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ConLoRA-Sat: Parameter-Efficient Synthetic Satellite Imagery Generation for Data-Scarce Humanitarian Contexts

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ABSTRACT

Data scarcity constrains Geospatial Artificial Intelligence (GeoAI) in regions such as the Horn of Africa. One example is United Nations peacekeeping training, which needs fictitious yet geographically plausible terrain rather than identifiable real locations. This article presents ConLoRA-Sat, a framework that generates satellite imagery with controllable land cover, together with a segmentation map for every generated image. The framework pairs Low Rank Adaptation (LoRA) with ControlNet on a Stable Diffusion XL backbone, adapting a general-purpose generative model to 0.5 m imagery from Mogadishu and Addis Ababa using only 322 training images. A segmentation model trained exclusively on synthetic imagery retains 90.1% of the real-data baseline, and supplementing 200 real images with 600 synthetic ones recovers 92.5% of full-data performance. In a perceptual study with 53 satellite imagery experts, synthetic images were misclassified as real in 20.8% of trials, and all three peacekeeping practitioners consulted stated that they would use the imagery to design training scenarios. The framework is released alongside an open pipeline and a curated dataset of more than 4,300 Horn of Africa image chips with paired segmentation maps and structured captions, offering a pathway for GeoAI in under-represented regions.

KEYWORDS

synthetic training data; training data scarcity; generative GeoAI; humanitarian GeoAI; Digital Earth

1. Introduction

Geospatial artificial intelligence (GeoAI) has become a central strand of Digital Earth research, combining advances in spatial data science, remote sensing, and deep learning to deepen the understanding of dynamic Earth systems [1, 2]. As the field matures and transitions from conventional machine learning toward foundation model-driven frameworks, new possibilities are emerging in spatial data synthesis, autonomous analysis, and knowledge discovery [3]. Yet higher-resolution satellite imagery is not equally available, with developing and underdeveloped regions being less covered [4]. This undermines the ability of GeoAI systems to support high-impact activities such as agriculture and food security, environmental monitoring, security and defense, disas-

ter response and humanitarian aid in the under-served regions, where they are most critically needed.

This inequality is felt acutely in the United Nations peacekeeping training, which relies on realistic satellite imagery to prepare personnel for deployment. For this purpose, the UN Department of Peacekeeping Operations, now the Department of Peace Operations (DPO), uses a fictitious and thus politically neutral country called *Carana*, in which repurposed and recontextualised existing satellite imagery is used, for crisis simulations. These simulations cover critical situations such as conflict resolution, refugee management and disaster response [5]. Nevertheless, the Horn of Africa, which Carana is designed to represent, has limited high-resolution imagery due to constrained commercial revisit intervals, persistent cloud cover, and political sensitivities around the operational use of real geographic data [6]. Furthermore, training scenarios may divert from available imagery. Consequently, the capability to generate realistic synthetic satellite imagery that accurately reflects the terrain of such regions can significantly enhance both training effectiveness and downstream model development.

While AI-generated satellite imagery sits at the intersection of remote sensing, computer vision and geospatial science, the literature has largely prioritised image quality (Section 2); from a GeoAI perspective, however, the relevant questions extend beyond realism to the preservation of geospatial semantics and spatial consistency [7, 8], the controllability of generation [8], and downstream geospatial utility [7, 9, 10]. In this article, besides fidelity to any particular scene, the peacekeeping training and simulation domain requires three further properties: the ability to generate fictitious yet realistic terrain, to avoid operational and political sensitivities; control over the spatial distribution of land cover, to generate training scenarios defined by the arrangement of settlements, routes, and water bodies; and a segmentation map alongside every generated image, to train downstream models using synthetic data under conditions of data scarcity. For the solution to be practically useful, it must also be feasible on modest hardware.

Despite the advances in generative modelling, and considering the idiosyncrasies of the peacekeeping training and simulation domain, several research gaps and opportunities exist. First, regarding the technical framework, LoRA [11] and ControlNet [12] have each been applied to satellite imagery synthesis, and recent work has begun to combine them, either across separate stages for remote sensing sample generation [13] or for reconstruction and unseen-concept generation [14, 15]. Their combination for controllable generation with explicit land-cover conditioning, in support of data-scarce and humanitarian applications, has not been demonstrated. LoRA constrains weight updates to low-rank decompositions, modifying only a fraction of the model’s weights while preserving its pretrained capability [16, 17], allowing an SDXL diffusion model to adopt the spectral and textural characteristics of satellite imagery. ControlNet enables precise spatial conditioning through zero-initialised trainable copies of encoder blocks, letting users specify where features appear without degrading image quality [12]. These methods have each been applied to satellite imagery, and their synergistic combination, where both domain-specific appearance and spatial precision are critical, underpins the framework developed here.

Second, despite the natural-language guidance large language models (LLMs) can provide to generative models, prompt engineering for satellite imagery generation remains largely underdeveloped [18].

Third, prior work is unevenly distributed across geography and application, concentrating on well-resourced regions with dense high-resolution archives, while sparsely covered regions remain largely unstudied and the Horn of Africa is virtually absent

from the literature. Applications are likewise dominated by general synthesis objectives (realistic sample generation, augmentation, cloud or gap reconstruction) rather than domain-specific ones, and no studies have targeted peacekeeping training for humanitarian situations.

Fourth, the field relies primarily on traditional image quality metrics, with limited use of evaluation protocols that incorporate geospatial utility. The lack of standardised benchmarks for synthetic satellite imagery also hampers direct comparison across methods.

Against this backdrop, the contributions of this work are:

- (1) **A ControlNet-LoRA synthetic satellite imagery generation framework:** ConLoRA-Sat combines LoRA for domain-style adaptation with ControlNet for spatial structure on a pretrained Stable Diffusion XL (SDXL) backbone. As far as is known, no prior work has applied LoRA with ControlNet to controllable generation with explicit land-cover conditioning, extending earlier remote sensing work that combined the two in other settings [13–15].
- (2) **Prompt engineering for satellite imagery:** The framework couples a vision-language model that derives standardised structured captions from each scene with a LoRA trigger token, so a single text prompt and the segmentation map together control both domain style and semantic content [19]. This natural-language route to specifying scenarios is evaluated through the training-scenario workflow.
- (3) **Training data for geospatial AI under scarcity:** Synthetic imagery generated under explicit land-cover control can substitute for real acquisitions, retaining 90.1% of real-data segmentation performance as the sole training source and recovering 92.5% from only a quarter of the real imagery, using just 322 images and about 24 A6000-equivalent GPU hours; adapting to a new region costs only retraining the style component (Section 6.1).
- (4) **An open resource for an under-represented region:** An end-to-end pipeline is released with a curated dataset of over 4,300 Horn-of-Africa image chips, paired segmentation maps, and structured captions, supporting humanitarian training and research on geographies that current Earth observation archives cover poorly.
- (5) **An evaluation protocol grounded in geospatial utility:** An evaluation protocol is presented to assess synthetic imagery based on their geospatial utility and expert scrutiny, rather than relying solely on image similarity. It combines downstream segmentation performance and expert evaluation with both standard and domain-specific image quality metrics, aiming to establish a suitable evaluation practice for Earth observation data.

2. Background and Related work

The pursuit of synthetic satellite imagery has moved from physics-based simulation to deep generative models. Early approaches relied on rendering engines such as DIRSIG [20], which modelled the complete imaging chain from atmospheric radiation to sensor response, but required extensive parametrisation and proved difficult to generalise. Statistical texture synthesis [21, 22] offered data-driven alternatives, but struggled to maintain global coherence while producing realistic local textures. Generative Adversarial Networks (GANs) [23] marked a shift toward learning-based synthesis,

which the remote sensing community rapidly adopted. For instance, CycleGAN [24] enabled unpaired translation between satellite sensors, while MARTA GANs [25] targeted terrain-adaptive generation. Nevertheless, GANs frequently suffer from mode collapse, training instability, and well-documented evaluation difficulties [26–28], limiting their reliability for operational use and deployment.

