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A comprehensive review of synthetic image generation methods in remote sensing

Julio Castro Lopes [a,b], Jose Luis Oliveira [b] and Rui Pedro Lopes [a,b]

[a]CeDRI, SusTEC, Instituto Politécnico de Bragança, Bragança, Portugal; [b]DETI/IEETA, LASI, University of Aveiro, Aveiro, Portugal

ABSTRACT
Satellite images are very useful across several domains since they offer a comprehensive view of the Earth's surface. A typical satellite image processing workflow involves several key steps: acquisition, pre-processing, segmentation, and classification. In the acquisition phase, satellite images are collected from remote sensors, and the pre-processing phase involves enhancing quality and removing distortions in the raw data. Afterwards, segmentation is used to divide the image into meaningful regions, which are then

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1. Introduction

An imaging satellite is an artificial device in orbit that captures images of the surface of the Earth, providing a comprehensive and real-time view of the planet's surface. Imagery is captured using Remote Sensing (RS) technologies, which are used to collect and analyse data on an entity, region, or event from a potentially distant location. RS allows covering the entire surface in less than a day as a result of government initiatives and the increased availability of commercial earth observation satellites, which are making satellite images more widely available (Young and Onoda 2017). Increasingly, satellite images are attracting attention from a wide variety of individual users, corporations, and organizations as they are increasingly used for environmental monitoring (Himeur et al. 2022), urban planning (Ouchra, Belangour, and Erraissi 2023), agriculture (Abozeid et al. 2022), disaster management (Ghaffarian, Kerle, and Filatova 2018), and many other fields (Corbane et al. 2010; Hede et al. 2017; Oughton and Mathur 2021; N. Xue et al. 2020).

To extract meaningful information from images, the standard workflow involves several steps, including acquisition, pre-processing, segmentation, feature extraction, and classification (Malik et al. 2024). A remote sensor captures satellite images during acquisition, and the subsequent pre-processing phase aims to correct distortions and enhance image quality. The segmentation process separates the image into coherent regions, while classification assigns labels to each seg- mented area, enabling automated interpretation of satellite data. However, labelling raw satellite images is a manual process and, therefore, time and labour-intensive, especially considering the plentiful supply of raw satellite images (Yao et al. 2016). This scarcity of annotation hampers Machine Learning

CONTACT Julio Castro Lopes juliolopes@ipb.pt CeDRI, SusTEC, Instituto Politécnico de Bragança, Bragança 5300-252, Portugal

(ML) models' full potential, limiting their ability to discern complex patterns and nuances within satellite images.

This review addresses the critical issue of limited annotated data by conducting a thorough examination and survey of synthetic data generation techniques. Synthetic data can be used to compensate for the lack of real-world annotated data, which can be generated in a variety of ways (Figueira and Vaz 2022). If annotated synthetic data is designed adeptly, it becomes a valuable resource for training robust ML models capable of handling satellite image analysis's intricacies (Marcal, Rodrigues, and Cunha 2010). The primary objective of this review is to provide a comprehensive understanding of synthetic data generation techniques specifically tailored for satellite image analysis.

2. Background

As the name implies, RS is the process of collecting and analysing information about the world and its objects from an instrument placed in Earth's orbit without any physical contact. This process is supported by specialized cameras, sensors, satellites in various orbits, or Unmanned Aerial Vehicles (UAVs) such as drones (Baghdadi and Zribi 2016). The RS technique is essential in studying and analysing various landscapes and terrains (Weiss, Jacob, and Duveiller 2020), as it can provide a greater amount of land data than other methods of data acquisition, such as field measurement and mapping, and because it is situated far from the earth, it can cover a larger surface with fewer costs as well (Muruganantham et al. 2022). Automatic computer vision methods are crucial to unlocking the full potential of remote sensing images since the scale of our planet makes manual analysis cost-prohibitive (Bastani et al. 2023).

Modern airborne sensors provide a large coverage of the Earth's surface with improved spatial, spectral, and temporal resolutions (Aleissaee et al. 2023), thereby playing a crucial role in different disciplines, including agriculture (Hazmy et al. 2024), water contamination (Singh et al. 2023), natural resource management (Kala and Kumar 2021), land surveying and analysis of the crust of the Earth (Tejado-Ramos et al. 2021).

Capturing images of the ground from RS can be accomplished with satellites or drones, both of which have advantages and disadvantages depending on the application. The advantages of the former seem to offset the disadvantages of the latter, and vice versa, indicating that there is a great deal of synergy potential between the two sources of RS data (Shao et al. 2021). Each platform is selected based on criteria such as spatial resolution, coverage area, cost, accessibility, and flexibility. In terms of spatial resolution and coverage area, satellites can capture images over larger areas and cover more terrain, whereas UAVs can provide higher resolution by capturing fine details and small-scale features due to their proximity to the ground (Figure 1). It is interesting to see the costs of both tools since a satellite is indeed more expensive than a UAV, even though it is very cost-effective for large-scale coverage, especially considering extensive areas as well. However, drone imagery must be retrieved by a professional drone pilot, along with the costs associated with data processing, making it unsuitable for covering large areas or obtaining frequent data. As far as accessibility is concerned, satellite imagery is widely available through a wide range of commercial and government agencies, which provide global coverage and consistent data availability (Alvarez-Vanhard, Corpetti, and Houet 2021). The use of drones offers direct, on-demand data collection, allowing flexibility in

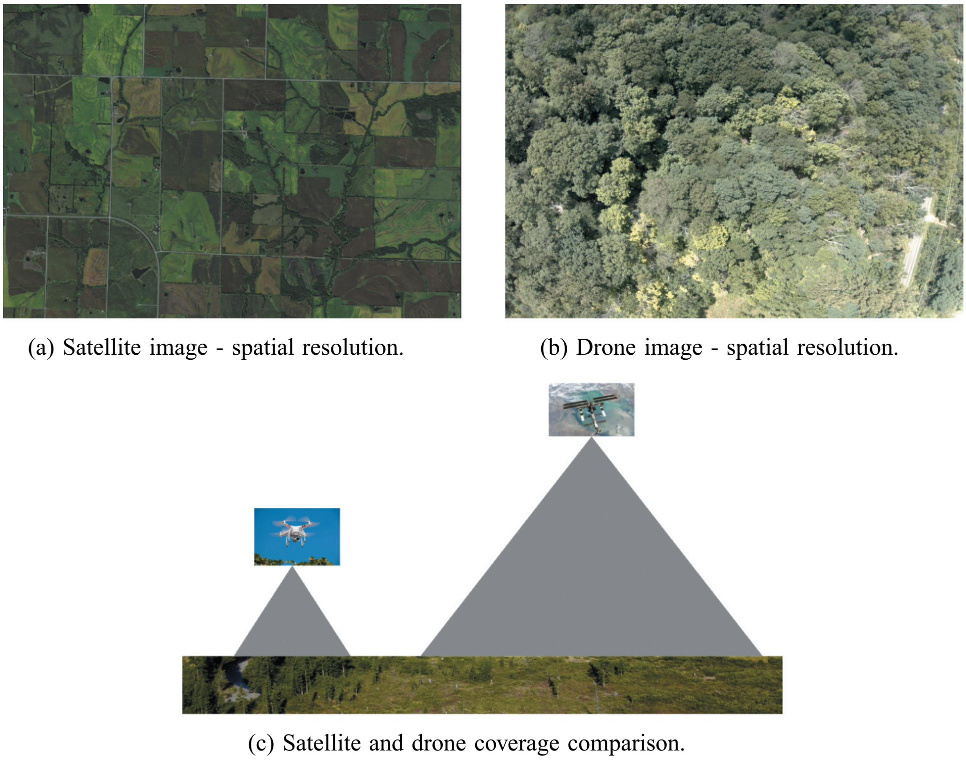

Figure 1. Comparison of satellite and drone imagery spatial resolution, along with coverage comparison.

scheduling and targeting specific areas. Airspace regulations, regulations governing drone operations, and logistical considerations must be considered when conducting drone operations. Satellites provide a consistent approach to routine monitoring, although orbit constraints limit the user's ability to control imaging timing, whereas drones provide exceptional flexibility in mission planning, permitting customization of flight paths and sensor settings, but they have weather and regulatory constraints to contend with. Drones also allow for the collection of images under clouds, whereas satellite imagery is difficult to obtain in those conditions.

2.1. Satellite image segmentation

Segmenting satellite images is a way to simplify the analysis and understanding of the images by creating multiple regions or segments. To enhance image quality and remove noise, images, in general, are very often pre-processed before segmentation (He, Zheng, and Sun 2016). After its preprocessing, there are several techniques to segment images (thresholding, clustering, edge detec- tion, machine learning algorithms, graph-based methods, among others (Rezaei and Asadi 2024)). As a direct and simple method, thresholding relies solely on intensity values to separate objects from backgrounds. Clustering involves grouping pixels into clusters based on similarity metrics. Edge detection can be accomplished by identifying boundaries between different regions using techniques such

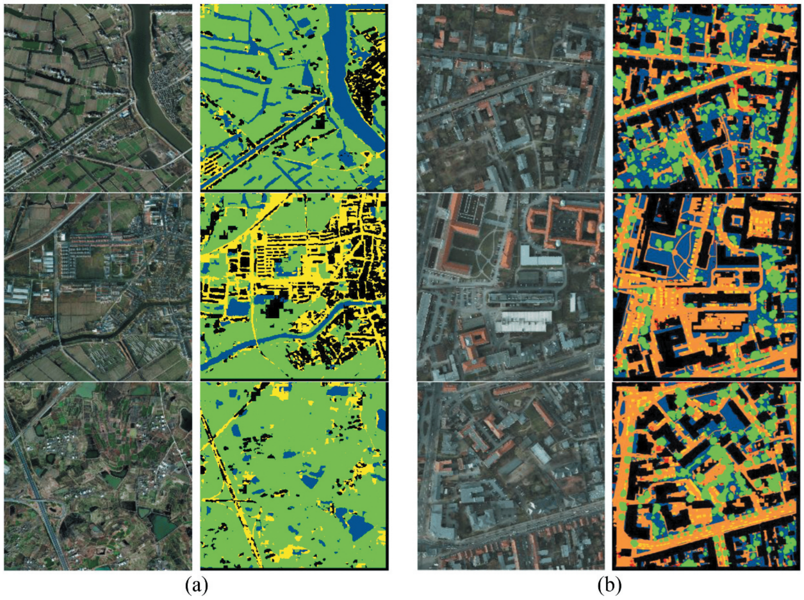

Figure 2. Semantic segmentation example. In (a) - green corresponds to vegetation, black to buildings, blue to water bodies, yellow to roads, and white to others. In (b) - orange corresponds to impervious surfaces, black to buildings, blue to low vegetation, green to trees, yellow to cars, and red to clutter (Liang and Seo 2022).

as Sobel, Prewitt, and Canny (Hazra et al. 2017). The automatic segmentation of satellite images can be achieved through the application of machine learning algorithms, which use supervised or unsupervised learning algorithms to automatically learn and segment features in images (Tehrani, Santinelli, and Herrera Herrera 2021). As another method, graph-based methods uti- lize techniques like minimum-cut to segment the image pixels using nodes in a graph (Siriapisith, Kusakunniran, and Haddawy 2020).

There are two types of image segmentation, that include Semantic Segmentation and Non-Semantic Segmentation. Semantic segmentation breaks the satellite image into class labels for each pixel, such as people, buildings, vegetation, water, etc. (Figure 2). Pixel-by-pixel segmentation of this type seeks to distinguish and identify various objects or areas. Non-semantic involves grouping similar pixels or regions based on specific properties like colour, texture, or intensity rather than applying specific semantic labels on them. Although semantic segmentation can extract more information from images by effectively identifying objects, it faces several challenges, including a lack of high-quality annotated training datasets (Yeung et al. 2022; Yuan, Shi, and Gu 2021). To overcome these challenges, DL models are needed that can either work with less training data or by the generation of synthetic images for the training of the model, as identified by (Bagwari, Kumar, and Singh Verma 2023). Manual segmentation of these images is also possible, although it is a laborious and time-consuming process that can be surpassed by DL methods (Khryashchev et al. 2018). Satellite image segmentation is a difficult challenge because images have a high scale, and objects on satellite images are often very small but densely grouped, which is justified by the satellite's distance from the ground (Wu et al. 2019).

