Semantic Segmentation on Remotely-Sensed Images Using Enhanced Global Convolutional Network with Channel Attention and Domain Specific Transfer Learning

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Version December 25, 2018 submitted to Preprints

1   **Abstract:** In remote sensing domain, it is crucial to annotate semantics, e.g., river, building, forest, etc,
2   on the raster images. Deep Convolutional Encoder Decoder (DCED) network is the state-of-the-art
3   semantic segmentation for remotely-sensed images. However, the accuracy is still limited, since
4   the network is not designed for remotely sensed images and the training data in this domain is
5   deficient. In this paper, we aim to propose a novel CNN for semantic segmentation particularly for
6   remote sensing corpora with three main contributions. First, we propose to apply a recent CNN
7   call "Global Convolutional Network (GCN)", since it can capture different resolutions by extracting
8   multi-scale features from different stages of the network. Also, we further enhance the network by
9   improving its backbone using larger numbers of layers, which is suitable for medium resolution
10   remotely sensed images. Second, "Channel Attention" is presented into our network in order to
11   select most discriminative filters (features). Third, "Domain Specific Transfer Learning" is introduced
12   to alleviate the scarcity issue by utilizing other remotely sensed corpora with different resolutions as
13   pre-trained data. The experiment was then conducted on two given data sets: (*i*) medium resolution
14   data collected from Landsat-8 satellite and (*ii*) very high resolution data called "ISPRS Vaihingen
15   Challenge Data Set". The results show that our networks outperformed DCED in terms of *F*1 for
16   17.48% and 2.49% on medium and very high resolution corpora, respectively.

17   **Keywords:** Deep Convolutional Neural Networks; Multi-Class Segmentation; Global Convolution
18   Network; Channel Attention; Transfer Learning; ISPRS Vaihingen, Landsat-8

1. Introduction

20   Semantic segmentation of earthly objects such as agriculture fields, forests, roads, urban and
21   water areas, from remotely-sensed images has been manipulated in many applications in various
22   domains, e.g., urban planning, map updates, route optimization, and navigation [1–5], allowing us to
23   better understand the domain's images and create important real-world applications.

24   Deep convolutional neural network (CNN) is a well-known technique for automatic feature
25   learning. It can mechanically learn features in different levels and abstractions from raw images by
26   multiple hierarchical stacking convolution and pooling layers [4–14]. To accomplish such a challenging

27 task, features at different levels are required. Specifically, abstract high-level features are more suitable
28 for the recognition of confusing manmade objects, while labeling of fine-structured objects could
29 benefit from detailed low-level features [1]. Therefore, different numbers of layers will effect the
30 performance of deep learning model.

31 In the past few years, the modern CNNs have been extensively proposed including Global
32 Convolutional Network (GCN) [15] in which the large kernel and effective receptive field play
33 an important role in performing classification and localization tasks simultaneously. The GCN is
34 proposed to address the classification and localization issues for semantic segmentation and to suggest
35 a residual-based boundary refinement for further refining object boundaries. However, this type of
36 architecture ignores the global context such as weights of the features in each stage. Furthermore, most
37 methods of this type are just summed up the features of adjacent stages without considering their
38 diverse representations. This leads to some inconsistent results that suffer from accuracy performance.
39 The primary challenge of this remote sensing task is a lack of training data. This, in fact, has become a
40 motivation of this work.

41 In this paper, we present a novel Global Convolutional Network for segmenting multi-objects
42 from aerial and satellite images. To this end, it is focused on three aspects: (*i*) varying backbones
43 using ResNet50, ResNet101, and ResNet152; (*ii*) applying "Channel Attention Block" [16,17] to assign
44 weights for the feature maps in each stage of backbone architecture, and (*iii*) "Domain Specific Transfer
45 Learning" [18–20] is employed to relieve the scarcity issue. The experiments were conducted using
46 satellite imagery (from the Landsat-8 satellite) which is provided by a government organization in
47 Thailand and well-known aerial imagery, ISPRS Vaihingen Challenge corpus [21], which is publicly
48 available. The results showed that our method outperforms the baseline including Deep Convolutional
49 Encoder-Decoder (DCED) in terms of *F*1 and mean of class-wise Intersection over Union (*Mean IoU*).

50 The remainder of this paper is arranged as follows. Related work is discussed in Section 2. Section
51 3 describes our proposed methodology. Experimental data sets and evaluations are described in
52 Section 4. Experimental results and discussions are presented in Section 5. Finally, we conclude our
53 work and discuss future work in Section 6.

2. Related Work

55 Deep learning has been successfully applied for remotely-sensed data analysis, notably land
56 cover mapping on urban areas [1–3] and has increasingly become a promising tool for accelerating
57 image recognition process with high accuracy results [4–14,22–30], and is a fast-growing field, and
58 new architectures appear every few days. This related work is divided into three subsections: we
59 first discuss deep learning concepts for semantic segmentation, followed by a set of multi-objects
60 segmentation techniques using modern deep learning architecture, and finally; modern technique of
61 deep learning are discussed.

2.1. Deep learning concepts for semantic segmentation

63 Semantic segmentation algorithms are often formulated to solve structured pixel-wise labeling
64 problems based on the deep convolutional neural network (CNN). Noh et al. [13] proposed a novel
65 semantic segmentation technique utilizing a deconvolutional neural network (DeCNN) and the top
66 layer from DCNN adopted from VGG16 [4,8]. DeCNN structure is composed of upsampling layers
67 and deconvolution layers, describing pixel-wise class labels and predicting segmentation masks,
68 respectively. Their proposed deep learning methods yield high performance in PASCAL VOC 2012
69 corpus, with the 72.5% accuracy in the best case scenario (the highest accuracy—as of the time of writing
70 this paper—compared to other methods that were trained without requiring additional or external
71 data). Long et al. [12] proposed an adapted contemporary classification networks incorporating
72 Alex, VGG and GoogLe networks into fully CNN. In this method, some of the pooling layers were
73 skipped: layer 3 (FCN-8s), layer 4 (FCN-16s), and layer 5 (FCN-32s). The skip architecture reduces
74 the potential over-fitting problem and has showed improvements in performance, ranging from 20%

to 62.2% in the experiments tested on PASCAL VOC 2012 data. Ronneberger et al. [14] proposed U-Net, a DCNN for biomedical image segmentation. The architecture consists of a contracting path and a symmetric expanding path that capture context and consequently, enable precise localization. The proposed network claimed to be capable to learn despite the limited number of training images, and performed better than the prior best method (a sliding-window DCNN) on the ISBI challenge for segmentation of neuronal structures in electron microscopic stacks. Vijay Badrinarayanan [31–33] proposed Deep Convolutional Encoder-Decoder network (DCED), namely "SegNet", consists of two main networks encoder and decoder, and some outer layers. The two outer layers of the decoder network are responsible for feature extraction task, the results of which are transmitted to the next layer adjacent to the last layer of the decoder network. This layer is responsible for pixel-wise classification (determining which pixel belongs to which class). There is no fully connected layer in between feature extraction layers. In the upsampling layer of decoder, pool indices from encoder are distributed to the decoder where kernel will be trained in each epoch (training round) at convolution layer. In the last layer (classification), softmax is used as a classifier for pixel-wise classification. DCED is one of the deep learning model that exceeds the state-of-the-art on many remote sensing corpus.

In this work, DCED method is selected as one of our baseline since it is the most popular architecture used in various networks for semantic segmentation.

2.2. Modern deep learning architecture for semantic segmentation

Recently, lots of approaches based on DCED have achieved high performance on different benchmarks [16,31–33]. However, most of them are still suffer from accuracy performance issues. Therefore, many works of modern deep learning architectures were proposed such as instance-aware semantic segmentation [34] which is slightly different from "semantic segmentation". Instead of labeling all pixels, it focuses on the target objects and labels only pixels of those objects. FCIS [28] is based techniques based on fully convolutional networks (FCN). Mask R-CNN [9] is also built around FCN and incorporates with a proposed joint formulation. Peng [15] presents concept of large kernel matters to improve semantic segmentation by global convolutional network (GCN). They proposes a GCN to address both the classification and localization issues for the semantic segmentation. Uses large separable kernels to expand the receptive field, also added a boundary refinement block to further improve localization performance near boundaries. From the Cityscapes challenge, GCN outperforms all the previous publications (all modern deep learning baselines) and reaches the new state-of-art. Therefore, GCN is selected to be the one of our proposed method and selected to be the main model on our work.

2.3. Modern technique of deep learning

Modern technique of deep learning is an important factor for an accuracy of CNN. While the most popular modern ideas tick for semantic segmentation tasks such as Global Context, Attention Module, Semantic Boundary Detection has been used for boosting accuracy.

Global Context [16] is some modern methods have proven the effectiveness of global average pooling in the semantic segmentation task. For example, PSPNet [30] and Deeplab v3 [5] respectively extend it to the Spatial Pyramid Pooling [30] and Atrous Spatial Pyramid Pooling [5], resulting in great performance in different benchmarks. However, to take advantage of the pyramid pooling module sufficiently, these two methods adopt the base feature network to 8 times downsample with atrous convolution [5] which is time-consuming and memory intensive.

Attention Module [16]: Attention is helpful to focus on what we want. Recently, the attention module becomes increasingly a powerful tool for deep neural networks [16,17]. The method in[16,17] pays attention to different scale information. In this work, we utilize channel attention block to select the features similar to Learning a Discriminative Feature Network [16].