Diffusion models [29, 30] have since reshaped the generative landscape. By learning to reverse a gradual noising process, they achieve more stable training, broader distribution coverage, and finer controllability than GANs. Latent Diffusion Models [31] reduce computational costs by operating in compressed latent spaces, while classifier-free guidance [32] supports effective conditional generation without external classifiers. Large-scale architectures such as Stable Diffusion XL [33] have established new standards for high-resolution synthesis. In the remote sensing domain, Diffusion-Sat [9] recently emerged as the first large-scale generative foundation model for satellite imagery, trained on Functional Map of the World (fMoW) and Sentinel-2 data. Subsequent research has demonstrated the versatility of diffusion models for tasks such as cloud removal [34], change detection from diffusion-derived features [35], and synthetic augmentation for rare land-cover classes [10].

A parallel line of work conditions generation on semantic or spatial structure. Mask-conditional synthesis [7] generates satellite imagery from land-cover masks to train downstream segmenters, while controllable models such as CRS-Diff [8] support multiple conditioning signals. Most recently, a decoupled latent diffusion framework has combined LoRA and ControlNet across separate stages for semantic segmentation sample generation [13]. To date, however, these mechanisms have not been unified within a single jointly-conditioned framework of the kind proposed here.

Beyond scene-level realism, a growing line of work uses generated satellite imagery directly as training data, motivated by the scarcity and cost of annotated real imagery. Mask-conditional synthesis has shown that models trained on synthetic imagery generated from land-cover masks approach the performance of models trained on real data, and that mixing real and synthetic samples can improve results [7]. SatSynth applies diffusion-based augmentation to aerial semantic segmentation, demonstrating gains on the FLAIR dataset [10]. Diffusion-based generation has likewise been adopted in low-data defence domains, where models fine-tuned with LoRA generate additional training imagery that improves military object detection [36], and parameter-efficient adaptation of latent diffusion models has been shown to generate realistic unseen scenes for very-high-resolution SAR imagery [15]. These results support the use of synthetic data as a complement to, or substitute for, real acquisitions where annotated imagery is scarce.

Text-to-image generation adds a further means of control through natural language. Recent frameworks condition remote sensing diffusion models on structured captions or prompts: RSVQ-Diffusion adapts a vector-quantised diffusion model for text-to-remote-sensing image generation [37], CC-Diff enhances contextual coherence in spatially controllable synthesis by coupling text with structural constraints [38], and vision-language models such as Qwen3-VL can derive consistent structured descriptions from imagery [19]. Yet prompt engineering for satellite imagery remains comparatively underdeveloped, and the use of automatically generated structured captions to drive both the style and semantic content of a single generation, as proposed here, has not been systematically explored.

Generative imagery is also increasingly considered for simulation and training, where content must be plausible without necessarily being real. In the defence domain, diffusion-based synthesis has been proposed to generate training imagery for

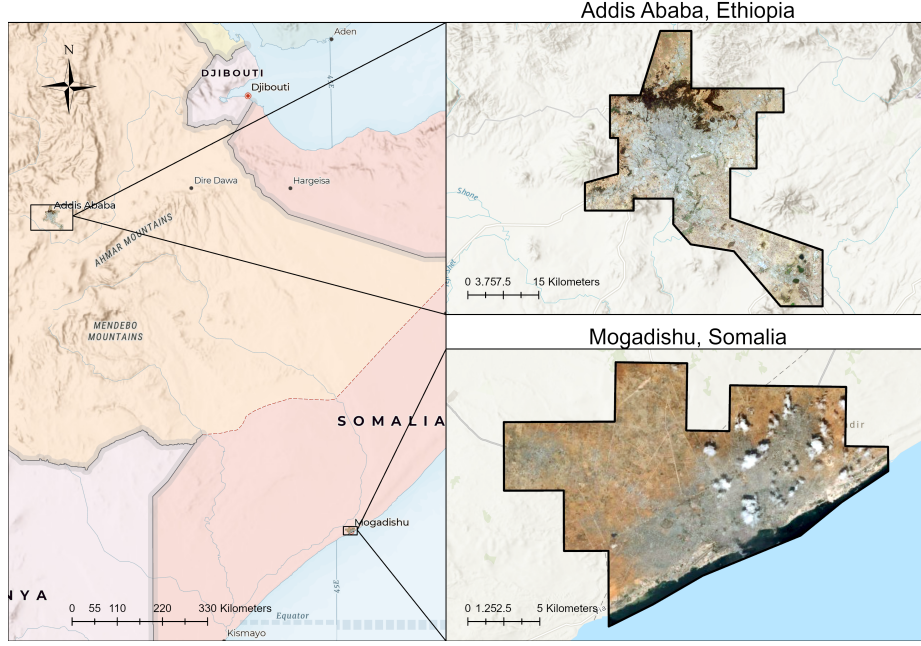


Figure 1. Study area maps: (top) Addis Ababa, Ethiopia ($9^{\circ}1'48''\text{N}$, $38^{\circ}44'24''\text{E}$), and (bottom) Mogadishu, Somalia ($02^{\circ}02'21''\text{N}$, $45^{\circ}20'31''\text{E}$). Both cities represent potential real areas for UN peacekeeping zones in East Africa.

object detection in low-data settings [36], and recent surveys document growing interest in generative AI for military simulation and training [39]. Peacekeeping training, which requires realistic satellite imagery of fictitious terrain so that personnel can be prepared without exposing identifiable real locations [5], belongs to this broader trend. No prior work is known to target the specific combination of parameter-efficient adaptation and spatial conditioning for this application, the five-class segmentation maps used here, or the data-scarce geographies and humanitarian domain that motivate this work.

3. Study area and data

3.1. Study area

Two cities in the Horn of Africa were selected to capture diverse urban characteristics representative of areas where UN peacekeeping operations are deployed (Figure 1). Mogadishu, Somalia, provides a coastal urban environment, while Addis Ababa, Ethiopia, offers a contrasting highland setting with varied building densities and heterogeneous vegetation. Both cities exhibit terrain, architectural styles, and land-cover patterns relevant to Carana training exercises. The current absence of active operations there ensures operational neutrality.

3.2. Data collection and preparation

Mogadishu’s satellite imagery was captured in June 2019 at a Ground Sample Distance (GSD) of approximately 0.5 m. Addis Ababa’s satellite imagery was acquired in

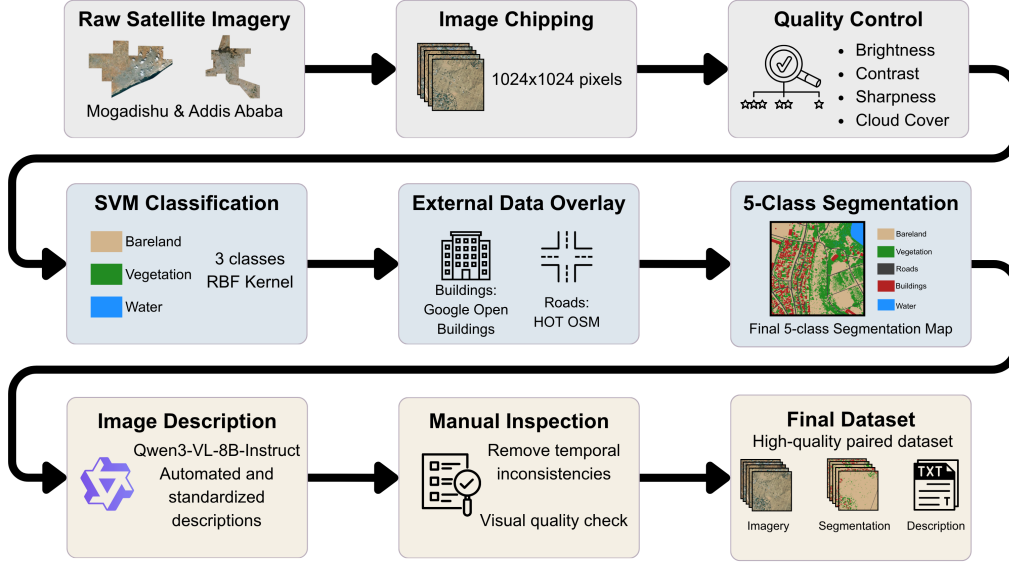


Figure 2. Dataset preparation pipeline, from raw satellite imagery to the final paired dataset of image chips, segmentation maps, and captions.

