Wide-Area Land Cover Mapping with Sentinel-1 Imagery using Deep Learning Semantic Segmentation Models

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Abstract—Land cover mapping and monitoring are essential for understanding the environment and the effects of human activities on it. The automatic approaches to land cover mapping are predominantly based on the traditional machine learning that requires heuristic feature design. Such approaches are relatively slow and often suitable only for a particular type of satellite sensor or geographical area. Recently, deep learning has outperformed traditional machine learning approaches on a range of image processing tasks including image classification and segmentation.

In this study, we demonstrated the suitability of deep learning models for wide-area land cover mapping using satellite C-band SAR images. We used a set of 14 ESA Sentinel-1 scenes acquired during the summer season in Finland representative of the land cover in the country. These imageries were used as an input to seven state-of-the-art deep-learning models for semantic segmentation, namely U-Net, DeepLabV3+, PSPNet, BiSeNet, SegNet, FC-DenseNet, and FRRN-B. These models were pre-trained on the ImageNet dataset and further fine-tuned in this study. CORINE land cover map produced by the Finnish Environment Institute was used as a reference, and the models were trained to distinguish between 5 Level-1 CORINE classes.

Upon the evaluation and benchmarking, we found that all the models demonstrated solid performance, with the top FC-DenseNet model achieving an overall accuracy of 90.7%. These results indicate the suitability of deep learning methods to support efficient wide-area mapping using satellite SAR imagery.

Index Terms—synthetic aperture radar, deep learning, semantic segmentation, land cover mapping, image classification, Sentinel-1 data, C-band, CORINE.

I. INTRODUCTION

Land cover mapping plays a central role in the characterization of the state of the environment. The changes in cover can be due to human activities as well as due to climate change on a regional scale. The land cover, on the other hand, influences climate by modifying water and energy exchanges with the atmosphere and by changing greenhouse gas and aerosol sources and sinks. Because of this, land cover belongs to the Essential Climate Variables [1]. Hence, timely assessment of land cover and its change is one of the most important applications in satellite remote sensing.

Thematic annual land cover maps are needed for various purposes in medium resolution (circa 250 m) with less than 15% measurement uncertainty and in high resolution (10-30 m) with less than 5% uncertainty.

CORINE Land Cover (CLC) is a notable example of a consistent Pan-European land cover mapping project [2], [3] coordinated by the European Environment Agency (EEA). [4] CORINE stands for coordination of information on the environment. It provides the only consistent classification system of long-term land cover data in Europe. The CORINE maps are essential as a source of operational land cover information for many sectors of the European economy. With its 44 classes, some of which are defined as mixed land cover and land use classes, CORINE provides a European scale map with 25 ha minimum mapping unit (MMU) for areal phenomena, and a minimum width of 100 m for linear phenomena [4].

National land cover maps in the CORINE framework can exhibit smaller mapping units. In Finland, the latest revision of CORINE land cover map at the time of this study was 2012 round produced by the Finnish Environment Institute. The map has an MMU of 20 meters and was produced by a combined automated and manual interpretation of the high-resolution satellite optical data followed by the data integration with existing basic map layers [5].

The state-of-the-art approaches used for land cover mapping mainly rely on the satellite optical imagery. The key role is played by the Landsat imagery often augmented by the MODIS or SPOT-5 imagery [6]–[8]. Other sources of information employed for land cover mapping include Digital Elevation Models (DEM) and very high-resolution imagery [9]. When it comes to the large-scale and multitemporal land cover mapping, a more recent optical imagery source is Copernicus Sentinel-2. With a revisit of 5 days, it has become another key data source [10].

International programs, such as the European Space Agency’s (ESA’s) Copernicus [11] behind the Sentinel satellites are taking significant efforts to make Earth Observation (EO) data freely available for commercial and non-commercial purposes. The Copernicus programme is a multi-billion investment by the EU and ESA aiming to provide essential services based on accurate and timely data from satellites. Its main goals are to improve the ways of managing the environment, to help mitigate the effects of climate change,
and enable the creation of new applications and services in the domains of agriculture, disaster recovery, climate change, urban development, and environmental monitoring.

The provision of free satellite data for mapping in the framework of such programs also enables application of methods that could not be used earlier because they require vast and representative datasets for training, for example deep learning. In recent years, deep learning has brought about several breakthroughs in the pattern recognition and computer vision [12]–[14]. The success of the deep learning models can be attributed to both their deep multilayer structure creating nonlinear functions and, hence, allowing extraction of hierarchical sets of features from the data, and to their end-to-end training scheme allowing for simultaneous learning of the features from the raw input and predicting the task at hand. In this way, the heuristic feature design is removed. This is advantageous compared to the traditional machine learning methods (e.g., support vector machine (SVM) and random forest (RF)), which require a multistage feature engineering procedure. In deep learning, such a procedure is replaced with a simple end-to-end deep learning workflow. One of the key requirements for successful application of deep learning methods is a large amount of data available from which the model can automatically learn the representative features for the prediction task [15]. The availability of open satellite imagery, such as from Copernicus, offers just that.

The land cover mapping systems based solely on optical imagery suffer from issues with cloud cover and weather conditions, especially in the tropical areas, and with a lack of illumination in the polar regions. Among the free satellite data offered by the Copernicus programme are synthetic aperture radar (SAR) images from the Sentinel-1 satellites. SAR is an active radar imaging technique that does not require illumination and is not hampered by cloud-cover due to penetration of microwave radiation through clouds. The utilisation of SAR imagery, hence, would allow mapping such challenging regions and increasing the mapping frequency in the orchestrated efforts like CORINE. One of the significant issues previously was the absence of timely and consistent high-resolution wide-area SAR coverage. With the advent of Copernicus Sentinel-1 satellites, operational use of imaging radar data becomes feasible for consistent wide-area mapping. ESA has launched the first of its Copernicus Sentinel-1 missions in April 2014. Sentinel-1A is capable of providing C-band SAR data in up to four imaging modes with a revisit time of 12 days. Once Sentinel-1B was launched in 2016 the revisit time has reduced to 6 days [11].

We studied wide-area SAR-based land cover mapping by methodologically combining the two discussed recent advances: the improved methods for large-scale image processing using deep learning and the availability of SAR imagery from the Sentinel-1 satellites.

A. Land Cover Mapping with SAR Imagery

While using optical satellite data is still a mainstream in land cover and land cover change mapping [5], [16]–[19], SAR data has been getting more attention as more suitable sensors appear. To date, several studies have investigated the suitability of SAR for land cover mapping, focusing primarily at L-band, C-band, and X-band polarimetric [20], [21] multitemporal and multi-frequency SAR [22]–[23], as well as, at the combined use of SAR and optical data [24]–[28].

