

# The Change You Want To Detect: Semantic Change Detection In Earth Observation With Hybrid Data Generation

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## Abstract

*Bi-temporal change detection at scale based on Very High Resolution (VHR) images is crucial for Earth monitoring. This remains poorly addressed so far: methods either require large volumes of annotated data (semantic case), or are limited to restricted datasets (binary set-ups). Most approaches do not exhibit the versatility required for temporal and spatial adaptation: simplicity in architecture design and pretraining on realistic and comprehensive datasets. Synthetic datasets are the key solution but still fail to handle complex and diverse scenes. In this paper, we present HySCDG a generative pipeline for creating a large hybrid semantic change detection dataset that contains both real VHR images and inpainted ones, along with land cover semantic map at both dates and the change map. Being semantically and spatially guided, HySCDG generates realistic images, leading to a comprehensive and hybrid transfer-proof dataset FSC-180k. We evaluate FSC-180k on five change detection cases (binary and semantic), from zero-shot to mixed and sequential training, and also under low data regime training. Experiments demonstrate that pretraining on our hybrid dataset leads to a significant performance boost, outperforming SyntheWorld, a fully synthetic dataset, in every configuration. All codes, models, and data are available here: <https://yb23.github.io/projects/cywd/>.*

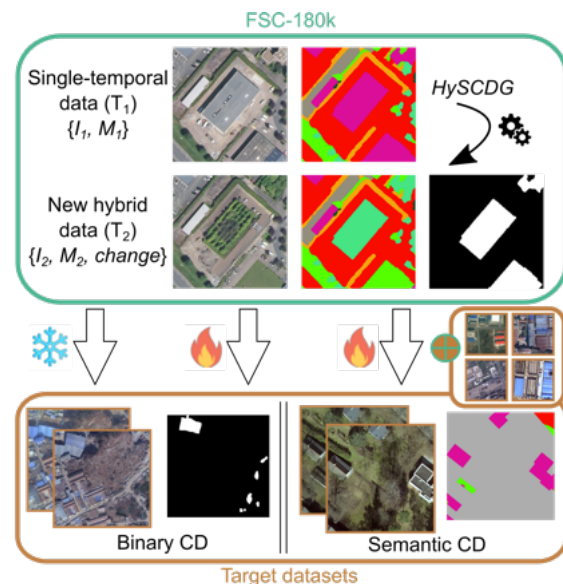


Figure 1. **Efficient and scalable change detection** requires a comprehensive training dataset that does not exist today. Using a single-temporal dataset (image+semantic map), we propose HySCDG that generates a **novel bi-temporal hybrid dataset** FSC-180k. This enables multiple transfer learning possibilities on either binary and semantic change detection tasks. 🔥/❄️: Transfer with/without fine-tuning our model, respectively.

## 1. Introduction

Efficient methods for change detection (CD) are crucial for monitoring territories and the various phenomena and activities that impact them [3]. As human and climatic pressures increase, this topic is of utmost importance and calls every year for higher spatial resolution and semantic accuracy [55]. Change detection at scale has benefited greatly from the contributions of deep learning in recent years [7, 12, 69, 73], but most methods are grounded on large volumes of annotated data [41, 60]. Creating a large-scale dataset for bi-temporal (pair-wise) remote sensing change detection poses signifi-

cant challenges and costs, especially when dealing with Very High Resolution (VHR) images (ground sampling distance: GSD <1 m, [30]). This is due to the need for expertise and considerable effort in collecting, preprocessing, and annotating images [59, 62], particularly in the case of VHR data and multiple labels (termed *semantic change detection*, SCD) [57, 61, 70, 74].

As an alternative, synthetic data generation is a promising direction for bi-temporal labeled data provision from a single temporal domain that is successful in diverse areas such as urban sprawl [17], disaster or climate change monitoring [42] or crop mapping [36]. Two main paradigms exist for CD: fully synthetic datasets (mainly graphics-based

[27, 53]), and hybrid solutions that mix real and modified images, often at the instance level [5, 69, 71], known as *data augmentation*. The first method synthesizes image pairs by rendering two versions of a 3D virtual world thanks to a computer graphics engine. On the other hand, hybrid approaches synthesize new image pairs by pasting or erasing object instances into existing images (*inpainting*). They propose a suitable trade-off and faster generation of large quantities of data, with likely higher realism. However, none of these solutions meet the requirements for scalable SCD with VHR imagery (Tab. 1): focus on single tasks, restricted geographical areas, limited diversity, no guarantee on semantic consistency between pairs [48] and subsequently poor transfer to real datasets. To address this challenge, we introduce a generative pipeline built upon Stable Diffusion [44] and ControlNet [65], designed to harness an existing VHR semantic land cover dataset [18] and instance masks, to generate an extensive hybrid semantic bi-temporal change detection dataset encompassing both real and inpainted images, semantic land cover maps at each date, and a change map (Fig. 1). Then, we evaluate the transferability of our synthetic dataset on five datasets for both binary and semantic change detection cases ranging from zero-shot to sequential and mixed training set-ups, as well as under low-data regime.

