

# Transfer learning between Sentinel-1 acquisition modes enhances the few-shot segmentation of natural oil slicks in the Arctic

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**Abstract**—Natural seepage is a significant contributor to marine hydrocarbon inputs. Remote and intermittent seeps are difficult to monitor in the field, yet oil slicks can be observed by spaceborne synthetic aperture radar (SAR) because they reduce backscatter, creating potential for automatic mapping. In mapping tasks like segmentation, deep learning models excel, albeit needing large amounts of labeled images. To deal with scarcity of labeled images, transfer learning is an approach commonly used in computer vision, though still underutilized in remote sensing. In the case of oil slicks, differences between Sentinel-1 acquisition modes, such as the interferometric wide (IW) in the North Sea and extra wide (EW) in the Arctic, complicate direct model transfer. Here, we present a use-case where transfer learning enhances the segmentation of natural oil slicks. We used labeled slicks in IW images in the North Sea to pretrain a series of DeepLabv3 and SAM models. These models were then fine-tuned on EW-labeled slicks from two documented Arctic seeps on which we have only limited observations. Our results show clear evidence that transfer learning improves few-shot segmentation, notably in challenging and noisy images. Overall, few studies have addressed transfer learning between SAR acquisition modes. This work contributes to improved monitoring of poorly understood or yet undiscovered hydrocarbon seeps.

**Index Terms**—Natural seepage, oil slicks, SAR, deep learning, transfer learning, segmentation, DeepLab, SAM

## I. INTRODUCTION

NATURAL seepage is a significant contributor of oil entering marine environments [1], yet the data required to update quantitative estimates of its global scale remain insufficient, especially outside of the U.S. continental shelf [2]. Because of difficulties in continuously monitoring remote offshore areas, data scarcity has restrained our possibilities of studying the ecosystem contribution and the behavior of hydrocarbon seeps. Synthetic aperture radar (SAR) is well suited to this task due to its capacity to operate in any lighting conditions, and its fine spatial resolution for its wide swath. Surface oil slicks are visible in SAR images because they return lower backscatter compared to surrounding waters, due to the oil damping sea roughness [3]–[5]. Precisely, SAR’s

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Corresponding author email address: julien.vadnais@uib.no. The entire data and code used in this study is accessible on the GitHub repository at [https://github.com/julvad/transfer\\_learning\\_S1\\_slicks\\_arctic](https://github.com/julvad/transfer_learning_S1_slicks_arctic)

capacity for detecting a slick relies on the damping ratio, the contrast in backscatter between oil- and oil-free pixels [6], [7].

Previous works have attempted to make use of the damping ratio for automatizing marine oil detection, with varying results. They face a common challenge which has been an ongoing topic of research for over three decades: the presence of oil look-alikes including ocean eddies, biogenic slicks and newly-formed ice [5], [6], [8], [9]. When trained with a large number of labeled examples, deep learning models, currently the benchmark in computer vision, can capture complex shape- and texture-related features for image classification or segmentation tasks [10]. When trained with a limited sample size, however, these models struggle to extract more abstract, higher-level features [11]. The issue of limited data is exacerbated in the case of oil slicks because of limited visibility. Not only will slicks only last a few hours on the surface [12]–[14], their visibility also depend on a specific window of surface wind conditions, outside of which the sea either has too many or too few capillary waves for a discriminative damping ratio [7], [15], [16]. Slick events are also highly intermittent. Seepage rates vary across both monthly and yearly timescales, and most active seeps have an occurrence rate below 10% [14], [17]. Some seeps remain dormant for months, or even years, before emitting oil again. In two distinct regions, studies found that only half of all seeps show activity at a given time [12], [18], and dormant seeps’ occurrence might be underestimated, considering that they are less likely to be discovered.

In this paper, we assess the potential of transfer learning for enhancing automatic mapping of natural oil slicks. Transfer learning, or deep transfer learning in the case of deep learning, aims at transferring valuable and generalizable features from one model to another, where contexts are similar but the target distributions differ [10]. We pretrained two image segmentation models using oil slicks mapped in Sentinel-1 images over the North Sea. These models were then fine-tuned on two known seeps in the Arctic, for which we have only limited observations. In the Arctic, Sentinel-1 scenes are mostly acquired in the extra wide (EW) mode at a 25-m pixel spacing with dual HH/HV polarization. However, elsewhere, oil mapping with Sentinel-1 more commonly uses the interferometric wide (IW) mode at a 10-m pixel spacing with VV/VH polarization, as it is the standard mode in oceans outside of polar regions. Little work, if any, has addressed transfer learning between SAR acquisition modes, and we believe natural oil slicks make a prime example of a real-life application of deep-learning mapping with few labeled data.