As microwave radiation responds to fundamental scattering processes that are determined by surface roughness, soil moisture, vegetation water content, and 3D structure of the scattering elements, a considerable number of classes can be differentiated in SAR images [20], [29]. However, majority of SAR classification algorithms use fixed SAR observables (e.g., polarimetric features) to detect certain land cover types, despite the large natural variability between observation sites, temporal acquisition, environmental conditions and calibration effects. This leads to a lack of generalisation capability and a need to use extensive and representative training/reference data and representative SAR data. The latter means the need to account for not only all variation of SAR signatures for a specific class but also the need to consider seasonal effects, as changes in moisture of soil and vegetation, as well as frozen state of land [30] that strongly affect SAR backscatter. On the other hand, when using multitemporal approaches, such seasonal variation can be used as an effective discriminator among different land cover classes.

When using exclusively SAR data for land cover mapping, reported accuracy often turn out to be relatively low for operational land cover mapping and change monitoring. Methodologically, reported solutions utilized supervised approaches, linking SAR observables and class labels to pixels, superpixels or objects in parametric or nonparametric manner [19]–[21], [29], [31]–[39].

However, few have aimed at the delineation of a large number of classes. For instance, in [40] it was found that P-band PolSAR imagery was unsatisfactory for mapping more than five classes with the iterated conditional mode (ICM) contextual classifier applied to the amplitude, the intensity of images, biomass index, and the polarimetric parameters (entropy, alpha angle, and anisotropy) extracted from the P-band. They achieved a Kappa value of 76.8% when mapping four classes. ALOS PALSAR L-band and RADARSAT-2 C-band data were tested for land cover classification in a moist tropical region [41]. L-band provided 72.2% classification accuracy for a coarse land cover classification system (forest, succession, agro-pasture, water, wetland, and urban) and C-band only 54.7%. Multitemporal and multi-polarization ENVISAT ASAR C-band data were investigated for principal component analysis and classification of five land cover classes in Korea [42]. Waske et al. [43] applied boosted decision tree and random forests to multi-temporal C-band SAR data reaching accuracy up to 84%. Several studies [21], [20] investigated specifically SAR suitability for the boreal zone, with reported accuracy up to 83% depending on the classification technique (maximum likelihood, probabilistic neural networks, etc.) when five super-classes (based on CORINE data) were used.

The potential of Sentinel-1 imagery for CORINE-type land cover mapping was recognised in a study that used Sentinel-1A data for mapping class composition in Thuringia [29]. Long-
time series of Sentinel-1 SAR data are considered especially suitable for crop type mapping \cite{44,47}, with increased number of studies attempting land cover mapping in general \cite{48,49}.

Moreover, as Sentinel-1 data are presently the only free source of SAR data routinely available for wide-area mapping at no cost for users, it seems the best candidate data for development and testing of improved classification approaches. Previous studies indicate a necessity for developing and testing new methodological approaches that can be effectively applied to a large-scale and deal with the variability of SAR observables concerning ecological land cover classes. We suggest adopting state-of-the-art deep learning approaches for this purpose.

Independently of the imagery used, the majority of land cover mapping methods so far are based on traditional supervised classification techniques \cite{50}. Widely used classifiers are support vector machines (SVM), decision trees, random forests (RF), and maximum likelihood classifiers (MLC) \cite{7,9,43,44,50}. However, in most cases, the process of extracting a large number of features needed for classification, i.e., the feature engineering process, is time-intensive, and requires lots of expert work in developing an fine-tuning classification approaches. This limits the applications of the traditional supervised classification methods on a large scale.

\subsection*{B. Deep Learning in Remote Sensing}

The advances in the deep learning techniques for computer vision, in particular, Convolutional Neural Networks (CNNs) \cite{12,51}, have led to the application of deep learning in several domains that rely on computer vision. Examples are autonomous driving, image search engines, medical diagnostics, and augmented reality. Deep learning approaches are starting to be adopted in the remote sensing domain, as well.

Zhu et al. \cite{52} provide a discussion on the specificities of remote sensing imagery (compared to ordinary RGB images) that result in specific deep learning challenges in this area. For example, remote sensing data are georeferenced, often multi-modal, with particular imaging geometries, there are interpretation difficulties, and the ground-truth or labelled data needed for deep learning is still often lacking. Additionally, most of the state-of-the-art CNNs are developed for three-channel input images (i.e., RGB) and so certain adaptations are needed to apply them on the remote sensing data \cite{53}.

Nevertheless, several research papers tackling remote sensing imagery with deep learning techniques were published in recent years. Zhang et al. \cite{54} review the field and find applications to image preprocessing \cite{55}, target recognition \cite{56,57}, classification \cite{58,60}, and high-level semantic feature extraction and scene understanding \cite{61,64}. The deep learning approaches are found to outperform standard methods applied up to several years ago, i.e., SVMs and RFs \cite{65,66}.

When it comes to deep learning for land cover or land use mapping, applications have been limited to optical satellite \cite{55,53,59,67} or aerial \cite{68} imagery, and hyperspectral imagery \cite{60,67} owing to the similarity of these images to ordinary RGB images studied in computer vision \cite{53}.

When it comes to SAR images, Zhang et al. \cite{54} found that there is already a significant success in applying deep learning techniques for object detection and scene understanding. However, for classification on SAR data, applications are scarce and advances are yet to be achieved \cite{54}. Published research include deep learning for crop types mapping using combined optical and SAR imagery \cite{66}, as well as use of SAR images exclusively \cite{69}. However, those methods applied deep learning only to some part of the task at hand and not in an end-to-end fashion. Wang et al. \cite{59}, for instance, just used deep neural networks for merging over-segmented elements, which are produced using traditional segmentation approaches. Similarly, Tuia et al. \cite{60} applied deep learning to extract hierarchical features, which they further fed into a multiclass logistic classifier. Duan et al. \cite{69} used first unsupervised deep learning and then continued with a couple of supervised labelling tasks. Chen et al. \cite{67} applied a deep learning technique (stacked autoencoders) to discover the features, but then they still used traditional machine learning (SVM, logistic regression) for the image segmentation. Unlike those methods, we applied the deep learning in an end-to-end fashion, i.e., from supervised feature extraction to the land class prediction. This makes our methods more robust and easily adaptable to the SAR data from new regions, as well as more efficient.