Refinement residual block [16]: The feature maps of each stage in feature network all go through the Refinement Residual Block. For our work, we use Boundary Refinement Block (BR) to be concept

123 of "Refinement residual block" from [15]. The first component of the block is a 1×1 convolution
124 layer. We use it to unify the number of channels to 21. Meanwhile, it can combine the information
125 across all channels. Then the following is a basic residual block [7], which can refine the feature
126 map. Furthermore, this block can strengthen the recognition ability of each stage, inspired from the
127 architecture of ResNet.

3. Proposed Method

129 In this section, the details of our proposed network are explained (shown in Figure 2). The network
130 is based on GCN with three aspects of improvements: (*i*) modification of backbone architecture (shown
131 in P1 in Figure 2), (*ii*) applying the "Channel Attention Block" (shown in P2 in Figure 2), and (*iii*) using
132 concept of domain specific "Transfer Learning" (shown in P3 in Figure 2).

3.1. Data Preprocessing

134 In this paper, there are two benchmark corpus including (*i*) ISPRS Vaihingen Challenge corpus
135 and (*ii*) Landsat-8 data set. They are very high and medium resolution images, consecutively. More
136 details of the data sets will be explained in Section 4.1 and Section 4.2. Before a discussion about the
137 model, it is worth to explain our data preprocessing procedure, since it is required when working with
138 neural network and deep learning models. Thus, the mean subtraction is executed.

139 In addition, data augmentation is often required on more complex object recognition tasks.
140 Therefore, a random horizontal flip is generated to increase the training data. For the ISPRS corpus, all
141 images are standardized and cropped into 512×512 pixels with a resolution of 9 cm^2/pixel. For the
142 Landsat-8 corpus, each image is also flipped horizontally and scaled to 512×512 with a resolution of
143 30 m^2/pixel from original images ($16,800 \times 15,800$ pixels).

3.2. Global Convolutional Network (GCN) with variations of backbones

145 GCN [15] as shown in Figure 1 is a modern architecture that surpasses the drawbacks of traditional
146 semantic segmentation network, such as, Deep Convolutional Encoder Decoder Networks (DCED). A
147 traditional network usually cascades convolutional layers in order to generate sophisticated features;
148 they can be considered as local features that is specialized only for a specific task. However, it is not
149 necessary to employ only specialized features, but the general features are also important. Thus, GCN
150 overcomes this issue by introducing a multi-level architecture that each level aims to capture different
151 resolution of features, so both local and global features are considered into the model.

152 As in Figure 1, there are two main blocks in GCN: localization block and classification block. First
153 from the localization view in the left block, the structure is a stack of classical fully-convolutional
154 layer called "level". Each level aims to construct features with different resolutions. Second from the
155 classification view, there are two modules: GCN and Boundary Refinement (BR). For the GCN module,
156 the kernel size of the convolutional structure should be as large as possible, which is motivated by
157 the densely-connected structure of classification models. Specially, if the kernel size increases to the
158 spatial size of feature map (named global convolution), the network will share the same benefit with
159 pure classification models. The BR module is added to further improve localization performance near
160 boundaries.
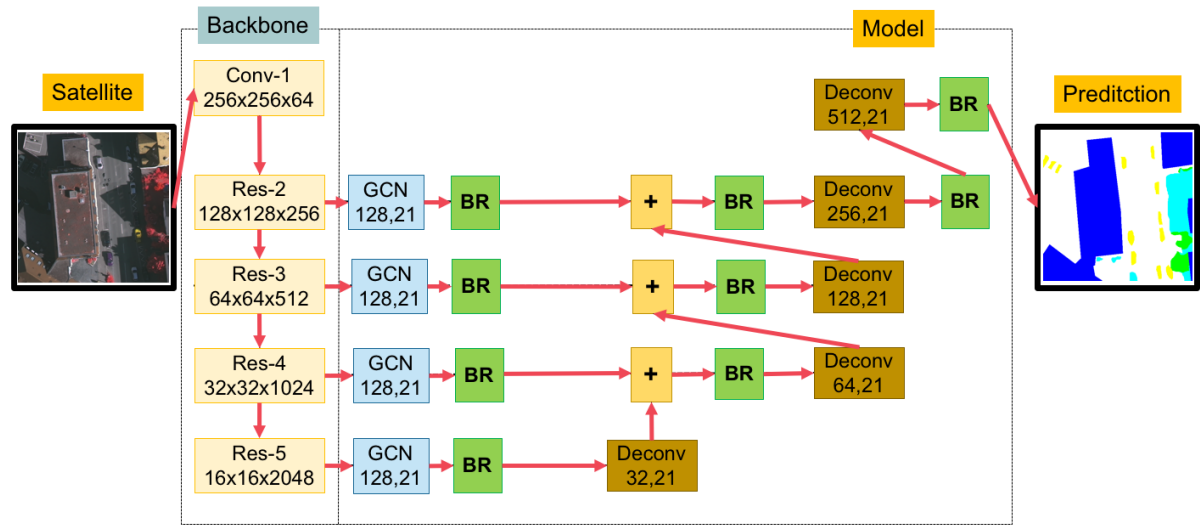
Figure 1. An overview of original Global Convolutional Network and Boundary Refinement (BR) [15].

161   Although the GCN architecture has shown promising prediction performance, it can still be
162 possible to further improved by varying backbones using ResNet [7] with different numbers of layers
163 as ResNet50, ResNet101, and ResNet152 as shown in Figure 3. Also, GCN is suggested to work on
164 large kernel size. In this paper, we set the large kernel size as 9 (this previous work [15]).
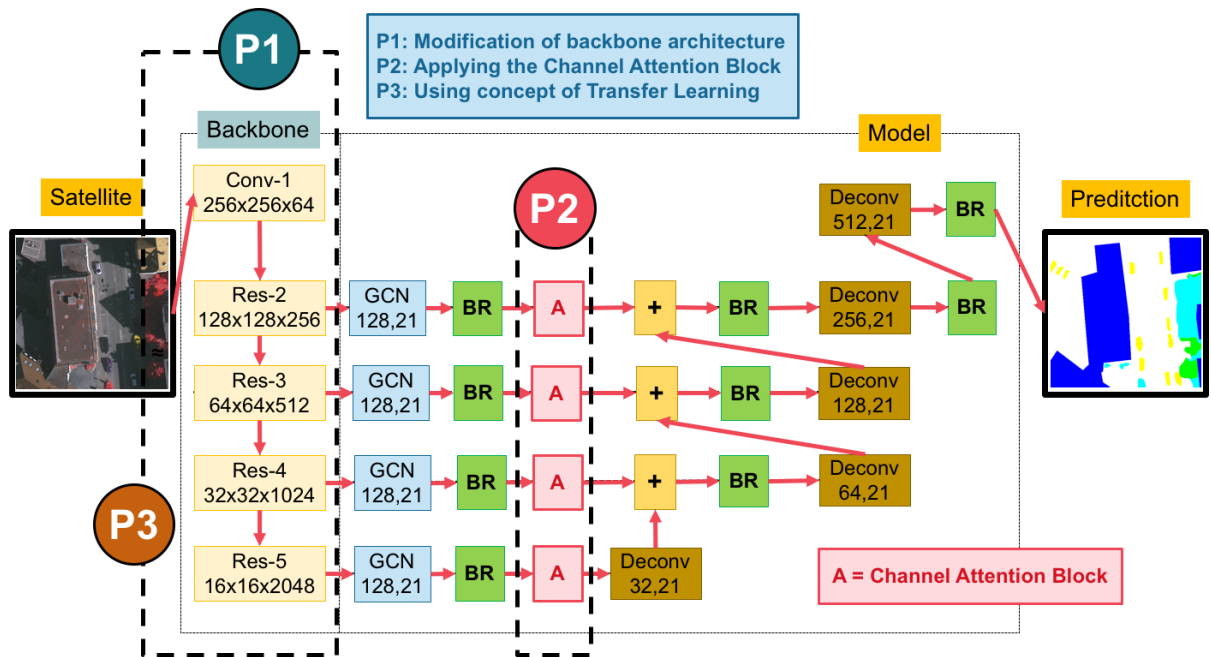
Figure 2. An overview of our proposed network.
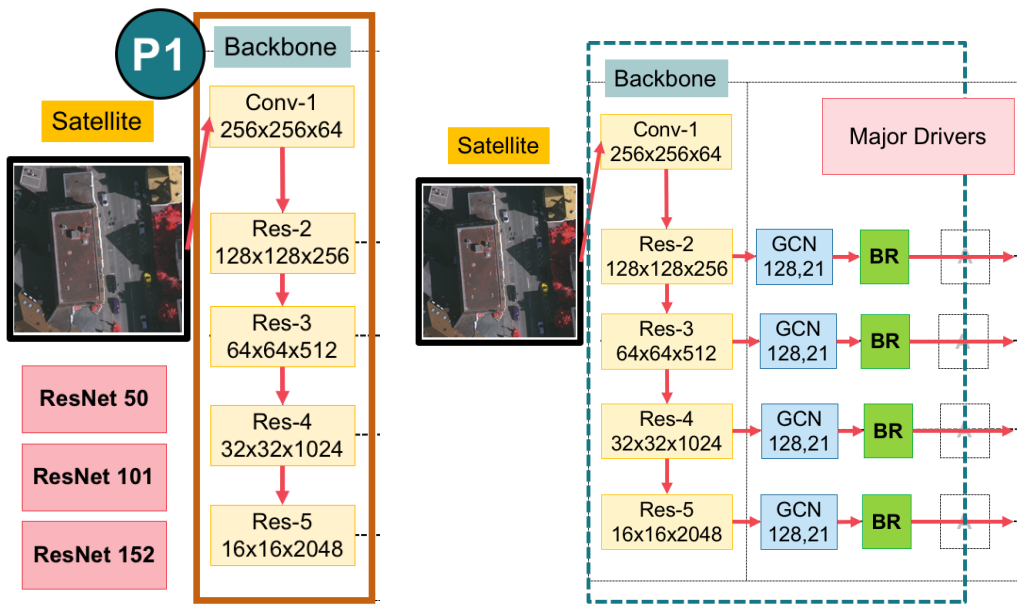
Figure 3. An overview of the whole backbone pipeline in (*left*) the main backbone with varying by ResNet50, ResNet101, and ResNet152; and (*right*) the major drivers of our main classification network (composed of of Global Convolutional Network (GCN) and Boundary Refinement (BR) block [15]).

