Residual U-Net with Attention for Detecting Clouds in Satellite Imagery

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Abstract

Semantic segmentation of clouds in Earth observation imagery is an important task in a variety of remote sensing contexts: from the application of atmospheric corrections to being able to accurately omit cloud pixels when extracting information about ground features. Here we introduce a deep learning approach based on the popular U-Net architecture. The core of the architecture is an U-Net with residual units that ease the training of the network. An attention mechanism is also incorporated to enable the model to more effectively learn and distinguish between cloud and non-cloud features. We also explore two complementary loss functions, Binary Cross Entropy and Jaccard, in order to overcome data imbalances common to this application. Our model is trained on a uniquely curated dataset spanning a wide variety of resolutions, scene contexts, lighting conditions, and seasonality. Our experiments demonstrate that this model is an accurate and robust model for the semantic segmentation of clouds in satellite imagery, and the model achieves state-of-the-art performance over many other models (including others based on CNN architectures) on common benchmark datasets, even without having been exclusively trained on images from the sources in those datasets.

Keywords remote sensing · cloud detection · Landsat-8 · Sentinel-2 · deep learning · U-Net · attention

1 Introduction

Approximately 70% of the Earth's surface is obfuscated by cloud at any given time when observed from space (King et al., 2013). This high degree of cloud cover is problematic for a variety of Earth observation applications that depend on passive remote sensing in the visible parts of the electromagnetic spectrum: image compositing (Roy et al., 2010), the application of atmospheric corrections (Vermote et al., 2002), calculation of vegetation indices (Huete et al., 2002), land cover classification (Zhang et al., 2002), and especially change detection (Zhu and Woodcock, 2014). Accurate identification and screening of clouds in satellite imagery is therefore an essential step toward producing high-quality geoinformatic products.

A variety of methods exist for the purpose of detecting clouds in remote sensing data. Many of these solutions rely on rule- or threshold-based methods which use the reflectance difference between cloud and non-cloud pixels across multiple spectral bands. Zhu and Woodcock (2012) proposed the Function of Mask (FMask) for detecting clouds, utilizing seven specific bands in Landsat data. FMask detects cloud pixels based on a threshold function and the physical characteristics of clouds such as whiteness, flatness, and temperature. Though several improvements have been made to the algorithm over time (Zhu et al., 2015; Qiu et al., 2019), threshold-based methods such as FMask can be unreliable when used in isolation, and often require additional information such as surface temperature. Li et al. (2017) proposed automatic multi-feature combined cloud detection (MFC). This method uses low-level features, such as textural and geometrical features across Red, Green, Blue (RGB), and near-infrared (NIR) bands. However, both FMask and MFC are limited in extracting high-level semantic cloud features and are prone to detection errors.

Deep learning models have recently begun to outperform rule- and threshold-based methods in detecting clouds. López-Puigdollers et al. (2021) demonstrated with an inter-class experiment on Landsat-8 (L8) data, in which the training and inference sets are independent but from the same satellite source, that deep learning models have considerably lower commission errors compared to FMask, while having similar accuracy scores. The authors compared several cloud segmentation models trained on L8 imagery and tested these on different combinations of L8 and Sentinel-2 (S2) data. One of the models in their benchmark is the lightweight U-Net proposed by Zhang et al. (2020). They find that although threshold-based methods can perform well in detecting thin clouds, deep learning-based approaches outperform such models in distinguishing low contrast differences, such as clouds from snow pixels.

Chen et al. (2021) proposed an Automatic Cloud Detection neural network (ACD net) to semantically segment clouds. ACD net integrates geospatial data and satellite imagery, which together with a novel cloud boundary refinement module, increases the accuracy of cloud detection by their network. The authors used the Gaofen-1 satellite imagery dataset (with image sizes of 512×512 pixels) provided by Li et al. (2017), selecting image patches that include cloud-snow coexistence scenes as well as different types of cloud patterns. The authors found ACD net outperforms other deep learning-based models in distinguishing such scenes, but does not cope well with thin cloud layers (Li et al., 2017; Zhan et al., 2017; Xia et al., 2019; Yang et al., 2019).

Hu et al. (2021) proposed a novel variation of U-Net they called CDUNet, that makes use of a ResNet-50 (He et al., 2016) as its encoder, which they then used to refine the edges of cloud segmentation regions. They performed their experiments on RGB bands of L8-SPARCS (256×256 pixels) and Google Earth's cloud and cloud shadow datasets (224×224 pixels). The authors proposed novel modules in the decoder to recover lost details in the encoding stage, reduce information redundancy, and reconstruct spatial information using a self-attention mechanism. However, CDUNet is computationally expensive, having 47.59-million parameters compared to the original U-Net model (2-million parameters), yielding only a roughly 2% improvement on both datasets.

Following the Attention U-Net architecture (Oktay et al., 2018), Guo et al. (2020) introduced a similar model with a soft-attention mechanism called Cloud-AttU to also detect clouds in L8 imagery. They used a cross-entropy loss function to train their model on 384×384 pixel images with RGB and NIR bands. Cloud-AttU outperforms the original U-Net by 2.7% in the Jaccard index on the Landsat-Cloud dataset (Mohajerani and Saeedi, 2019), and successfully distinguishes between snow and cloud pixels. However, the authors did not experiment with other inference image datasets.

In this paper we introduce a new cloud segmentation model based on a U-Net architecture with an attention mechanism (Oktay et al., 2018) that utilizes residual blocks in the decoder (He et al., 2016). We compare the effectiveness of using a BCE versus Jaccard loss function (Rahman and Wang, 2016) in training the model. We report the results of rigorous experiments on challenging scenarios, in mixed environmental scenes, and explore the model's ability to generalize when tested on completely unseen datasets. These experiments demonstrate the robustness of our model to different sensors and spatial resolutions. Our model is trained and tested exclusively on RGB data. This further simplifies the architecture in comparison to other such deep-learning models and further emphasizes the robustness of our model with respect to the sensor type.

This paper is organized as follows: Section 2 describes our SkyWatch Cloud Segmentation dataset. Section 3 introduces the semantic segmentation model (which we refer to as Attention ResUNet) and the methodology used in this study. In Section 4 we report on the performance and results of this network on a variety of intra- and inter-class experiments. Finally, Section 5 concludes this paper with a brief summary and a discussion of potential improvements for future work.

2 SkyWatch Cloud Segmentation Dataset

The SkyWatch Cloud Segmentation (SW-CS) dataset consists of a combination of high and low spatial resolution images captured in RGB by several different sensors. In order to produce a dataset with sufficient variations in scenes, resolution, and image quality that adequately captures a variety of realistic imaging conditions we assembled a unique dataset from four smaller subsets. Each subset has been manually annotated to ensure high fidelity of the resulting ground truth. Different pre-possessing techniques are then applied to each of these subsets, which are then shuffled together before being split into training and test sets.

