Detecting Out-Of-Distribution Earth Observation Images with Diffusion Models

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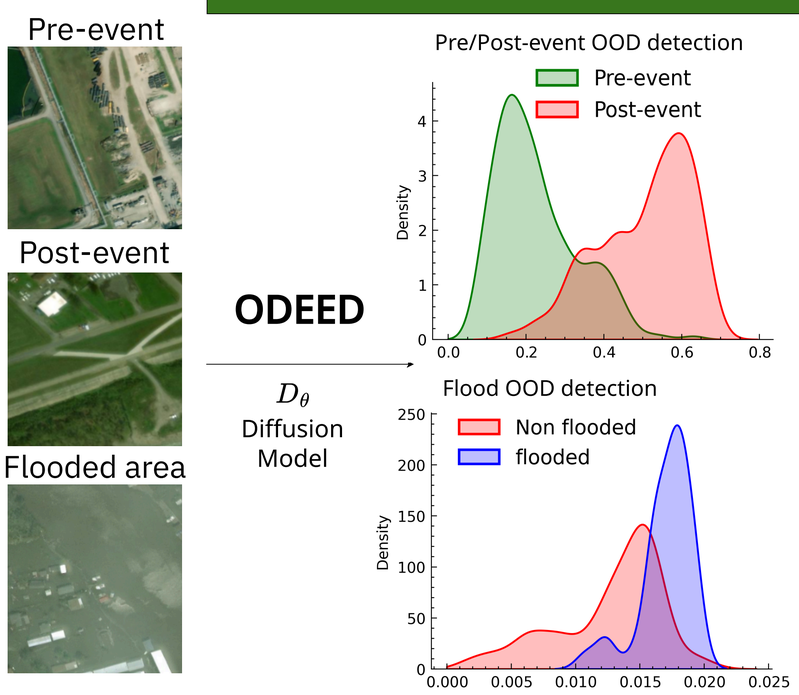
Earth Observation Context



Out-Of-Distribution detection:
- Avoid degraded model predictions & dataset curation
- Leverage generative models for OOD detection
- Diffusion models trained on **ordinary images only**

Diffusion Models

Stochastic (SDE)

Forward (diffusion)

$$dx_t = f(x_t, t)dt + g(t)dw_t$$

Backward (denoising)

$$dx_t = \left[f(x_t, t) - g(t)^2 \nabla_x \log p_t(x_t)\right]dt + g(t)d\bar{w}_t$$

Determinist (PF-ODE)