April 2020 at approximately 0.3 m and resampled to 0.5 m via bicubic interpolation to maintain consistency. Because the imagery (acquired in 2019 and 2020) and the vector datasets reflect different acquisition periods, the layers are not strictly contemporaneous; this temporal misalignment is revisited in Section 6.5. Constructing the corresponding segmentation maps required vector data in addition to the imagery, since buildings and roads cannot be separated reliably from spectral information alone at this resolution. Building footprints were obtained from the Google Open Buildings dataset and road centrelines from the Humanitarian OpenStreetMap Team (HOT). Both cover the study area at continental scale, so their extent does not constrain where chips are sampled. Being geometric rather than raster products, they rasterise to the 0.5 m grid without resampling loss. Positional accuracy, not coverage or scale, is therefore the limiting factor. The Addis Ababa tiles were not fully orthorectified, so residual misregistration between imagery and vector layers introduces a degree of label noise, which is not quantified further here but is revisited in Section 6.5. Building footprints are closed polygons and were rasterised directly. Road centrelines carry no width, so each was buffered by road type in projected coordinates before rasterisation. The buffer gives every road its true width in the conditioning map, so that the model learns to construct a road surface of the correct extent rather than to draw a thin line.

Large satellite scenes were partitioned into 1024×1024 pixel chips (512×512 m at 0.5 m GSD) using random spatial sampling, balanced across both cities. An automated quality control pipeline filtered the chips by brightness, contrast, sharpness, edge density, cloud-like artefacts. All retained chips were visually inspected. Figure 2 summarises the full-data preparation pipeline.

Semantic segmentation maps were produced through a hybrid approach that combines machine learning classification with the external vector data, using each source for the classes it describes best. A Support Vector Machine (SVM) with Radial Basis Function kernel, trained on 50 to 100 manually labelled patches per class, classified bareland, vegetation, and water bodies. The rasterised building and road layers were then overlaid with the SVM output to produce five-class segmentation maps. The resulting classes and their respective RGB encodings, selected for maximum contrast in ControlNet conditioning, are: bareland (#D2B48C), vegetation (#228B22), roads (#404040), buildings (#B22222), and water (#1E90FF).

Standardised image captions were generated with the vision-language model Qwen3-VL-8B-Instruct [19] through a single structured prompt used for every image. The prompt in Listing 1 comprised four description dimensions, a controlled vocabulary, and three example captions.

Listing 1 Structured prompting template used to generate image captions with Qwen3-VL during training.

```
Analyse this satellite/aerial image and provide a concise description (2-3
sentences) covering:
1. Primary land use/scene type (urban, rural, coastal, industrial, etc.)
2. Built infrastructure (buildings, roads - specify paved/unpaved)
3. Vegetation coverage (sparse, moderate, dense)
4. Key features (water bodies, bareland, development density)

Use terminology like: "high/moderate/low building density,"
"sparse/moderate/dense vegetation," "paved/unpaved roads," "bareland,"
"water body."

Examples:
- Urban settlement with central vegetated area surrounded by dense
  buildings. Unpaved roads creating grid pattern. Mixed bareland and
  moderate vegetation throughout residential zone.
- Arid landscape with isolated building clusters and paved road. Sparse
  vegetation on bareland. Minimal development with scattered structures.
- Coastal scene with water body adjacent to urban area. Buildings and
  paved roads visible along shoreline. Minimal vegetation with
  predominantly water and built environment.

Provide a similar factual description for this image.
```

The resulting captions follow a consistent structure and vocabulary. An example reads: “Mixed-use urban settlement with moderate building density, featuring clusters of residential structures along paved main roads. Unpaved tracks connect interior areas where sparse vegetation and patches of bareland are visible between buildings. The eastern portion shows denser development transitioning to open terrain.” This systematic captioning approach addresses a recognised gap in prompt design for satellite imagery generation [18]. Next, captions were attached to every image in the ControlNet training set; for LoRA training, the same captions were used, with the trigger phrase “satellite imagery, aerial view” prepended as an anchor. The final training dataset comprised 322 images for LoRA training (curated for maximum scene diversity), 4,333 image and segmentation pairs for ControlNet training, and 1,002 held-out images reserved for evaluation.

Neither set size was chosen as a target. The 4,333 pairs are every chip that passed quality control and could be matched to a complete segmentation map, and the 1,002 evaluation chips are those remaining after the spatially disjoint split described below.

The 322 LoRA images are the subset that survived manual curation for scene diversity, retaining one representative chip per settlement pattern, vegetation regime, and coastal configuration while discarding near duplicates. Establishing how far it could be reduced would require a dataset size ablation, which is noted as a limitation in Section 6.5.

To reduce spatial leakage between training and evaluation, chip sampling was constrained so that the 1,002 held-out evaluation chips were sourced from regions spatially disjoint from the training chips within each city. Furthermore, chips adjacent to the split boundaries were discarded to ensure total separation. This approach does not constitute a geographic generalisation test, however, which would require imagery from a third city. This limitation is further addressed in Section 6.5.

4. Methods

4.1. Framework overview

ConLoRA-Sat combines two complementary adaptation mechanisms applied to a pre-trained SDXL backbone. LoRA adapts the model’s internal representations to satellite imagery spectral and textural characteristics, while ControlNet enforces spatial structure by conditioning generation on semantic segmentation maps. The two components are trained separately and composed at inference, preventing interference between style adaptation and structural conditioning objectives.

Both mechanisms augment the SDXL backbone itself, which is never updated and supplies the frozen denoising model (i.e., U-Net) and text encoders. LoRA consists of a small set of trainable weights inserted into the backbone’s attention layers, which shift its output toward the appearance of satellite imagery. ControlNet is a trainable copy of the backbone’s encoder that takes a segmentation map and injects spatial structure into SDXL’s frozen decoder.

Figure 3 summarises this architecture at inference time, showing the user input (a text prompt and a hand-drawn 5-class segmentation map), the trained models (LoRA and ControlNet), the SDXL 1.0 backbone, and the synthetic output. The prompt is supplied directly at inference, unlike training, where captions were generated automatically by Qwen3-VL from each image (Section 3.2).

The subsections below successively detail the backbone, each adaptation mechanism and its training, and finally, how they are composed at inference time.

4.2. SDXL backbone

All experiments build on SDXL 1.0 Base [33], a latent diffusion model for native 1024×1024 synthesis comprising a 2.3B parameter U-Net backbone and dual text encoders (CLIP ViT-L/14 and OpenCLIP ViT-bigG/14). A Variational Autoencoder (VAE) compresses images to $128 \times 128 \times 4$ latent representations, an $8 \times$ reduction in each spatial dimension ($64 \times$ in total pixel count). Text conditioning is handled entirely by SDXL’s own encoders, so during training, the captions described in Section 3.2 are consumed by the backbone rather than by LoRA or ControlNet directly.

Both training stages optimise the standard denoising objective:

$$\mathcal{L} = \mathbb{E}_{t, x_0, \epsilon} \left[\|\epsilon - \epsilon_{\theta}(z_t, t, c)\|^2 \right] \quad (1)$$

where z_t is the noised latent at timestep t , ϵ is the noise added during the forward

diffusion process, ϵ_θ is the noise predicted by the network, and c represents conditioning (text prompt for LoRA training; text prompt plus segmentation map for ControlNet training).