3.3. Channel Attention Block

Attention Mechanisms [16,17] in neural networks are very loosely based on the visual attention mechanism found in humans and equips a neural network with the ability to focus on a subset of its inputs (or features): it selects specific inputs. Human visual attention is well-studied and while there exist different models, all of them essentially come down to be able to focus on a certain region of an image with "very high resolution", while perceiving the surrounding image in "medium resolution", and then adjusting the focal point over time.

To apply this atttentional layer to our network, the channel attention block is shown in Block "A" in Figure 2 and its detailed architecture is shown in Figure 4. It is designed to change the weights of the remote sensing features on each stage (level), so that the weights are assigned more values on important features adaptively.
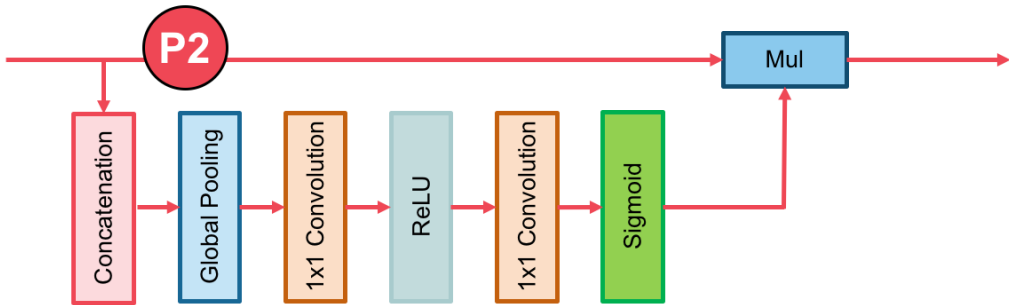
Figure 4. Components of Channel Attention Block. The red lines represent the downsample operators, respectively. The red line cannot change the size of feature maps, just a path of information passing.

In the our proposed architecture, the convolution operator outputs a score map, which gives the probability of each class at each pixel. In equations 1 as the final score at score map is just summed over all channels of feature maps.

$$y_k = F(x; w) = \sum_{i=1, j=1}^{D} w_{i,j} x_{i,j} \tag{1}$$

where x is the output feature of network. w represents the convolution kernel and $k \in 1, 2, 3, 4, 5, 6, 7, ..., K$. the number of channels is represented by K. D is the set of pixel positions.

$$\delta_i(y_k) = \frac{exp(y_k)}{\sum_{j=1}^{k} exp(y_j)} \tag{2}$$

where δ is the prediction probability. y is the output of network. As shown in equation 1 and equation 2, the final predicted label is the category with highest probability. So, we suppose that the prediction result is y_0 of a certain patch, while its true label is y_1. Therefore, we can introduce a parameter α to change the highest probability value from y_0 to y_1, as equation 3 shows.

$$\bar{y} = \alpha y = \begin{bmatrix} \alpha_1 \\ . \\ . \\ . \\ \alpha_k \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ . \\ . \\ . \\ y_k \end{bmatrix} = \begin{bmatrix} \alpha_1 w_1 \\ . \\ . \\ . \\ \alpha_k w_k \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ . \\ . \\ . \\ x_k \end{bmatrix} \tag{3}$$

where $\bar{y}$ is the new prediction of network and $\alpha = Sigmoid(x; w)$

Based on the above formulation of the Channel Attention Block, we can explore its practical significance. In equation 1, it implicitly indicates that the weights of different channels are equal. However, the features in different stages have different degrees of discrimination, which results in different consistency of prediction. Consequently, in equation 3, the α value applies on the feature maps x, which represents the feature selection with Channel Attention Block.

3.4. Domain Specific Transfer Learning

The overall idea of transfer learning is to use knowledge learned from tasks for which a lot of labeled data is usable in settings where only little-labeled data is available. Creating labeled data is expensive, so optimally leveraging existing data set is key. Certain low-level features, such as edges, shapes, corners and intensity, can be shared across tasks and learn new high-level features specific to the target problem [18]. Also, knowledge from an existing task acts as an additional input when learning a new target task.

Although the deep learning approach often performs promising prediction performance, it requires a large amount of training data. Since it is difficult to obtain annotated satellite images, the perform in prior works should be limited.

Fortunately, there is a recent concept called "Domain Specific Transfer Learning" [18–20] that allows to reuse the weights obtaining from other domains' inputs. It is currently very popular in the field of Deep Learning because it enables you to train Deep Neural Networks with comparatively insufficient data. This is very useful since most real-world problems typically do not have millions of labeled data points to train such complex models.

From the inadequacy issue, we propose an effective Transfer Deep Neural Network to perform knowledge transfer between Very High Resolution (VHR) corpus and Medium Resolution (MR) corpus. It is shown in Figure 5.
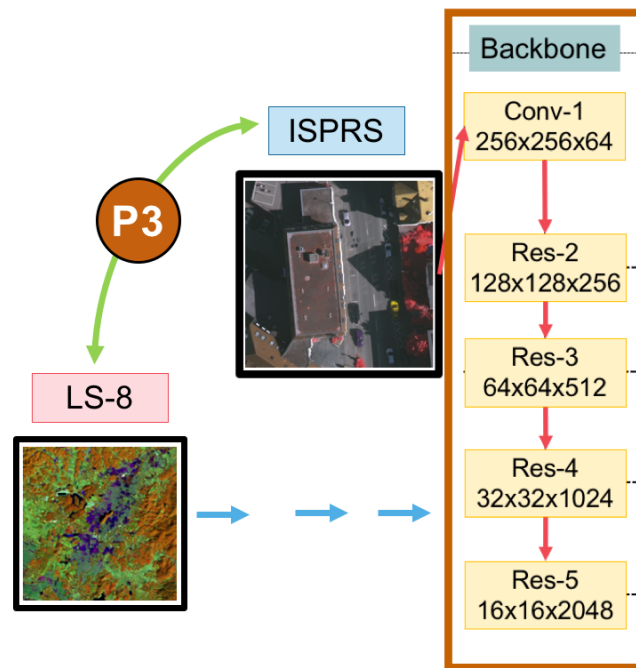
Figure 5. Domain Specific Transfer Learning strategy reuses pre-trained weights of models between two data sets – very high (ISPRS) and medium (Landsat-8; LS-8) resolution images.

4. Experimental Data Sets and Evaluation

In our experiments, two types of data sets are used: (i) medium resolution imagery (satellite images; Landsat-8 data set) made by the government organization in Thailand, name as GISTDA (Geo-Informatics and Space Technology Development Agency (Public Organization)) and (ii) very high resolution imagery (aerial images; ISPRS Vaihingen data set). All experiments are evaluated based on major metrics, such as *Average Accuracy*, *F1 Score* and *Mean IoU Score*.

4.1. Landsat-8 Data Set

Landsat-8 is an American earth observation satellite and it collect and archive medium resolution (30-meter spatial resolution) multispectral image data affording seasonal coverage of the global landmasses for a period of no less than 5 years. Landsat-8 [35] images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. The ultra blue Band 1 is useful for coastal and aerosol studies. Band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. Thermal bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. The approximate scene size is 170 km north-south by 183 km east-west (106 *mi* by 114 *mi*). Since Landsat-8 data includes additional bands, the combinations used to create RGB composites differ from Landsat 7 and Landsat 5. For instance, bands 4, 3, 2 are used to create a color infrared (CIR) image using Landsat 7 or Landsat 5. To create a CIR composite using Landsat 8 data, bands 5, 4, 3 are used.

In this type of data, the satellite images are from Nan, province in Thailand. The data set is obtained from Landsat-8 satellite consisting of 1,012 satellite images as shown some samples in Figure 6.