Further, considerable work has been done using so-called end-to-end approaches. For instance, Mohammadianesh et al. \cite{70} used fully polarimetric SAR (PolSAR) imagery from RADARSAT-2 to classify wetland complexes, for which they have developed a specifically tailored semantic segmentation model. However, the authors have tackled a small test area (around 10km x 10km) and have not explored how their model generalizes to other types of areas. Similarly, Wang et al. \cite{71} adapted existing CNN models into a fixed-feature-size CNN that they have evaluated on a small scale RADARSAT-2 or AIRSAR (i.e., airborne SAR data). In both cases, they have used more advanced fully polarimetric SAR imagery at better resolution as opposed to Sentinel-1, which means the imagery with more input information to the deep learning models. Importantly, it is only Sentinel-1 that offers open operational data with up to every 6 days repeat. Thus, the approaches developed and tested specifically for PolSAR imagery at higher resolution cannot be considered applicable for a wide-area mapping. Similarly, Ahishali et al. \cite{72} applied end-to-end approaches to SAR data. They have also worked with single polarized COSMO-Skymed imagery. However, all the imagery they considered was X-band SAR contrary to C-band imagery we use here and again only on a small scale. The authors proposed a compact CNN model that they found had outperformed some of the off-the-shelf CNN methods, such as Xception and Inception-ResNet-v2. It is important to note that compared to those, the off-the-shelf models that we consider here are more advanced semantic segmentation methods, some which employ Xception or ResNet but only in their feature extraction parts.

In summary, the capabilities of the deep learning approaches for the classification have been examined to a lesser extent for SAR imagery than for optical imagery. The attempts to use SAR data for land cover classification were relatively limited.
in scope, area, or the number of used SAR scenes. Particularly, wide area land cover mapping was never addressed. The reasons for this include comparatively poor availability of SAR data compared to optical (greatly changed since the advent of Sentinel-1), complex scattering mechanisms leading to ambiguous SAR signatures for different classes (which makes SAR image segmentation more difficult than the optical image segmentation), as well as the speckle noise caused by the coherent nature of the SAR imaging process.

C. Study goals

Present study partly addresses the identified research gaps. We achieve this by training, fine-tuning, and evaluating a set of suitable state-of-the-art deep learning models from the class of semantic segmentation models and demonstrating their suitability for land cover mapping. Moreover, our work is the first to examine and demonstrate the suitability of deep learning for land cover mapping from SAR images on a large-scale, i.e., across the whole country.

Specifically, we applied supervised semantic segmentation models on the SAR images taken over a large area across Finland. We focused on the images of Finland because there is the land cover mask of a high enough resolution that can be used for training labels (i.e., CORINE). The training is performed with the state-of-the models, which have encoder modules pre-trained on the large RGB image corpus ImageNet 2012[2]. Those models are freely available[1]. In other words, we reused existing segmentation architectures with pre-trained weights on RGB images and we fine-tuned them. Our results (with over 90% overall accuracy) demonstrate the effectiveness of deep learning methods for the land cover mapping.

We studied land cover mapping using SAR images from Finland. There are two main reasons for which we chose to focus on Finland. The first reason is that there is a high-resolution CORINE map that can serve as a ground-truth (labels) for training the deep learning models. The second reason is that Finland is a northern country with frequent cloud cover, which means that using optical imagery for wide-area mapping is often not feasible. Hence, demonstrating usability of radar imagery for land cover mapping is particularly useful here.

Even though Finland is a relatively small country, there is still considerable heterogeneity present in terms of land cover types and how they appear in the SAR images. Namely, SAR backscattering is sensitive to several factors that likely differ between countries or between distant areas within a country. Examples of such factors are moisture levels, terrain variation and soil roughness, predominant forest biome and tree species proportions, types of shorter vegetation and crops in agricultural areas, specific types of built environments. Hence, demonstrating the suitability of our methods across wide areas in Finland could indicate their potential generalizability. Namely, by applying similar techniques as presented here, these models can be fine-tuned and adapted to work on data from another regions or countries with somewhat different SAR signatures.

However, we took into account that the same areas will appear somewhat different on SAR images across different seasons. Scattering characteristics of many land cover classes change considerably between the summer and winter months, and sometimes even within weeks during seasonal changes. These include snow cover and melting, freeze/thaw of soils, ice on rivers and lakes, crops growing cycle, leaf-on and leaf-off conditions in deciduous trees. In this study, we focused only on scenes acquired during the summer season. However, we did allow our training dataset to contain several images of the same area, taken during different times during the summer season. This way not only spatial, but also temporal variation of SAR signatures is introduced.

In summary, our contributions are twofold:

C1: We thoroughly benchmarked seven selected state-of-the-art semantic segmentation models for wide-area land cover mapping using Sentinel-1 SAR imagery. We provide insights on the best models in terms of both possible accuracy and efficiency.

C2: Our results demonstrate the power of deep learning models along with SAR imagery for successful large-scale land cover mapping in cloud obscured and polar regions.

II. Deep Learning Terminology

As with other representation learning models, the power of deep learning models comes from their ability to learn rich features (representations) from the dataset automatically[15]. The automatically learned features are usually better suited for the classifier or other task at hand than hand-engineered features. Moreover, thanks to a large number of layers employed, it has been proven that the deep learning networks can discover hierarchical representations, so that the higher level representations are expressed in terms of the lower level, simpler ones. For example, in the case of images, the low-level representations that can be discovered are edges, and using them, the mid-level ones can be expressed, such as corners and shapes, and this helps to express the high-level representations, such as object elements and their identities[15].

The deep learning models in computer vision can be grouped according to their main task in three categories. In Table I[3] we provide a description for those categories. However, the deep learning terminology for those tasks does not always correspond well to the terminology used in the remote sensing community. Relevant to our task, a number of remote sensing studies uses the term classification in the context of land cover mapping, inherently meaning pixel- or region-based classification, which in the deep learning terminology corresponds to semantic segmentation. In Table II[3] we list the corresponding terminology that we encountered being used for each task in both, the deep learning and remote sensing communities. This is helpful to disambiguate when talking about different and recognize when talking about the same tasks in the two domains. In the present study, the focus is on

1http://image-net.org/challenges/LSVRC/2012
2https://github.com/tensorflow/models/tree/master/research/slim#pre-trained-models
TABLE I
TERMINOLOGY FOR THE MAIN TASKS IN COMPUTER VISION AND ITS USE IN THE DEEP LEARNING VERSUS REMOTE SENSING COMMUNITIES.

| Deep learning | Remote sensing | Task description |
|---------------|----------------|------------------|
| Classification | Image, Annotation, Scene Understanding, Scene Classification | Assigning a whole image to a class based on what is (mainly) represented in it, for example a ship, oil tank, sea or land. |
| Object Detection, Localization, Recognition | Automatic Target Recognition | Detecting (and localizing) presence of particular objects in an image. These algorithms can detect several objects in the given image. For instance ship detection in SAR images. |
| Semantic Segmentation | Image Classification, Clustering | Assigning a class to each pixel in an image based on which image object or region it belongs to. These algorithms not only detect and localize objects in the image, but also output their exact areas and boundaries. |

land cover mapping. Hence, we tackle semantic segmentation in the deep learning terminology and image classification, i.e., pixel-wise classification, in the remote sensing terminology.

