Chula
Chulalongkorn University

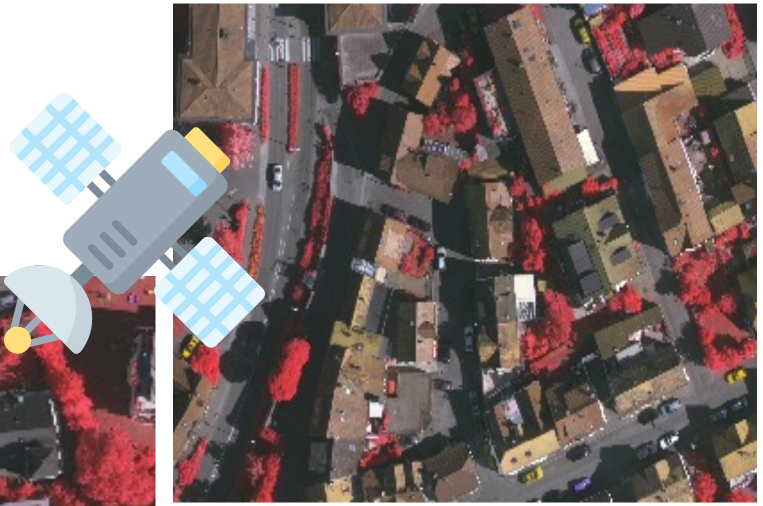
Dissertation Defense

Semantic Segmentation on Remotely Sensed Images Using Deep Convolutional Encoder-Decoder Neural Network

Teerapong Panboonyuen (ID: 6071467821)

Ph.D. Candidate (Computer Engineering, Chulalongkorn University)

https://kaopanboonyuen.github.io



CHULA ENGINEERING Foundation toward Innovation COMPUTER

GISTDA

CHULA ENGINEERING Foundation toward Innovation

PhD Defense *Date: July 9, 2020*

Evaluation Result: Very Good (the highest thesis grade at Chulalongkorn University)

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    - Michigan State University, USA
- Panu Srestasathiern, Ph.D. (External Examiner)
    - The Ohio State University, USA

Teerapong Panboonyuen successfully defended his Ph.D. dissertation on July 9, 2020, at the Department of Computer Engineering, Chulalongkorn University, before a distinguished committee of Thai scholars with international doctoral credentials.

Moments from my PhD Defense Day

PhD defense accomplished!

Grateful for the support of my committee during this journey, especially navigating it over Zoom due to COVID-19.

Excited to officially be on the other side and ready for what's next in AI!

PhD Defense *Date: July 9, 2020*

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Outline

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and Reference

Outline | Introduction

- Introduction
- Related Theory
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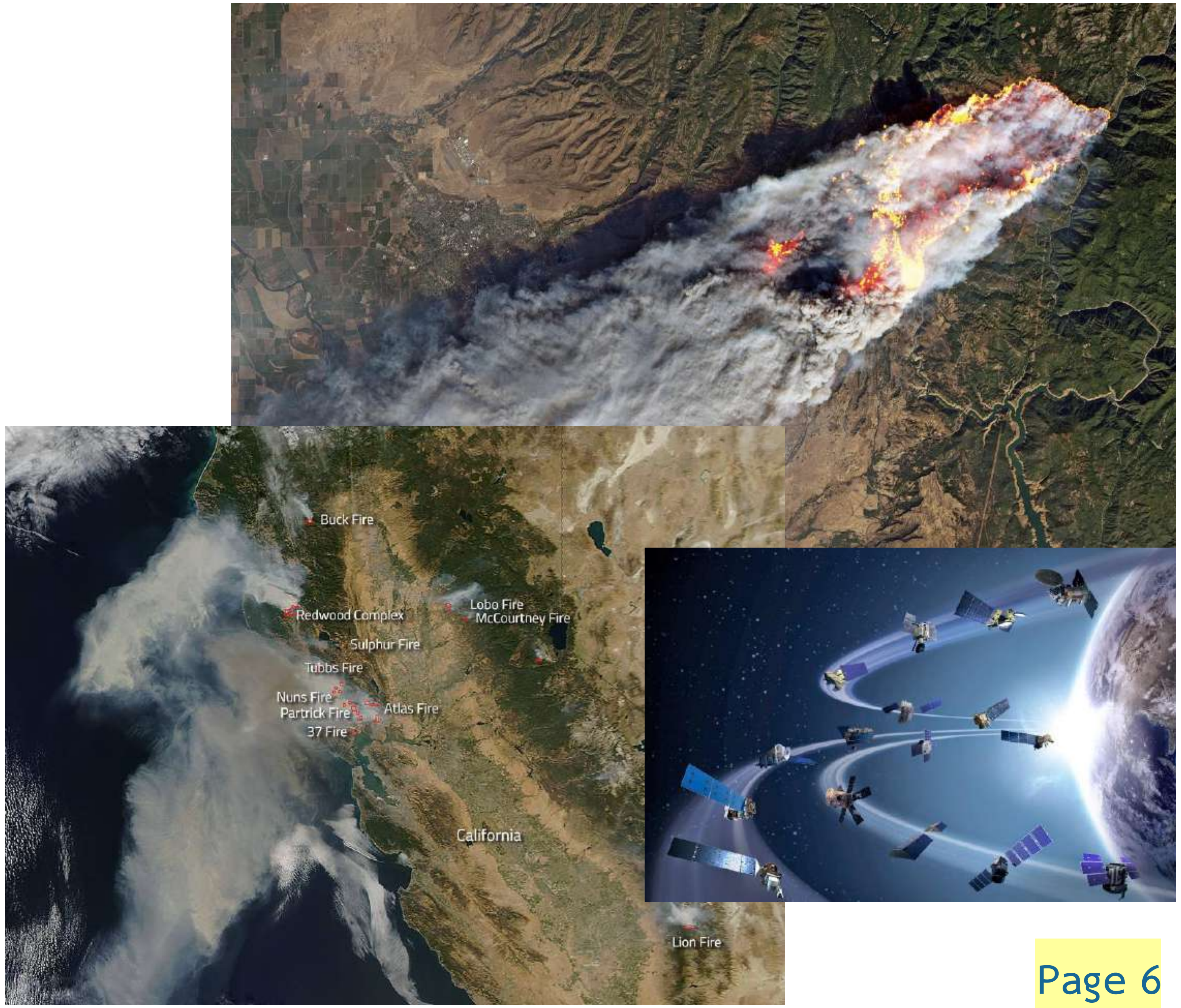
Introduction

- Semantic segmentation of remotely-sensed corpora
  - Aerial (or Very-High Resolution, VHR) images
  - Satellite (or Medium-Resolution, MR) images
- Convolution Neural Network (CNNs)
  - Classification of images has becomes very efficient and smart
  - Can create the pre-trained deep CNNs with fixed parameters are transferred for remote scene classification
  - Overcomes the traditional method (K-means, Neural Nets) on Remote Sensing corpora



Introduction

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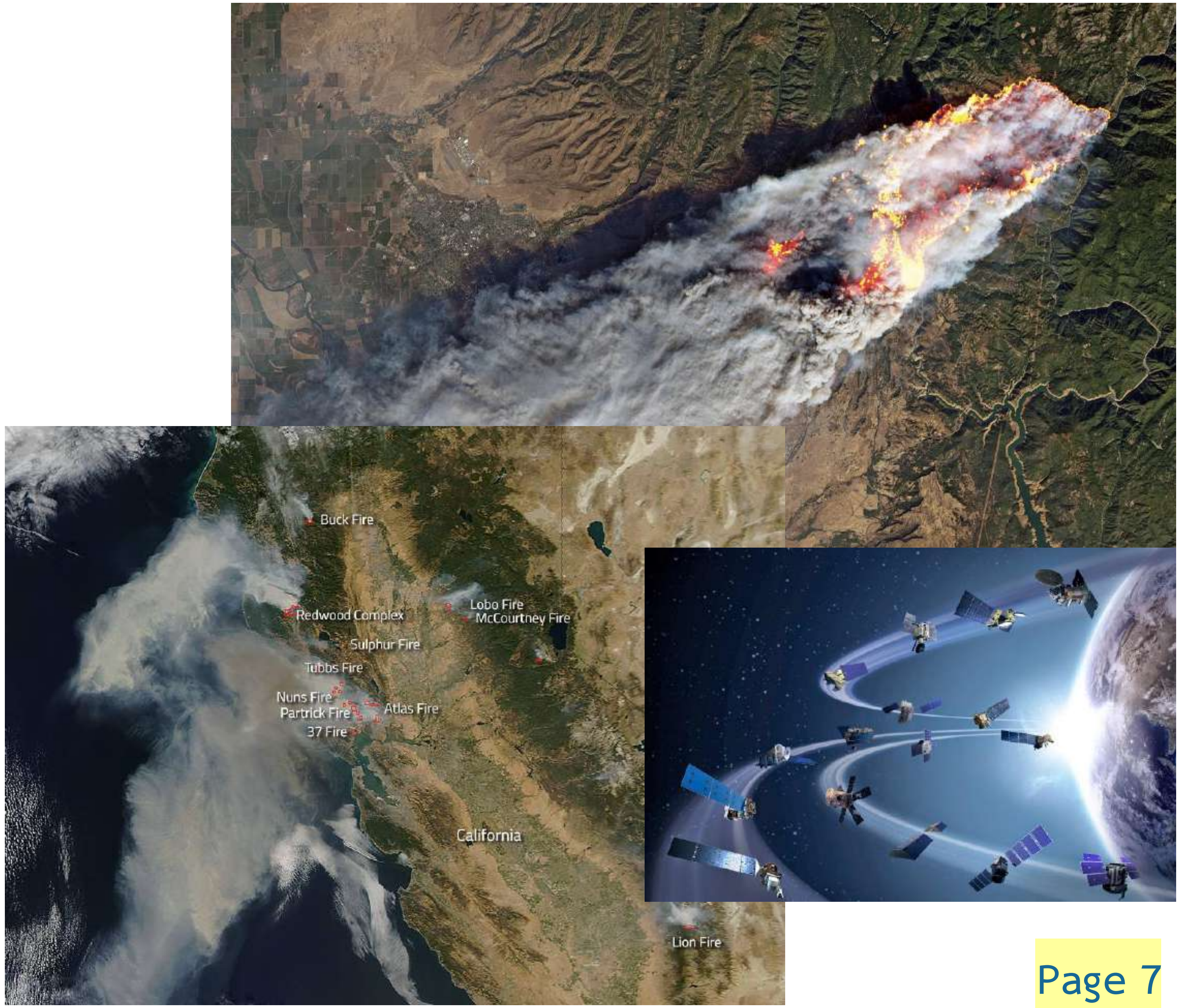

Introduction

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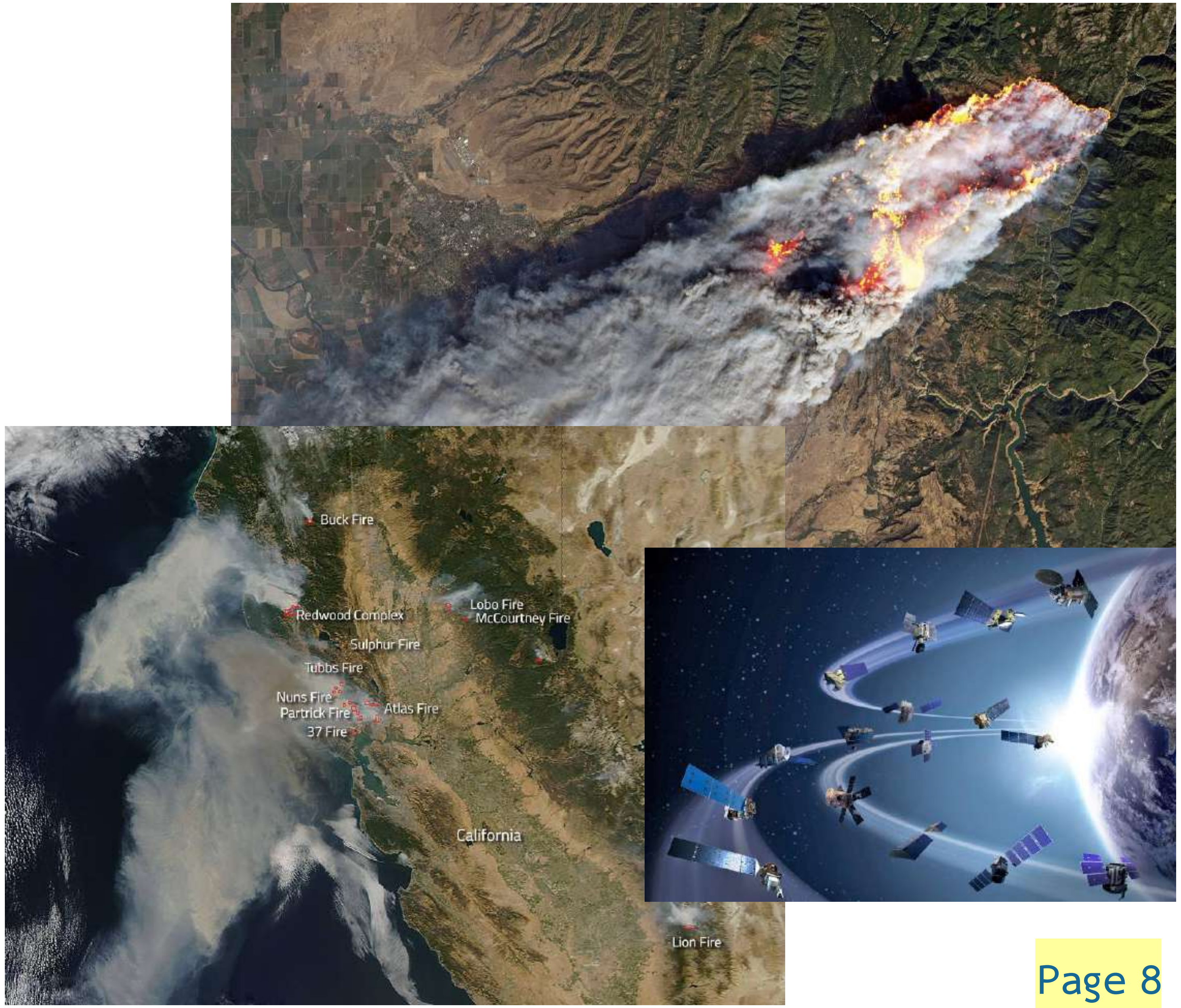

Introduction (cont.)

- It has been implemented in many applications in various domains
  - Urban planning, map updates, route optimization, and navigation
  - Allowing us to better understand the domain's images and create important real-world applications
- It is mainly used for the agricultural purpose
  - Crop mapping, forest inventory, land cover
- The most widely used satellite for agriculture is LANDSAT 8
  - It contains operational land imager (OLI) and thermal infrared sensor (TIRS)
  - It covers the landmass, agriculture and remote areas

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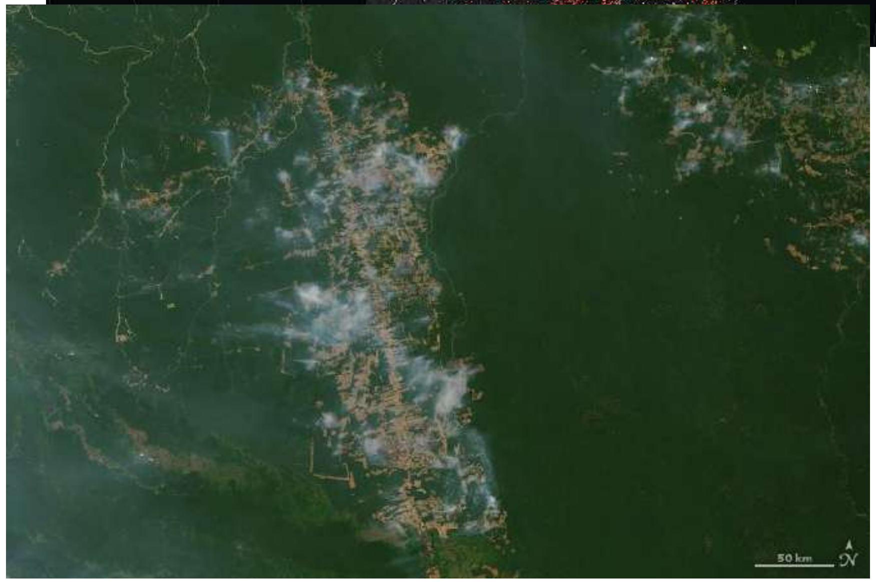
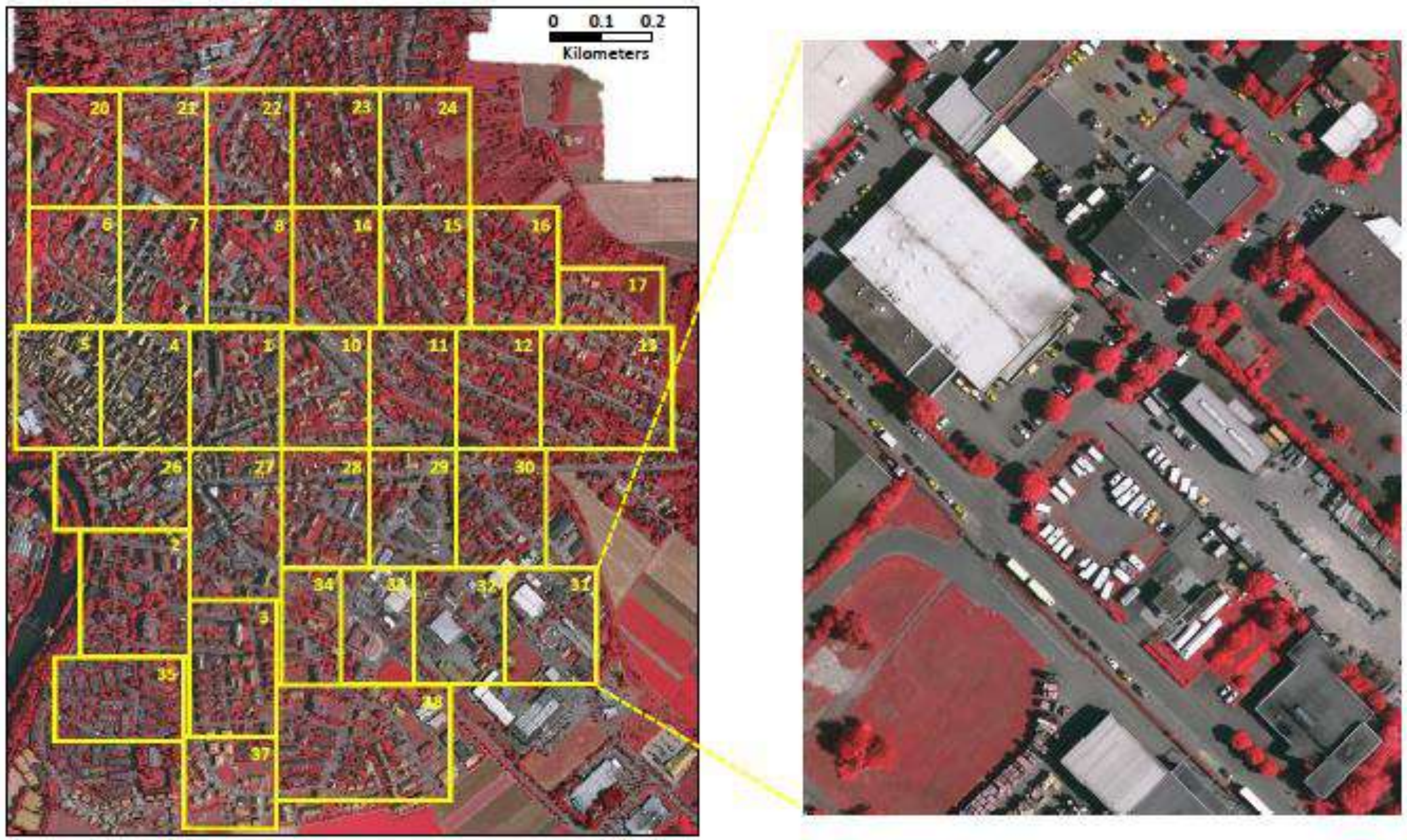
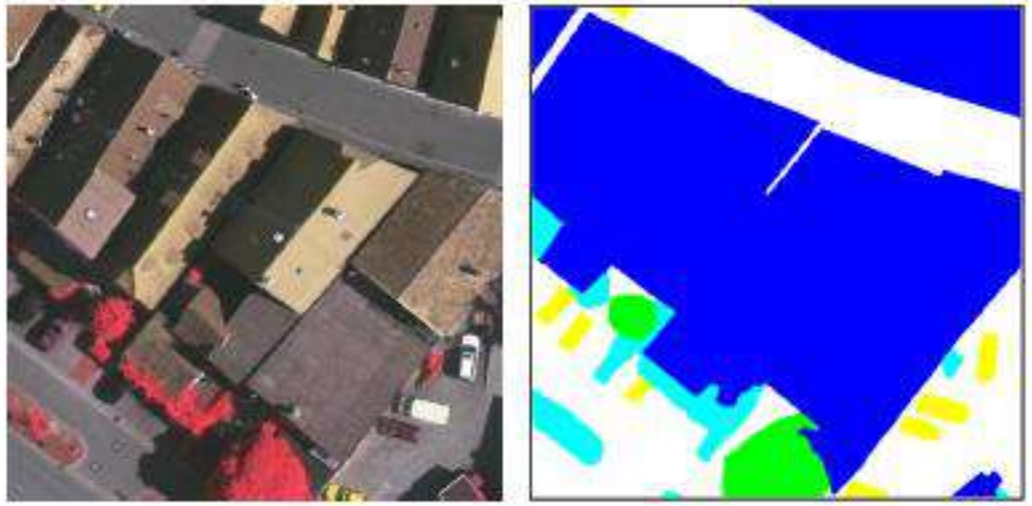


https://earthobservatory.nasa.gov/images/145498/uptick-in-amazon-fire-activity-in-2019