2.2. Satellite image classification

As part of remote sensing and satellite image analysis, image classification and segmentation are closely related tasks. The process of segmentation focuses on dividing an image into meaningful regions, whereas classification aims to categorize or label each of these regions or the entire image based on their content and features. Image classification, particularly object or region classification, is highly dependent on the segmentation process, meaning that better segmentation leads to more accurate classification outcomes. As a result of the large amount of information and the with-class variance characteristics of these images, segmentation can be interesting since various geo-objects, and even an identical geo-object, appear at multiple scales in satellite images (L. Shen et al. 2017). Many studies have been conducted using multiple segments before classification, also comparing the classification accuracy after selecting optimal segmentation parameters (Haque, Al-Ramadan, and Johnson 2016). It is possible to perform pixel-based image classification, but it has several limitations, including the fact that as spatial resolution increases, single pixels cannot capture the characteristics of classification targets, resulting in lower accuracies on very high-resolution images, which can be improved by segmenting the image into meaningful parts before classification (Kavzoglu, Yildiz Erdemir, and Tonbul 2017). The segmentation process can be considered fundamental to provide important information and specific details of an image, to be able to perform classification (Belgiu and Csillik 2018; Z. Chen et al. 2024; Deticio et al. 2023; Kaur et al. 2024).

2.3. Synthetic image generation

As identified by previous research, synthetic image generation can be seen as a way to improve model accuracy when predicting and segmenting satellite images indirectly by adding new samples to the training data (Adedeji et al. 2022; Barthakur, Kumar Sarma, and Mastorakis 2020; Illarionova et al. 2021; Yan et al. 2020). This process eliminates the need to manually label satellite images since the label attribution takes into account previously labelled images when synthetically generated. As such, the process of generating synthetic images in this field must be studied, along with the respective methods to create high-quality synthetic images.

There are several possible methods to generate synthetic images. The most common are Generative Adversarial Networks (GANs), Variational Autoencoders and Diffusion models. Essentially, these methods aim to learn a mapping from a simple distribution (e.g. Gaussian noise) to a complex distribution of real images. During training, the model learns to capture the details and variations present in real images, so it can generate realistic and diverse synthetic images. The usual training process uses loss functions to measure the difference between real and generated images.

Since their introduction in 2014 (Goodfellow et al. 2014), GANs have been a fast-moving topic due to their ability to generate high-quality synthetic images. GANs are based on two neural networks: a generator that learns to produce synthesis images and a discriminator that estimates the probability that a sample came from the training data or the generator model. By using adversarial training, where the networks compete against each other, GANs can produce high-quality samples that closely mimic the distribution of training data. In the training process, the generator and discriminator are trained alternately rather than against static adversaries. During generator training, the discriminator's weights remain fixed, and similarly, the generator's weights are held constant while the discriminator is being trained. The general pipeline of a GAN is demonstrated in Figure 3.

To reduce the need for labelled data and human supervision, unsupervised learning is essential in ML. A GAN is an implicit generative model that generates samples directly from a latent space rather than explicitly defining a probability distribution function (Ruthotto and Haber 2021), which has been a common practice in traditional modelling approaches. Due to their implicit modelling, GANs are capable of handling complex data distributions, including high-resolution images, which traditional methods struggle to capture accurately (Shi et al. 2023). As a result of the complex interplay between the generator and discriminator networks, GANs pose unique challenges in training and convergent learning (Y. Shen et al. 2018).

This methodology has proven particularly effective in producing realistic images, and it has been applied to a wide range of domains beyond image generation, including medical imaging (Nie et al. 2018), art (Shahriar 2022; A. Xue 2021), agriculture (Drees et al. 2021; Espejo-Garcia et al. 2021), satellite imagery (Lütjens et al. 2023), and many others (Sabuhi et al. 2021; Yinka-Banjo and Ugot 2020; Zhang et al. 2022). GANs can be a solution for cloud removal in satellite imagery, as they are capable of simulating and reconstructing regions of the image occluded by clouds. This process is a form of inpainting, where missing or corrupted parts of an image are filled in with realistic content, making GANs particularly effective for cloud occlusion correction (Darbaghshahi, Reza Mohammadi, and Soryani 2022; Zheng, Liu, and Wang 2021). Figure 4 shows how GANs can be effective in producing high-quality realistic images and detecting changes.

As a physics and mathematics concept, diffusion processes describe how particles or information are gradually spread through a system over time (Guidolin and Manfredi 2023). This concept was adapted to an image generation in 2015 (Sohl-Dickstein et al. 2015) although, at their first appearance, they did not reveal to be very effective. Later in 2020, they became state-of-the-art with Ho, Jain, and Abbeel (2020) proposal. In contrast

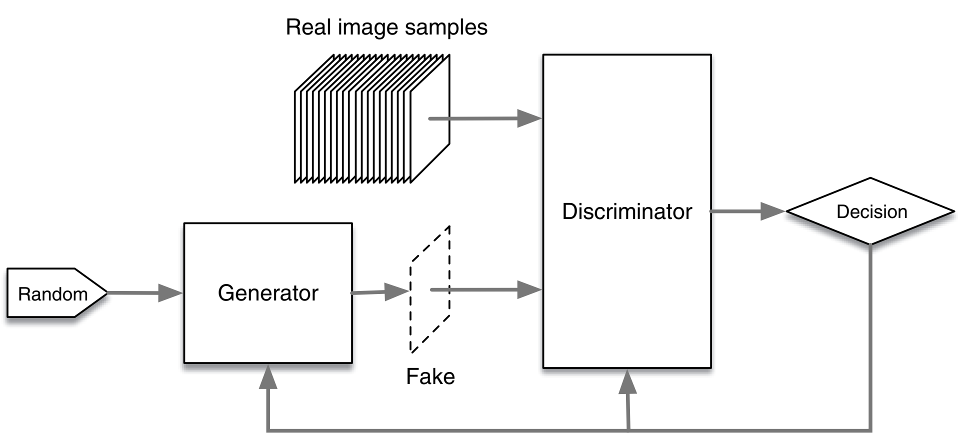

Figure 3. GAN pipeline illustrating the interaction of the generator and discriminator during training.

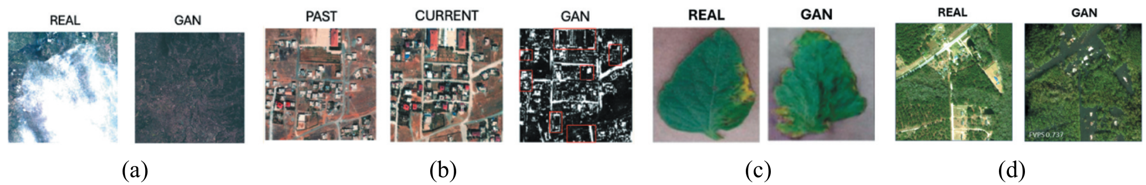

Figure 4. GANexample applications. (a) - cloud Removal (Sebastianelli et al. 2022); (b) - change Detection (Yang et al. 2025); (c) - agriculture (Espejo-Garcia et al. 2021); (d) - satellite imagery (Lütjens et al. 2023).

to traditional generative models, diffusion models incorporate noise gradually into data through a Gaussian conditional parameterization (Equation 1: the forward process in a diffusion model). The diffusion model introduces progressive coding, which facilitates image encoding and decoding, providing insight into their inductive biases as well as their potential as autoregressive models. Figure 5 illustrates an example of a diffusion modelling process pipeline. In the forward diffusion stage, Gaussian noise is gradually added (right to left) to the input data over several steps, and as part of the reverse diffusion stage, a generative model is in charge of recovering the original input data (left to right) from the diffused (noisy) data by gradually reversing the diffusion process (Equation 2: the reverse process in a diffusion model).

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}\left(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}\right) \tag{1}$$

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \tag{2}$$

Researchers have investigated several additions and enhancements to the initial design, such as changes to the architecture (Dhariwal and Nichol 2021), training methods (Rombach et al. 2022), and applications to a variety of fields outside image synthesis (Guo et al. 2023; Huang et al. 2023; Zou, Myung Kim, and Kang 2023). As a result of these initiatives, diffusion models are now a hot topic in generative modelling research due to improvements in sample quality, training stability, and scalability (D. Chen et al. 2024). They are now competitive alternatives to other state-of-the-art generative models, like GANs (X. Chen et al. 2023; Xiao et al. 2024), due to their capacity to capture complex data distributions and generate a variety of samples. Diffusion model research promises to further enhance the field of generative modelling and open the door to new applications in image synthesis and other fields (Croitoru et al. 2023).

Given the rapid evolution of these models and their increasing adoption in a variety of domains, it is critical to conduct a systematic review of recent advances, identify key trends, and highlight emerging issues. This article aims to fill that gap by providing a thorough examination of synthetic image generation techniques in satellite imagery.

The rest of the article is organized as follows: Section 4 presents the methodology used in this review. Section 5 describes the selected studies along with a background of the methods used. Section 6 presents a discussion and a table summarizing the described studies and their particularities. Finally, Section 7 rounds up the article with the conclusions extracted from this work.

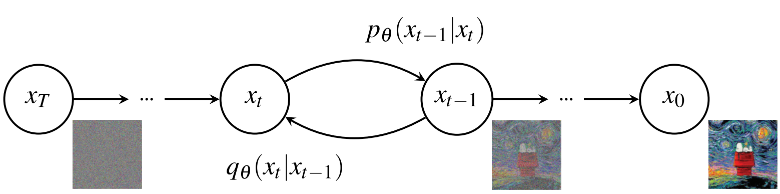

Figure 5. Illustration of forward (q_θ) and reverse (p_θ) steps in the diffusion process.

3. Related work

This article aims to advance the understanding of synthetic data generation for satellite image analysis by providing a structured, up-to-date, and technically focused review that fills critical gaps in the current literature. As such, the purpose of this section is to provide a comprehensive understanding of existing related reviews, gaps in the literature, and how the current review differs from the others.

Lalitha and Latha (2022) focused on data augmentation techniques using basic image transformations such as flipping, rotating, and clipping, along with limited discussion of more advanced generative approaches, including Variational Autoencoders (VAEs) and GANs. Regarding the more advanced generative methods, this review only presents one study that involved the generation of synthetic images, using a CycleGAN. The review primarily targeted generic augmentation strategies rather than synthetic image generation at scale.

Abady et al. (2022) provided a comprehensive overview of synthetic and manipulated satellite image generation and detection. Their contribution covers a wide range of satellite data types (e.g. EO, SAR, multispectral) and includes image generation methods (GANs, VAEs) as well as forensic detection techniques. Nonetheless, the review does not address diffusion models, and much of the research it does include predates the recent wave of generative model advances.

Mansourifar et al. (2022) explored GAN-based techniques in satellite imaging, categorizing applications into seven categories, including segmentation, image translation, cloud removal, and surveillance. The study provided insights into challenges like occlusion, resolution limitations, and multimodal data handling. However, this work focuses solely on GANs and does not address diffusion models or other recent architectural innovations.

Hao et al. (2023) presented a structured review of data augmentation methods for remote sensing target recognition, categorizing them as data-based or network-based. While they include deep generative models (GANs, VAEs, and flow models), diffusion models are not specifically addressed. Their review is conceptually organized, but it focuses less on the technical and practical development of generative models in remote sensing.

In contrast, the current review presents a thorough and technically detailed synthesis of synthetic image generation methods for remote sensing, guided by PRISMA principles. It focuses on using GANs and diffusion models to create synthetic terrain and scene-level imagery, rather than isolated object augmentation. This review assesses the impact of synthetic data on downstream tasks such as classification and segmentation, highlighting potential performance improvements where applicable. A key feature of this work is its emphasis on diffusion models, which are largely absent or only briefly mentioned in previous reviews. It also organizes reviewed methods according to architectural characteristics, task specificity, and empirical performance across benchmark datasets. Beyond synthesis, this review identifies long-standing issues in the field, such as high spatial and spectral variability, inconsistent resolutions, and semantic sparsity. It also highlights a significant research gap: current generative models, including both GANs and diffusion models, have limited ability to produce annotated satellite images from structured prompts (for example, specific vegetation indices or carbon content).