This corpus is comprised of a large, diverse set of medium resolution ($16,800 \times 15,800$) pixels, where 1,012 of these images have high quality pixel-level labels of 5 classes: Agriculture, Forest, Miscellaneous, Urban, and Water Class. The 1,012 images are split into 800 training and 112 validation images with publicly available annotation, as well as 100 test images with annotations withheld and comparison to other methods are performed via a dedicated evaluation server. For quantitative evaluation, mean of class-wise Intersection over Union (*Mean IoU*) and *F1* score are used.
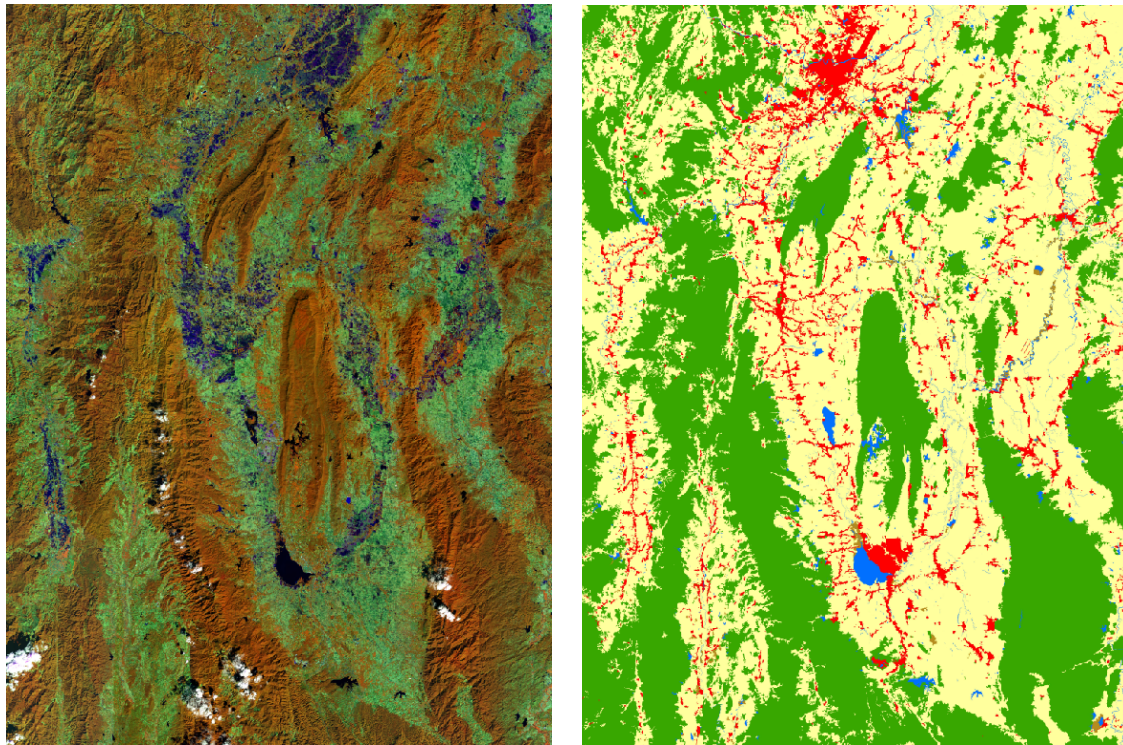
Figure 6. Sample satellite images from Nan, a province in Thailand (left) and corresponding ground truth (right). The label of medium resolution data set includes five categories: Agriculture (yellow), Forest (green), Miscellaneous (Misc, brown), Urban (red) and Water (blue).

4.2. ISPRS Vaihingen Data Set

One of the major challenges in remote sensing is the automated extraction of urban objects from data acquired by airborne sensors. Semantic Labeling Contest provides two state-of-the-art airborne image corpora, consisting of (*i*) Vaihingen corpus is a relatively small village with many detached buildings and small multi-story buildings, and (*ii*) Potsdam corpus shows a typical historic city with large building blocks, narrow streets and dense settlement structure. In our experiments, Vaihingen corpus was selected and used.

ISPRS 2D Semantic labeling challenge in Vaihingen [21] (Figure 7 and Figure 8) is used to be our benchmark data set. It consists of three spectral bands (i.e., red, green and near-infrared bands), corresponding DSM (Digital Surface Model) and NDSM (Normalized Digital Surface Model) data. Overall, there are 33 images of about $2,500 \times 2,000$ pixels at a Ground sampling distance (GSD) of about 9 cm in image data. Among them, the ground truth of only 16 images are available, and those of the remaining 17 images are withheld by the challenge organizer for online test. For offline validation, we randomly split the 16 images with ground truth available into a training set of 10 images, and a validation set of 6 images. For this work, DSM and NDSM data in all the experiments on this data set are not used. Following other methods, 4 tiles (image numbers 5, 7, 23, 30) are removed from the training set as a validation set. Experimental results are reported on the validation set if not specified.
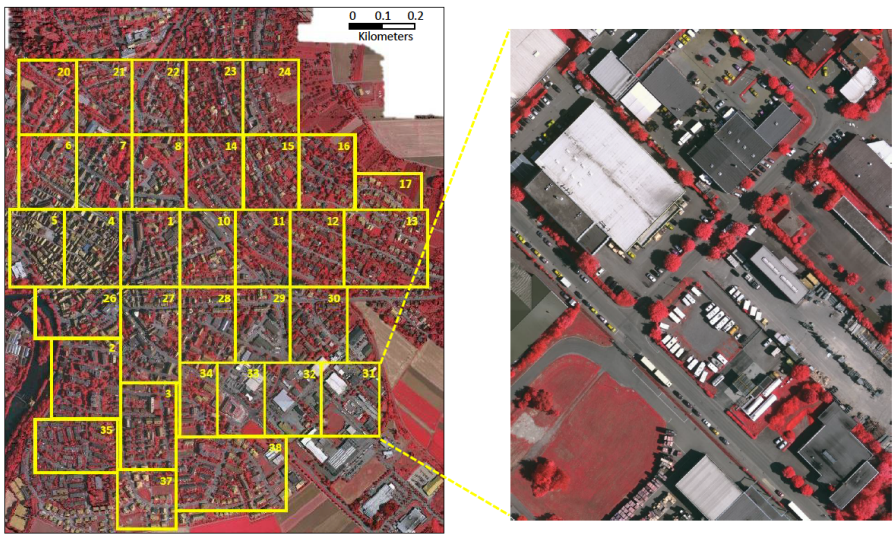
Figure 7. Overview of the ISPRS 2D Vaihingen Labeling corpus. There are 33 tiles. Numbers in the figure refer to the individual tile flag.
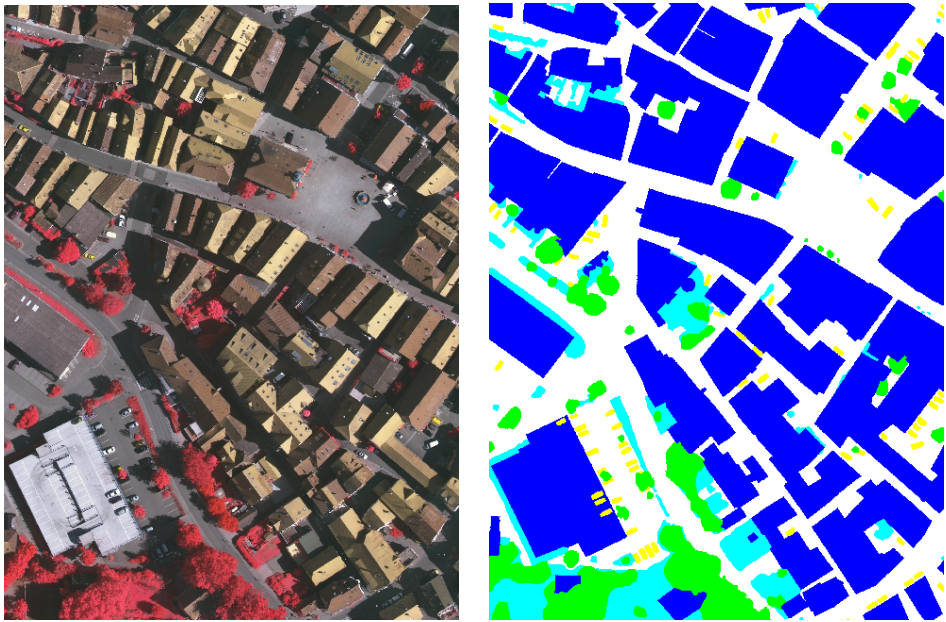
Figure 8. The sample input tile from Figure7 (left) and corresponding ground truth (right). The label of Vaihingen challenge includes six categories: impervious surface (imp surf, white), building (blue), low vegetation (low veg, cyan), tree (green), car (yellow) and clutter/background (red).

4.3. Evaluation

The multi-class classification task can be considered as multi-segmentation, where class pixels are positives and the remaining non-spotlight pixels are negatives. Let TP denotes the number of true positives, TN denotes the number of true negatives, FP denotes the number of false positives, and FN denotes the number of false negatives.

Precision, *recall*, *F*1, and *Mean IoU* are shown in equations (4-8). Precision is the percentage of correctly classified main pixels among all predicted pixels by the classifier. Recall is the percentage of correctly classified main pixels among all actual main pixels. *F*1 is a combination of *precision* and *recall*.

²⁶²   To evaluate the performance of different comparing deep models, we will discuss the above two
²⁶³ major metrics (*F*1) and mean of class-wise Intersection over Union (*Mean IoU*)) on each category, and
²⁶⁴ the mean value of metrics to assess the average performance.

$$Accuracy = \frac{TP + TN}{TP + +FP + FN + TN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precison + Recall} \tag{7}$$

$$Mean\ IoU = \frac{TP}{TP + FP + FN} \tag{8}$$

5. Experimental Results and Discussions

²⁶⁶   The implementation is based on a deep learning framework, called "Tensorflow-Slim" [36], which
²⁶⁷ is extended from Tensorflow. All experiments were conducted on servers with Intel® Xeon® Processor
²⁶⁸ E5-2660 v3 (25M Cache, 2.60 GHz), 32 GB of memory (RAM), Nvidia GeForce GTX 1070 (8 GB), Nvidia
²⁶⁹ GeForce GTX 1080 (8 GB) and Nvidia GeForce GTX 1080 Ti (11 GB). In stead of using the whole image
²⁷⁰ (1,500×1,500 pixels) to train the network, we randomly crop all images to be 512×512 as inputs of each
²⁷¹ epoch.