Public and Private Corpora

Public corpus (ISPRS Vaihingen Corpus)

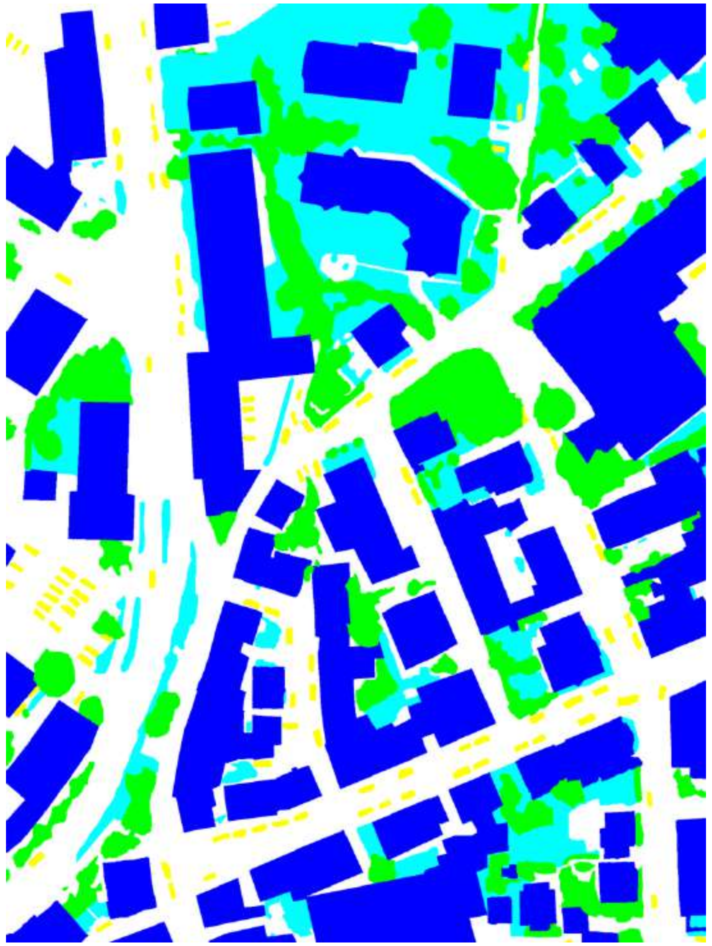




(a) image (b) ground truth

Public and Private Corpora

Public corpus (ISPRS Vaihingen Corpus)



Color	Class
	Car
	Building
	Tree
	Low Vegetation
	Imp Surfaces
	Clutter

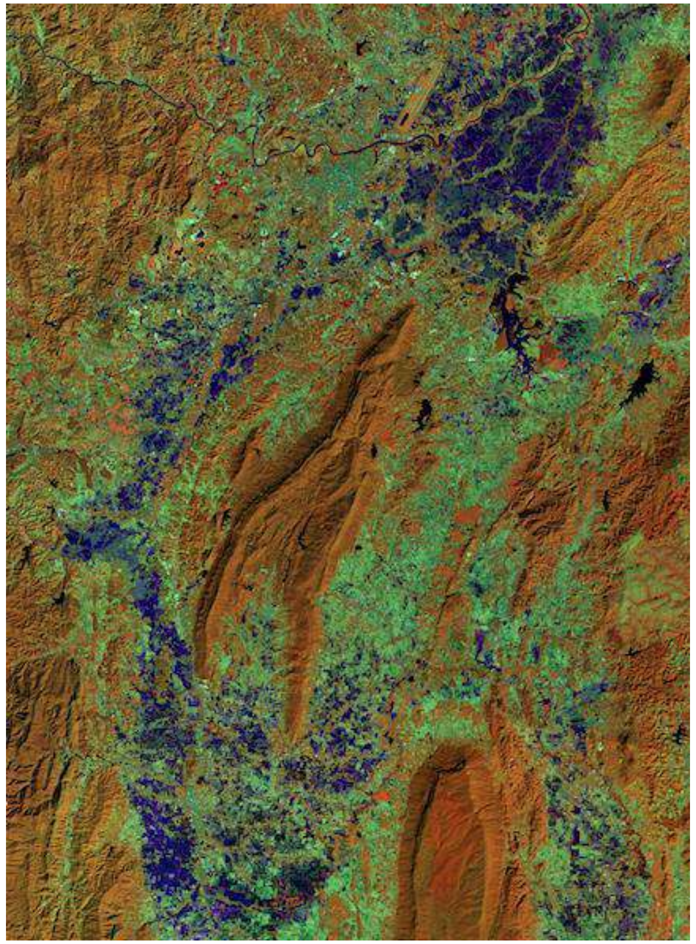
Public and Private Corpora

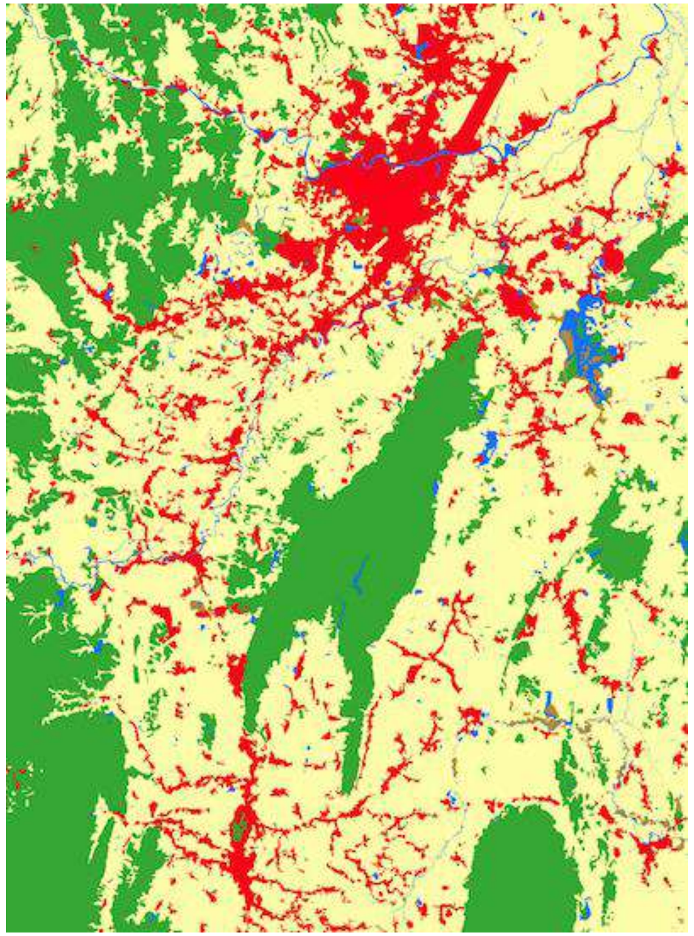
Public corpus (ISPRS Vaihingen Corpus)

- There are 33 images of about 2,500 × 2,000 pixels at a ground sampling distance (GSD) of about 9 cm in the image data
- We randomly split the 16 images with ground truth available
  - into a training set of 10 images and a validation set of 6 images
- 4 tiles (Image Numbers 5, 7, 23, and 30) were removed from the training set as the testing corpus

Public and Private Corpora

Private corpus (GISTDA Nan Province Corpus)





Color	Class
	Agriculture
	Forest
	Miscellaneous
	Urban
	Water

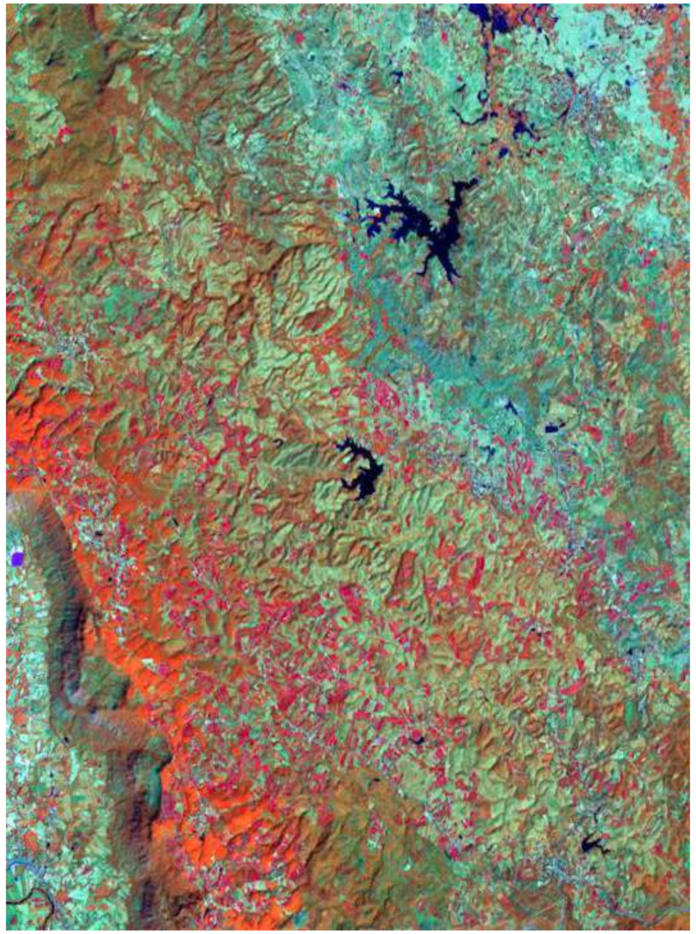
Public and Private Corpora

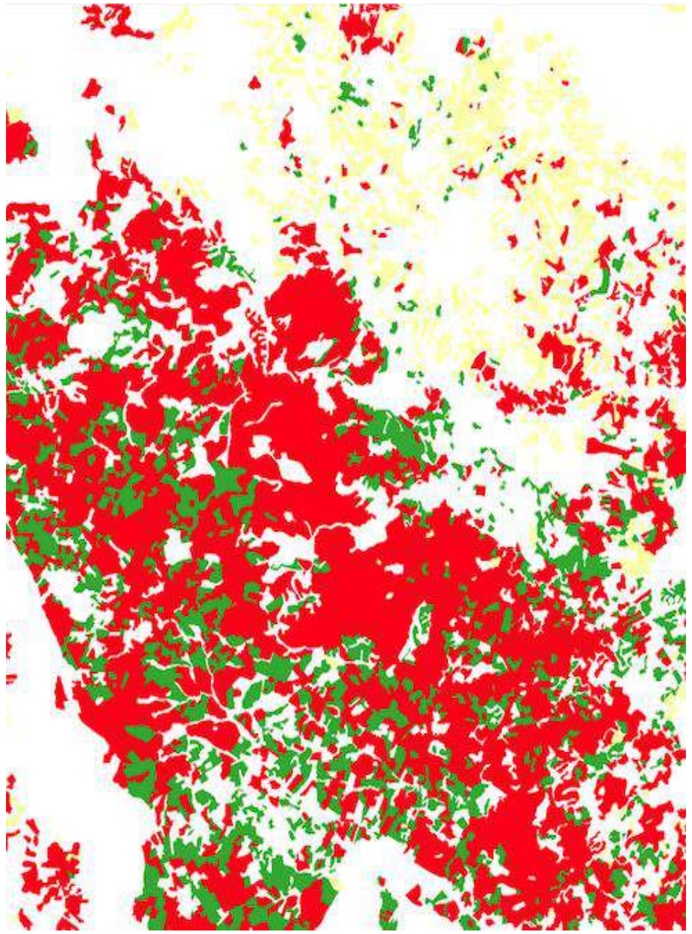
Private corpus (GISTDA Nan Province Corpus)

- The dataset is obtained from Landsat-8 satellite consisting of 1,012 satellite images
- Bands 5, 4, and 3 are used
- Capture at Nan, a province in Thailand
- Medium resolution (16,800 × 15,800)
- The 1,012 images were split into 800 training and 112 validation images with publicly available annotation, as well as 100 testing images with annotations withheld

Public and Private Corpora

Private corpus (GISTDA ISAN Zone Corpus)



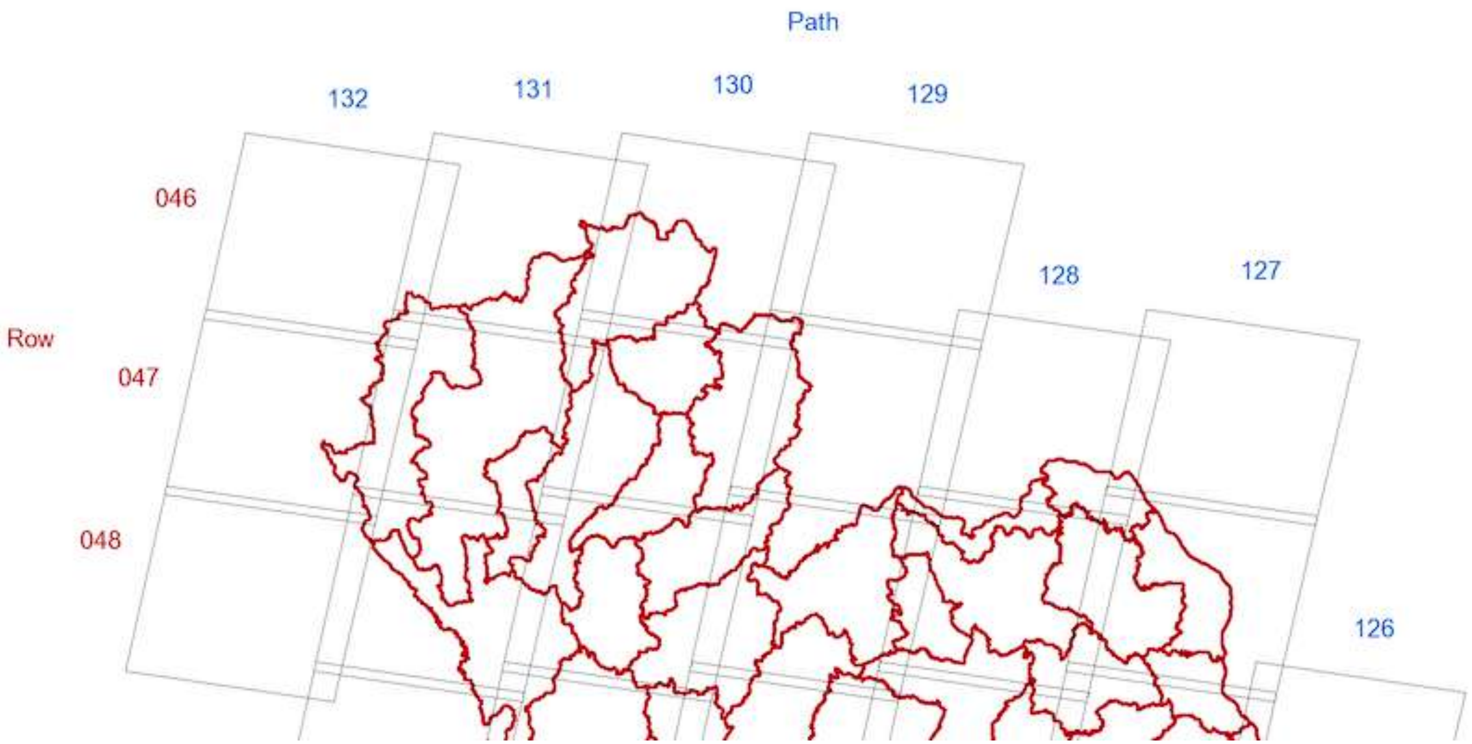


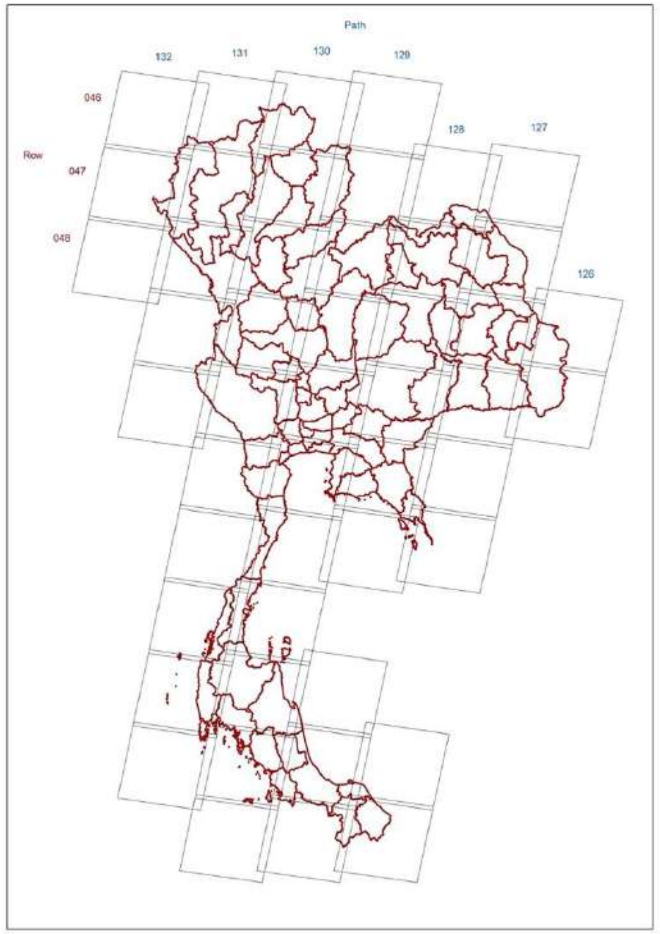
Color	Class
	Corn
	Pineapple
	Para Rubber
	Miscellaneous

Public and Private Corpora

Private corpus (GISTDA ISAN Zone Corpus)

