FOREST SEMANTIC SEGMENTATION BASED ON DEEP LEARNING USING SENTINEL-2 IMAGES

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KEY WORDS: Deep Learning, Semantic Segmentation, Sentinel-2, Remote Sensing, Stand Map.

ABSTRACT:

Forests are invaluable for maintaining biodiversity, watersheds, rainfall levels, bioclimatic stability, carbon sequestration and climate change mitigation, and the sustainability of large-scale climate regimes. In other words, forests provide a wide range of ecosystem services and livelihoods for the people and play a critical role in influencing global atmospheric cycles. Providing sustainable, reliable, and accurate information on forest cover change is essential for an holistic forest management, efficient use of resources, neutralizing the effects of global warming and better monitoring of deforestation activities. Within the scope of this study, it is aimed to perform semantic segmentation of 5 different tree species (larch, red pine, yellow pine, oak, spruce) from Sentinel-2 satellite images. For this purpose, the regions where these tree species are densely populated in Turkey (Marmara, Aegean, Eastern Black Sea) were selected as pilot regions. A unique data set was created using the data of the selected pilot regions. As a result of the study, it was possible to determine the forest types temporally for the selected classes with more than 90% Intersection over Union score for all classes. The developed deep learning model with the created forest data set can be implemented to the other forests areas with same species in other parts of the world.

1. INTRODUCTION

In Europe, there are 200 different forest habitats defined according to the European Union (EU) Habitats Directive (Natura 2000, 2011). Today, it is stated that one of the most important impacts of climate change is on forests that will affect the diversity of tree species. Although there is no comprehensive legally binding document on forests at the global level, various legislation has been established in various conventions such as the Convention on Biological Diversity (CBD), the UN Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol. UN Convention to Combat Desertification (UNCCD), developed in the early 1990s. The European Union (EU) has also put focus on biodiversity, climate change and desertification. In line with the 2050 vision; by 2050, the EU aims to protect, value and appropriately restore biodiversity and prevent biodiversity loss due to its essential contribution to ecosystem services, natural capital, natural value and the environment (EEA Report, 2016).

Although the EU has legal frameworks, strategies, and action plans to protect nature and restore habitats and species, protections remain incomplete. Restoration has been implemented on a small scale and implementation and enforcement of legislation has been insufficient. This situation requires further global efforts (EU Biodiversity Targets, 2020).
The SMART FOREST study has been successful in this regard, aiming to develop new methods and techniques that take into account the future impacts of climate change and its effects on the forest ecosystem and biodiversity, taking into account that more than half of the global GDP depends on nature and the services it provides, and also in line with EU objectives and vision.

Forests, which cover about 1/3 of the world's land surface and account for more than 3/4 of the biological mass, are natural resources that provide important benefits for the world. However, the existence and continuity of these benefits of forests are threatened by various destruction factors. Among these factors, biotic and abiotic threats have an important place. In terms of biotic threats, especially pests and invasive species are among the most destructive factors on natural forests (Ivantsova, et al., 2019). The effects of insect and pathogen infestations on climate change in the world, forest management interactions and prediction methods are important for the assessment and mitigation of these impacts (FAO, 2021).

Forest conservation, sustainable forest management, renewable energy, determination of forest biomass (Verkerk et al., 2019), carbon emission accounting (Spawn et al., 2020) and forest restoration practices (Goldstein et al., 2020) are of vital importance. Global forest management mapping is important to facilitate decision-making processes and mitigate the environmental impacts of global warming. Changes in precipitation patterns, increased drought and flood risks, threats to biodiversity are some of the important environmental threats that climate change may cause (Puletti et al., 2018).

Today, deep learning models are widely used in semantic segmentation, object detection and classification applications of remote sensing data. These models can detect and classify objects more accurately and efficiently than traditional methods. Considering that the mapping of forests has become a necessity, the use of deep learning models in forest detection and classification has become a valuable method. In contrast to

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traditional forest segmentation, detection, and classification applications, it has been observed that deep learning-based forest segmentation, detection and classification methods are faster, more accurate and time efficient.