TABLE I  
LABLED SLICKS IN THE SOURCE AND TARGET DOMAINS

Sentinel-1 mode/pol.	Source domain		Target domain	
	IW / VV		EW / HH	
Area	North Sea	Svalbard	Barents Sea	
Number of images	463	70	88	
Period	2017-2021	2015-2024	2015-2020	
Number of slicks	~ 1723	~ 81	~ 250	

## II. DATA AND METHODS

### A. Data

Traditional transfer learning in remote sensing imply that the *target domain*  $D_T$  and the *source domain*  $D_S$  have similar probability distributions between a common raster band  $x_i$  and a common label  $y_i$  [19]. Deep transfer learning is more robust to distribution shifts and can even handle different target classes, yet, this often requires training on massive datasets (e.g. [20], [21]). Our approach is rather a targeted form of deep transfer learning, with a  $D_S$  dataset of smaller size, but closer to the  $D_T$ . We will now introduce those two domains.

Researchers recently documented two seepage areas in the Norwegian waters. First, [22] investigated an intermittent seeping point west of the Svalbard archipelago ( $10.42^\circ\text{E}$ ,  $78.49^\circ\text{N}$ ). At this location, we manually delineated 81 slicks in 70 images taken between 2015 and 2024. Second, [23], [24] found extensive evidence of a wide seepage area in the Barents Sea ( $31.33\text{-}32.37^\circ\text{E}$ ,  $75.15^\circ\text{N}\text{-}75.35^\circ\text{N}$ ). This area is part of Sentralbanken high, a geological structure with prospective hydrocarbon potential, although it remains largely unexplored [25]. There, we delineated 250 slicks in 88 images taken between 2015 and 2020. At these two locations, labeled samples from the horizontal co-polarization (HH) band of Sentinel-1 EW images constitute the  $D_T$  (Fig. 1a, 1b). At lower latitudes, various kinds of oil slicks can be observed in the North Sea, a hydrocarbon-rich and seepage-active region [26]. With the same procedure, we delineated over 1700 slicks, this time using the vertical co-polarization (VV) band of 463 Sentinel-1 IW images. Labeled samples in the North Sea constitute the  $D_S$  (Fig. 1c). In this study, only the co-polarization bands were used because of their oil-discrimination capacity [3], [27], [28]. Since slicks can be split into segments, we give slick numbers in Table I as approximations only.

Transfer learning of remote sensing imagery requires data alignment [19]. To deal with shape distortion, particularly at higher latitudes, we reprojected all Sentinel-1 scenes into their corresponding UTM zone. This corresponds to the 31N zone for the North Sea, the 32N zone offshore Svalbard, and the 36N zone in the Barents Sea. Because the pixel spacing of EW scenes is 25 m, compared to 10 m for IW scenes, we ran a bilinear interpolation to align the spatial resolutions. A bilinear interpolation is generally preferred when working with continuous raster values such as the SAR backscatter intensity [29]. In the  $D_T$ , 30 out of the 158 annotated Sentinel-1 EW HH scenes were retained for the test split—about 19%—and 10% of the training samples were used for validation. We extracted four combinations of square raster tiles, using a tile width of

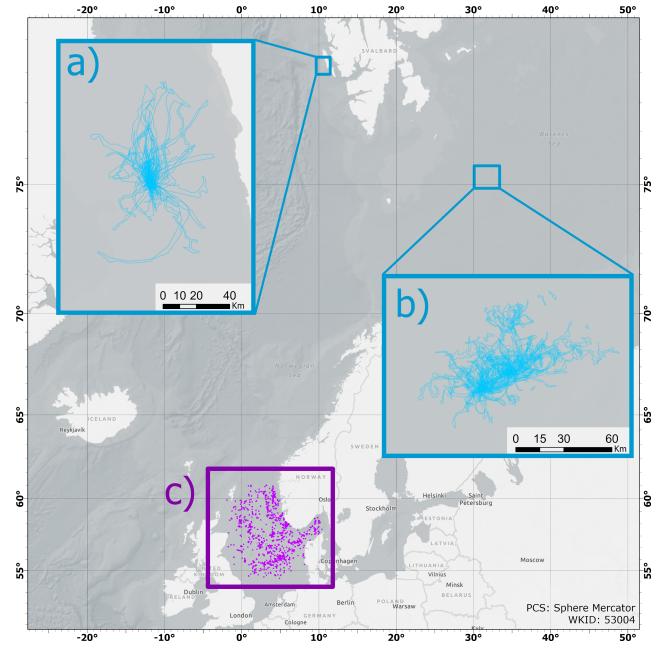


Fig. 1. a) Target domain  $D_T$ : Mapped slicks offshore Svalbard  
b) Target domain  $D_T$ : Mapped slicks in Sentralbanken high, Barents Sea  
c) Source domain  $D_S$ : Mapped slicks in the North Sea