This issue has been identified as a key area for future research, emphasizing the potential of prompt-based generation with automatic labelling to meet the growing demand for annotated datasets in remote sensing.

4. Methodology

This literature review follows the approach proposed by Materla, Cudney, and Antony (2019) and Subhash and Cudney (2018). It consists of three phases: planning, operation (conducting), and dissemination (reporting). The planning phase includes both defining the bibliography databases and selecting the query term. This review was performed using four well-known databases: Scopus, Web of Science (WoS), ACM, and IEEE Xplore. The definition and application of the string query began in January 2024, but the query was run again in October 2024 to include the most recent and relevant papers in this review. The query - ((‘satellite image’ OR ‘satellite imagery’) AND generation AND synthetic) was applied in all the databases to search for the specific terms in the abstract, title, and keywords. Only articles and conference papers written in English were accepted, disregarding review papers, and only studies published by or after 2019 were considered. The query retrieved 160 studies on the Scopus database, 7 in ACM, 37 in IEEE Explore, and 52 on WoS, which encompasses a total of 256 studies. First of all, the existence of duplicated studies was checked, which resulted in the elimination of 53 papers (203 remaining). Based on the initial screening considering only the articles’ abstract and title, 129 articles were further removed, as they did not match the objective of this review because they did not approach synthetic image generation methods (74 papers left). The full text of all the 74 considered papers has been read to decide whether or not the papers meet the scope of this review. To be admitted in this review, the papers needed to fulfil all the assessment criteria questions:

(1) Is the mentioned dataset about satellite imagery?
(2) Does the research include image generation techniques?
(3) Does the research focus on image generation for creating new terrain samples rather than solely objects?
(4) Is the image generation methodology rigorous and clearly described?

The first question aims at eliminating papers that did not consider evaluating their method in a satellite imagery dataset. The subsequent question aims to eliminate papers that do not include image-generation techniques in their methodology. The next question is to eliminate papers that only consider object detection and generation based on satellite images instead of terrain images. The last question is to eliminate papers that meet all the other criteria, although the methodology is not well explained or reproducible. This selection process resulted in a total of 16 relevant papers. In the selected studies, cross-referencing was performed to also include studies that were considered relevant in these papers and could match the topic of this review. Following this, 6 relevant studies were found in this process, resulting in a total of 22 papers. Figure 6 shows a scheme that illustrates the article selection process.

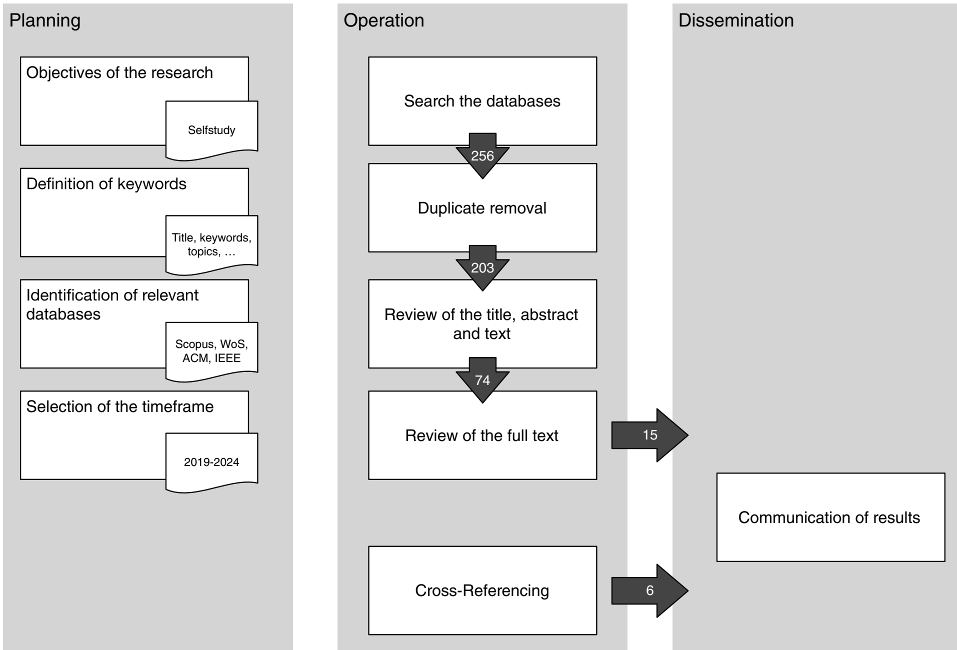

Figure 6. Comprehensive review workflow detailing the planning, execution, and result communication phases for evaluating synthetic image generation in satellite imagery.

5. Advances in synthetic satellite image generation

This section describes selected studies' findings to illustrate how image-generation methods are being used in the satellite imagery field. From the 21 relevant studies, the majority of the studies (16) reported the use of GANs to generate synthetic data, except for three that used diffusion models. Demonstrating a range of innovative architectures designed to tackle challenges such as data imbalance and the pressing need for high-quality labelled datasets.

It should be noted that GANs, in rigour, are not models, but rather a training technique in which two networks, a generator, and a discriminator, compete against each other mutually improving. While they all have the same basic idea, GANs differ in how they are structured, the type of data they generate, and how stable or efficient their training is. Some GANs are better at producing high-resolution images, while others are better at handling multiple data sources or generating specific features. In satellite applications, these variations enable researchers to select or modify the GAN type based on whether they need to simulate textures, preserve geographic structures, or generate multi-spectral images.

Abady et al. (2024) used CycleGAN (Jun-Yan et al. 2017) and Pix2Pix (Isola et al. 2017) to perform multispectral transformations, such as seasonal and land-cover changes, while employing a Gram Schmidt Adaptive (GSA) pansharpening step (Ko 1991) to enhance spatial detail. Andrade and Fernandes (2022) utilized a Pix2Pix to create satellite-like urban images from historical maps, combining outputs from urban and natural-specific models to enhance realism. Shumilo et al. (2023) addressed class imbalance in crop classification by generating synthetic satellite images (using a Pix2Pix) paired with artificial ground truth masks, enhancing classification performance for minority crop types. Shamsolmoali et al. (2021) used a domain adaptation GAN with feature pyramid networks (Adelson et al. 1983) for road segmentation, achieving high accuracy even in complex backgrounds. Hu et al. (2023) utilized GAN-assisted training with conditional SinGAN (cSinGAN) and GeoPalette to generate diverse synthetic road networks for segmentation tasks, reducing reliance on real data. Qing et al. (2023) proposed a dual distortion-adaptive GAN (integrating Pix2Pix and CycleGAN models) for high-resolution Electro-optical to Synthetic Aperture Radar (EO-SAR) translation, incorporating geometric correction modules to address nonlinear distortions. Mirzaei, Bagheri, and Khosravi (2023) employed CTGANs to address class imbal- ances in agricultural datasets, improving minority class accuracy while maintaining major class performance. Yates et al. (2022) compared PGGAN (Karras et al. 2018), StyleGAN2 (Karras, Laine, et al. 2020), and Conditional Coordinate GAN (CoCoGAN) for synthesizing aerial imagery, with StyleGAN2 outperforming the others in producing realistic outputs. Ghozatlou, Datcu, and Chapron (2024) used StyleGAN2 with Adaptive Discriminator Augmentation (ADA) (Karras, Aittala, et al. 2020) to produce high-fidelity SAR images with strong classification performance. Anuradha et al. (2024) applied Deep Convolutional Generative Adversarial Networks (DCGANs) to generate agricultural field images, significantly improving yield prediction accuracy. Gautam, Sit, and Demir (2022) used PGGAN to create high-resolution river satellite imagery, refining details at increasing resolutions. Kostagiolas, Nicolaou, and Panagakis (2022) used a wavelet-based GAN to synthesize satellite imagery guided by semantic concepts like urbanization and vegetation growth, thereby improving data quality and classification accuracy.

Diffusion models are gaining popularity as an alternative to GANs due to their ability to produce high-quality images with precise semantic control. Graikos et al. (2024) used Self-Supervised Learning (SSL) embeddings to guide LDMs (Rombach et al. 2022), resulting in large, spatially consistent images from smaller patches while maintaining global coherence. Shipard et al. (2023) used LDMs to generate diverse synthetic samples for zero-shot classification tasks, demonstrating improvements in satellite image categorization. Espinosa and Crowley (2023) used ControlNet to generate satellite images conditioned on OpenStreetMap (OSM) data, which allowed for precise control over image synthesis. May et al. (2023) used CLIP (Ramesh et al. 2022) trained on par- tially synthetic satellite datasets for forensic analysis and manipulation detection. Shendy and Nalepa (2024) showed that DALL-E 2 diffusion models can improve few-shot learning in satellite image classification by augmenting datasets with synthetic imagery.

Super-resolution methods, while distinct from pure generative approaches, incorporate a generative process into their pipeline. Sebaq and ElHelw (2024) developed RSDiff, a two-stage pipeline that refines low-resolution satellite images generated from text prompts using a super-resolution diffusion model to produce semantically accurate outputs. Zhao et al. (2023) developed SA- GAN, which uses second-order attention mechanisms and region-aware strategies to generate high-resolution, artefact-free images. Romero, Luis, and Vilaplana (2020) used an Enhanced Super-Resolution GAN (ESRGAN) to upscale Sentinel-2 images to WorldView-level resolution while maintaining spatial and spectral fidelity. Karwowska and Wierzbicki (2022) also employed an ESRGAN-based approach for high-resolution image patch reconstruction, reducing artefacts during large-scale image synthesis. Pham and Bui (2021) used SRGAN to improve Landsat imagery by integrating multispectral and panchromatic bands, which resulted in visually sharp outputs validated by perception and classification metrics. These methods help generative models by ensuring that synthetic satellite images have the spatial precision needed for demanding applications.

6. Discussion

The previous section (Section 5) described all the studies selected for this review. For comprehension, Table 1 presents general information about the datasets used in the reviewed studies. The information includes the dataset's name, the source of the images (i.e. the sensor used to collect the images or the portal where they were collected), the type of images used (e.g. RGB, NIR, Multispectral, etc.), the sensor's resolution, the number of images in the dataset, and a brief description.

Some of the works rely on private/custom datasets, which can be explained by the fact that they rely on a specific application rather than comparing its methods to the state-of-the-art. Furthermore, most works that use public datasets do not compare the performance of their method to others because they use different datasets. This suggests the need for more accessible standardized datasets in this field. As for the type of data used in the studies, RGB imagery dominates, with multispectral and SAR (Synthetic Aperture Radar) data appearing less frequently. Regarding the applications of the datasets, there are various, such as road segmentation, seasonal transformations, EO-SAR translation, and agricultural analysis. In terms of the size of the datasets, it varies widely, from small datasets like the OPS-SAT Challenge (80 images) to massive datasets such as the Chesapeake Land Cover dataset (667,000 patches). This variance showcases the diversity in the scale of studies, from focused experiments to large-scale applications. Resolutions are typically high for detailed tasks but vary depending on the type and purpose of the study.

This review includes studies with distinct particularities and goals. While some studies encompassed an entire pipeline of segmentation and classification, others performed direct image classification, and others only presented an image generation method, leaving classification to future research. As such, Table 2 provides a comparative overview of various studies utilizing synthetic image generation techniques, highlighting the image generation algorithm and the evaluation of the performance with and without augmenting the dataset. The results given in this table are based solely on the original papers, and all effort was made to include as much available information as possible.

