 (+1.29) |
| ImageNet | o | 60.33 | 60.78 (+0.45) | 68.75 | 69.16 (+0.41) |
| SUN397 | s | 58.51 | 60.07 (+1.56) | 62.51 | 63.79 (+1.28) |
| Aircraft | f | 17.34 | 21.94 (+4.60) | 24.81 | 30.78 (+5.97) |
| Birdsnap | f | 34.33 | 38.05 (+3.72) | 41.90 | 46.84 (+4.94) |
| Cars | f | 55.63 | 56.93 (+1.30) | 65.23 | 66.86 (+1.63) |
| CUB | f | 46.69 | 56.94 (+10.25) | 55.23 | 63.79 (+8.56) |
| Flower | f | 66.08 | 67.05 (+0.97) | 71.30 | 72.60 (+1.30) |
| Food | f | 80.34 | 80.35 (+0.01) | 88.75 | 88.83 (+0.08) |
| Pets | f | 85.80 | 86.81 (+1.01) | 89.10 | 90.41 (+1.31) |
| DTD | t | 42.23 | 43.19 (+0.96) | 44.39 | 44.92 (+0.53) |
| EuroSAT | si | 37.51 | 55.37 (+17.86) | 47.77 | 59.86 (+12.09) |
| ImageNet-Sketch | r | 33.29 | 36.55 (+3.26) | 46.20 | 48.47 (+2.27) |
| ImageNet-R | r | 56.16 | 59.37 (+3.21) | 74.01 | 76.41 (+2.40) |
| Average | / | 55.13 | 59.47 (+4.31) | 65.42 | 68.32 (+2.90) |

Table 1: **Main Results on Zero-shot Image Recognition.** All results are top-1 accuracy on test set. o: object-level. s: scene-level. f: fine-grained. t: textures. si: satellite images. r: robustness.

Synthetic text-image datasets generated by generative models can significantly improve image classification performance, as demonstrated in (He et al., 2023).

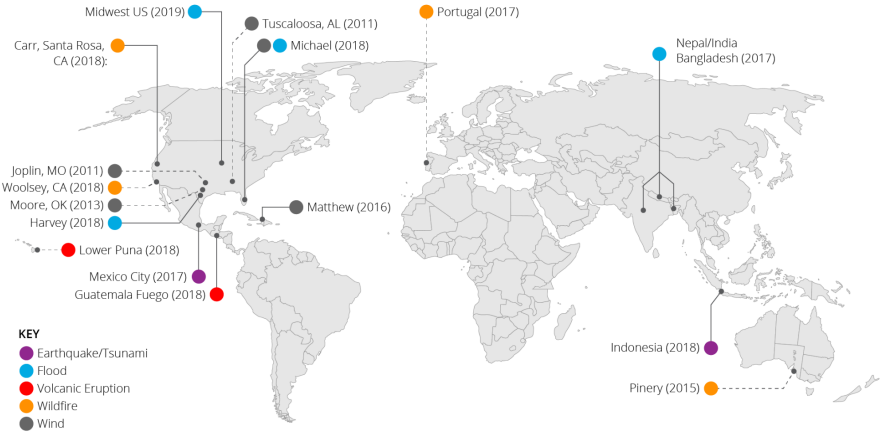
He, et al. Is synthetic data from generative models ready for image recognition?, ICLR, 2023.

# xBD: A Large-Scale Disaster Damage Dataset

Pre-disaster imagery (top) and post-disaster imagery (bottom). From left to right: Hurricane Harvey; Joplin tornado; Lower Puna volcanic eruption; Sunda Strait tsunami. Imagery from DigitalGlobe.
**xBD** (Gupta et al., 2019)

Gupta, et al. xBD: A Dataset for Assessing Building Damage from Satellite Imagery, arXiv, CVPRW, 2019.

# xBD: Global Coverage of Disaster Types




Disaster types and disasters represented in xBD around the world.
**xBD** (Gupta et al., 2019)

Gupta, et al. xBD: A Dataset for Assessing Building Damage from Satellite Imagery, arXiv, CVPRW, 2019.