Our contributions are as follows:

- We present a **generation pipeline** *HySCDG* for creating VHR bi-temporal SCD datasets based on a land cover real-world dataset by using Stable Diffusion and ControlNet with tunable and semantically-guided inpainting of individual objects. It can be easily configured or finetuned on any land-cover dataset, generating images with the dataset's distinctive traits.
- We provide *FSC-180k*: a **Hybrid Semantic Change Detection pretraining dataset**, created from FLAIR [18] along with the instance masks for 300k objects for the corresponding images.
- We provide a comprehensive evaluation of the proposed synthetic dataset on multiple transfer learning scenarios on five change datasets, in particular for SCD.

## 2. Related work

**Detecting changes in the deep learning era.** We target bi-temporal land cover change detection in VHR images [32]. This historical task [22, 37, 52] consists in detecting the *meaningful* elements of a given area that have changed between two acquisitions and providing the land cover categories at each period (also known as *change trajectory*). It presents challenges: radiometric variations, geometric variations and non permanent changes. They have been extensively addressed with supervised deep learning techniques [70]: from CNN [11, 12, 64] to Transformers [2, 7, 13, 55, 72, 73], mainly with Siamese architecture. Multiple datasets, accompanied with ad-hoc methods, have been

created to feed such models. They are often limited by their size [6, 25, 39, 56, 63], geographical extent [6, 56, 57, 63], low geometrical or annotation quality [11]. Also, most of the effort focuses on binary change detection, *i.e.*, restricted to a unique category, mainly *buildings* [6, 25, 39, 40, 50] or *disasters* [67]. Such scarcity in high quality, diverse, large-scale labels is alleviated with transfer learning [4, 51], by fine-tuning models pretrained on large-scale datasets for different image domains, even for semantic change detection [56, 57, 63].

### Synthesizing and inpainting remote sensing images.





*Synthetic* remote sensing data is useful *e.g.*, for cloud removal [10], image restoration [16], or training deep supervised models [58], before transfer to real examples. Solutions based on patches, [35, 68], autoencoders [23], GAN [28, 34], -aligned generation [24] have been proposed, but with limited image quality and no semantic control. Diffusion models (DM) have improved such quality [44], but most models have applied DM directly on mid-resolution RGB images [14, 26, 58], neglecting both the multi-spectral dimension [9] and VHR spaces. However, a key finding remains: semantically control the synthesis, *e.g.*, by directly synthesizing text [26], semantic maps [58] or with a control module guided by edges [9], semantic maps [14] or metadata [26]. In our work, we fine-tune a Stable Diffusion and a ControlNet models to achieve semantically-controlled inpainting of VHR images as a basis to take advantage of existing images, and generate an hybrid semantic change detection dataset at scale and with high diversity.
















**Generating synthetic change datasets.** Two main approaches exist: fully synthetic or hybrid solutions. The first paradigm leverages advanced 3D rendering engines to create fully synthetic datasets [17, 27]. This procedural approach allows complete control over rendering parameters (instance placement, semantic classes, lighting conditions, etc.) generated from scratch. *E.g.*, SyntheWorld [53] effectively leverages DM prompted by GPT-4 to create a diverse and large-scale fully synthetic dataset. On the other hand, hybrid approaches generate (semi-)synthetic data by inserting fake changes into real images.

Such modifications can be random crops [49], instance copy-pasting, or inpainting made by GAN [5, 49, 71] or DM [54, 69]. Blending or style transfer methods are often used to enhance diversity [5, 49].

A pivotal challenge is the semantic guidance: modifying few elements of images to mimic real scarce changes, *e.g.*, with instance footprints extracted from external datasets [5] or segmentation model outputs [69]. [54] adopt a Denoising diffusion probabilistic model to generate a new image directly from a modified semantic map and a degraded version of the corresponding snapshot. Changen2 [69] is the closest

work to ours, with a full pipeline to synthesize a hybrid semantic dataset, again with a DM conditioned by a semantic map. However, Changen2 creates synthetic data specific to a given target dataset in terms of image resolution, size, or change characteristics. In this paper, we explore semantically controlled inpainting based on DM and ControlNet to the intertwined challenge of diverse and multi-class modification of VHR images. It is termed  $\text{HySCDG}$  and leads to the hybrid dataset named FSC-180k. Tab. 1 provides a comparison with main synthetic change detection datasets.

Table 1. **Synthetic Change Datasets.** Land cover change detection in remote sensing imagery. For the total number of pixels, we only consider strictly different images. The geographical zone’s extension can be local , national  or global . We denote open-access (OA) and directly downloadable datasets with . In the case of IAUG, we sum the number of pixels of the two datasets provided in this work. OEM means *OpenEarthMap*.