Convolutional Neural Networks (CNNs) [12], [13] are the deep learning model that has transformed the computer vision field. Initially, CNNs are defined to tackle the image classification (deep learning terminology) task. Their structure is inspired by the visual perception of mammals [76]. CNNs are named after one of the most important operations, which is particular to them compared to other neural networks, i.e., convolutions. Mathematically, a convolution is a combination of two other functions. A convolution is applied on the image by sliding a filter (kernel) of a given size $k \times k$ which is usually small compared to the original image size. Different purpose filters are designed; for example, a filter can serve as a vertical edge detector. Application of such a convolution operation on an image results in a feature map. Another common operation that is usually applied after a convolution is pooling. Pooling reduces the size of the feature map while providing robustness to the extracted features. Common CNNs end with a fully connected layer which is used for final predictions, commonly for image classification. By employing a large number of convolutional layers (depth), CNNs are able to extract gradually more complex and abstract features. The first CNN model to demonstrate their impressive effectiveness in image classification (of hand digits) was LeNet [12]. Several years later, Krizhevsky et al. [13] developed AlexNet, the deep CNN to dramatically push the limits of classification accuracy on the famous ImageNet computer vision challenge [77]. Since then, a variety of CNN-based models are proposed. Some notable examples are: VGG network [14], ResNet [78], DenseNet [79], and Inception V3 [80]. The effectiveness of CNNs has been also proven in various real-world applications [81], [82].

Once CNNs have proven their effectiveness to classify images, Long et al. [75] were the first to discover how they can augment a given CNN model to make it suitable for the semantic segmentation task – they proposed the Fully Convolutional Neural Network (FCN) framework. This generic architecture can be used to adapt any CNN network used for classification into a segmentation model. Namely, the authors have shown that by replacing the last, fully connected layer, with an appropriate convolutions layer, so that they will upsample and recover the spatial resolution of the input at the output layer, CNNs can be transformed to successfully perform semantic segmentation. The basic idea is as follows. The encoder is used to learn the feature maps, and is usually based on a pre-trained deep CNN for classification, such as ResNet, VGG, or Inception. The decoder part serves to upsample the discriminative features that the encoder has learned from the coarse-level feature map to the fine, pixel level. Long et al. [75] have shown that this upsampling (backward) computation can be efficiently performed using backward convolutions (deconvolutions). Moreover, this means that the specific CNN models, such as those mentioned above, can all be incorporated in the FCN framework for segmentation, giving rise to FCN-AlexNet [75], FCN-ResNet [78], FCN-VGG16 [75], FCN-DenseNet [83] etc. We present a diagram of the generic FCN architecture in Figure 1.

![Figure 1. The architecture of Fully Convolutional Neural Networks (FCNs)](Image 325x307 to 550x424)

III. MATERIALS AND METHODS

Here, we first describe the study site, SAR, and reference data. This is followed by an in-depth description of the deep learning terminology and the models used in the study. We finish with the description of the experimental setup and the evaluation metrics.

A. Study site

Our study site is covering the area of Finland at latitudes from 61° to 67.5°. The processed area is shown in Figure 2. The study area includes central and northern areas of Finland, covered primarily by boreal forestland with inclusions of water bodies (primarily lakes), urban settlements and agricultural areas, as well as marshland and open bogs. We have omitted Lapland due to potential snow cover during the months of data acquisition. The terrain height variation is moderate and mostly within 100 – 300 meters range.
B. SAR data

Presently, Sentinel-1 is a C-band SAR dual-satellite system with two satellites orbiting 180° apart [11], launched in 2014 and 2016, respectively. The acquisition modes are Stripmap (SM), Interferometric Wide-Swath (IW), Extra Wide Swath (EW), and Wave Mode (WV). The SM, IW, and EW modes acquire data at a single transmit polarisation (H or V) and dual receive polarisation (HV or VH). The WV mode only has a single polarisation (HH or VV). The default mode over land is the IW, which provides a 250 km swath composed of three sub-swaths at 5 m by 20 m spatial resolution in a single look. It uses a new type of ScanSAR mode called Terrain Observation with Progressive Scan (TOPS) SAR, which is shrinking the azimuth antenna pattern along the track direction.

The SAR data acquired by Sentinel-1 satellites in IW mode are used in the study. Altogether, 14 Sentinel-1A images acquired during summers of 2015 and 2016 were used in the study, more concretely during June, July, and August in those two years. Their geographical coverage is schematically shown in Figure 2.

Original scenes were downloaded as Level-1 Ground Range Detected (GRD) products that consist of focused SAR that has been detected, multi-looked and projected to ground-range using an Earth ellipsoid model. They were orthorectified in ESA SNAP S1TBX software using local digital terrain model (with 2 meters resolution) available from National Land Survey of Finland. The pixel spacing of ortho-rectified scenes was set to 20 meters. Orthorectification included terrain flattening to obtain backscatter in gamma-nought format [84]. The scenes were further re-projected to the ERTS89 / ETRS-TM35FIN projection (EPSG:3067) and resampled to a final pixel size of 20 metres.

C. Reference data

In Finland, the Finnish Environment Institute (SYKE) is responsible for production of the CORINE maps. While for most of the EU territory, the CORINE mask of 100m × 100m spatial resolution is available, the national institutions might choose to create more precise maps, and SYKE, in particular, had produced a 20m × 20m spatial resolution mask for Finland (Figure 3). Since then, the updates have been produced regularly, the latest one at the time of this study, which we used, being CLC2012. There are 48 different land use classes in the map that can be hierarchically grouped into 4 CLC Levels. In detail, there are 30 classes on CLC Level-3, 15 classes on CLC Level-2, and 5 top CLC Level-1 classes. According to the information provided by SYKE, the accuracy of the CLC Level-3 is 61%, of the CLC Level-3, 83%, and of the CLC Level-1, it is 93%. The selected classes and their corresponding color codes used for our segmentation results are shown in Table II.

D. Semantic Segmentation Models

We selected following seven state-of-the-art [87] semantic segmentation models to test for our land cover mapping
Fig. 3. Zoomed in area fragment with our reference data, i.e., CORINE shown on top (left) along with the Google Earth layer (right).

Fig. 5. The architecture of SegNet-based Encoder-Decoder with Skip connections [88]. Blue tiles represent Convolution + Batch Normalisation + ReLU, green tiles represent Pooling, red – Upsampling, and yellow – a softmax operation.

Fig. 4. The architecture of BiSeNet. ARM stands for the Attention Refinement Module and FFM for the Feature Fusion Module introduced in the model’s paper [90].

