1 Multi-sensor cloud and cloud shadow segmentation with a convolutional 2 neural network

3 Marc Wieland ¹*, Yu Li ¹, Sandro Martinis ¹

4 ¹ German Remote Sensing Data Center (DFD), German Aerospace Center (DLR), Oberpfaffenhofen, D-82234
5 Wessling, Germany

6 * Correspondence: marc.wieland@dlr.de
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8 Abstract

9 Cloud and cloud shadow segmentation is a crucial pre-processing step for any application that uses multi-
10 spectral satellite images. In particular, disaster related applications (e.g., flood monitoring or rapid damage
11 mapping), which are highly time- and data-critical, require methods that produce accurate cloud and cloud
12 shadow masks in short time while being able to adapt to large variations in the target domain (induced by
13 atmospheric conditions, different sensors, scene properties, etc.). In this study, we propose a data-driven
14 approach to semantic segmentation of cloud and cloud shadow in single date images based on a modified U-Net
15 convolutional neural network that aims to fulfil these requirements. We train the network on a global database of
16 Landsat OLI images for the segmentation of five classes (“shadow”, “cloud”, “water”, “land” and “snow/ice”).
17 We compare the results to state-of-the-art methods, proof the model’s generalization ability across multiple
18 satellite sensors (Landsat TM, Landsat ETM+, Landsat OLI and Sentinel-2) and show the influence of different
19 training strategies and spectral band combinations on the performance of the segmentation. Our method
20 consistently outperforms Fmask and a traditional Random Forest classifier on a globally distributed multi-sensor
21 test dataset in terms of accuracy, Cohen’s Kappa coefficient, Dice coefficient and inference speed. The results
22 indicate that a reduced feature space composed solely of red, green, blue and near-infrared bands already
23 produces good results for all tested sensors. If available, adding shortwave-infrared bands can increase the
24 accuracy. Contrast and brightness augmentations of the training data further improve the segmentation
25 performance. The best performing U-Net model achieves an accuracy of 0.89, Kappa of 0.82 and Dice
26 coefficient of 0.85, while running the inference over 896 test image tiles with 44.8 seconds/megapixel (2.8
27 seconds/megapixel on GPU). The Random Forest classifier reaches an accuracy of 0.79, Kappa of 0.65 and Dice
28 coefficient of 0.74 with 3.9 seconds/megapixel inference time (on CPU) on the same training and testing data.
29 The rule-based Fmask method takes significantly longer (277.8 seconds/megapixel) and produces results with an
30 accuracy of 0.75, Kappa of 0.60 and Dice coefficient of 0.72.

31 Keywords

32 Cloud; Cloud shadow; Convolutional neural network; Landsat; Sentinel-2

33 1 Introduction

34 Given current population growth rates and the increasingly visible effects of climate change on the environment
35 and human activities, continuous monitoring of the spatio-temporal dynamics of earth surface processes is
36 becoming ever more important. This becomes particularly prominent in emergency response applications for
37 which near-real time geo-information about a disaster situation is crucial to target often limited resources and
38 prioritize response actions (Voigt et al., 2016). To assure that earth observation based geo-information products
39 have the highest possible spatial and temporal resolutions and information content, it is critical to simultaneously
40 harvest data from a large variety of satellite sensors. While Synthetic Aperture Radar (SAR) sensors are widely
41 used in emergency response applications due to their capability of penetrating through clouds and acquiring
42 images during day and night, many tasks require the use of multi-spectral images to overcome limitations of
43 SAR data and/or to improve the temporal resolution and timespan. In particular, time-series analysis benefit
44 from the vast and consistent image archives of multi-spectral satellite sensors (Banskota et al., 2014). Also,
45 urban (Wieland, 2016) and flood (Pekel et al., 2016) mapping and monitoring systems widely use multi-spectral
46 images due to their extended thematic information content and simpler reflection characteristics in complex
47 environments. The inherent potentials of multi-spectral satellite images are, however, being hampered by the
48 presence of clouds and cloud shadows that may obstruct objects of interest and can bias image statistics, which
49 can negatively impact on the performance of image analysis methods. Therefore, the usefulness of this imagery
50 depends strongly on the ability to reliably mask clouds and cloud shadows from clear sky pixels. Being able to
51 quickly and accurately identify cloud and cloud shadow pixels is fundamental for unbiased down-stream analysis
52 and thus an essential step in producing analysis ready data.

53 Significant work has been undertaken to detect and segment clouds and cloud shadows in multi-spectral satellite
54 images (Foga et al., 2017; Goodman and Henderson-Sellers, 1988; Pankiewicz, 2007). The existing methods can
55 broadly be categorized into rule-based and machine learning approaches. The majority of rule-based methods
56 exploit variations of reflectance in visible, shortwave-infrared and thermal bands and develop rule-sets that
57 combine thresholds (Oishi et al., 2018) or functions over several spectral bands (Luo et al., 2008) to distinguish
58 clouds from clear sky pixels. Cloud shadows are more difficult to detect than clouds, because their spectral
59 signatures overlap with other dark surface materials (Main-Knorn et al., 2017). In particular, water surfaces are
60 known to introduce false positives into shadow segmentation. Consequently, methods have been developed that
61 consider spatial context information, sensor and solar geometry to estimate the occurrence of cloud shadows
62 relative to the location of clouds (Hutchison et al., 2009). Zhu et al. (2012) (Zhu and Woodcock, 2012) introduce
63 the Function of mask (Fmask) algorithm that uses rules based on physical cloud properties to identify potential
64 cloud pixels from temperature, spectral variability, and brightness in Landsat TM and ETM+ images. The view
65 angles of the satellite sensor, the illuminating angle and estimates of cloud altitude from thermal information are
66 used to predict possible cloud shadow locations. Water and snow are reported as additional classes in their