In recent years, remote sensing techniques have been applied to biodiversity monitoring, precision agriculture, forest management and environmental studies (Szostak et al., 2018). In the last 10 years, deep learning techniques have become especially popular in the field of image semantic segmentation for the purposes of creating land use/cover maps from satellite imagery (Ma et al., 2019). In addition, these models can also be used in various applications such as monitoring deforestation, assessing disasters, and managing natural resources. Data sources such as Copernicus Sentinel-2 provide a wide opportunity to monitor the Earth's surface and environmental dynamics, including forest plantations (Isaienkov et al., 2021).

Considering the role of forests in climate regulation and carbon sequestration, this study aims to develop a deep learning-based solution to provide sustainable, reliable, and accurate information on forest cover types. This solution would aid authorities and decision-makers to further improve forest management, efficient use of resources, neutralisation of the effects of global warming and monitoring of deforestation activities. For this purpose, a stand map consisting of 5 forest types (larch, red pine, yellow pine, oak, spruce) in selected pilot areas in Türkiye (Marmara, Aegean, Eastern Black Sea Regions) was created using atmospherically corrected Sentinel-2 satellite images. The labelling process was carried out in cooperation with Forest Engineering experts to maximize the accuracy of the created dataset.

Forest species mapping is crucial for forest management, forest degradation monitoring, habitat and biodiversity assessment, as well as carbon cycle and energy budget estimation (Fassnacht et al., 2016). The use of both optical and RADAR remote sensing data and methods can provide useful information on the composition of forest stand types and allow the study of large and inaccessible areas in less time compared to traditional field studies (Sedliak et al., 2021). Artificial intelligence and its use in remote sensing have become increasingly widely used in recent years (Martins et al., 2021).