1) BiSeNet (Bilateral Segmentation Network): BiSeNet model is designed to decouple the functions of encoding additional spatial information and enlarging the receptive field, which are fundamental to achieving good segmentation performance. As can be seen in Figure 4, there are two main components to this model: Spatial Path (SP) and Context Path (CP). Spatial Path serves to encode rich spatial information. Context Path serves to provide sufficient receptive field and uses global average pooling and pre-trained Xception [90] or ResNet [78] as the backbone. The goal of the creators was not only to obtain superior performance but to strike a balance between the speed and performance. Hence, BiSeNet is a relatively fast semantic segmentation model.

2) SegNet (Encoder-Decoder-Skip): Similarly to BiSeNet, SegNet is also designed with computational performance in mind, this time, particularly during inference. Because of this, the network has a significantly smaller number of trainable parameters compared to most of the other architectures. The encoder in SegNet is based on VGG16: it consists of its first 13 convolutional layers, while the fully connected layers are omitted. Hence, the novelty of this network lies in its decoder part, as follows. The decoder consists of one decoder layer for each encoder layer and so it also has 13 layers. Each individual decoder layer utilizes max-pooling indices memorized from its corresponding encoder feature map. The authors have showed that this enhances boundary delineation between classes. The final decoder output is sent to a multi-class soft-max function yielding class probabilities for each pixel (see Figure 5).

3) Mobile U-Net: Mobile U-Net is based on the U-Net [97] semantic segmentation architecture shown in Figure 6. In designing U-Net, Fully Convolutional approach was generally employed with a following modification. Their upsampling part of the architecture has no fully convolutional layer but is nearly symmetrical to the feature extraction part due to the use of the similar feature maps. This results in a u-shaped architecture (see Figure 6), and hence the name of the model. While originally developed for biomedical images, the U-net architecture has proven successful for image segmentation

task: SegNet [88], PSPNet [89], BiSeNet [90], DeepLabV3+ [91], U-Net [93], FRRN-B [95], and FC-DenseNet [83]. In the following, we describe specific architectures of these DL models evaluated in the study. We will use the following common abbreviations across the DL models: conv for convolution operation, concat for concatenation, max pool for max pooling operation, BN for batch normalisation, and ReLU for the rectified linear unit activation function.

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Fig. 4. The architecture of BiSeNet. ARM stands for the Attention Refinement Module and FFM for the Feature Fusion Module introduced in the model’s paper [90].

Fig. 5. The architecture of SegNet-based Encoder-Decoder with Skip connections [88]. Blue tiles represent Convolution + Batch Normalisation + ReLU, green tiles represent Pooling, red – Upsampling, and yellow – a softmax operation.
other domains, as well. Here, we somewhat modify the U-Net architecture, according to MobileNets [94] framework, to improve its efficiency. In particular, the MobileNets framework uses Depthwise Separable Convolutions, a form which factorizes standard convolutions (e.g., $3 \times 3$) into a depthwise convolution (applied separately to each input band) and a pointwise ($1 \times 1$) convolution to combine the outputs of depthwise convolution.

![Fig. 6. The architecture of U-Net [97]](image6)

4) DeepLab-V3+: DeepLab-V3+ [91] is an improved version of DeepLab-V3 [98], while the latter is an improved version the original DeepLab [92] model. This segmentation model does not follow the FCN framework like the previously discussed models. The main features that distinguish the DeepLab model from FCNs are the atrous convolutions for upsampling and the application of probabilistic machine learning models, concretely, conditional random fields (CRFs) for a finer localization accuracy in the final fully connected layer. Atrous convolutions, in particular, allow to enlarge the context from which the next layer feature maps are learned, while preserving the number of parameters (and, thus, the same efficiency). Using a chain of atrous convolutions allows to compute the final output layer of a CNN at an arbitrarily high resolution (removing the need for the upsampling part as used in FCNs). In the follow up work, proposing DeepLab-V3+, Chen et al. [98] change the approach to atrous convolutions to gradually double the atrous rates, and show that with an adapted version, their new algorithm outperforms the previous one, even without including the fully connected CRF layer. Finally, in their newest adaption to the model, called DeepLab-V3+, Chen et al. [91] turn to a similar approach to the FCNs, i.e., they add a decoder module to the architecture (see Figure 7). That is, they employ the features extracted by the DeepLab-V3 module in the encoder part, and add the decoder module consisting of $1 \times 1$ and $3 \times 3$ convolutions.

5) FRRN-B (Full-Resolution Residual Networks): As we have seen, most of the semantic segmentation architectures are based on some form a FCN, and so they utilize existing classification networks, such on ResNet or VGG16 as encoders. We also discussed the main reason for such approaches, which is to take advantage of the learned weights from those architectures pretrained for the classification task. Nevertheless, one disadvantage of the FCN approach is that the resulting network outputs of the encoder part (particularly, after the pooling operations) are at a lower resolution, which deteriorates localization performance of the overall segmentation model. Pohlen et al. [95] proposed to tackle this by having two parallel network streams processing the input image: a pooling and a residual stream (Figure 8). As the name says, the pooling stream performs successive pooling and then unpooling operations, and it serves to obtain good recognition of the objects and classes. The residual stream computes residuals at the full image resolution, which enables that low level features, i.e., object pixel-level locations, are propagated to the network output. The name of the model comes from its building blocks, i.e., full-resolution residual units. Each such a unit simultaneously operates on the pooling and the residual stream. In the original paper [95], the authors...
propose two alternative architectures FRRN-A, and FRRN-B, and they show that FRRN-B achieves superior performance on the Cityscapes benchmark dataset. Hence, we employ the FRRN-B architecture.

Fig. 9. The architecture of PSPNet [89]

6) **PSPNet (Pyramid Scene Parsing Network):** Zhao et al. [89] propose the Pyramid Scene Parsing as a solution to the challenge of making the local predictions based on the local context only, and not considering the global image scene. In remote sensing, an example for this challenge happening could be when a model wrongly predicts the water with waves present in it as the dry vegetation class, because they appear similar and the model did not consider that these pixels are being part of a larger water surface, i.e., it missed the global context. In similarity to the other FCN-based approaches, PSPNet uses a pre-trained classification architecture to extract the feature map, in this case, ResNet. The main module of this network is the pyramid pooling, which is enclosed by a square in Figure 9. As can be seen in the Figure, this module fuses features at four different scales: from the coarsest (red) to the finest (green). Hence, the output of each level in the pyramid pooling module contains the feature map of a different resolution. In the end, the different features are concatenated yielding the final pyramid pooling global feature for predictions.