product. In a more recent study, they proposed an expansion of the Fmask algorithm to run on Landsat OLI and Sentinel-2 (Zhu et al., 2015). Despite their wide usage, rule-based methods strongly depend on the particular sensor models, are sensitive to changes in atmospheric conditions and scene properties and lack generalization ability when transferring to other sensors. Multi-date methods use dense time-stacks of images acquired over the same location at different times to integrate temporal change vectors in their rule-sets for a more robust detection (Hagolle et al., 2010) (Roy et al., 2010). Their main limitation, however, is that they require a clear sky reference image and dense data, which increases operational costs and limits their applicability in time-critical emergency situations (Lyapustin et al., 2008).

In recent years, machine learning methods have been proposed to extract more robust high-level information from images (Bai et al., 2016; Lee and Lin, 2016). Li et al. (2017) (Li et al., 2017) use a Support Vector Machine to segment clouds from reflectance and texture information. Hollstein et al. (2016) (Hollstein et al., 2016) present an overview of several ready-to-use machine learning algorithms to detect “cloud”, “cloud shadow”, “snow/ice”, “water”, “flooded” and “clear sky” pixels in Sentinel-2 images. The algorithms they present include Classical Bayes, Decision Trees, Support Vector Machine and Stochastic Gradient Descent. Hughes and Hayes (2014) (Hughes and Hayes, 2014) introduce the Spatial Procedures for Automated Removal of Cloud and Shadow (SPARCS) algorithm that uses neural networks and rule-based post-processing to determine “cloud”, “cloud shadow”, “water”, “snow/ice” and “clear sky pixels” in Landsat images. Convolutional Neural Networks (CNNs), which extract features directly from raw images by combining convolutional and pooling layers, gradually appear in recent studies on cloud segmentation (Chen et al., 2018; Mateo-Garcia et al., 2017; Zi et al., 2018). First results show superior accuracy, generalization ability and inference speed compared to rule-based and classical machine learning approaches. Zhaoxiang et al. (2018) (Zhaoxiang et al., 2018) use a lightweight U-Net (Ronneberger et al., 2015) architecture and combine it with wavelet image compression for computationally efficient cloud detection on-board small satellites. Ozkan et al. (2018) (Ozkan et al., 2018) adapt a deep pyramid network to produce cloud masks from noisy labelled RGB colour images. Zhan et al. (2017) (Zhan et al., 2017) specifically focus on distinguishing cloud and snow from Gaofen1 imagery using a modified VGG network (Simonyan and Zisserman, 2014). Despite the promising results for cloud detection achieved in above mentioned deep learning studies, none of them specifically considers cloud shadows. Isikdogan, Bovik and Passalacqua (2017) (Isikdogan et al., 2017) use a Fully Convolutional Network for semantic segmentation of Landsat ETM+ images into five classes that include amongst others “cloud” and “shadow”. Their main objective is large-scale surface water mapping, but generalization ability across sensors is not considered. Sholar (2018) (Sholar, 2017) confirms the observed lack of research and available deep learning models that specifically consider a shadow class and concludes that future work should focus on improving on this regard. Furthermore, additional research is needed to train models that generalize well across different sensors and images with varying atmospheric conditions and surface reflectance characteristics.

In this study, we propose a cloud and cloud shadow segmentation method that is based on a modified U-Net

102 CNN and trained on freely available reference data. We aim to fulfil the requirements imposed by emergency
103 response applications. In particular, our objective is to provide a rapid and simple to use method that is able to
104 mask cloud and cloud shadow pixels in single date images from a large variety of multi-spectral satellite sensors
105 without the need for re-training or manual interference. We proof the generalization ability of our method across
106 multiple satellite sensors (Landsat TM, Landsat ETM+, Landsat OLI and Sentinel-2) and compare it to the
107 widely used Fmask algorithm (Zhu et al., 2015) and a traditional Random Forest classifier as baseline models. In
108 this context, we also show the influence of different training strategies and spectral band combinations on the
109 performance of the semantic segmentation. Compared to previous work in this direction, our study specifically
110 focuses on multi-sensor generalization ability, simplicity and computational efficiency and provides an extensive
111 performance evaluation across different sensors, seasons and locations. Furthermore, we consider a shadow class
112 and distinguish between cloud, snow/ice, water and land pixels.