Dataset	OA	Pixels $\times 10^6$	GSD (m)	Classes	Source	Zone	Type
SynCW [27]		37	0.6	1	X		Synthetic
SMARS [17]		110	0.3-0.5	2	X		Synthetic
IAug [5]		1,167	0.075-0.5	1	LEVIR-CD [6], WHU-CD [25]		Hybrid
Ce-100K [54]		6,553	0.25-0.5	8	OEM [62]		Synthetic
Changen2 [69]		7,077	0.25-0.5	8	OEM [62]		Hybrid
Changen [71]		11,796	0.8	1	xView2 [43]		Hybrid
SyntheWorld [53]		18,350	0.3-1	1	X	X	Synthetic
<b>FSC-180k (Ours)</b>		<b>80,740</b>	<b>0.2</b>	<b>16</b>	FLAIR [18]		Hybrid

**Transfer learning from synthetic/hybrid datasets.** Transfer learning is used to assess the validity of the generated image pairs, and vary with the operational set-up [33]. SCD at scale is performed through sequential learning: pre-training on such datasets and fine-tuning on real-world cases [5, 27, 69, 71]. Fewer works [53] evaluate on mixed training sets (single training mixing both real and synthetic samples), which can help to prevent overfitting. An orthogonal solution considers low data regimes, *i.e.*, fine-tuning on a very small train set [5, 53, 54], or even under zero-shot scenarios [54]. We evaluate our proposed dataset in the four conceivable transfer scenarios.

### 3. Hybrid generation of semantic changes

Much of the success of deep learning methods for Earth observation relies on large-scale training datasets with reliable annotations [18, 45]. However, no large-scale publicly available dataset exists for bi-temporal SCD: we propose  $\text{HySCDG}$  for **Hybrid Semantic Change Detection Generation**, a procedure to leverage existing large-scale land cover datasets and state-of-the-art image inpainting methods to simulate visually realistic bi-temporal semantic changes.

This leads to the generation of the FSC-180k dataset.

Our paper is grounded on two main ideas: (i) **Adapting and fine-tuning a Stable Diffusion Model** enables efficient inpainting of VHR images with a semantic control and geographical instance selection; (ii) Changes can be simulated with **sufficient diversity by randomly selecting instances (and modifying their labels) within an existing land cover map** that is paired with the image used as input. The pipeline is shown in Fig. 2. Details are provided in the following.

#### 3.1. Adaptation of Stable Diffusion for Inpainting.

We use Stable Diffusion (SD) [44], an open and state-of-the-art text-to-image synthesis method. Our objective is to modify SD to manage controllable inpainting specifically in remote sensing aerial images, for various landscapes or semantic classes. Though SD models are effective in generating natural images with clear focal points and layered depth, with artistic or cinematic styles, they require adaptation to be used for remote sensing images [26]: acquisition distance, intricate textures, no domination of a single element. Starting from a Stable Diffusion 2 Inpainting checkpoint<sup>1</sup>, we sequentially fine-tune the Autoencoder and the Diffusion U-Net, before adding and training a ControlNet [65] that leverages information extracted from an existing large-scale land cover dataset (namely, FLAIR [18], see Sec. 3.3). Our pipeline allows to generate **5-band images** that incorporate infrared and elevation along with RGB channels, for the first time in satellite image synthesis.

**Adaptation of the Variational Autoencoder.** Unlike most SD extensions, which focus on fine-tuning the central U-Net, we also adapted the Variational Autoencoder (VAE) that encodes images into the diffusion latent space. This adaptation targets efficient encoding of multi-band VHR images from the FLAIR dataset. The original VAE, trained with a KL-regularization factor [15], uses a combination of L1 and perceptual loss [66] alongside KL-divergence. To improve compression of remote sensing images, we added both L2 and Focal losses [31]: minimizing high-frequency errors reduces blurriness. Additionally, we included a “color loss” (L2 loss on each  $5 \times 5$  patch) to limit oversaturation, which affects ground object color realism. Fine-tuning of the VAE took 160 hours A100 GPU.

**Stable Diffusion training.** We then fine-tuned the Diffusion U-Net for inpainting, adapting it to the new VAE and teaching it to synthesize and inpaint VHR images. Special attention was given to prompt selection. Although inpainting is the model’s primary function, we included direct image generation from prompts in 10% to 20% of cases, as in standard SD. This training required 300 hours on a A100 GPU (30,000 iterations, batch size of 32).