Subset 1	Subset 2	Subset 3	SPARCS & CCA

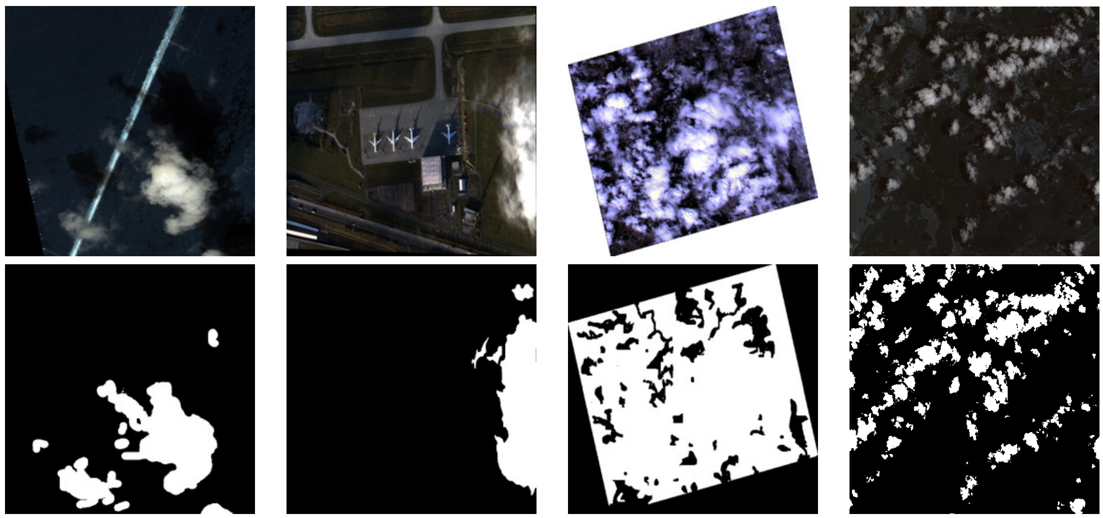

Table 1: Examples of RGB images (top row) and their corresponding cloud masks (bottom row) for each of the subsets in the SW-CS dataset. Subset 1 & 2: Tiled 0.5-m resolution scenes. Subset 3: 0.7-m to 2.2-m resolution scenes. SPARCS & CCA: Tiled 30-m resolution scenes.

2.1 Composition of the Dataset

The bulk of the SW-CS dataset consist of 2,443 full scene products. These products consist of high spatial resolution imagery (0.5-m per pixel edge) from several independent Earth-observing satellites in a variety of sizes and dimensions. These subsets of high resolution imagery are tiled as the full products can be computationally expensive to ingest and process, often being ten or more thousands of pixels in a single dimension. We use a combination of techniques to crop and rescale these products to produce two subsets of image tiles (each being 512×512 pixels) that reflect a variety of circumstances in which they might acquired, and to allow the network to more easily process and ingest the imagery, while attempting to preserve the full context of the features in each scene.

One subset of the full scene products are down-sampled to be 2,048 pixels along its longest dimension (Subset 1). The remainder of the high resolution full scene products are down-sampled to be 1,000 pixels in width while preserving the overall aspect ratio of the image (Subset 2). Each resized scene is then divided into a set of 512×512 pixel tiles, with individual tiles containing fewer than 50% valid pixels being discarded. The original cloud mask labels for all of these scenes are then manually refined in order to ensure the most accurate possible cloud masks for each image.

An additional 189 full scene products obtained between 0.7-m and 2.2-m spatial resolution have also been incorporated into the into the SW-CS dataset (Subset 3). Similar to the high resolution imagery, each of these additional scenes is rescaled from its original size into single tiles of size 512×512 pixels. The cloud masks in these scenes have also been manually annotated from scratch to ensure their accuracy.

Finally, we add the SPARCS (Hughes and Hayes, 2014) and CCA (Foga et al., 2017) datasets into the SW-CS dataset. This addition consist of L8 imagery and associated cloud masks. The spatial resolution of these images is 30-m per pixel edge. Each SPARCS image is split into 4 tiles (with no overlap). Each tile is then resized to be 512×512 pixels. Each CCA image is also tiled into 512×512 image segments so that none of the images contain invalid pixels. The result is a collection of 1,039 image tiles from these two datasets. The original labels for all of these image tiles are not refined as they were evaluated to be sufficiently accurate. The inclusion of these datasets provides low-resolution examples for the model to train and test using sources that are widely publicly available.

2.1.1 Data Pre-processing

All of the aforementioned subsets of the SW-CS dataset are shuffled together and then split into training, testing, and validation sets in a $0.8 : 0.1 : 0.1$ ratio. The training set is then augmented using the following procedure:

- Tiles are rotated between $[-20, +20]$ degrees.
- Zoom in and out $[-20, +20]\%$.

- Flip tiles in the x-direction 80% of the time.
- Flip tiles in the y-direction 80% of the time.
- Change the pixel intensity values in the range of $[-20, +35]$.
- Adjust the contrast by scaling pixel values, $255 \times (v/255)^{\gamma}$, with γ in the range $[0.66, 1.9]$.
- Add additive Gaussian noise per pixel, sampling from the normal distribution $N\ (0, 0.06 * 255)$. 50% of the time this noise is added to a single channel, and 50% of the time it is added equally to all three channels.

3 Semantic Segmentation

U-Net (Ronneberger et al., 2015) is a popular neural network model consisting of an encoder-decoder architecture, and which has gradually been improved since its original publication (Oktay et al., 2018; Piao and Liu, 2019; Cao and Zhang, 2020; Isensee and Maier-Hein, 2020). In this paper, we incorporate the suggestions provided by Oktay et al. (2018) and Isensee and Maier-Hein (2020) for improving U-Net's accuracy. We exploit an attention mechanism at the skip connections in U-Net's decoder path. The implemented attention mechanism suppresses activations at irrelevant regions, improving the accuracy of the feature representation sent to the decoder. We further make use of ResNet-50 (He et al., 2016) pre-trained on ImageNet (Deng et al., 2009) as the decoder of our model. The skip connections in the model's residual blocks help address the problem of vanishing gradients (Pascanu et al., 2013; `conv1_conv`, `conv2_block3_1_relu`, and `conv3_block4_1_relu`, in the Keras implementation for example, and as illustrated in Figure 1). The resulting encoder-decoder structure has 11.2-million trainable parameters. In this study, we refer to our model as an Attention ResUNet. Figure 1 shows the architecture of our Attention ResUNet, and Figure 2 shows the structure of the attention gate used in the model.

The encoder's weights are not frozen during training. Stochastic gradient descent is facilitated with the Adam optimizer (Kingma and Ba, 2014), and early stopping (Caruana et al., 2000) is used to prevent over-fitting during training, where the validation loss is monitored. If the loss does not decrease for 50 consecutive epochs, the training process is stopped.