113 **2 Data**

114 In a supervised machine learning setup, a model is fit on a training dataset that is a set of labelled samples with
115 associated feature vector. For semantic segmentation tasks these are typically a labelled pixel mask and a multi-
116 band image. During hyperparameter tuning of the model, a validation dataset is used to provide an unbiased
117 evaluation of a model fit on the training dataset. The testing dataset is independent on the training and validation
118 data and provides an unbiased evaluation of a trained model. The freely available Spatial Procedures for
119 Automated Removal of Cloud and Shadow (SPARCS) dataset (USGS, 2016) is used in this study as training
120 dataset. The dataset was originally created and first described by Hughes and Hayes (2014) (Hughes and Hayes,
121 2014). It contains 80 subsets (1,000 x 1,000 pixels) of globally distributed Landsat OLI Level-1 scenes
122 accompanying manually delineated thematic masks (Figure 1). The masks contain the classes “cloud”, “cloud
123 shadow”, “snow/ice”, “water”, “flooded” and “land” and are provided in PNG image format. The Landsat
124 images are delivered with 11 spectral bands in GeoTIFF format with associated quality assessment band and
125 metadata. In this paper, we use only spectral bands that are available across different satellite sensors to ensure a
126 high degree of transferability of the trained models (Figure 2). Specifically, we use Landsat OLI bands 2 (Red),
127 3 (Green), 4 (Blue), 5 (Near-Infrared NIR), 6 (Shortwave-Infrared SWIR1) and 7 (Shortwave-Infrared SWIR2).
128 We transform Digital Numbers (DN) to Top of Atmosphere (TOA) reflectance (USGS, 2013), convert the masks
129 into GeoTIFF format and combine classes “water” and “flooded”, because the “flooded” class is
130 underrepresented in the dataset and largely overlapping with the “water” class in terms of spectral response
131 characteristics and thematic content.

Figure 1: Worldwide Reference System 2 (WRS2) path/row locations of training, validation and testing data. Training and validation data are derived from the SPARCS dataset (Landsat OLI) (USGS, 2016). Stratified random sampling has been applied on the basis of a global biomes map (Olson et al., 2001) to choose WRS2 path/row locations for independent testing data from multiple sensors (Landsat TM, ETM+, OLI and Sentinel-2). Testing data samples are labelled with their unique identifier given by the respective path/row combination.

The processed images and accompanying masks are randomly split into training (70 %) and validation (30 %) datasets. In order to keep memory consumption low during training, we further split the training and validation datasets into tiles with 256 x 256 pixels size, which results in 896 tiles for training and 336 tiles for validation. Three augmentations with random contrast and brightness within $\pm 20\%$ of the original values were created for each of the 896 training tiles, providing us with 3,584 tiles for training. Image augmentation allows the network to learn invariance to changes in the augmented domains to a degree that may go beyond what is present in the raw training images (Dosovitskiy et al., 2014). This is particularly important in remote sensing applications, since image properties are strongly affected by changes in atmospheric conditions, seasonality, land-use/land-cover and other scene and image properties (sun elevation, radiometric resolution, etc.) and even a large training dataset may not cover all eventualities that may occur in real-world applications. Due to the spatial resolution of the input images and the natural variety of shapes of the classes of interest, we did not consider geometrical augmentations. In order to evaluate different training strategies on the performance of the segmentation, we define four training setups with varying number of spectral bands with and without augmentation. An overview of the training setups that we refer to throughout this study is provided in Table 1.

Figure 2: Comparison of spectral bands and spatial resolution across different satellite sensors superimposed on atmospheric transmission in grey. Modified after (USGS, 2018).

ID	Sensor	Resolution	Spectral bands	Augmentation	Samples	Classes
L8B6	Landsat OLI	30 m	Red, Green, Blue, NIR, SWIR1, SWIR2	None	896	5
L8B6A	Landsat OLI	30 m	Red, Green, Blue, NIR, SWIR1, SWIR2	Contrast/brightness	3,584	5
L8B4	Landsat OLI	30 m	Red, Green, Blue, NIR	None	896	5
L8B4A	Landsat OLI	30 m	Red, Green, Blue, NIR	Contrast/brightness	3,584	5

Table 1: Training setups.

We take a stratified random sample of WRS2 path/row locations with a minimum distance constraint of 370 km (this equals twice the swath width of a Landsat scene) to identify 14 globally distributed locations, for which we acquire independent test images from Landsat TM, ETM+, OLI and Sentinel-2 sensors. The strata of our sampling scheme are formed by biomes that were derived from a global layer of terrestrial ecoregions (Olson et al., 2001). Biomes are distinct biological communities that have formed in response to shared environmental conditions. By stratifying over biomes we make sure that our test dataset covers a large variety of climatic, atmospheric and land-cover conditions. Figure 1 provides an overview of the Worldwide Reference System 2 (WRS2) path/row locations of imagery used in training, validation and testing. Acquisition times across test sample locations cover different seasons, whereas acquisition times across sensors at a single location are chosen as close as possible to each other to strengthen the significance of a cross-sensor comparison. The minimum cloud-cover percentage for image acquisitions was set to 5 % in order to guarantee a certain degree of cloud-cover per sample.

We resample Sentinel-2 data to 30 m to make sure that all images match the spatial resolution of the training and validation data. Furthermore, we create a 1,024 x 1,024 pixels subset for each test sample, stack the image bands together and convert DN to TOA reflectance. In case of Landsat images this is done by using radiometric rescaling coefficients provided in the metadata file of the Level-1 product. Sentinel-2 images are already

delivered in TOA reflectance but need to be rescaled by a scaling factor that is provided in the respective metadata file. We also delineate scene classification masks that cover the same classes as our training dataset for each of the samples. Masks are generated manually by a single analyst by digitizing the respective images using QGIS software. Finally, we split the images and corresponding masks into 256 x 256 pixels tiles, which provides us with a total test data size of 896 tiles (224 tiles per sensor) for Landsat TM, ETM+, OLI and Sentinel-2.