4.3. LoRA model training

Low Rank Adaptation. Rather than updating all parameters of the pretrained model, LoRA constrains weight updates to a low-rank decomposition:

$$W = W_0 + \frac{\alpha}{r} BA \quad (2)$$

where $W_0 \in \mathbb{R}^{d \times k}$ is the frozen pretrained weight matrix, $B \in \mathbb{R}^{d \times r}$ and $A \in \mathbb{R}^{r \times k}$ are the trainable low-rank factors with rank $r \ll \min(d, k)$, and α is a scaling factor controlling the magnitude of the update. Matrix B is initialised to zero so that the adapted weights equal the pretrained weights at training start.

LoRA modules were applied to cross-attention query and value projections with rank $r = 32$ and scaling factor $\alpha = 16$; rank and alpha values were chosen after small pilot experiments with $r \in \{16, 32, 64\}$, which indicated diminishing returns beyond $r = 32$. Training used the 322 curated images (selection rationale in Section 3.2) with the Prodigy optimiser [40] for adaptive learning rate management, and minimum signal-to-noise ratio (Min-SNR) loss weighting ($\gamma = 5$) [41] to reduce the contribution of high noise timesteps. Training converged within approximately 4,000 steps (around 2 hours).

4.4. ControlNet model training

ControlNet. Spatial conditioning is achieved by creating a trainable copy of the pretrained U-Net encoder blocks, connected through zero-initialised convolutions:

$$y_c = F(x; \Theta) + \mathcal{Z}_2(F(x + \mathcal{Z}_1(c); \Theta_c)) \quad (3)$$

where $F(x; \Theta)$ is the frozen pretrained block, $F(\cdot; \Theta_c)$ is its trainable copy, c is the conditioning input (segmentation map), and $\mathcal{Z}_1, \mathcal{Z}_2$ are 1×1 convolutions with weights and biases initialised to zero. Because both zero convolutions start at zero, the model’s output is identical to the pretrained model at the beginning of training, and spatial control is introduced gradually as these weights grow, preventing catastrophic forgetting.

ControlNet was initialised by copying SDXL’s encoder path, with zero-initialised 1×1 convolutions added as residual connections injected into the frozen decoder. Training was performed using all 4,333 image and segmentation pairs that passed quality control, optimised with AdamW (learning rate 5×10^{-6} , 500 step linear warm-up, gradient norm clipping at 1.0) and the standard denoising diffusion probabilistic model (DDPM) noise schedule (1,000 timesteps, linear β , ϵ prediction); the remaining settings are given in Table 1. Across both stages the total compute was approximately 24 A6000-equivalent GPU hours: 2 hours on two T4 cards (roughly 1 A6000 hour) plus 22 hours on one A6000. Table 1 summarises the key hyperparameters.

Table 1. Training hyperparameters for the LoRA and ControlNet stages.

Parameter	LoRA	ControlNet
Training images	322	4,333
Resolution	1024×1024	1024×1024
Effective batch size	4	4
Precision	fp16 (VAE fp32)	fp32
Total steps	~4,000	12,000
LoRA rank / α	32 / 16	n/a
Optimiser	Prodigy	AdamW
Learning rate	1.0 (adaptive)	5×10^{-6}
Hardware	2× T4 (16 GB)	1× A6000 (48 GB)
Training time	~2 h	~22 h

4.5. Combined inference configuration

Combined inference. At generation time, the two mechanisms compose as:

$$\epsilon_{\text{ConLoRA}} = \epsilon_{\theta_{\text{LoRA}}}(z_t, t, c_{\text{text}}) + \mathcal{Z}(F_{\text{CN}}(z_t, c_{\text{seg}})) \quad (4)$$

where θ_{LoRA} denotes the frozen SDXL weights augmented by LoRA adaptations, c_{text} is a user-provided text prompt, and c_{seg} is the user-provided segmentation map that specifies where each land-cover class should appear; it can be drawn by the user with a simple raster editing tool, or be a real or previously generated segmentation map, and is processed by the ControlNet encoder. LoRA biases generation toward satellite-specific spectral and textural characteristics, while ControlNet enforces where each land-cover class should appear.

Providing the prompt. The text prompt is written freely by the user in plain language and mirrors the structured captions used during training (Section 3.2). Describing the scene in the same terms the model was trained on produces the most accurate output. The prompt states land use, whether roads are paved or unpaved, vegetation density, and any water bodies or bareland. No fixed template is required. The prompt determines what the scene looks like, and the segmentation map determines where each class appears.

At inference, segmentation maps are processed by the ControlNet encoder for spatial conditioning, text prompts are encoded by SDXL’s dual text encoders, and LoRA weights are applied dynamically (scale 1.0) to attention layers, as illustrated in Figure 3. Images are generated at 1024×1024 using the DPM++ 2M Karras sampler with 50 denoising steps and classifier-free guidance (CFG) scale of 7.5. A dual-pass strategy is used. Land regions use a ControlNet conditioning scale of 1.0 for strict adherence to the layout, while water regions use 0.8. Strong conditioning on water produced unnaturally sharp coastlines and repetitive textures, so the lower scale yields smoother, more plausible transitions. Deployment requires approximately 12.5 GB of storage and between 16 and 20 GB of inference VRAM on consumer-grade hardware.

4.6. Evaluation framework

The hybrid, multifaceted evaluation protocol spans five complementary dimensions. It combines geospatial and downstream utility (dimensions 3 to 5) with traditional visual quality and distributional properties (dimensions 1 and 2). Relying on quality and

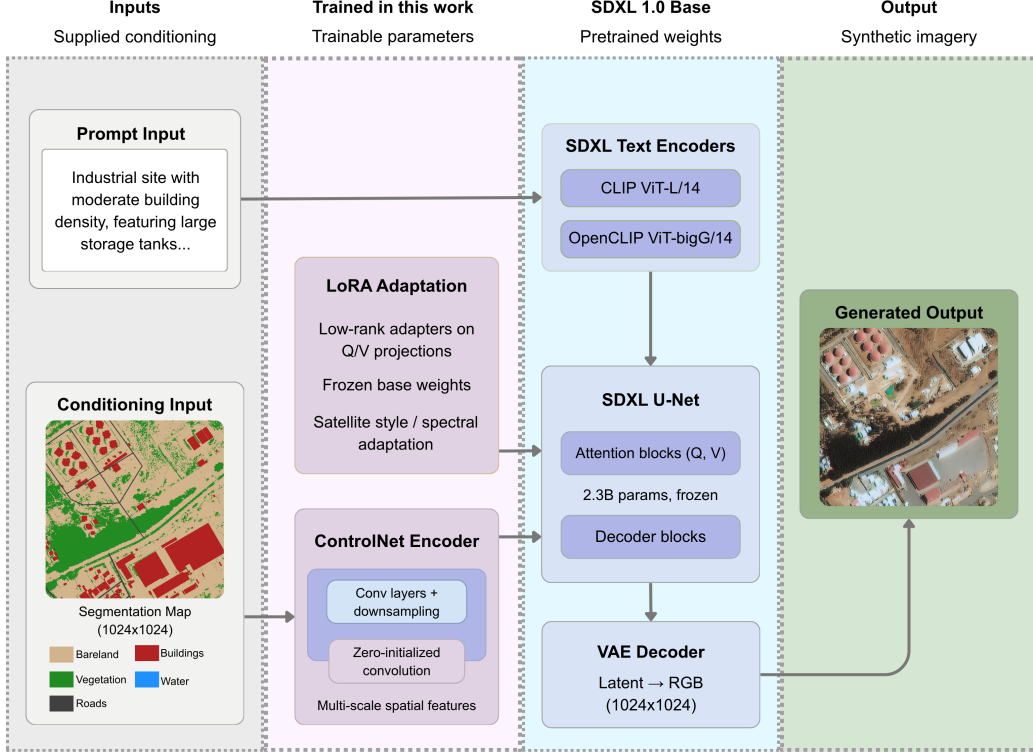


Figure 3. Inference time architecture of ConLoRA-Sat, showing integration of ControlNet spatial conditioning with LoRA domain adaptation on the SDXL backbone.

distributional metrics alone is unsupported by recent benchmarking of Earth observation data quality measures [42], which finds a misalignment between such automatic metrics and human perception of downstream tasks. Downstream task performance and expert judgement therefore carry greater weight. The five dimensions, reported in turn in the Results:

(1) *Standard image quality*: metrics include Fréchet Inception Distance (FID), CLIP Maximum Mean Discrepancy (CMMD) [43], Learned Perceptual Image Patch Similarity (LPIPS), and CLIPScore for text-to-image alignment. An ablation study compares LoRA, ControlNet, and the complete ConLoRA-Sat framework.