<sup>1</sup><https://huggingface.co/stabilityai/stable-diffusion-2-inpainting>

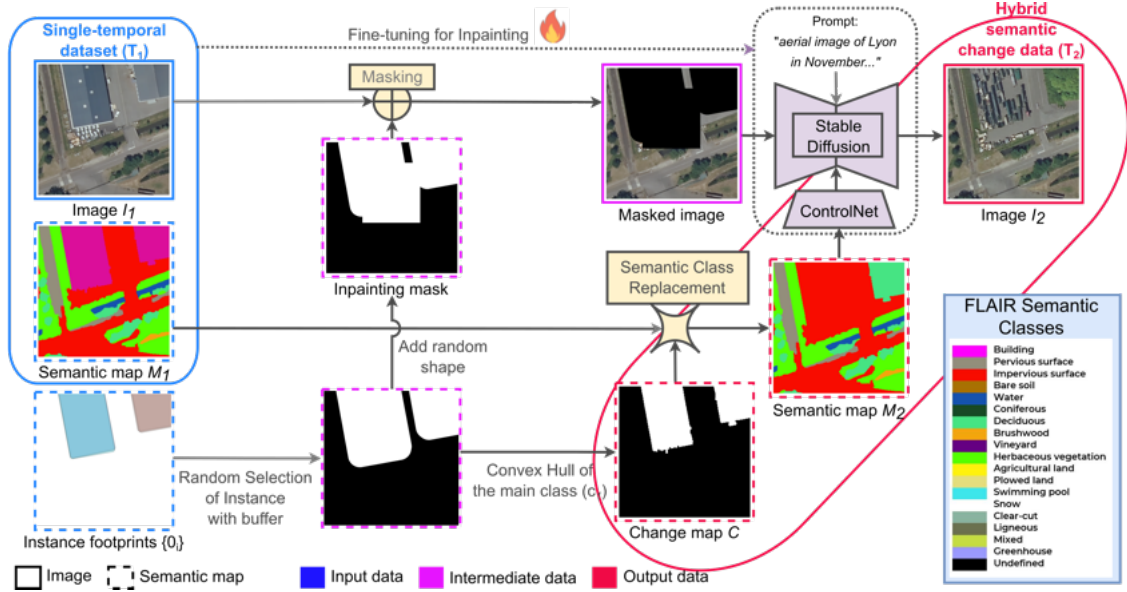


Figure 2. **HySCDG pipeline.** From a single-temporal dataset composed of one VHR image  $I_1$ , a semantic map  $M_1$ , and some openly available labeled instances, we generate a new VHR image  $I_2$ , a new map  $M_2$  and subsequently a change map  $C$ . This results in the FSC-180k hybrid dataset. The two pivotal novelties consists in: (i) **Adapting and fine-tuning a Stable-Diffusion Model from image inpainting** and (ii) **exploiting open geospatial data** for inpainting prompt control and semantically guiding the objects to be modified. The combination of both solutions ensures a **diverse at-scale VHR multi-class change detection** dataset.

**Prompt Engineering.** Prompts are designed using both each image’s geographic coordinates and open land cover data (*OpenStreetMap* [38]). To avoid learning irrelevant details, prompts are composed of three elements: (i) Spatial (place name, city, region), (ii) Temporal (time of day, season), (iii) Semantic (frequent classes in the inpainted area, compared to the overall dataset).

**Prompt example:** “*Grass and agricultural vegetation next to a highway, locality of Savigny-en-Revermont, Bourgogne-Franche-Comté, in the morning, during Summer.*”

### 3.2. Conditional change inpainting with ControlNet

Driven by our goal to control the new classes in the inpainted zones, we add a ControlNet (CN) architecture [65] to build a model that generates realistic VHR images from a semantic segmentation map (here land cover). CN is designed to add task-specific conditioning to a pretrained image DM. It allows injecting explicit semantic guidance during the diffusion process, conditioning the outputs on some reference image (a color map of the semantic class), in addition to a text prompt. Our training method enables CN to perform both inpainting and text-to-image synthesis, using the semantic condition. Training took 240 hours on a A100 GPU.

### 3.3. Select, Mask, Change, Inpaint : the HySCDG pipeline

Inspired by [46], the core of our method lies in our “Select and Inpaint” mechanism. Given a VHR image along with

its semantic segmentation and instances<sup>2</sup>, we inpaint these instances using the SD+CN inpainting method: the label of the instance is changed, the texture of the image is substituted accordingly. This results in a pair of VHR images, both with semantic maps and the corresponding semantic change maps. The complete HySCDG is provided in Fig. 2 and detailed below. It is illustrated for one image but is applied several times to each image of the single temporal dataset.

**HySCDG uncovered.** For an image  $I_1$  with its semantic map  $M_1$ , and  $\{O_i\}$  the set of  $N_I$  instances lying on the extent of  $I_1$ .

- Randomly select  $N_{change}$  instances among  $\{O_i\}$ .
- For each instance, generate an **inpainting mask** : footprint+spatial buffer.
- Using  $M_1$ , take as “ $T_1$  class” the most frequent class inside the footprint:  $c_1$ . Then, select the larger convex hull of pixels of this class inside the buffered zone. These pixels correspond to the **change mask**:  $C$ .
- Randomly select another class  $c_2$  at  $T_2$  and replace the previous label by this new label.
- Randomly select  $N_{nochange}$  random shapes in the image: such masks appear **only on the inpainting mask**, not on the change mask, letting their labels unchanged.
- Apply SD+CN to masked image and new semantic map.
- Cumulate the previous steps: we obtain our inpainting

<sup>2</sup>A panoptic segmentation is the most suitable case but not mandatory, assuming a sufficient number of instances ensures enough diversity.



mask, change mask, and for  $T_2$  a new semantic map  $M_2$  and the corresponding new image  $I_2$ .

