Received 26 July 2022, accepted 26 August 2022, date of publication 1 September 2022, date of current version 19 October 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3203405

RESEARCH ARTICLE

Deep Learning Model Development for Detecting Coffee Tree Changes Based on Sentinel-2 Imagery in Vietnam

QUANG TOAN LE[1], (Member, IEEE), KINH BAC DANG[2], (Member, IEEE), TUAN LINH GIANG[2], THI HUYEN AI TONG[1], VU GIANG NGUYEN[1,3], (Member, IEEE), THI DIEU LINH NGUYEN[2], AND MUHAMMAD YASIR[4]

[1]Space Technology Institute, Vietnam Academy of Science and Technology, Cau Giay, Hanoi 10000, Vietnam
[2]Faculty of Geography, VNU University of Science—Vietnam National University, Thanh Xuan, Hanoi 10000, Vietnam
[3]Division Forest, Nature and Landscape, KU Leuven, 3001 Heverlee, Belgium
[4]College of Oceanography and Space Informatics, China University of Petroleum, Qingdao 266580, China

Corresponding author: Kinh Bac Dang (dangkinhbac@hus.edu.vn)

This work was supported in part by the Science and Technology Project of the Vietnam Academy of Science and Technology (VAST) under Grant VAST01.07/21-22.

ABSTRACT Scientists and land managers have spent considerable time and resources monitoring coffee forests in the great basalt plateau. Deep learning models for coffee classification using remote sensing data have developed into a tool that may eventually replace manual image interpretation. This study proposes a U-Net model for classifying coffee planting regions using Sentinel-2 data, which aid in the annual monitoring of coffee plantation area changes. Numerous optimizer methods were evaluated and compared to support-vector-machine and random-forest methods. Twelve U-Net models were trained and compared in total. The trained deep learning models outperformed the two benchmark methods. As a result, the U-Net model with the Adadelta optimizer and $128 \times 128 \times 4$ input data size was chosen due to its near-95 percent accuracy and 0.12 loss function value. The model was used to successfully detect location of the Vietnamese coffee ecosystem. The Net-Adadelta-128 model's output is consistent with data from statistical reports, which estimated the area of the coffee land cover to be 684, 681, and 676 thousand hectares in 2019, 2020, and 2021, respectively. The best U-Net model, which takes approximately 30 minutes to create a new classification for 55,000 square kilometres, may one day be used for coffee research and management.

INDEX TERMS Deep learning, coffee, U-Net, loss function, optimization.

I. INTRODUCTION

Each year, consumers drink over 400 billion cups of coffee, sustaining a worldwide business worth more than $100 billion USD [1], [2], [3]. As a result, coffee is a significant worldwide commodity that is critical to the economy of a number of tropical nations. Before coming a major commercial commodity around the globe, coffee plants were discovered for the first time in Ethiopia's highlands in the 9th century [4]. The French missionaries first planted them in Vietnam in 1857 [5], [6]. As the second largest coffee exporter in the world, Vietnam produces 2.7 million tons of coffee per hectare on a total area of about 670,000 ha [7]. Compared to 1980, Vietnam's coffee area in 2000 increased 23 times and its production increased 83 times [8]. Therefore, Vietnam has a high potential to become the largest coffee exporter in the world if the farmers and forestry managers have good management policies with support from high technology in the 21st century [9]. It has been raised the issue of how coffee production impacts the regeneration, maintenance, or removal of tropical forests. Therefore, mapping coffee plantations is critical for determining the geographic locations of coffee production hubs. When it comes to monitoring and mapping vegetation, remote sensing technology has been extensively shown to

The associate editor coordinating the review of this manuscript and approving it for publication was Yongming Li.

be a cost-effective, rapid, and efficient approach [10], [11]. Additionally, the use of machine learning to remote sensing analysis seeks to enhance the lives of coffee farmworkers and their families, boost the productivity of current coffee production regions, and avert either forest clearance or depletion of other natural resources [7], [12].

However, it is difficult to detect or classify precisely the coffee land cover based on pixel-based methods due to the differences in their canopy structures. Meanwhile, monoculture coffee systems have transitioned to unshaded systems, while the number of canopy forms and management methods have diversified among shaded systems [13]. It makes their ecosystem services and environmental effects more diverse, compared to the traditional plantation methods [2]. Four typical shaded coffee systems that are often identified based on their variety of vertical and compositional shading, include (1) rustic polyculture, (2) traditional polyculture, (3) commercial polyculture, and (4) shaded monoculture [13]. In rustic polyculture systems, the forest canopy remains intact and understory changes are limited. Coffee and other shade-tolerant plants are included in conventional polyculture systems to preserve the canopy integrity, but growers must completely replace the understory with coffee plants. Commercial polyculture methods eliminate both the understory and canopy, replacing these elements with coffee and other commercially valuable smaller trees. Shaded monoculture, a kind of contemporary shaded system, is produced by eliminating both the canopy and understory and replacing them with a leguminous canopy that is nearly entirely dedicated to shading the coffee below.

With the variety of coffee land cover shape, the object-based classification based on the integration of remote sensing data and deep learning models therefore can become a potential method to identify this land cover on remote sensing data [10]. This integration is a subset of artificial intelligence in which computers learn from samples, human knowledge, raw data, previous outcomes and new data sources [14], [13], [15], [16]. Artificial neural networks are made up of linked nodes that seem to mimic the structure of a massive brain's neural network [17]. Based on the programmed neural networks, humans can anticipate land use/cover changes and natural disasters and make intelligent choices in real-time without human involvement [18]. Nowadays, different types of neural networks have been developed in deep learning fields. Deep learning (DL) has been applied in remote sensing studies to identify ships and turtles, and also to classify complex ecosystems such as wetlands and estuaries [19], [20], [21]. DL models may provide a wide range of information that can benefit global investments in coffee production in mountain communities, which include the promotion of biodiversity, less deforestation, and sustainable production.

In recent years, the DL has significantly changed the state of the art in processing remote sensing data [16], [22]. These previously underutilized technologies include unsupervised learning, Random Forest, pixel-based, and Support Vector Machines. The applications of DL may increase the efficacy and accuracy of land cover categorization models in real-time and on a geographical scale while reducing the costs of physical-based models [23], [24]. Many kinds of DL models, including Bayesian, Convolutional, U-Net, Mask-RCNN, and different lightweight-structured models (such as MobileNet, ShuffleNet) have developed in recent years [10], [25]. Most studies used satellite images provided by the Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat, and Sentinel-2 for coffee classification [10], [26], [27], [28]. The aim of this study is to (1) develop an effective DL model for coffee land-cover classification based on remote sensing images, and (2) apply the DL model for monitoring the changes of coffee farming areas in the central highlands of Vietnam. The main contributions of this research article are listed below:

- Why combine machine learning and medium-resolution images for coffee land cover monitoring?
- Is it possible to use U-Net networks to classify coffee plantation area on Sentinel-2 image?
- How do coffee land cover changes in Vietnam?

II. MATERIAL AND METHODS

A. RESEARCH AREA

From 1980s to 2010s, the coffee production in Vietnam did not have effective technological pest control for Arabica type, the government has advocated to expand the Arabica coffee area on the basalt red soil in the Central Highlands provinces, especially Daklak province – selected as the focus area in this study [29] (Figure 1). In which, Robusta coffee accounts for 93%, Arabica coffee is over 6% and jackfruit coffee is less than 1%. Up to now, the area produces about 1 million tons of coffee of all kinds, but there is still a significant lack of Arabica coffee output [30].

In sampling area (more information in section 2.2), coffee is the main plants of Dak Lak province. In the period 2015-2020, the area of coffee tended to slightly decrease in order to increase its production. In 2020, the area of coffee was 202,140 ha, a decrease of 1,217 ha compared to 2015 [31]. The average yield was 23.54 quintals/ha, and the total output was estimated at 468,200 tons, an increase of 23,156 tons compared to 2015. Based on the application of irrigation technology in the coffee production since 2010, farmers in Buon Ma Thuot city have been able to control soil moisture, yield increased from 1.6 tons/ha in 2009 to 4 tons/ha in 2011, reducing 20 labor/year and saving 40% of irrigation water. Successful application of new foliar fertilizer product increased yield by 5 – 30 [32].