- For the Dissertation, we select **LC129048, LC130050** zone as the LC3W corpus

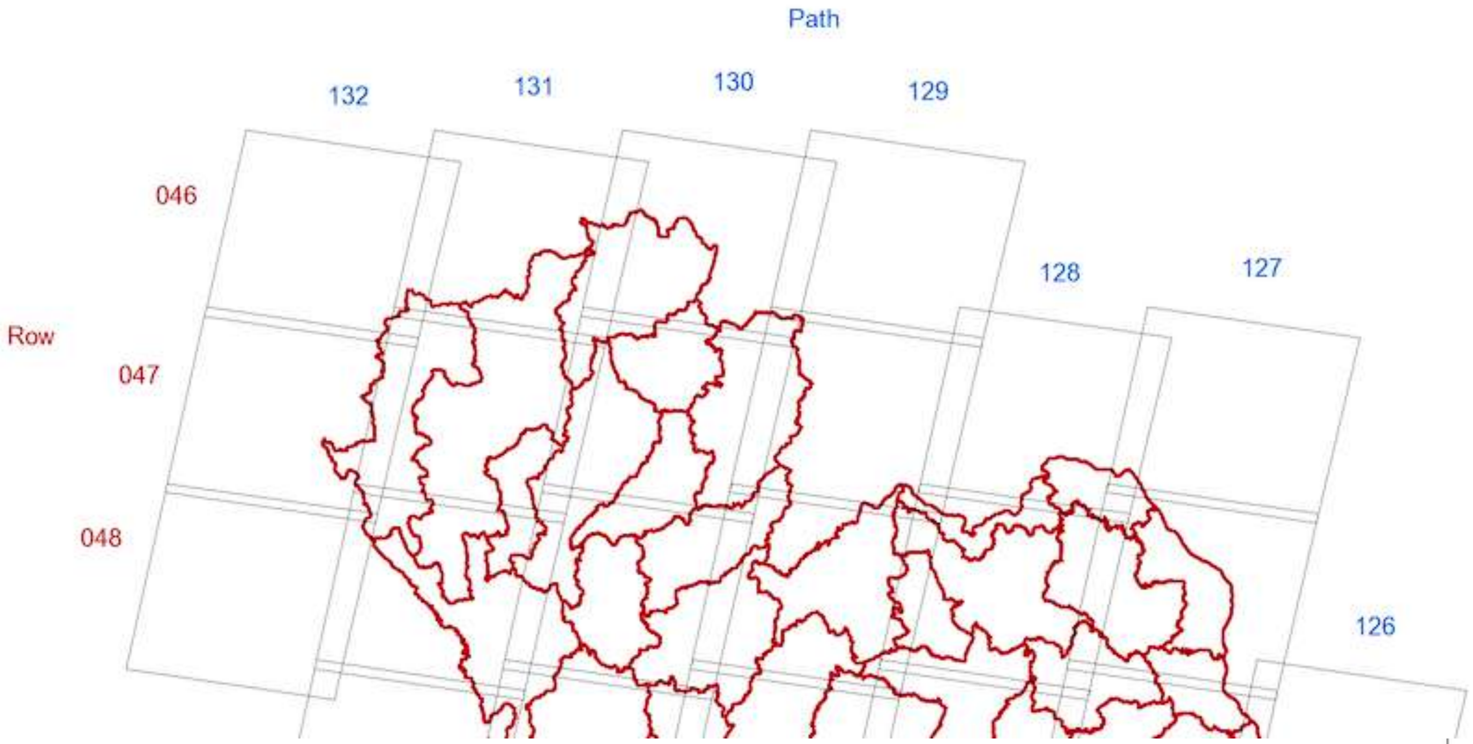


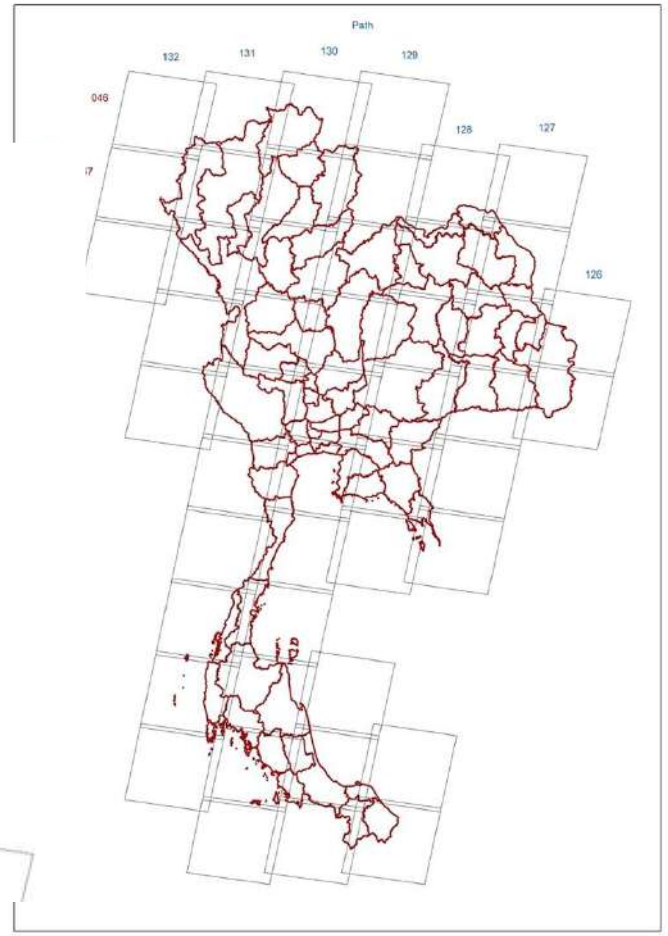


Public and Private Corpora

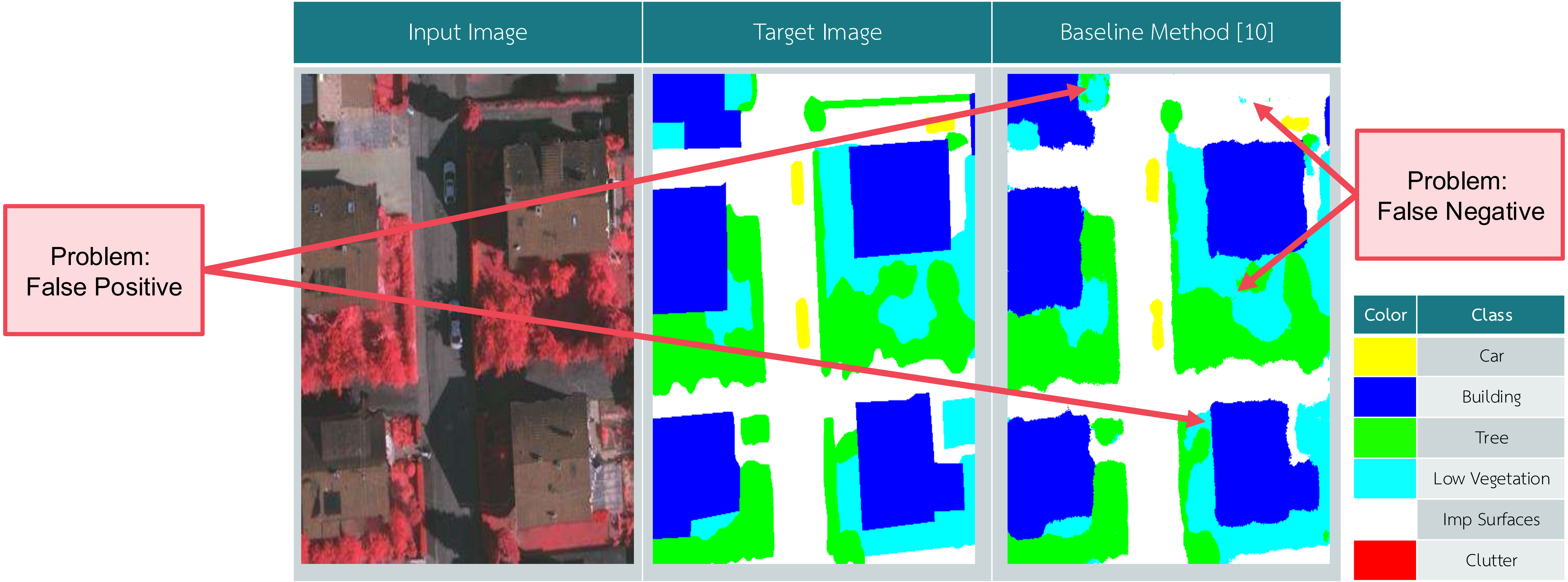
Private corpus (GISTDA ISAN Zone Corpus)

- For the Dissertation, we select **LC129048, LC130050** zone as the LC3W corpus
- Medium resolution (15,376x15,872) pixels
- 764 training
- 112 validating
- 100 testing





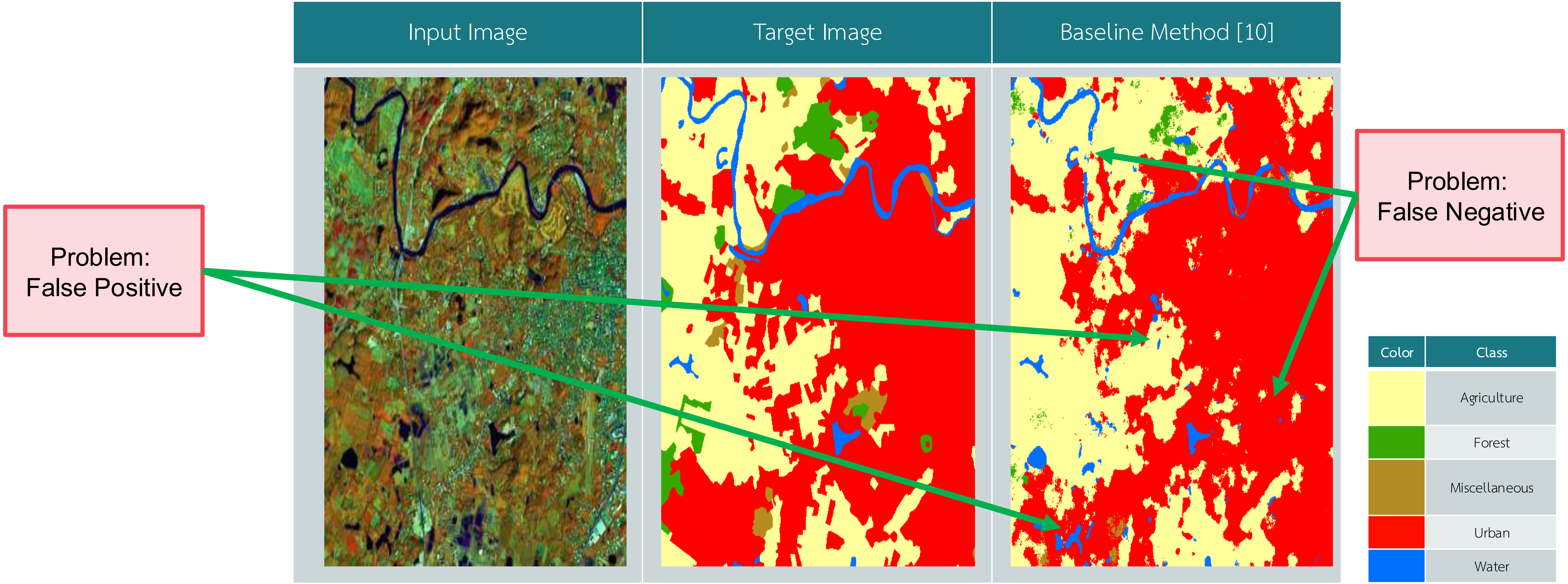
Statement of Problem (1) Very High Resolution



Color	Class
Yellow	Car
Blue	Building
Green	Tree
Cyan	Low Vegetation
White	Imp Surfaces
Red	Clutter

[10] Liu, Y., Fan, B., Wang, L., Bai, J., Xiang, S., & Pan, C. (2018). Semantic labeling in very high resolution images via a self-cascaded convolutional neural network. ISPRS Journal of Photogrammetry and Remote Sensing, 145, 78-95.

Statement of Problem (2) Medium Resolution

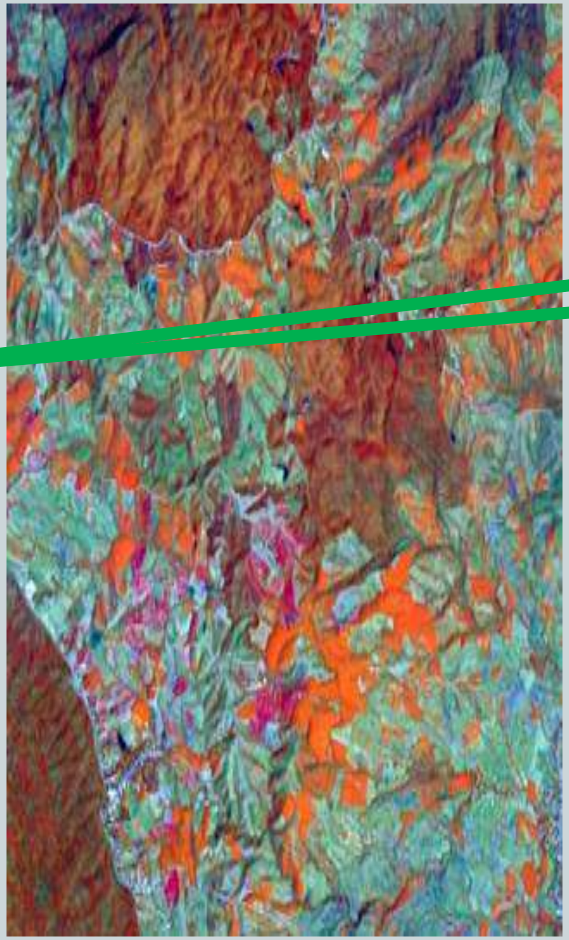
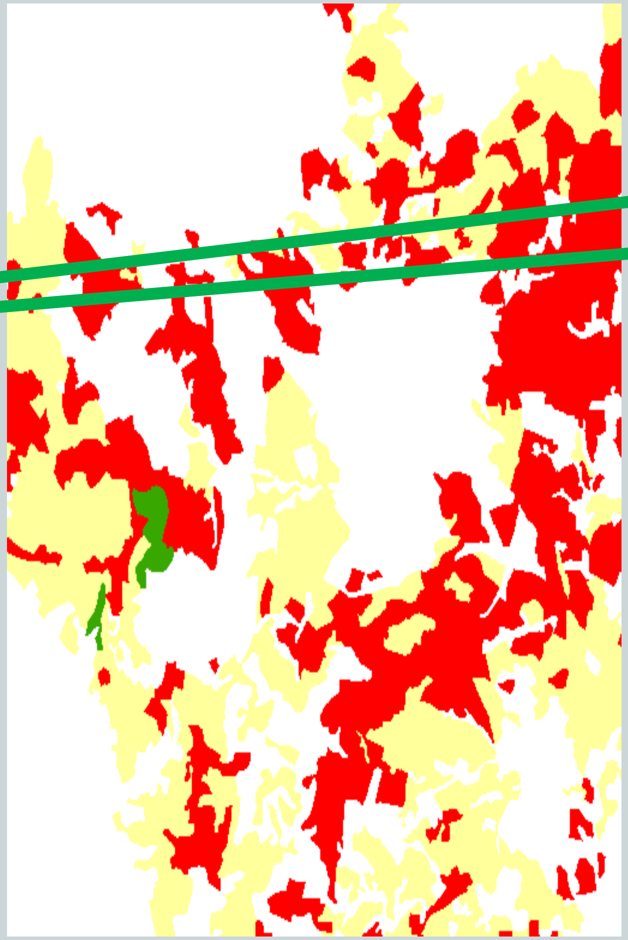
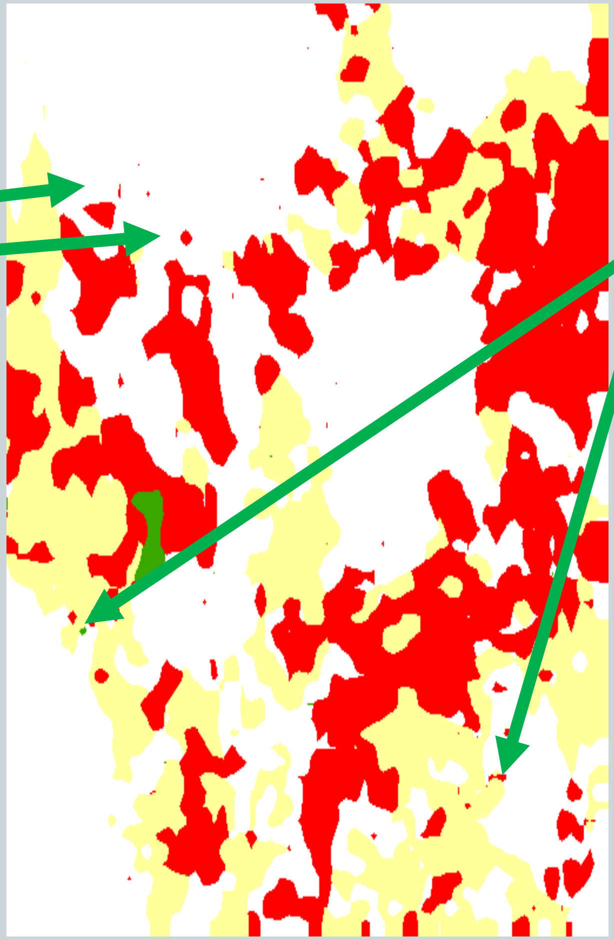


Color	Class
	Agriculture
	Forest
	Miscellaneous
	Urban
	Water

[10] Liu, Y., Fan, B., Wang, L., Bai, J., Xiang, S., & Pan, C. (2018). Semantic labeling in very high resolution images via a self-cascaded convolutional neural network. ISPRS Journal of Photogrammetry and Remote Sensing, 145, 78-95.

Statement of Problem (3) Medium Resolution

Problem:
False Positive

Input Image	Target Image	Baseline Method [10]
		

Problem:
False Negative

Color	Class
	Corn
	Pineapple
	Para Rubber
	Miscellaneous

[10] Liu, Y., Fan, B., Wang, L., Bai, J., Xiang, S., & Pan, C. (2018). Semantic labeling in very high resolution images via a self-cascaded convolutional neural network. ISPRS Journal of Photogrammetry and Remote Sensing, 145, 78-95.

Statement of Problem (4)

- False Positive Problem
  - High Level (Sharp Boundary Object) such as Building Object, Rubber Tree (Zone)
- False Negative Problem
  - Rare Class (Low-Level Class) such as Water Class
- Motivation
  - This leads to some inconsistent results that suffer from accuracy performance
  - The primary challenge of this remote sensing task is a lack of training data
  - This, in fact, has become a motivation of this work

Outline | Related Theory

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Related Theory

- (1) Transfer Learning
- (2) Channel Attention
- (3) Feature Fusion
- (4) Depthwise Convolution
- (5) Design CNNs

Related Theory

- **(1) Transfer Learning**
- (2) Channel Attention
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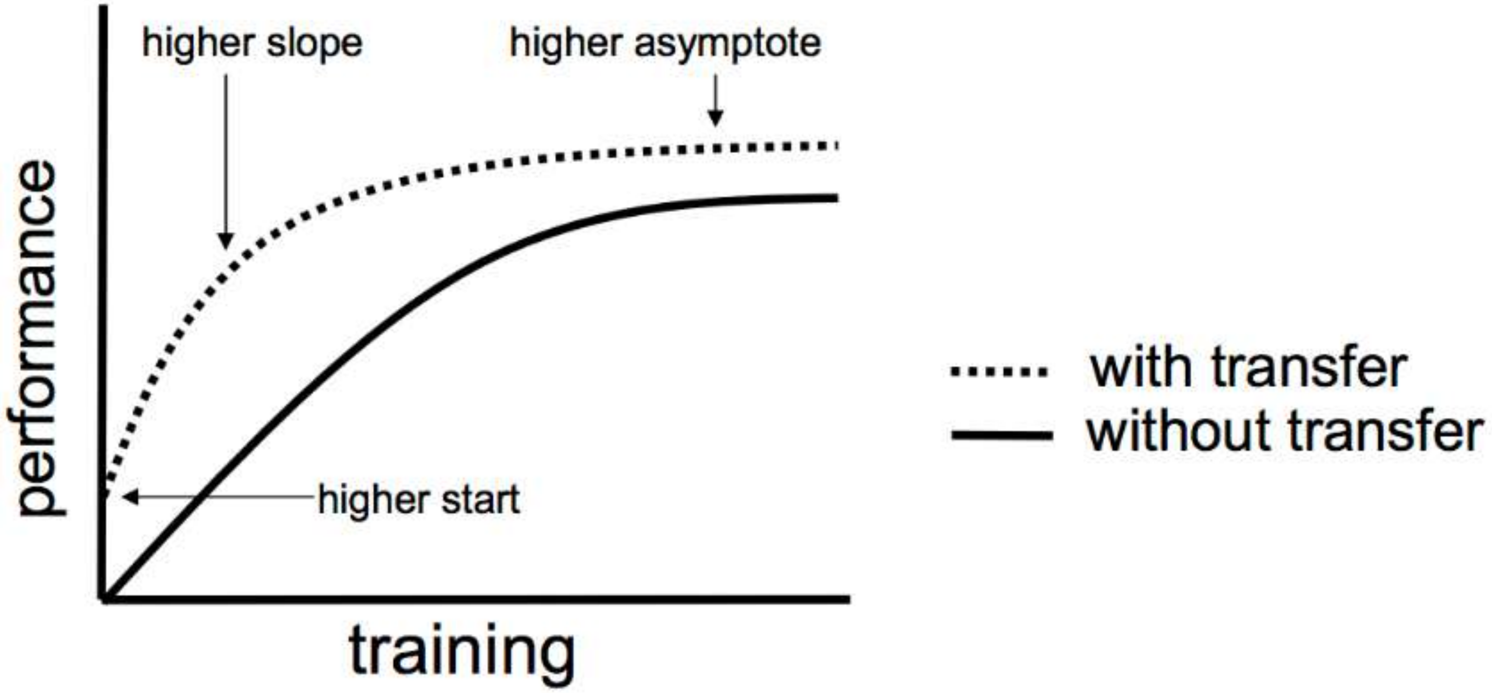
"Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned."



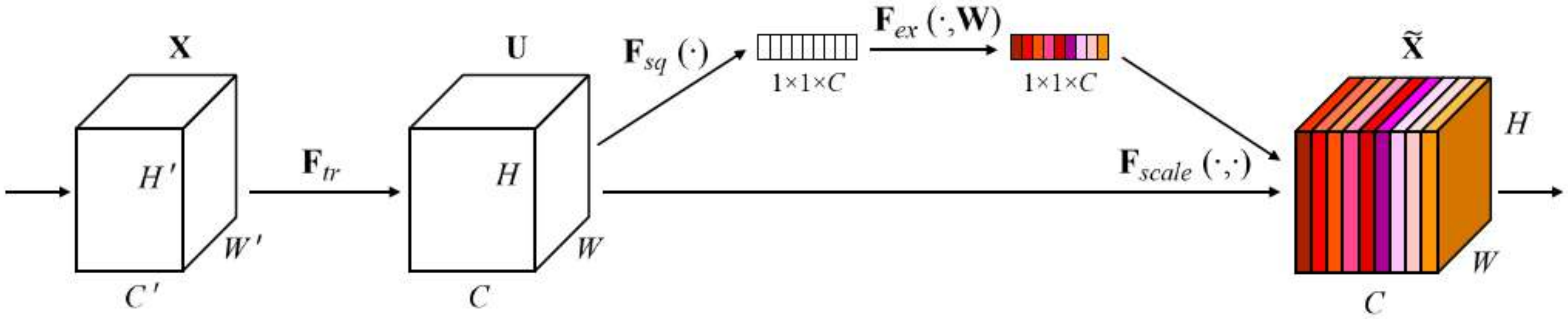
https://machinelearningmastery.com/transfer-learning-for-deep-learning/

Related Theory

Self Attention

- (1) Transfer Learning
- **(2) Channel Attention**
- (3) Feature Fusion
- (4) Depthwise Convolution
- (5) Design CNNs

- Attention is helpful to focus on what we want
- We utilize channel attention to select the important features



One word “attends” to other words in the same sentence differently.

