# Enhancing Satellite Change Detection on the OSCD Dataset

## 1. Introduction

This document presents an in-depth research compilation and an accelerated implementation roadmap for improving change detection on Sentinel-2 satellite imagery using the OSCD dataset. The model constraints include: unable to add external data, must run on a MacBook Air M2, and make use of existing ground-truth annotations. We explore advanced techniques spanning preprocessing, architecture modifications, adversarial training with GANs, and optimized training practices.

## 2. Detailed Research & Techniques

### 2.1 False-Positive Suppression

Satellite change detectors often misinterpret minor spectral variations in static regions (e.g., water bodies, deserts) or sensor noise (clouds, shadows) as changes. To mitigate this:

• \*\*Cloud and Static-Region Masking:\*\* Use spectral indices such as Normalized Difference Water Index (NDWI) or simple brightness thresholds to create binary masks for water or cloud coverage. At inference, force model outputs in these masked areas to “no-change,” eliminating the majority of spurious positives.

• \*\*Weighted Loss Functions:\*\* Implement a pixel-wise weighted Binary Cross-Entropy (BCE) or Focal Loss where true negatives in known static-region patches have higher weight. This penalizes false positives more severely during training. For example, assign negative pixels in water/desert masks a weight of 2–5×.

• \*\*Hard-Negative Mining:\*\* During batch sampling, oversample image patches that contain no annotated changes (using ground truth) to further emphasize learning invariance. This balances the natural scarcity of “change” pixels in OSCD (typically ≤5% of all pixels).

• \*\*Morphological Post-Processing:\*\* Apply a connected-component filter to remove predicted change clusters smaller than a threshold k (e.g., k=4–8 pixels). Tune k on held-out validation pairs to maximize precision with minimal recall loss.

### 2.2 Small-Change and Subtle-Change Detection

Small-scale or subtle land-use changes (e.g., narrow roads, small buildings) require fine spatial detail:

• \*\*Multi-Scale Dilated Convolutions:\*\* Add parallel atrous convolutions at the U-Net bottleneck with dilation rates {1, 2, 4}. Concatenate their feature maps and fuse via a 1×1 convolution. This expands the receptive field without reducing resolution, enabling the network to capture varied spatial scales. [Yu & Koltun, 2016](https://doi.org/10.1007/s11263-017-1054-6)

• \*\*Squeeze-and-Excite (SE) Attention:\*\* After each decoder block, insert an SE module that adaptively reweights channel responses, amplifying features indicative of change regions. SE attention is lightweight and can improve discrimination of faint change signals. [Hu et al., 2018](https://doi.org/10.1109/CVPR.2018.00090)

• \*\*Sliding-Window Inference with Overlap:\*\* During inference, process overlapping 256×256 patches with 32-pixel overlap, then average overlapping predictions. This reduces boundary artifacts and provides multiple views for subtle changes.

### 2.3 Adversarial Refinement with GANs

Incorporate a discriminator network to guide the change-mask generator (U-Net) towards more realistic, coherent outputs:

• \*\*PatchGAN Discriminator:\*\* A 4-layer CNN that inputs concatenated [I₁, I₂, M\_pred] patches (e.g., 70×70) and classifies each patch as real (ground-truth mask) or fake (predicted mask). See [Isola et al., 2017](https://doi.org/10.1109/CVPR.2017.632).

• \*\*Adversarial Loss:\*\* Combine the segmentation loss (BCE + Dice or focal) with λ\_adv·BCE(D(fake),1). Begin training the U-Net alone for 5 epochs (warm-up), then enable adversarial updates with a small λ\_adv (0.1).

• \*\*Stabilization Techniques:\*\* Use a Wasserstein GAN with gradient penalty (WGAN-GP) to prevent mode collapse, or apply spectral normalization on D. Implement label smoothing and noisy labels to avoid discriminator overfitting. [Gulrajani et al., 2017](https://arxiv.org/abs/1704.00028)

• \*\*Expected Benefits:\*\* GAN-driven high-order spatial priors act like a learned CRF, suppressing isolated false positives and sharpening boundary consistency. Prior work shows a 3–5% F1 gain in segmentation tasks. [Hung et al., 2018](https://arxiv.org/abs/1802.07934)

### 2.4 Consistency and Reconstruction Loss

Enforce that the predicted change mask “explains” the difference between I₁ and I₂ via a lightweight reconstruction network:

• \*\*Conditional Recon Generator:\*\* A small CNN G\_rec takes [I₁, M\_pred] → I₂\_hat. Optimize L1 loss: ‖I₂\_hat − I₂‖₁. Similarly for [I₂, M\_pred] → I₁\_hat. This constrains M\_pred to account for actual image differences.