3 Method

Figure 3 shows an overview of the performance evaluation framework that is used in this study to train, validate and test different CNN models and compare them against Random Forest and Fmask benchmarking methods.

Figure 3: Overview of the performance evaluation framework.

Our CNN is based on the U-Net architecture (Ronneberger et al., 2015), which consists of encoder and decoder parts for semantic segmentation (Figure 4). The encoder takes an input image and generates a high-dimensional feature vector with aggregate features at multiple scales. In the elementary convolutional block we repeatedly apply two 3 x 3 convolutions with Rectified Linear Unit (ReLU) activation function, followed by batch normalization and a 2 x 2 max pooling operation with stride 1 for down-sampling. We use five convolutional blocks, where in each block the number of feature channels is doubled starting from 32. In the decoder part, the feature map is up-sampled by a 2 x 2 transpose convolution followed by a concatenation with the correspondingly cropped feature map from the encoder and two 3 x 3 convolutions with ReLU activation and batch normalization. This effectively halves the number of feature channels at each step. At the final layer a 1 x 1 convolution with softmax activation function is used to map each feature vector x to the desired number of classes N (Equation 1).

$$\sigma(x)_i = \frac{e^{x_i}}{\sum_{n=1}^N e^{x_n}} \quad (1)$$

The output of the network is a vector that contains the predicted class probabilities associated with the sample defined as in Equation 2 with $p_i(x)$ being the predicted probability of x to belong to class i .

$$p(x) = \{p_1(x), p_2(x), \dots, p_i(x), \dots, p_n(x)\} \quad (2)$$

195 The final categorical output y of a given input is achieved by maximizing the corresponding predicted
 196 probability vector $p(x)$:

$$y = \operatorname{argmax} p(x) \quad (3)$$

197 The U-Net architecture was initially developed for bio-medical image segmentation. We chose U-Net as base
 198 architecture, because of its capacity to learn from very little data while achieving state-of-the-art results on
 199 semantic segmentation benchmark datasets (Ronneberger et al., 2015). It is, moreover, a lightweight network
 200 with 7,766,981 trainable parameters for the given segmentation task and image type. Comparable state-of-the-art
 201 architectures such as Fully Convolutional Networks are more complex with a higher amount of trainable
 202 parameters and considerably longer training and inference times (Long et al., 2015). A common strategy to
 203 reduce the computational burden during training of CNNs is to use a pre-trained base network and replace and
 204 re-train the top layer of the classifier on a new dataset. Optionally also the weights of the pre-trained network
 205 may be fine-tuned by backpropagation. In practise, this strategy works well when original and new datasets are
 206 similar, such as natural pictures and very high resolution optical satellite images (Zhu et al., 2017). Given the
 207 difference between images that available pre-trained networks are trained on and medium resolution satellite
 208 images, which we target in this study, in terms of spectral bands and image scales, and given the availability of a
 209 large training dataset (with respect to the U-Net architecture), we decided to train the network from scratch. This,
 210 moreover, allowed for a greater flexibility in the network architecture.

211

212 *Figure 4: Architecture of the U-Net used in this study.*

213 During training, we optimize the weights using adaptive moment estimation (Adam) algorithm (Kingma and Lei,
 214 2015). We use default hyper-parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$ and set the initial learning rate based on the
 215 method described in Smith (2017) (Smith, 2017). Even though Adam already computes adaptive learning rates

216 to reduce the impact of tuning the hyper-parameters on convergence, it has been shown that additional learning
 217 rate adaptation can improve convergence speed and accuracy (Smith, 2017). Therefore, we use a step decay
 218 scheduler to further adapt the learning rate during training. We track several metrics for model evaluation,
 219 including categorical cross-entropy loss, accuracy, Cohen’s Kappa coefficient, Dice coefficient and inference
 220 speed. Categorical cross-entropy loss is defined as in Equation 4 with $\hat{p}_i$ being the predicted probability for class
 221 i and p_i being the true probability for that class.

$$H(p, \hat{p}) = - \sum_i p_i \log(\hat{p}_i) \quad (4)$$

222 Accuracy is measured simply by the number of correctly classified pixels over the total number of pixels. A
 223 more robust metric is Cohen’s Kappa coefficient as it takes into account the possibility of the agreement
 224 occurring by chance. It is defined as in Equation 5, where p_o is the empirical probability of agreement on the
 225 label assigned to any sample, and p_e is the expected agreement when both classifiers assign labels randomly. p_e
 226 is estimated using a per-classifier empirical prior over the class labels.

$$K = \frac{p_o - p_e}{1 - p_e} \quad (5)$$

227 In addition we also report the Dice coefficient, which is defined as twice the size of the intersection divided by
 228 the sum of the size of each the predicted and the true categorical sample sets A and B (Equation 6).

$$D(A, B) = \frac{2|A \cap B|}{|A| + |B|} \quad (6)$$

229 Inference time (measured in seconds/megapixel) is included to account for the fact that our focus is on
 230 applications in the emergency response sector, where computation time is a critical performance criterion. We
 231 report CPU inference times, because only our U-Net implementation supports GPU inference, but not the
 232 benchmark methods.