Input image tiles to the Attention ResUNet model are 512×512 pixels in size. Each image tile consists of three wavelength bands: red, green, and blue. The model's output is a segmentation mask, also referred to as a cloud mask, which is a single band 512×512 pixel image. The pixel values in the cloud mask correspond to the probability ($[0, 1]$) of that pixel being all or part of a cloud. In this context, we refer to the *background* versus *cloud* classes.

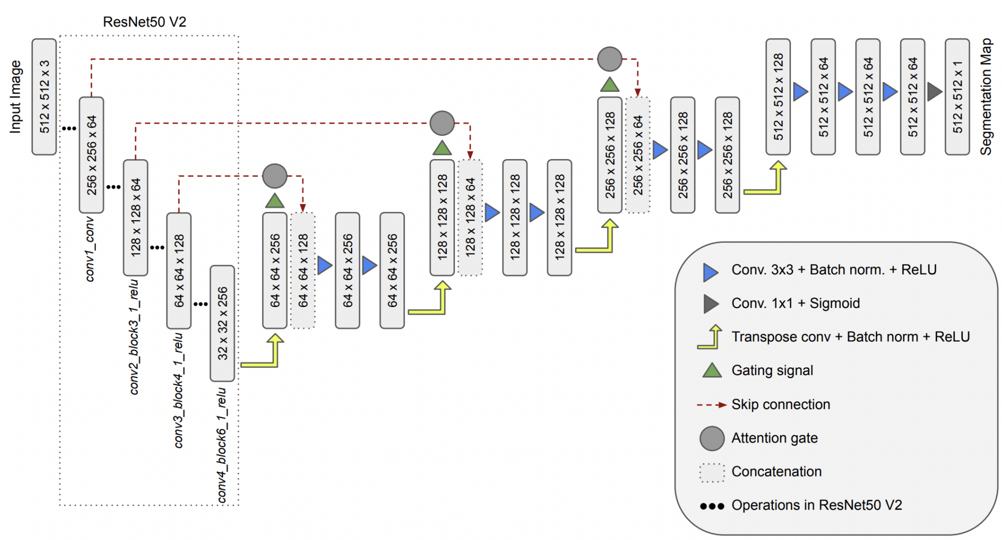

Figure 1: Block diagram of the Attention ResUNet segmentation model. The input image is filtered and down-sampled by the ResNet-50 V2 architecture in the encoder. Attention gates filter features coming from the encoder. The structure of the attention gate is shown in Figure 2 below.

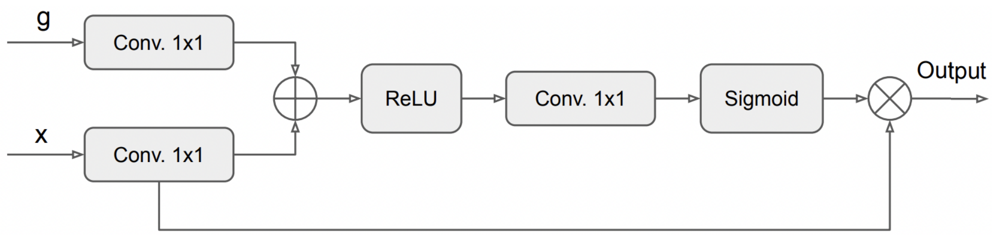

Figure 2: The structure of the attention gate in the Attention ResUNet, where g is the gating signal and x is the skip connection obtained from the encoder. The $\oplus$ symbol represents the addition operation, and $\otimes$, the dot product operation.

3.1 Loss Functions

Janocha and Czarnecki (2017) note that cross-entropy loss is often used for training neural networks without consideration for the alternatives. Indeed, cross-entropy has been the fiducial loss function in applications of deep learning to cloud detection (Hu et al., 2021; Guo et al., 2020). In the case of highly imbalanced images where the cloud pixels are few, however, this loss function can lead to simplistic solutions because many pixels can be wrongly classified as the background class to ensure a low loss value. Jaccard loss, also known as Intersection over Union (IoU) Rahman and Wang (2016), is a great candidate for dealing with highly imbalanced datasets. Therefore, we have trained three variations of our cloud detection model.

We trained one of the variations of our model using Binary Cross Entropy (BCE) loss, as in equation 1. Here T_x refers to true labels or the ground truth of pixel x, and P_x refers to the network's prediction of pixel x.

$$L_{BCE} = \sum_{x} -(T_x log(P_x) + (1 - T_x) log(1 - P_x)) \tag{1}$$

The second variation of our model is trained using Jaccard loss, introduced in equation 2. Here T stands for the true label while P stands for the prediction. The notation $| \quad |$ is the 1-norm. $T * P$ is the element-wise multiplication. The nominator of this formula is the approximate intersection based on the probabilities of P and T.

$$L_{Jaccard} = \frac{|T * P|}{|T + P - (T * P)|} \tag{2}$$

Finally, equation 3 expresses the third variation of our model, which is trained using the average of both the BCE and Jaccard losses:

$$L_{avg} = \frac{L_{BCE} + L_{Jaccard}}{2} \tag{3}$$

4 Results

In this section, we measure and discuss the performance of our Attention ResUNet model as trained on the SW-CS dataset. We then evaluate the perform of our model (without retraining) on the inter-class datasets mentioned in (Skakun et al., 2022). We aim to evaluate our model against these latter datasets as a common benchmark, and for this we follow the methodology of the Cloud Mask Inter-comparison eXercise (hereafter CMIX, Skakun et al., 2022).

4.1 Performance Metrics

As in Skakun et al. (2022) we use overall accuracy (OA), balanced overall accuracy (BOA; Brodersen et al., 2010), user's accuracy (UA, equivalent to precision P), and producer's accuracy (PA, or recall R), to report the performance of models in both experiments. These metrics are calculated using the total number of true positives, false positives, and false negatives in our inference experiments. For the inter-class experiment we additionally calculated the precision and recall per inference image and report the average performance of both, which we denote as $\mathrm{P_{mean}}$ and $\mathrm{R_{mean}}$, respectively. We also report the F1 and IoU scores. $\mathrm{F1_{mean}}$ and $\mathrm{IoU_{mean}}$ are the averages of these scores on all inference images, while $\mathrm{F1_{total}}$ and $\mathrm{IoU_{total}}$ are calculated using the total number of true positives, false positives, and false negatives in the inference dataset.

4.2 Loss Functions

The output of the segmentation network is a mask in which each pixel's value represents the probability of that pixel being part of a cloud. In other words, each pixel value determines the confidence of the network in identifying cloud vs ground features. A threshold on this probability can be applied to fix each pixel as being either a cloud or non-cloud pixel. Higher threshold values result in fewer false positives (increasing precision and decreasing recall), whereas lower threshold values result in decreased precision and increased recall. Throughout our experiments below we use a threshold of 50% to ensure a balance between the model's precision and recall.