The selected studies employ a range of generative models, including GAN-based architectures (DCGAN, Pix2Pix, StyleGAN2-ADA, Wavelet-GAN) and Diffusion Models (DALL-E 2, CLIP, LDMs). The reviewed studies demonstrate the transformative power of advanced ML techniques and synthetic image generation methods in satellite imagery analysis. These studies evaluated a variety of GAN approaches, demonstrating their efficacy in distinct scenarios. Diffusion models also provided interesting results, acting as a promising solution when compared with GANs. Most of the studies used different datasets to evaluate the effectiveness of their method, therefore it is not possible to quantitatively compare their performance.

Table 1. Summary of selected datasets used in recent studies on synthetic image generation in Remote Sensing.

Dataset Name	Source	Type	Number of images	Description	Ref
W-S Set1 (Private)	Sentinel-2, WorldView-2, WorldView-3	RGB	32 large images	Super Resolution Dataset	Romero, Luis, and Vilaplana (2020)
W-S Set2 (Private)	Sentinel-2, WorldView-2, WorldView-3	RGB	32 large images	Super Resolution Dataset	Romero, Luis, and Vilaplana (2020)
DeepGlobe (Public)	-	RGB	9739	Road segmentation tasks	Shamsolmoali et al. (2021)
Massachusetts (Public)	-	RGB	1171	Road segmentation tasks	Shamsolmoali et al. (2021)
EPFL (Public)	Google Maps	RGB	150	Road segmentation tasks	Shamsolmoali et al. (2021)
EuroSat (Public)	Sentinel-2	RGB, NIR	27000	Road segmentation tasks	Pham and Bui (2021)
RESISC-70 (Private)	Northwestern Polytechnical University (NWPU)	RGB	31500	NWPU RESISC45 variation	Kostagiolas, Nicolaou, and Panagakis (2022
RESISC-35 (Private)	NWPU	RGB	31500	NWPU RESISC45 variation	Kostagiolas, Nicolaou, and Panagakis (2022)
RESISC-10 (Private)	NWPU	RGB	31500	NWPU RESISC45 variation	Kostagiolas, Nicolaou, and Panagakis (2022)
AID (Public)	Google Earth	RGB	10000	30 scene classes	Kostagiolas, Nicolaou, and Panagakis (2022)
UC-Merced (Public)	United States Geological Survey (USGS) National Map	RGB	2100	21 scene classes	Kostagiolas, Nicolaou, and Panagakis (2022)
Dataset A (Private)	Google Earth	RGB	1000	River imagery	Gautam, Sit, and Demir (2022))
Dataset B (Private)	Google Earth	RGB	11000	River imagery	Gautam, Sit, and Demir (2022)
- (Private)	Google Earth	RGB	-	Historical cartographic documents and real images	Andrade and Fernandes (2022)
INRIA (Public)	National Map service	RGB	180 tiles	Building detection	Yates et al. (2022))
- (Private)	World View 2 (WV2)	Multispectral	29500 LR + 29500 HR	Super Resolution Dataset	Karwowska and Wierzbicki (2022)
Kyiv Region (Private)	Sentinel-1, Sentinel-2	RGB, NIR	4250	Agricultural land in the Kyiv region	Shumilo et al. (2023)
DeepGlobe (Public)	-	RGB	9739	Road segmentation tasks	Hu et al. (2023)
SAR2Opt (Public)	TerraSAR-X satellite and Google Earth Engine	SAR, EO	724 pairs	High-resolution EO-SAR translation	Qing et al. (2023)
Agricultural (Private)	RapidEye and UAVSAR	RGB, NIR and RE	-	Class imbalance in agriculture	Mirzaei, Bagheri, and Khosravi (2023)
EuroSat (Public)	Sentinel-2	RGB, NIR	27000	Road segmentation tasks	Shipard et al. (2023))
Mainland Scotland (Private)	World Imagery	RGB	94096	Convert OpenStreetMap into its satellite view	Espinosa and Crowley (2023)
Central Belt (Private)	World Imagery	RGB	81834	Convert OpenStreetMap into its satellite view	Espinosa and Crowley (2023)
Carvalho DSO-1 (Public)	MapBox, Google Maps	RGB	453000	Forensic research in synthetic overhead imagery	May et al. (2023))

(*Continued*)

Table 1. (Continued).

Dataset Name	Source	Type	Number of images	Description	Ref
- (Private)	GF	RGB, NIR	9246 image pairs	Super Resolution Dataset	Zhao et al. (2023))
Scandinavian (Private)	Sentinel-2	RGB	9000	Seasonal transformations	Abady et al. (2024)
China (Private)	Sentinel-2	RGB	8522	Seasonal transformations	Abady et al. (2024)
Chesapeake Land Cover (Public)	Landsat 8	RGB	667000 patches	Land cover identification	Graikos et al. (2024)
TenGeoP-SARwv (Public)	Sentinel-1A WV	SAR	37560	Ocean SAR imagery	Ghozatlou, Datcu, and Chapron (2024)
RSI-CB256 (Public)	-	RGB	5631	Land cover identification	Anuradha et al. (2024)
RSICD (Public)	Google Earth, Baidu Map, MapABC, Tianditu	RGB	10921	Remote sensing image captioning task	Sebaq and ElHelw (2024)
OPS-SAT Challenge (Public)	OPS-SAT CubeSat Camera	RGB	80	Land cover identification	Shendy and Nalepa (2024)

Segmentation and classification performance improvements by incorporating synthetic samples are shown in Table 2. In studies that evaluated their method's performance using segmentation algorithms, there was a significant improvement in segmentation performance (IoU scores). ASNP (Shamsolmoali et al. 2021) increased IoU from 46.24 to 69.58 on the DeepGlobe dataset, 44.25 to 78.66 in the Massachusetts Road dataset, and 48.53 to 81.68 in the EPFL Road segmentation. U-Net enhanced IoU from 64.1 to 66.2 for the Kyiv Region agricultural segmentation dataset (Shumilo et al. 2023). This demonstrates GAN-based augmentation's ability to improve feature learning and generalization while reducing misclassification of small or underrepresented regions.

Using augmented datasets can also improve classification algorithms, such as SWAGAN (Kostagiolas, Nicolaou, and Panagakis 2022), which improved ResNet50 classification performance from 0.827 to 0.842 in RESISC-70, 0.804 to 0.833 in RESISC-35, 0.776 to 0.808 in RESISC-10, 0.716 to 0.783 in AID dataset, and 0.776 to 0.816 in UC-Merced. In Mirzaei, Bagheri, and Khosravi (2023) with CTGAN, XGBoost increased sensitivity from 0.895 to 0.956, while DCGAN improved CNN overall accuracy from 0.961 to 0.986 on the RSI-CB256 dataset, with significant jumps in preci- sion (0.075) and recall (0.031), confirming that synthetic data enhances generalization. Using the diffusion model DALL-E 2 (Shendy and Nalepa 2024), the best classification algorithm improved its accuracy from 0.68 to 0.78 on the OPS-SAT challenge dataset.

The studies use a variety of evaluation metrics to assess image quality, segmentation accuracy, and classification performance. FID (Fréchet Inception Distance) is the most commonly used metric for assessing generative models, with lower FID scores indicating higher synthetic image realism. When evaluating segmentation performance, it is important to note that IoU and Mean IoU (mIoU) are critical. Finally, in classification, accuracy is the most popular metric.

Table 2. Summary of algorithms and Evaluation results in selected studies on synthetic image generation.

Process	Image Gen. Alg.	Seg. Alg.	Class. Alg.	Dataset	Res. (No Aug.)	Res. (Aug.)	Ref
Classification	Wavelet- based GAN (SWA-GAN Gal et al. (2021)	-	ResNet-50	RESISC-70	Acc. =0.827,Imb.Acc.= 0.638	Acc. =0.842,Imb.Acc.= 0.760	Kostagiolas, Nicolaou, and Panagakis (2022)
Classification	Wavelet-based GAN (SWA-GAN Gal et al. (2021)	-	ResNet-50	RESISC-35	Acc. =0.804,Imb.Acc.= 0.463	Acc. =0.833,Imb.Acc.= 0.673	Kostagiolas, Nicolaou, and Panagakis (2022)
Classification	Wavelet-based GAN (SWA-GAN Gal et al. (2021)	-	ResNet-50	RESISC-10	Acc. =0.776,Imb.Acc.= 0.235	Acc. =0.808,Imb.Acc.= 0.494	Kostagiolas, Nicolaou, and Panagakis (2022)
Classification	Wavelet-based GAN (SWA-GAN Gal et al. (2021)	-	ResNet-50	AID	Acc. = 0.716, Imb.Acc. = 0.425	Acc. = 0.783, Imb.Acc. = 0.732	Kostagiolas, Nicolaou, and Panagakis (2022))
Classification	Wavelet-based GAN (SWA-GAN Gal et al. (2021)	-	ResNet-50	UC-Merced	Acc. = 0.776, Imb.Acc. = 0.420	Acc. = 0.819, Imb.Acc. = 0.660	Kostagiolas, Nicolaou, and Panagakis (2022))
Classification	Diffusion models with the proposed "bag of tricks"	-	ResNet50, ResNet 101′ Mo-bileNetV3, ViT and Con-vNeXt	EuroSat	-	Top 1 Acc. = 42.59	Shipard et al. (2023))
Classification	CLIP Diffusion Model	-	Forensic Similar- ity Graphs (FSG)	Carvalho DSO-1 (Public)	-	AUC = 0.62, Cali- brated Acc. = 0.59, MCC = 0.279	May et al. (2023))
Classification	CTGAN	-	XGBoost, RF and KNN	Agricultural (Private)	Sensitivity = 0.895; G-Mean = 0.970	Sensitivity = 0.956; G-Mean = 0.984	Mirzaei, Bagheri, and Khosravi (2023)
Classification	DCGAN	-	CNN	RSI-CB256 (Public)	Accuracy = 0.961; Precision = 0.907; Recall = 0.939; F1-Score = 0.896; MSE = 0.18	Accuracy = 0.986; Precision = 0.982; Recall = 0.97; F1-Score = 0.96; MSE = 0.082	Anuradha et al. (2024))

(*Continued*)

Table 2. (Continued).

Process	Image Gen. Alg.	Seg. Alg.	Class. Alg.	Dataset	Res. (No Aug.)	Res. (Aug.)	Ref
Classification	DALL-E 2 Ramesh et al. (2022) (Diffu- sion Model)	-	Efficient NetLite, -B0 Mo- bileNetV3, Xcep- tion, Mo- bileNetV2	OPS- SAT Chal- lenge Dataset	Acc. = 0.68	Acc. = 0.78	Shendy and Nalepa (2024)
Classification and Image Generation Evaluation	Style GAN2 -ADA	-	ResNet18	TenGeoP- SARwv (Public)	-	ACC_0 = 0.976, ACC_1 = 0.952, ACC_2 = 0.612, FID = 11.116	Ghozatlou, Datcu, and Chapron (2024)
Segmentation	ASNP (GAN based)	ASNP (GAN based)	VGG-16	Deep Globe (Public)	IoU = 46.24, iIoU = 37.89	IoU = 69.58, iIoU = 55.61	Shamsolmoali et al. (2021)
Segmentation	Pix2Pix (GAN based)	U-Net	U-Net	Kyiv Region (Pri- vate)	IoU = 64.1	IoU = 66.2	Shumilo et al. (2023))
Segmentation and Image Generation Evaluation	ASNP (GAN based)	ASNP (GAN based)	VGG-16	Massa chusetts Road (Public)	IoU = 44.25, iIoU = 36.78	IoU = 78.86, iIoU = 63.74, FID = 20.36, PRI = 0.837, VOI = 1.683, GCE = 0.178, BDE = 10.58	Shamsolmoali et al. (2021)
Segmentation and Image Generation Evaluation	ASNP (GAN based)	ASNP (GAN based)	VGG-16	EPFL Road Seg- menta- tion (Public)	IoU = 48.53, iIoU = 39.67	IoU = 81.68, iIoU = 67.43, PRI = 0.885, VOI = 1.676, GCE = 0.166, BDE = 10.43	Shamsolmoali et al. (2021))
Segmentation and Image Generation Evaluation	Geo Palette	D- linkNet	-	Deep Globe (Public)	-	IoU = 0.64, BQS = 0.621, FID = 161.24, BSS = 3.246	Hu et al. (2023)
Segmentation and Image Generation Evaluation	cSinGAN	D- linkNet	-	Deep Globe (Public)	-	IoU = 0.64, BQS = 0.568, FID = 172.43, BSS = 3.270	Hu et al. (2023)
Image Generation Evaluation	PGGAN	-	-	Dataset A (Pri- vate)	-	Laplacian SWD = 0.00322; IS = 2.915	Gautam, Sit, and Demir (2022))
Image Generation Evaluation	PGGAN	-	-	Dataset B (Pri- vate)	-	Laplacian SWD = 0.00976	Gautam, Sit, and Demir (2022))
Image Generation Evaluation	Style GAN2	-	-	INRIA (Public)	-	FID = 16.59, KID = 7.28	Yates et al. (2022)
Image Generation Evaluation	Pix2Pix and Cy- cleGAN con- nected with DA module	-	-	SAR2Opt - SAR to EO (Public)	-	PSNR = 15.72, SSIM = 0.24, FID = 178.96, LPIPS = 0.491	Qing et al. (2023))

(*Continued*)

Table 2. (Continued).