Nowadays, raw coffee is a key export product of the province, accounting for more than 86% of the local export products, contributing over 60% of the total annual budget revenue of the locality [33]. Coffee beans have been exported to 60 countries. However, only 10% of the coffee production area in the province is in specialized farming areas that are managed by high-technological companies, the remaining coffee area is managed by the local

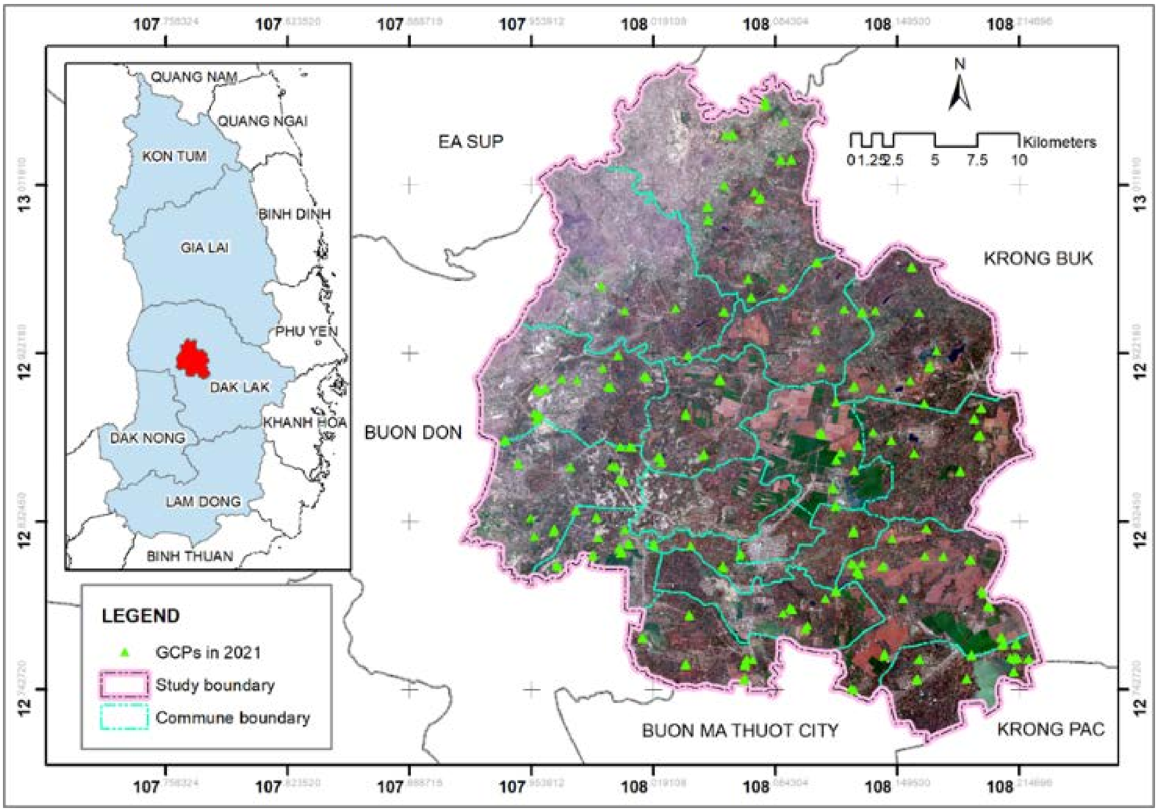

FIGURE 1. The research area with the location of coffee samples in the center part of Daklak province, Vietnam.

households [32]. It reduced the total production of coffee over a long-term period. The plantation based on a monocultural coffee model with fruit trees (such as Avocado and Pepper) provide more than three times of economic value in industrial farms than traditional planting. Due to the coffee farms have been mainly belonged to local households, the coffee plantation in Dak Lak is fragmented and heterogeneous [34]. The use of low-resolution remote sensing image such as MODIS data are difficult to identify coffee growing areas. It is necessary to integrate this data with medium-or high-resolution remote sensing data to more accurately determine the location of coffee growing areas in the province.

B. PROCESSING DATA

In order to collect information for image interpretation, verify the results of image classification and determine the ecological conditions related to the distribution of coffee trees in the study area, the study conducted fieldwork in the years 10/2020 and 09/2021 to collect coating status information. The collected information is designed on the field survey form. The total number of collected points is 249 ground control points. These points are collected according to the criteria of uniform distribution over the whole Cu M'gar district, Dak Lak province. At each survey site, the authors collect information about the current state of the land cover such as coordinates, type of cover, quality of vegetation cover, soil type, four-dimensional photographs and description of telltale signs on high-resolution satellite images. The data collected in the field is standardized and updated into the field database to interpret remote sensing images and analyze information on ecological conditions related to the distribution of coffee trees for the land-cover classification in the research areas.

C. U-NET ARCHITECTURE FOR COFFEE TREE DETECTION

The U-Net approach was initially designed for various image segmentation in environmental and geographical fields [22], [35]. It consists of two paths: one contracting (on the left) and one expanding (on the right). The contracting path may be compared to a standard convolutional neural network (CNN) extractor. The right-hand side executes up-sampling operations, or the conversion of prediction values to the initial image size. Figure 2 depicts the U-Net architecture. As with a CNN, a U-layers Net's are composed of three-dimensional neurons: width, length, and depth [16]. The thickness of an image is determined by the amount of input bands or variables. For instance, in this study, the image's depth parameter is the number of UAV bands — the red, green, blue, and near-infrared spectral bands.

D. PROCESSING DATA

As a result, the three dimensions of the input sub-images are width, height, and number of bands. Besides the number of bands is fixed at four, the width and height are changed to choose the optimal size. It is explained in detail in the optimization section. Rather of constructing neurons using

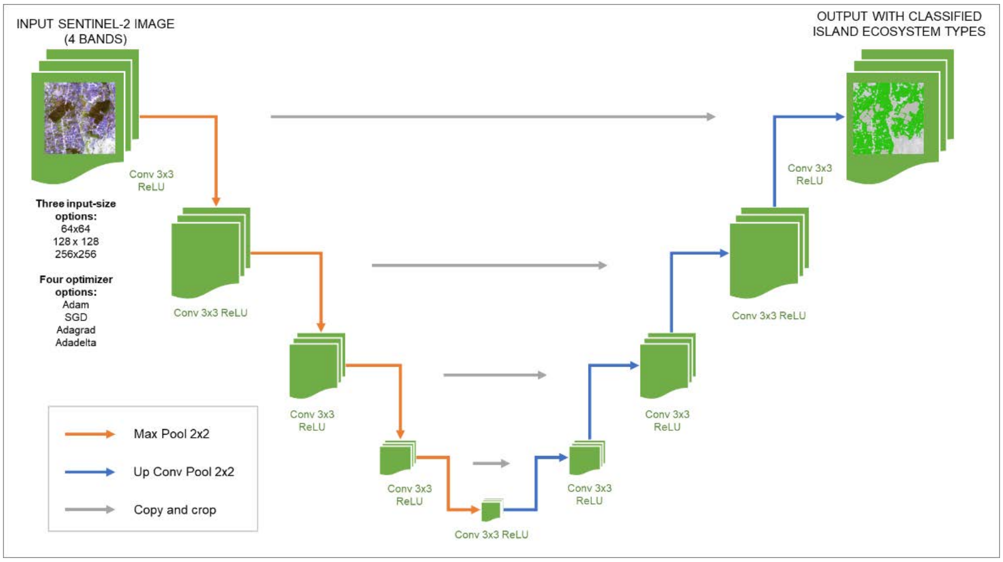

FIGURE 2. **The architecture of a convolutional neural network for land cover detection.**

complete sub-images at once, the neurons in a layer were constructed using tiny matrices of sub-images [36], [37].