Refers to Squeeze-and-Excitation Networks and BiseNet

Related Theory

Self Attention

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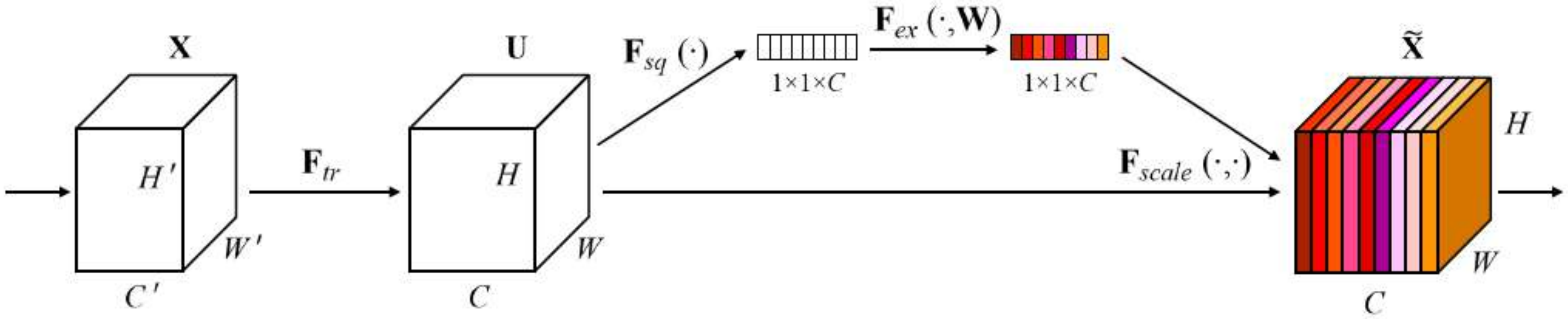

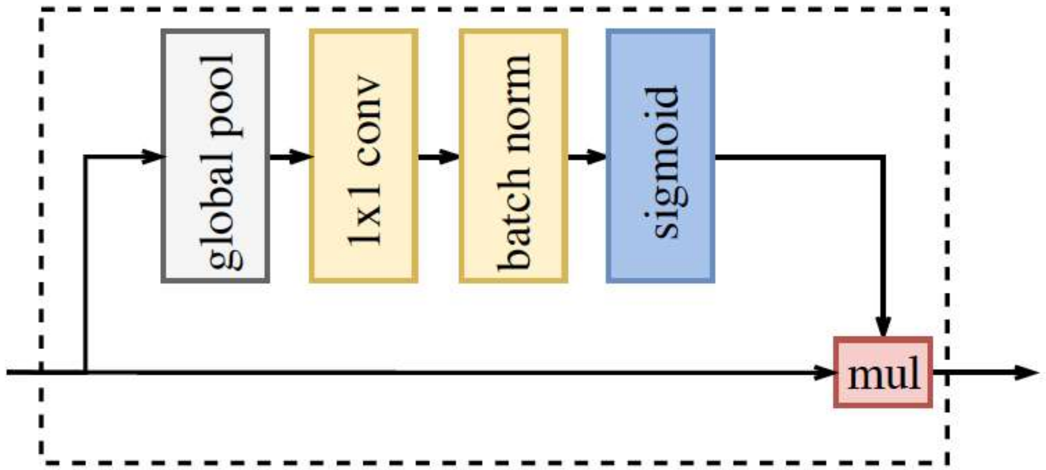

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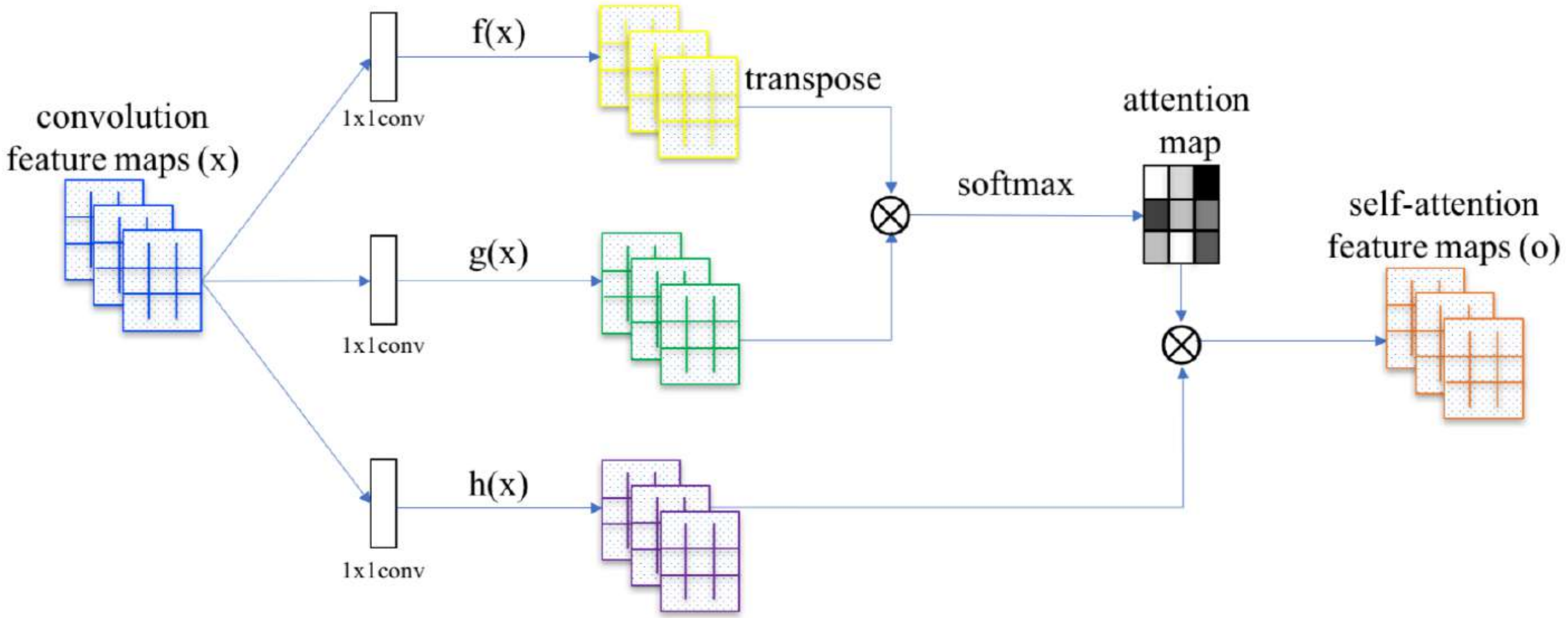


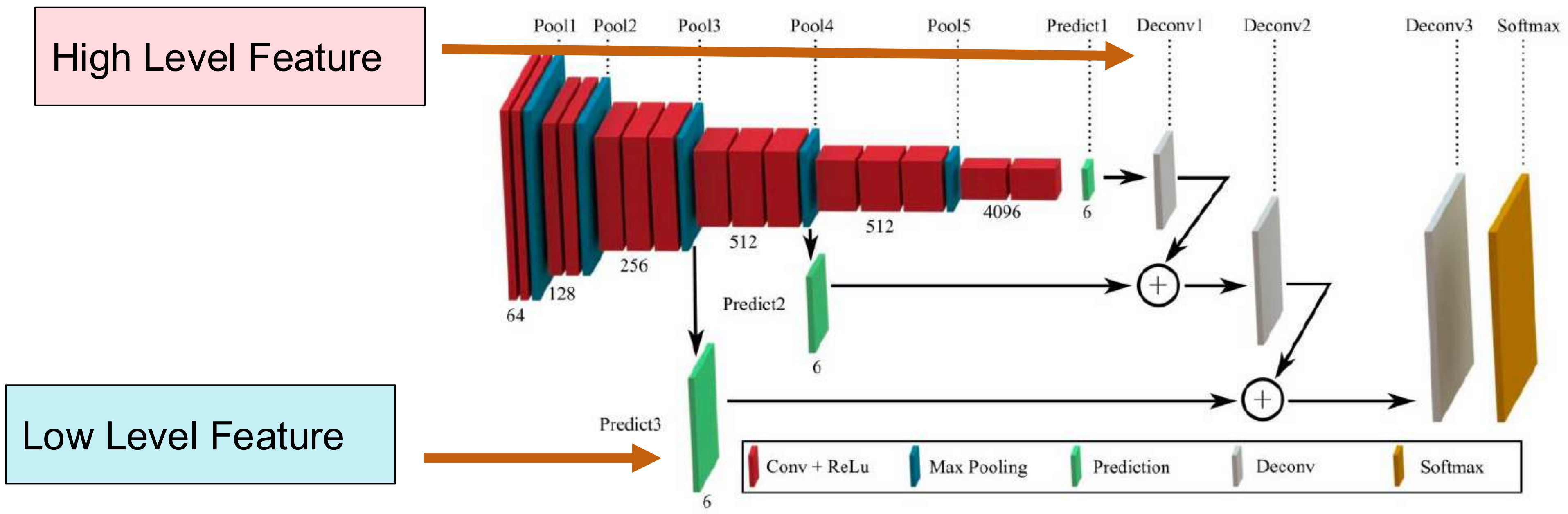
https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

Related Theory

Feature Fusion (1)

- (1) Transfer Learning
- (2) Channel Attention
- **(3) Feature Fusion**
- (4) Depthwise Convolution
- (5) Design CNNs

- The features of the two paths are different in level of feature representation
- Simply sum up low and high features
  - Utilization of low-level features for objects refinement



Tai, Lei, et al. "PCA-aided fully convolutional networks for semantic segmentation of multi-channel fMRI." 2017 18th International Conference on Advanced Robotics (ICAR). IEEE, 2017.

Related Theory

Feature Fusion (2)

- (1) Transfer Learning
- (2) Channel Attention
- **(3) Feature Fusion**
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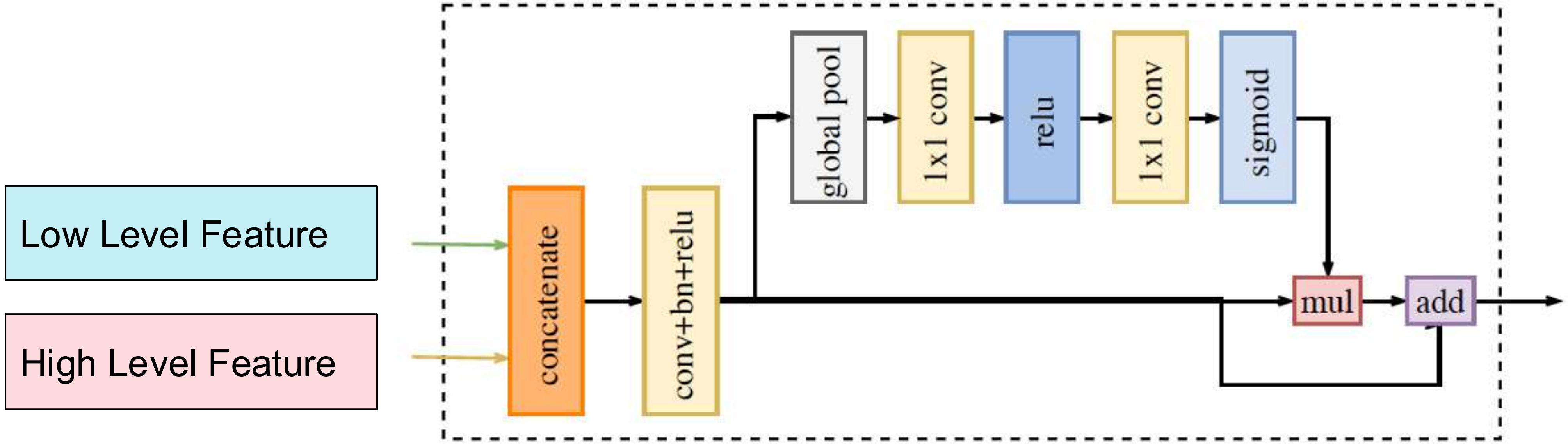
- (5) Design CNNs

- The features of the two paths are different in level of feature representation
- Fuse spatial path (low level features) and context path (high level feature) together



(c) Feature Fusion Module

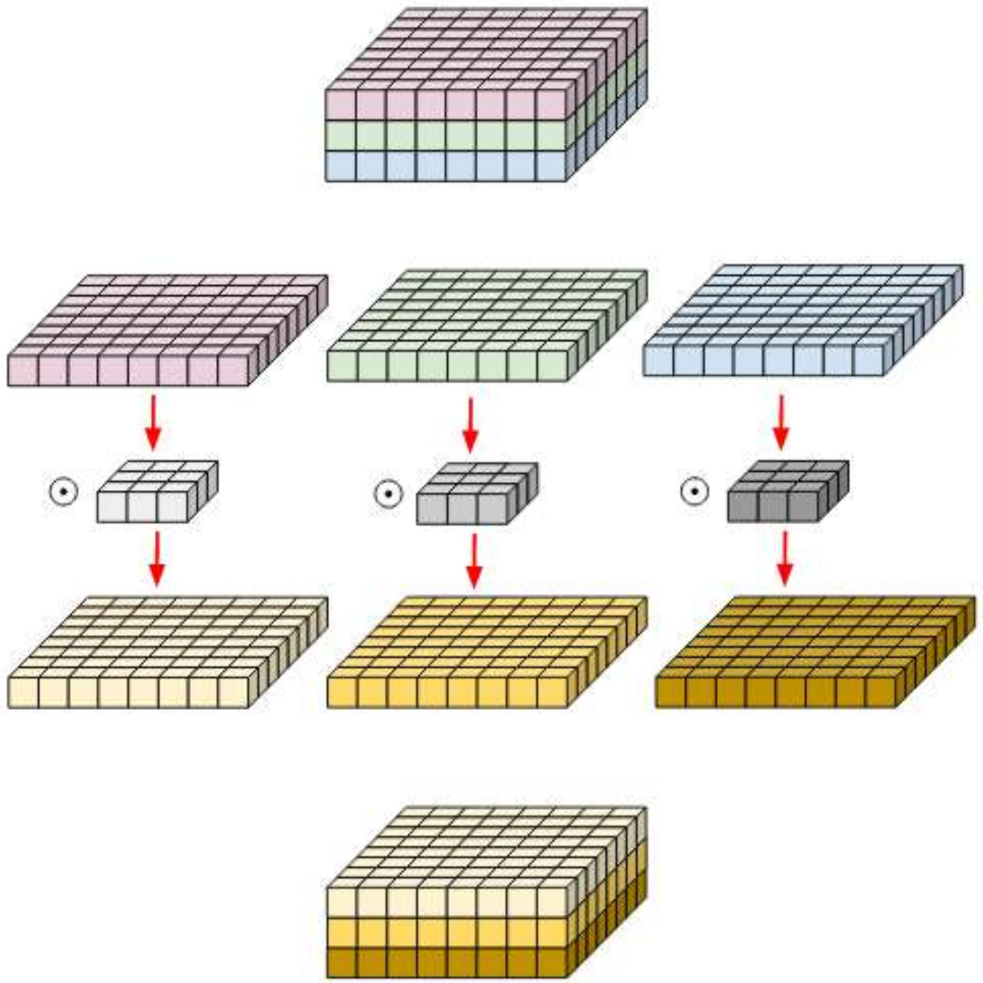
Yu, C., Wang, J., Peng, C., Gao, C., Yu, G., & Sang, N. (2018). Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 325-341).

Related Theory

Depth-wise Convolution

- (1) Transfer Learning
- (2) Channel Attention
- (3) Feature Fusion
- **(4) Depthwise Convolution**
- (5) Design CNNs

- Filters and image **have been broken into three different channels** and then convolved separately and stacked thereafter



https://medium.com/@zurister/depth-wise-convolution-and-depth-wise-separable-convolution-37346565d4ec

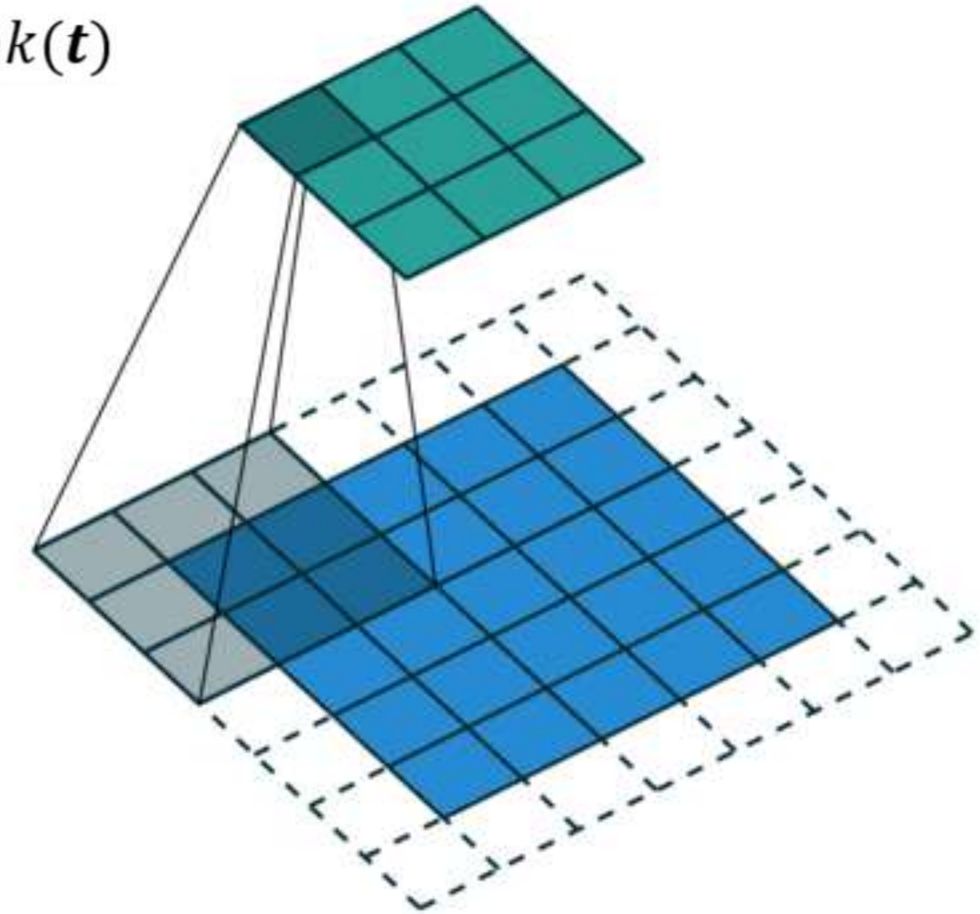
Related Theory

Point-wise Convolution

- (1) Transfer Learning
- (2) Channel Attention
- (3) Feature Fusion
- **(4) Depthwise Convolution**
- (5) Design CNNs

This is the standard discrete convolution:

$$(F * k)(\boldsymbol{p}) = \sum_{\boldsymbol{s}+\boldsymbol{t}=\boldsymbol{p}} F(\boldsymbol{s})k(\boldsymbol{t})$$



https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Dilated Convolution (Atrous Convolution)

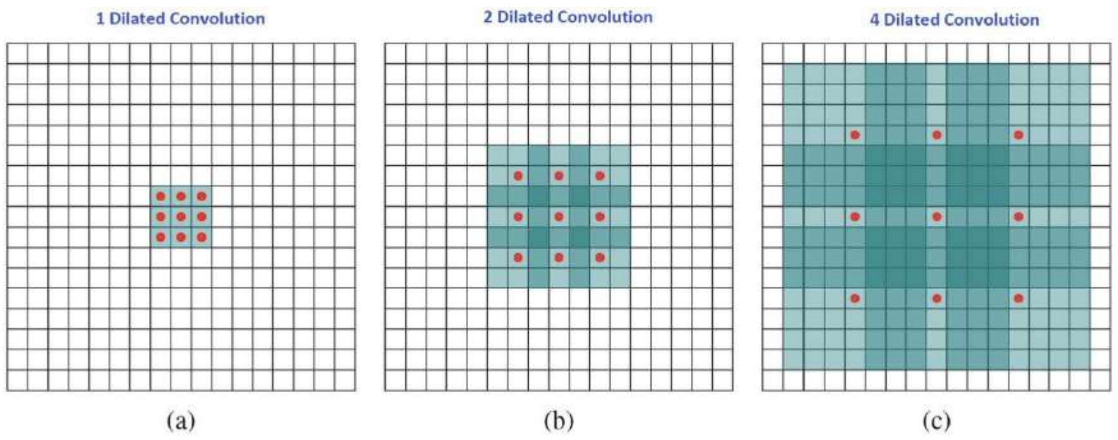
- (1) Transfer Learning
- (2) Channel Attention
- (3) Feature Fusion
- **(4) Depthwise Convolution**
- (5) Design CNNs

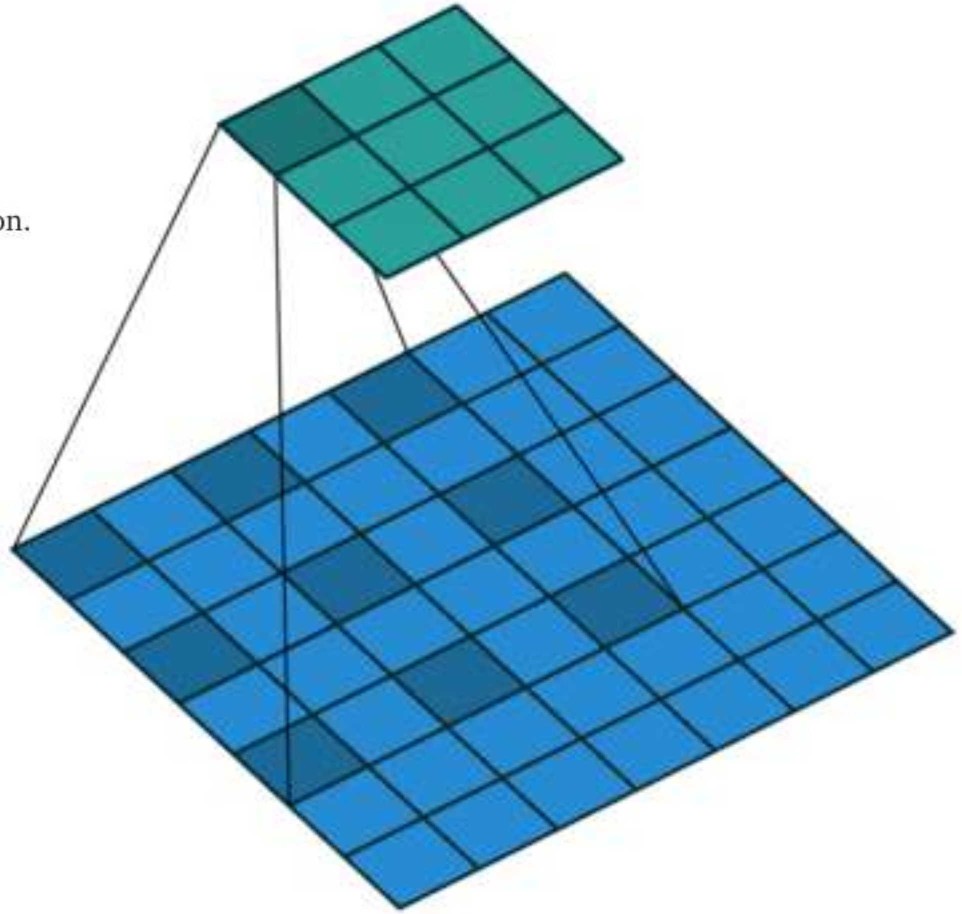
- **Multi-scale context aggregation** by dilated convolutions

The dilated convolution follows:

$$(F *_l k)(\boldsymbol{p}) = \sum_{\boldsymbol{s}+l\boldsymbol{t}=\boldsymbol{p}} F(\boldsymbol{s})k(\boldsymbol{t})$$