Process	Image Gen. Alg.	Seg. Alg.	Class. Alg.	Dataset	Res. (No Aug.)	Res. (Aug.)	Ref
Image Generation Evaluation	Pix2Pix and Cy- cleGAN con- nected with DA module	-	-	SAR2Opt - EO to SAR (Public)	-	PSNR = 15.22, SSIM = 0.203, FID = 116.29, LPIPS = 0.380	Qing et al. (2023))
Image Generation Evaluation	RSDiff (Diffu- sion Model)	-	-	RSICD (Public)	-	IS = 7.22, FID = 66.49	Sebaq and ElHelw (2024))
Image Generation Evaluation	LDMs (based on Varia- tional Autoen- coders)	-	-	Chesa peake Land Cover (Public)	-	Vanilla FID = 11.5; Crop FID = 43.76; CLIP FID = 6.86	Graikos et al. (2024)
Image Generation Evaluation	Pix2Pix with GSA pansharp- ening	-	-	China (Pri- vate)	-	Overall PIQUE = 51.79 (22.33 with GSA pan- sharpen- ing)	Abady et al. (2024))
Super Resolution	ESRGAN	-	-	W-S Set1 (Pri- vate)	SR_0: PSNR = 28.099, SSIM = 0.622, ERGAS = 25.389, SAM = 0.096, CC = 0.959	-	Romero, Luis, and Vilaplana (2020))
Super Resolution	ESRGAN	-	-	W-S Set2 (Pri- vate)	SR_1: PSNR = 27.912, SSIM = 0.676, ERGAS = 29.810, SAM = 0.146, CC = 0.951	-	Romero, Luis, and Vilaplana (2020))
Super Resolution	SRGAN and Patch- Gan	VGG16, ResNet50	-	EuroSat (Public)	acc = 0.96, Land- cover classifica- tion similarity = 0.816	-	Pham and Bui (2021))
Super Resolution	ESRGAN	-	-	- (Pri- vate)	Blackman window: MSE = 3.23, RMSE = 1.80, PSNR = 43.03, UQI = 1.00, SCC = 0.89, SAM = 0.01, SSIM = 1.00, RASE = 87.88, VIFP = 0.97, NRMSE = 0.01	-	Karwowska and Wierzbicki (2022))
Super Resolution	SA-GAN	-	-	- (Pri- vate)	PSNR = 26.7169, SSIM = 0.6890, FID = 0.2329, LPIPS = 17.9571	-	Zhao et al. (2023))

It is worth noting that all the publications considered for this review are very recent, with just one publication in 2020 (Romero, Luis, and Vilaplana 2020), two in 2021 (Pham and Bui 2021; Shamsolmoali et al. 2021), five more in 2022 (Andrade and Fernandes 2022; Gautam, Sit, and Demir 2022; Karwowska and Wierzbicki 2022; Kostagiolas, Nicolaou, and Panagakis 2022; Yates et al. 2022), eight in 2023 (Espinosa and Crowley 2023; Hu et al. 2023; May et al. 2023; Mirzaei, Bagheri, and Khosravi 2023; Qing et al. 2023; Shipard et al. 2023; Shumilo et al. 2023; Zhao et al. 2023) and six in 2024 (Abady et al. 2024; Anuradha et al. 2024; Ghozatlou, Datcu, and Chapron 2024; Graikos et al. 2024; Sebaq and ElHelw 2024; Shendy and Nalepa 2024). It should be noted that this review only takes into account studies available at the selected databases until October 2024, demonstrating that the tendency over time is to increase the number of relevant new studies. This can be justified by the dynamic nature of satellite imagery analysis and synthetic image generation research (Abady et al. 2022), which reflects ongoing efforts to harness the power of advanced ML techniques to address real-world challenges and open up new opportunities in RS and geospatial analysis (Glinka et al. 2023; Han et al. 2023).

It is consensual, among all the analysed studies, that synthetic image-generation techniques for augmenting a dataset drastically improve the classification capability of the models. It proves that generative methods are very effective in the generation of real-quality images that can be confounded with real satellite images.

The goal of this investigation was to eliminate biases and preconceived ideas about the applications and outcomes associated with mainstream imaging techniques. This new perspective enabled us to evaluate the problem of synthetic data generation in satellite imagery in its own technical terms, revealing several domain-specific challenges that set it apart from typical computer vision tasks. Satellite imagery is distinguished by high spatial and spectral variability, inconsistent resolutions due to varying orbital altitudes and sensors, and temporal inconsistencies caused by seasonal or atmospheric fluctuations. Furthermore, semantic sparsity – in which meaningful objects occupy only a small portion of large image areas – complicates data generation. These factors limit the effectiveness of unmodified standard GAN or diffusion models. The methods discussed in this article address these issues using strategies such as domain adaptation, geospatial and temporal conditioning, and architecture designs that are tailored to the complexities of remote sensing data. This technical specificity emphasizes the importance of a focused review separated from the general synthetic data generation literature.

A significant gap identified in this review is the lack of attention given to specific prompt design, structure, and influence in synthetic satellite image generation. For instance, in Shipard et al. (2023), the authors describe the process in which the prompt is encoded via CLIP into an intermediate representation that is injected into the latent diffusion model's denoising UNet through cross-attention, guiding the transformation of Gaussian noise into a latent image that is finally decoded into the final pixel-based output. In the proposed Bag of Tricks, prompts like 'a {domain} of a {class}' were sufficient for generating diverse images in general datasets like CIFAR, but generating realistic satellite images required more specific and structured prompts such as 'a satellite photo of a class in the style of a {domain}', illustrating the added complexity and domain sensitivity involved in prompt-based generation for remote sensing applications. Using only class names as prompts led to confusion in datasets like CIFAR100. For example, 'Apple' generated both fruit and tech logos, 'Beetle' insects and cars, and 'Ray' sunrays, stingrays, and people. This emphasizes the need for more descriptive prompts, especially in satellite datasets like EuroSAT, where additional context is required for accurate image generation. These prompts are frequently fixed, shallow, or do not account for domain-specific characteristics such as vegetation type, carbon content, or topography. This specific study demonstrate how synthetic image generation is different from general applications and should be investigated with more caution and depth.

While much of the reviewed works focused on creating highly realistic images to improve classification, several studies show that even synthetic images that deviate from photorealism can result in significant performance gains. These studies show that the value of synthetic data lies not only in its visual fidelity but also in the variety of features it provides for training, even if those features are derived from abstract or imaginative representations. This is especially relevant in cases like satellite imagery, where capturing context is frequently more important than achieving pixel-perfect realism. The Dreamer framework (Hafner et al. 2020) supports this viewpoint by demonstrating that agents can learn effective long-horizon behaviours solely through latent imagination, thereby eliminating the need for full image reconstruction. Extending on this, Dreaming (Okada and Taniguchi 2021) works by removing the image decoder and replacing it with a contrastive InfoMax objective, supporting the idea that useful representations for learning can emerge without ever generating realistic images, and implying that similar abstraction-based methods could benefit classification tasks based on synthetic data. Comparably, G-SWM (Generative Structured World Models) (Lin et al. 2020) shows that object-centric models can learn to simulate complex scenes with multimodal uncertainty and situation awareness, achieving high performance even without high-fidelity image outputs. This demonstrates how abstraction and imagination can be more valuable than realism for some learning tasks.

The lack of standardized datasets and evaluation benchmarks makes it difficult to directly compare and assess the effectiveness of various synthetic data generation methods over time. While Generative Adversarial Networks (GANs) are widely used, they frequently experience training instability and mode collapse, limiting their performance in complex domains such as satellite imagery. In contrast, diffusion models have recently demonstrated more promising and consistent results in producing high-quality images. However, one major gap remains: current models' limited ability to generate annotated satellite images based on structured prompts. For example, producing an image with specific carbon content, vegetation density, or terrain inclination remains a significant challenge. To address this limitation, further integration of prompt-based generation with automatic labelling capabilities is required. Diffusion models and autoencoders appear to be more adaptable to prompt-driven generation than GANs, but more research is needed to determine their efficacy in this context. Future research should prioritize the creation of universal benchmark datasets and evaluation metrics to allow for fair comparisons and to support more robust and scalable synthetic satellite image generation solutions.

7. Conclusion

Synthetic image generation techniques, as demonstrated in the studies reviewed, are an effective tool for reducing data scarcity while increasing the diversity of satellite image datasets. The reviewed studies show that generative models, particularly GANs and diffusion models, significantly improve training datasets by producing high-quality synthetic images that closely resemble real-world images. These techniques not only increase dataset diversity but also improve the robustness and generalization capabilities of ML models.

The studies analysed highlight that GAN-based architectures, including DCGAN, Pix2Pix, StyleGAN2-ADA, and Wavelet-GAN, have been widely adopted for synthetic image generation in various remote sensing applications. The effectiveness of diffusion models, such as Latent Diffusion Models (LDMs) and ControlNet, is also evident in their ability to produce high-resolution, semantically accurate synthetic images. These advancements make a significant contribution to the fields of environmental monitoring, land cover classification, and spatial analysis.

Despite these positive developments, several challenges remain. The lack of standardized datasets, as well as the limited benchmarking of different generative models, make quantitative comparisons between studies difficult. Furthermore, while synthetic image generation improves segmentation and classification tasks, more research is required to determine the long-term impact of synthetic augmentation on DL model performance. Future research should concentrate on developing more comprehensive evaluation metrics for synthetic image quality, encouraging the use of open-access datasets for benchmarking, and integrating interdisciplinary approaches to fully realize the potential of generative techniques in satellite imagery. Finally, incorporating generative models into remote sensing workflows has the potential to transform how we approach data scarcity, improve classification performance, and open up new avenues for geospatial research.

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ORCID

Julio Castro Lopes http://orcid.org/0000-0003-3354-8956
Jose Luis Oliveira http://orcid.org/0000-0002-6672-6176
Rui Pedro Lopes http://orcid.org/0000-0002-9170-5078

References

Abady, L., M. Barni, A. Garzelli, and B. Tondi. 2024. "Generation of Synthetic Generative Adversarial Network-Based Multispectral Satellite Images with Improved Sharpness." *Journal of Applied Remote Sensing* 18 (1): 014510. https://doi.org/10.1117/1.JRS.18.014510.

Abady, L., E. Daniele Cannas, P. Bestagini, B. Tondi, S. Tubaro, and M. Barni. 2022. "An Overview on the Generation and Detection of Synthetic and Manipulated Satellite Images." ArXiv:2209.08984 [cs, eess]. Accessed Jan 22, 2024. http://arxiv.org/abs/2209.08984.

Abozeid, A., R. Alanazi, A. Elhadad, A. I. Taloba, R. M. Abd El-Aziz, and A. M. Khalil. 2022. "A large-Scale Dataset and Deep Learning Model for Detecting and Counting Olive Trees in Satellite Imagery." *Computational Intelligence and Neuroscience* 2022:e1549842. https://doi.org/10.1155/2022/1549842.