(2) *Domain-specific evaluation*: metrics comprise (1) segmentation consistency, computed by running a DeepLabV3+ model trained on real imagery over the synthetic images and evaluating mean Intersection over Union (mIoU) against the segmentation maps used to generate them; (2) spectral fidelity, RGB histogram intersection between real and synthetic image pairs; (3) edge coherence, the F1 score comparing edges from generated imagery against segmentation boundaries; and (4) texture similarity, a Gray-Level Co-occurrence Matrix (GLCM) feature comparison [44]. The individual measures are standard, but no published protocol is known that combines them for synthetic satellite imagery.

(3) *Downstream task evaluation*: it uses four experimental conditions with identical DeepLabV3+ architectures (ResNet-50 backbone, 30 epochs, 200 held-out real test images), selected as a known and reproducible baseline for fair cross-condition comparison: (A) baseline with 800 real images; (B) 800 synthetic only; (C) 800 real and 800 synthetic; and (D) 200 real and 600 synthetic (simulating low resource conditions).

This downstream utility-driven evaluation rigorously assesses synthetic-image quality by measuring their effectiveness for training machine learning models [45].

(4) *Expert evaluation*: participants were contacted by email and asked to provide their informed consent using the online survey tool Tally. The study did not require approval from the university’s ethics committee, as the survey did not collect socio-demographic information from the participants. Fifty-three satellite imagery experts (62.3% with three or more years of experience in the field, 75.5% familiar with AI-generated imagery, 49.1% with prior experience regarding satellite imagery of Africa) conducted a Turing test using 20 images (10 real and 10 synthetic; the synthetic subset was selected via stratified random sampling from the total generation set, covering diverse scene types to avoid selection bias) and evaluated their quality on a 5-point Likert scale across four dimensions. An optional free-text item asked participants to indicate which visual characteristics most influenced their judgments. These responses were analysed with a deductive content analysis and a fixed six-category codebook encompassing colour and spectral cues, texture and smoothing, geometric and structural cues, water boundaries, overall plausibility, and residual observations.

(5) *Application-domain evaluation*: a complementary survey was conducted with peacekeeping practitioners themselves, who are the intended end-users of the framework. Three participants with direct experience in peacekeeping or peacekeeping training (two with over ten years of experience and one currently active) were consulted to assess the training scenarios generated and the sketch-to-image workflow. This evaluation differs from the previous one (4): instead of asking remote sensing specialists whether generated images are technically plausible (i.e., realistic), operational practitioners are consulted on whether the images are useful for training tasks.

5. Results

5.1. Standard image quality

To validate each architectural component, an ablation study with three configurations on 1,002 held-out test images was performed (Table 2). LoRA alone achieves the lowest CMMD (0.034), indicating effective style transfer, but produces poor structural alignment (LPIPS = 0.640) because text prompts alone cannot enforce spatial layout. ControlNet alone provides substantially better structural control (LPIPS = 0.490) but lacks spectral refinement: its CMMD of 0.063, against 0.034 for LoRA alone, is an 85% higher distributional discrepancy in the metric most sensitive to colour and tone. The combined ConLoRA-Sat framework achieves the best overall performance, reducing FID by 9.1% relative to LoRA alone and 5.2% relative to ControlNet alone.

Two reasons cause all three FID values to lie well above the range typically reported for SDXL-class models: FID uses ImageNet-pretrained Inception-v3 features that under-represent the textural and spectral statistics of overhead imagery [43], and the test distribution is narrow (two cities, 0.5 m, RGB only), so small distributional shifts inflate it. This unreliability is not particular to satellite imagery: SDXL likewise scores worse on COCO zero-shot FID than earlier Stable Diffusion models despite being preferred by human assessors, a known negative correlation between FID and aesthetics [33]. FID is therefore treated as an internal comparison metric, and primary weight is placed on the domain-specific and downstream metrics below. Figure 4 shows representative generation results, and Figure 5 presents a qualitative comparison of the three configurations. In both figures the real imagery is shown only as a visual

Table 2. Ablation study: quantitative comparison of architectural configurations. Arrows indicate preferred direction.

Configuration	FID↓	LPIPS↓	CMMD↓	CLIPScore↑
LoRA only	110.98	0.640	0.034	0.249
ControlNet only	106.44	0.490	0.063	0.246
ConLoRA-Sat	100.88	0.474	0.061	0.248



Figure 4. Representative results across diverse scene types: real satellite imagery (top), segmentation maps (middle), and ConLoRA-Sat generated imagery (bottom).

reference for what 0.5 m imagery looks like. Each generated image is a new scene produced from the segmentation map alone and is not intended to match the real image alongside it; the figures should therefore be read as evidence of spatial agreement with the conditioning map and of visual realism, not of reproduction of the real scene.

5.2. Domain-specific evaluation

A DeepLabV3+ model (ResNet-50 backbone) trained on 1,000 real chips (mIoU = 0.623 on a 200-image validation set) was applied to 1,000 synthetic images, with predicted segmentations compared against the original segmentation maps. The overall segmentation consistency score, computed as the ratio of synthetic to real mIoU, reaches 89.0%, indicating strong preservation of semantic structure. Per-class analysis, Table 3, shows that roads and buildings achieve higher IoU on synthetic imagery than on real imagery, consistent with the generation process producing cleaner class boundaries for built infrastructure. Water bodies exhibit the largest degradation (-0.228), likely because the diffusion model’s learned priors about gradual water transitions conflict with the hard boundaries specified in segmentation maps. The low road IoU of 0.169 on real imagery shows that the segmenter itself struggles to detect roads even in real-data. The road figures in Table 3 therefore carry large uncertainty and should not be read as a precise measure of conditioning adherence for this class.

Spectral fidelity, assessed via histogram intersection between 500 real and synthetic pairs, yielded a score of 62.4%, the weakest domain-specific metric. Synthetic imagery



Figure 5. Qualitative ablation: real imagery, segmentation maps, and generation results from LoRA only (text prompt), ControlNet only, and ConLoRA-Sat across diverse scenes.

exhibits a systematic rightward shift in peak intensities across all RGB channels, particularly the blue channel, consistent with known colour palette differences between diffusion models pretrained on natural images and satellite sensors [9]. Edge coherence ($F1 = 67.1\%$; recall 77.5% , precision 63.0%) confirms that conditioning boundaries are reliably rendered, with additional detected edges reflecting internal texture variation that enriches visual realism. GLCM-based texture similarity of 75.5% indicates that the majority of texture patterns are captured, though elevated contrast and homogeneity values suggest some smoothing in generated outputs. Table 4 summarises all domain-specific metrics.

5.3. Downstream task evaluation

Regarding the downstream task evaluation, Table 5 presents segmentation performance across four experimental conditions, all evaluated on 200 held-out real images (Figure 6).

Experiment A, a model trained on 800 real images, reaches mIoU 0.521 and establishes the reference point to which all percentages below are relative (computed from unrounded values before the rounding in Table 5). A model trained exclusively on synthetic imagery retains 90.1% of this baseline (Experiment B). The imagery therefore transfers to real-world segmentation despite the model never observing real satellite data during training. Augmentation with synthetic imagery exceeds the real-data baseline by 2.0% (Experiment C), consistent with the framework providing complementary training signal through controlled variations. Most critically, using only 200 real images

Table 3. Segmentation consistency: per class IoU on real versus synthetic imagery.