²⁷²   For training, Adam optimizer [11] is chosen with an initial learning rate of 0.004 and weight decay
²⁷³ of 0.00001. Batch normalization [10] is used before each convolutional layer in our implementation
²⁷⁴ to ease the training and make it be able to concatenate feature maps from different layers. To avoid
²⁷⁵ overfitting, common data augmentations are used as details in Section 3.1. For the measurements, we
²⁷⁶ use the mean pixel intersection-over-union (*mean IoU*) and *F*1 score as the metric.

²⁷⁷   Inspired by [16,27,37], we use the "poly" learning rate policy where the learning rate is multiplied
²⁷⁸ by Eq. 9 with power 0.9 and initial learning rate as $4e^{-3}$. The learning rate is scheduled by multiplying
²⁷⁹ the initial as seen in Eq. 9.

$$learning\ rate = (1 - \frac{epoch}{MaxEpoch})^{0.9} \tag{9}$$

²⁸⁰   All models are trained for 50 epochs with mini-batch size of 4, and each batch contains the cropped
²⁸¹ images that are randomly selected from training patches. These patches are resized to 521 × 521 pixels.
²⁸² . The statistics of batch normalization is updated on the whole mini-batch.

²⁸³   This section illustrates details of our experiments. The proposed deep learning network is based
²⁸⁴ on GCN with three improvements: (*i*) varying backbones using ResNet, (*ii*) Channel Attention and
²⁸⁵ Global Average Pooling, and (*iii*) Domain Specific Transfer Learning. From all proposed strategies,
²⁸⁶ there are six acronyms of strategies as shown in Table 1.

Table 1. Abbreviations on our proposed deep learning methods

Abbreviation	Description
A	Channel Attention Block
GCN	Global Convolutional Network
GCN50	Global Convolutional Network with ResNet50
GCN101	Global Convolutional Network with ResNet101
GCN152	Global Convolutional Network with ResNet52
TL	Domain Specific Transfer Learning

For the experimental setup, there are three experiments on two remotely-sensed data sets: Landsat-8 data set and ISPRS Vaihingen challenge data set (details in Section 4.1 and Section 4.2). The experiments aim to illustrate that each proposed strategy can really improve the performance. First, "GCN152" method is compared to "GCN50" method and "GCN101" method for the varying backbones using ResNet with different numbers of layers on GCN networks strategy. Second, "GCN152-A" method is compared to "GCN152" method for the "Channel Attention" strategy. Third, the full proposed technique "GCN152-TL-A" method is compared to existing methods for the concept of domain specific transfer learning.

5.1. Results on Landsat-8 Corpus with Discussion

In this subsection, the experiment was conducted on the Landsat-8 corpus. The result is shown in Table 2 and Table 3 by comparing between baseline and variations of the proposed techniques. It shows that our network with all strategies "GCN152-TL-A" outperforms other methods. More details will be discussed to show that each of the proposed techniques can really improve an accuracy. Only in this experiment, there are state of the art baseline, including Deep Convolutional Encoder-Decoder (DCED) [31–33].

5.1.1. Effect of enhanced GCN on Landsat-8 corpus

Our first strategy aims to increase an $F1$ and $Mean\ IoU$ score of the network by varying backbones using ResNet 50, ResNet 101, and ResNet 152 rather than the traditional one, DCED method. From Table 2 and Table 3, $F1$ of GCN152 (0.7563) outperforms that of GCN50 (0.6847) and GCN101 (0.7290), and baseline method; DCED (0.6495); this yields higher $F1$ at 2.74%, 3.52%, and 4.43% respectively. $Mean\ IoU$ of GCN152 (0.6364) outperforms that of GCN50 (0.5734), GCN101 (0.6154), and baseline method; DCED (0.5384); this yields higher $Mean\ IoU$ at 2.10%, 3.50%, and 4.20% consecutively. The main reason is due to higher precision, but slightly lower recall. This can imply that enhanced GCN is more significantly efficient than DCED method (baseline) for this medium resolution corpus and ResNet with a large number of layers is more robust than the small number of layers.

When comparing the results between the original GCN method and the enhanced GCN methods on Landsat-8 corpus (Table 2), it clearly shows that GCN with the larger layer of the backbone can improve the network performance in term of $F1$ and $mean\ IoU$

5.1.2. Effect of using "Channel Attention" on Landsat-8 corpus

Our second mechanism focuses on applying "Channel Attention Block" (details in Section 3.4) to change the weights of the features on each stage to enhance the consistency. From Table 2 and 3, the $F1$ of GCN152-A (0.7897) is greater than that of GCN152 (0.7563); this yields higher $F1$ score at 3.34%. and the $Mean\ IoU$ of GCN152-A (0.6726) is superior to that of GCN152 (0.6364); this yields higher $Mean\ IoU$ score at 3.62%. The result (Figure 9e and Figure 12e) shows that can make the network to obtain discriminative features stage-wise to make the prediction intra-class consistent. This is based on the consideration that we re-weighted all feature maps of each layer.

5.1.3. Effect of using "Domain Specific Transfer Learning" on Landsat-8 corpus

Our last strategy aims to use approach of domain specific "Transfer Learning" (details in Section 3.3) by reusing the pre-trained weight from "GCN152-A" model on ISPRS Vaihingen corpus. From Table 2 and Table 3, $F1$ of "GCN152-TL-A" method is the winner; it clearly outperforms not only the baseline, but also all previous generations. Its $F1$ is higher than DCED (baseline) at 17.80%. Its $Mean\ IoU$ is higher than DCED at 17.94%. Also, the result illustrates that concept of domain specific "Transfer Learning" can enhance both precision (0.8293) and recall (0.8476).

Figure 9 and Figure 12 shows twelve sample results from the proposed method. By applying all strategies, the images in the last column (Figure 9f and Figure 12f) are similar to the ground truths

332 (Figure 9b and Figure 12b). Furthermore, *F1*-results and *Mean IoU* scores are improved for each
333 strategy we added to the network as shown in Figure 9(c-f) and Figure 12(c-f).

Table 2. Results on the testing data of Landsat-8 corpus between baseline and five variations of our proposed techniques in terms of *precision*, *recall*, *F1* and *Mean IoU*.

	Pretrained	Backbone	Model	*Precision*	*Recall*	*F1*	*Mean IoU*
Baseline	-	-	DCED [31–33]	0.6137	0.7209	0.6495	0.5384
Proposed Method	-	Res50	GCN [15]	0.6678	0.7333	0.6847	0.5734
	-	**Res101**	GCN	0.6899	0.8031	0.7290	0.6154
	-	**Res152**	GCN	0.7115	0.8131	0.7563	0.6364
	-	**Res152**	**GCN-A**	0.7997	0.7937	0.7897	0.6726
	TL	**Res152**	**GCN-A**	**0.8293**	**0.8476**	**0.8275**	**0.7178**
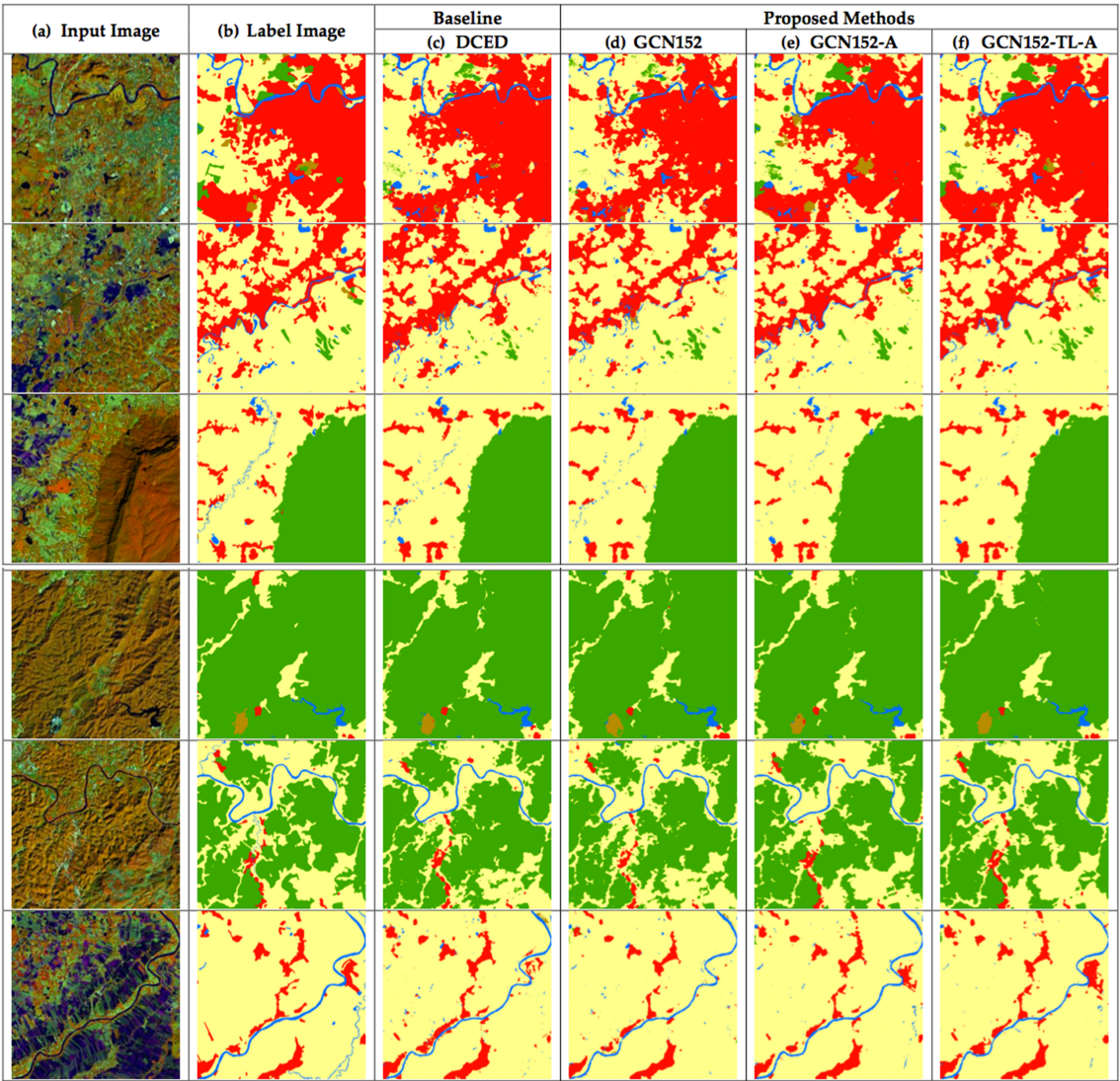
Figure 9. Six testing sample input and output satellite images on Landsat-8 in Nan provinces in Thailand, where rows refer different images. (a) Original input image; (b) Target map (ground truth); (c) Output of Encoder Decoder (Baseline); (d) Output of GCN152; (e) Output of GCN152-A; and (f) Output of GCN152-TL-A. The label of medium resolution data set includes five categories: Agriculture (yellow), Forest (green), Miscellaneous (Misc, brown), Urban (red) and Water (blue).