Adedeji, O., P. Owoade, O. Ajayi, and O. Arowolo. 2022. "Image Augmentation for Satellite Images." ArXiv:2207.14580 [cs, eess]. Accessed May 20, 2024. http://arxiv.org/abs/2207.14580.

Adelson, E., C. Anderson, J. Bergen, P. Burt, and J. Ogden. 1983. "Pyramid Methods in Image Processing." *RCA Engineer* 29 (6): 33–41.

Aleissaee, A. A., A. Kumar, R. Muhammad Anwer, S. Khan, H. Cholakkal, G.-S. Xia, and F. Shahbaz Khan. 2023. "Transformers in Remote Sensing: A Survey." *Remote Sensing* 15 (7): 1860. https://doi.org/10.3390/rs15071860.

Alvarez-Vanhard, E., T. Corpetti, and T. Houet. 2021. "UAV & Satellite Synergies for Optical Remote Sensing Applications: A Literature Review." *Science of Remote Sensing* 3:100019. https://doi.org/10.1016/j.srs.2021.100019.

Andrade, H. J. A., and B. J. T. Fernandes. 2022. "Synthesis of satellite-Like Urban Images from Historical Maps Using Conditional GAN." *IEEE Geoscience & Remote Sensing Letters* 19:1–4. https://doi.org/10.1109/LGRS.2020.3023170.

Anuradha, D., R. Kuchipudi, B. Ashreetha, J. Venkata, N. Ramesh, and A. Rami. 2024. "Enhancing Agricultural Yield Forecasting with Deep Convolutional Generative Adversarial Networks and Satellite Data." *International Journal of Advanced Computer Science and Applications (IJACSA)* 15 (2). https://doi.org/10.14569/IJACSA.2024.0150269.

Baghdadi, N., and M. Zribi. 2016. "Optical Remote Sensing of Land Surface: Techniques and Methods." *Elsevier*. Google-Books-ID: Ine0CwAAQBAJ.

Bagwari, N., S. Kumar, and V. Singh Verma. 2023. "A Comprehensive Review on Segmentation Techniques for Satellite Images." *Archives of Computational Methods in Engineering* 30 (7): 4325–4358. https://doi.org/10.1007/s11831-023-09939-4.

Barthakur, M., K. Kumar Sarma, and N. Mastorakis. 2020. "Modified semi-Supervised Adversarial Deep Network and Classifier Combination for Segmentation of Satellite Images." *Institute of Electrical and Electronics Engineers Access* 8:117972–117985. https://doi.org/10.1109/ACCESS.2020.3005085.

Bastani, F., P. Wolters, R. Gupta, J. Ferdinando, and A. Kembhavi. 2023. "satlaspretrain: A large-Scale Dataset for Remote Sensing Image Understanding." Accessed May 13, 2024. https://openaccess.thecvf.com/content/ICCV2023/html/Bstani_SatlasPretrain_A_LargeScale_Dataset_for_Remote_Sensing_Image_Understanding_ICCV_2023_paper.html.

Belgiu, M., and O. Csillik. 2018. "Sentinel-2 Cropland Mapping Using Pixel-Based and Object-Based Time-Weighted Dynamic Time Warping Analysis." *Remote Sensing of Environment* 204:509–523. https://doi.org/10.1016/j.rse.2017.10.005.

Chen, D., X. Qi, Y. Zheng, Y. Lu, Y. Huang, and Z. Li. 2024. "Synthetic Data Augmentation by Diffusion Probabilistic Models to Enhance Weed Recognition." *Computers and Electronics in Agriculture* 216:108517. https://doi.org/10.1016/j.compag.2023.108517.

Chen, X., X. Gao, J. Zhao, K. Ye, and C.-Z. Xu. 2023. "AdvDiffuser: Natural Adversarial Example Synthesis with Diffusion Models." Accessed Jan 27, 2024. https://openaccess.thecvf.com/content/ICCV2023/html/Chen_AdvDiffuser_Natural_Adversarial_Example_Synthesis_with_Diffusion_Models_ICCV_2023_paper.html .

Chen, Z., J. Chen, Y. Yue, Y. Lan, M. Ling, X. Li, H. You, X. Han, and G. Zhou. 2024. "Tradeoffs Among Multi-Source Remote Sensing Images, Spatial resolution, and Accuracy for the Classification of

Wetland Plant Species and Surface Objects Based on the mrs_deeplabv3+ Model." *Ecological Informatics* 81:102594. https://doi.org/10.1016/j.ecoinf.2024.102594.
Corbane, C., L. Najman, E. Pecoul, L. Demagistri, and M. Petit. 2010. "A Complete Processing Chain for Ship Detection Using Optical Satellite Imagery." *International Journal of Remote Sensing* 31 (22): 5837–5854. https://doi.org/10.1080/01431161.2010.512310.
Croitoru, F.-A., V. Hondru, R. Tudor Ionescu, and M. Shah. 2023. "Diffusion Models in Vision: A Survey." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 45 (9): 10850–10869. https://doi.org/10.1109/TPAMI.2023.3261988.
Darbaghshahi, F. N., M. Reza Mohammadi, and M. Soryani. 2022. "Cloud Removal in Remote Sensing Images Using Generative Adversarial Networks and sar-To-Optical Image Translation." *IEEE Transactions on Geoscience & Remote Sensing* 60:1–9. https://doi.org/10.1109/TGRS.2021.3131035.
Deticio, R., A. Bandala, J. Anthony Jose, R. Concepcion II II, M. Angelo Purio, E. Sybingco, and R. Josiah Tan Ai. 2023. "Improving the u-Net Segmentation Model for Land Cover Classification in Satellite Image Processing." In *TENCON 2023 - 2023 IEEE Region 10 Conference (TENCON)*, 76–80. Chiang Mai, Thailand. https://ieeexplore.ieee.org/document/10322481.
Dhariwal, P., and A. Nichol. 2021. "Diffusion Models Beat GANs on Image Synthesis." *Advances in Neural Information Processing Systems* 34:8780–8794. https://proceedings.neurips.cc/paper_files/paper/2021/hash/49ad23d1ec9fa4bd8d77d02681df5cfa-Abstract.html.
Drees, L., L. Verena junker-Frohn, J. Kierdorf, and R. Roscher. 2021. "Temporal Prediction and Evaluation of Brassica Growth in the Field Using Conditional Generative Adversarial Networks." *Computers and Electronics in Agriculture* 190:106415. https://doi.org/10.1016/j.compag.2021.106415.
Espejo-Garcia, B., N. Mylonas, L. Athanasakos, E. Vali, and S. Fountas. 2021. "Combining Generative Adversarial Networks and Agricultural Transfer Learning for Weeds Identification." *Biosystems Engineering* 204:79–89. https://doi.org/10.1016/j.biosystemseng.2021.01.014.
Espinosa, M., and E. J. Crowley. 2023. "Generate Your Own Scotland: Satellite Image Generation Conditioned on Maps." ArXiv:2308.16648, Accessed Nov 02, 2024. http://arxiv.org/abs/2308.16648 .
Figueira, A., and B. Vaz. 2022. "Survey on Synthetic Data generation, Evaluation Methods and GANs." *Mathematics* 10 (15): 2733. https://doi.org/10.3390/math10152733.
Gal, R., D. Cohen, A. Bermano, and D. Cohen-Or. 2021. "SWAGAN: A Style-Based Wavelet-Driven Generative Model." ArXiv:2102.06108 [cs, eess]. Accessed Jan 27, 2024. http://arxiv.org/abs/2102.06108 .
Gautam, A., M. Sit, and I. Demir. 2022. "Realistic River Image Synthesis Using Deep Generative Adversarial Networks." *Frontiers in Water* 4. https://doi.org/10.3389/frwa.2022.784441.
Ghaffarian, S., N. Kerle, and T. Filatova. 2018. "Remote sensing-Based Proxies for Urban Disaster Risk Management and Resilience: A Review." *Remote Sensing* 10 (11): 1760. https://doi.org/10.3390/rs10111760.
Ghozatlou, O., M. Datcu, and B. Chapron. 2024. "Gan-Generated Ocean SAR Vignettes Classification." *IEEE Geoscience and Remote Sensing Letters* 21:1–5. https://doi.org/10.1109/LGRS.2024.3466970.
Glinka, S., J. Bajer, D. Wierzbicki, K. Karwowska, and M. Kedzierski. 2023. "The Use of Deep Learning Methods for Object Height Estimation in High Resolution Satellite Images." *Sensors (Switzerland)* 23 (19): 8162. https://doi.org/10.3390/s23198162.
Goodfellow, I., J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. 2014. "Generative Adversarial Nets." *Advances in Neural Information Processing Systems* 27. https://papers.nips.cc/paper_files/paper/2014/hash/5ca3e9b122f61f8f06494c97b1afccf3-Abstract.html.
Graikos, A., S. Yellapragada, M.-Q. Le, S. Kapse, P. Prasanna, J. Saltz, and D. Samaras. 2024. "Learned Representation-Guided Diffusion Models for Large-Image Generation." ArXiv:2312.07330, Accessed Oct 30, 2024. http://arxiv.org/abs/2312.07330.
Guidolin, M., and P. Manfredi. 2023. "Innovation Diffusion Processes: Concepts, Models, and Predictions." *Annual Review of Statistics and Its Application* 10 (1): 451–473. https://doi.org/10.1146/annurev-statistics-040220-091526.

Guo, Z., J. Liu, Y. Wang, M. Chen, D. Wang, D. Xu, and J. Cheng. 2023. "Diffusion Models in Bioinformatics and Computational Biology." *Nature Reviews Bioengineering*: 1–19. https://doi.org/10.1038/s44222-023-00114-9.

Hafner, D., T. Lillicrap, J. Ba, and M. Norouzi. 2020. "Dream to Control: Learning Behaviors by Latent Imagination." ArXiv:1912.01603 [cs], Accessed June 01, 2025. http://arxiv.org/abs/1912.01603.

Han, W., X. Zhang, Y. Wang, L. Wang, X. Huang, J. Li, S. Wang, et al. 2023. "A Survey of Machine Learning and Deep Learning in Remote Sensing of Geological Environment: Challenges, Advances, and Opportunities." *ISPRS Journal of Photogrammetry and Remote Sensing* 202:87–113. https://doi.org/10.1016/j.isprsjprs.2023.05.032.

Hao, X., L. Liu, R. Yang, L. Yin, L. Zhang, and X. Li. 2023. "A Review of Data Augmentation Methods of Remote Sensing Image Target Recognition." *Remote Sensing* 15 (3): 827. https://doi.org/10.3390/rs15030827.

Haque, M. E., B. Al-Ramadan, and B. A. Johnson. 2016. "Rule-Based Land Cover Classification from Very High-Resolution Satellite Image with Multiresolution Segmentation." *Journal of Applied Remote Sensing* 10 (3): 036004. https://doi.org/10.1117/1.JRS.10.036004.

Hazmy, A. I., A. Hawbani, X. Wang, A. Al-Dubai, A. Ghannami, A. Abdullah Yahya, L. Zhao, and S. Hamood Alsamhi. 2024. "Potential of satellite-Airborne Sensing Technologies for Agriculture 4.0 and climate-Resilient: A Review." *IEEE Sensors Journal* 24 (4): 4161–4180. https://doi.org/10.1109/JSEN.2023.3343428.

Hazra, A., A. Dey, S. Kumar Gupta, and A. A. Md. 2017. "Brain Tumor Detection Based on Segmentation Using MATLAB." In *2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)*, 425–430. Chennai, India. https://ieeexplore.ieee.org/abstract/document/8390202.

He, H. J., C. Zheng, and D. W. Sun. 2016. "Chapter 2 - Image Segmentation Techniques." In *Computer Vision Technology for Food Quality Evaluation*, (2nd Ed) edited by D.-W. Sun, 45–63. San Diego: Academic Press. https://www.sciencedirect.com/science/article/pii/B9780128022320000025.