When $l = 1$, the dilated convolution becomes as the standard convolution.





https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Related Theory

Dilated Convolution (Atrous Convolution)

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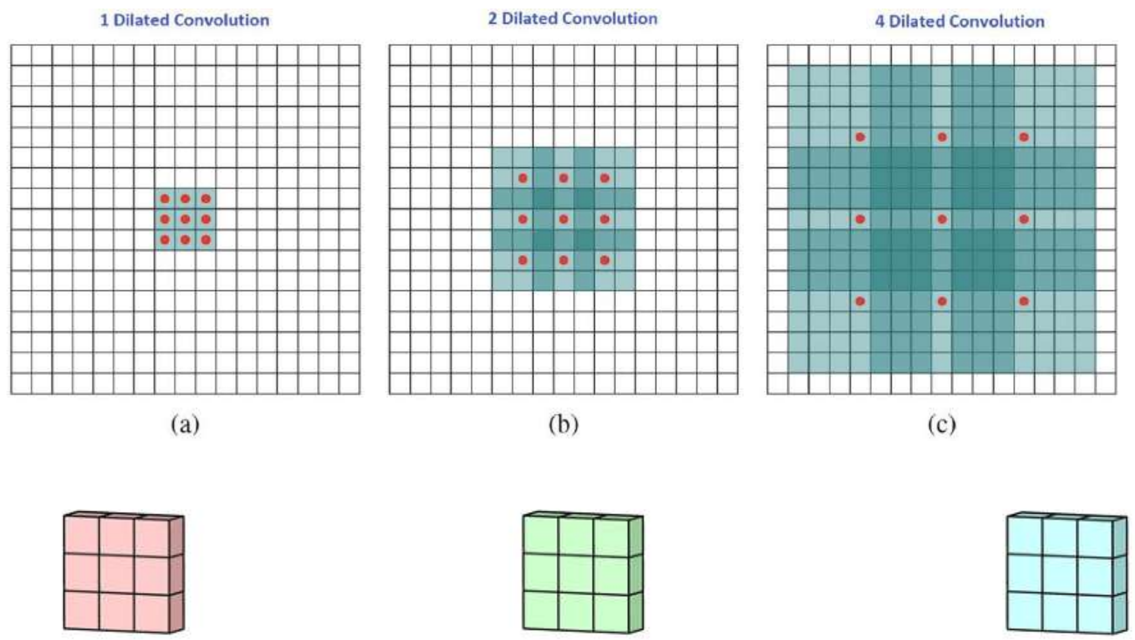
- **Multi-scale context aggregation** by dilated convolutions



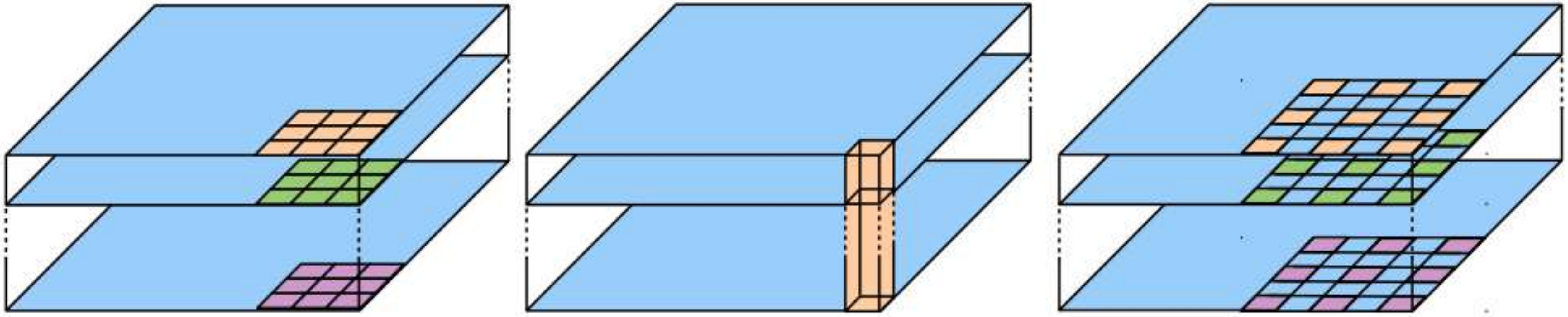
https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Related Theory

Dilated Convolution (Atrous Convolution)

- (4) Depthwise Convolution

- **Multi-scale context aggregation** by dilated convolutions
- 3x3 Depthwise separable convolution decomposes a standard convolution into
- (a) a depthwise convolution (applying a single filter for each input channel)
- (b) a pointwise convolution (combining the outputs from depthwise convolution across channels).
- In this example, we explore atrous separable convolution where atrous convolution is adopted in the depthwise convolution, as shown in (c) with rate = 2.



(a) Depthwise conv. (b) Pointwise conv. (c) Atrous depthwise conv.

https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

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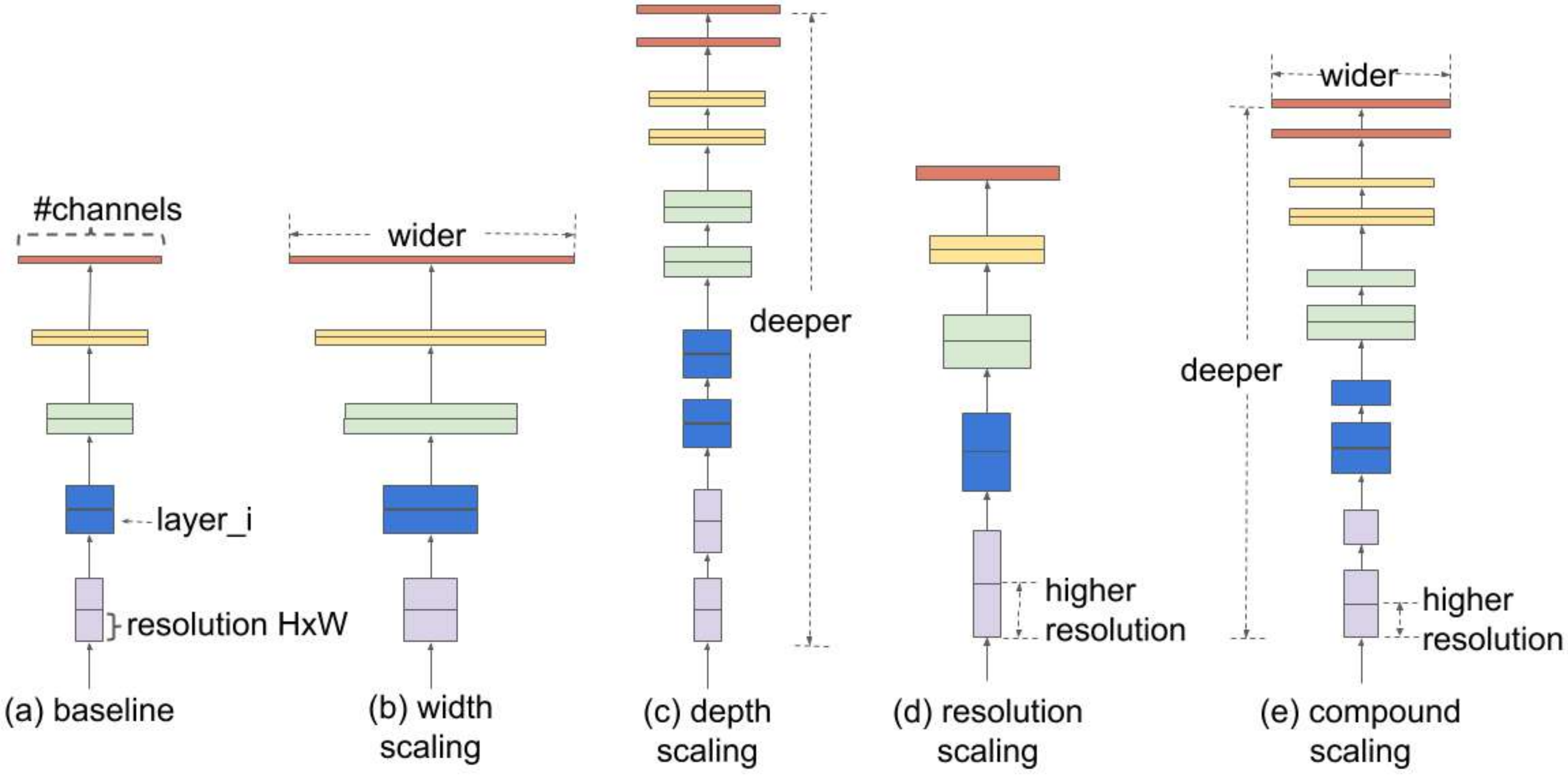

EfficientNet: Improving Accuracy and Efficiency through AutoML and Model Scaling

https://ai.googleblog.com/2019/05/efficientnet-improving-accuracy-and.html

Related Theory

- (1) Transfer Learning
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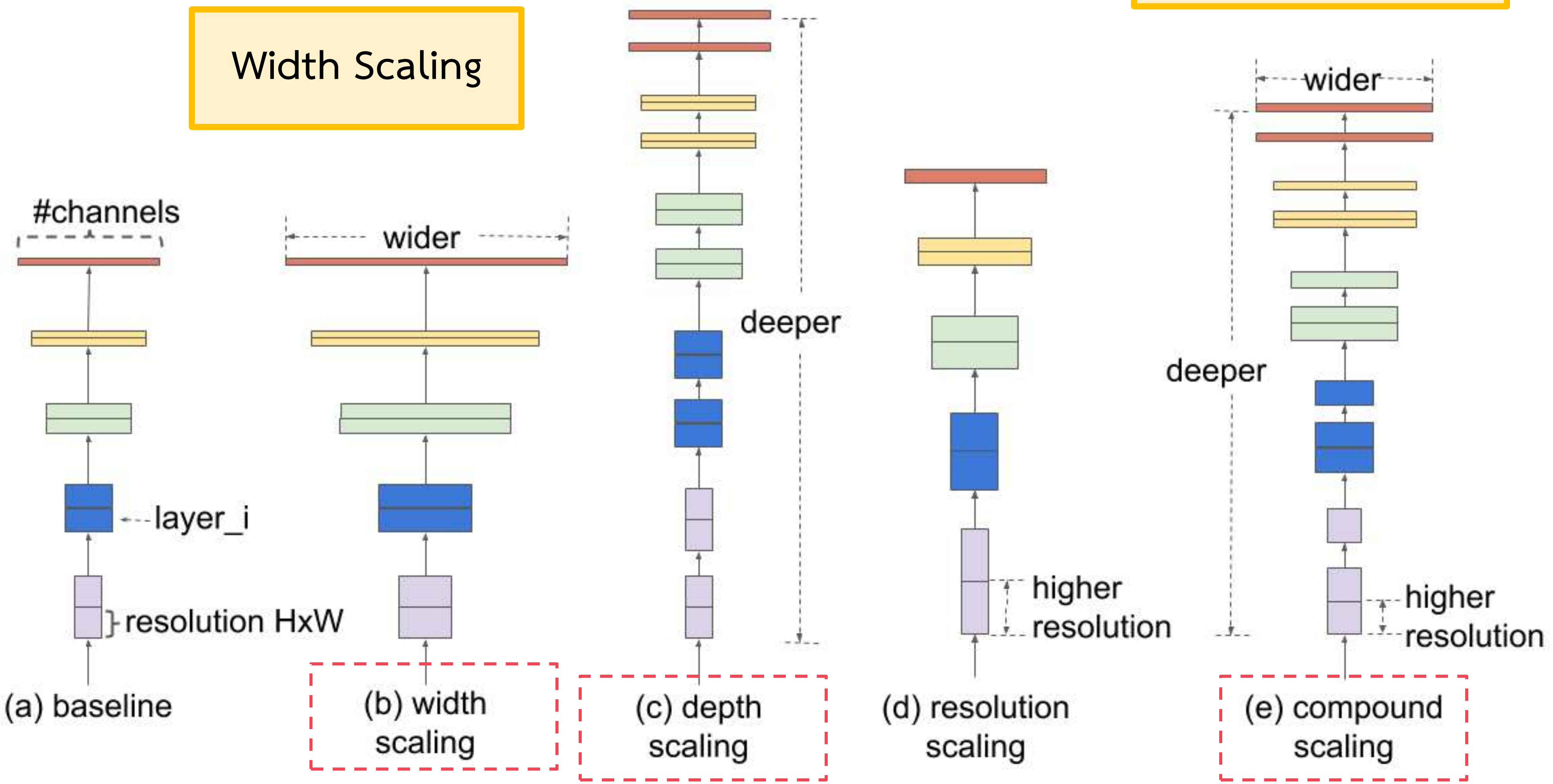
- **(5) Design CNNs**

Width Scaling

Depth Scaling

Compound Scaling



EfficientNet: Improving Accuracy and Efficiency through AutoML and Model Scaling

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Related Theory

Dept Scaling | Width Scaling | Compound Scaling

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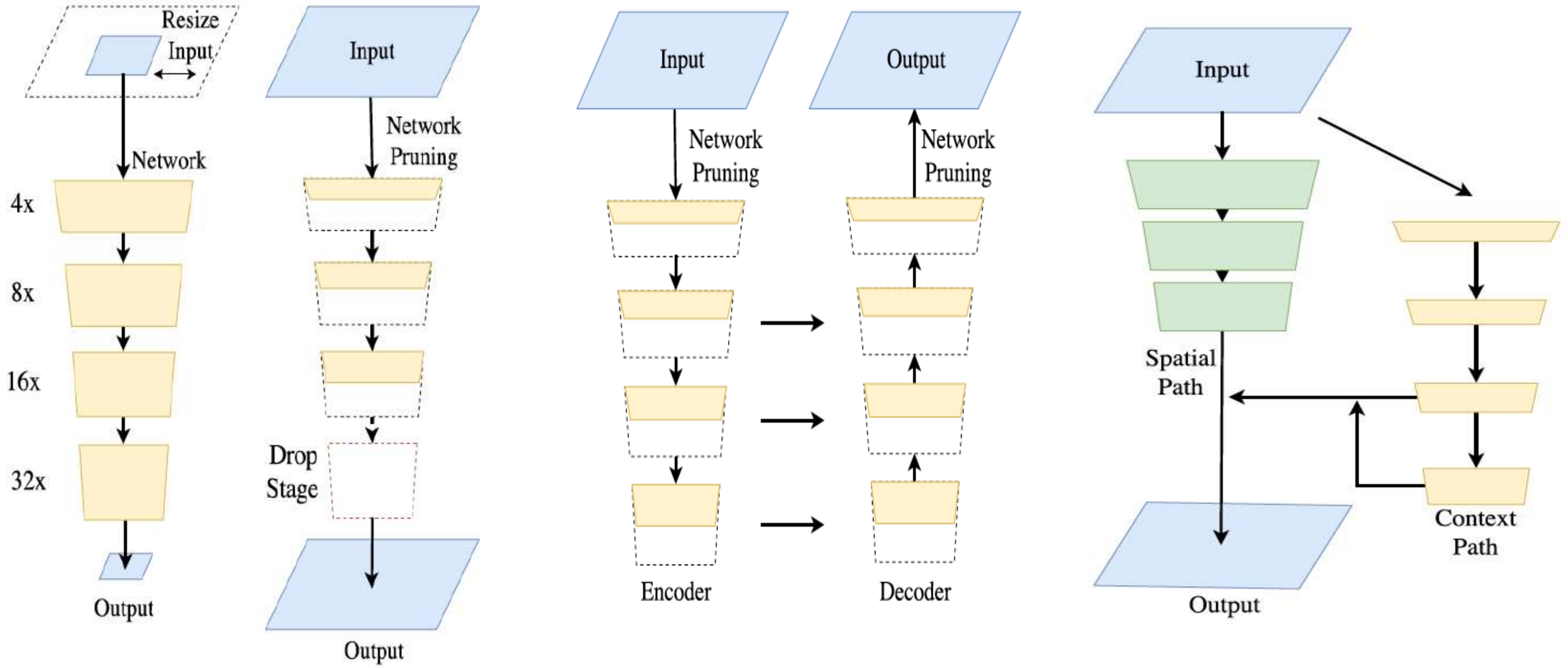
VGG Style (Depth Scaling)	U-Shape Style (Width Scaling)	Context Path Style (Compound Scaling)



Yu, C., Wang, J., Peng, C., Gao, C., Yu, G., & Sang, N. (2018). Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 325-341).

Outline | Related Works

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and Reference

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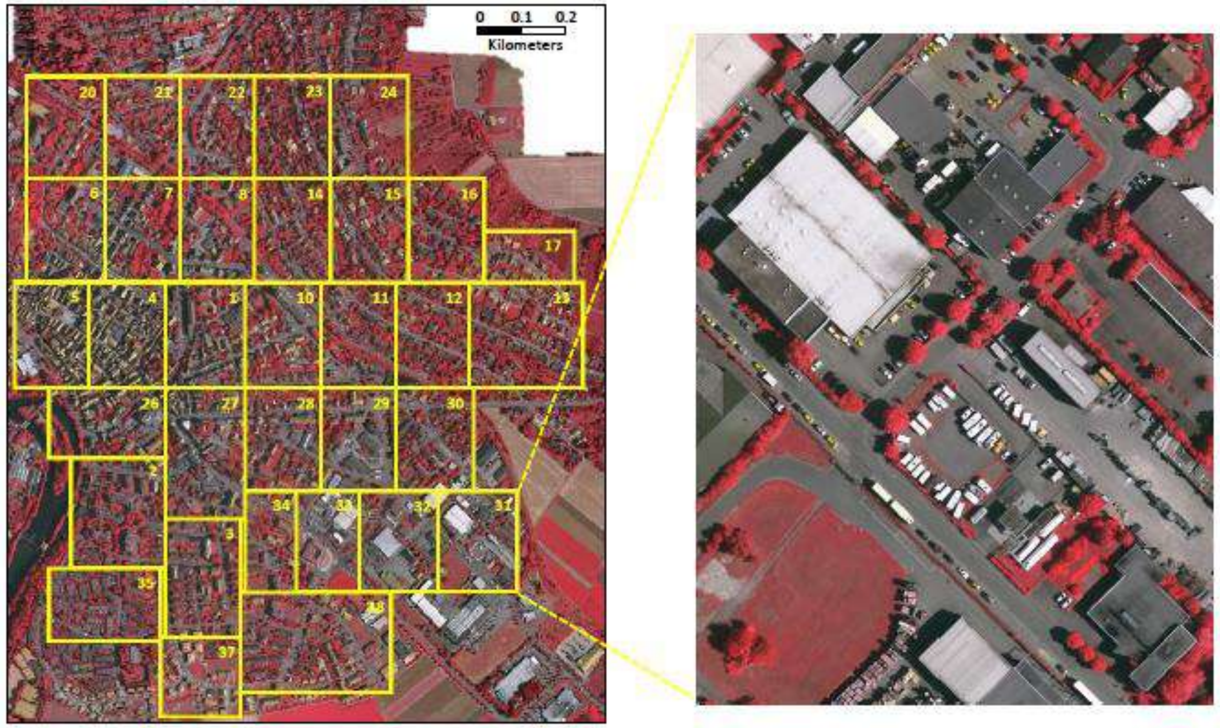

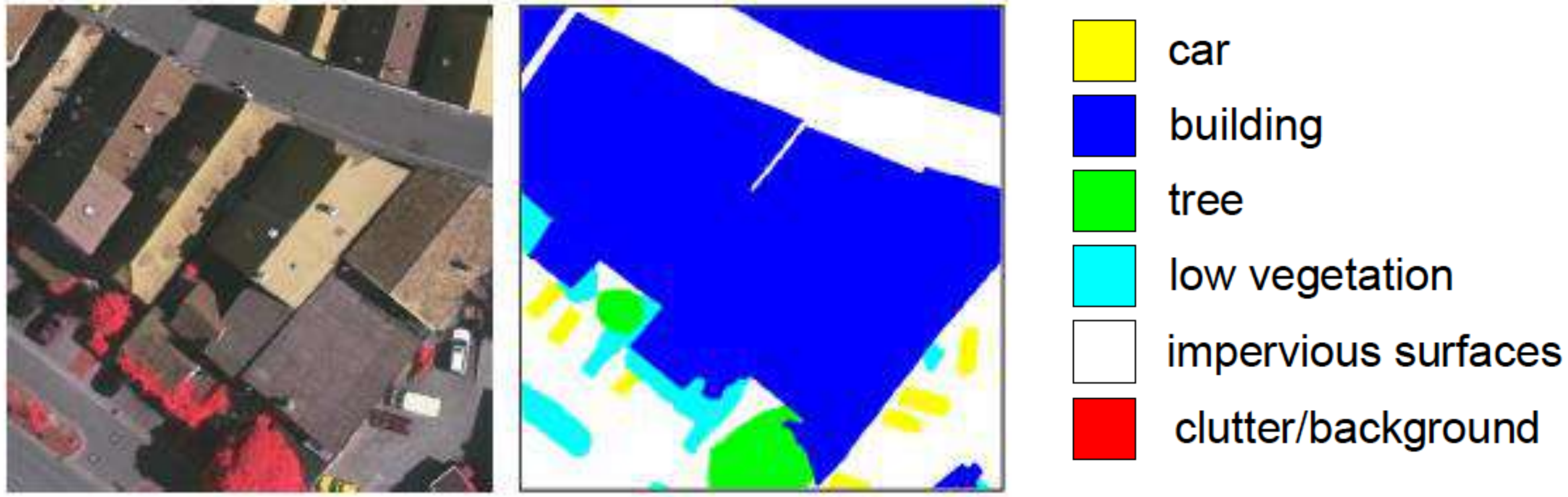

(a) image (b) ground truth

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Winner

Winner is Encoder-Decoder (ScasNet-based)