Class	Real IoU	Synthetic IoU	Difference
Water	0.955	0.727	−0.228
Bareland	0.870	0.820	−0.050
Vegetation	0.727	0.564	−0.163
Roads	0.169	0.190	+0.021
Buildings	0.396	0.467	+0.072
Mean IoU	0.623	0.553	−0.070

Table 4. Summary of domain-specific evaluation metrics.

Metric	Score	Assessment
Segmentation consistency	89.0%	Strong
Spectral fidelity	62.4%	Moderate
Edge coherence (F1)	67.1%	Good
Texture similarity	75.5%	Good

(25% of baseline) supplemented with 600 synthetic ones recovers 92.5% of full-data performance (Experiment D).

Differences of 0.01 to 0.02 mIoU are small relative to the scale of the metric. The 2.0% augmentation improvement and the 92.5% low-resource recovery are therefore best read as directional evidence rather than as precise effect sizes.

5.4. Expert evaluation

The 53 participants in dimension 4 (Section 4.6) achieved an overall accuracy of 75.1% across the 1,060 classifications (15.0 correct of 20 per participant). Because each participant contributed 20 correlated observations, all inferential tests were computed on participant-level values rather than individual judgements. A one-sample Wilcoxon signed rank test confirmed that accuracy exceeded chance ($p < 0.001$, $r = 0.855$). The fooling rate, defined as synthetic images mistakenly classified as real, was 20.8% (95% CI: 16.8–24.8), so approximately one synthetic image in five passed expert inspection. However, fooling rates differed by scene type, reaching 26.4% for rural scenes against 17.6% for urban and 16.4% for coastal scenes (Figure 7).

Each participant also rated five generated images on four dimensions, scored on an ordinal scale from 1 (clearly deficient) to 5 (convincingly realistic) and averaged across the five images. Mean ratings were: colour and tone accuracy 2.99 ± 0.73 , overall realism 2.94 ± 0.67 , structural accuracy 2.84 ± 0.65 , and surface texture quality 2.77 ± 0.69 . Although the ordering of means places colour highest and texture lowest, consistent with LoRA capturing spectral characteristics more successfully than fine texture, the differences are within measurement noise at this sample size. The ranking is therefore not interpreted as evidence of dimension-specific behaviour. What the ratings suggest is that all four dimensions cluster near the midpoint of the scale, indicating imagery that experts judged neither clearly deficient nor convincingly realistic.

In addition, participants provided free-text descriptions of the cues that informed their judgements (Figure 8). Geometric and structural cues predominated: of the 41 participants who provided free-text responses, 75.6% (31) mentioned these aspects,

Table 5. Downstream task results: segmentation mIoU for models trained on different data compositions. Relative-to-baseline percentages (Section 5.3) are computed from unrounded mIoU values before the three-decimal rounding shown here.

Exp.	Condition	Real	Synthetic	mIoU
A	Baseline (real only)	800	0	0.521
B	Synthetic only	0	800	0.469
C	Augmentation	800	800	0.531
D	Low-resource	200	600	0.482

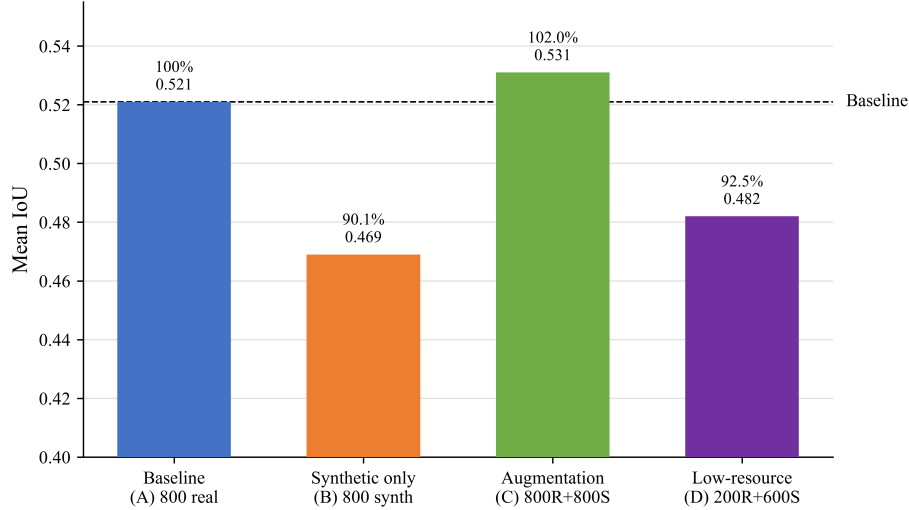


Figure 6. Downstream task performance across training configurations.

noting implausible building outlines, discontinuous roads, and excessive regularity in the built environment; one participant noted that when the model generated urban areas “it missed straight lines of the roofs”. Texture and smoothing was the second most frequent theme at 56.1%, typically described as an absence of sensor noise or an unnaturally homogeneous surface, with one respondent observing that large man-made areas “appear very homogeneous in terms of texture and colour”, which “is rather uncommon in reality”. Colour and tone was raised by 43.9%, consistent with the spectral fidelity of 62.4% reported in Section 5.2. Water bodies and coastlines were mentioned by 12.2%, all referring to an unnaturally flat sea surface, and a further 22.0% identified shadow direction, lighting, and contrast inconsistencies that fall outside the four rated quality dimensions. Only 7.3% stated that they found the imagery broadly convincing, although these respondents reported that no single reliable discriminating criterion was available to them.

5.5. Application-domain evaluation

To evaluate dimension 5 (Section 4.6), which focused on application domain practitioners, five training scenarios were generated covering various types of settlements, ranging from coastal urban areas to rural homesteads in densely forested areas (Figure 9). Each scenario was created by specifying a new segmentation map, rather than by acquiring new imagery. This shows how trainers can generate diverse conditions for

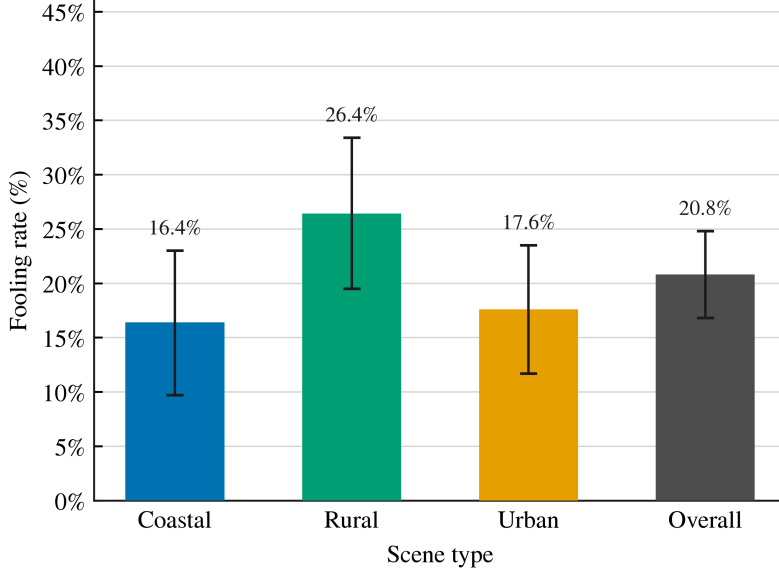


Figure 7. Fooling rates by scene type across 53 experts, with 95% CI computed at participant level. Differences between scene types are not statistically significant.

humanitarian training exercises. This section also describes how these scenarios and the underlying sketch-to-image workflow were assessed by peacekeeping practitioners.

The segmentation maps for these five scenarios were drawn using the class colour codes from Section 3.2. A generative model arranged buildings, roads, vegetation, and water bodies into a plausible layout for each one. Each scenario is then generated from its segmentation map and a text prompt (Section 4.1). Generating the map itself this way is a convenience rather than a requirement. Because conditioning depends only on the class colours and the prompt, an equivalent map can be drawn by hand in any basic paint application, with no geospatial software or source imagery.