$$dx_t = \left[f(x_t, t) - \frac{g(t)^2}{2}\nabla_x \log p_t(x_t)\right]dt$$

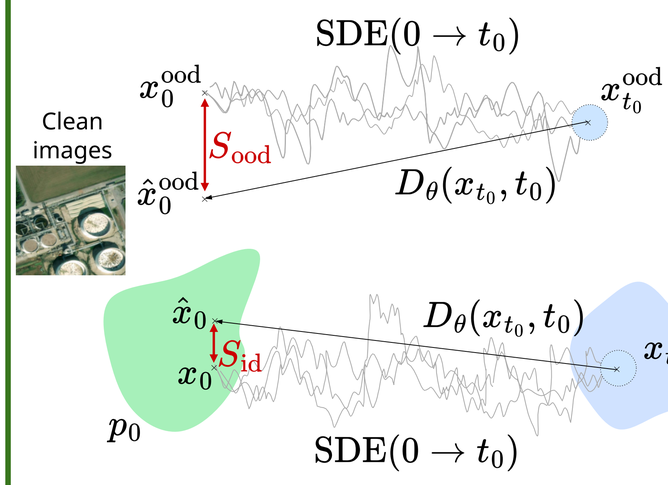
Score function

$$\nabla_x \log p_t(x) = \frac{1}{t^2}\Big(D(x,t) - x\Big)$$

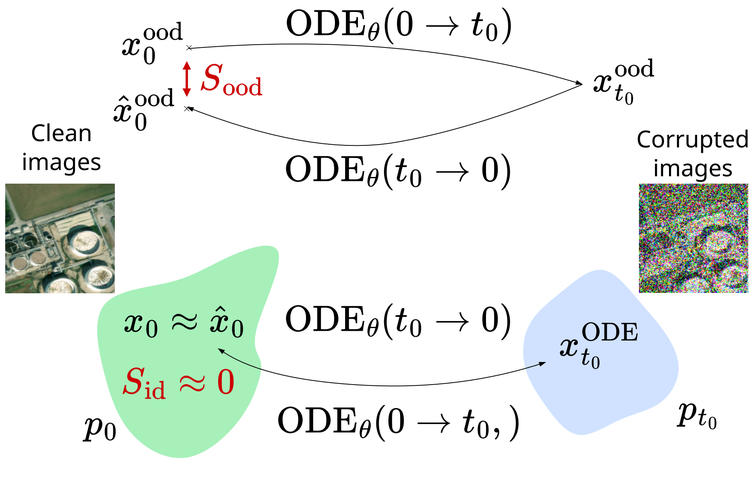
Perfect Denoiser

Method

One-step denoising



ODEED

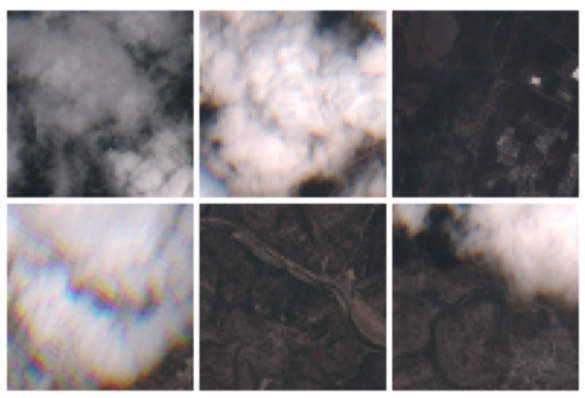


- Use diffusion models **reconstruction as OOD scorer**

ID samples → **good** reconstruction
OOD samples → **worse** reconstruction

- **One-step denoising:** small noise corruption / denoising
- **ODEED (ODE Encoding Decoding):** determinist diffusion / denoising
- Reconstruction metrics: MSE and LPIPS

Cloud Coverage



- 64x64 RGB images from the Sentinel-2 Cloud Mask Catalogue
- Denoiser trained on **cloud-free** images
- **ID** images with cloud coverage < 10%
- **OOD** cloud coverage > 10%

Method	AUC ↑	FPR95% ↓	R^2 ↑
Image mean	**88.3**	41.6	**58.4**
Diffusion MSE	85.1	**29.1**	49.4
Diffusion LPIPS	84.3	29.2	37.6

Main Results

- 256x256 SpaceNet 8 RGB images
- Germany and Louisiana
- Results: AUC/FPR@95%
- **Baselines:**
  - Discriminative models (segmentation models)
  - Generative losses
  - Reconstruction losses (autoencoders and diffusion models)

	Method	Pre-flood/Post-flood Germany	Pre-flood/Post-flood Louisiana	Non-flooded/flooded Germany	Non-flooded/flooded Louisiana	Domain OOD Germany	Domain OOD Louisiana
Discriminative Segmentation	MPC	52.6/98.9	41.1/98.4	67.4/80.0	61.0/94.3	69.8/93.4	47.7/95.5
	Neg-Entropy	59.6/97.7	42.8/95.9	64.3/80/0	60.7/97.1	76.3/92.2	48.8/94.3
	DeepKNN (k=5)	51.9/80.7	76.4/38.9	70.1/86.7	54.3/100	**93.6**/28.7	80.9/**38.6**
	Energy Logits	67.9/88.6	67.9/88.6	56.4/80.0	60.9/97.1	84.7/70.9	50.4/92.0
Generative Diffusion Loss	Training	50.4/84.1	52.3/88.5	59.7/100	71.0/71.4	67.0/86.0	55.9/98.8
	Linear	49.2/85.2	53.2/88.5	70.0/100	75.7/71.4	60.4/83.1	57.0/98.0
Reconstruction based							
Autoencoder	MSE	28.4/96.6	26.3/95.1	57.9/100	68.5/85.7	84.9/79.9	28.3/96.6
	LPIPS	21.1/97.7	27.5/96.3	55.6/100	69.5/77.1	75.2/54.9	41.4/100
	Mahalanobis	48.9/95.1	30.8/97.1	51.4/94.9	72.5/90.6	49.6/95.0	52.0/94.8
1-step denoising	MSE	28.8/81.8	42,2/73.3	68.5/100	73.4/77.1	86.3/**20.9**	33.5/97.7
	LPIPS	74.5/59.1	90.9/35.7	60.5/100	76.8/65.7	79.6/52.5	**82.1**/85.2
ODEED (Ours)	MSE	65.6/76.1	69.0/80.3	**83.6/33.3**	**86.9/42.9**	41.2/97.1	60.9/95.4
	LPIPS	**87.9/20.5**	**94.5/24.6**	75.3/73.3	64.1/85.7	54.3/97.5	68.3/70.4

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- **How to select t_0 ?**
  - Local changes (e.g. floodings): MSE + small t_0
  - Global changes (e.g. pre/post): LPIPS + small t_0

- **Cross-domain performances:** we can use a diffusion model trained on images from another geographical area and preserve OOD detection performances.