# Baseline Models for Scene Classification and Super-Resolution

**Scene Image Classification:**

- **CLIP** (Radford et al., 2021)
- **RemoteCLIP** (Liu, Chen, Guan, et al., 2024)
- **Git-RSCLIP** (Liu, Chen, Zhao, et al., 2025)

Radford, et al. Learning Transferable Visual Models From Natural Language Supervision, ICML, 2021.
Liu, Chen, Guan, et al. RemoteCLIP: A Vision Language Foundation Model for Remote Sensing. TGRS. 2024.
Liu, Chen, Zhao, et al. Text2Earth: Unlocking text-driven remote sensing image generation with a global-scale dataset and a foundation model. GRSM. 2025.

# Additonal Datasets for Text-to-Image Generation

**Text-to-Image Generation:**

- **RSICD** (Lu et al., 2018): Remote Sensing Image Captioning Dataset with 10,921 images and five captions per image.
- **RSICap** (Hu et al., 2025): High-quality dataset with 2,585 human-annotated image-caption pairs.
- **UCM-Captions** (Qu et al., 2016): Derived from the UC Merced Land Use Dataset, containing 2,100 images with five captions each.

Lu, et al. Exploring Models and Data for Remote Sensing Image Caption Generation. TGRS. 2018.
Hu, et al. RSGPT: A remote sensing vision language model and benchmark. ISPRS. 2025.
Qu, et al. Deep semantic understanding of high resolution remote sensing image, CITS, 2016.

# Appendix

# Generative Modeling

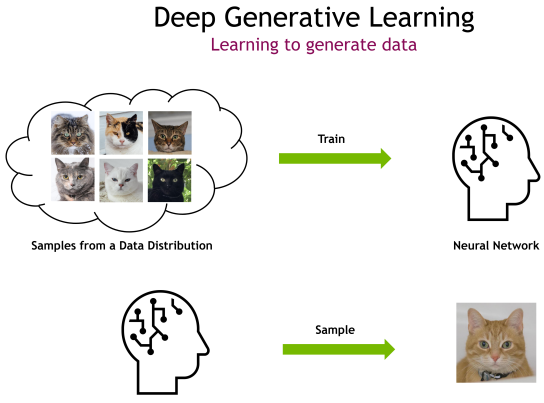



Figure: Illustration of generative modeling (Vahdat Arash, Song, and Meng, 2023).

Vahdat Arash et al. CVPR 2023 Tutorial Denoising Diffusion-based Generative Modeling: Foundations and Applications, 2023.

# Timeline of Generative Models

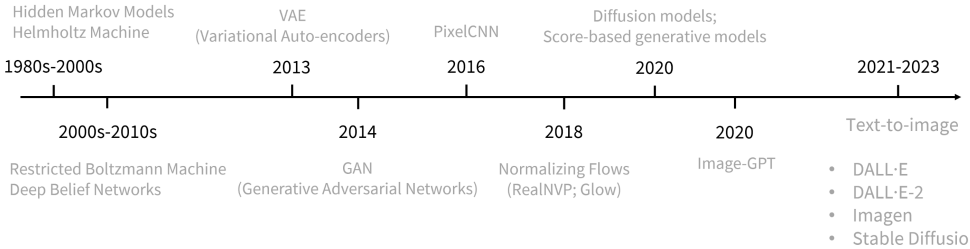



Figure: Timeline of key developments in generative models (Deng, 2024).

# Background: Diffusion Models

**Denoising diffusion models consist of two processes:**

- A forward diffusion process that gradually adds noise to the input.
- A reverse denoising process that learns to generate data by denoising.

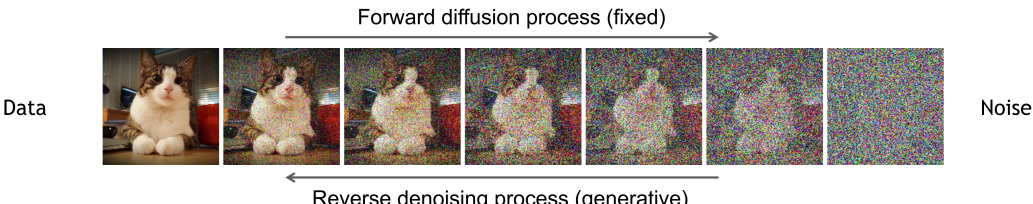



Figure: Diffusion models generate data through iterative denoising (Sohl-Dickstein et al., 2015; Ho, Jain, and Abbeel, 2020).