The practical benefit is that the scenario is specified before the imagery exists. Trainers set settlement density, road layout, vegetation cover, and water placement directly, and each generated scene comes with the segmentation map that produced it. Exercise material can therefore be prepared for any chosen terrain without commissioning satellite imagery or obtaining overflight permissions. Because the land-cover is approximately known by construction, the same scenario can serve both as exercise imagery and as labelled data for training downstream models.

The three practitioners (trainers) consulted stated that, given appropriate training, they would use the tool for scenario design. Two considered the imagery realistic enough for training exercises (one reported minor issues, the one moderate ones), and two believed that such AI-generated images could be used for peacekeeping training in general. The third respondent, while more cautious, indicated that he would use them subject to proper training. One respondent with a decade of operational experience described the imagery as “very realistic” and encouraged the work to continue.

The survey also surfaces concrete requirements that frame the remaining gaps. The most experienced respondent described the desired workflow as generating imagery “directly based on textual information” rather than from a hand-drawn sketch, and asked for contiguous, tileable generation: “there should be a step where starting from one image the AI could generate a neighboring image,” with output covering “at least

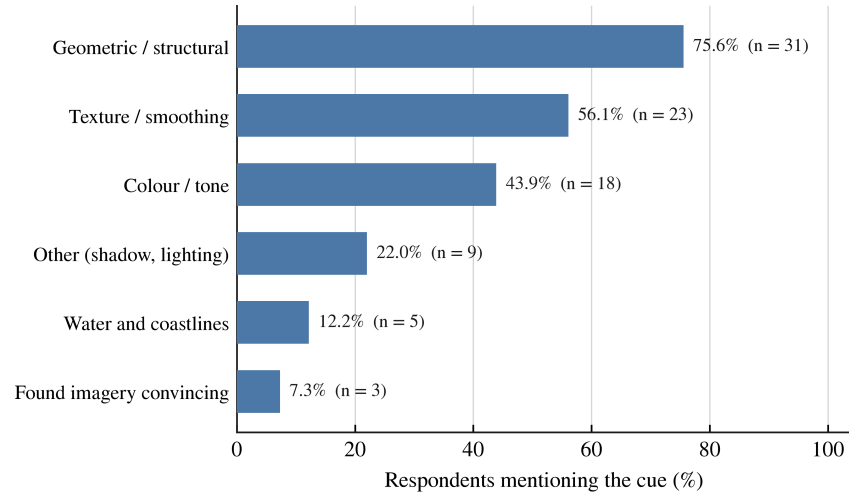


Figure 8. Visual cues reported by experts in free text responses, as a percentage of the participants who answered the optional item.

an entire city and its suburbs.” Training tasks that respondents considered within reach include “detailed patrol planning, identifying choke points, and reporting points,” object placement for analyst exercises, and “exercises for troops.” These responses indicate that the scenario generation capability is considered useful in its current form, but that its practical implementation requires a text-driven specification, larger area coverage, and seamless tiling.

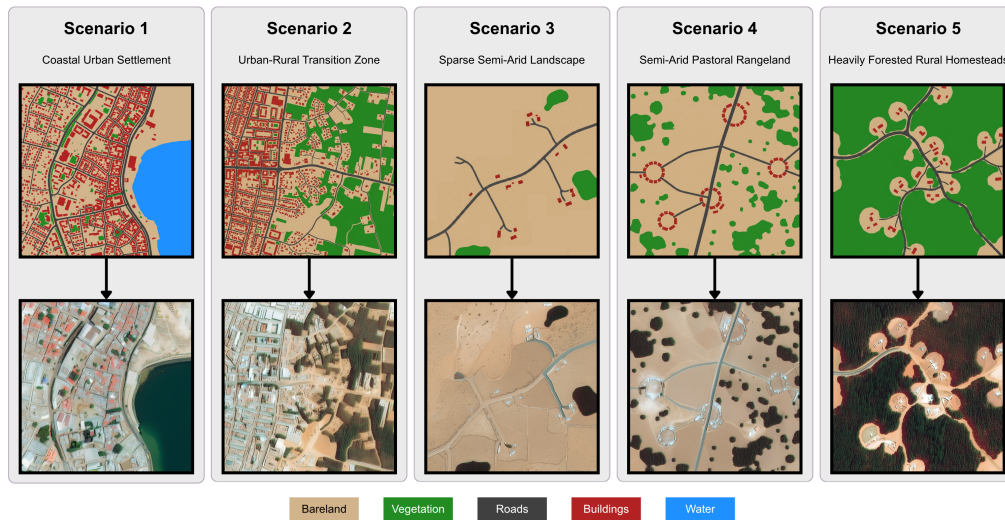


Figure 9. Five generated training scenarios with the segmentation maps used to produce them.

6. Discussion

6.1. Complementarity of LoRA and ControlNet

The ablation study (Table 2) shows that LoRA and ControlNet make complementary, non-redundant contributions, confirming that domain-style adaptation and spatial conditioning are separable objectives. The modularity carries practical advantages. ControlNet (about 22 hours of training) can be reused unchanged for any region whose spatial structure resembles the training areas, so only the LoRA weights need retraining, which is feasible on consumer-grade hardware. Transferring to a similar region, such as a nearby city, requires roughly 300 curated chips and about two hours on two mid-range GPUs. A substantially different urban or landscape style would need new ControlNet data. The five land-cover classes are not specific to the Horn of Africa, so the conditioning scheme transfers directly, making the framework a replicable method rather than a single fitted model.

6.2. Implications for GeoAI in data-scarce regions

The downstream task results provide the strongest evidence of practical utility. Synthetic-only training retains 90.1% of real-data performance, which compares favourably with augmentation studies in other domains, where synthetic data typically achieves 70–85% of real-data effectiveness [18]. Most significantly, the low-resource result directly addresses peacekeeping training in regions without comprehensive satellite coverage.

For humanitarian training, limited reconnaissance imagery can be supplemented with synthetic data to build complete training sets, while fictitious yet realistic configurations preserve operational security. The 89.0% segmentation consistency means generated imagery reliably depicts specified land-cover. Trainers control infrastructure placement, vegetation density, and terrain configuration. Every scene comes paired with its segmentation map, which real imagery does not provide.

The implication extends beyond this application. Wherever labelled imagery rather than model capacity is the bottleneck, the same substitution applies: a segmenter trained largely on constructed, pre-labelled data reached most of the accuracy of one trained on real acquisitions. This reverses the usual Earth observation order in which imagery is acquired and then annotated at considerable expense. The results also bound this substitution. The generated imagery is spectrally shifted, so radiometric tasks remain out of reach, and the class vocabulary is only as rich as the conditioning schema. Within those bounds, the ability to construct labelled coverage for regions that Earth Observation archives under-serve is the contribution most likely to generalise beyond this case.

6.3. Perceptual plausibility

The expert evaluation was a substantial perceptual study rather than an indicative check: fifty-three experts made 1,060 judgements, 530 on synthetic imagery, enough for interval rather than point estimates. Two findings pull in opposite directions. First, experts identify synthetic imagery reliably and with a large effect size, so it is not perceptually indistinguishable from real acquisitions and should not be described as such. Second, the fooling rate of 20.8% falls within a narrow interval (16.8–24.8%), so roughly one synthetic image in five passes expert inspection. For the intended applica-

tion, this second number is the more informative: training material need not deceive a specialist actively searching for generation artefacts under forced-choice conditions, but must represent an environment that behaves realistically for exercise participants, whose attention is on the scenario rather than the images.

Two further observations bear on deployment. Plausibility varies far more across individual synthetic images (3.8–50.9%) than across scene categories, suggesting that it is driven by specific scene content rather than broad terrain class, and that curating generated output would raise effective plausibility more than adjusting the scene mix. Experts’ free-text comments indicate where improvement should be focused: improving building outlines and road continuity addresses the dominant detection cue (Section 5.4). The quality ratings, by contrast, cluster near the scale midpoint with no significant differences between dimensions, so they offer no basis for prioritising one dimension over another.