Hede, A. N. H., K. Koike, K. Kashiwaya, S. Sakurai, R. Yamada, and D. A. Singer. 2017. "How Can Satellite Imagery Be Used for Mineral Exploration in Thick Vegetation Areas?" *Geochemistry Geophysics Geosystems* 18 (2): 584–596. https://onlinelibrary.wiley.com/doi/pdf/10.1002/2016GC006501 .

Himeur, Y., B. Rimal, A. Tiwary, and A. Amira. 2022. "Using Artificial Intelligence and Data Fusion for Environmental Monitoring: A Review and Future Perspectives." *Information Fusion* 86-87:44–75. https://doi.org/10.1016/j.inffus.2022.06.003.

Ho, J., A. Jain, and P. Abbeel. 2020. "Denoising Diffusion Probabilistic Models." *Advances in Neural Information Processing Systems* 33:6840–6851. https://proceedings.neurips.cc/paper/2020/hash/4c5bcfec8584af0d967f1ab10179ca4b-Abstract.html.

Hu, W., Y. Yin, Y. Kiat Tan, A. Tran, H. Kruppa, and R. Zimmermann. 2023. "gan-Assisted Road Segmentation from Satellite Imagery." *ACM Trans Multimedia Computer Communication Application* 21 (1): 1–29. https://doi.org/10.1145/3635153.

Huang, L., H. Zhang, T. Xu, and K.-C. Wong. 2023. "MDM: Molecular Diffusion Model for 3D Molecule Generation." *Proceedings of the AAAI Conference on Artificial Intelligence* 37 (4): 5105–5112. https://doi.org/10.1609/aaai.v37i4.25639.

Illarionova, S., S. Nesteruk, D. Shadrin, V. Ignatiev, M. Pukalchik, and I. Oseledets. 2021. "mixchannel: Advanced Augmentation for Multispectral Satellite Images." *Remote Sensing* 13 (11): 2181. https://doi.org/10.3390/rs13112181.

Isola, P., J.-Y. Zhu, T. Zhou, and A. A. Efros. 2017. "image-To-Image Translation with Conditional Adversarial Networks." In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 5967–5976. Honolulu, Hawaii. ISSN: 1063-6919, Accessed Jan 28, 2024. https://ieeexplore.ieee.org/document/8100115.

Jun-Yan, Z., T. Park, P. Isola, and A. A. Efros. 2017. "Unpaired image-To-Image Translation Using cycle-Consistent Adversarial Networks." Accessed January 28, 2024. https://openaccess.thecvf.com/content_iccv_2017/html/Zhu_Unpaired_Image-To-Image_Translation_ICCV_2017_paper.html.

Kala, A. K., and M. Kumar. 2021. "Role of Geospatial Technologies in Natural Resource Management." In *Climate Impacts on Sustainable Natural Resource Management*, edited by P. Kumar, R. K. Singh, M. Kumar, M. Rani, and P. Sharma, 19–34. UK: John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119793403.ch2.

Karras, T., T. Aila, S. Laine, and J. Lehtinen. 2018. "Progressive Growing of GANs for Improved Quality, Stability, and Variation." ArXiv:1710.10196 [cs, stat]. Accessed 2024-01- 29. http://arxiv.org/abs/1710.10196.

Karras, T., M. Aittala, J. Hellsten, S. Laine, J. Lehtinen, and T. Aila. 2020. "Training Generative Adversarial Networks with Limited Data." ArXiv:2006.06676 [cs], Accessed January 07, 2025. http://arxiv.org/abs/2006.06676.

Karras, T., S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila. 2020. "Analyzing and Improving the Image Quality of stylegan." ArXiv:1912.04958 [cs], Accessed Jan 08, 2025. http://arxiv.org/abs/1912.04958.

Karwowska, K., and D. Wierzbicki. 2022. "Improving Spatial Resolution of Satellite Imagery Using Generative Adversarial Networks and Window Functions." *Remote Sensing* 14 (24): 6285. https://doi.org/10.3390/rs14246285.

Kaur, A., G. Singla, M. Singh, A. Mittal, R. Mittal, and V. Malik. 2024. "Cotton Crop Classification Using Satellite Images with Score Level Fusion Based Hybrid Model." *Pattern Analysis and Applications* 27 (2): 43. https://doi.org/10.1007/s10044-024-01257-0.

Kavzoglu, T., M. Yildiz Erdemir, and H. Tonbul. 2017. "Classification of Semiurban Landscapes from Very High-Resolution Satellite Images Using a Regionalized Multiscale Segmentation Approach." *Journal of Applied Remote Sensing* 11 (3): 035016. https://doi.org/10.1117/1.JRS.11.035016.

Khryashchev, V., L. Ivanovsky, V. Pavlov, A. Ostrovskaya, and A. Rubtsov. 2018. "Comparison of Different Convolutional Neural Network Architectures for Satellite Image Segmentation." In *2018 23rd Conference of Open Innovations Association (FRUCT)*, 172–179. Bologna, Italy. ISSN: 2305-7254, Accessed May 14, 2024. https://ieeexplore.ieee.org/abstract/document/8588071?casa_token=T-W9Ocz9Ai8AAAAA:RLVotdEXwh_lQcEQd6XG18Vx91P4Q3TUtErXzFto4T7hvxiMY_Dyt9Bv0D5HRmKm0OvtX7s29A.

Ko, C. C. 1991. "On the Performance of Adaptive gram-Schmidt Algorithm for Interference Cancelling Arrays." *IEEE Transactions on Antennas & Propagation* 39 (4): 505–511. https://doi.org/10.1109/8.81464.

Kostagiolas, N., M. Nicolaou, and Y. Panagakis. 2022. "Unsupervised Discovery of Semantic Concepts in Satellite Imagery with Style-Based Wavelet-Driven Generative Models." In *Proceedings of the 12th Hellenic Conference on Artificial Intelligence*, SETN '22, New York, NY, USA: 1–9. Association for Computing Machinery. https://doi.org/10.1145/3549737.3549777.

Lalitha, V., and B. Latha. 2022. "A Review on Remote Sensing Imagery Augmentation Using Deep Learning." *Materials Today: Proceedings* 62:4772–4778. https://doi.org/10.1016/j.matpr.2022.03.341.

Liang, H., and S. Seo. 2022. "lpass-Net: Lightweight Progressive Attention Semantic Segmentation Network for Automatic Segmentation of Remote Sensing Images." *Remote Sensing* 14 (23): 6057. https://doi.org/10.3390/rs14236057.

Lin, Z., Y.-F. Wu, S. Peri, B. Fu, J. Jiang, and S. Ahn. 2020. "Improving Generative Imagination in object-Centric World Models." ArXiv:2010.02054 [cs], Accessed June 01, 2025. http://arxiv.org/abs/2010.02054.

Lütjens, B., B. Leshchinskiy, C. Requena-Mesa, F. Chishtie, N. Díaz-Rodríguez, O. Boulais, A. Sankaranarayanan, et al. 2023. "physically-Consistent Generative Adversarial Networks for Coastal Flood Visualization." ArXiv:2104.04785 [cs, eess]. Accessed Jan 27, 2024. http://arxiv.org/abs/2104.04785 .

Malik, V., R. Mittal, A. Kaur, G. Singla, A. Mittal, and M. Singh. 2024. "Enhancement and Analysis of Hyperspectral Satellite Images for Soil Study and Behavior." *Multimedia Tools & Applications* 83 (11): 33879–33902. https://doi.org/10.1007/s11042-023-16729-4.

Mansourifar, H., A. Moskovitz, B. Klingensmith, D. Mintas, and S. J. Simske. 2022. "Gan-Based Satellite Imaging: A Survey on Techniques and Applications." *Institute of Electrical and Electronics Engineers Access* 10:118123–118140. https://doi.org/10.1109/ACCESS.2022.3221123.

Marcal, A. R. S., A. Rodrigues, and M. Cunha. 2010. "Evaluation of Satellite Image Segmentation Using Synthetic Images." In *2010 IEEE International Geoscience and Remote Sensing Symposium*, 2210–2213. Honolulu, HI, USA. ISSN: 2153-7003, Accessed Jan 03, 2024. https://ieeexplore.ieee.org/abstract/document/5649930?casa_token=ZZag2vR82gAAAAAA:Z5p_gZbvg98xof013-RLfdJMOUK4kuXq-O8KHTyv_2ProGoWWSJx9AvzP1FUh9Vb7sXGGnnnDCQ .

Materla, T., E. A. Cudney, and J. Antony. 2019. "The Application of Kano Model in the Healthcare Industry: A Systematic Literature Review." *Total Quality Management & Business Excellence* 30 (5–6): 660–681. https://doi.org/10.1080/14783363.2017.1328980.

May, B. B., K. Trapeznikov, S. Fang, and M. Stamm. 2023. "Comprehensive Dataset of Synthetic and Manipulated Overhead Imagery for Development and Evaluation of Forensic Tools." *Proceedings of the 2023 ACM Workshop on Information Hiding and Multimedia Security*, New York, NY, USA: 145–150. Association for Computing Machinery. https://dl.acm.org/doi/10.1145/3577163.3595101 .

Mirzaei, A., H. Bagheri, and I. Khosravi. 2023. "Enhancing Crop Classification Accuracy Through Synthetic sar-Optical Data Generation Using Deep Learning." *ISPRS International Journal of geo-Information* 12 (11): 450. https://doi.org/10.3390/ijgi12110450.

Muruganantham, P., S. Wibowo, S. Grandhi, N. Hoque Samrat, and N. Islam. 2022. "A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing." *Remote Sensing* 14 (9): 1990. https://doi.org/10.3390/rs14091990.

Nie, D., R. Trullo, J. Lian, L. Wang, C. Petitjean, S. Ruan, Q. Wang, and D. Shen. 2018. "Medical Image Synthesis with Deep Convolutional Adversarial Networks." *IEEE Transactions on Biomedical Engineering* 65 (12): 2720–2730. https://doi.org/10.1109/TBME.2018.2814538.

Okada, M., and T. Taniguchi. 2021. "Dreaming: Model-Based Reinforcement Learning by Latent Imagination without Reconstruction." In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 4209–4215. Xi'an, China: Accessed June 01, 2025. https://ieeexplore.ieee.org/document/9560734.

Ouchra, H., A. Belangour, and A. Erraissi. 2023. "Machine Learning Algorithms for Satellite Image Classification Using Google Earth Engine and Landsat Satellite Data: Morocco Case Study." *Institute of Electrical and Electronics Engineers Access* 11:71127–71142. https://doi.org/10.1109/ACCESS.2023.3293828.

Oughton, E. J., and J. Mathur. 2021. "Predicting Cell Phone Adoption Metrics Using Machine Learning and Satellite Imagery." *Telematics and Informatics* 62:101622. https://doi.org/10.1016/j.tele.2021.101622.

Pham, V.-D., and Q.-T. Bui. 2021. "Spatial Resolution Enhancement Method for Landsat Imagery Using a Generative Adversarial Network." *Remote Sensing Letters* 12 (7): 654–665. https://doi.org/10.1080/2150704X.2021.1918789.

Qing, Y., J. Zhu, H. Feng, W. Liu, and B. Wen. 2023. "two-Way Generation of high-Resolution EO and SAR Images via Dual distortion-Adaptive GANs." *Remote Sensing* 15 (7): 1878. https://doi.org/10.3390/rs15071878.

Ramesh, A., P. Dhariwal, A. Nichol, C. Chu, and M. Chen. 2022. "Hierarchical text-Conditional Image Generation with CLIP Latents." ArXiv:2204.06125 [cs], Accessed Jan 28, 2024. http://arxiv.org/abs/2204.06125.

Rezaei, A., and F. Asadi. 2024. "Systematic Review of Image Segmentation Using Complex Networks." ArXiv:2401.02758 [cs], Accessed May 14, 2024. http://arxiv.org/abs/2401.02758.

Rombach, R., A. Blattmann, D. Lorenz, P. Esser, and B. Ommer. 2022. "high-Resolution Image Synthesis with Latent Diffusion Models." Accessed Jan 27, 2024. https://openaccess.thecvf.com/content/CVPR2022/html/Rombach_High-Resolution_Image_Synthesis_With_Latent_Diffusion_Models_CVPR_2022_paper.html.