233 All experiments are carried out on a standard desktop PC with Intel Xeon CPU E5-1630 v4 @ 3.7 GHz, 4 cores
 234 and 20 GB RAM. We use Keras with Tensorflow backend (“Keras,” 2018) as deep learning framework and train
 235 the network in batches of size 10 (to maximize GPU memory usage) over the four training datasets (Table 1)
 236 separately until convergence (Figure 5). We standardize the input image feature space to zero mean and unit
 237 variance with mean and standard deviation being computed on the training dataset and applied to the validation
 238 and testing datasets, and shuffle the training set once between every training epoch. Training takes
 239 approximately 1 hour for the datasets with augmentation and 20 minutes for the datasets without augmentation
 240 on a NVIDIA M4000 GPU.

Figure 5: Visualization of the training history for U-Net models. A description of the different training setups can be found in Table 1 (e.g., UNETL8B4A refers to a U-Net model that has been trained on four Landsat OLI bands with contrast/brightness augmentation).

As a benchmark, we also train a traditional Random Forest classifier on the same standardized training datasets. This classifier has been widely used in remote sensing applications and proved successful for the detection of clouds and cloud shadows in multi-spectral satellite images (Hollstein et al., 2016). We use the Scikit-learn (“Scikit-learn,” 2018) implementation of the classifier for our experiments, which fits a number of optimized C4.5 decision tree classifiers (Breiman, 2001) on sub-samples of the training data and makes use of averaging to control over-fitting and improve the accuracy of the predictions. We tune hyper-parameters for each classification separately according to a ten-fold cross-validation and grid-search method during the training phase of the classifier.

Furthermore, we apply the rule-based Fmask algorithm (Zhu and Woodcock, 2012) to the test images and compare its results with our method. In contrast to the machine learning methods, the rule-sets that underlie Fmask are sensor specific and make use of all available spectral bands including thermal and cirrus bands where present (Zhu et al., 2015). In addition to that, the view angles of the satellite sensor, the illuminating angle and estimates of cloud altitude from thermal information are computed as intermediate products to feed into the prediction of possible cloud shadow locations. We use the pythonfmask package in version 0.5.2 in this study, which implements the Fmask algorithm as a Python module (“Python Fmask,” 2018). According to the developers, with default settings the package should produce results that are equivalent to the masks that are included in the quality assessment layers of Landsat Collection-1 data.

4 Results

A description of the different training setups used for U-Net (UNET) and Random Forest (RF) classifiers can be found in Table 1 (e.g., UNETL8B4A refers to a U-Net model that has been trained on four Landsat OLI bands with contrast/brightness augmentation). Figure 6 and Table 2 show a summary of the results for each tested

model grouped by sensor and considering all classes (“cloud”, “cloud shadow”, “snow/ice”, “water” and “land”). Over the globally distributed 896 test tiles for Landsat TM, ETM+, OLI and Sentinel-2, it can be seen that UNETL8B6A (U-Net trained on six Landsat OLI bands with contrast/brightness augmentation) outperforms the other U-Net models with respect to accuracy, Cohen’s Kappa coefficient and Dice coefficient. Only on the Landsat ETM+ testing dataset augmentation seems to not significantly affect the performance of the prediction and the model without augmentation shows slightly better performance metrics. On all other datasets the model trained with augmentation shows superior results. The best results are achieved on the Landsat OLI testing dataset, which is not surprising since the model has been trained on data of the same sensor. The performance difference between sensors is minor, which indicates good generalization ability of this model across sensors.

With mean accuracy of 0.89, mean Kappa coefficient of 0.82 and mean Dice coefficient of 0.85 measured across all sensors, the UNETL8B6A model performs consistently better than the benchmarking methods. Fmask produces acceptable results that for Landsat TM are comparable with the performance of the U-Net models, but it still lacks behind the UNETL8B6A model. On the other test data even U-Net models that were trained without augmentation and on only four spectral bands show higher performance values compared to Fmask, which makes use of all the available spectral bands and requires ancillary information such as view and illumination angles. In general, it can be observed that Fmask performs better on Landsat data than on Sentinel-2 data. Random Forest performs consistently worse than the U-Net models but comparable to Fmask. On Landsat TM Fmask is superior to Random Forest, whereas on Sentinel-2 Random Forest produces more accurate predictions. Similarly to the U-Net models, Random Forest performs better when more spectral bands are included in the feature space. Augmentation, however, seems to have no significant influence on the prediction performance of Random Forest. It scores in terms of the faster inference time, which is in the order of 1/10 of the inference time of the U-Net models (running on CPU) and even 1/60 of the Fmask inference time. Running the U-Net models on GPU, however, can significantly improve their inference speed beyond Random Forest on CPU.

Figure 6: Summary of the results for each model, grouped by satellite sensor.