Each layer of the U-Net transforms original input into new states using a predefined function. Six significant sorts of layers are frequently used to construct U-Net architectures: (1) INPUT Layer, (2) Convolutional Layer (CONV), (3) Batch Normalization Layer, (4) Pooling Layer (POOL), and (5) Concatenate Layer. As follows, these six-layer types were combined to make a complete U-Net architecture:

The raw pixel values of all the sub-images with four bands are copied to the training model using the INPUT layer. CONV layers use a collection of filters to determine the outputs of neurons. "ConvTrans" is a transposed convolution matrix, which increases the size of a smaller matrix by up-sampling it. To be able to filter out sub-images, the filter weight and length must be less than those of the input sub-images. The filter traveled from one end of the sub-images to the other. Each time an input is supplied, new pixel values are calculated by using the functions assigned to the filters (more detailed in section 2.4). Based on a proposed idea in the work by [36], [38], the authors used a total of 19 CONV layers in this study. To keep training and validation time to a minimum, the 19 CONV layers utilize filters ranging from 16 to 256. Each filter has a width and length that are set to 3∗3.

After all CONV layers have been trained, converting data from one scale to another before arriving to a new computation is one usage of the BATCH NORMALIZATION layer. This layer is used to minimize the changes in activation functions when they are distributed during training. This issue is sometimes referred to as an internal covariate shift [39]. the four parameters that comprise the batch normalization will be employed. Using the mean (β) and standard deviation (or variance - γ) parameter of the data in the current batch, the current batch-specific mean and standard deviation are applied to each input layer to normalize it.

$$\mathrm{y_i} = \gamma \widehat{\mathrm{x}}_i + \beta \tag{1}$$

whereas the $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are trainable parameters, $\hat{\boldsymbol{x}}_i$ can be calculated by using mean ($\boldsymbol{\mu_B}$) and variance ($\boldsymbol{\sigma_B^2}$) of mini-batch B = {x1…m} as the following Equation 2-4:

$$\mu_\mathrm{B} \leftarrow \frac{1}{\mathrm{m}} \sum\nolimits_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{x_i} \tag{2}$$

$$\sigma_\mathrm{B}^2 = \frac{1}{\mathrm{m}} \sum\nolimits_{\mathrm{i=1}}^{\mathrm{m}} (\mathrm{x_i} - \mu_\mathrm{B})^2 \tag{3}$$

$$\hat{\mathrm{x}}_i \leftarrow \frac{\mathrm{x_i} - \mu_\mathrm{B}}{\sqrt{\sigma_\mathrm{B}^2 + \varepsilon}} \tag{4}$$

• POOL layer resized width and height of data to a 2 × 2 spatial matrix based on downscaling process.

• Concatenate layer is utilized to merge the pieces of data on a contracting path with the information on an expanded path [35]. When the data for the prior layers was first contracted, it was simplified in order to facilitate the acquisition of fresh data, which allowed the U-Net models to integrate the data from the previous layers to generate a more accurate forecast.

• Instead of training the data on the original network, the DROPOUT layer randomly deactivates the neurons. Deactivating superfluous neurons reduces overfitting and generalization mistakes. A dropout value of 0.5 is often used to keep every node's output in a concealed layer. A value close to 1.0 is often used to retain visible layer inputs [40].

The blocks in green color shown in Figure 2 are the input and output of each calculation layer, whereas the processing layers are presented in arrows. Excepting the last convolutional layer, the other 18 CONV layers are always processed before the batch normalization layers. In the contracting path, the POOL layers run before the Dropout layers to downscale data. Meanwhile, the transposed convolution matrixes integrated with the Dropout layers are used for the upscaling process in the expansive layers.

The final Conv2D layer's output is a vector with six values, corresponding to 2 land cover types corresponding to coffee and non-coffee land covers. Based on 76 layers (1xINPUT, 19xCONV, 4xConv2DTrans, 4xPOOL, 18xBatch-Normalization, 4xConcatenate, 18x Activation, and 8x Dropout layers), the trained U-Net transformed the initial pixel values in input sub-images to the land cover classes. 23 CONV and 18 Batch Normalization layers contain parameters that can be optimized to improve U-Net model's performance and accuracy. The parameters in the CONV and Batch Normalization layers are changed with alternative choices of activation and optimizer functions. It will be explained in detail in section 2.4. The accuracy of both training and testing data was checked during U-Net development to avoid overfitting and under-fitting issues. The best U-Net will be chosen if it is land cover prediction is compatible with the labels assigned in the input image from the training and testing data. The equation 5 were used to calculate the accuracy of all training models:

$$ACC = \frac{2TP}{2TP + FP + FN} \tag{5}$$

TP and FP are the true/false positive values, whereas TN and FN are true/false negative values between prediction and ground truth points. In order to better identify mining ecosystem types, we will use a trained model that has the lowest values of all loss functions. The min and max ACC values for training and testing data were collected for the duration of 50 epochs throughout the training phase to study how the ACC fluctuated. Even though the optimal ACC value will be computed in the trained models, the ACC value observed to verify the correctness of outcome models would still use training data.

Minimizing the Cost function (C) or Loss function, which are both convex functions, involves selecting optimal values for the weights [41]. Weight values, training pictures, and labeled output results all have a role in the loss function. Furthermore, the weight values may help to minimize the loss function, which ultimately helps to provide better predictions for future training data. Accordingly, When the full training sub-image data set was put in, the average loss values were calculated by the sixth equation:

$$\mathcal{J} = \frac{1}{n}\sum\nolimits_{x=1}^{n} \mathcal{L}^{(x)} \tag{6}$$

with n denoting the size of the training data collection and L((x)) denoting the loss value associated with a particular training sub-image during the training phase.

The U-Net model is created using the Keras API, which makes it simple to manipulate using Tensorflow - the Google-developed open-source machine learning framework [42], [43], [44]. During training, we measure the performance criteria that include test and validation accuracy. The U-Net training procedure can go no farther than 100 loops (or epochs - times through the training data), however if the coefficient on the training data set converges, the process may be terminated.

E. OTHER METHODS FOR MODIFYING U-NET FRAMEWORK

To build the U-Net, three kinds of functions may be chosen: analyzing input size and optimizer technique. These functions choose optimum parameters for hidden layer filters during new prediction. Firstly, the analyzing size of sub-images that were cut from the original images with four bands can decide whether the computer can identify all characteristics of objects or not. If the sub-image size is small, although the computer has more samples for training and testing, the coffee region cannot be fully on one sub-image and the computer cannot learn all characteristics of this region, leading to the reduction of accuracy. However, the higher sub-image size can provide more information for the computer to identify coffee tree objects, it can reduce the number of input samples. Therefore, it requires more samples for training and testing data. Additionally, a large sub-image can contain much information of other objects. It also can make noise in the region between two objects. In this study, three options of input sizes were chosen are $64 \times 64 \times 4$; $128 \times 128 \times 4$; and $256 \times 256 \times 4$.

To remove the cost functions, optimization techniques using a stochastic gradient descent algorithm are frequently used. This technique improves accuracy and reduces loss by updating weights in the negative gradient direction [45], [46]. During optimization, the trained models' (or loss function's) errors must be computed frequently. Each epoch of data flowing through the U-Net model requires updating the weights of filters depending on optimizer functions [16]. It will use the previous parameters' gradient decline to determine the best position for the new ones. Thus, the new filter weight will be computed using the updated parameters. The new filters may distinguish virtually identical objects on satellite images, lowering the next evaluation's loss value. Filter settings and weights directly influence the 19 CONV layers during U-Net construction. Four optimizer functions were chosen for comparison in this study include: (1) Adam (Adaptive Moment Estimation), (2) Traditional SGD (Stochastic Gradient Descent algorithm), and (3) Adagrad (Adaptive Gradient Algorithm), and (4) Adadelta. Table 1 describes various optimization methods. Final results should be greatest accuracy and lowest loss function values.