Romero, S., J. M. Luis, and V. Vilaplana. 2020. "super-Resolution of Sentinel-2 Imagery Using Generative Adversarial Networks." *Remote Sensing* 12 (15): 2424. https://doi.org/10.3390/rs12152424.

Ruthotto, L., and E. Haber. 2021. "An Introduction to Deep Generative Modeling." *GAMM-Mitteilungen* 44 (2): e202100008. https://onlinelibrary.wiley.com/doi/pdf/10.1002/gamm.202100008.

Sabuhi, M., M. Zhou, C.-P. Bezemer, and P. Musilek. 2021. "Applications of Generative Adversarial Networks in Anomaly Detection: A Systematic Literature Review." *Institute of Electrical and Electronics Engineers Access* 9:161003–161029. https://doi.org/10.1109/ACCESS.2021.3131949.

Sebaq, A., and M. ElHelw. 2024. "RSDiff: Remote Sensing Image Generation from Text Using Diffusion Model." ArXiv:2309.02455, Accessed Nov 02, 2024. http://arxiv.org/abs/2309.02455.

Sebastianelli, A., E. Puglisi, M. Pia Del Rosso, J. Mifdal, A. Nowakowski, P. Philippe Mathieu, F. Pirri, and S. Liberata Ullo. 2022. "PLFM: Pixel-Level Merging of Intermediate Feature Maps by Disentangling and Fusing Spatial and Temporal Data for Cloud Removal." *IEEE Transactions on Geoscience and Remote Sensing* 60:1–16. https://doi.org/10.1109/TGRS.2022.3208694.

Shahriar, S. 2022. "GAN Computers Generate Arts? A Survey on Visual Arts, Music, and Literary Text Generation Using Generative Adversarial Network." *Displays* 73:102237. https://doi.org/10.1016/j.displa.2022.102237.

Shamsolmoali, P., M. Zareapoor, H. Zhou, R. Wang, and J. Yang. 2021. "Road Segmentation for Remote Sensing Images Using Adversarial Spatial Pyramid Networks." *IEEE Transactions on Geoscience & Remote Sensing* 59 (6): 4673–4688. https://doi.org/10.1109/TGRS.2020.3016086.

Shao, R., C. Du, H. Chen, and J. Li. 2021. "SUNet: Change Detection for Heterogeneous Remote Sensing Images from Satellite and UAV Using a dual-Channel Fully Convolution Network." *Remote Sensing* 13 (18): 3750. https://doi.org/10.3390/rs13183750.

Shen, L., L. Wu, Y. Dai, W. Qiao, and Y. Wang. 2017. "Topic Modelling for object-Based Unsupervised Classification of VHR Panchromatic Satellite Images Based on Multiscale Image Segmentation." *Remote Sensing* 9 (8): 840. https://doi.org/10.3390/rs9080840.

Shen, Y., P. Luo, J. Yan, X. Wang, and X. Tang. 2018. "Faceid-Gan: Learning a Symmetry three-Player GAN for identity-Preserving Face Synthesis." 821–830. https://openaccess.thecvf.com/content_cvpr_2018/html/Shen_FaceID-GAN_Learning_a_CVPR_2018_paper.html.

Shendy, R., and J. Nalepa. 2024. "Few-Shot Satellite Image Classification for Bringing Deep Learning on Board ops-Sat." *Expert Systems with Applications* 251:123984. https://doi.org/10.1016/j.eswa.2024.123984.

Shi, Z., S. Peng, Y. Xu, A. Geiger, Y. Liao, and Y. Shen. 2023. "Deep Generative Models on 3D Representations: A Survey." ArXiv:2210.15663 [cs], Accessed Jan 27, 2024. http://arxiv.org/abs/2210.15663.

Shipard, J., A. Wiliem, K. Nguyen Thanh, W. Xiang, and C. Fookes. 2023. "Diversity is Definitely Needed: Improving model-Agnostic zero-Shot Classification via Stable Diffusion." 769–778. Accessed Jan 25, 2024. https://openaccess.thecvf.com/content/CVPR2023W/GCV/html/Shipard_Diversity_Is_Definitely_Needed_Improving_Model-Agnostic_Zero–Shot_Classification_via_Stable_CVPRW_2023_paper.html .

Shumilo, L., A. Okhrimenko, N. Kussul, S. Drozd, and O. Shkalikov. 2023. "Generative Adversarial Network Augmentation for Solving the Training Data Imbalance Problem in Crop Classification." *Remote Sensing Letters* 14 (11): 1129–1138. https://doi.org/10.1080/2150704X.2023.2275551.

Singh, D., D. Suhaga, Y. Gaurav, P. Himanshu, and S. Virendra. 2023. "Chapter 6 - Polluted Water Bodies Remediation by Using GIS and Remote Sensing Approach: A Deeper Insight." In *Water, land, and Forest Susceptibility and Sustainability*, edited by U. Chatterjee, B. Pradhan, S. Kumar, S. Saha, M. Zakwan, B. D. Fath, and D. Fiscus, 155–169. London, UK: Elsevier. https://www.sciencedirect.com/science/article/pii/B9780323918800000210 .

Siriapisith, T., W. Kusakunniran, and P. Haddawy. 2020. "Pyramid Graph Cut: Integrating Intensity and Gradient Information for Grayscale Medical Image Segmentation." *Computers in Biology and Medicine* 126:103997. https://doi.org/10.1016/j.compbiomed.2020.103997.

Sohl-Dickstein, J., E. Weiss, N. Maheswaranathan, and S. Ganguli. 2015. "Deep Unsupervised Learning Using Nonequilibrium Thermodynamics." In *Proceedings of the 32nd International Conference on Machine Learning*, 2256–2265. Lille, France. https://proceedings.mlr.press/v37/sohl-dickstein15.html.

Subhash, S., and E. A. Cudney. 2018. "Gamified Learning in Higher Education: A Systematic Review of the Literature." *Computers in Human Behavior* 87:192–206. https://doi.org/10.1016/j.chb.2018.05.028.

Tehrani, F. S., G. Santinelli, and M. Herrera Herrera. 2021. "multi-Regional Landslide Detection Using Combined Unsupervised and Supervised Machine Learning." *Geomatics, Natural Hazards and Risk* 12 (1): 1015–1038. https://www.tandfonline.com/doi/abs/10.1080/19475705.2021.1912196.

Tejado-Ramos, J.-J., M. Chocarro-León, I. Barrero-Béjar, A. Valverde-Calvo, M. Ferreras-Moreno, F. Giraldo-Pavón, and C. Tarragona-Pérez. 2021. "Enhancement of the Sustainability of Wolfram Mining Using Drone Remote Sensing Technology." *Remote Sensing Applications: Society & Environment* 23:100542. https://doi.org/10.1016/j.rsase.2021.100542.

Weiss, M., F. Jacob, and G. Duveiller. 2020. "Remote Sensing for Agricultural Applications: A Meta-Review." *Remote Sensing of Environment* 236:111402. https://doi.org/10.1016/j.rse.2019.111402.

Wu, M., C. Zhang, J. Liu, L. Zhou, and X. Li. 2019. "Towards Accurate High Resolution Satellite Image Semantic Segmentation." *Institute of Electrical and Electronics Engineers Access* 7:55609–55619. https://doi.org/10.1109/ACCESS.2019.2913442.

Xiao, Y., Q. Yuan, K. Jiang, J. He, X. Jin, and L. Zhang. 2024. "EDiffSR: An Efficient Diffusion Probabilistic Model for Remote Sensing Image super-Resolution." *IEEE Transactions on Geoscience & Remote Sensing* 62:1–14. https://doi.org/10.1109/TGRS.2023.3341437.

Xue, A. 2021. "End-To-End Chinese Landscape Painting Creation Using Generative Adversarial Networks." Accessed Jan 27, 2024. https://openaccess.thecvf.com/content/WACV2021/html/Xue_End-toEnd_Chinese_Landscape_Painting_Creation_Using_Generative_Adversarial_Networks_WACV_2021_paper.html.

Xue, N., L. Niu, X. Hong, Z. Li, L. Hoffaeller, and C. Pöpper. 2020. "deep-Sim: GPS Spoofing Detection on UAVs Using Satellite Imagery Matching." *Proceedings of the 36th Annual Computer Security Applications Conference*, ACSAC '20, New York, NY, USA: 304–319. Association for Computing Machinery. https://doi.org/10.1145/3427228.3427254.

Yan, P., F. He, Y. Yang, and F. Hu. 2020. "semi-Supervised Representation Learning for Remote Sensing Image Classification Based on Generative Adversarial Networks." *Institute of Electrical and Electronics Engineers Access* 8:54135–54144. https://doi.org/10.1109/ACCESS.2020.2981358.

Yang, G., X. Han, L. Zhang, W. Gao, Y. Hu, Y. Zhao, and C. Sun. 2025. "A gan-Based Cyclic Iterative Unsupervised Change Detection Network." *International Journal of Remote Sensing* 46 (2): 745–774. https://doi.org/10.1080/01431161.2024.2421935.

Yao, X., J. Han, G. Cheng, X. Qian, and L. Guo. 2016. "Semantic Annotation of high-Resolution Satellite Images via Weakly Supervised Learning." *IEEE Transactions on Geoscience & Remote Sensing* 54 (6): 3660–3671. https://doi.org/10.1109/TGRS.2016.2523563.

Yates, M., G. Hart, R. Houghton, M. Torres Torres, and M. Pound. 2022. "Evaluation of Synthetic Aerial Imagery Using Unconditional Generative Adversarial Networks." *ISPRS Journal of Photogrammetry and Remote Sensing* 190:231–251. https://doi.org/10.1016/j.isprsjprs.2022.06.010.

Yeung, H. W. F., M. Zhou, Y. Ying Chung, G. Moule, W. Thompson, W. Ouyang, W. Cai, and M. Bennamoun. 2022. "Deep-Learning-Based Solution for Data Deficient Satellite Image Segmentation." *Expert Systems with Applications* 191:116210. https://doi.org/10.1016/j.eswa.2021.116210.

Yinka-Banjo, C., and O.-A. Ugot. 2020. "A Review of Generative Adversarial Networks and Its Application in Cybersecurity." *Artificial Intelligence Review* 53 (3): 1721–1736. https://doi.org/10.1007/s10462-019-09717-4.

Young, O. R., and M. Onoda. 2017. "Satellite Earth Observations in Environmental problem-Solving." In *Satellite Earth Observations and Their Impact on Society and Policy*, edited by M. Onoda and O. R. Young, 3–27. Singapore: Springer. https://doi.org/10.1007/978-981-10-3713-9_1.

Yuan, X., J. Shi, and L. Gu. 2021. "A Review of Deep Learning Methods for Semantic Segmentation of Remote Sensing Imagery." *Expert Systems with Applications* 169:114417. https://doi.org/10.1016/j.eswa.2020.114417.

Zhang, D., H. Dongru, L. Kang, and W. Zhang. 2022. "The Generative Adversarial Networks and Its Application in Machine Vision." *Enterprise Information Systems* 16 (2): 326–346. https://doi.org/10.1080/17517575.2019.1701714.

Zhao, J., Y. Ma, F. Chen, E. Shang, W. Yao, S. Zhang, and J. Yang. 2023. "SAGAN: A Second Order Attention Generator Adversarial Network with Region Aware Strategy for Real Satellite Images

Super Resolution Reconstruction." *Remote Sensing* 15 (5): 1391. https://doi.org/10.3390/rs15051391.

Zheng, J., X.-Y. Liu, and X. Wang. 2021. "Single Image Cloud Removal Using u-Net and Generative Adversarial Networks." *IEEE Transactions on Geoscience & Remote Sensing* 59 (8): 6371–6385. https://doi.org/10.1109/TGRS.2020.3027819.

Zou, H., Z. Myung Kim, and D. Kang. 2023. "A Survey of Diffusion Models in Natural Language Processing." June. ArXiv:2305.14671 [cs], Accessed Jan 27, 2024. http://arxiv.org/abs/2305.14671.