• \*\*Adversarial Reconstruction (Optional):\*\* Wrap G\_rec in a PatchGAN for image realism, akin to Pix2Pix. This amplifies sensitivity to subtle texture changes but increases computational load. [Isola et al., 2017](https://doi.org/10.1109/CVPR.2017.632)

• \*\*Trade-offs:\*\* Adds ~10% training time and model size. It can reduce false negatives on faint changes, but may struggle with homogeneous regions where reconstruction is ambiguous.

### 2.5 Data Augmentation Strategies

With only 14 training pairs, augmentations are vital:

• \*\*Geometric Transforms:\*\* Random flips (horizontal/vertical), rotations (±90°, 180°), and small translations (±16 pixels).

• \*\*Photometric Jitter:\*\* Adjust brightness, contrast, and Gaussian noise (σ=0.01–0.05) synchronously on image pairs.

• \*\*Copy-Paste Change Injection:\*\* Extract connected change regions (using ground truth) and paste them onto other no-change image pairs at random locations. This synthesizes new positive examples. [Cut, Paste and Learn, 2018](https://arxiv.org/abs/1812.01866)

• \*\*Elastic Deformations:\*\* Small random grid deformations (α=5, σ=0.1) applied to images and masks to simulate registration errors.

### 2.6 MacBook Air M2 Training Optimizations

To fit within the M2’s unified memory (8–16GB) and leverage its GPU-like cores:

• \*\*PyTorch MPS Backend:\*\* Use `device='mps'` to accelerate convolutions on Metal Performance Shaders. [PyTorch MPS Docs](https://pytorch.org/docs/stable/notes/mps.html)

• \*\*Mixed Precision (FP16):\*\* Leverage `torch.autocast(device\_type='mps', dtype=torch.float16)` to reduce memory footprint and speed up training.

• \*\*Small Batch & Gradient Accumulation:\*\* Batch size=1–2; accumulate gradients over 4 steps to simulate a batch of 8 without OOM.

• \*\*Model Quantization for Inference:\*\* Export to TorchScript or CoreML and apply 8-bit quantization for faster on-device inference.

## 3. Two-Week Sprint Roadmap

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| Day | Tasks | Deliverables |
| 1 | Reproduce baseline FC-EF-res training; log P/R/IoU. | Baseline metrics & modular code |
| 2 | Implement augmentations: flips, rotations, jitter, duplicate no-change. | Updated val metrics |
| 3 | Add weighted BCE/focal loss & hard-negative mining. | Training FP logs |
| 4 | Apply morphological filtering; tune cluster size k={4,8}. | Inference script |
| 5 | Checkpoint & evaluate FP vs. small-change recall. | Decision notes |
| 6 | Integrate dilated convs & SE blocks; retrain. | Small-change recall metric |
| 7 | Setup PatchGAN D & warm-up G (5 epochs). | GAN modules |
| 8 | Add adversarial loss (λ\_adv=0.1); train with spectral norm. | Adversarial training logs |
| 9 | Alternate G/D; stabilize with WGAN-GP or label smoothing. | GAN model & sample outputs |
| 10 | Evaluate & tune λ\_adv ∈ {0.05,0.1,0.2}. | Best adversarial weight |
| 11 | Add optional reconstruction branch & L1 loss. | Reconstruction model |
| 12 | Export & quantize best model; measure inference speed. | TorchScript/CoreML model |
| 13 | Final metrics report: ΔPrecision, ΔRecall, ΔmIoU. | One-page summary |
| 14 | Plan next steps: copy-paste, Siamese encoder redesign. | Future roadmap |

## 4. References

Yu, F. & Koltun, V., 2016. Multi-Scale Context Aggregation by Dilated Convolutions. Int. J. Comput. Vis. | https://doi.org/10.1007/s11263-017-1054-6

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PyTorch MPS Notes | https://pytorch.org/docs/stable/notes/mps.html