PROPOSITION DE SUJET DE THESE

Intitulé : Generative models for dense detection of rare events in multimodal remote sensing data

Référence : **TIS-DTIS-2026-37** *(à rappeler dans toute correspondance)*	
Début de la thèse : 01/10/2026	**Date limite de candidature : 31/05/2026**

Mots clés

Anomaly detection, generative models, segmentation.

Profil et compétences recherchées

Candidates should be pursuing or hold a Master's degree in Computer Science or Applied Mathematics. They should have a strong interest in scientific research and a solid background in machine learning and deep learning. Prior experience or interest in Earth observation data is a plus.

Proficiency in Python programming is strongly recommended, although experience with other programming languages (e.g., Java, C, or C++) is also acceptable. Familiarity with at least one major deep learning framework, such as PyTorch or TensorFlow, is highly appreciated.

Présentation du projet doctoral, contexte et objectif

Context

Remote sensing (RS) imagery provides a unique opportunity to monitor the Earth and its dynamics, offering continuous and large-scale observations of both environmental and human activities. Detecting rare or extreme events in these data, such as floods, wildfires, or infrastructure damage, is essential for timely response and risk management. Yet, these events typically affect small areas, occur briefly, and often lack reliable annotations, which makes their automatic detection particularly challenging. Automation could improve accuracy and response time from crisis cells, such as CIEST2 (https://dinamis.data-terra.org/dispositifs-urgence/) or Copernicus EMS (https://emergency.copernicus.eu/).

Most existing approaches for natural hazard detection in RS imagery rely on supervised learning [2]. While these methods have achieved notable success in detecting large-scale phenomena such as deforestation or floods, they depend on large labeled datasets that are expensive and often unavailable for rare or unexpected situations. In addition, supervised models tend to generalize poorly to new event types or geographical contexts. These challenges motivate the exploration of unsupervised approaches, where models can learn normal patterns from abundant unlabeled data and identify deviations as potential anomalies. In particular, generative models (e.g., VAEs [11], GANs [5], and more recently diffusion models [7] and flow matching [13]) have emerged as a promising direction, including recent models trained on Earth observation data [10, 8]. These models have demonstrated remarkable capabilities in generating realistic and diverse images. More interestingly, beyond image synthesis, they also implicitly or explicitly learn the underlying data distribution of the images, which makes them particularly valuable for detecting out-of-distribution samples or "anomalies," since deviations from the learned distribution can reveal rare or unexpected events [6, 12], without the need for explicit labels.

However, most existing generative estimators produce a single likelihood or anomaly score per image, which is not well suited to remote sensing data. In practice, rare events often occupy only a very small fraction of large satellite images, as sensors capture wide areas (often thousands of pixels per side) while the regions of interest may cover only a few dozen pixels. As a result, global anomaly scores may overlook subtle, localized changes, such as construction sites.

To overcome these limitations, this PhD will focus on developing models capable of producing dense anomaly maps across the image. In the first step, we will assume that we have access to specific imagery in which an exceptional event has occurred, e.g. a trigger of Copernicus EMS, and aim to localize the anomalous regions in the image without supervision, using methods such as referring segmentation [17, 9], saliency-based explanations [15, 3, 19], or unsupervised object localization [16], to highlight the most informative areas. In the second step, we will try to go further and fully automate the anomaly detection, i.e. localize anomalies in general imagery. To do so, we design spatially resolved generative estimators that directly produce dense, pixel-level anomaly scores based on likelihood estimation [6].

To ensure the proposed methods can be realistically evaluated, the project will leverage existing benchmark datasets for rare event detection in remote sensing, such as xView2 [1] for disaster assessment, and Burn Scars HLS [14] for wildfire impact mapping.

Objectives

The main goal of this PhD is to develop novel methodologies for the dense detection of rare events in multimodal remote sensing imagery, including optical, SAR and multimodal sources. In particular, we will target Sentinel-1/2 and SPOT-6/7, Pléiades/Neo to combine multiple modalities, resolutions and revisit frequencies.

Objective 1: Localizing anomalies in images known to contain rare events.

Given that an image is known or suspected to contain an anomaly, i.e. an image acquired post-disaster, the first objective is to explore methods for localizing the anomalous regions. This will involve leveraging referring segmentation, saliency maps, and explainable AI techniques to highlight the most informative areas that contribute to the anomaly. The goal is to assess how these techniques can help bridge the gap between global anomaly detection (image-level) and dense spatial understanding (pixel-level).

Objective 2: Designing dense generative anomaly detection models.

The second objective is to design spatially resolved generative estimators capable of producing dense likelihood or anomaly maps [18 , 4]. Building upon recent advances in generative modeling (e.g., diffusion and flow-based models), the aim is to develop methods that model local data distributions and provide per-pixel or region-level out-of-distribution estimates. These models will be evaluated on their ability to detect fine-grained, localized anomalies in multimodal remote sensing data, extending current global OOD frameworks toward dense detection. In particular, we will explore ways to condition the generative models on contextual information, such as location and date, to enhance spatial and temporal coherence in anomaly detection.

References

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Collaborations envisagées

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