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Method	Imp surf	Building	Low veg	Tree	Car	F1-score
FCN-8s {Long, 2015 #6}	0.871	0.918	0.752	0.861	0.638	0.808
SegNet {Badrinarayanan, 2017 #7}	0.867	0.891	0.763	0.839	0.657	0.847
DeconvNet {Noh, 2015 #8}	0.891	0.932	0.814	0.857	0.684	0.835
GSN {Wang, 2017 #9}	**0.892**	**0.945**	0.749	0.875	0.798	0.852
Encoder-Decoder {Liu, 2018 #10}	0.872	0.893	**0.841**	**0.914**	**0.815**	**0.854**

Winner

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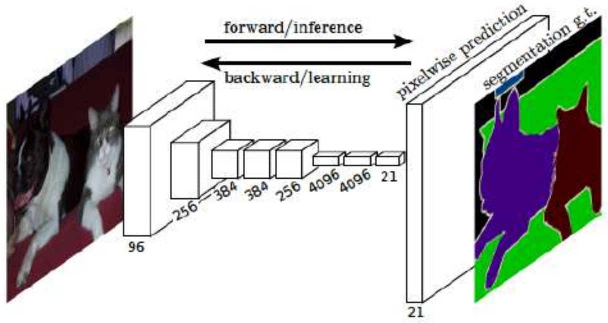
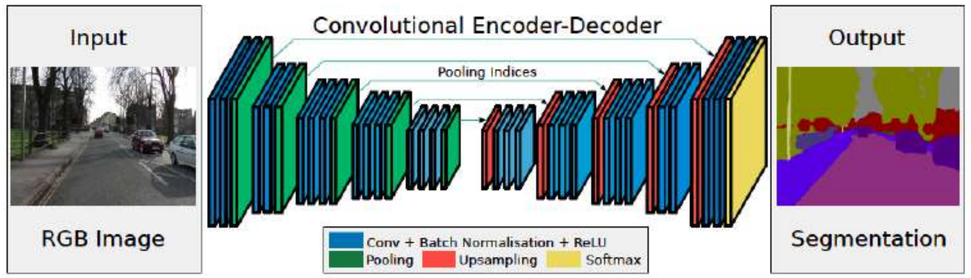


  - Segnet: A Deep Convolutional Encoder-Decoder Architecture
  - by Badrinarayanan, V. et al. (PAMI, 2017)
    - F1-Score on Test Set is 75.5%



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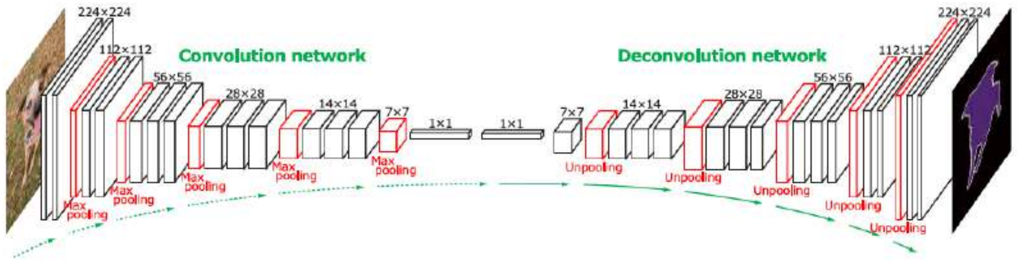

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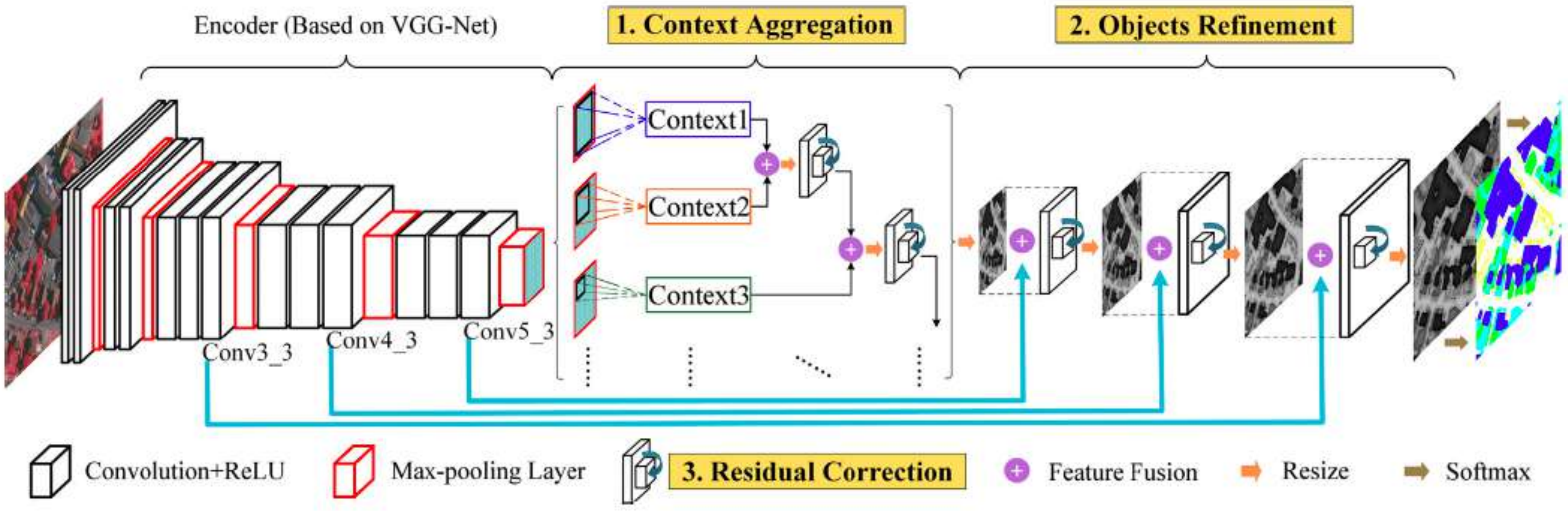

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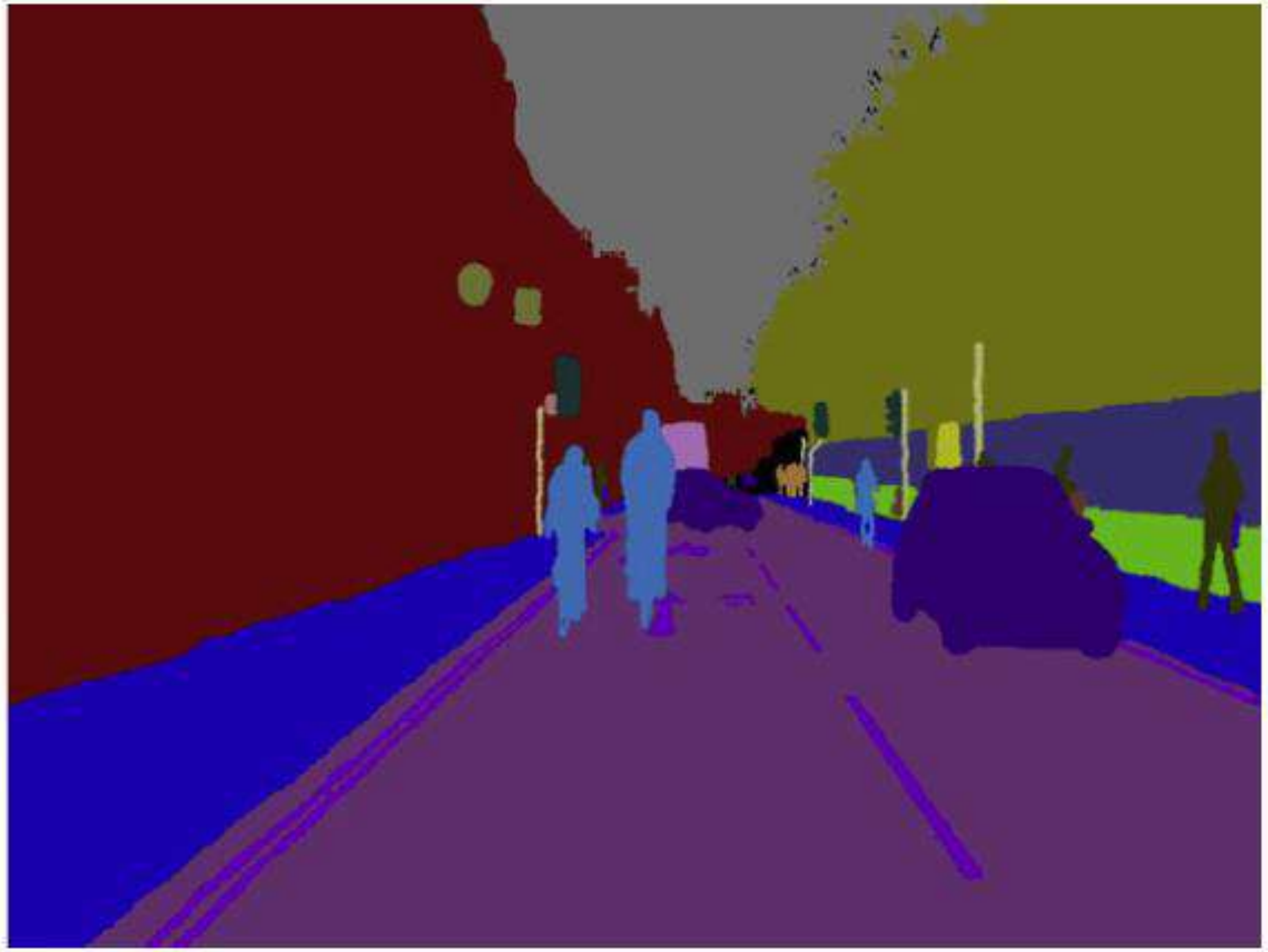
CamVid Corpus

The Cambridge-driving Labeled Video Database

Void	Building	Wall	Tree	VegetationMisc
Fence	Sidewalk	ParkingBlock	Column_Pole	TrafficCone
Bridge	SignSymbol	Misc_Text	TrafficLight	Sky
Tunnel	Archway	Road	RoadShoulder	LaneMkgsDriv
LaneMkgsNonDriv	Animal	Pedestrian	Child	CartLuggagePram
Bicyclist	MotorcycleScooter	Car	SUVPickupTruck	Truck_Bus
Train	OtherMoving			

32 semantic classes



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Winner

Winner is Global Convolution Network (GCN)

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Deep Learning Model	Precision	Recall	F1-Score
PSPNet {Zhao, 2017 #1}	0.74	0.74	0.74
DenseNet (Tiramisu) {Badrinarayanan, 2017 #2}	0.74	0.77	0.75
GCN {Peng, 2018 #3}	**0.85**	**0.87**	**0.86**
DeepLabV3 {Chen, 2018 #4}	0.72	0.63	0.67
BiseNet {Yu, 2018 #5}	0.84	0.82	0.83

Winner

Related Works

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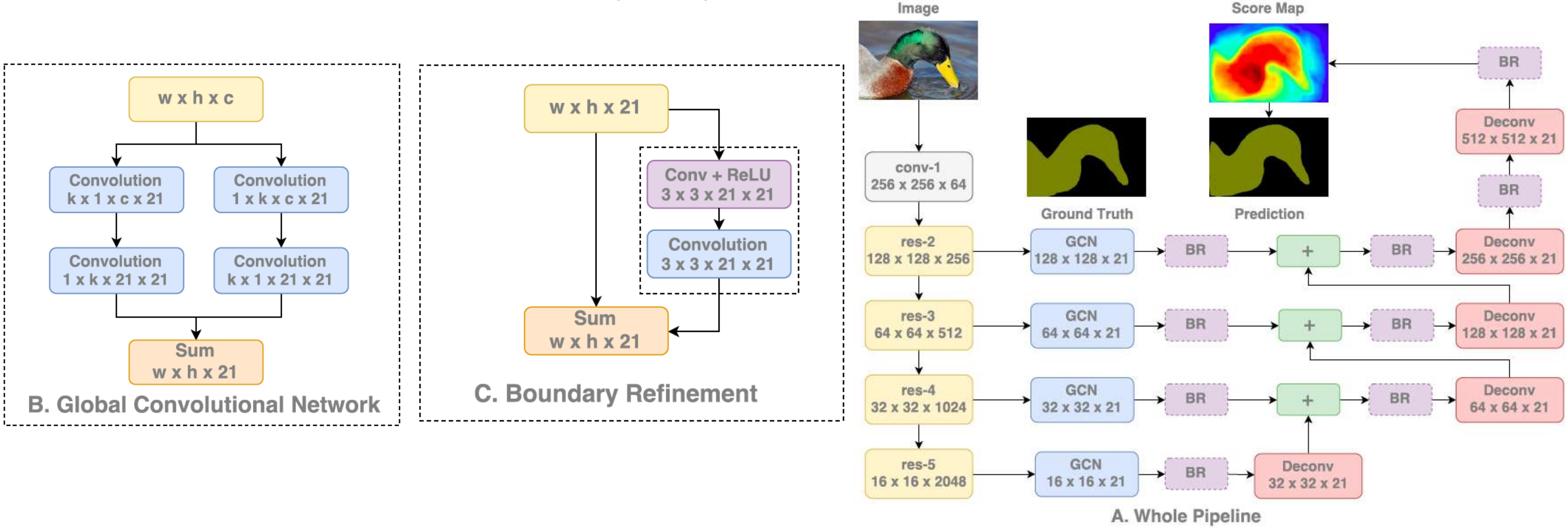

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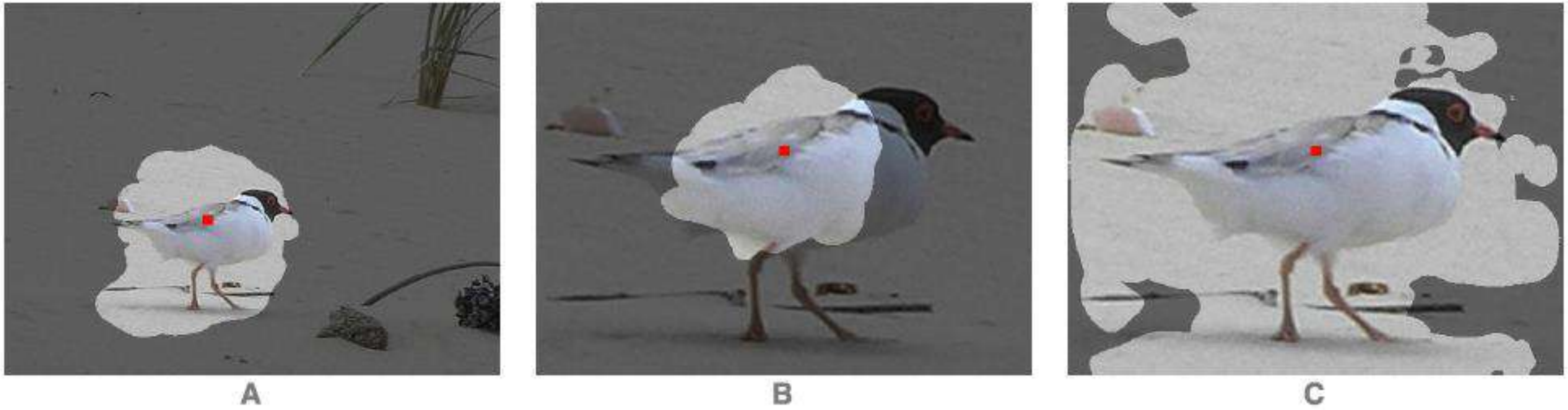
** Valid Receptive Field (VRF)



(A) and fails to hold the entire object if the input resized to a larger scale (B). As a comparison, their Global Convolution Network significantly enlarges the VRF (C).

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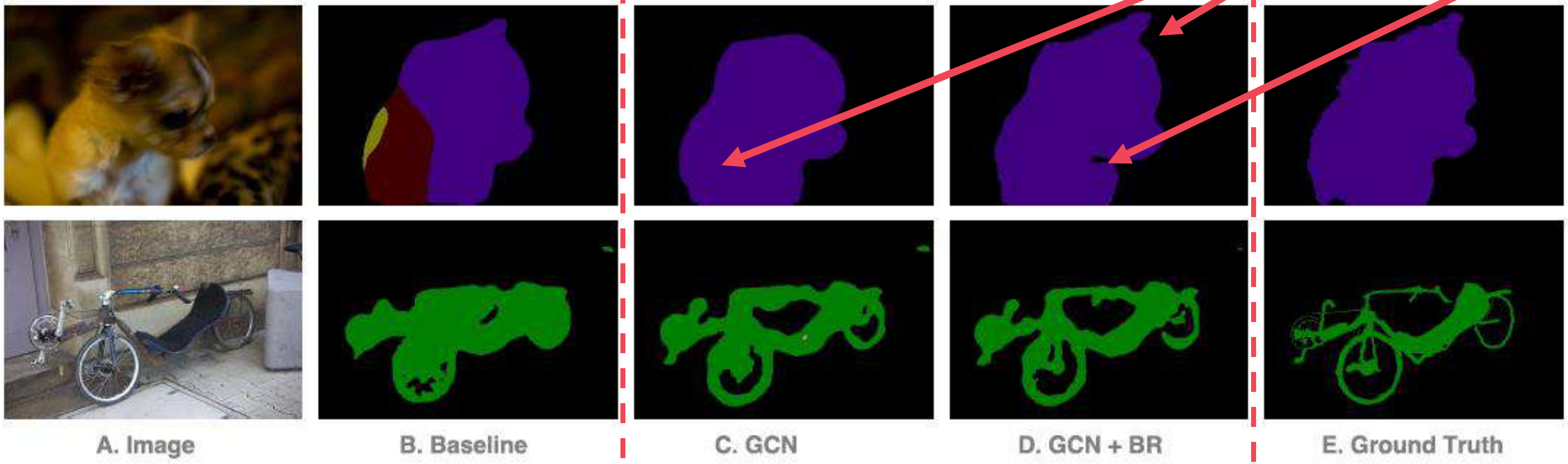
Solve: False Negative and False Positive



Effect of GCN and Boundary Refinement

Related Works

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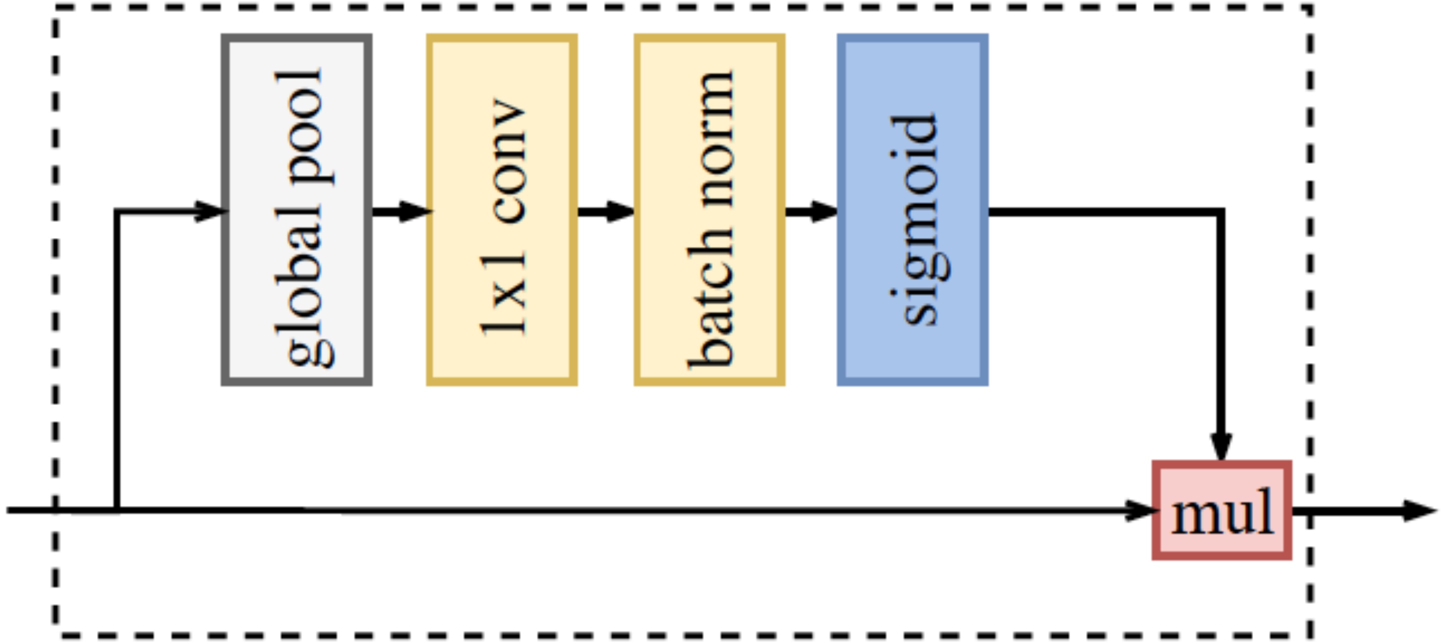
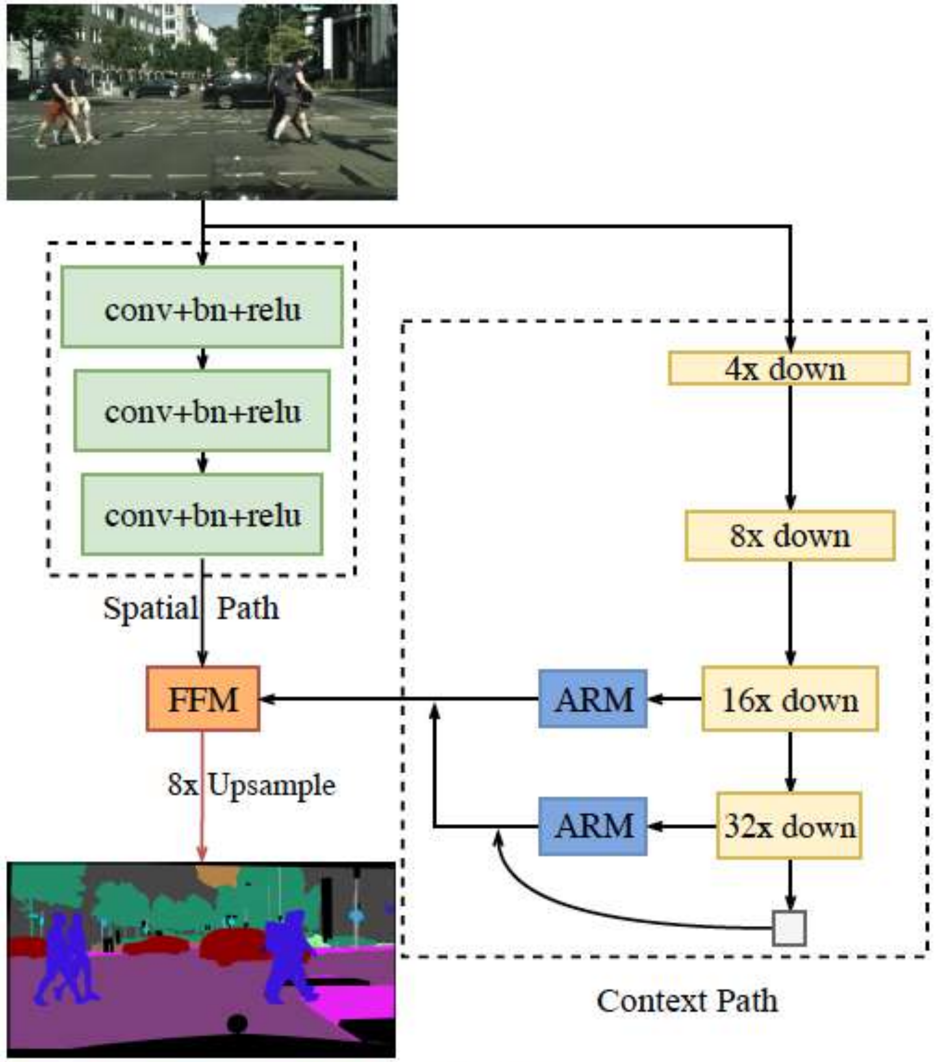