either 256 or 512 pixels, and either downsampling resolution to 25 m or upsampling to 10 m. Contrast normalization is another important preprocessing step, which needs to be robust to outliers [10], [29]. Here, we applied a linear stretch of two standard deviations on clipped tiles, normalizing values over the 8 bit range (0,255):

$$X' = \frac{X - \mu}{2 \cdot \sigma} \cdot 255 \quad (1)$$

in which  $X'$  is the new value of image pixels  $X$ , using the mean  $\mu$  and the standard deviation  $\sigma$  of the image.

### B. Methods

We pretrained two deep learning models: DeepLabv3 and the Segment Anything Model (SAM). DeepLabv3 is a convolutional neural network architecture for semantic segmentation, which uses atrous convolutions and introduced atrous spatial pooling layers [30]. It is considered state-of-the-art in many fields of application including remote sensing [31]. SAM is a novel zero-shot learning vision transformer for image segmentation [21]. While SAM itself does not assign classes, the SamLoRA variation extends its use by adding trainable classification layers to SAM's mask encoder [32]. Data augmentation was generated in the form of a  $30^\circ$  rotation, brightness and contrast shifts, soft zooms, and cropping. We trained models with two backbones to investigate if a deep or a shallow model would perform best. For DeepLabv3, we used the ResNet-50 and ResNet-101 backbones [20]; ViT-B and ViT-L checkpoints were used for SAM [21]. The learning rate was determined from a pretraining learning curve [33], [34]. We used a training batch size of 64 for the 256x256 tiles, and 16 for the 512x512 tiles. Model inference was performed

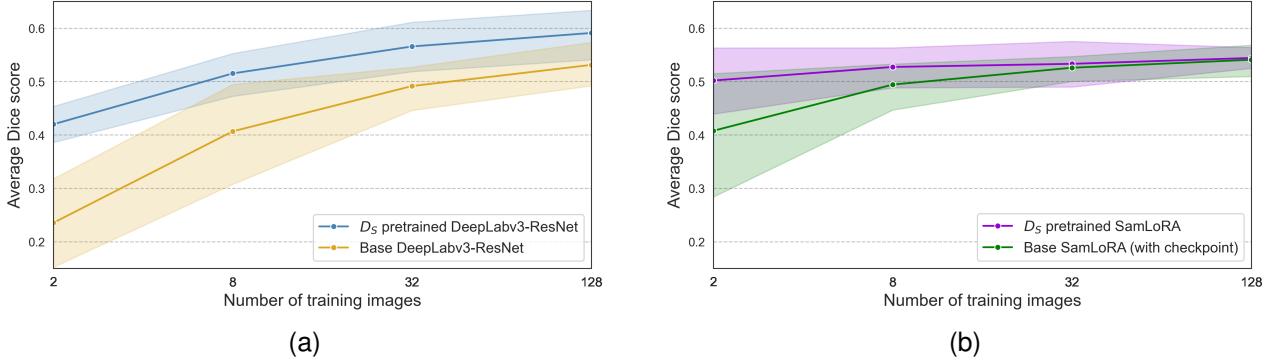


Fig. 2. Average test-set Dice score with 95% statistical interval, depending on the number of training images. (a) DeepLabv3 (b) SamLoRA

in Python using ArcPy and PyTorch, with an RTX 4500 Ada Generation GPU.

We first experimented by training with a weighted binary cross-entropy loss function, defined by:

$$L_{CE} = -\frac{w}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (2)$$

Here,  $y_i$  represents the ground truth label (0: water; 1: slick) and  $\hat{y}_i$  is the softmax predicted value of the  $i$ -th pixel. This function introduces  $w$ , a weight parameter calculated as a scalar inversely proportional to slick pixel frequency [35]. To further handle the frequency imbalance between oil and water pixels, we added a term based on the loss function from [36] ( $L_{Dice}$ ), resulting in the Dice-weighted function:

$$L = (1 - \alpha) \cdot L_{CE} + \alpha \cdot L_{Dice} \quad (3)$$

where  $\alpha$  is a float between 0 and 1, a tunable hyperparameter indicating the Dice loss fraction. With  $\alpha$  set to 0.5, as in [37], this Dice-weighted function ( $L$ ) proved the most effective during preliminary tests.