Sohl-Dickstein, et al. Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML, 2015.
Ho, et al. Denoising Diffusion Probabilistic Models, NeurIPS, 2020.

# Diffusion Models: Forward and Reverse Processes

**Forward (Diffusion) Process:**

$$q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\,\mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

$$q(\mathbf{x}_{1:T} \mid \mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t \mid \mathbf{x}_{t-1})$$

$$\text{Equivalently, } \mathbf{x}_t = \sqrt{\bar{\alpha}_t}\,\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\,\boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

**Reverse (Denoising) Process:**

$$p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t))$$

$$p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t)$$

where $\mathbf{x}_0$ is the data, $\beta_t$ is the noise schedule, and $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$. $p(\mathbf{x}_T) = \mathcal{N}(\mathbf{0}, \mathbf{I})$.
**Diffusion models generate data by learning to reverse a gradual noising process.** (Sohl-Dickstein et al., 2015; Ho, Jain, and Abbeel, 2020)

Sohl-Dickstein, et al. Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML, 2015.
Ho, et al. Denoising Diffusion Probabilistic Models, NeurIPS, 2020.

# Diffusion Models: Training and Inference

**Training Objective:**

$$\mathcal{L}_{\text{simple}} = \mathbb{E}_{\mathbf{x}_0, \boldsymbol{\epsilon}, t}\left[\left\|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t)\right\|^2\right]$$

where $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$.

**Inference (Sampling):**

- Start from pure noise: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- For $t = T, \ldots, 1$:
  - Predict noise: $\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)$
  - Compute mean: $\boldsymbol{\mu}_\theta(\mathbf{x}_t, t)$
  - Sample: $\mathbf{x}_{t-1} \sim \mathcal{N}(\boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t))$
- Repeat until $\mathbf{x}_0$ (generated sample)

**Training:** Minimize the simplified objective (Ho, Jain, and Abbeel, 2020).
**Inference:** Iteratively denoise from random noise to generate data.

Ho, et al. Denoising Diffusion Probabilistic Models, NeurIPS, 2020.

# Application in Remote Sensing Image Generation: Text2Earth

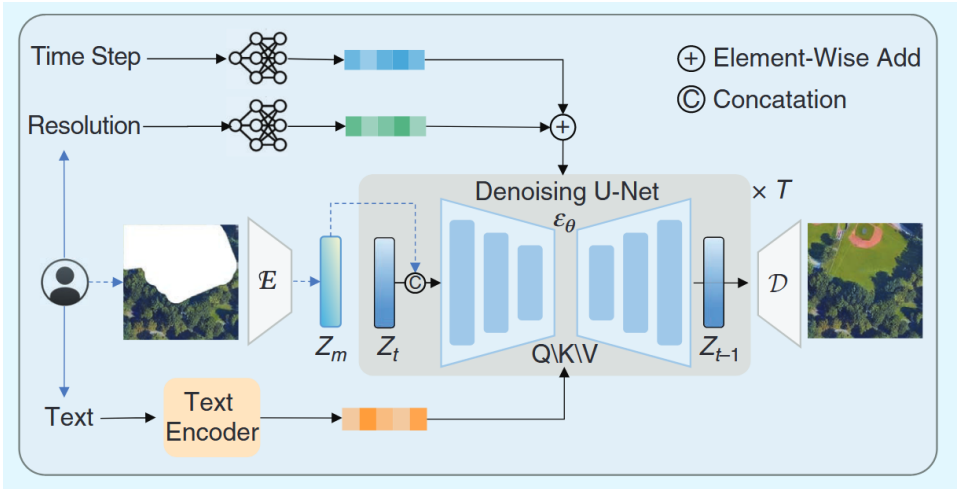



Figure: Text2Earth: Foundation model for text-driven Earth observation (Liu et al., 2025).

Liu, et al. Text2Earth: Unlocking text-driven remote sensing image generation with a global-scale dataset and a foundation model. GRSM. 2025.