In experimenting with both BCE and Jaccard loss we find that the cloud masks of the network when trained with Jaccard loss are strongly determined, with probabilities being always close to 0 or 1. With BCE loss the inferred cloud masks are often more "gray", with pixel values taking on a much more uniform distribution of values between 0 and 1. The combination of both losses resulted in cloud masks that are not as discriminatory as using the Jaccard loss alone, nor is there as much variance in the output as there is with BCE by itself. An example is provided in Figure 3.

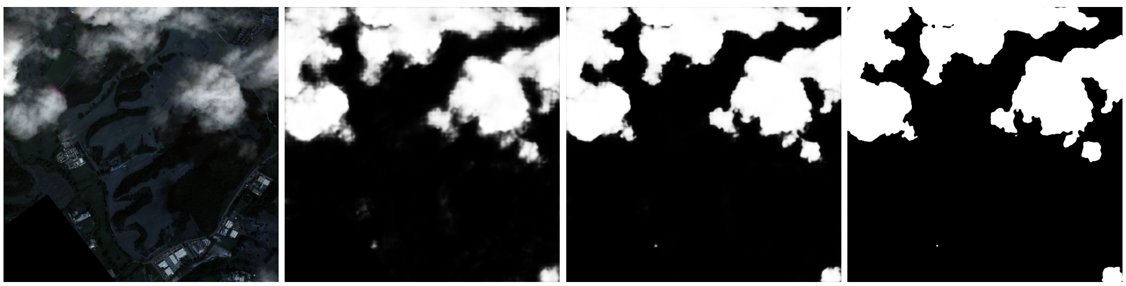

Figure 3: Examples of inferred cloud masks as determined using different loss functions for the model during training. From left to right: The inference RGB image; the model's inferred cloud mask trained with BCE loss, trained with a loss that is the average of the BCE and Jaccard losses, trained with Jaccard loss.

Table 2 shows the quantitative results of our model trained using Jaccard, BCE, and the combination of these losses, on 364 image tiles from the SW-CS dataset. The model trained using the Jaccard loss outperforms the other two variations in nearly all performance metrics. Therefore the model trained using the Jaccard loss is selected as the "final" version of the model used in the subsequent experiments of this paper.

Loss	OA	BOA	PA	UA	$\mathbf{F1_{total}}$	$\mathbf{IoU_{total}}$	$\mathbf{R_{mean}}$	$\mathbf{P_{mean}}$	$\mathbf{F1_{mean}}$	$\mathbf{IoU_{mean}}$
Jaccard	**96.4**	**95.4**	93.1	93.9	**93.5**	**87.8**	**87.7**	**85.7**	**82.6**	**76.2**
BCE	96.3	95.0	91.9	**95.0**	93.3	87.6	86.4	83.4	79.5	72.8
Combination	96.2	95.3	**93.2**	93.4	93.3	87.5	87.6	81.9	79.4	72.8

Table 2: Performance of our Attention ResUNet using Jaccard, BCE, and a combination of both, on the internal SW-CS dataset.

4.3 SW-CS Dataset

The SW-CS dataset contains imagery from various satellites with different spatial resolutions, and our model is robust enough to achieve a BOA of 95.4% and an F1 score of 93.5%. A random selection of inference results from the model is shown in Figure 4. The model capably learns to identify opaque clouds but struggles with thin clouds, as seen in the fourth row of Figure 4 (though labels for thin clouds were not included for the model during training). Even with the relatively large input image sizes of 512×512 pixels, the time to inference is < 2 seconds on CPU (3.3-GHz Intel Xeon Scalable processor) and a mere 190-ms on a NVIDIA K80 GPU with 2,496 parallel processing cores and 12-GB of GPU memory.

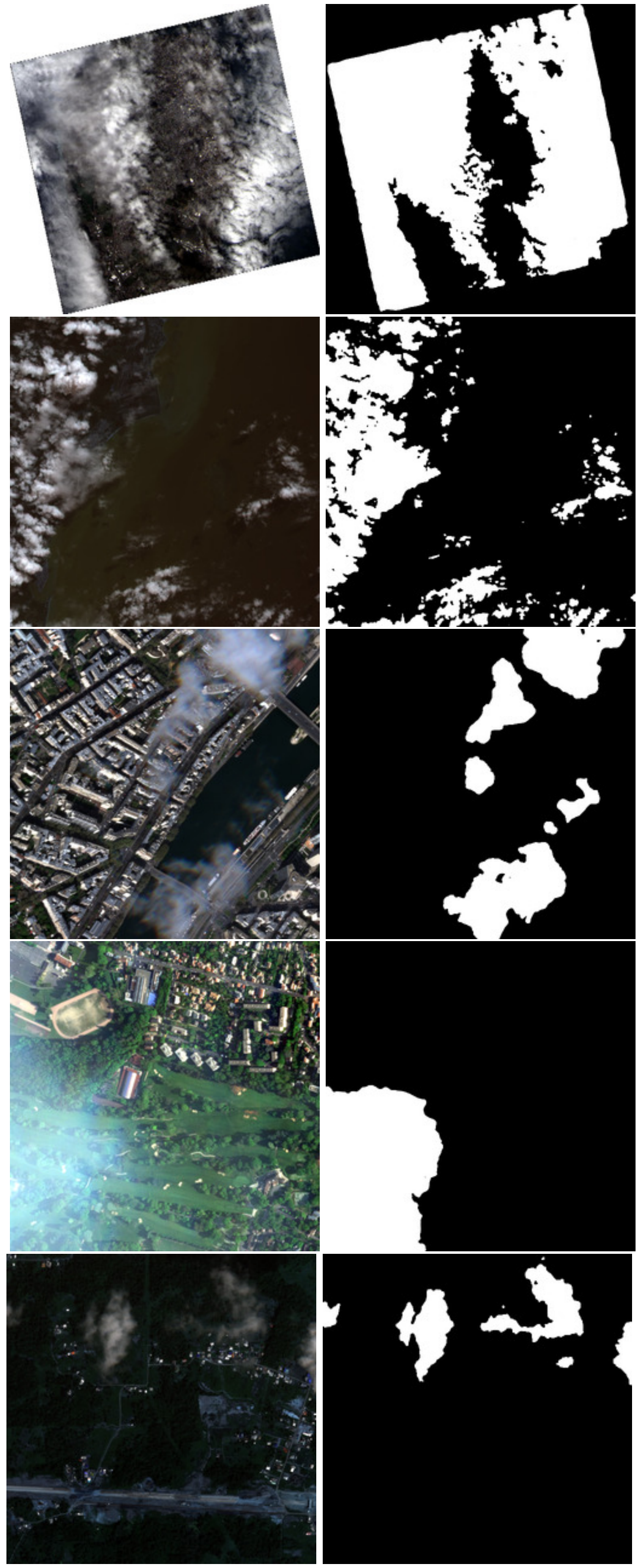

Figure 4: Examples of inference results by the model on the SW-CS dataset. The columns from left to right: The input RGB image, and the model's predicted cloud mask.