F. COFFEE LAND COVER CHANGES USING TRAINED U-NET MODELS

One of the most essential functions of coffee classification system is to assess the changes of this land use/cover overtime [22]. This research examines the changes of coffee land cover types in Central Highland region, Vietnam. Due to the Sentinel-2 sensor was launched since 2014 and the cloud and shadows affected land covers in mountainous areas,

TABLE 1. Different optimization algorithms for training parameters of the U-Net model in coffee classification, adapted from [43], [44], [45], [46], [47].

Formula	Models	Optimizer options	Algorithms
7	UN-Adam	Adam	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{s}_t}+\epsilon}\hat{f}_t$
8	UN-SGD	SGD	$\theta_{t+1} = \theta_t - \eta_t.\nabla_\theta\, Q(\theta_t; x^{(i)}; y^{(i)})$
9	UN-Adagrad	Adagrad	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t+\epsilon}}g_t$
10	UN-Adadelta	Adadelta	$\Delta\theta = -\frac{RMS[\Delta\theta]_{t-1}}{RMS[g]_t}g_t$ and $\theta_{t+1} = \theta_t + \Delta\theta_t$

θ − parameter value; η – the learning rates; t – time step; ∈ = 10-8; g_t is – gradient; f & s – estimates of first and second moments; η – step size.

54 images were collected from 2019 to 2021 to assess the changes of coffee land cover during three years. Furthermore, section 2.2 and 2.3 describes images gathering and preprocessing as well. The new image was fed into the trained U-Net, and then the model accessed the trained parameters to generate 76 intermediate matrixes. In addition, the model applies the trained spatial matrices to transform the new images into specific spatial matrices and generates the final land cover classes for every pixel. No further training data is required.

III. RESULTS

A. MODEL PERFORMANCE IN MODEL TRAINING PROCESS

12 U-Net models were trained using a variety of different training sizes, filter counts, and optimizer strategies. To compare the performance of these U-Net models, the total accuracy and loss function values were employed (Table 2). Although there was no evident trend in the loss and accuracy values as the training size increased, the training size of 256 × 256 × 4 produced the more accurate prediction in all situations of the optimizer approaches. In four different types of optimizer algorithms, the UNet-SGD models performed the least well. These models typically have an average loss value of 0.41 and an average accuracy of 80%. Compared to the models using SVM and Random Forest methods, all 12 trained U-Net models provided a higher accuracy although their training time is significantly longer.

Five U-Net models achieved greater than 94% accuracy: UNet-Adam-64, UNet-Adam-256, UNet-Adadelta-128, UNet-Adagrad-128 and UNet-Adagrad-256. The UNet-Adadelta-128 model, in particular, was found to perform the best, with an accuracy of nearly 95 percent and a loss function value of 0.12. (Figure 3 and Table 2). By and large, the values of the loss and accuracy fluctuated over the first 15 epochs before converging over the final 50. The UNet-Adam-256 model has a speedier convergence procedure. The UNet-Adagrad-128 and UNet-Adadelta-128 model were trained in nearly 40 minutes, slower than other models. Meanwhile,

TABLE 2. The performance of 14-trained models for classify coffee land cover.

No.	Model	Training size	Loss	Accuracy	Training time (s)
1	Unet-Adam-64	64	0.13	94.3	1443
2	Unet-Adam-128	128	0.14	93.6	2607
3	Unet-Adam-256	256	0.12	94.9	2081
4	Unet-Adadelta-64	64	0.15	93.3	1230
5	Unet-Adadelta-128	128	0.12	94.9	2373
6	Unet-Adadelta-256	256	0.26	88.1	1098
7	Unet-SGD-64	64	0.32	85.7	904
8	Unet-SGD-128	128	0.53	72.4	863
9	Unet-SGD-256	256	0.4	82.1	983
10	Unet-Adagrad-64	64	0.16	93.5	1482
11	Unet-Adagrad-128	128	0.13	94.2	2323
12	Unet-Adagrad-256	256	0.14	94.2	2036
13	SVM			68.9	762
14	Random Forest			65.4	645

while the UNet-Adam-64 model was trained in more than 24 minutes but its performance is the lowest, compared to others.

B. MODEL PERFORMANCE IN NEW INTEPRETATION

Due to the model performance values of the best five U-Net models are nearly similar, they were used to interpreted coffee land cover in the Central Highlands, Vietnam. Based on 54 Sentinel-2 images, three large images with nearly 55,000km2 was generated for three years (2019, 2020 and 2021). The models using 64 × 64 × 4 input images took more than 100 minutes for new interpretation. The models using 128 × 128 × 4 input images interpreted new data three time faster than the Unet-Adam-64 model (Table 3). Meanwhile, the models with 256 × 256 × 4 input images are six times faster than the Unet-Adam-64 model at processing new data. In Figure 4, the coffee land covers were separated well with residential and forest areas. Meanwhile, the wetland areas could not be separated well by the U-Net-Adagrad-128 and U-Net-Adagrad-256 models. Two models using Adam optimizer functions interpreted commercial polyculture coffee land cover that is mixed by more than one species of shade trees. As a result, the U-Net-Adadelta-128 mode provide more accurate results in more than 35 minutes per one image for all cases than other models.

C. COFFEE LAND COVER IN VIETNAM

The coffee land cover maps in the Central Highlands, Vietnam in 2019, 2020 and 2021 are shown in Figure 5. In five results, the U-Net-Adam-64 model interpreted a narrow area of the coffee land cover, especially in 2021, the coffee area of only 440,000 ha was identified. The interpretation from

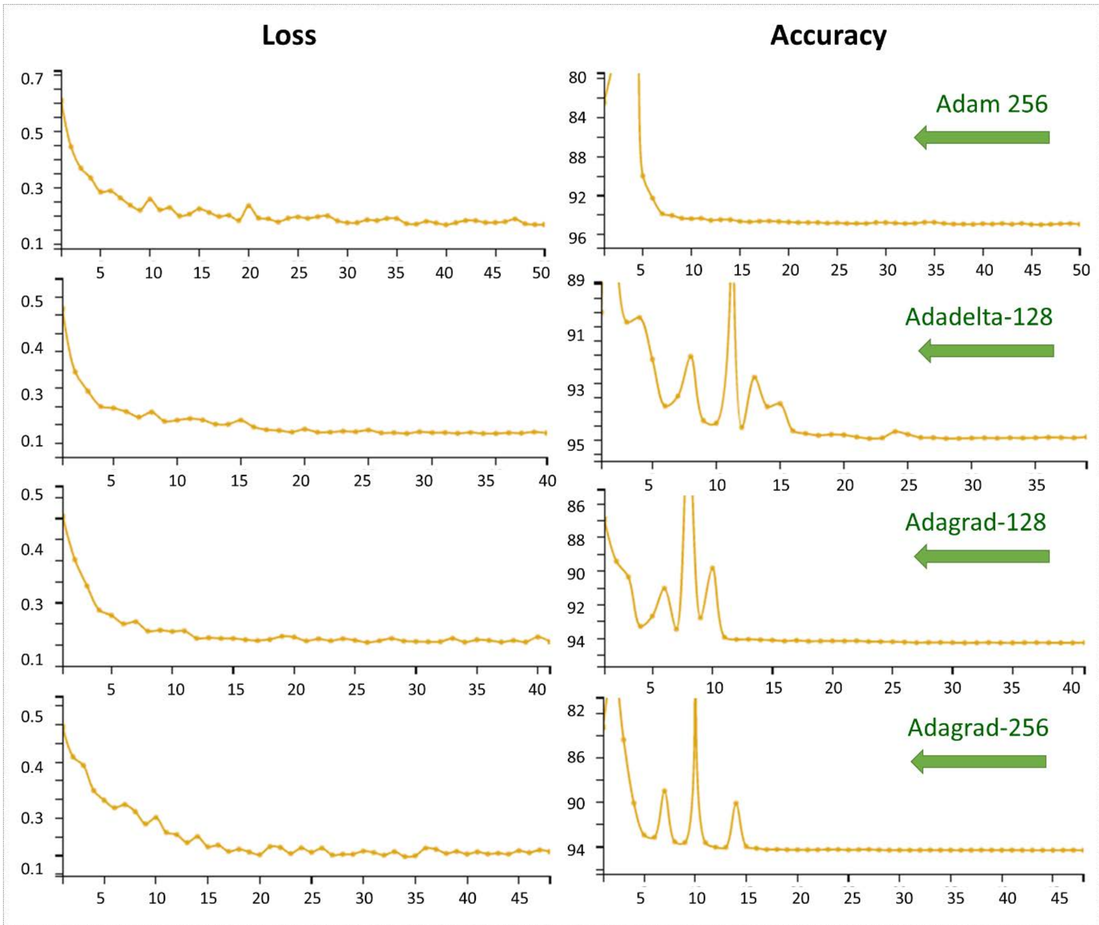

FIGURE 3. **The training process over 50 epochs of the best for U-Net models for coffee classification.**