Model	Landsat TM				Landsat ETM+				Landsat OLI			
	Acc.	K	Dice	Time	Acc.	K	Dice	Time	Acc.	K	Dice	Time
UNETL8B6	0.84	0.70	0.80	40.4 (2.7)	0.89	0.82	0.81	40.4 (2.7)	0.88	0.79	0.80	41.3 (2.9)
UNETL8B6A	0.89	0.81	0.84	43.7 (2.6)	0.87	0.77	0.82	45.1 (2.7)	0.91	0.86	0.87	44.9 (2.9)
UNETL8B4	0.80	0.65	0.75	39.6 (2.7)	0.84	0.75	0.77	40.0 (2.6)	0.86	0.86	0.80	40.6 (2.9)
UNETL8B4A	0.80	0.65	0.76	42.9 (2.6)	0.80	0.67	0.76	43.8 (2.6)	0.90	0.83	0.86	43.1 (2.9)
RFL8B6	0.75	0.58	0.70	4.1	0.80	0.68	0.76	4.0	0.80	0.68	0.76	4.1
RFL8B6A	0.73	0.51	0.69	4.2	0.77	0.61	0.72	4.4	0.77	0.61	0.72	4.4
RFL8B4	0.69	0.49	0.65	4.0	0.71	0.55	0.68	3.9	0.75	0.59	0.71	3.9
RFL8B4A	0.68	0.43	0.64	4.6	0.72	0.53	0.70	4.7	0.75	0.56	0.71	4.6
Fmask	0.83	0.73	0.80	249.6	0.75	0.61	0.71	252.9	0.78	0.61	0.75	310.4

Table 2 (Part1): Summary of the results for Landsat TM, ETM+, OLI and Sentinel-2 testing data. Times are in seconds/megapixel for CPU inference on the test dataset. For U-Net additionally the GPU inference times are provided in brackets.

Model	Sentinel-2				All sensors ($\mu+\sigma$)			
	Acc.	K	Dice	Time	Acc.	K	Dice	Time
UNETL8B6	0.86	0.76	0.80	41.9 (2.9)	0.87+-0.019	0.77+-0.045	0.80+-0.004	41.0+-0.6 (2.8+-0.1)
UNETL8B6A	0.90	0.83	0.86	45.4 (3.1)	0.89+-0.014	0.82+-0.033	0.85+-0.019	44.8+-0.6 (2.8+-0.2)
UNETL8B4	0.79	0.64	0.75	38.9 (3.0)	0.82+-0.029	0.73+-0.089	0.77+-0.020	39.8+-0.6 (2.8+-0.2)
UNETL8B4A	0.81	0.69	0.78	44.4 (3.0)	0.83+-0.042	0.71+-0.071	0.79+-0.041	43.6+-0.6 (2.8+-0.2)
RFL8B6	0.79	0.64	0.75	4.0	0.79+-0.021	0.65+-0.041	0.74+-0.025	4.1+-0.1
RFL8B6A	0.79	0.64	0.75	4.6	0.77+-0.022	0.59+-0.049	0.72+-0.021	4.4+-0.1
RFL8B4	0.73	0.55	0.68	3.9	0.72+-0.022	0.55+-0.036	0.68+-0.021	3.9+-0.04
RFL8B4A	0.75	0.56	0.72	4.6	0.73+-0.029	0.52+-0.053	0.69+-0.031	4.6+-0.04
Fmask	0.64	0.46	0.61	298.3	0.75+-0.069	0.60+-0.096	0.72+-0.069	277.8+-26.9

Table 2 (Part2): Summary of the results for Landsat TM, ETM+, OLI and Sentinel-2 testing data. Times are in seconds/megapixel for CPU inference on the test dataset. For U-Net additionally the GPU inference times are provided in brackets.

Figure 7 shows normalized error matrices for the best performing U-Net (UNETL8B6A) and Random Forest (RFL8B6) models and Fmask over the combined test data for Landsat TM, ETM+, OLI and Sentinel-2. It can be seen that all three models perform well for classes “land” and “cloud” with main differences coming from the U-Net model being more precise (Table 3). Major misclassifications arise for the classes “shadow”, “water” and “land”. The Random Forest RFL8B6 model falsely classifies “shadow” as “water” or “land”, and “water” as “shadow”. The UNETL8B6A model significantly improves precision and recall for these classes, but still shows a tendency to misclassify “shadow”, “water” and “land”. The model also reduces the confusion between “snow/ice” and “cloud” as well as “land” and “cloud” compared to the other methods. Fmask shows high recall

for the “cloud” class but the results indicate problems related to distinguishing “snow/ice” from “cloud”. Moreover, a significant amount of “shadow” is falsely classified as belonging to the “cloud” and “land” classes. Confusion between “water” and “shadow” is present in the Fmask results, but it is not as strong as for Random Forest. A qualitative comparison of the results for different sensors and locations confirms these findings (Figure 8).

Figure 7: Error matrices for the best performing U-Net and Random Forest models and Fmask over the 896 test tiles for Landsat TM, ETM+, OLI and Sentinel-2.

Class	UNETL8B6A			RFL8B6			Fmask		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Shadow	0.73	0.64	0.69	0.34	0.52	0.41	0.31	0.48	0.38
Water	0.77	0.90	0.83	0.83	0.61	0.70	0.96	0.55	0.70
Snow	0.81	0.88	0.85	0.73	0.84	0.78	0.76	0.37	0.50
Land	0.92	0.96	0.94	0.88	0.85	0.87	0.92	0.76	0.83
Cloud	0.94	0.78	0.85	0.73	0.74	0.73	0.62	0.91	0.74
Total	0.89	0.89	0.89	0.80	0.78	0.79	0.81	0.75	0.76

Table 3: Per-class comparison between best performing U-Net and Random Forest models and Fmask over the 896 test tiles for Landsat TM, ETM+, OLI and Sentinel-2.