4.4 Cloud Reference Dataset

Following the results presented in the recent Cloud Mask Inter-comparison eXercise (Skakun et al., 2022) we test our model using existing L8 and S2 reference cloud datasets, which include the datasets of Hollstein (Hollstein et al., 2016), GSFC (Skakun et al., 2021), L8Biome (Foga et al., 2017), CESBIO (Baetens and Hagolle, 2018), and PixBox (Paperin, 2021a,b). This allows us to evaluate the performance of our model using common points of comparison against which the most popularly employed cloud detection algorithms have also been evaluated (Zhu and Woodcock, 2012; Chen et al., 2021; Hu et al., 2021). For each exercise we compare the performance of our Attention ResUNet to the individual model(s) evaluated to have the best performance (in OA, BOA, PA, and UA) for each of these respective datasets. As our model is trained to detect opaque clouds it is tested only on the opaque cloud annotations of these different datasets (where available). No distinction is made between thick and thin clouds in the case of the GSFC-L8 and CESBIO datasets, which is therefore anticipated to impact the relative performance of our model on these two datasets.

4.4.1 Pre- and Post-processing

The following pre-processing steps are taken in order to prepare the image/label pairs for each of the aforementioned datasets. Images are cropped to the minimum area containing all annotated clouds for the Hollstein and GFSC datasets. All images are zero-padded and tiled into 512×512-pixel images. Labels are created such that a pixel value of 0 is transparent, 127 represents no data (and is not considered in quantitative performance evaluations), and a pixel value of 255 denotes a cloud pixel. Labels are padded to meet the padding of the corresponding input image. No pre-processing steps for changing the contrast or spatial resolutions of the images are taken.

The output inferences (cloud mask) produced by the model are combined to recover an inference that corresponds to the original full-size input image. For the CESBIO dataset it is necessary to resize the original image to fit the ground truth label dimensions, as the ground truth labels for this dataset are provided at a smaller size than the input images.

4.4.2 Hollstein

The Hollstein dataset includes 59 scenes obtained by S2 (at 20-m pixel resolution). The cloud labels for this dataset are provided as polygons, meaning only some of the pixels in each scene are actually annotated explicitly. Table 3 shows the quantitative inference results of our model on the Hollstein dataset (without thin clouds). The CD-FCNN model (López-Puigdollers et al., 2021) was the best-performing model in the CMIX, based on OA and BOA scores. CD-FCNN is itself a deep learning model that also uses a UNet-based architecture and is trained on L8Biome and SPARCS datasets with a spatial resolution of 30-m. Our model performs comparably to the CD-FCNN on this dataset even without having been exclusively exposed to images at this resolution during training and using only three bands instead of the six bands used by CD-FCNN (RGBISWIR - B2, B3, B4, B5, B6 and B7 of Landsat-8 and B2, B3, B4, B8, B11 and B12 of Sentinel-2).

Algorithm	OA	BOA	PA	UA
CD-FCNN	**97.8**	**97.8**	98.3	96.7
FMASK 4.0 CCA	94.9	95.4	**99.9**	89.8
InterSSIM	97.5	97.4	96.8	**97.5**
Ours	97.2	97.5	99.6	94.6

Table 3: Hollstein - Opaque clouds only.

4.4.3 GSFC

The GSFC dataset consists of two parts. The first part includes six scenes of L8 data, namely GSFC-L8. The GSFC-L8 dataset does not distinguish between thin and opaque clouds in its ground truth annotations. Table 4 shows the performance of our model compared to the top-performing algorithms mentioned in the CMIX (Skakun et al., 2022). Although CD-FCNN takes a similar approach to our own and is specifically trained on this dataset, our model is able to achieve better performance without being exclusively trained on L8 data. The performance of our satellite-agnostic model is the same as FMASK 4.0 which is designed specifically for L8 data and S2 images and utilizes more of the available bands.

The second part of this dataset is referred to as GSFC-S2 and is comprised of 28 scenes of S2 data. The clouds are annotated with polygon shapes, with separate annotations for translucent and opaque clouds. Table 5 shows the performance metrics of our model and the other highly ranked algorithms from the CMIX (Skakun et al., 2022). The results show that our model achieves 100% UA, which means there were no false positives in the predictions. The PA is lower than other algorithms however, indicative of the high number of false negative predictions made by the model. Such discrepancies are generally a result of class imbalance, and indeed the ground truth labels of the GSFC-S2 dataset is imprecise. Numerous pixels are incorrectly classified as clouds when they clearly belong to the background class. In other words, the ground truth cloud masks significantly over-classify cloudy regions in these images. In spite of our model's apparent performance, Figure 5 shows this discrepancy between the RGB images, the ground truth cloud masks, and that our model inferences produce substantially more accurate cloud masks.

Algorithm	**OA**	**BOA**	**PA**	**UA**
CD-FCNN	97.3	97.3	94.6	100.0
FMASK 4.0 CCA	**98.7**	**98.7**	**97.3**	**100.0**
Ours	**98.7**	**98.7**	**97.3**	**100.0**

Table 4: GSFC-L8 - No distinction is made between translucent versus opaque clouds, and for which many pixels are incorrectly classified in the ground-truth labels.

Algorithm	**OA**	**BOA**	**PA**	**UA**
LaSRC	**98.0**	**97.9**	**98.5**	97.8
ATCOR	86.9	88.2	76.4	**100.0**
CD-FCNN	92.9	93.6	87.3	99.9
Ours	87.4	88.4	77.0	**100.0**

Table 5: GSFC-S2 - Opaque clouds only. Many pixels are incorrectly classified in the ground-truth labels of this set as well.

4.4.4 L8Biome

The L8Biome dataset consists of 96 scenes of L8 data at a spatial resolution of 30-m per pixel edge. In this dataset regions with thin translucent clouds belong to a separate class and are distinguished from more opaque clouds. Every image is fully annotated at the pixel level. Table 6 shows the inference results of the best algorithms mentioned in the CMIX (Skakun et al., 2022) as well for our model on the opaque cloud class. Our model outperforms the most accurate algorithms on this dataset across all performance metrics. Note that the CD-FCNN is not measured against this dataset as the L8Biome dataset is a subset of the data on which that model was trained.

Algorithm	**OA**	**BOA**	**PA**	**UA**
LaSRC	92.8	93.5	97.8	86.9
ATCOR	89.6	89.2	86.8	88.6
Fmask 4.0 CCA	92.1	93.1	99.7	84.6
Ours	**93.5**	**94.2**	**98.9**	**87.7**

Table 6: L8Biome - Opaque clouds only.