# Text2Earth: Example Results

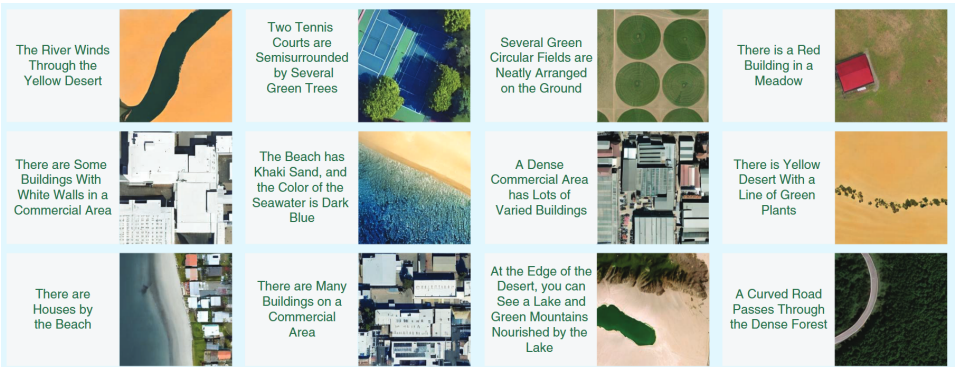



Figure: Example results generated by Text2Earth (Liu et al., 2025).

Liu, et al. Text2Earth: Unlocking text-driven remote sensing image generation with a global-scale dataset and a foundation model. GRSM. 2025.

# Application in Remote Sensing Image Generation: CRS-Diff

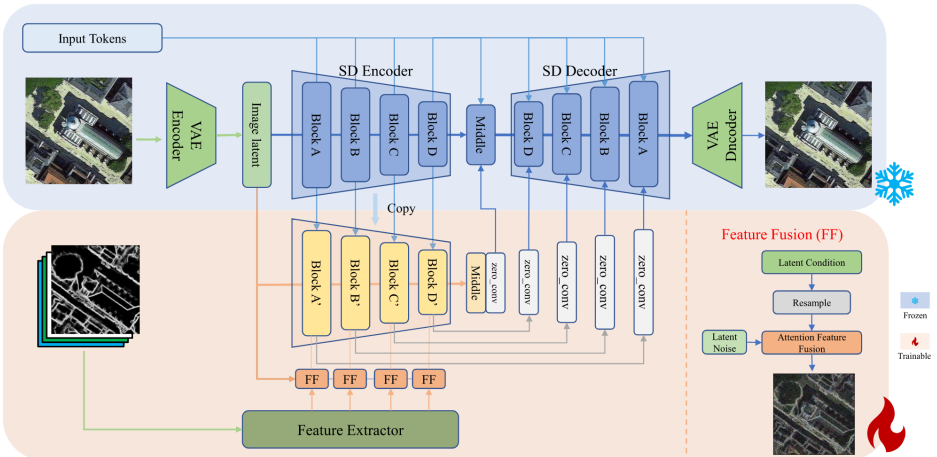



Figure: CRS-Diff: Controllable remote sensing image generation framework (Tang, Li, et al., 2024).

Tang, et al. CRS-Diff: Controllable Remote Sensing Image Generation with Diffusion Model. TGRS. 2024.

# CRS-Diff: Example Results

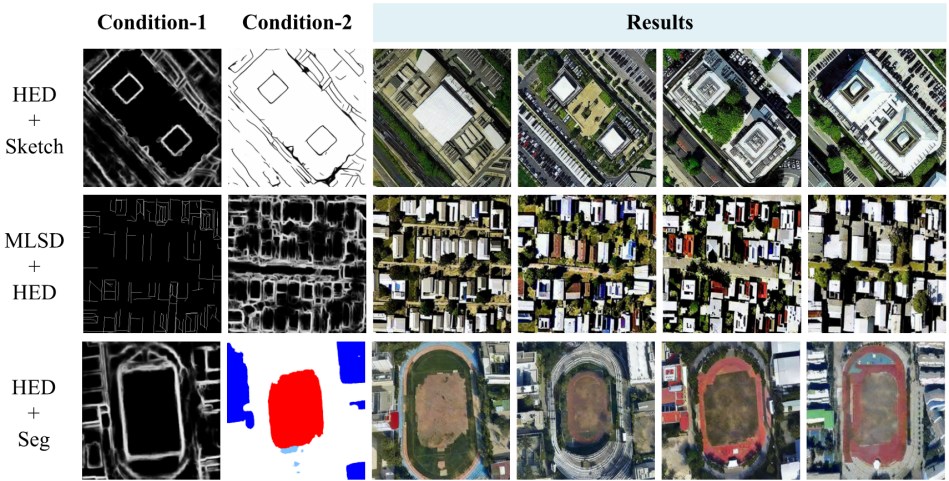



Figure: Example results generated by CRS-Diff (Tang, Li, et al., 2024).