Using all 463 images from the  $D_S$ , we pretrained models for a maximum of 100 epochs with validation-loss early-stopping as a means of limiting overfitting [38]. We then generated 8 bootstrapped sets for each value in the set  $N = \{2, 8, 32, 128\}$ , where  $N$  is the number of training images from the  $D_T$ . No bootstrapping was done at  $N = 128$  as the entire training split was in use. We compared *base models*, which used default backbone weights, and *fine-tuned models*, which were instead initialized with full weights from the model pretrained on the  $D_S$ . These weights are left unfrozen in the  $D_T$  fine-tuning stage [39]. We calculated the Dice score for a total of 128 models on the test split, considering only the oil slick class to ignore the trivial classification of water. The Dice score, closely related to the F1, is calculated as:

$$\text{Dice} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \quad (4)$$

Bootstrapped testing helps assess model consistency with small and high-variance test sets [40]. In Fig. 2 and Table II, we provide a 95% statistical interval for the test-set Dice score, following the bootstrapping method described in [41].

TABLE II  
AVERAGE DICE AND CHANGE OBSERVED WITH TRANSFER LEARNING,  
BASED ON THE SPATIAL ALIGNMENT METHOD

Tile size	25 m downampling	10 m upsampling
<b>256x256</b>	0.49(+0.13 ± 0.13)	0.49(+0.05 ± 0.04)
<b>512x512</b>	0.42(+0.11 ± 0.28)	0.51(+0.03 ± 0.05)

### III. RESULTS AND DISCUSSION

Fig. 2 illustrates the change in Dice score as the number of training images increases. We show clear evidence that both the convolutional neural network (Fig. 2a) and the vision transformer (Fig. 2b) benefit from transfer learning. This result is more evident in the case of DeepLabv3, in which  $D_S$  pretraining increased the Dice score at all values of  $N$ . While SamLoRA also benefits, the effect is rapidly reduced as the number of training samples grow, and its effect is indistinguishable with values of  $N > 8$ . Despite this, transfer learning has an overall positive effect, particularly with fewer training images. Until  $N > 8$ , SamLoRA outperforms DeepLabv3. This is consistent with larger models being more efficient at fine-tuning on a small number of samples [42]. DeepLabv3's Dice scores grow steadily with an increasing number of training images, and we can expect this trend to continue beyond the limits of our sample size (Fig. 2a). In contrast, it remains unclear whether SamLoRA would benefit from transfer learning with larger training datasets (Fig. 2b).

After comparing model architectures, we investigated the effect of transfer learning depending on the resampling method used to geographically align images from two Sentinel-1 acquisition modes. Table II compares these methods, presenting the average Dice score accompanied by a 95% statistical interval for the change in Dice resulting from transfer learning. In most cases, transfer learning improves model performance, but its effect is strongest—yet highly variable—when down-sampling images to 25 m, meaning that we align the  $D_S$  IW images with the  $D_T$  EW images. Similar work by [43] found that fine-tuning improved deep learning segmentation of oil spills. In that study, however, the researchers downsampled the resolution of training images to create a synthetic pre-training dataset. Moreover, tile size has no apparent effect on transfer learning. This is an interesting finding, because large