The pair of images ( $I_1, I_2$ ) with their corresponding semantic maps ( $M_1, M_2$ ), and the change map  $C$  (difference between  $M_2$  and  $M_1$ ), are the samples of the hybrid dataset.

**Label and instance extraction.** For comprehensive multi-class learning, we select FLAIR dataset [18], a large-scale semantic segmentation map for 16 land cover classes over more than 800 km<sup>2</sup>. FLAIR offers the advantage of covering areas where geographical instances of many FLAIR labels are publicly available<sup>3</sup>, alleviating requiring a panoptic segmentation. Around 300,000 instance masks have been extracted for this work.

**Inpainting signature mitigation.** Inpainting produces realistic changes but new areas tend to have sometimes a high-frequency signature, as reported by other works [20, 29]. In order to discourage the model from simply learning this inpainting noise instead of learning the actual changes between images, we also inpaint random areas of the image without changing the semantic class in a similar way to the “not changed regions” from [46]. Besides, to obtain the best transition between the original image and the inpainted area, we use a continuous mask in the inference [1].

**Selection of the new label.** For each change area, we randomly select the new class  $c_2$  among all classes weighted by their frequency in the whole dataset divided by their frequencies in the change area.

**Adoption of a buffer zone.** For inpainting, we add a buffer around the footprint of each modified instance. This gives SD more freedom to generate smoother borders around the changed areas. It also helps handling small spatial discrepancies between footprints and the VHR image content [19].

### 3.4. Structure of the FSC-180k dataset

For each image in the FLAIR training set, we generate three unique modified images, resulting in 180,000 synthetic images, each with a corresponding 512×512 semantic map covering 16 distinct semantic classes. We call this dataset FSC-180k, short for FLAIR Synthetic Change. FSC-180k includes approximately 80 billion pixels with a ground resolution of 0.2 m per pixel. Note that we can expand the dataset by pairing synthetic images that were generated (differently) from a single real image, process that we use at training time, effectively doubling the number of image pairs. Tab. 1 compares FSC-180k with other synthetic change detection datasets and shows that FSC-180k offers a much broader range of semantic changes beyond simple building modifications, is of higher spatial resolution, and is nearly ten times larger than comparable datasets. It should also be noted that the proportion of changes in FSC-180k is closer to the real

scenarios observed in Europe (prevalence of 5% change) than other academic datasets (see Tab. 2), excepting HiUCD.

**Quality assessment of FSC-180k.** ControlNet is the most error-prone module: it may sometimes fail to respect the semantic map. We evaluated how unchanged the semantic map remains by performing 15-class semantic segmentation on real and generated images, thanks to a UNet trained for this task, leading to a satisfactory error rate below 20% between both outputs. We also leveraged standard metrics for image generation evaluation to assess the realism of the synthesis. We got an Inception Score [47] of 6.2 on the inpainted images, which is comparable to real images, and a low FID score [21] of 0.43 between inpainted and real images.

## 4. Experiments

We conduct various transfer learning experiments to validate hybrid data pretraining, comparing FSC-180k with the fully artificial SyntheWorld [53], the only available synthetic dataset with a size comparable to ours (see Tab. 1).

### 4.1. Pretraining approaches with FSC-180k

We assess FSC-180k’s effectiveness by exploiting existing open datasets as targets under various settings (see Tab. 2 and Supplementary Material). Here, we first present the different transfer learning approaches adopted, and then, dive into the deep models and datasets considered (Sec. 4.2). Our objective is to demonstrate how pretraining on a hybrid dataset improves performance, for both binary and semantic change detection.

The four scenarios are:

- **Sequential Transfer Learning.** Models are pretrained on FSC-180k, and then fine-tuned on the target data.
- **Low Data Regime.** The same as above but with a fraction of the available training set.
- **Mixed Training.** Models are trained on a blend of FSC-180k and the target data.
- **Zero-Shot Learning.** A model pretrained on FSC-180k is directly applied on the target dataset, with only a remapping of FSC-180k classes to align labels.

### 4.2. Experimental protocol

#### 4.2.1. Target datasets and metrics

Our transfer experiments span five diverse datasets, among which three contain semantic labels (Tab. 2). This ensures variety in landscapes, sizes, and change types, *i.e.*, a comprehensive evaluation. Among the plethora of (S)CD datasets, we selected the most popular ones: Levir-CD [6], S2Looking [50], SECOND [63] and HiUCD-mini [56].

We used classical metrics from the change detection literature: Intersection over Union (IoU) and F1 score for binary

<sup>3</sup><https://www.data.gouv.fr/en/datasets/bd-topo-r/>

cases and mainly the Semantic Change Segmentation score (SCS) from [59] for semantic evaluation. In this latter case, the Separated Kappa (SeK) from [63] is also informative though it tends to be more biased towards detection task than semantic prediction.