Tang, et al. CRS-Diff: Controllable Remote Sensing Image Generation with Diffusion Model. TGRS. 2024.

# DiffusionSat: Framework Overview

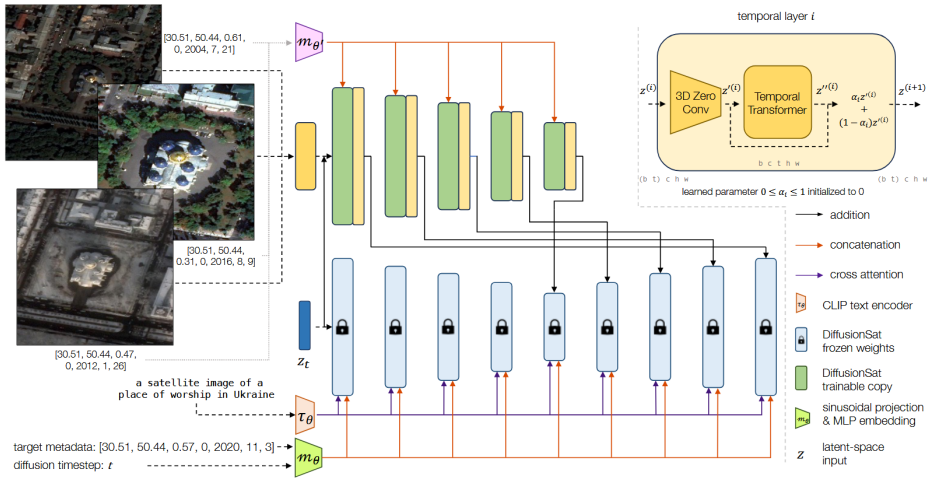



Figure: DiffusionSat: A generative foundation model for satellite imagery (Khanna et al., 2024).

Khanna, et al. DiffusionSat: A Generative Foundation Model for Satellite Imagery, ICLR, 2024.

# DiffusionSat: Super-Resolution Results


Figure: Example results: DiffusionSat for multi-spectral super-resolution (Khanna et al., 2024).

Khanna, et al. DiffusionSat: A Generative Foundation Model for Satellite Imagery, ICLR, 2024.

# DiffusionSat: Inpainting Results

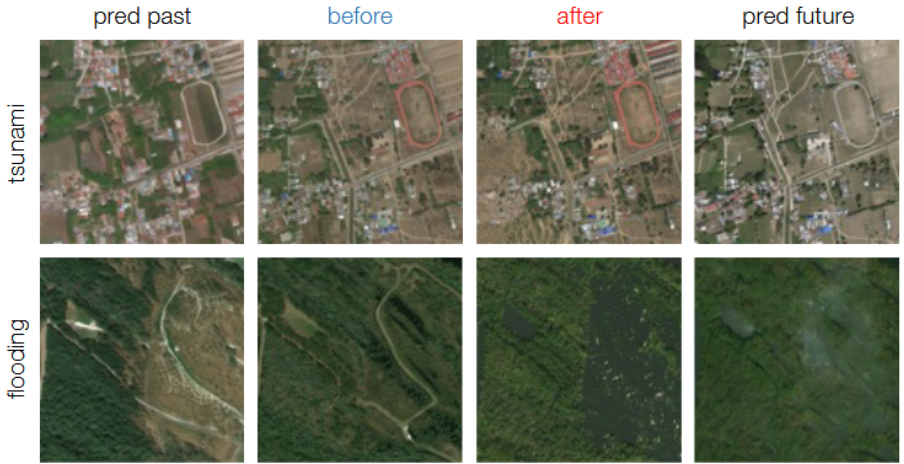



Figure: Example results: DiffusionSat for remote sensing image inpainting (Khanna et al., 2024).

Khanna, et al. DiffusionSat: A Generative Foundation Model for Satellite Imagery, ICLR, 2024.