Table 3. Results on the testing data of Landsat-8 corpus between each class with our proposed techniques in terms of *Average Accuracy*

	Model	Agriculture	Forest	Misc	Urban	Water
Baseline	DCED [31–33]	0.9616	0.7472	0.0976	0.7878	0.4742
Proposed Method	GCN50 [15]	0.9407	0.8258	0.1470	**0.8828**	0.5426
	GCN101	0.9677	0.8806	0.2561	0.7971	0.5480
	GCN152	0.9780	0.8444	0.4256	0.7158	0.5937
	GCN152-A	0.9502	**0.9118**	0.6689	0.8675	0.6001
	GCN152-TL-A	**0.9781**	0.8472	**0.8732**	0.7988	**0.6493**

334   To achieve highest accuracy, the network must be configured and trained many epochs until all
335   parameters in the network are converged. Figure 11(a) illustrates that the proposed network has been
336   properly set and trained until it is really converged and ran more smoothly than baseline in Figure
337   10(a). Furthermore, Figure 10(b) and Figure 11(b) show that the higher number of epochs tend to show
338   better $F1$ score. Thus, the number of chosen epochs based on the validation data is 49 (The best model
339   for this data set).

(a)   **(b)**
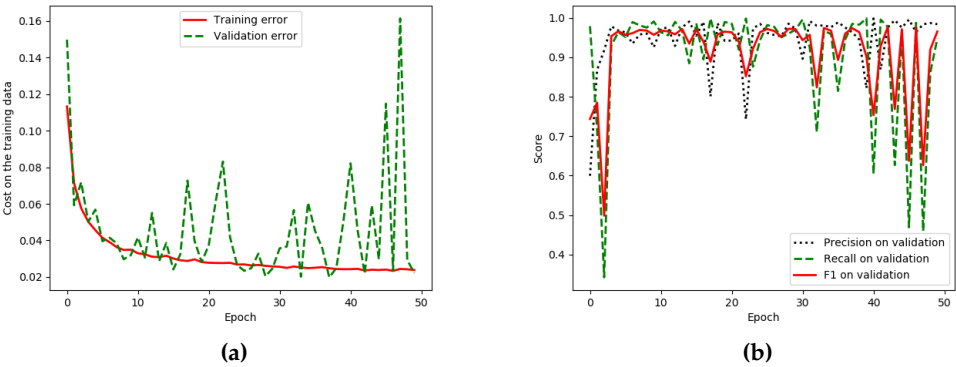
Figure 10. Iteration plot on Landsat-8 corpus of the baseline technique, DCED [31–33]; x refers to epochs and y refers to different measures **(a)** Plot of model loss (cross entropy) on training and validation data sets and **(b)** Performance plot on the validation data set.

(a)   **(b)**
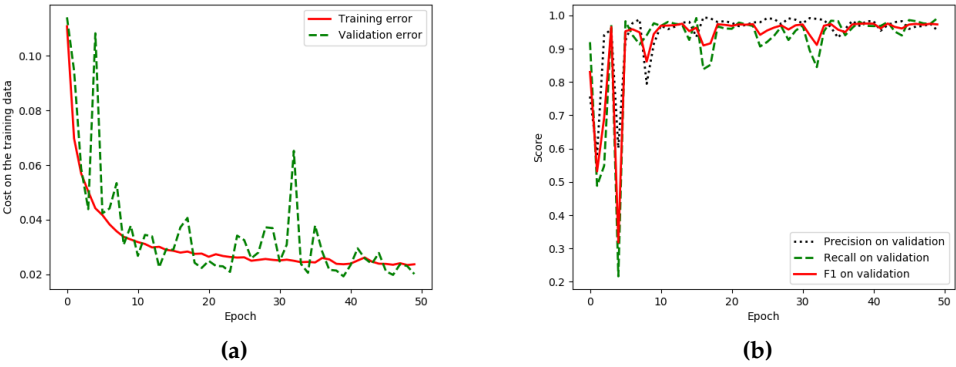
Figure 11. Iteration plot on Landsat-8 corpus of the proposed technique, "GCN152-TL-A"; x refers to epochs and y refers to different measures **(a)** Plot of model loss (cross entropy) on training and validation data sets, **(b)** Performance plot on the validation data set.

340   Twelve sample testing results (shown as Figure 9 and Figure 12) from the proposed method
341   on Nan provinces (is one of the northern provinces (changwat) of Thailand and agriculture is the

province's main industry). The results of the last column look closest to the ground truth in the second column.
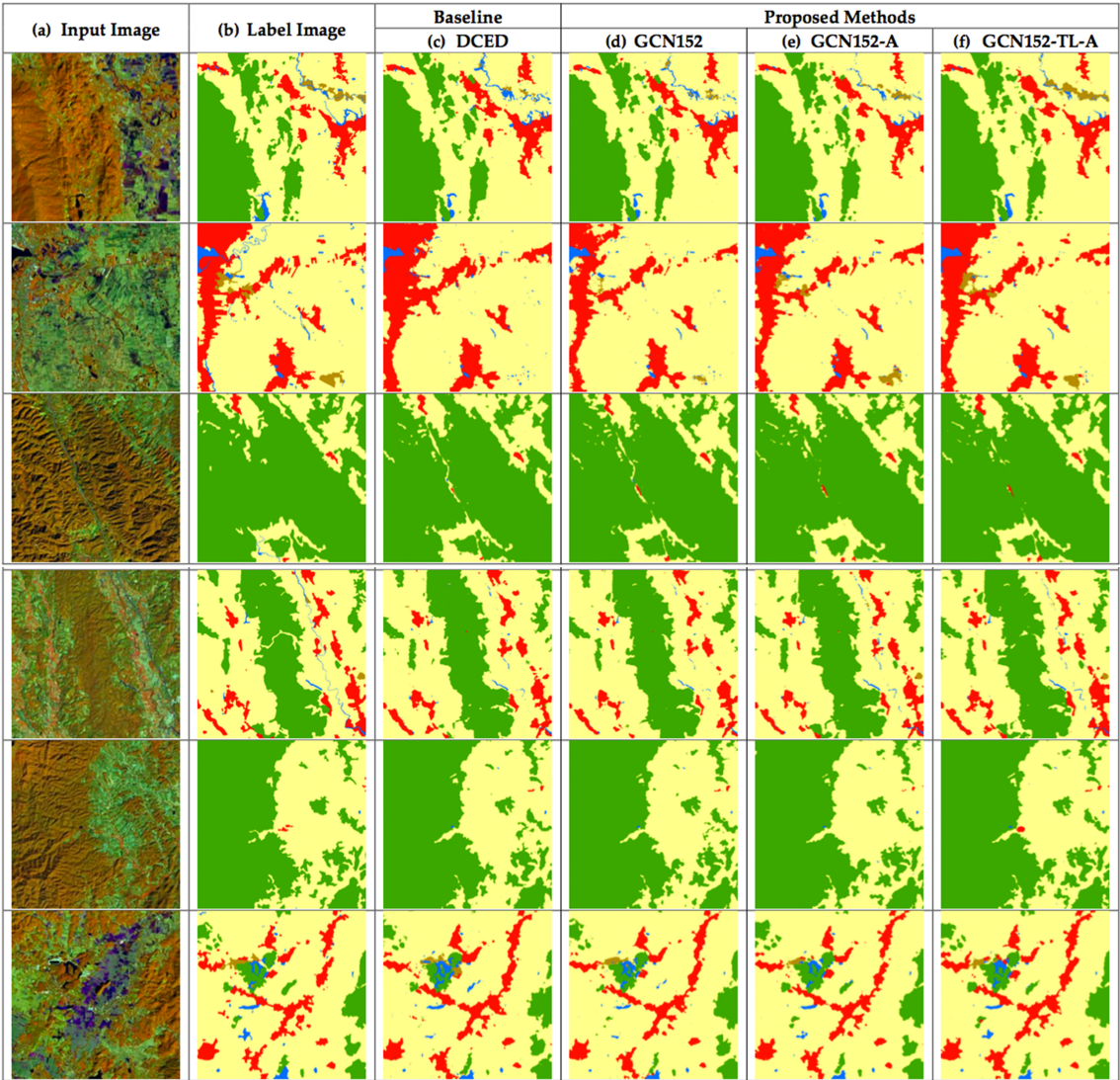
Figure 12. Six testing sample input and output satellite images on Landsat-8 in Nan provinces in Thailand, where rows refer different images. (a) Original input image; (b) Target map (ground truth); (c) Output of Encoder Decoder (Baseline); (d) Output of GCN152; (e) Output of GCN152-A; and (f) Output of GCN152-TL-A. The label of medium resolution data set includes five categories: Agriculture (yellow), Forest (green), Miscellaneous (Misc, brown), Urban (red) and Water (blue).