There are various studies using Sentinel-2 satellite imagery for forest semantic segmentation with deep learning methods. Bragagnolo et al. (2019) evaluated the performance of U-Net architecture for mapping forest cover in Amazon using Sentinel-2 satellite imagery. They have extracted forest cover without going into species level and achieved precision, recall and F1-score as 0.9356, 0.9676 and 0.9513, respectively. Freudenberg et al. (2019) exploited the U-Net architecture to detect palm trees from satellite images in two study areas in Indonesia and India. The authors used high resolution WorldView-2 and WorldView-2 satellite imagery and obtained accuracy between 0.89 and 0.92 and F1-Score between 0.875 and 0.957. Hamdi et al. (2019) tested and applied an algorithm based on convolutional neural networks (CNN) in ArcGIS environment for automatic detection and mapping of damaged forest areas after-storm in Bavaria, Germany. A modified U-Net architecture optimized for pixel-wise classification of aerial orthophotos consisting of RGB and NIR bands with 0.2 meters spatial resolution was used. The authors have achieved 92% overall test accuracy. Miranda et al. (2019) proposed an CNN-based segmentation method for forest monitoring in Semarang area, Central Java, Indonesia using Sentinel-2 satellite imagery, including spectral feature, spectral index, and spatial feature. The authors have focused on three forest classes namely primary dry forest, secondary dry forest, and plantation forest and obtained 0.9766 overall accuracy. Forstmaier et al. (2020) used Sentinel-2 satellite imagery with Feedforward Neural Networks to map Eucalyptus trees in parts of Portugal and Spain, focusing on Natura 2000 sites within Portugal. The overall accuracy achieved is 92.5%. Gargiulo (2020) presented an approach to fuse of Sentinel-1 and Sentinel-2 data for land cover mapping to overcome cloud cover issue in Sentinel-2. They proposed a multi-temporal W-Net approach for segmentation of interferometric wide-area mode (IW) Sentinel-1 data to map rice, water, and bare soil. (Astola et al., 2021) produced a canopy height model using Sentinel-2 satellite imagery, metadata, and topography data to predict increased stock volume with deep neural networks (DNN) in four forest regions in Central Finland. Ao et al. (2021) developed a super-resolution CNN to produce 10-m NDVI time series by fusion of Landsat-8 and Sentinel-2 satellite imagery. They used the Structural Similarity Index (SSIM) metric for accuracy analysis and calculated the SSIM value for forest as 0.8487. Awad (2021) proposed a self-organizing deep learning (SO-Unet) network to classify forests in urban and peri-urban environments using multispectral, multi-temporal and medium spatial resolution Sentinel-2 satellite imagery. SO-UNet, which is a combination of two different machine learning technologies, is a combination of Son and U-Net architectures. The maximum accuracies obtained are 83.25% and 82.50% for the city and the urban environment, respectively. Borges da Costa (2021) compared six architectures (U-Net, DeepLabv3+, FPN, MANet, PSPNet, LinkNet) with four encoders (ResNet-101, ResneXt-101, Efficientnet-b3 and Efficientnet-b7) to detect Eucalyptus areas using 10 spectral bands of Sentinel-2. Overall, the best model was DeepLabv3+ with Efficient-net-b7 backbone, achieving 76.57% Intersection over Union (IoU). Isaienkov et al. (2021) presented a basic U-Net model for deforestation detection in the forest-steppe zone using Sentinel-2 imagery. Malcolm et al. (2021) used Sentinel-2 imagery to model multivariate tree species composition in a forest stand in south-central Ontario, Canada. The accuracy of random forest (RF) and CNN estimates was tested using species-specific based area information. According to the average R2 values, the improvements in RF and CNN models were approximately 1.5 and 2.1 times, respectively. Shumilo et al. (2021) integrated Sentinel-2 and Sentinel-1 satellite data for object detection and applied a U-Net based neural network trained using semi-supervised learning technique. Solorzano et al. (2021) used a U-Net architecture to generate ten class land use/land cover maps using different image inputs from Sentinel-1 and Sentinel-2 satellites, MS, SAR and a combination of both (MS+SAR). The highest overall accuracy obtained was 76%. David and Ce (2022) performed semantic segmentation using Sentinel-2 imagery to detect deforestation within two forest biomes in South America, the Amazon Rainforest and the Atlantic Forest. They used the Attention U-Net architecture for this purpose and achieved 0.9550, 0.9769 and 0.9461 F1-score for each study area, respectively.

The literature review shows that even though Sentinel-2 satellite imagery and deep learning methods are widely used, tree species specific are quite limited. Therefore, in this study we aim to develop a deep learning model that is able to segment larch, red pine, yellow pine, oak, and spruce tree species. The outcomes of the study will provide the opportunity to be integrated with other satellite images and will also provide an important inventory and database for future studies. The created Sentinel-2 satellite imagery-based stand map dataset within the scope of the study is an essential data source for forest semantic segmentation.

2. MATERIALS AND METHODS

2.1 Dataset

Within the scope of the study, semantic segmentation of larch, red pine, yellow pine, oak and spruce tree species belonging to Izmir, Rize, Trabzon, Istanbul, Ankara, Amasya and Giresun regions, taking forest characteristics into account, was carried out using Sentinel-2 satellite images. Sentinel-2 continuously shares high-resolution multi-spectral and multi-temporal data obtained by observing the earth's surface. Sentinel-2 satellite images can be accessed free of charge from the Openhub website provided by the European Space Agency (ESA).

Cloudless Sentinel-2 satellite images of the pilot regions determined within the scope of the study for May-September 2015-2022 were downloaded. Red, Green, Blue and NIR bands of the downloaded satellite images with a resolution of 10 meters were used. The images obtained from satellites are affected by the absorption and scattering of radiation by the earth's surface or by atmospheric particles. In order to remove these effects from the downloaded images, atmospheric correction was applied with the Sen2Cor application, an interface developed by ESA. Using the tree species data prepared by the experts, a different layer was created over the open source QGIS application for 5 different tree species to be segmented in the study and a class was assigned to each tree species. New layers were created for 5 different tree types by making the selections according to the tree types through the relevant tools. This classification process was done by assigning a grey level colour to a different pixel value for each species and thus each tree species was assigned to a colour class. Tree layers were created one by one for each region and saved as a shape file.