7) **FC-DenseNet (Fully Convolutional DenseNets):** This semantic segmentation algorithm is built using DenseNet CNN [79] as a basis for the encoder, followed by applying the FCN approach [83]. The specificity of the DenseNet architecture is the presence of blocks where each layer is connected to every other layer in a feed-forward fashion. Figure 10 shows the architecture of FC-DenseNet where the blocks are represented by the **Dense Block** units. According to [79], such architecture scales well to hundreds of layers without any optimization issues, while yielding excellent results in classification tasks. In order to efficiently upsample the DenseNet feature maps, Jegou et al. [83] substitute the upsampling convolutions of FCNs by **Dense Blocks** and **Transitions Up**. The **Transition Up** modules consist of transposed convolutions, which are then concatenated with the outputs from the input skip connection (the dashed lines in Figure 10).

**E. Training approach**

The performance of supervised machine learning strongly depends on the availability of high-quality reference (labelled) data for training [15], [99]. This is also the case with our selected semantic segmentation models. If the set of available training images is limited in size (such as SAR images), there is an option to pre-train the model using a larger set of available images of another type (such as ordinary RGB). This pre-training is done on a similar task. Using the pre-trained model to continue training with the limited set of images (SAR), the knowledge becomes effectively transferred from the RGB to the SAR task [100]. In this work, we tested the approach of fine-tuning the deep learning architectures trained for the RGB ImageNet segmentation task. Differently to [53], we used SAR instead of optical imagery, and studied land cover mapping across a country instead of a small selected test site.

**F. Experimental Setup**

In this section, we describe first how we prepared the SAR images for training with the deep learning models which are designed for RGB images. Then we provide the details of our implementation.

1) **SAR Data Preprocessing for Deep Learning:** Sentinel-1 imagery have two polarization channels, each of them being more informative about certain types of land cover. Hence, using their combination is expected to yield better land cover mapping results than using any of them independently. Moreover, the previous work has shown the benefits of also using the DEM model for land cover mapping [9]. Hence, as the third layer, we used the DEM of Finland from the National Land Survey.

SAR backscatter for both polarizations were converted to decibels by applying the \((10 \cdot \log_{10})\) transformation. In addition, for the deep learning models, each band should be normalized so that the distribution of the pixel values would resemble a Gaussian distribution centered at zero. This makes convergence faster while training the network. The data normalization is done by subtracting the mean from each pixel, and then dividing the result by the standard deviation. In addition, given that the semantic segmentation models expect pixel values in the range \((0,255)\), we scaled the normalized...
TABLE III
THE PROPERTIES OF THE EXAMINED SEMANTIC SEGMENTATION ARCHITECTURES

| Architecture      | Base model | Parameters |
|-------------------|------------|------------|
| RISNet            | ResNet101  | 24.75M     |
| SegNet            | VGG16      | 34.97M     |
| Mobile U-Net      | Not applicable | 8.87M     |
| DeepLabV3+        | ResNet101  | 47.96M     |
| FRRC-B            | ResNet101  | 24.75M     |
| PSPNet            | ResNet101  | 56M        |
| FC-DenseNet       | ResNet101  | 9.27M      |

data and also the DEM values to this range. Such preprocessed layers are then used to create the image dataset for training.

We named the created dataset SAR RGB-DEM. The naming comes from the process used to create the images in this dataset. Namely, one of the two channels of a Sentinel-1 image is assigned to R and the other to G channel. For the third, B channel, we use the DEM layer.

2) Train/Development and Test (Accuracy Assessment) Dataset : The images from the SAR RGB-DEM dataset needed to be split into 512px × 512px partial images (further in the text called imagelets) for training. Thus, each imagelet represented an area of roughly 10 × 10 km². The first reason for this preprocessing is about the squared shape: some of the selected models required squared-shaped images. Some other of the models were flexible with the image shape and size but we wanted to make the setups for all the models the same so that their results are comparable. The second reason for the preprocessing is about the computational capacity: with our hardware setup (described below), this was the largest image size that we could work with.

Upon splitting the SAR RGB-DEM images, we discarded those imagelets that were completely outside the land mass area, as well as those for which we did not have a complete CORINE label (such as if they fell in part outside the Finnish borders). This resulted in more than 7K imagelets of size 512px × 512px.

Given the geography of Finland, to have representative training data, it seems useful to include imagelets from both northern and southern (including the large cities) parts of the country into the model training. On the other hand, some noticeable differences are found also in the gradient from east to west of the country. To achieve representative training dataset, we selected all imagelets between the longitudes of 24° west of the country. To achieve representative training dataset, noticeable differences are found also in the gradient from east to west of the country. On the other hand, some no noticeable differences are found also in the gradient from east to west of the country. To achieve representative training dataset, we selected all imagelets between the longitudes of 24° and 28° for the accuracy assessment (model testing), and all other imagelets for model training (that is training & development in the computer vision terminology). In this way, we prevented the situation in which two images of the same area but acquired at different times are used one for training and the other one for testing. Images that were overlapping any border of the introduced strip were discarded. The procedure resulted in 3104 images in the training & development set and 3784 images in the test (accuracy assessment) set. Finally, we used 60% from the training & development set for training and the rest for development of the deep learning models.

3) Data Augmentation: Further, we have employed the data augmentation technique. The main idea behind the data augmentation is to enable improved learning by reusing original images with slight transformations such as rotation, flipping, adding Gaussian noise, or slightly changing the brightness. This provides additional information to the model and the dataset size is effectively increased. Moreover, an additional benefit of the data augmentation is in helping the model to learn some invariant data properties for which no examples are present in the original dataset.

Given the sensitivity of the SAR backscatter, we did not not want to augment the images in terms of the color, brightness, or by adding noise. However, we could safely employ rotations and flipping. For rotations, we only used the 90° increments, giving three possible rotated versions of an image. For image flipping, we applied horizontal and vertical flipping, or both at the same time, giving another three possible versions of the original image. Notice that our images are square, so the transformations did not change the image dimensions. Finally, we applied the online augmentation, as opposite to the offline version. In the online process, each augmented image is seen only once, and so this process yields a network that generalises better.

4) Implementation: To apply the described semantic segmentation models, we adapted the open-source Semantic Segmentation Suite. We used Python with TensorFlow backend.

5) Hardware and Training Setup: We trained and tested separately each of the deep learning models on a single GPU (NVIDIA GeForce GTX 1080) on a machine with 32GB of RAM.

We used the RMSProp optimisation algorithm, learning rate of 0.0001, and decay of the learning rate of 0.9954. Each model was trained for an equal number of epochs = 500 and during the process, the checkpoint for the best model was saved. Then we used that model for evaluation on the test set and we report those results.