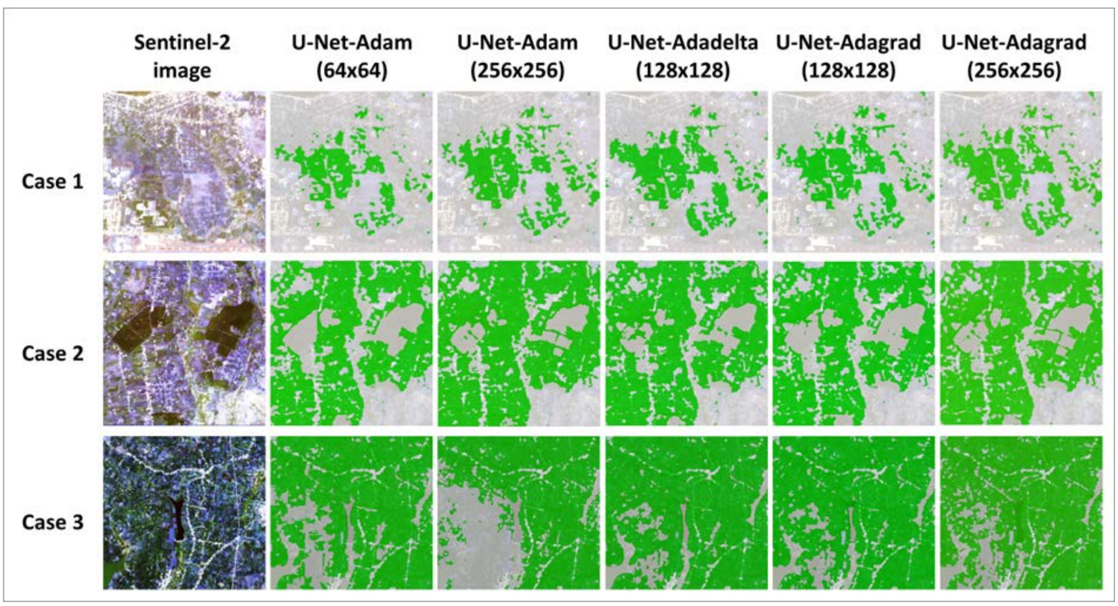

FIGURE 4. **Coffee land cover classification in Central Highland province, Vietnam based on the best five U-Net models.**

U-Net-Adam-256, U-Net-Adagrad-128 and U-Net-Adagrad-256 models has more fluctuated with an increase in 2019 and a decrease in 2020. Meanwhile, the coffee area in the research area has been increasing slightly since 2015 (Figure 6). The

TABLE 3. Interpretation time of the best-five u-net models for coffee land cover.

No.	Optimizer	Time to analyze Sentinel-2 image (s)		
		2019	2020	2021
1	Unet-Adam-64	6,496	5,212	6,585
2	Unet-Adam-256	1,245	1,101	1,279
3	Unet-Adadelta-128	2,119	1,189	2,249
4	Unet-Adagrad-128	2,140	1,797	2,240
5	Unet-Adagrad-256	1,265	1,032	1,275

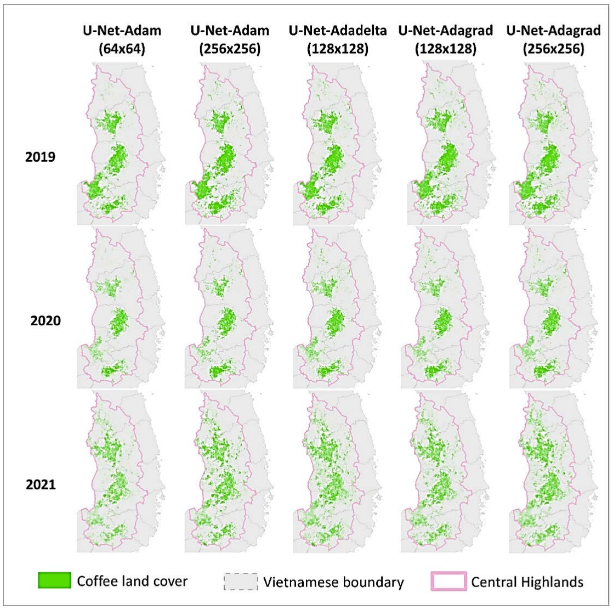

FIGURE 5. Coffee land cover interpretation based on the trained U-Net models using the best five optimizer functions in the Central Highlands, Vietnam.

outcome from the U-Net-Adadelta-128 model is close to the recorded from the statistical report when the area of the coffee land cover was interpreted at 694, 566 and 726 thousand hectares, respectively for the years 2019, 2020 and 2021. The significant reduction of the coffee plantation area was recorded in statistical data, as well as in the interpretation from all U-Net models. Since local statistics often only update the total area of coffee plantations, including the area of newly harvested and newly planted trees, it causes a discrepancy between the interpretation results and the statistical data. In general, the fluctuation trend of the coffee plantation area interpreted from U-Net models is harmonized with the statistical report data.

IV. DISCUSSION

A. ADVANCE OF DEEP LEARNING MODELS FOR COFFEE DETECTION

Separation of coffee plantation area from other land uses/covers is directly related to local water quality and land management, help to predict precisely the annual quality

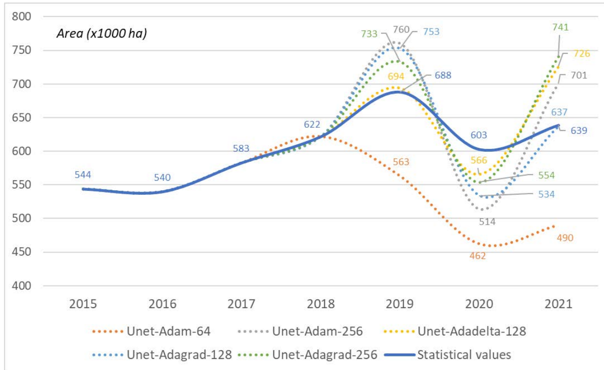

FIGURE 6. Areal changes of coffee land cover based on interpretation from the best five U-Net models and statistical reports.

and productivity of this industrial plant. Several researchers, including [48], [49], [50], [51], all used low/medium-spatial resolution satellite images for classify coffee plantation area mixed with different land covers, instead of separating coffee plantation area from all others in this study. The accuracy of coffee separation reached about 58% with the use of Landsat TM data [50]. The polyculture coffee system in Vietnam is planted in high heterogeneity areas, which are known to be hard to detect due to lack of spatial information. The research took specific characteristics of the Sentinel-2 images, such as texture, shape, and spatial distribution to train final U-Net prediction models. Therefore, the input samples collected for pixel-based classification is ineffective to serve as a mask. In this study, a mask was created in the form of an object generalization for training U-Net models. According to the results, this study proved that the modified U-Net architecture is able to generate coffee land cover maps that outperform Random Forest and SVM benchmark classifications.

Additionally, the conventional approach shows a better performance in identifying coffee plantation area from digital images using trained U-Net models. Related to the time and effort expense, scientists usually interpret land-use types from satellite images by using a lots of ground control points. For the whole interpretation process, they must put in a lot of effort in both your working environment and living space. Therefore, a land-use map for a given period may take as long as a month or a year. Additionally, the collected ground control points cannot be used for new regions. Based on the DL models, users may now quickly produce coffee plantation maps using trained U-Net-Adadelta-128 model (about 30 minutes for 55,000 km2 in this study). Additionally, the trained models might be utilized in other coffee regions based on free satellite images obtained from the Sentinel-2 sensor.