We added some experiments related to HiUCD-XL [57], a follow-up dataset of HiUCD-mini [56] using semantic mIoU and change mIoU, metrics provided on the evaluation platform<sup>4</sup> as test labels are kept private.

Table 2. **Target datasets.** Overview of the real-world datasets used for our transfer learning experiments.

Dataset	Change (%)	Pixels $\times 10^6$	GSD (m)	Classes	Period	Zone
Levir-CD [6]	28.4	1,067	0.5	1	2002/18	Texas
S2Looking [50]	25.6	8,389	0.3-0.8	1	2017/20	World
SECOND [63]	20.0	1,222	0.3-0.6	6	?	China
HiUCD-mini [56]	6.6	567	0.1	9	2017/19	Estonia
HiUCD-XL [57]	1.2	10,695	0.1	9	2017/19	Estonia
<b>FSC-180k (Ours)</b>	<b>7.0</b>	<b>80,740</b>	<b>0.2</b>	<b>16</b>	2018/21	France

#### 4.2.2. Model architecture

We consider that designing a new architecture is out of the scope of this paper and that numerous solutions have already been proposed (see Sec. 2). Therefore, we initially used a simple U-Net model [8] with a segmentation head for semantic change detection. Although effective for binary change, it lacked expressiveness for semantic tasks. Similarly to [11], we developed a simple **Dual UNet model** composed of 2 **nearly identical** parallel UNets for (i) change detection, and (ii) semantic segmentation, with ResNet-50 backbones pretrained on ImageNet and trained in a *multi-task setting*. The change branch incorporates features from the semantic encoder. We keep the training strategy simple and constant to focus on data and transfer, this enhances interpretability.

**Can a binary model be sufficient ?** We tested both a pure binary CD model and the Dual UNet, for which, when, switching to binary-only tasks, the semantic decoder is inactive but the encoding part remains active (as it provides features to the change detection branch). Such *selective change detection* ability allows training on a multi-class dataset and focusing on specific binary tasks. Experiments show that even for binary tasks, the Dual UNet outperforms the binary-only model, *e.g.*, achieving an IoU of 0.83 on Levir-CD (compared to 0.80). Learning more information than just change pixels, the Dual UNet gains a deeper scene understanding, leading to more reliable predictions.

**Existing architectures.** We tested more complex transformer-based architectures, namely ChangeFormer [2],

MambaCD [7], and SCanNet [13], both on HiUCD-mini and SECOND datasets. SCanNet performed best, balancing high performance and straightforward implementation due to its lightweight design (see Supplementary Material). SCanNet is kept hereafter for comparisons (see Tab. G).

**Transfer for varying semantic classes.** In the semantic case, we faced the issue of distinct classes between source and target datasets. This required to choose which classes should be kept for model training.

- **Sequential case:** for both pretraining and fine-tuning strategies, we use the classes of the processed dataset. The semantic head of the model is reinitialized and adapted to the new number of classes before fine-tuning.
- **Mixed case:** Classes from the target dataset are used, manually mapping pretraining classes to their closest counterparts.

#### 4.2.3. Experimental setting

We apply basic augmentations on the images: horizontal and vertical flips, 90° rotations, and small rescaled crops (scales above 0.8). Normalization by mean and variance from the target dataset is used in all experiments. For optimization, we use the AdamW algorithm with default parameters (0.01 weight decay), and an initial learning rate of 3e-4 with exponential decay (0.99 per epoch). For sequential training, models are pretrained for 40h on a A100 GPU, with fine-tuning requiring up to 20h on a V100. For mixed training, we limit the total training time to 20h on a A100.

### 4.3. Results and Analysis

#### 4.3.1. Sequential training

**Binary Case.** Models pretrained on synthetic datasets outperform those without pretraining on all target datasets (Fig. 3). SyntheWorld maintains commendable performance on the the single-class “*building*” change case, similarly to Levir-CD. Pretraining on FSC-180k yields the strongest results, compared to SyntheWorld on all five target datasets, with gains of 2-3% of IoU. Details are provided in the Supplementary Material.

**Semantic Case.** Pretraining on FSC-180k outperforms the baseline and SyntheWorld on the three SCD datasets in the sequential **orange** (Tab. G). Indeed, pretraining on SyntheWorld, that focuses solely on the “*building*” class, shows limitations in multiclass tasks on HiUCD-mini and HiUCD-XL compared to the baseline. Our FSC-180k dataset is particularly beneficial for HiUCD-mini and HiUCD-XL. The types of landscapes and spatial resolution are relatively similar, which facilitates effective transfer learning. For HiUCD-mini, our pretraining results in a SeK of 0.19 and a SCS of 0.78, representing respective increases of 11% and 7%