(b) Attention Refinment Module



(a) Network Architecture

Related Works

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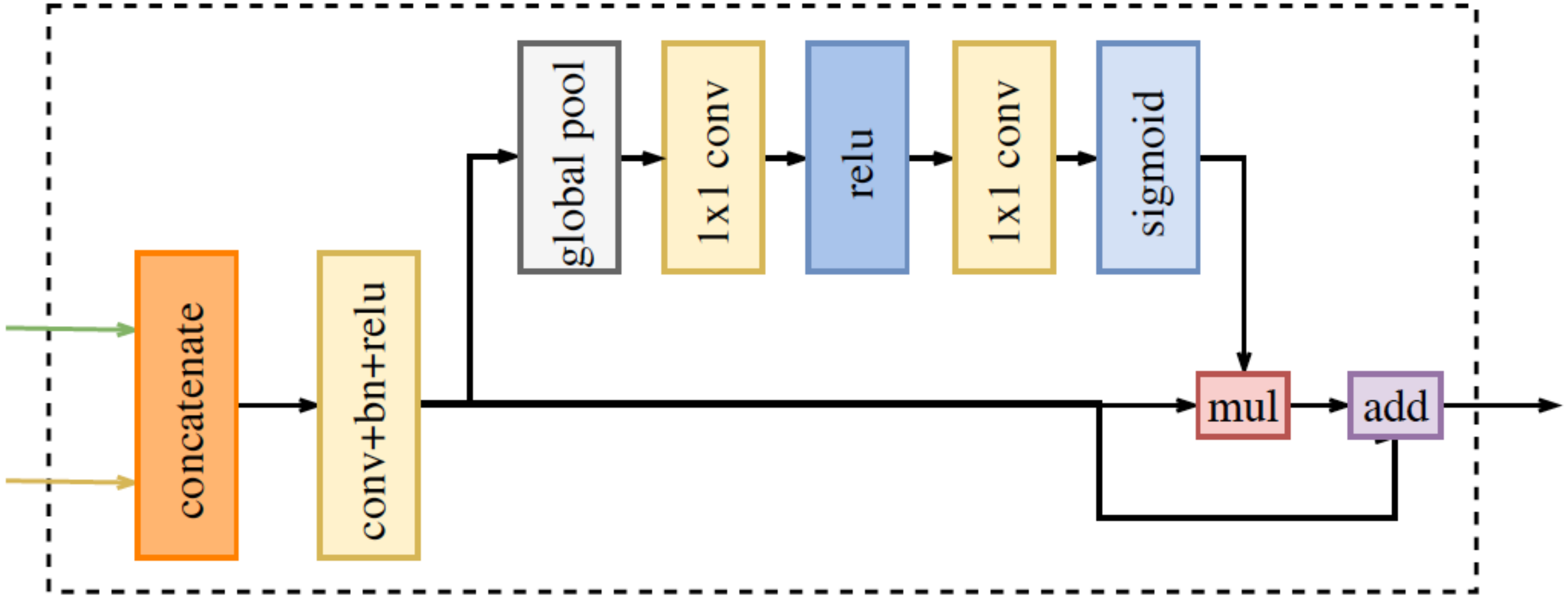
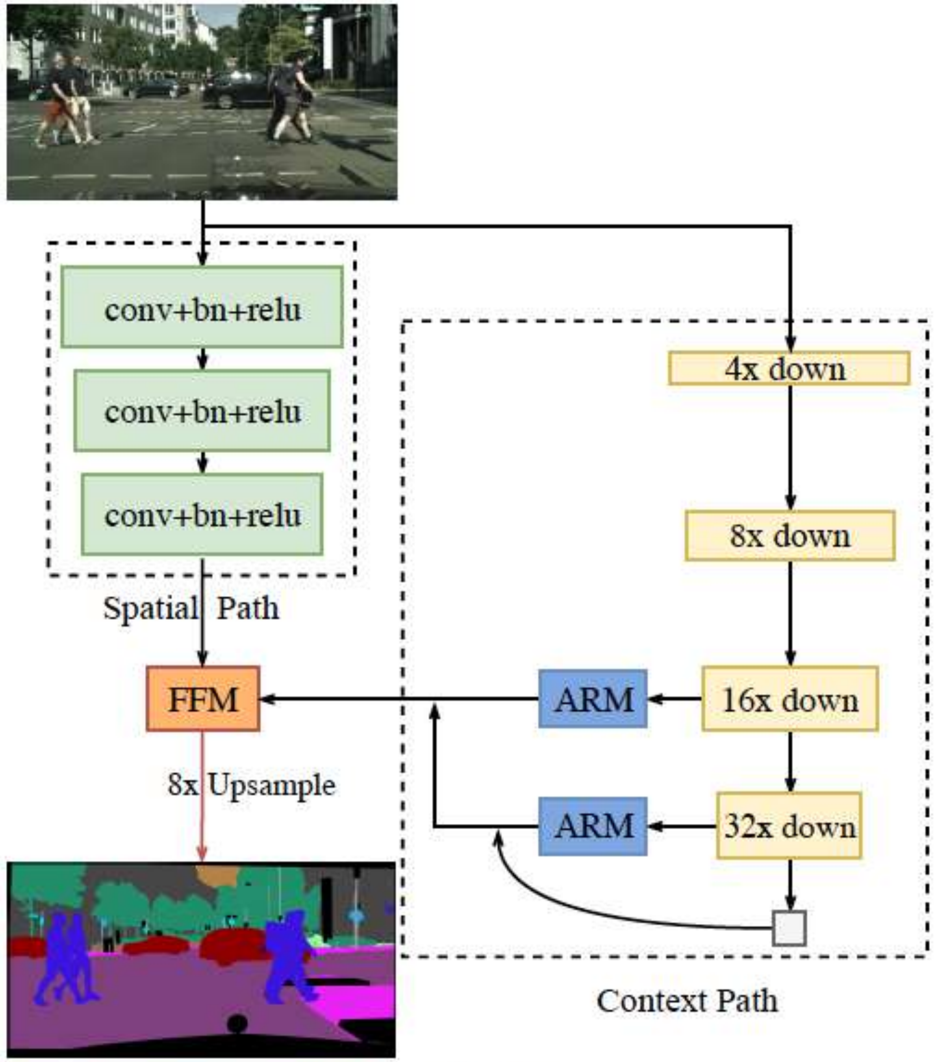


(c) Feature Fusion Module



(a) Network Architecture

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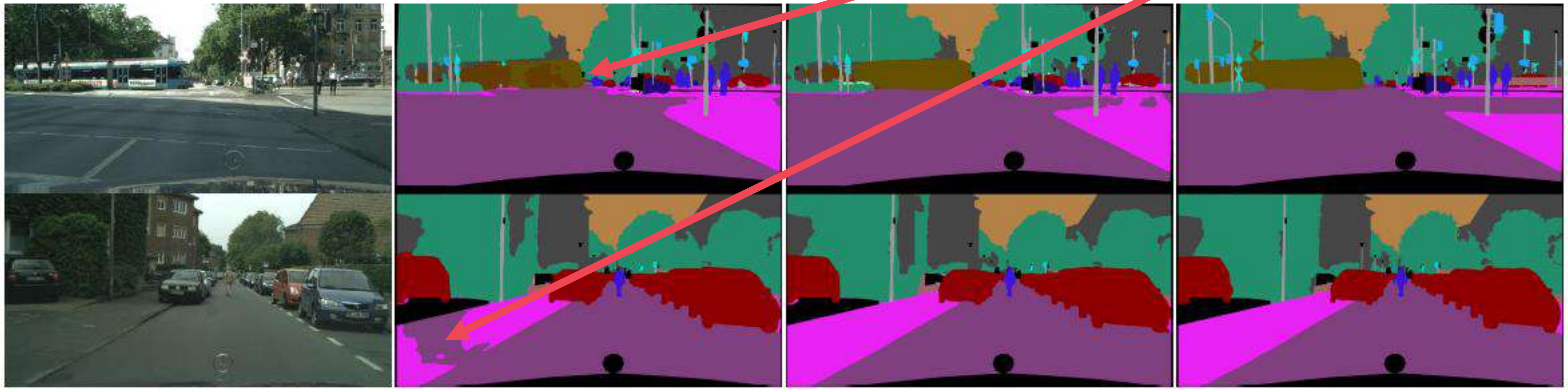
Problem: False Positive



(a) Image (b) U-Shape (c) BiSeNet (d) GT

Recap: Each Techniques from Related Theory and Work

- From Remote Sensing Challenge, Encoder-Decoder ScasNet-based by Liu, Y. et al. (ISPRS Journal of Photogrammetry and Remote Sensing 2018) is the winner.
- From CamVid Challenge, Global Convolutional Network (Large Kernel Matters) by Peng, C (CVPR 2018) is the winner.
- Modern Technique from modern deep learning researches:
  - Global Convolutional (Large Kernel Matter, Dynamic Kernel Size)
  - Channel Attention
  - Domain Specific Transfer Learning
  - Feature Fusion
  - Depthwise Atrous Convolution

Outline | Methodology (Proposed Method)

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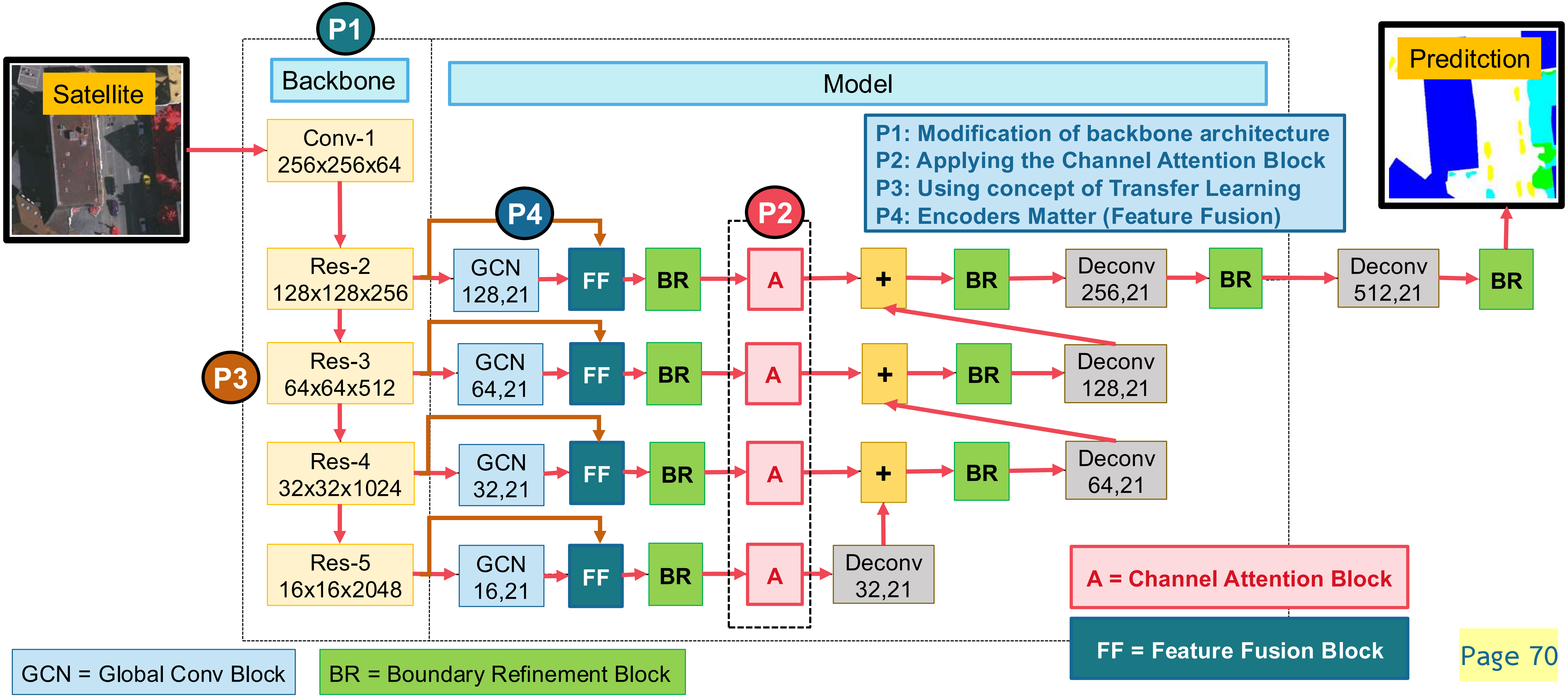
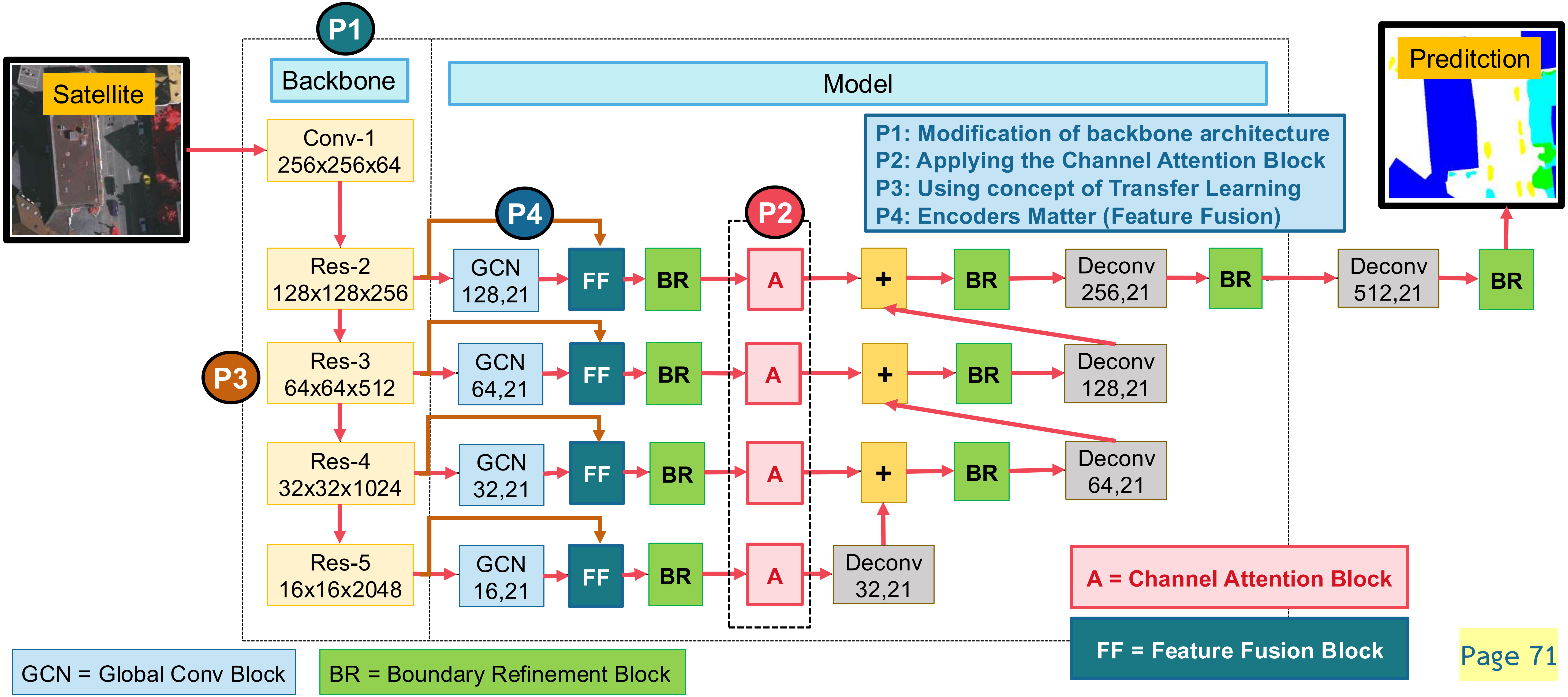
Proposed Method

Stage: Design Deep Learning Architecture



Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



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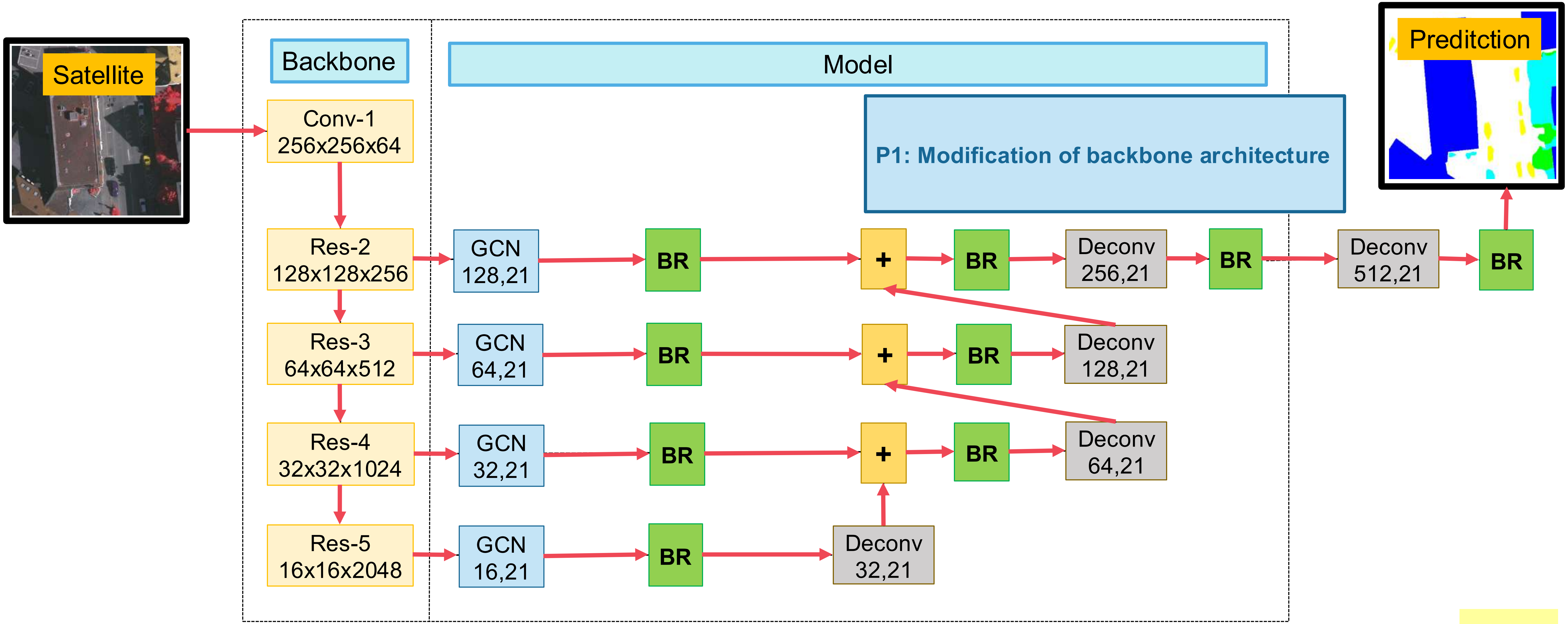