B. UPDATING COFFEE DETECTION MODELS

In the model development process, the comparison between the model outcomes with the field surveys showed that 6.4% of the coffee area is difficult to be classified with other types. Therefore, the initial sample was updated before the standard input data for the models were obtained. Compared with the field sites, some areas of coffee growing for about 7-8 years (1) are cut down for new development, or (2) converted from low-yielding old coffee areas to other perennial cash crops were classified into annual crops and bare ground. In the study area, some annual trees are intercropped with the coffee trees, that has not yet closed its canopy. So, when the annual trees are harvested, the area that is mixed with the coffee trees. According to the growth cycle, old coffee is cut down after about 15 years and planted with other annual trees. On the other hand, coffee in the Central Highlands is often intercropped with many different types of shade trees such as cashew, pepper, fruit trees, etc., except in more homogeneous farming areas. Therefore, it is difficult for coffee in the Central Highlands to separate each type of coffee that is intercropped with other large trees in the image classification process. In the process of classifying the current state of the coffee land cover, the area of young coffee was included in the annual tree class. The area of young coffee that has not yet closed its canopy was separated from the annual tree when analyzing the series of fluctuations in many time periods. While classifying the area of coffee trees, it was found that most of the errors of the coffee class were related to annual trees, bare land and sparse forest and shrubs. The results showed that the newly planted coffee areas have similar reflectance spectrum with the annual tree class. In the Central Highlands, some annual trees are intercropped with the area of unclosed coffee, so when classifying this area of young coffee, it was confused with the annual crop. These issues reduced the accuracy of the models significantly. To improve this issue, it is better to use the multi-temporal remote sensing images to detect the area of other annual plants in the research study.

The fact is that 80% of the coffee area in Dak Lak is owned by households, so it is difficult to form a homogeneous and sustainable production. In order to improve this issue, managers need to conduct a clear review and assessment, to remove unsuitability areas for cultivating coffee trees. In addition, the government should ban the spontaneous development of coffee outside the planning area; encourage the expansion of certified coffee production programs. Therefore, the supporting high-tech tools based on AI models and multi-temporal remote sensing images can completely help with these tasks. For example, AI models that select ecologically suitability areas for coffee trees, whereas other models can be developed to monitor the area of coffee trees using high-resolution satellite images based on unmanned aerial vehicles. It can become a promising approach for the sustainable development of the coffee production in tropical countries in the future.

V. CONCLUSION

Based on the application of a U-Net model to categorize coffee plantation areas in the Central Highlands, Vietnam, the individual study questions stated in the introduction section were addressed. The combination can save the time and expense to collect samples when land-use planning managers, scientists, and other users require to interpret coffee plantation areas from updated Sentinel-2 images. Once a U-Net model is trained completely, the new samples can be updated to the model and be used to analyze rapidly new data. The best U-Net model with a nearly 95% accuracy rate interpreted effectively the location of the coffee plantation area in the largest coffee exporter region in Vietnam, using data acquired from the Sentinel-2 data. The outcomes from the U-Net-Adadelta-128 model are in harmony with the records from statistical reports. In the future, this model can become a promising tool for forestry managers in charge of coffee plantation management.

ACKNOWLEDGMENT

The paper was conducted under the science and technology project of the Vietnam Academy of Science and Technology (VAST): "Research on integrating remote sensing data with natural conditions and plant ecological characteristics in coffee tree cover classification, case study in Cu M'gar, Dak Lak," (Code: VAST01.07/21-22).

CONFLICT DECLARATION

Authors have no conflict of interest.

REFERENCES

[1] R. Poole, S. Ewings, J. Parkes, J. A. Fallowfield, and P. Roderick, "Misclassification of coffee consumption data and the development of a standardised coffee unit measure," *BMJ Nutrition, Prevention Health*, vol. 2, no. 1, pp. 11–19, Jun. 2019, doi: 10.1136/bmjnph-2018-000013.

[2] L. Meylan, A. Merot, C. Gary, and B. Rapidel, "Combining a typology and a conceptual model of cropping system to explore the diversity of relationships between ecosystem services: The case of erosion control in coffee-based agroforestry systems in Costa Rica," *Agricult. Syst.*, vol. 118, pp. 52–64, Jun. 2013, doi: 10.1016/j.agsy.2013.02.002.

[3] J. Del Coso, J. J. Salinero, B. Lara, S. Studies, and R. Juan, "Effects of caffeine and coffee on human functioning nutrients effects of caffeine and coffee on human functioning," *Nutrients*, vol. 12, no. 125, pp. 1–5, 2020.

[4] T. G. Ango, K. Hylander, and L. Börjeson, "Processes of forest cover change since 1958 in the coffee-producing areas of Southwest Ethiopia," *Land*, vol. 9, no. 8, pp. 9–11, 2020, doi: 10.3390/land9080278.

[5] *International Coffee Organization*, Country Coffee Profile, Vietnam, Asia, Mar. 2019.

[6] D. Gaitán-Cremaschi, F. Van Evert, D. Jansen, M. Meuwissen, and A. O. Lansink, "Assessing the sustainability performance of coffee farms in Vietnam: A social profit inefficiency approach," *Sustainability*, vol. 10, no. 11, p. 4227, Nov. 2018, doi: 10.3390/su10114227.

[7] N. H. Anh, W. Bokelmann, D. T. Nga, and N. Van Minh, "Toward sustainability or efficiency: The case of smallholder coffee farmers in Vietnam," *Economies*, vol. 7, no. 3, pp. 1–25, 2019, doi: 10.3390/economies7030066.

[8] L. Jolliffe, H. T. Bui, and H. T. Nguyen, "The buon ma thuot coffee festival, Vietnam," in *International Perspectives of Festivals and Events*. Amsterdam, The Netherlands: Elsevier, 2009, pp. 125–137, doi: 10.1016/b978-0-08-045100-8.00008-9.

[9] B. B. Wyss, J. Don, L. Kerstin, H. Walz, N. T. Van, and R. H. Van, "Climate change and Vietnamese coffee production-training manual imprint produced for coffee farmers and trainers in Vietnam," in *Coffee Climate Care-C3*. UTZ (Implementing Agent), 2016.

[10] D. A. Hunt, K. Tabor, J. H. Hewson, M. A. Wood, L. Reymondin, K. Koenig, M. Schmitt-Harsh, and F. Follett, "Review of remote sensing methods to map coffee production systems," *Remote Sens.*, vol. 12, no. 12, p. 2041, 2020, doi: 10.3390/rs12122041.