<sup>4</sup><https://www.codabench.org/competitions/3485/>

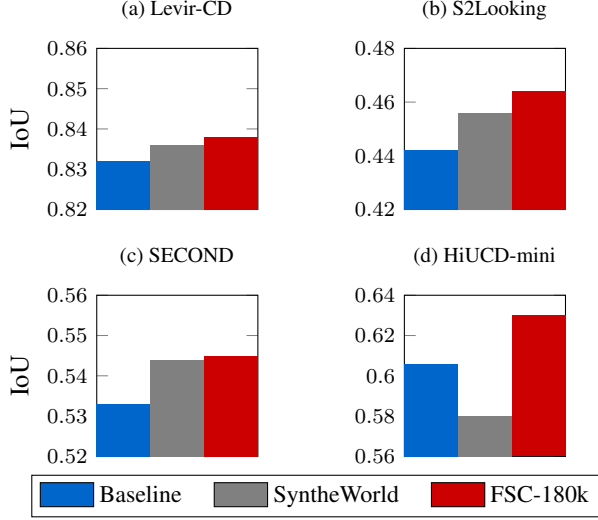


Figure 3. **Sequential training in binary change detection.** After pretraining our Dual U-Net on either [nothing](#), SyntheWorld or [FSC-180k](#), we finetune and test it on each of the 4 target datasets and represent the binary IoU.

compared to the baseline. The gains rise to 28% and 8% against SyntheWorld. For SECOND, SyntheWorld partially narrows the gap: SeK of 0.17 and a SCS of 0.84, while the FSC-180k’s pretrained Dual UNet achieves 0.18 and 0.87.

Table 3. **Sequential training in the semantic change detection framework.** We report the binary change detection scores (IoU or Chg. mIoU) as well as semantic scores (SCS or mIoU) on three datasets in the sequential scheme. Models were initially pretrained (SyntheWorld or [FSC-180k](#)) or not ([Baseline](#)).

Pretraining	Model	SECOND		HiUCD-mini	
		IoU	SCS	IoU	SCS
<a href="#">None</a>	Dual UNet	0.53	0.83	0.61	0.73
SyntheWorld	Dual UNet	0.54	0.84	0.58	0.73
<a href="#">FSC-180k</a>	Dual UNet	0.55	<b>0.89</b>	<b>0.63</b>	<b>0.78</b>
<a href="#">None</a>	SCanNet	0.54	0.84	0.60	0.66
<a href="#">FSC-180k</a>	SCanNet	<b>0.56</b>	<b>0.89</b>	<b>0.63</b>	0.71

Pretraining	HiUCD-XL	
	Chg. mIoU	mIoU
<a href="#">None</a>	0.17	0.58
SyntheWorld	0.17	0.58
<a href="#">FSC-180k</a>	<b>0.19</b>	<b>0.60</b>

**Dependence on a CD model.** We compared two CD model by running the same experiments on SECOND and HiUCD-mini with a SCanNet model (Tab. G). We were un-

able to reproduce the results reported in the original paper [13], despite following the described learning scheme. SCanNet still performs well on the SECOND dataset, achieving a SCS of 0.84, compared to 0.83 for the Dual UNet. The opposite trend is observed on HiUCD, where the Dual UNet reaches a SCS of 0.73, while SCanNet reaches 0.66. As neither of the two models stands out, we mainly present the results obtained with our Dual UNet.

#### 4.3.2. Mixed training

Our experiments show, that the optimal ratio between synthetic and target data lies around 50% for HiUCD-XL, S2Looking or SECOND (Fig. 4) conversely to the conclusions in [53], where performance always increases with the amount of target data included in the training mix. Nevertheless, the optimal ratio is 90% for smaller dataset such as Levir-CD or HiUCD-mini, that may be too specific. However, the mixed training strategy proves to be really effective, outperforming the sequential one on HiUCD-XL with a balanced blend as training base, as noticed in Fig. 4, compared to Tab. G. We can deduce that:

- **Sequential training maybe suboptimal:** The lengthy fine-tuning process can lead the model to “forget” pre-training, and instead overfits on the target data, which finally reduces the benefits of pretraining.
- In contrast, **mixed training** augments the initial set and **adds diversity** throughout the training process. The model sees as many images from the target dataset as in the sequential mode, but continues to benefit from the pretraining dataset.
- A “**balanced blend**” of synthetic and target data appears optimal, **providing a sufficient frequency of target images** for exploitation while strategically incorporating new synthetic images to enable exploratory learning and notably avoid overfitting.

#### 4.3.3. Low Data regime

We apply a sequential scheme but limit fine-tuning to small subsets of the target data: specifically, 1%, 10%, and 30% of the training set. Each experiment was repeated 10 times, with a random sampling of the training set. We consider these to be the most meaningful experiments, as this scenario closely matches real-world use cases. The primary objective of pretraining is to develop a model that can either **swiftly** adapt to new target datasets or perform well when **only limited training data is available**. One can observe on Fig. 5 a clear advantage for pretrained models at very low level (1%). With such little data, the model cannot fully learn the specificities of the target dataset and relies primarily on its general knowledge and on the task itself (*detecting changes*), rather than on dataset-specific features. Unsurprisingly, models pretrained for this task perform significantly better. However, as the amount of available data increases, the gap tends to narrow. Models increasingly rely