As can be seen in Figure 9 and Figure 12, the performance of our best model outperforms other advanced models by a considerable margin on each category, especially for the Agriculture, Miscellaneous (Misc), and Water. Furthermore, the loss curves shown in Figure 11(a) exhibit that, our best model performs better on all the given categories.

5.2. Results on ISPRS Vaihingen Challenge Corpus with Discussion

In this subsection, the experiment was conducted on the ISPRS Vaihingen Challenge corpus. The result is shown in Table 4 and Table 5 by comparing between baseline and variations of the proposed techniques. It shows that our network with all strategies (GCN152-TL-A) outperforms other methods. More details will be discussed to show that each of the proposed techniques can really improve an accuracy. Only in this experiment, there are one baseline, including DCED network.

354 5.2.1. Effect of enhanced GCN on ISPRS Vaihingen corpus

355   Our first strategy aims to increase an *F*1 and *Mean IoU* score of the network by varying backbones
356 using ResNet 50, ResNet 101, and ResNet 152 rather than the traditional one, DCED method. From
357 Table 4 and Table 5, *F*1 of GCN152 (0.7864) outperforms that of GCN50 (0.776), GCN101 (0.768),
358 and baseline method; DCED (0.7693); this yields higher *F*1 at 0.02%, 0.68%, and 1.01% respectively.
359 *Mean IoU* of GCN152 (0.8977) outperforms that of GCN50 (0.8776), GCN101 (0.8972), and baseline
360 method; DCED (0.8651); this yields higher *Mean IoU* at 0.02%, 0.68%, and 1.01% consecutively. This
361 can imply that enhanced GCN is also more accurate than DCED approach on very high resolution
362 data set. ResNet with large number of layers is still more robust than small number of layers same as
363 that performed on Landsat-8 corpus (Section 5.1.1).
364   When comparing the results between the original GCN method and the enhanced GCN methods
365 on Landsat-8 corpus (Table 4), it clearly shows that GCN with the larger layer of the backbone can
366 improve the network performance in term of *F*1 and *mean IoU*

367 5.2.2. Effect of using "Channel Attention" on ISPRS Vaihingen corpus

368   Our second mechanism focuses on utilizing "Channel Attention Block" to change the weights of
369 the features on each stage to enhance the consistency. From Table 4 and 5, the *F*1 of GCN152-A (0.7902)
370 is greater than that of GCN152 (0.7864); this yields higher *F*1 score at 0.38%. and the *Mean IoU* of
371 GCN152-A (0.9057) is better than that of GCN152 (0.8977); this yields higher *Mean IoU* score at 0.80%.
372 The results (Figure 13e and Figure 14e) show that can also make the network to obtain discriminative
373 features stage-wise to make the prediction intra-class consistent on very high resolution images.

374 5.2.3. Effect of using "Domain Specific Transfer Learning" on ISPRS Vaihingen corpus

375   Our last strategy aims to performing approach of domain specific "Transfer Learning" (details in
376 Section 3.3) by reusing the pre-trained weight from "GCN152-A" model on Landsat-8 corpus. From
377 Table 4 and Table 5, *F*1 of "GCN152-TL-A" method is the winner; it clearly outperforms not only the
378 baseline, but also all previous generations. Its *F*1 is higher than DCED (baseline) at 2.49% and 1.82%
379 consecutively. Its *Mean IoU* is higher than DCED and GCN at 4.76% and 3.51% respectively. Also,
380 the result illustrates that concept of domain specific "Transfer Learning" can enhance both precision
381 (0.7888) and recall (0.8001).
382   Figure 13 and Figure 14 shows twelve sample results from the proposed method. By applying all
383 strategies, the images in the last column (Figure 13f and Figure 14f) are similar to the ground truths
384 (Figure 13b and Figure 14b). Furthermore, *F*1-results and *Mean IoU* scores are improved for each
385 strategy we added to the network as shown in Figure 13(c-f) and Figure 14(c-f).
386   To further evaluate the effectiveness of the proposed "GCN152-TL-A" comparisons with baseline'
387 method on the one challenging benchmark and one private benchmark are presented as follows as
388 Table 2 and Table 3 for Landsat-8 data set on Nan province (Thailand) corpus and Table 4 and Table 5
389 for Vaihengen data set. All extensive experiments on the Landsat-8 and ISPRS dataset demonstrate
390 that the proposed method achieve clear promising gains compared with the baseline approache.

Table 4. Results on the testing data of ISPRS 2D semantic labeling challenge corpus between baseline
and five variations of our proposed techniques in terms of *precision*, *recall*, *F*1 and *Mean IoU*.

	Pretrained	Backbone	Model	*Precision*	*Recall*	*F*1	*Mean IoU*
Baseline	-	-	DCED [31–33]	0.7519	0.7925	0.7693	0.8651
Proposed Method	-	Res50	GCN [15]	0.7636	0.7917	0.776	0.8776
	-	**Res101**	GCN	0.7713	**0.8059**	0.7862	0.8972
	-	**Res152**	GCN	0.7736	0.8021	0.7864	0.8977
	-	**Res152**	**GCN-A**	0.7847	0.7961	0.7902	0.9057
	TL	**Res152**	**GCN-A**	**0.7888**	0.8001	**0.7942**	**0.9123**
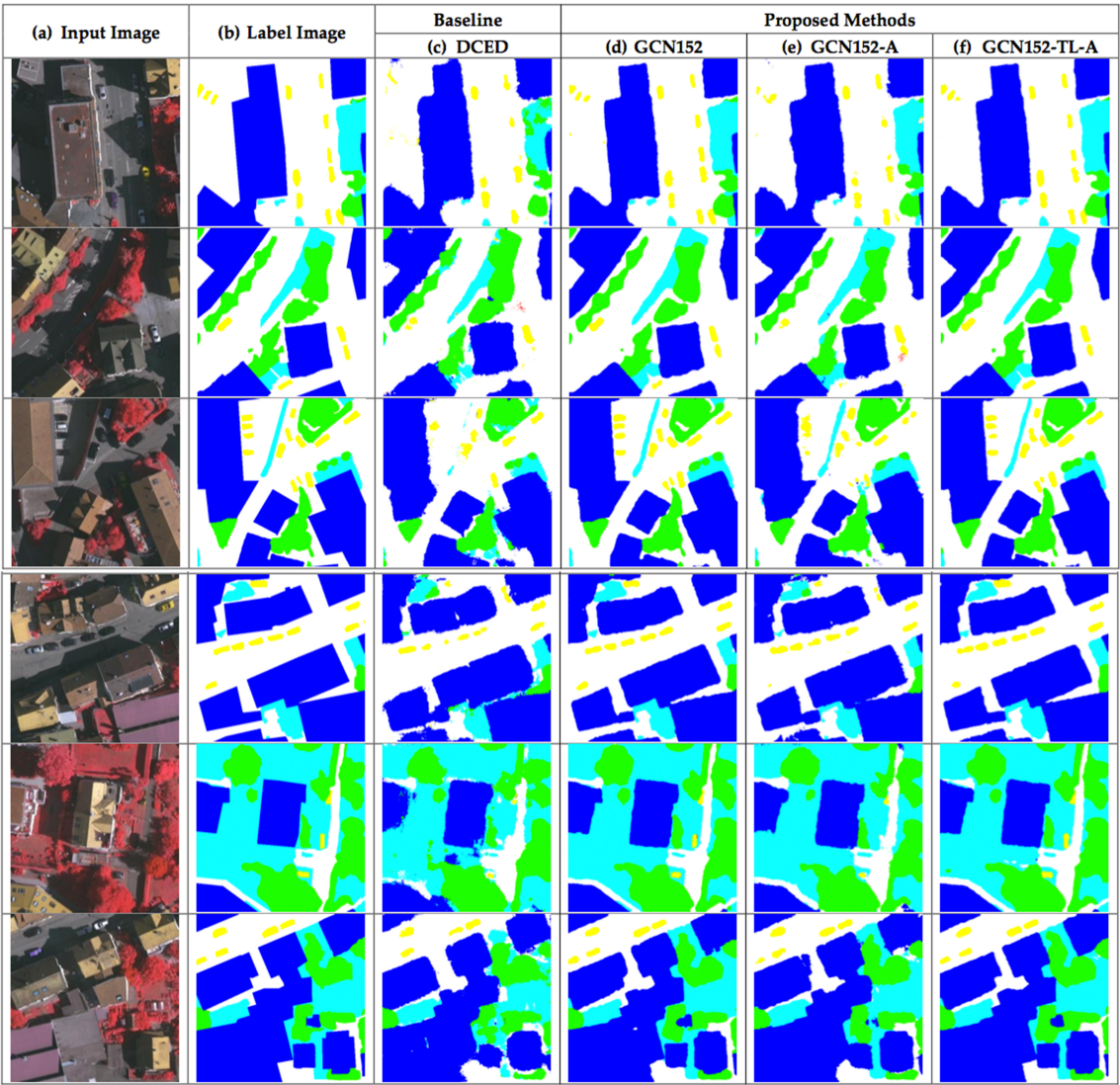
Figure 13. Six testing sample input and output aerial images on ISPRS Vaihingen challenge corpus, where rows refer different images. (a) Original input image; (b) Target map (ground truth); (c) Output of Encoder Decoder (Baseline); (d) Output of GCN152; (e) Output of GCN152-A; and (f) Output of GCN152-TL-A. The label of Vaihingen challenge includes six categories: impervious surface (imp surf, white), building (blue), low vegetation (low veg, cyan), tree (green), car (yellow) and clutter/background (red).