[11] A. Tridawati, K. Wikantika, T. M. Susantoro, and A. B. Harto, "Mapping the distribution of coffee plantations from multi-resolution, multi-temporal, and multi-sensor data using a random forest algorithm," *Remote Sens.*, vol. 12, no. 23, p. 3933, 2020.
[12] R. Vignola, C. A. Harvey, P. Bautista-Solis, J. Avelino, B. Rapidel, C. Donatti, and R. Martinez, "Ecosystem-based adaptation for smallholder farmers: Definitions, opportunities and constraints," *Agricult., Ecosyst. Environ.*, vol. 211, pp. 126–132, Dec. 2015, doi: 10.1016/j.agee.2015.05.013.
[13] C. Allinne, S. Savary, and J. Avelino, "Delicate balance between pest and disease injuries, yield performance, and other ecosystem services in the complex coffee-based systems of Costa Rica," *Agricult., Ecosyst. Environ.*, vol. 222, pp. 1–12, Apr. 2016, doi: 10.1016/j.agee.2016.02.001.
[14] L. Garg, P. Shukla, S. Singh, V. Bajpai, and U. Yadav, "Land use land cover classification from satellite imagery using mUnet: A modified unet architecture," in *Proc. 14th Int. Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl.*, 2019, pp. 359–365.
[15] P. Feng, B. Wang, D. L. Liu, and Q. Yu, "Machine learning-based integration of remotely-sensed drought factors can improve the estimation of agricultural drought in south-eastern Australia," *Agricult. Syst.*, vol. 173, pp. 303–316, Jul. 2019, doi: 10.1016/j.agsy.2019.03.015.
[16] K. B. Dang, M. H. Nguyen, D. A. Nguyen, T. T. H. Phan, T. L. Giang, H. H. Pham, T. N. Nguyen, T. T. V. Tran, and D. T. Bui, "Coastal wetland classification with deep U-net convolutional networks and sentinel-2 imagery: A case study at the Tien Yen estuary of Vietnam," *Remote Sens.*, vol. 12, no. 19, p. 3270, 2020, doi: 10.3390/rs12193270.
[17] K. B. Dang, V. B. Dang, Q. T. Bui, V. V. Nguyen, T. P. N. Pham, and V. L. Ngo, "A convolutional neural network for coastal classification based on ALOS and NOAA satellite data," *IEEE Access*, vol. 8, pp. 11824–11839, 2020, doi: 10.1109/ACCESS.2020.2965231.
[18] Z. Liu, C. Peng, W. Xiang, D. Tian, X. Deng, and M. Zhao, "Application of artificial neural networks in global climate change and ecological research: An overview," *Chin. Sci. Bull.*, vol. 55, no. 34, pp. 3853–3863, Dec. 2010, doi: 10.1007/s11434-010-4183-3.
[19] Q. Shi, W. Li, R. Tao, X. Sun, and L. Gao, "Ship classification based on multifeature ensemble with convolutional neural network," *Remote Sens.*, vol. 11, no. 4, p. 419, Feb. 2019, doi: 10.3390/rs11040419.
[20] P. C. Gray, A. B. Fleishman, D. J. Klein, M. W. Mckown, V. S. Bézy, K. J. Lohmann, and D. W. Johnston, "A convolutional neural network for detecting sea turtles in drone imagery," *Methods Ecol. Evol.*, vol. 10, no. 3, pp. 345–355, 2019, doi: 10.1111/2041-210X.13132.
[21] K. B. Dang, T. Ha, T. Nguyen, H. D. Nguyen, Q. H. Truong, and T. P. Vu, "U-shaped deep-learning models for Island ecosystem type classification, a case study in Con Dao Island of Vietnam," *One Ecosyst.*, vol. 7, Feb. 2022, Art. no. e79160, doi: 10.3897/oneeco.7.e79160.
[22] T. L. Giang, K. B. Dang, Q. Toan Le, V. G. Nguyen, S. S. Tong, and V.-M. Pham, "U-net convolutional networks for mining land cover classification based on high-resolution UAV imagery," *IEEE Access*, vol. 8, pp. 186257–186273, 2020, doi: 10.1109/ACCESS.2020.3030112.
[23] X. Qin, Z. Zhang, C. Huang, M. Dehghan, O. R. Zaiane, and M. Jagersand, "U^2-Net: Going deeper with nested U-structure for salient object detection," *Pattern Recognit.*, vol. 106, Oct. 2020, Art. no. 107404, doi: 10.1016/j.patcog.2020.107404.
[24] G. Jakovljevic, M. Govedarica, and F. Alvarez-Taboada, "A deep learning model for automatic plastic mapping using unmanned aerial vehicle (UAV) data," *Remote Sens.*, vol. 12, no. 9, p. 1515, May 2020, doi: 10.3390/RS12091515.
[25] X.-Y. Tong, G.-S. Xia, Q. Lu, H. Shen, S. Li, S. You, and L. Zhang, "Land-cover classification with high-resolution remote sensing images using transferable deep models," *Remote Sens. Environ.*, vol. 237, Feb. 2020, Art. no. 111322, doi: 10.1016/j.rse.2019.111322.
[26] L. C. Kelley, L. Pitcher, and C. Bacon, "Using Google Earth engine to map complex shade-grown coffee landscapes in Northern Nicaragua," *Remote Sens.*, vol. 10, no. 6, p. 952, Jun. 2018, doi: 10.3390/rs10060952.
[27] T. Bernardes, M. A. Moreira, M. Adami, A. Giarolla, and B. F. T. Rudorff, "Monitoring biennial bearing effect on coffee yield using MODIS remote sensing imagery," *Remote Sens.*, vol. 4, no. 9, pp. 2492–2509, Aug. 2012, doi: 10.3390/rs4092492.
[28] D. Velásquez, A. Sánchez, S. Sarmiento, M. Toro, M. Maiza, and B. Sierra, "A method for detecting coffee leaf rust through wireless sensor networks, remote sensing, and deep learning: Case study of the caturra Variety in Colombia," *Appl. Sci.*, vol. 10, no. 2, pp. 1–27, 2020, doi: 10.3390/app10020697.
[29] P. Thuy, L. Niem, T. Ho, P. Burny, and P. Lebailly, "Economic analysis of perennial crop systems in Dak Lak province, Vietnam," *Sustainability*, vol. 11, no. 1, p. 81, Dec. 2018, doi: 10.3390/su11010081.
[30] I. Palacios-Agundez, M. Onaindia, P. Barraqueta, and I. Madariaga, "Provisioning ecosystem services supply and demand: The role of landscape management to reinforce supply and promote synergies with other ecosystem services," *Land Use Policy*, vol. 47, pp. 145–155, Sep. 2015, doi: 10.1016/j.landusepol.2015.03.012.
[31] V. Byrareddy, L. Kouadio, S. Mushtaq, and R. Stone, "Sustainable production of robusta coffee under a changing climate: A 10-year monitoring of fertilizer management in coffee farms in Vietnam and Indonesia," *Agronomy*, vol. 9, no. 9, p. 499, Aug. 2019, doi: 10.3390/agronomy9090499.
[32] N. H. Anh, W. Bokelmann, N. T. Thuan, D. T. Nga, and N. Van Minh, "Smallholders' preferences for different contract farming models: Empirical evidence from sustainable certified coffee production in Vietnam," *Sustainability*, vol. 11, no. 14, pp. 9–13, 2019, doi: 10.3390/su11143799.
[33] M. P. Nguyen, P. Vaast, T. Pagella, and F. Sinclair, "Local knowledge about ecosystem services provided by trees in coffee agroforestry practices in northwest Vietnam," *Land*, vol. 9, no. 12, pp. 1–27, 2020, doi: 10.3390/land9120486.
[34] G. Kissinger, "Policy responses to direct and underlying drivers of deforestation: Examining rubber and coffee in the Central Highlands of Vietnam," *Forests*, vol. 11, no. 11, pp. 1–25, 2020, doi: 10.3390/F11070733.
[35] Z. Liu, R. Feng, L. Wang, Y. Zhong, and L. Cao, "D-resunet: Resunet and dilated convolution for high resolution satellite imagery road extraction," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Jul. 2019, pp. 3927–3930, doi: 10.1109/IGARSS.2019.8898392.
[36] P. Zhang, Y. Ke, Z. Zhang, M. Wang, P. Li, and S. Zhang, "Urban land use and land cover classification using novel deep learning models based on high spatial resolution satellite imagery," *Sensors*, vol. 18, no. 11, p. 3717, Nov. 2018, doi: 10.3390/s18113717.
[37] F. H. Wagner, A. Sanchez, Y. Tarabalka, R. G. Lotte, M. P. Ferreira, M. P. Aidar, E. Gloor, O. L. Phillips, and L. E. Aragao, "Using the U-net convolutional network to map forest types and disturbance in the Atlantic rainforest with very high resolution images," *Remote Sens. Ecol. Conservation*, vol. 5, no. 4, pp. 360–375, 2019, doi: 10.1002/rse2.111.
[38] A. Stoian, V. Poulain, J. Inglada, V. Poughon, and D. Derksen, "Land cover maps production with high resolution satellite image time series and convolutional neural networks: Adaptations and limits for operational systems," *Remote Sens.*, vol. 11, no. 17, pp. 1–26, 2019, doi: 10.3390/rs11171986.
[39] Y. Wang, X. Wang, and J. Jian, "Remote sensing landslide recognition based on convolutional neural network," *Math. Problems Eng.*, vol. 2019, Sep. 2019, Art. no. 8389368, doi: 10.1155/2019/8389368.
[40] J.-H. Lai, C.-L. Liu, X. Chen, J. Zhou, T. Tan, N. Zheng, and H. Zha, *Pattern Recognition and Computer Vision Colloquium* (Lecture Notes in Computer Science). 2018.
[41] M. Dai, X. Leng, B. Xiong, and K. Ji, "Sea-land segmentation method for SAR images based on improved BiSeNet," *J. Radars*, vol. 9, no. 5, pp. 886–897, 2020, doi: 10.12000/JR20089.
[42] M. Studer and M. D. Falbel. (2019). *Keras Package Manual*. [Online]. Available: https://keras.rstudio.com
[43] A. Gulli and S. Pal, *Deep Learning With Keras—Implement Neural Networks With Keras on Theano and TensorFlow*. Birmingham, U.K.: Packt, 2017.
[44] D. Falbel, "R interface to Keras," *Comprehensive R Arch. Netw.*, vol. 2, no. 9, pp. 1–493, 2019.
[45] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, M. Hasan, B. C. Van Essen, A. A. Awwal, and V. K. Asari, "A state-of-the-art survey on deep learning theory and architectures," *Electronics*, vol. 8, no. 3, pp. 1–67, 2019, doi: 10.3390/electronics8030292.
[46] V. Iglovikov, S. Mushinskiy, and V. Osin, "Satellite imagery feature detection using deep convolutional neural network: A kaggle competition," 2017, *arXiv:1706.06169*.
[47] L. Wang, Y. Yang, R. Min, and S. Chakradhar, "Accelerating deep neural network training with inconsistent stochastic gradient descent," *Mach. Learn. Comput. Sci.*, vol. 3, pp. 1–12, 2017.
[48] A. Mukashema, A. Veldkamp, and A. Vrieling, "Automated high resolution mapping of coffee in Rwanda using an expert Bayesian network," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 33, pp. 331–340, Dec. 2014.