G. Evaluation Metrics

In the review on the metrics used in land cover classification, Costa et al. [102] have found a lack of consistency, complicating intercomparison of different studies. To avoid such issues and ensure that our results are easily comparable with the literature, we thoroughly evaluated our models. For each model and class, we report the following measures of accuracy: precision, also known as producer’s accuracy (PA), recall, also known as user’s accuracy (UA), and overall accuracy and Kappa coefficient. The formulas are as follows.

For each segmentation class (land cover type) c, we calculate precision (producer’s accuracy):$$P_c = \frac{T_{pc}}{T_{pc} + F_{pc}},$$
and recall (user’s accuracy):$$R_c = \frac{T_{pc}}{T_{pc} + F_{nc}},$$

4Vertical flip operation switches between top-left and bottom-left image origin (reflection along the central horizontal axis), and horizontal flip switches between top-left and top-right image origin (reflection along the central vertical axis)
where $T_{PC}$ represents true positive, $F_{PC}$ false positive, and $F_{NC}$ false negative pixels for the class $c$.

When it comes to accuracy \[\text{Acc}_{c} = \frac{C_{ii}}{G_{i}},\]

and overall pixel accuracy:

\[\text{Acc}_{OP} = \frac{\sum_{i=1}^{L} C_{ii}}{\sum_{i=1}^{L} G_{i}},\]

where $C_{ij}$ is the number of pixels having a ground truth label $i$ and being classified/predicted as $j$, $G_{i}$ is the total number of pixels labelled with $i$, and $L$ is the number of classes. All these metrics can take values from 0 to 1.

Finally, we also use a Kappa statistic (Cohen’s measure of agreement), indicating how the classification results compare to the values assigned by chance \[\text{Kappa} = \frac{P_{o} - P_{e}}{1 - P_{e}}.\]

Depending on the value of Kappa, the observed agreement is considered as either poor (0.0 to 0.2), fair (0.2 to 0.4), moderate (0.4 to 0.6), good (0.6 to 0.8) or very good (0.8 to 1.0).

### IV. RESULTS AND DISCUSSION

Using the experimental setup described in previous section, we evaluated the seven selected semantic segmentation models: SegNet \[88\], PSPNet \[89\], BiSeNet \[90\], DeepLabV3+ \[91\], \[92\], U-Net \[93\], \[94\], FRRN-B \[95\], and FC-DenseNet \[83\]. The overall classification performance statistics for all studied models is gathered in Table IV. Figure 11 shows maps produced for several imagelets with the best performing model, FC-DenseNet. Obtained results are compared to prior work and classification performance for different land cover classes is discussed further.

### A. Classification Performance

All the models performed relatively well in terms of classification, achieving the overall accuracy above 83%. Three models performed particularly well, achieving the accuracy score above 89%: SegNet, FRRN-B, and the best performing model FC-DenseNet, which achieved the accuracy of 90.7%.

Before further analysis, let us recall that CORINE is not exclusively a land cover map, but rather land cover and land use map, thus for specific classes can differ from ecological classes observed by Sentinel-1. Also, the aggregation to Level-1 is sometimes not strictly “ecological” or complies to physics surface scattering considerations. For example, roads, airports, major industrial areas and road network often exhibit areas similar to field, presence of trees and green vegetation near summer cottages can cause them exhibit signatures close to forest rather than urban, sometimes forest on the rocky terrain can be misclassified as urban instead due to presence of very bright targets and strong disruptive features, while confusion between peatland and field areas is also often a common place. Finally, the accuracy of the CORINE data is only somewhat higher than 90%.

As for the results across the different land classes, all the models performed particularly well in recognising the water bodies and forested areas, while the urban fabric represented the most challenging class for all the models. We expect that the inclusion of the DEM as one layer in the training images has helped to achieve good results on the water bodies class for most of the models (except for BiSeNet, all the models achieved both the user and producer accuracy above 90%). The urban class was particularly challenging for the following main reasons. First, this class changes the most, as new houses, roads, and urban areas are built. While we took the most suitable available CORINE class in terms of time for our Sentinel-1 images, there are almost certain differences between the urban class as it was in 2012 and in 2015-2016. Second, the CORINE map itself does not have a perfect accuracy, neither aggregation rules are perfect. As a matter of fact, in majority of studies where SAR based classification was done versus CLC or similar data, a poor or modest overall agreement was observed for this class \[20\], \[21\], \[39\], \[74\], while the user’s accuracy was strongly higher than producer’s \[105\]. The latter is exactly due to radar being able to sense sharp boundaries and bright targets very well whereas such bright targets often don’t dominate the whole CORINE Level-1 urban class. We argue that any inaccuracies present will be particularly attenuated in our models for the urban class because of the sharp and sudden boundary changes in this class, unlike for the others, such as forest and water. The top performing model, i.e., FC-DenseNet, performed the best across all the classes. It is particularly notable that it achieved the user accuracy, i.e., precision for the urban class of 62%, improving on it significantly compared to all the other models. Nevertheless, its score on the producer accuracy, i.e., recall on this class of 27% is outperformed by the two other top models, i.e., SegNet and FRRN-B.

We mentioned the issues of SAR backscattering sensitivity to several ground factors so that the same classes might appear
TABLE IV
Summary of the classification performance and efficiency of various Deep Learning models (UA-user’s accuracy, PA-producer’s accuracy, average inference time is per image in the dataset)

| LC classes          | Test scale (km²) | Accuracy (UA, PA %) | BiSeNet | DeepLabV3+ | SegNet | FRRN-B | U-Net | PSPNet | FC-DenseNet |
|---------------------|-----------------|---------------------|---------|------------|--------|--------|-------|--------|-------------|
| Urban fabric (100)  | 10816           | 26, 21              | 15, 14  | 36, 31     | 38, 30 | 45, 23 | 38, 18 | 62, 27 |
| Agricultural areas  | 25160           | 49, 51              | 50, 49  | 69, 66     | 68, 68 | 66, 66 | 53, 48 | 72, 71 |
| Forested areas (300)| 285462          | 90, 91              | 88, 96  | 93, 94     | 92, 95 | 92, 95 | 89, 95 | 93, 96 |
| Peatland, bogs and | 20990           | 54, 43              | 56, 13  | 67, 57     | 71, 55 | 70, 52 | 65, 31 | 74, 58 |
| marshes (400)      | 53564           | 85, 91              | 94, 92  | 96, 95     | 96, 96 | 94, 94 | 96, 96 | 96, 96 |
| Water bodies (500) |                 |                     |         |            |        |        |        |        |
| Overall Accuracy (%)|                |                     |         |            |        |        |        |        |
|                     |                 | 88.86               | 85.49   | 89.03      | 89.27  | 89.25  | 86.51  | 90.66  |
| Kappa               |                 | 0.634               | 0.649   | 0.754      | 0.758  | 0.754  | 0.680  | 0.785  |
| Average inference time (s) |         | 0.0389              | 0.0267  | 0.0761     | 0.1424 | 0.0848 | 0.0495 | 0.1930 |