Tree Species	Class
Background	0
Black Pine	1
Scotch Pine	2
Red Pine	3
Oak	4
Spruce	5

Table 1. Tree Species Stand Information and Class Values

The dataset consisting of original and mask images were separated as 60% train, 20% validation, 20% test and in accordance with the deep learning architectures to be used for segmentation. Since the raw size of Sentinel-2 satellite images (10980x10980) is too large to be used as a dataset in a deep learning architecture, the images were divided into 512x512 image patches with the help of GDAL. A total of 3480 image pairs are obtained. Sample image patches and corresponding masks are given in Figure 1.

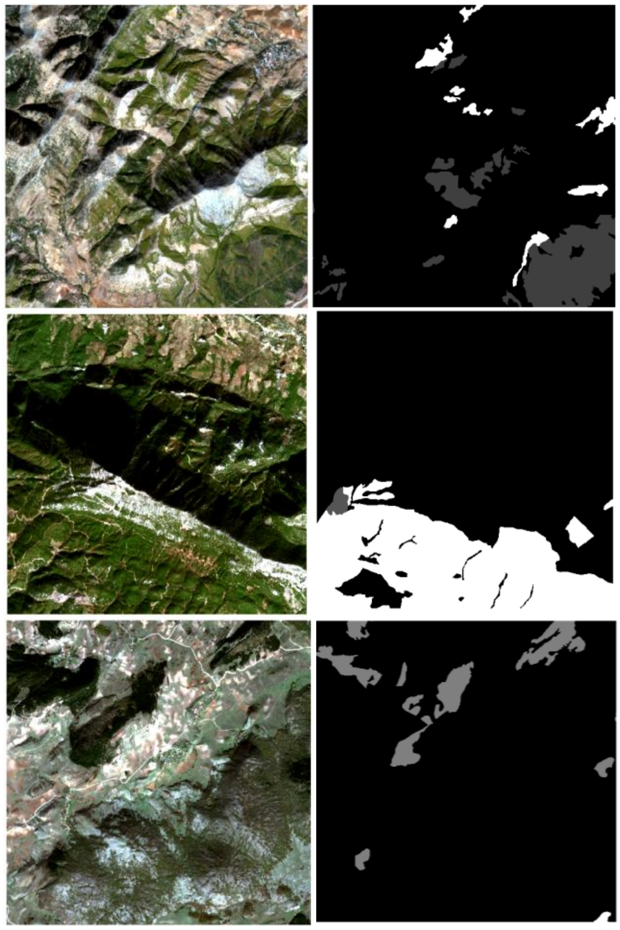

Figure 1. Sample image patches and corresponding labels from the dataset

2.2 Segmentation Methods

Deep learning based semantic segmentation process is carried out using Segmentation Models Pytorch library. Therefore, first the dataset was re-generated in accordance with the used library.

Due to their performance in multi-class segmentation in the literature, we preferred to utilize DeepLabv3+ and Pyramid Scene Parsing Network (PSPNet) architectures.

In 2014, Chen et al. (2014) introduced the initial version of the DeepLab architecture, utilizing Atrous convolution and a fully connected conditional random field (CRF) to regulate feature map resolution. The subsequent DeepLabv2 demonstrated enhanced performance by incorporating the Atrous spatial pyramid pooling (ASPP) module, enabling object segmentation across various scales (L. Chen et al., 2018). DeepLabv3 came up with the removal of the CRF module while enhancing the ASPP module with batch normalization and integrating image-level features for global context encoding (Chen et al., 2017). Finally, DeepLabv3+ represents the pinnacle of this architecture, combining the strengths of the ASPP module's multi-scale contextual information encoding with an encoder-decoder structure.