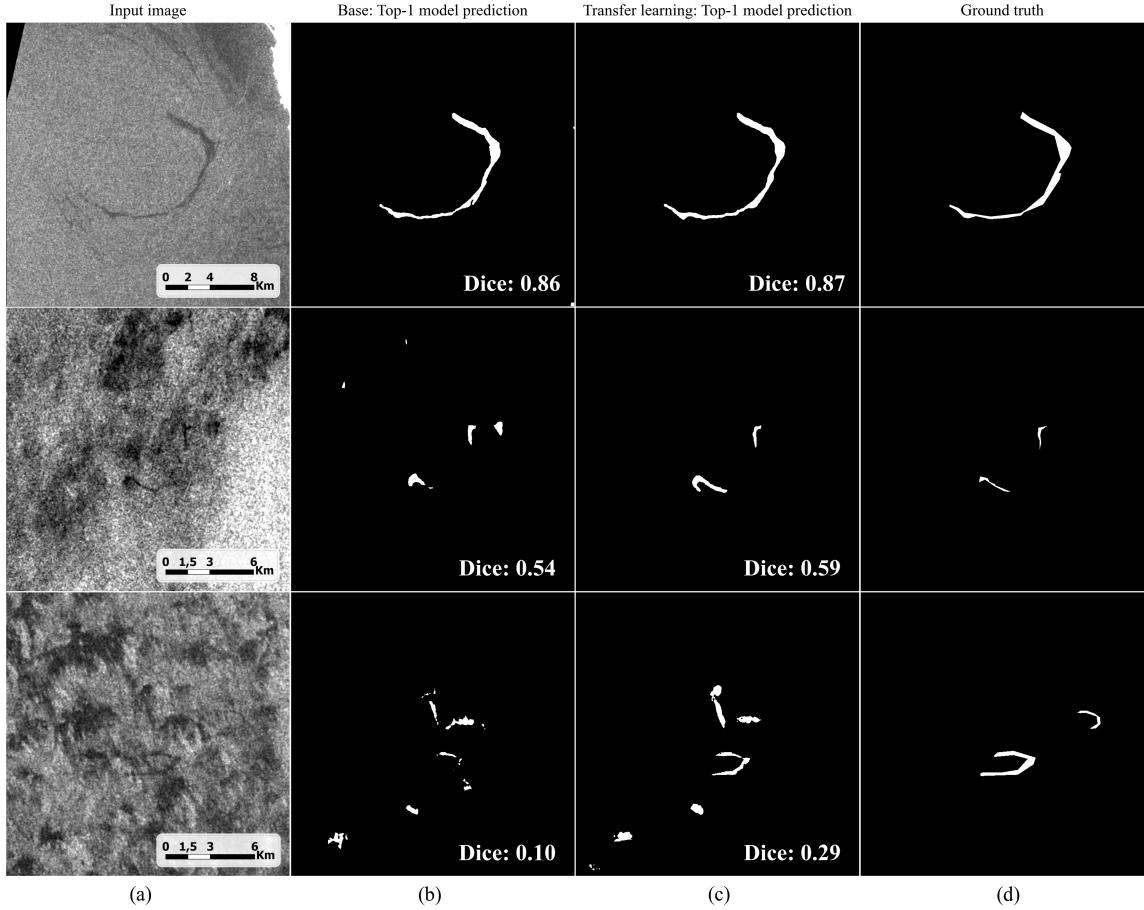


Fig. 3. Top-1 model performance through examples. Top row: An easier case, with some ocean eddies. Middle: A more challenging example with various look-alike features. Bottom: Arguably one of the most challenging cases. A small, low-contrast slick is missed by models in the center right of the image.

geophysical processes, such as oil slicks, often need to be split into smaller tiles for processing. This typically results in performance loss and slower computing.

Fig. 3 displays the segmentation predictions from the top-performing model (Top-1). We compare predictions from the base (Fig. 3b) and the fine-tuned (Fig. 3c) versions, showing how the model benefited from transfer learning across different examples. The examples are taken from the test set, with a 25 m resolution and predicting with a tile width of 512 pixels, the most challenging format evaluated (Table II). First, we see a typical arc-shaped slick with a clear SAR damping ratio (top, Fig. 3a). Both the base and the fine-tuned model delineate the slick, while correctly leaving out ocean eddies and a low-wind area on top of the image. The second row presents a common appearance of natural slicks in an SAR image, where several dark features may trigger false detections (middle, Fig. 3a). Nonetheless, both models detect the two slicks (middle, Fig. 3d) and transfer learning help reduce false detections, despite a somewhat undervalued Dice score (middle, Fig. 3c). The last row (bottom, Fig. 3a) exemplifies one of the most challenging cases for SAR slick mapping. If two low-contrast slicks can be seen among look-alike features, only the main slick (bottom, Fig. 3d) is detected by the fine-tuned model (bottom, Fig. 3c), illustrating the challenge of harsh mapping conditions.

#### IV. CONCLUSION

Applications of transfer learning must be carefully evaluated. In many cases, its use can be inefficient, even detrimental, if the contexts are too different [44]. In this study, we made use of labeled slicks from a different area and imaged in a different SAR acquisition mode. We show that transfer learning in the form of fine-tuning is effective for the few-shot SAR segmentation of natural oil slicks, improving model performance (average Dice increase of 0.03–0.13) despite accessing only a few examples in the target domain. Indeed, both deep learning models benefited from transferring pretrained model weights, with DeepLabv3 performing best overall, though SAM achieved top accuracy with fewer training images.

Transferability between IW and EW modes is especially important in the Arctic. In this region, the absence of large offshore spills—which oil segmentation models typically rely on for training—limits the availability of training data. In contrast, Arctic seeps emit slicks that are generally thinner, with low oil concentrations and reduced backscatter damping. This poses a challenge for detection, which partly explains why these remote seeps are still under-investigated today. Our method, validated on two documented seepage sites, offers promising perspectives for identifying and studying additional, as yet undiscovered remote seeps.

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