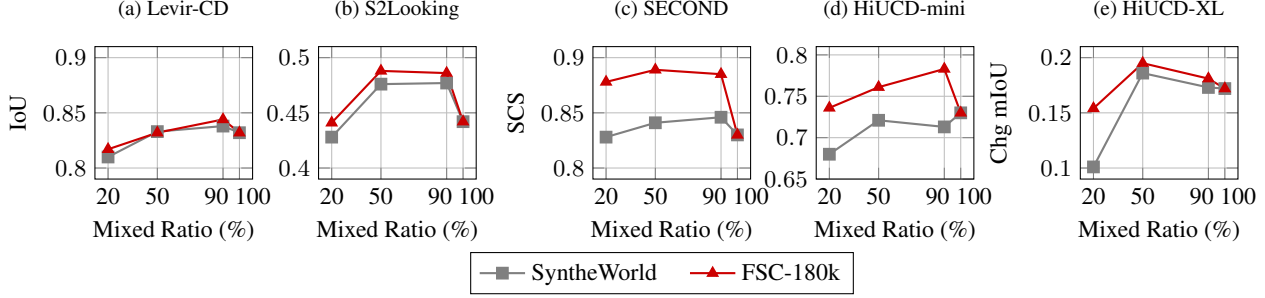


Figure 4. **Mixed training (Binary and Semantic)**. Training on a blend of target and synthetic/hybrid (SyntheWorld or FSC-180k) train sets, containing a ratio of  $x\%$  samples from the target (including repetitions). Testing is performed on the target test set. 100% corresponds to fine-tuning exclusively on target dataset (without pretraining).

on data itself, to which they have equal access, yet pretraining on FSC-180k still yields better performance than using SyntheWorld or training from scratch.

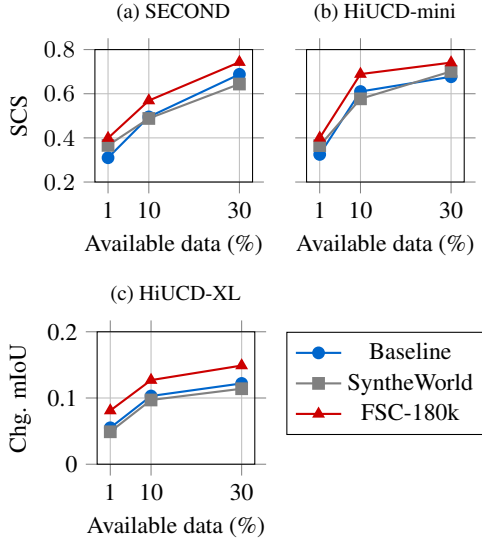


Figure 5. **Low data regime (Semantic)**. Fine-tuning on a limited part of the target train set (either 1%, 10% or 30% of randomly sampled examples) and evaluating on the whole test set. Models are initially pretrained (SyntheWorld or FSC-180k) or not (Baseline). Metrics are averaged on 10 runs for SECOND and HiUCD-mini.

#### 4.3.4. Zero-Shot evaluation

While models pretrained on SyntheWorld struggle to transfer effectively without target sample exposure, pretraining on FSC-180k delivers respectable results, achieving IoU scores of 0.37 on SECOND and 0.36 on HiUCD-mini, showing performance drops of 31% and 40%, compared to the fully supervised models (details are provided in the Supplementary Material). However, FSC-180k is less effective on Levir-CD, where the performance drop reaches 60% (0.33 vs. 0.83 IoU). We argue that performance in this scenario is directly

linked to dataset similarities: the limited realism in SyntheWorld hinders transferability, while FSC-180k’s diverse landscapes and sparse changes further limit its effectiveness. For the semantic task, pretraining on FSC-180k enhances the model’s understanding of change trajectories, achieving SCS of 0.24 on SECOND and 0.25 on HiUCD-mini.

#### 4.3.5. Qualitative assessment

Qualitative analysis of the various segmentation results indicates that FSC-180k pretraining significantly enhances the network’s ability to localize features in input images. This improvement leads to both more accurate segmentation within VHR images and higher semantic prediction accuracy for main classes of interest in the semantic case (*e.g.*, *buildings*, *roads*, *bare land* for HiUCD-mini, *buildings* or *non-vegetated ground surface* for SECOND). Qualitative examples for the different datasets are provided in the Supplementary Material.

## 5. Conclusion

We introduced HySCDG, a new, simple bi-temporal change detection generation pipeline. It lies on Stable Diffusion and ControlNet for creating hybrid content of VHR images. HySCDG leverages an existing large-scale semantic land cover map to overcome the lack of diversity and size of real-world datasets. We provide FSC-180k, a pretraining dataset based on FLAIR [18], which includes bi-temporal real/in-painted images, and their associated semantic maps. The proposed solution was evaluated for transferability, on five datasets over four distinct training setups. Our experiments on both binary and semantic cases demonstrated strong transferability, confirming FSC-180k robustness and adaptability as well as HySCDG relevance.



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