Table V
Confusion matrix for classification with FC-DenseNet model

| CLC2012 | Sentinel-1 class |
|---------|------------------|
|         | urban | water | forest | field | peatland | total |
| 1       | 7301999 | 412074 | 115892791 | 3212639 | 2211476 | 127042255 |
| 2       | 78331 | 128294872 | 3457634 | 171029 | 1935276 | 133937142 |
| 3       | 366398 | 2703632 | 686788977 | 12795703 | 7730444 | 713682454 |
| 4       | 766200 | 121609 | 16527970 | 44866048 | 620934 | 62902761 |
| 5       | 56097 | 1866020 | 19164137 | 109108 | 3039189 | 52486451 |
| total   | 11866325 | 133399206 | 741831489 | 62136627 | 40817319 | 990050966 |

UA 61.5 96.2 92.6 72.2 74.3 90.7

Fig. 11. Illustration of the FC-DenseNet model performance: selection of classification results, i.e., direct output of the network, without any post-processing (bottom row) versus reference Corine data (upper row).

B. Computational Performance

The training times with our hardware configuration took from 6 days up to 2 weeks for the different models. This could be significantly improved by training each model using a multi-GPU system instead of a single-GPU, as we did.

In terms of the inference time, we also saw the differences in the performance. In Table IV, we present the average inference time per the 512px × 512px imagelets that we worked with. The results show that there is a trade-off between classification and computational performance: the best models in terms of classification results (i.e., FC-DenseNet and FRRN-B) take several times longer inference time compared to the rest. Nevertheless, depending on the application, this might not represent a significant difference.

C. Comparison to Similar Work

Obtained results compare favourably to previous similar studies on land cover classification with SAR data [20], [21], [28], [29], [39], [74]. Depending on the level of classes...
aggregation (4-5 major classes or more), with using mostly statistical or classical machine learning approaches reported classification accuracies were as high as 80-87% to as low as 30% when only SAR imagery were used.

Two recent studies that employed neural networks to SAR imagery classification (albeit in combination with satellite optical data) for land cover mapping were [28] and [66], with reported classification accuracies of up to 97.5% and 94.6%, respectively.

The best model in our experiments achieved the overall accuracy of 90.7%. However, our results are obtained using solely the SAR imagery. In contrast, SAR imagery (PALSAR) alone yielded the overall accuracy of 78.1% in [28]. The types of classes they studied are also different compared to ours (crops versus vegetation versus land cover types) and our study is performed on a larger area. Importantly, the previous studies have applied different types of models (regular NNs versus CNN versus semantic segmentation). In particular, the CNN models work on the $7 \times 7$ resolution windows, while we have applied more advanced semantic segmentation models, which work on the level of a pixel. Keeping in mind findings from [28] that the addition of optical images on top of SAR improved the results for over 10%, we expect that our models would perform comparably well or outperform these previous works if applied to a combined SAR and optical imagery.

In terms of the deep learning setup, the most similar to ours are the studies [53] and [70]. However, RapidEye optical imagery at 5 m spatial resolution was used in [53], and the test site was considerably smaller. Study [70], similar to our research, relied exclusively on SAR imagery, however, fully polarimetric images, and acquired by RADARSAT-2 at considerably better resolution. They have developed an FCN-type of a semantic segmentation model specifically designed for the classification of wetland complexes using PolSAR imagery. Using this model to classify eight wetland map classes, they achieved the overall accuracy of 93%. However, because their model is designed specifically for wetland complexes, it is not clear if such a model would generalize to other types of areas. Compared to our study, they have focused on a considerably smaller area (nearly the size of our imagelets), and on a very specific task (wetland types mapping). Thus, it is not readily clear how general their approach is.

D. Outlook and Future Work

There are several lines for potential improvement based on results of this study, as well as future work directions.

First, using even a larger set of Sentinel-1 images can be recommended since for the supervised deep learning models large amounts of data are crucial. Here, we processed only 6888 imagelets altogether, but deep learning algorithms become efficient typically only once they are trained with hundreds of thousands or millions of images.

Second, if SAR images and reference data of a higher resolution are used, we expect better classification performance, too, as smaller details could be potentially captured. Also, better agreement in acquisition timing of reference and SAR imagery can be recommended. The reference and training data should come from the same months or year if possible, and that the reference maps should represent the reality as accurately as possible. The models in our experiments were certainly limited by the CORINE’s own limited accuracy.

Third, in this study we have tested the effectiveness of off-the-shelf deep learning models for land cover mapping from SAR data. While the results show their effectiveness, it is also likely that the novel types of models, specifically developed for the radar data (such as [70]), will yield even better results. In particular, one could develop the deep learning models to handle directly the SLC data which preserve the phase information.

Focusing on single season is both advantage and limitation. Importantly, we have avoided confusion between SAR signatures varying seasonally for several land cover classes. However, multitemporal dynamics itself can be potentially used as an additional useful class-discriminating parameter. Incorporating seasonal dynamics of each land cover pixel (as a time series) is left for future work, perhaps with additional need to incorporate recurrent neural networks into the approach.

As discussed in Section 3.1.1, it could be suitable to use more detailed (specific) land cover classes, as aggregation of smaller LC classes into Level-1 CORINE classes is not exactly ecological, leading to mixing several distinct SAR signatures in one class, and thus causing additional confusion for the classifier. Later, classified specific classes can be aggregated into larger classes, potentially showing improved performance.

Finally, we have used only SAR images and a freely-available DEM model for the presented large-scale land cover mapping. If one were to combine other type of remote sensing images, in particular the optical images, we expect that the results would significantly improve. This is true for those areas where such imagery can be collected due to cloud coverage, while in operational scenario it would potentially require use of at least two models (with and without optical satellite imagery). It is also important to access added value of SAR imagery with deep learning models when optical satellite images are available, as well as possible data fusion and decision fusion scenarios, before a decision on mapping approach is done [19].

V. Conclusion

Our study demonstrated the potential for applying existing state-of-the-art deep learning models to SAR image classification with high accuracy. Several state-of-the-art deep learning models were benchmarked in a country wide classification experiment using Sentinel-1 IW-mode SAR data, reaching nearly 91% overall classification accuracy with the best performing model (FC-DenseNet). This indicates strong potential for using pretrained CNNs for further fine-tuning, and seems particularly suitable when the number of training images is limited (to thousand or tens of thousands instead of millions). Several possible improvements and limitations of suggested approach were identified, including necessity for testing multitemporal approaches and very high resolution SAR imagery, as well as
developing models specifically for SAR, and will be addressed in future work.

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