Table 5. Results on the testing data of ISPRS Vaihingen challenge corpus between each class with our proposed techniques in terms of *Average Accuracy*

	Model	IS	Buildings	LV	Tree	Car
Baseline	DCED [31–33]	0.9590	0.9778	0.9108	0.9805	0.6832
	GCN50 [15]	0.9595	0.9628	0.9403	0.9896	0.7292
Proposed Method	GCN101	0.9652	0.9827	**0.9615**	0.9797	0.7387
	GCN152	0.9543	**0.9962**	0.9445	0.9754	0.7710
	GCN152-A	0.9614	0.9865	0.9554	0.9871	0.8181
	GCN152-TL-A	**0.9664**	0.9700	0.9499	**0.9901**	**0.8567**

391 Figure 13 and Figure 14 show twelve sample testing results from the proposed method on ISPRS
392 Vaihingen corpus. The results of the last column are also similar to the ground truth in the second

393 column same as performed on Landsat-8 corpus. Considering to each class (are shown in Table 3 and
394 Table 5), almost every classes (three out of five) from our proposed methods are the winner in term
395 *Average Accuracy.*
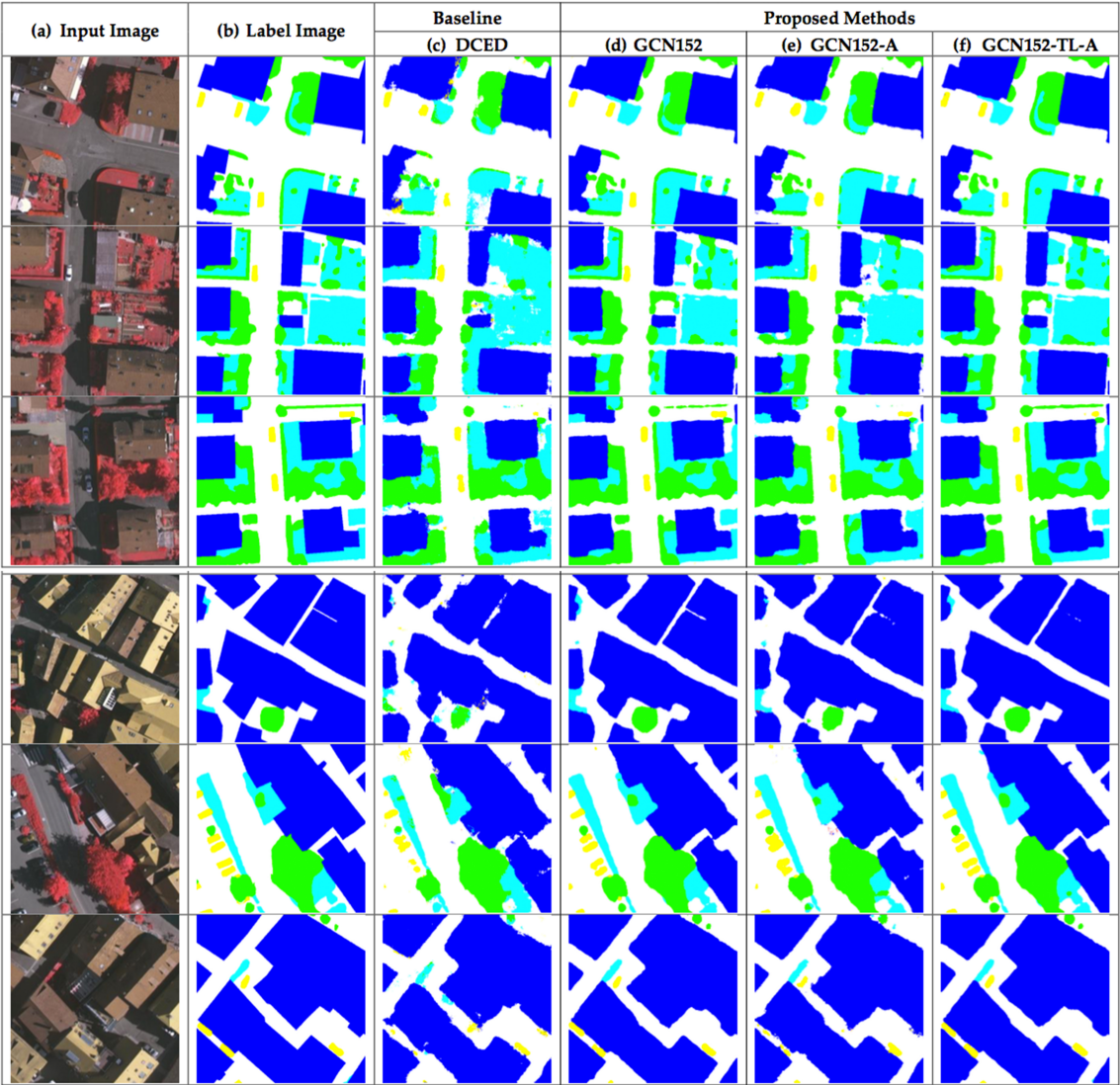
Figure 14. Six testing sample input and output aerial images on ISPRS Vaihingen challenge corpus, where rows refer different images. (a) Original input image; (b) Target map (ground truth); (c) Output of Encoder Decoder (Baseline); (d) Output of GCN152; (e) Output of GCN152-A; and (f) Output of GCN152-TL-A. The label of Vaihingen challenge includes six categories: impervious surface (imp surf, white), building (blue), low vegetation (low veg, cyan), tree (green), car (yellow) and clutter/background (red).

396 As can be seen in Figure 13 and Figure 14, the performance of our best model outperforms
397 other advanced models by a considerable margin on each category, especially for the Impervious
398 Surfaces (IS), Tree, and Car. To show the effectiveness of the proposed methods, we have performed
399 comparisons against a number of state-of-the-art semantic segmentation methods, as listed in Table
400 4, Table 5 that performs on ISPRS corpus and Table 2, Table 3 that performs on Landsat-8 corpus.
401 Encoder Decoder (DCED) [31–33] and GCN [15] are the versions with ResNet-50 as their backbone. In
402 particular, we re-implement the DCED with Tensorflow-Slim [36], since the released code is built on
403 Caffe [38]. We can see that our proposed methods significantly outperforms other methods on both
404 *F1 score* and *mean IoU.*

In terms of the computational cost, our framework requires slightly additional training time compared to the baseline approach, DCED, by about 6.25% (6-7 hours), and GCN, by about 4.5% (4-5 hours). In our experiment, DCED's training procedure took approximately 16 hours per data set, and finished after 50 epochs with 1,152 second per epoch. Our framework is modify on GCN-based deep learning architecture. The "Channel Attention" model increases the time 20 minutes from "GCN152" method. There is no additional time required by reusing pre-trained weights.

6. Conclusions and Future Work

In this study, we propose a novel CNN framework to perform semantic labeling on remote-sensed images. Our proposed method achieves excellent performance by presenting three aspects. First, Global Convolutional Network (GCN) is employed and enhanced by adding larger numbers of layers to better capture the complex features. Second, "Channel Attention" is proposed to assign a proper weight for each extracted feature on different stages of the network. Finally, "Domain Specific Transfer Learning" is introduced to to allay the scarcity issue by training the initial weights using other remotely sensed corpora whose resolutions can be different. The experiments were conducted on two data sets: Landsat-8 (medium resolutions) and ISPRS Vaihingen Challenge (very hign resolution) data sets. The results show that our model that combines all proposed strategies outperforms baseline models in terms of $F1$ and $MeanIoU$. The final results show that our enhanced GCN outperforms the baseline (DCED)—17.48% for F1 on Landsat-8 corpus and 2.48% on ISPRS corpus.

In the future, more choices of semantic labeling, modern optimization techniques and/or other novel activation functions will be investigated and compared to obtain the best GCN-based framework for semantic segmentation in remotely-sensed images. Moreover, incorporating other data sources (e.g. digital surface model) might be needed to increase the accuracy of the Deep Learning for both the CNN and modern Deep Learning layer with very low confidence simultaneously. These aforementioned issues will be investigated in future research.

Acknowledgments: T. Panboonyuen thanks the scholarship from The 100th Anniversary Chulalongkorn University Fund granted and The 90th Anniversary Chulalongkorn University Fund (Ratchadaphiseksomphot Endowment Fund). We greatly acknowledge Geo-informatics and Space Technology Development Agency (GISTDA), Thailand, for providing satellite imagery used in this study.

Author Contributions: Teerapong Panboonyuen performed all the experiments and wrote the paper; and Peerapon Vateekul performed the results analysis and edited manuscript. Kulsawasd Jitkajornwanich, SiamLawawirojwong and Panu Srestasathiern reviewed results. Teerapong Panboonyuen revised manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BR	Boundary Refinement
CNN	Convolutional Neural Network
DCED	Deep Convolutional Encoder-Decoder
GCN	Global Convolutional Network
IS	Impervious Surfaces
Misc	Miscellaneous
MR	Medium Resolution
RGB	Red-Green-Blue
LS	Landsat
LV	Low Vegetation
TL	Transfer Learning
VHR	Very High Resolution

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