Figure 9 summarizes the results for the best performing U-Net (UNETL8B6A) and Random Forest (RFL8B6) models and Fmask over the combined test data for Landsat TM, ETM+, OLI and Sentinel-2 grouped by location (see Figure 1 for details about locations). The U-Net model shows the highest performance values at all locations except location 127038 (“Temperate broadleaf and mixed forests”) where the Random Forest model performs marginally better in terms of Kappa coefficient. The range of Kappa values across locations is higher for Random Forest ($\Delta K=0.50$ [0.26, 0.76]) and Fmask ($\Delta K=0.47$ [0.29, 0.76]) than for U-Net, which shows more stable behaviour across locations with $\Delta K=0.24$ [0.66, 0.90]. This indicates, moreover, that performance variations across locations are higher than the variations across sensors (RFL8B6 $\Delta K=0.10$ [0.58, 0.68], Fmask $\Delta K=0.27$ [0.46, 0.73] and UNETL8B6A $\Delta K=0.09$ [0.77, 0.86]). Location 134036 (“Montane grasslands and shrublands”) shows the lowest Kappa values, whereas location 157071 (“Tropical and subtropical moist

325 broadleaf forests”) is the best segmented by all models. The location with highest inter-model variation is
 326 025032 (“Temperate grasslands, savannas, and shrublands”), and the location for which the different models
 327 show the most comparable performance is 127038 (“Temperate broadleaf and mixed forests”).

328
 329 *Figure 8: Selected results for the best performing U-Net and Random Forest models and Fmask on Landsat OLI*
 330 *for different sensors and locations.*

Figure 9: Summary of the results for the best performing U-Net and Random Forest models and Fmask, grouped by location.

5 Discussion

In this study, we used a freely available global training dataset based on Landsat OLI and developed a multi-sensor reference dataset that we used for testing our models. Our reference dataset has been sampled globally under consideration of terrestrial biomes to account for a large variety of climatic, atmospheric and land-cover conditions. Training, validation and test masks are derived by manual interpretation and digitization of the respective satellite images. The results presented in this study are therefore to be regarded as relative to the performance of a human analyst and not to an absolute ground-truth. Especially clouds and shadows have fuzzy outlines and their interpretation and delineation are at least partially subjective. Moreover, cross-sensor comparison may be biased by a temporal shift between acquisition dates at single test sample locations. This is particularly prominent when comparing Landsat TM and ETM+ with Landsat OLI and Sentinel-2, due to the non-overlapping lifetime of the satellites. We tried to minimize this temporal bias by choosing images that were acquired during the same season for each sample location.

We trained a U-Net CNN using different training strategies and spectral band combinations derived from the SPARCS dataset. The results were compared to a Random Forest classifier and the widely used Fmask method. We could show that even U-Net models that use only four spectral bands (Red, Green, Blue and NIR) can produce competitive prediction results. This becomes particularly relevant when sensors with limited spectral resolution, such as RapidEye or Planet Scope, are targeted by an application. Adding SWIR bands to the input feature space could improve the results by 0.04 for Kappa over all sensors and locations compared to using visible and NIR bands alone (Table 2). Atmospheric aerosols have a stronger effect on shorter wavelengths (mainly in the visible spectrum), whereas the SWIR wavelengths show improved atmospheric transparency and

can aid in the distinction between clouds, snow and ice. Augmentation proved to be important for the network to learn invariance to changes in the target domain, which is strongly affected by atmospheric conditions, seasonality, land-use/land-cover and other scene and image properties such as sun elevation or radiometric resolution. However, this statement only holds for the six band training data where an improvement of 0.05 for Kappa compared to the non-augmented training data could be observed over all sensors (Table 2). Augmenting the four band training data resulted in a reduction of the performance by 0.02 for Kappa over all sensors. Interestingly, this reduction seems to be driven by the performance on the Landsat sensors, as an increase for Kappa can be observed for Sentinel-2. It seems that the simple contrast/brightness augmentation could not sufficiently account for the variations in the visible and NIR target domain and potentially even introduced noise, which bias the network and lead to a higher risk of overfitting (Figure 5) and reduced generalization ability of the model. More research into other transformations or more sophisticated augmentation techniques (e.g., generating synthetic training samples via Generative Adversarial Networks) would be needed to investigate their potential to account for more complex variations and to improve the performance given a reduced four band feature space. More experiments should be conducted to understand the causes for cross-sensor differences.

Compared to our method, Fmask also utilizes the Thermal Infrared (TIR) bands where available. The results of Fmask seem to be strongly dependent on the availability of TIR bands as can be seen in the performance decrease from Landsat (with thermal bands) to Sentinel-2 (no thermal bands) by 0.15-0.27 for Kappa (Table 2). We specifically decided against using the TIR bands in our study in favour of a higher degree of transferability across sensors. For sensor-specific applications, however, including TIR bands into the input feature space of the network may have a positive effect on the accuracy.