[49] C. Gomez, M. Mangeas, M. Petit, C. Corbane, P. Hamon, S. Hamon, A. De Kochko, D. Le Pierres, V. Poncet, and M. Despinoy, ''Use of high-resolution satellite imagery in an integrated model to predict the distribution of shade coffee tree hybrid zones,'' *Remote Sens. Environ.*, vol. 114, no. 11, pp. 2731–2744, Nov. 2010.

[50] S. Cordero-Sancho and S. A. Sader, ''Spectral analysis and classification accuracy of coffee crops using Landsat and a topographic-environmental model,'' *Int. J. Remote Sens.*, vol. 28, no. 7, pp. 1577–1593, 2007.

[51] B. Chen, X. Li, X. Xiao, B. Zhao, J. Dong, W. Kou, Y. Qin, C. Yang, Z. Wu, R. Sun, G. Lan, and G. Xie, ''Mapping tropical forests and deciduous rubber plantations in Hainan Island, China by integrating PALSAR 25-m and multi-temporal Landsat images,'' *Int. J. Appl. Earth Observ. Geoinf.*, vol. 50, pp. 117–130, Aug. 2016.

QUANG TOAN LE (Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in mapping remote sensing and GIS from the Faculty of Geography, VNU University of Science—Hanoi National University, in 2007, 2011, and 2019, respectively.

He worked with the Center for Applied Research in Remote Sensing and GIS, in 2007, and moved to the Space Technology Institute, Vietnam Academy of Science and Technology (VAST), in 2008. He has worked as a Remote Sensing and GIS Specialist for different projects funded from FSDP, World Bank (WB), International Union for Conservation of Nature and Natural (IUCN), and the Netherlands Development Organization (SNV). His research interests include using remote sensing and GIS for management of environment and natural resources toward the sustainable development, establishing and updating database for environment and natural resources assessment using remote sensing and GPS data, and organizing and carrying out training transfer program in the field of remote sensing and GIS.

KINH BAC DANG (Member, IEEE) received the B.S. degree in geomorphology and natural hazards and the M.S. degree in cartographic, remote sensing and GIS from the Faculty of Geography, VNU University of Science, in 2010 and 2013, respectively, and the Ph.D. degree in agricultural sciences/ecology from Kiel University, Kiel, Germany.

From 2016 to 2018, he was a Research Assistant with the Institute for Natural Resource Conservation, Kiel University. Since 2019, he has been a Lecturer with the Faculty of Geography, VNU University of Science. He is the author of different articles published in *Environmental Modeling & Software*, *Journal of Environmental Management*, and *Ecological Indicators* journals. His research interests include interdisciplinary sciences and applications of deep learning, remote sensing and GIS in ecological modeling, sustainable agriculture, and natural hazards. He is a Senior Reviewer of the *Ecological Indicators* journal.

TUAN LINH GIANG received the B.S. degree in cartographic, remote sensing and GIS from the Faculty of Geography, VNU University of Science, in 2010, and the M.S. degree in environmental bio-agriculture from Navarra Public University, Spain, in 2013. She is currently pursuing the Ph.D. degree with Vietnam National University.

Since 2010, she has been a Research Assistant in different NGO agricultural organization (such as CIAT SKYMAP and GREENFIELD) in Vietnam. Therefore, she has experience on land use/cover policies. She has focused on applications of deep learning, remote sensing and GIS in ecological modeling, sustainable agriculture, and land management.

THI HUYEN AI TONG received the Graduate and master's degrees in mapping, remote sensing, and GIS majors from the Faculty of Geography, Hanoi University of Science, in 2010 and 2013, respectively.

She was a Researcher with the International Center for Advanced Research on Global Change, Vietnam National University, from 2010 to 2014. Since 2014, she has been working with the Space Technology Institute, Vietnam Academy of Science and Technology (VAST). She has participated in different projects funded by Denmark, the World Bank (WB), the space science and technology programs, local cooperation projects in Vietnam. Her research interests include the application time series of remote sensing and GIS for management urban development and resources, environmental changes, establish and update the database for resources and environmental change, and organize and training on satellite image processing and GIS.

VU GIANG NGUYEN (Member, IEEE) is currently pursuing the Ph.D. degree in the fields of urbanization, disaster prevention, and nature landscape with KU Leuven University, Belgium.

He is currently a Researcher and the Deputy Chief Manager with the Department of Remote Sensing Technology, GIS and GPS, Space Technology Institute (STI), Vietnam. His studies focus on the application of remote sensing and GIS for investing, monitoring, and managing the use of natural resources. He has worked as a Technical Consultant for NGOs and NPOs, such as Asian Development Bank (ADB), International Union for Conservation of Nature (IUCN), and The Netherlands Development Organization (SNV), where he carried out capacity building training on land use planning and rural livelihood development, creating land use, land cover maps, and forest cover change analysis. His research interests include modeling of land use/cover change, estimating biomass, and creating emission maps from multi-sources using remote sensing data.

THI DIEU LINH NGUYEN received the bachelor's degree in natural geography from the University of Natural Sciences, Vietnam National University, Hanoi, in 2021. She is currently pursuing the master's degree in environmental and natural resource management with VNU, in management and coastal management in Vietnam. She is also joining the research team with the Department of Geography, University of Natural Sciences, VNU. Her research interests include geomorphological resources and ecosystem services. Her awards include NAGAO Scholarship, Japan, and the title of Central Five Good Student, in 2021.

MUHAMMAD YASIR received the B.S. degree in geology from the University of Peshawar (UOP), Pakistan, in 2018, and the master's degree in geological engineering from the China University of Petroleum, Qingdao, China, in 2021, where he is currently pursuing the Ph.D. degree with the College of Oceanography and Space Informatics. He has several research publications in well-reputed international journals as a first, and co-authors. His research interests include machine learning algorithms, remote sensing image processing techniques, object detection, and systematic literature review.