The PSPNet architecture incorporates a pyramid pooling module designed to capture the broader global context within an image (Zhao et al., 2017). Within its encoder subnetwork, the architecture integrates a CNN backbone consisting of convolutions. These convolutions operate on feature maps, which are pooled at various sizes and subsequently upsampled to match the original feature map size. After this process, the upsampled feature maps are combined or concatenated with the original feature maps.

3. RESULTS AND DISCUSSION

The trainings for preliminary results with DeepLabv3+ and PSPNet were performed using the 4-band (RGB and NIR) dataset with the hypermeters listed in Table 2. The listed hyperparameters are determined empirically.

Epoch	100
Batch Size	4
Learning Rate	0.001
Optimizer	Adam
Encoder	Resnet34
Activation Function	Softmax2d
Class Number	6

Table 2. Hyperparameters used in the trainings.

Since the training result was much lower than expected and one class was not predicted at all. Sentinel-2 images in the original dataset contain 4 bands (Red, Green, Blue, NIR) with a resolution of 10 meters. Since the number of images in the dataset is not sufficient to train a network from scratch, in order to use pre-trained network weights, the dataset was created as three bands. In the 3-band (Red, Green, NIR) dataset, the near infrared (NIR) band is especially used since that the band composition is useful for analyzing vegetation. The conversion of the images from 4 to 3 bands was performed with the help of the Geographic Data Abstraction Library (GDAL) in Python environment. Once the dataset with 3-bands is created, training for both architectures was performed using the same hyperparameters as the 3-band data set. Additionally, we have used Imagenet weights for the pre-trained encoder weights.

Class	**IoU**	
	PSPNet	**DeepLabv3+**
Background	0.81684534	0.89005732
Black Pine	0.61107649	0.76234377
Scotch Pine	0.53619071	0.7255401
Red Pine	0.49261042	0.67852724
Oak	0.00000000	0.00000000
Spruce	0.64043717	0.77678646

Table 3. IoU scores for both architectures trained with 3-band dataset with 512x512 pixel size.

The analysis of the results showed that the oak species could not be distinguished and mostly is mixed with the background. Therefore, we have deeply examined the oak tree class in the dataset and found that mislabeled data were produced due to the construction of roads, buildings, etc. in the areas seen as forest over the years. In order to enhance the dataset further for a more robust solution, the dataset was pre-processed using the Normalised Difference Vegetation Index (NDVI), which is used to measure the health and density of vegetation cover.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

NDVI = Normalised Difference Vegetation Index
NIR = Near-Infrared Band
RED = Red Band

NDVI for each of the images is calculated and all green areas in the image were saved as shape data. The intersections of the recorded forest shape file and the data prepared by the experts were obtained on QGIS software and a more accurate label file corresponding to Sentinel-2 images was obtained.

As a result of the training, it was observed that the DeepLabv3+ architecture provided higher performance in the segmentation of the dataset, so training trials were continued with the DeepLabv3+ architecture with the new dataset.

It was also concluded that the pixel size of image chips was too large for the architecture. In the subsequent training trials, we created new datasets with different image chip sizes in order to assess the effect of the pixel size. Two new datasets were created using image chips with 128x128 and 64x64 pixel sizes using 3-band dataset. The new datasets have 9412 and 52250 image chips for 128x128 and 64x64 pixel sized datasets, respectively.

The training results with a 3-band 128x128 pixel resolution dataset provided IoU values of 66.97%, 47.14%, 50.09%, 55.28%, 60.06% and 55.54% for background, larch, scotch pine, red pine, oak, and spruce classes, respectively. Even though the accuracy metrics have increased, the values were still insufficient for future studies. One main reason for these results is the high background ratio within the dataset. Considering that the tree labels are irregular and discontinuous (Figure 1), we performed another training using the 64x64 pixel sized dataset which has less background information and making sure to have a more balanced dataset among classes. For this purpose, image chips having background more than 70% are removed from the dataset. The accuracy assessment of the training conducted with the 64x64 pixel sized dataset achieved IoU values of 74.81%, 68.98%, 73.42%, 78.58%, 78.28% and 74.32% for background, larch, scotch pine, red pine, oak, and spruce classes, respectively.