4.4.5 CESBIO

The CESBIO dataset is composed of S2 imagery. It consists of 30 scenes with a spatial resolution of 60-m per pixel edge. Each image is fully annotated at the pixel level, and there is no distinction made between thin versus opaque clouds. Table 7 shows the performance of our model and other top-performing algorithms on this dataset from the CMIX study (Skakun et al., 2022). Our model performs worse in comparison to FORCE, especially as measured by PA. Our model produces a large number of false negatives because of discrepancies between the ground truth labels in our proprietary training set. That is, translucent clouds are defined as belonging to the "background" class in the ground truth annotations in our SW-CS dataset. A few examples of this discrepancy are shown in Figure 6 in which our model detects opaque clouds well, but ignores thin translucent clouds. The relatively low UA means that there are also a large number of false positives in our model's results as well. In Figure 7 it's apparent that, not only does our training dataset lack training imagery at a comparable spatial resolution (60-m per pixel edge), but also that our training dataset does not include a sufficient number of textured arid and snowy regions. In fact, a significant number of misclassifications made by our model on this dataset are attributable to this similarity between the texture of arid scenes and of clouds, as shown in Figure 7.

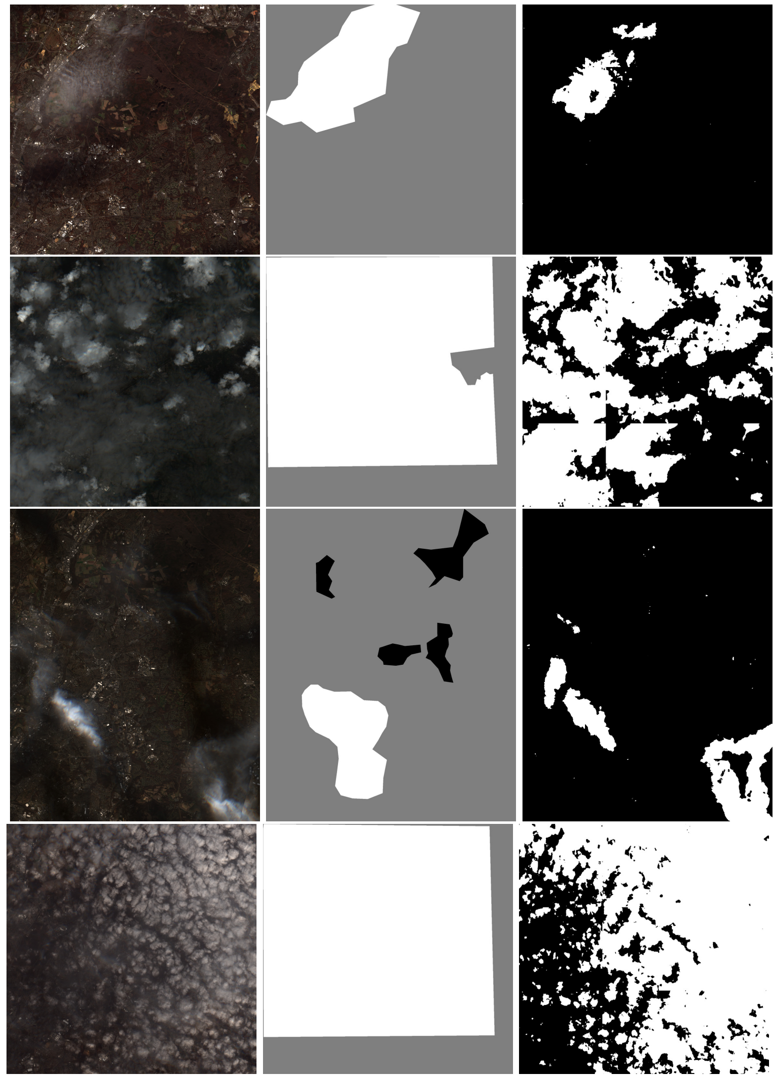

Figure 5: Examples of label discrepancies in the GSFC-S2 dataset between the true color image (left), and the ground truth cloud mask (center), compared to the inferred cloud mask predicted by our model (right). This type of misclassification is common throughout the samples in this dataset. In the ground truth images, gray areas are unlabeled.

Algorithm	**OA**	**BOA**	**PA**	**UA**
CD-FCNN	89.5	79.5	60.3	**94.1**
Fmask 4.0 CCA	93.3	88.9	80.4	90.8
FORCE	**91.1**	**88.9**	**84.7**	79.9
LaSRC	81.2	82.7	85.6	57.6
MAJA* (28/30)	89.2	90.5	92.9	72.7
Ours	88.4	80.4	64.7	83.8