Fmask is a transparent rule-set that can be closely related to physical and geometrical remote sensing principals. Compared to such rule-based and expert-driven approaches, CNNs are less transparent and further fundamental research is needed to better understand their internal reasoning. Random Forest is a well-understood machine-learning method with a relatively high degree of transparency. Nevertheless, in the given experimental setup Random Forest produced consistently lower accuracies than the CNN models. Even the best performing Random Forest model seems to have significant problems to distinguish between “shadow” and “water” classes. Shadow prevents the spectral characteristics of the underlying surface from being fully represented, which may cause an overlap of the spectral signatures of shadow and water pixels. Classifiers that only consider the spectral characteristics of single pixels in their input feature space, like the Random Forest classifier used in this study, may hence inevitably have problems to distinguish these classes. The CNN models seem to largely overcome this problem by their non-linear function mapping capability, and by the convolutional features that are being learned directly from the data under consideration of neighbourhood information at various scales. In case of Random Forest, the use of additional hand-crafted features (e.g., first and second order statistics or high-level features like bag of visual words) computed over a sliding-window or as part of an object-based image analysis could improve the results, but would also involve longer computation time during inference.

389 In the tested setup, Random Forest has the shortest inference time when running on CPU, followed by U-Net and
390 Fmask. We showed that a modern GPU can highly accelerate inference times of the U-Net models that even
391 outperform Random Forest models. The comparably long inference times of Fmask are likely related to the fact
392 that the method needs to compute several additional layers (view angles of the satellite sensor, illuminating angle
393 and estimates of cloud altitude from thermal information) before the actual rule-set can be applied. It should be
394 noted that we use Fmask as a Python package, which may also influence computation time compared to using
395 for example CFmask directly. Recently, Fmask results are provided as part of the quality assessment band of
396 Landsat Collection-1 data. However, we have decided to run Fmask ourselves in order to consistently compare
397 processing times across different sensors and methods.

398 Hughes and Hayes (2014) (Hughes and Hayes, 2014), who developed the SPARCS dataset, achieve highly
399 accurate results by using a traditional neural network and rule-based spatial post-processing. They train and test
400 their model on independent subsets of the same reference data and specifically target Landsat OLI in their study.
401 Compared to their study, we do not apply any post-processing steps and focus on multi-sensor generalization
402 ability. Accordingly, we test our results against an independently acquired multi-sensor dataset with potentially
403 more complex variations in the target domain. Similar to our study, Zhaoxiang et al. (2018) (Zhaoxiang et al.,
404 2018) use a lightweight U-Net, but train and test it exclusively on a modified version of the SPARCS dataset.
405 Their focus lies on on-board cloud detection and accordingly they consider a binary classification task, with
406 minimal feature space (Red, Green, Blue and NIR bands) and investigate the influence of image compression on
407 the results. Isikdogan, Bovik and Passalacqua (2017) (Isikdogan et al., 2017) use a Fully Convolutional Network
408 to segment an image into the same classes as used in our study with their main objective being surface water
409 mapping. Similarly to the aforementioned studies, they train and test their models on independent subsets of the
410 same dataset (Landsat ETM+ with corresponding label masks from the GLCF inland water dataset (Feng et al.,
411 2016)), but do not specifically target transferability between sensors.

412 **6 Conclusions**

413 In this study, we introduced a rapid and simple to use method to segment multi-spectral satellite images into five
414 major classes including “cloud” and “cloud shadow”, which are particularly relevant for any application that
415 uses optical data. The proposed U-Net CNN has been trained on different variations of the freely available
416 SPARCS dataset (based on Landsat OLI) (USGS, 2016). The best performing model uses six spectral bands
417 (Red, Green, Blue, NIR, SWIR1 and SWIR2) and has been trained on a contrast and brightness augmented
418 version of the training data. We showed that it is possible for a single model to generalize between different
419 satellite sensors and locations without the need for atmospheric correction, relative normalization, re-training, or
420 other domain adaptation techniques. Our method consistently outperformed the widely used Fmask and Random
421 Forest methods in terms of accuracy, Cohen’s Kappa coefficient, Dice coefficients, and inference time on a
422 globally sampled test dataset derived from Landsat TM, ETM+, OLI and Sentinel-2 data. Future research efforts

will focus on the development and evaluation of a new training dataset that incorporates data from different sensors and more locations world-wide with the aim to further improve the accuracy, while decreasing performance variations across sensors and locations. Furthermore, it is planned to test the method on additional medium to high resolution sensors (e.g., RapidEye, ALOS-AVNIR2, Planet Scope), and to adapt the method to very high resolution satellite and aerial imagery (e.g., WorldView, Pleiades), which impose particular challenges related to their sub-meter spatial resolution and the limited spectral resolution. The findings of this study will be applied within a flood monitoring system that uses imagery from multiple SAR and optical satellite sensors to produce timely flood maps for situational awareness in emergency situations (Martinis et al., 2013; Twele et al., 2016). Compared to other available solutions, the proposed method allows us to rapidly and accurately segment cloud and cloud shadow pixels in a large range of multi-spectral satellite image types without relying on ancillary datasets, multi-temporal analysis, or manual adjustments of rule-sets and parameters. Being able to quickly and accurately identify cloud and cloud shadow pixels is fundamental for unbiased down-stream analysis, particularly in emergency applications where time is critical and all available data sources need to be utilized to provide timely information products about an evolving disaster situation.

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