The experiments within this study showed that the dataset with a resolution of 64x64 pixels consisting of 3 bands (RGNIR) using DeepLabv3+ architecture provided the best IoU metrics for all tree classes. Finally, in order to fine-tune the results we performed some hyperparameter tests. The final hyperparameter settings that achieved the best results are given in Table 4 and Table 5, respectively.

Epoch	200
Batch Size	8
Learning Rate	0.0003
Optimizer	Adam
Encoder	Timm-regnety_320
Encoder Weights	Imagenet
Activation Function	Softmax2d
Class Number	6

Table 4. Final Hyperparameters

	Black Pine	**Red Pine**	**Scotch Pine**	**Oak**	**Spruce**
IoU Score	0.9194	0.9436	0.9461	0.9608	0.9470
Precision	0.9526	0.9637	0.9665	0.9756	0.9667
Recall	0.9635	0.9781	0.9844	0.9845	0.9789
F1-Score	0.9580	0.9709	0.9723	0.9800	0.9728

Table 5. Accuracy metrics for the final training using the 3-band 64x64 pixel sized dataset with the updated hyperparameters.

The results show that all tree species were segmented above 90% on all accuracy metrics in the test dataset. Confusion matrix calculated from the test dataset is given in Figure 2. Confusion matrix shows that tree species do not generally mix with each other. We can see that the most confused tree classes are Black Pine and Scotch Pine. However, they are all mostly mixed with the background class. Considering that the background class also consists other tree species, one solution could be creating an additional "other trees" class. This can prevent the confusion between other trees and roads, buildings, etc.

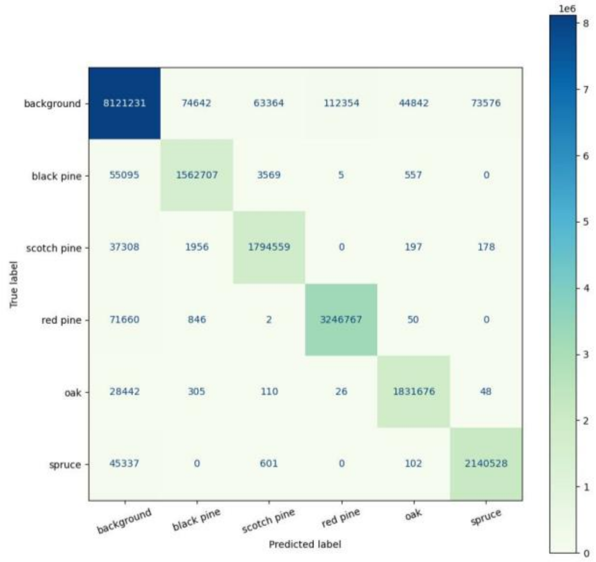

Figure 2. Confusion Matrix

Sample predictions from the trained deep learning architecture are given in Figure 3. Similar to the accuracy metric results, visual interpretations also show promising results.

4. CONCLUSION

The existence of forests is of great importance due to the benefits they provide for living life. Forests need to be protected to provide a more sustainable life for living organisms. In addition to providing habitat for most living things, forests improve air quality, prevent most natural disasters, provide important nutrients, and the water cycle necessary for life.

Forest mapping is of great importance in protecting the existence of forests. Nowadays, in addition to forest identification, determination of forest type has become a necessity to prevent damage to forests. Thanks to fast and reliable forest mapping, legal protection and management of forests can be easier. In addition, forest fires can be prevented, and necessary information can be provided to protect forest biodiversity.

Within the scope of this study, a tree segmentation model based on deep learning for 5 tree species using remote sensing data was developed. The accuracy and visual interpretations show that the trained model is sufficient for producing stand maps, monitoring temporal change and management of forests.