Table 7: CESBIO

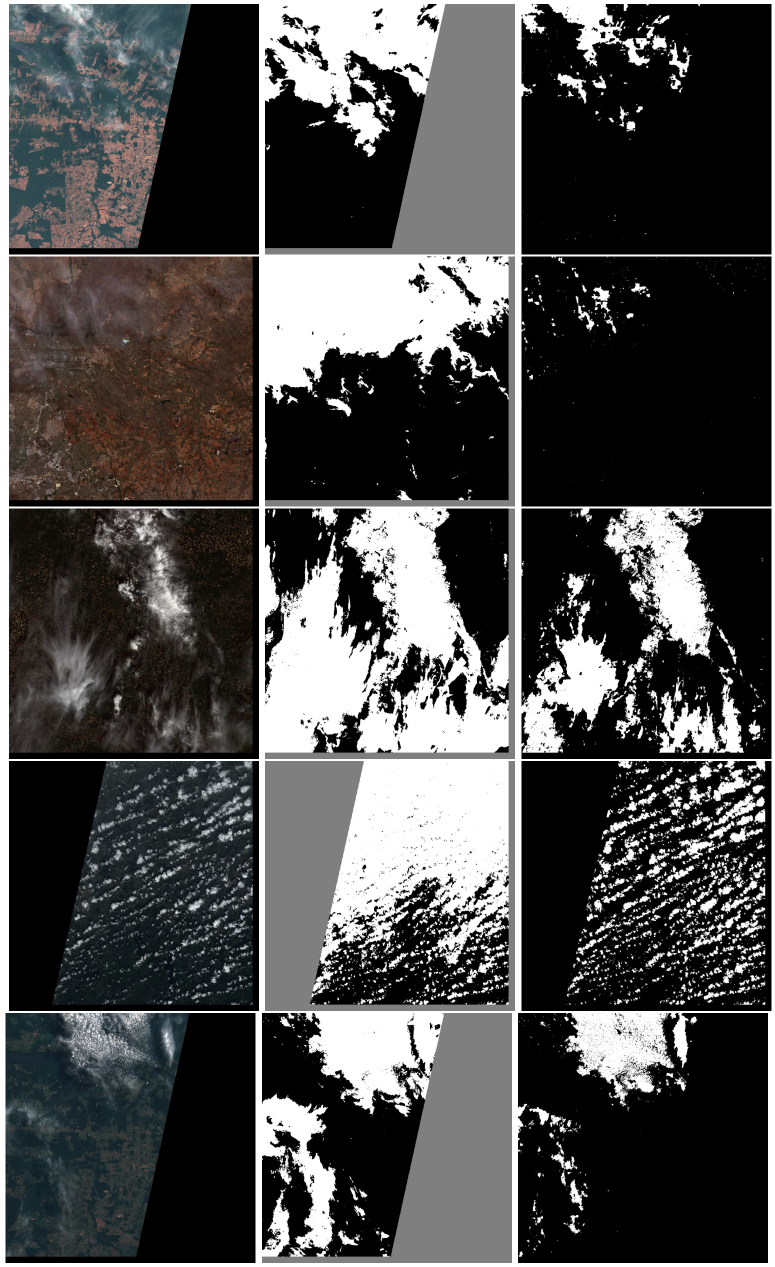

Figure 6: Examples of label discrepancies on the CESBIO dataset. Columns from left to right: True color images, ground truth labels, and our model's predicted cloud masks. Note the significance with which thin clouds dominate the ground truth labels, which our Attention ResUNet ignores by design.

4.4.6 PixBox

The PixBox dataset consists of two component datasets. Both component datasets are partially annotated, meaning only selected pixels in each image have been classified. In both components thin clouds are annotated as a separate class from opaque clouds. The first component dataset includes 29 scenes of S2 data at 10-m spatial resolution. The inference results on PixBox-S2 without thin clouds are provided in table 8. Our model outperforms every other model in this category in OA, BOA, and PA, achieving an OA of 97.4% and BOA of 96.7%. The second part of the dataset includes L8 imagery with a spatial resolution of 30-m in 11 scenes. Table 9 shows the inference results where our model has the highest OA (98.8%) compared to every other model in this category, as found in Skakun et al. (2022); while having a BOA of 98.7%, the same as the top-performing model.

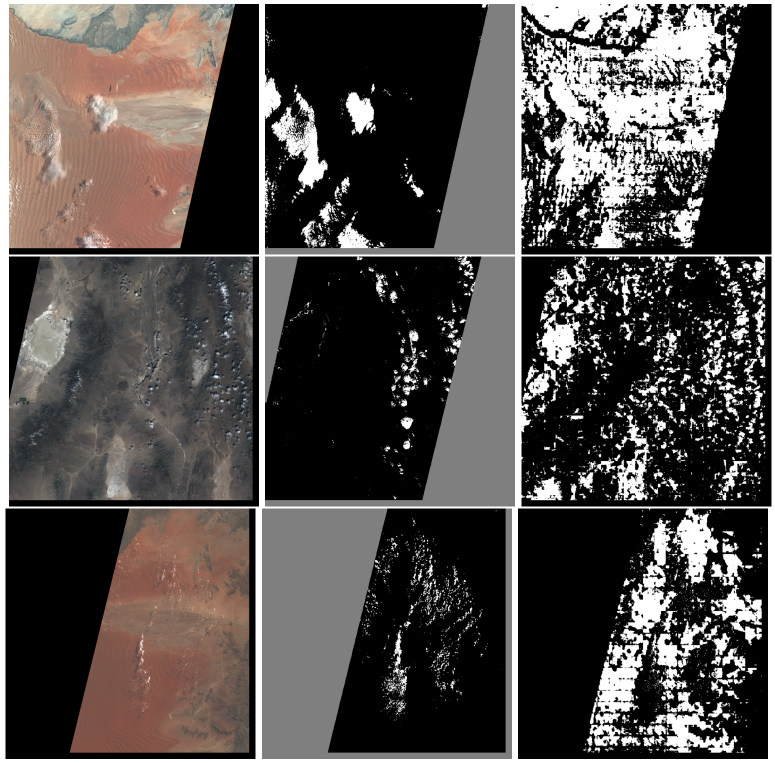

Figure 7: Examples of textured arid regions in the CESBIO dataset that our model is confused by. Columns from left to right: True color images, ground truth labels, and our model's predicted cloud masks.

Algorithm	OA	BOA	PA	UA
InterSSIM	91.9	90.7	86.2	**91.3**
S2cloudless	91.6	91.6	91.6	86.4
CD-FCNN	89.5	88.1	82.7	87.9
Ours	**97.4**	**96.7**	**97.4**	85.7

Table 8: PixBox-S2 - Opaque clouds only.

Algorithm	OA	BOA	PA	UA
ATCOR	98.4	96.7	94.1	**95.6**
CD-FCNN	97.8	98.7	**99.9**	87.4
Ours	**98.8**	98.7	98.5	95.0

Table 9: PixBox-L8 - Opaque clouds only.

4.5 Error Sources

Most of the errors in the inference dataset are due to haze and small clouds not being detected by our model. The magnitude of these errors is tolerable for two key reasons: 1. The network was not trained to detect thin clouds such as haze, and 2. Small clouds do not contribute significantly to the overall cloud cover percentage. However, there remain some problematic inference samples that do not belong to these two categories. These remaining erroneously classified samples are generally the result of patterns similar to clouds (e.g., patterns in arid areas, structures, and some highly textured snow scenes). Figures 8 and 7 show a few examples of these problematic inference images, from our own SW-CS dataset and found in the CESBIO dataset, respectively. The first row of images in Figure 8 shows an example of farmland with a repetitive pattern of crops that our model incorrectly classifies as clouds. In the second row, several buildings are classified as clouds as well. Our model accurately distinguishes clouds from snow in a variety of scenarios. However, in scenes dominated by snow, the network struggles to distinguish clouds from snow as accurately as in scenes where snow occupies only a portion of the total scene. Figure 9 shows several examples of how

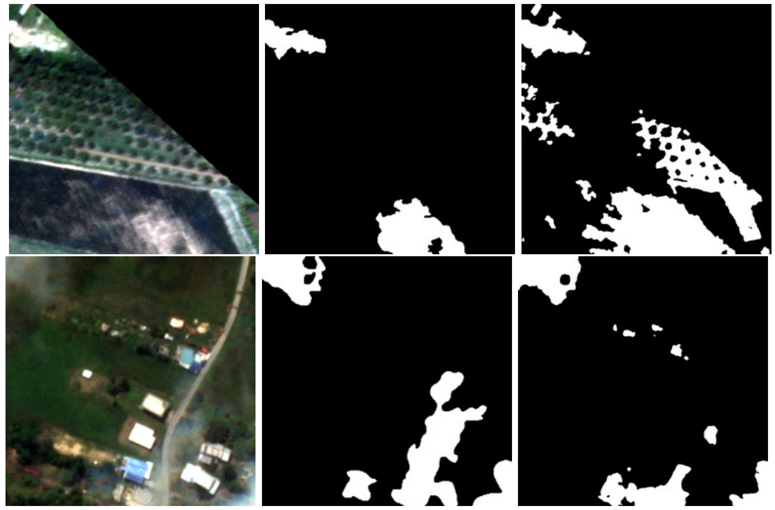

Figure 8: Examples with specific objects or textures that our model misclassifies as cloud. Columns from left to right: True color images, ground truth cloud masks, and our model's inferred cloud masks.

our model performs on different scenes containing various degrees of land and snow cover. Additional samples (and augmentation) of scenes similar to these problematic cases can be added to the training dataset to help the network better distinguish these types of features in future.