The application-domain survey adds the end-use perspective. Where satellite imagery experts focused on rendering, peacekeeping practitioners, who would actually operate the framework, focused on whether it supports a training task. All three practitioners said they would use the tool for scenario design given appropriate training, and two considered the imagery realistic enough for a training exercise. The requirements they raised align with and extend the technical limitations identified above. The request for imagery generated “directly based on textual information” reinforces the role of prompt engineering developed here, and the demand for contiguous coverage of “at least an entire city and its suburbs” identifies tiling scalability as the main operational gap. This convergence between a technical limitation and an end-user requirement supports the relevance of the framework and gives future work a clear, practitioner-grounded priority.

6.4. Comparison with related work

The approaches more closely related to ConLoRA-Sat are discussed in Section 2. ConLoRA-Sat differs from them in three key respects.

First, it combines LoRA and ControlNet for controllable synthetic satellite imagery with explicit land-cover conditioning. The two mechanisms provide complementary style and structure control that neither achieves alone. They have been combined in related remote sensing studies on the reconstruction and generation of unseen concepts [14, 15], but their use for controllable generation of the type developed here remains largely unexplored.

Second, the parameter-efficient approach requires only approximately 24 A6000-equivalent GPU hours. By comparison, DiffusionSat trains its single-image base model on eight NVIDIA A100 GPUs for 100,000 iterations at batch size 128, and trains each ControlNet variant separately on four A100 GPUs for a further 40,000 to 50,000 iterations [9]. Because wall-clock times are not reported, the two budgets cannot be reduced to a single comparable figure. The difference in hardware scale is nonetheless what separates adapting a general-purpose backbone from training a domain foundation model, and it places the approach within reach of groups without high-performance computing facilities.

Third, the explicit focus on data-scarce humanitarian contexts addresses an application need absent in prior work.

A direct numerical comparison with these systems is deliberately not reported, because it would be misleading: they operate on different sensors and resolutions (Diffu-

sionSat on Sentinel-2 multispectral imagery, SatSynth on the French FLAIR dataset, and ConLoRA-Sat on 0.5m RGB imagery of two East African cities), and none is driven by a five-class segmentation map of the kind used here. The metrics are defined relative to a reference set and class schema, so cross-dataset comparison is hard to defend, and benchmarking shows ImageNet-pretrained features are unreliable indicators for Earth observation imagery [42]. A fair comparison would require a shared conditioning protocol and a common held-out set; no such benchmark yet exists for conditional satellite imagery synthesis, and the evaluation protocol proposed here is intended to help establish one.

6.5. Limitations

The most significant limitation is spectral fidelity (62.4%). The RGB-only SDXL architecture cannot generate multispectral imagery, and blue-channel intensities are systematically shifted. The framework therefore supports visual and structural tasks, not radiometric ones such as vegetation indices or radiometric change analysis.

The Addis Ababa imagery was resampled from about 0.3m to 0.5m and was not fully orthorectified. Resampling smooths high-frequency texture that the LoRA may learn as a “satellite” property, and residual misregistration with the vector layers adds label noise beyond the temporal misalignment noted in Section 3.2.

Structural consistency is the main generation weakness, as urban and coastal scenes exhibit lower fooling rates than rural ones. Three-quarters of commenting experts cited implausible building outlines or discontinuous roads, and slightly over half mentioned unnaturally homogeneous surfaces (e.g., water bodies, large man-made areas) as a basis for identifying synthetic imagery. The scene-type differences are not individually significant, but the two lines of evidence converge.

The framework has limited scope in four respects. It generates single images without temporal consistency, which rules out change-detection training. The fixed 1024×1024 output (about 500×500 m) limits coverage without tiling. The surveyed practitioners name this as the main barrier to operational use. The downstream experiments use a single ResNet-50 DeepLabV3+ backbone, so whether the 2.0% augmentation gain holds for other dataset splits and backbones remains untested. The LoRA training set size was not varied; 322 images are sufficient for domain adaptation but are not shown to be minimal before style adaptation degrades.

Finally, the dual-use character of this work is acknowledged: plausible satellite imagery could support disinformation or fabricated evidence. The released dataset is restricted to fictitious scenarios over areas without ongoing operations; a use-restricted licence is proposed for the trained weights, and users are encouraged to embed meta-data identifying synthetic origin.

7. Conclusions

This paper presented ConLoRA-Sat, a parameter-efficient framework that generates synthetic satellite imagery by combining LoRA and ControlNet with SDXL. SDXL provides the generative capability, LoRA imprints spectral and textural characteristics, and ControlNet enforces spatial structure. Trainers generate a realistic scene from a five-class segmentation map and a text prompt, and the modular design allows adaptation to new regions with minimal retraining.

The multi-faceted evaluation shows that modest computational resources suffice for

effective synthesis in data-scarce contexts. Generated imagery reaches 89.0% segmentation consistency and retains 90.1% of real-data performance in downstream segmentation tasks. It recovers 92.5% of full-data performance with only 25% real-data.

Experts still detect most synthetic images (20.8% fooling rate), mainly through artefacts in building outlines and road continuity, yet the peacekeeping practitioners consulted said they would use the framework to design training scenarios. The images therefore have genuine geospatial utility even though they do not deceive a specialist under forced-choice conditions.

The wider consequence concerns who can build geospatial models. Shared representations of the planet grow quickly where data acquisition is commercially and politically easy, and the least-covered regions are often those where analysis would yield the greatest humanitarian value. Generating labelled imagery with explicit land-cover control does not resolve this imbalance, but it makes training data attainable where imagery is sparse.

Future work should first address the practitioners' needs: seamless tile-based generation over contiguous areas and text-driven scenario specification. Beyond these, multispectral and temporally consistent generation, a richer class vocabulary (e.g., temporary structures, vehicle concentrations, agricultural patterns), and standardised benchmarks for synthetic satellite imagery would broaden the range of Earth observation tasks ConLoRA-Sat can support.

Author contributions (CRediT)

Seyed Amir Muhammad Qureshi: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing, Original Draft, Visualization. **Carlos Granell:** Methodology, Investigation, Validation, Writing, Supervision. **Sven Casteleyn:** Methodology, Investigation, Validation, Writing, Supervision.

Disclosure statement

The authors report that there are no competing interests to declare. The views, findings, interpretations, and conclusions expressed in this article are those of the authors and do not necessarily reflect the views or policies of the United Nations, the United Nations Global Service Centre (UNGSC), or any UN Member State. Any reference to the United Nations Department of Peace Operations or the Carana training scenario is included for academic and illustrative purposes only and does not constitute an official UN position, product, model, or endorsement.

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Declaration of generative AI use

Generative AI was used in two capacities in this work. First, as a research instrument: Stable Diffusion XL 1.0 Base, Low-Rank Adaptation, ControlNet, and Qwen3-VL-8B-Instruct were used to generate and caption the synthetic satellite imagery that is the subject of this study. Second, in manuscript preparation: Claude (Anthropic) was used for copyediting and language refinement of the manuscript text, and Claude and Claude Code (Anthropic) and ChatGPT (OpenAI) were used to assist with drafting and debugging software code. Generative AI was not used to develop the argument or to draw conclusions. The manuscript’s diagrams and charts were drawn manually, and no generative AI was used to generate or suggest references.

All AI-assisted content, including text and code, has been reviewed by the authors for originality and accuracy. The authors have checked the terms of use of the tools named above and confirm their suitability for publication. The authors take full responsibility for the integrity of the entire content.

Data availability statement

The data (paired image chips, segmentation maps, and structured captions) that support the findings of this study are openly available in Zenodo at <https://doi.org/10.5281/zenodo.22747581>. The data and code (model weights, training scripts, evaluation code, inference examples) that support the findings of this study are available from the first author upon reasonable request.

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