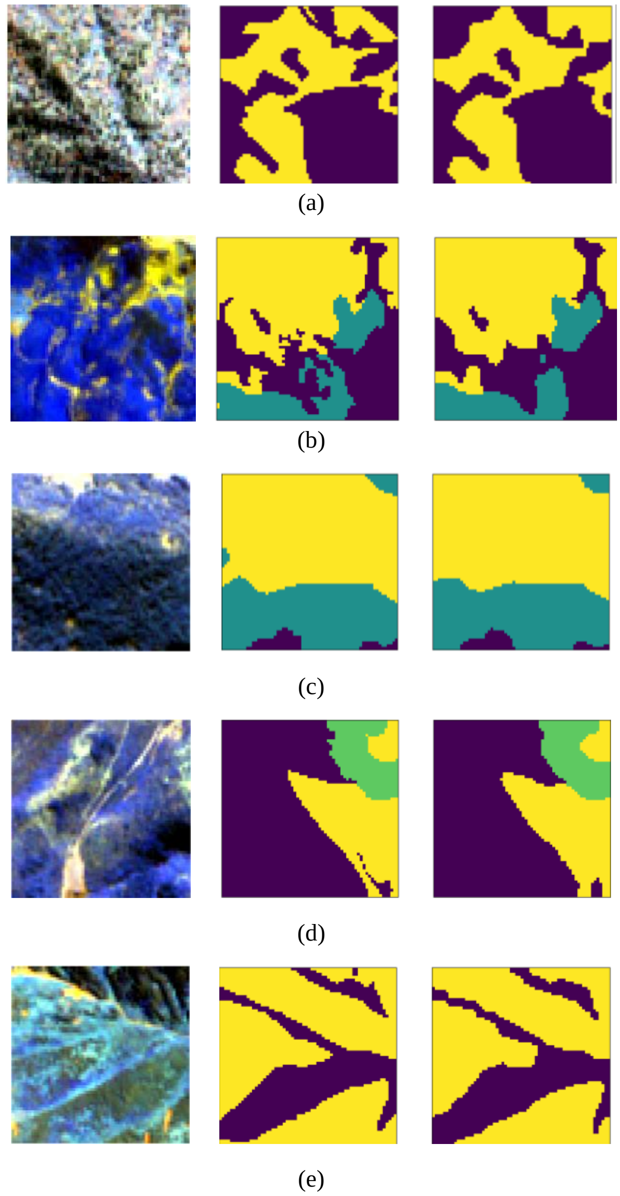

Figure 3. Sample predictions from the test dataset. Left Column: Sentinel-2 Image Patch, Middle Column: Ground Truth, Right Column: Prediction Result

In order to train deep learning architectures to sufficiently, an accurate and well-balanced dataset is essential. Since forests are large and mixed communities, there are often problems in the production of their labels. The fact that the growth ages of the trees are not known accurately, the frequency of occurrence within a region and the canopy openness ratios vary greatly which are also important factors affecting the quality of the labels. The experiments in this study showed that use of NDVI significantly smooths labelling process. Hence, in this study, we created a novel tree species dataset with Sentinel-2 imagery.

It was determined that one of the most important parameters affecting the accuracy is the band combination used in the dataset. The initial weights could not be used when a 4-band data set was used. Deep learning algorithms require a large amount of data while training, however we were not able to expand our dataset further due to the limited pilot regions. Considering that this deficiency directly affects the accuracy of the training, use of pre-trained weights was the only for the purposes of the study. Therefore, it is concluded that the most appropriate band combination for a deep learning-based forest classification within the scope of this study should be 3 bands as Red, Green and near infrared (NIR).

The created dataset is exploited for training DeepLabv3+ and PSPNet architectures. The problems encountered during the study showed that some parameters highly affect the performance of the trained model. For example, using small sized image chips is more effective for irregular and discontinuous objects.

As a result of the study, deep learning methods can be effectively used for forest type mapping with accurate and reliable results. This approach minimizes manual labor with cost-effective solutions.

In the future work, we plan to enrich our dataset with more tree species and add “other trees” class in order to prevent mixing tree classes with the background.

ACKNOWLEDGEMENTS

This study has been supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK) under 2209-B project number: 1139B412200297.

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