All of the samples with an F1 score of less than 80% were manually examined in order to determine on which samples our Attention ResUNet had the greatest difficulty in identifying clouds. We find that where the F1 score is below 80% (in 51 out of the 364 images on which the model was tested) there are greater variations in the correspondence of the ground truth cloud mask and the actual RGB image. This is evident in the standard deviation of IoU scores between these two sub-samples (below and above an F1 score of 80%): The IoU of our model when the F1 score of the prediction is above 80% is 0.90 ± 0.06; on images where the F1 score of the prediction is below 80% the IoU falls dramatically to 0.49 ± 0.28, with a significant increase in the standard deviation as well. This suggests some of the labels in the ground truth of the SW-CS dataset itself may need to be revised. Moreover, we noticed specific characteristics that are confusing to the model. Rare farmland texture, strong cloud shadows and the cut-off between thick clouds and haze are a few examples for which there are insufficient samples in the training dataset.

5 Conclusion

In this paper, we have demonstrated a semantic segmentation network that is an excellent model for identifying opaque clouds in satellite imagery. Our model uses just three bands (RGB) without the need for additional information such as from NIR bands or secondary sensor information for input and accepts relatively large image sizes (512×512 pixels). Our model makes use of the U-Net architecture, skip connections, and an attention mechanism. The incorporation of residual units in the encoder stage allows us to ease the training of a model of this size. Also unique to other deep learning approaches that have been employed for the semantic segmentation of clouds is our use of Jaccard loss during training to account for class imbalance in cases where clouds occupy considerably fewer numbers of pixels compared to the total image size. Further, our model is trained on imagery produced by multiple satellite sensors and displays considerable robustness to changes in spatial resolution.

We evaluated our model using two experiments. The first experiment we performed on a challenging proprietary dataset, the SW-CS dataset. In this experiment our model trained with Jaccard loss achieves an F1 score of 93.5% and a BOA of 95.4%. For the benchmark experiments we applied our model to several popular cloud segmentation datasets as mentioned in the CMIX (Skakun et al., 2022). Our model outperforms the best-in-class models tested in that paper on GSFC-L8, L8Biome and PixBox datasets. Though our model underperforms the best-in-class models from Skakun et al. (2022) on the GSFC-S2 and CESBIO datasets, it does not do so unexpectedly, as the ground truth labels of these datasets include a large number of false positives, for which we have provided examples of herein. In the CESBIO dataset we find additional confusing samples in arid and snowy regions in which the landscape itself can appear cloud-like, and which our Attention ResUNet struggles with. We speculate these difficulties can be surmounted by exposing the model to a sufficient number of related samples during training.

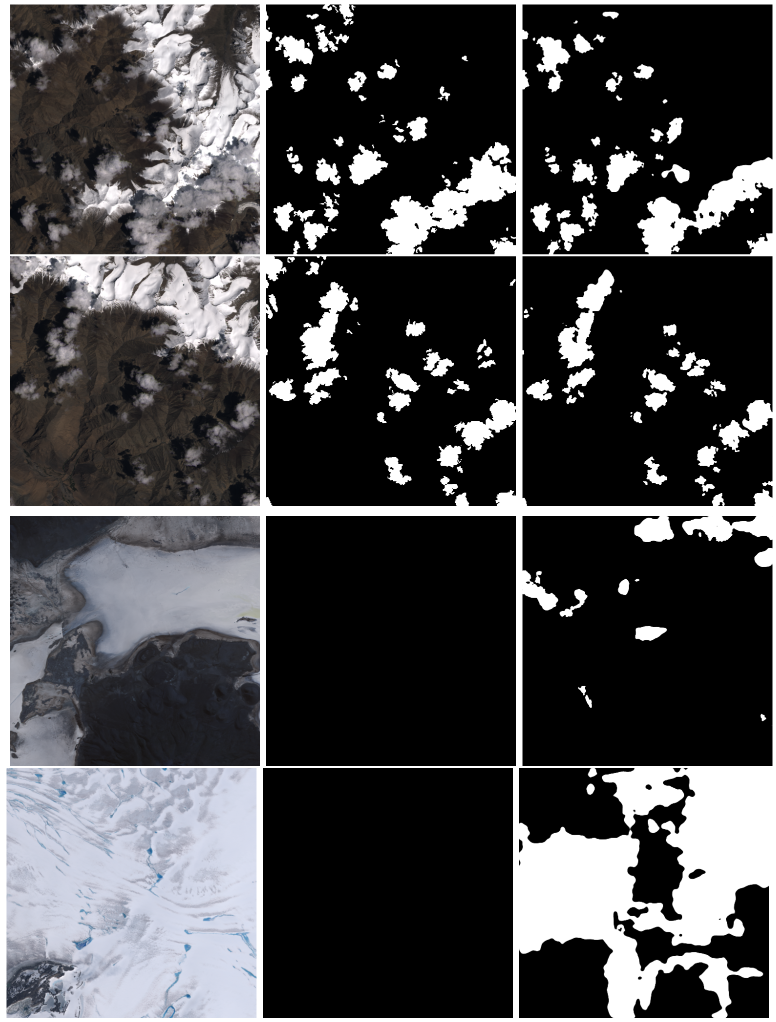

Figure 9: Examples of our model's inferences on snowy regions with and without clouds. The first two rows show acceptable performance, and the last two rows show snowy areas misclassified as containing clouds. Columns from left to right: True color images, ground truth cloud masks, our model's inferred cloud mask.

Our Attention ResUNet is therefore a novel architecture for cloud segmentation, which together with our proprietary dataset, is a significant improvement in the application of generalized cloud detection. In particular, similar deep-learning approaches (such as the CD-FCNN evaluated in the CMIX Skakun et al., 2022) rely on the availability of the six bands in L8 and S2 data on which that model was trained. Our Attention ResUNet requires only three bands (RG), and in several scenarios significantly outperforms this model (such as on the PixBox dataset).

We expect future studies will be able to improve this architecture further still. Knowledge distillation can reduce the number of trainable parameters of the model enabling it to be deployed on resource-limited architectures such as those onboard a satellite. We further expect General Adversarial Network (GAN) augmentation (e.g., Nyborg and Assent, 2021) could also be used to improve the model's performance in identifying clouds on those samples where we have shown our model still exhibits difficulty in producing accurate cloud masks. The use of GANs in this way may be particularly attractive as arid and snowy regions are far less represented in the majority of publicly available datasets.

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