GCN = Global Conv Block

BR = Boundary Refinement Block

Proposed Method

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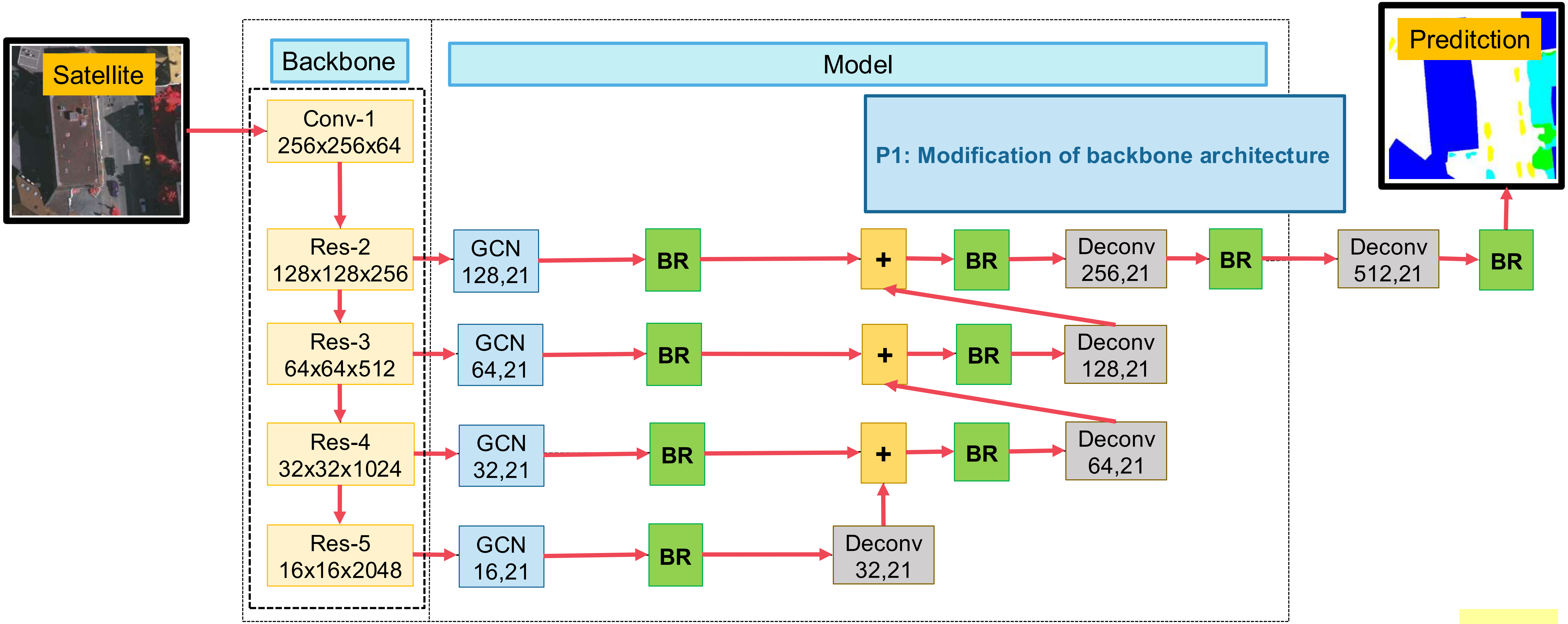

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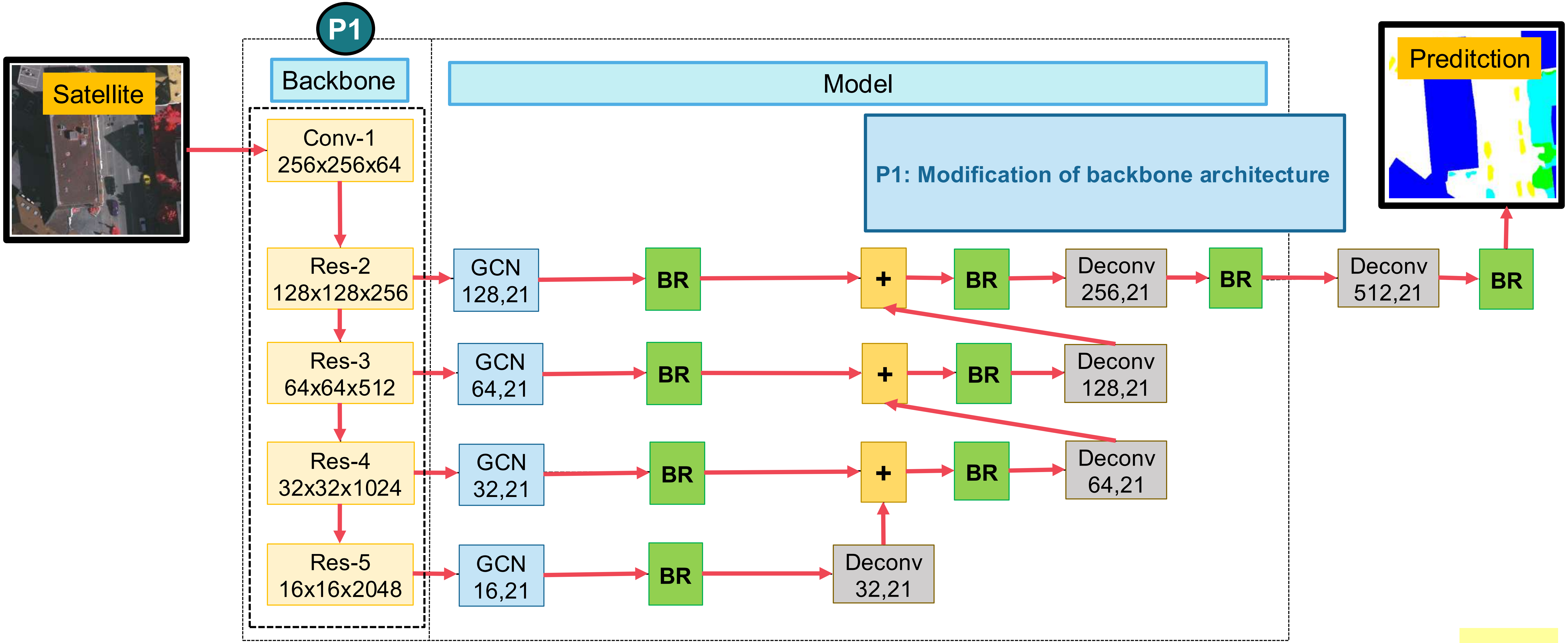

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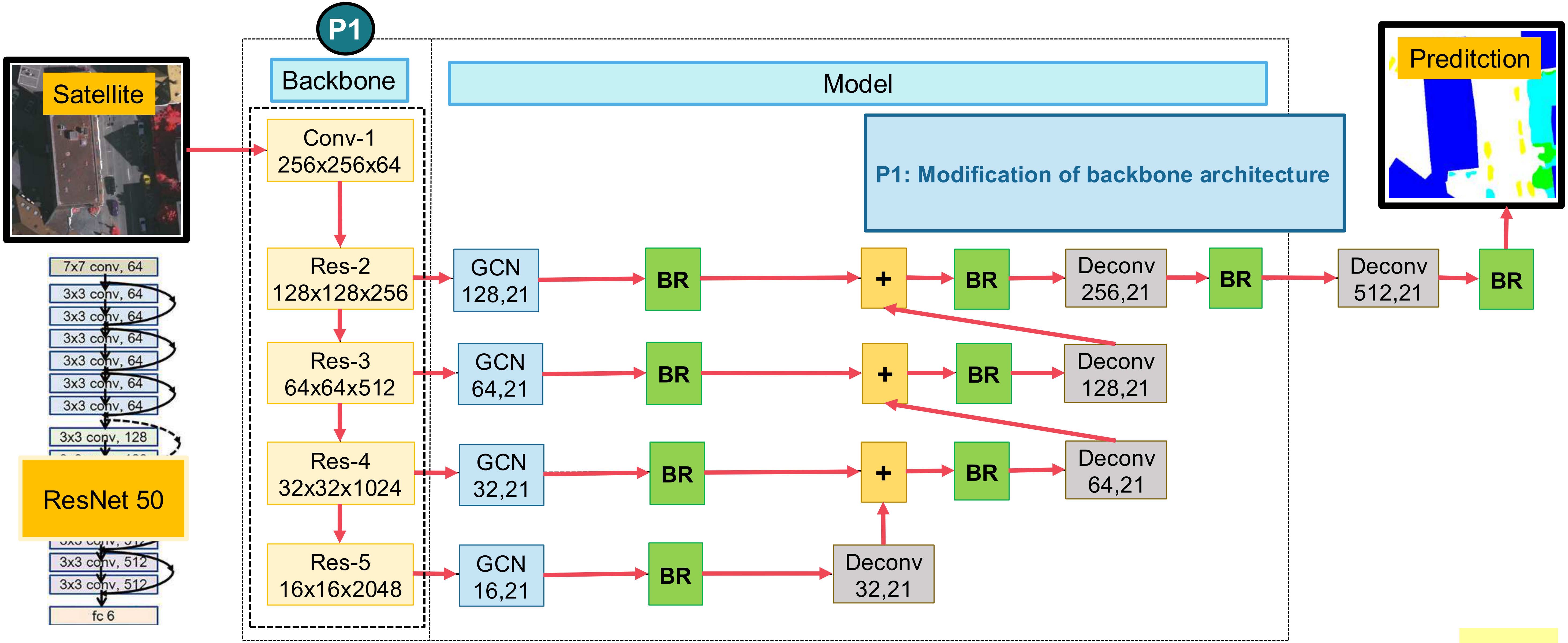
BR = Boundary Refinement Block

Proposed Method

P1 Backbone | P2 Attention (A) | P3 Transfer Learning (TL) | P4 Feature Fusion (FF) | P5 Depthwise Atrous (DA)

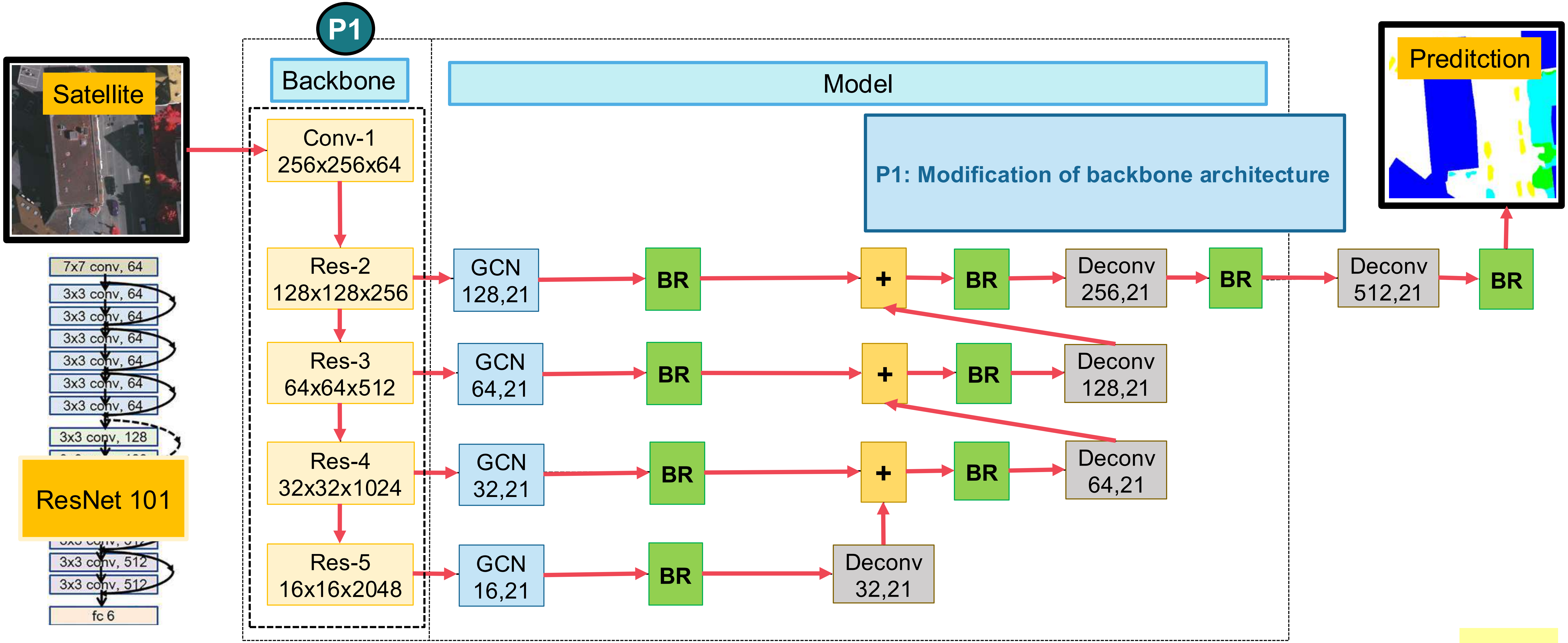


GCN = Global Conv Block

BR = Boundary Refinement Block

Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



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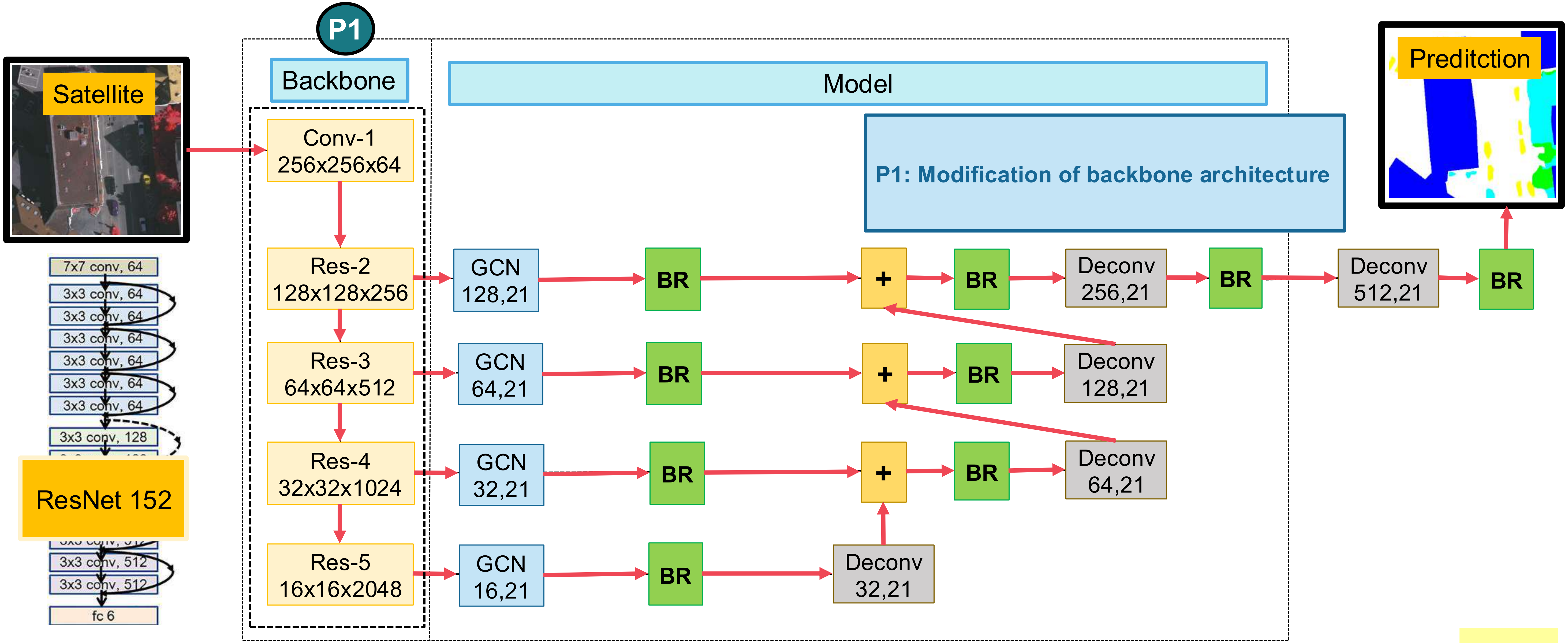
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



GCN = Global Conv Block

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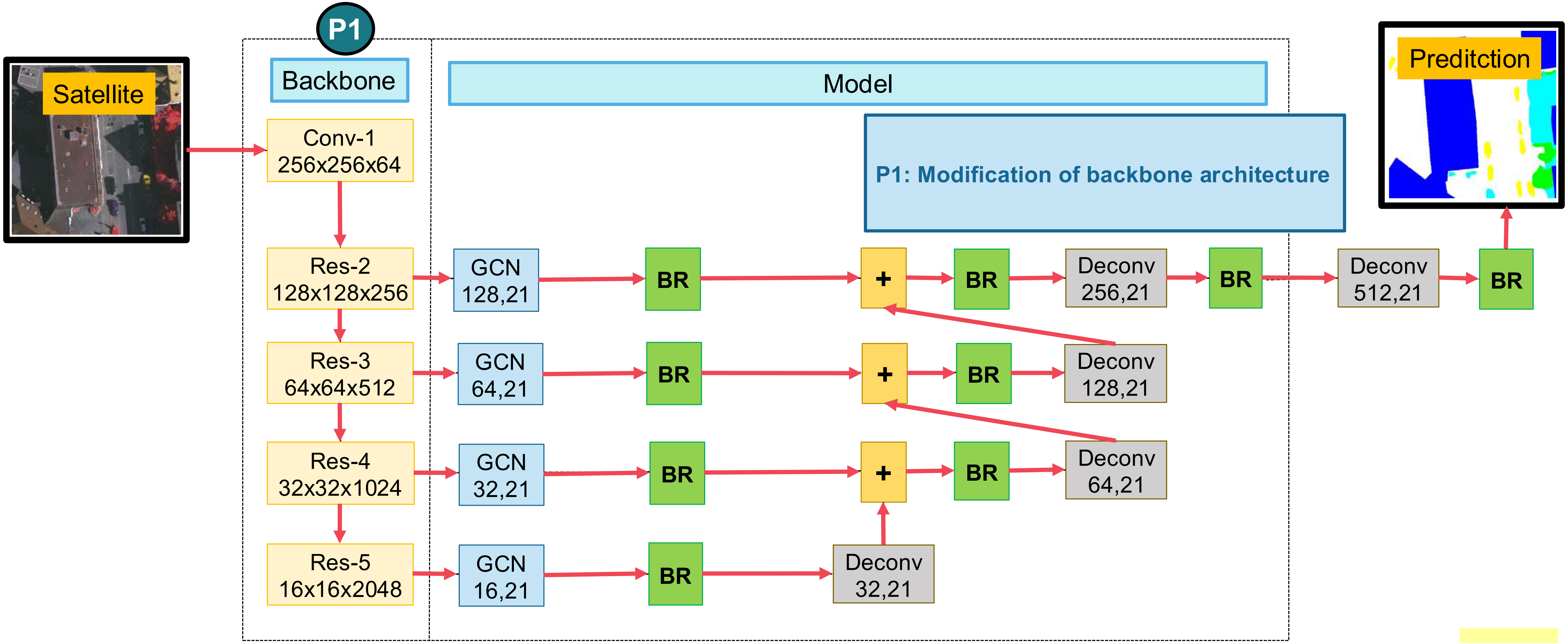
Proposed Method

P1 Backbone | P2 Attention (A) | P3 Transfer Learning (TL) | P4 Feature Fusion (FF) | P5 Depthwise Atrous (DA)

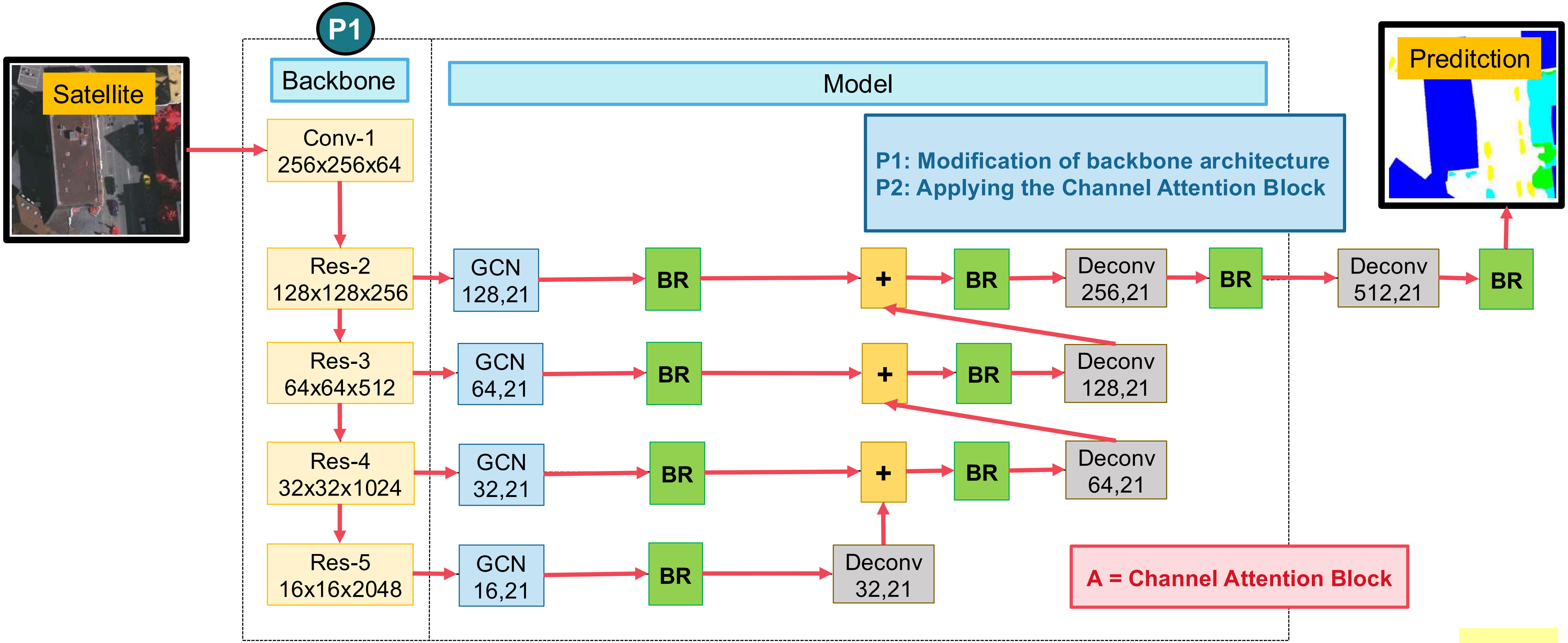


GCN = Global Conv Block

BR = Boundary Refinement Block

Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

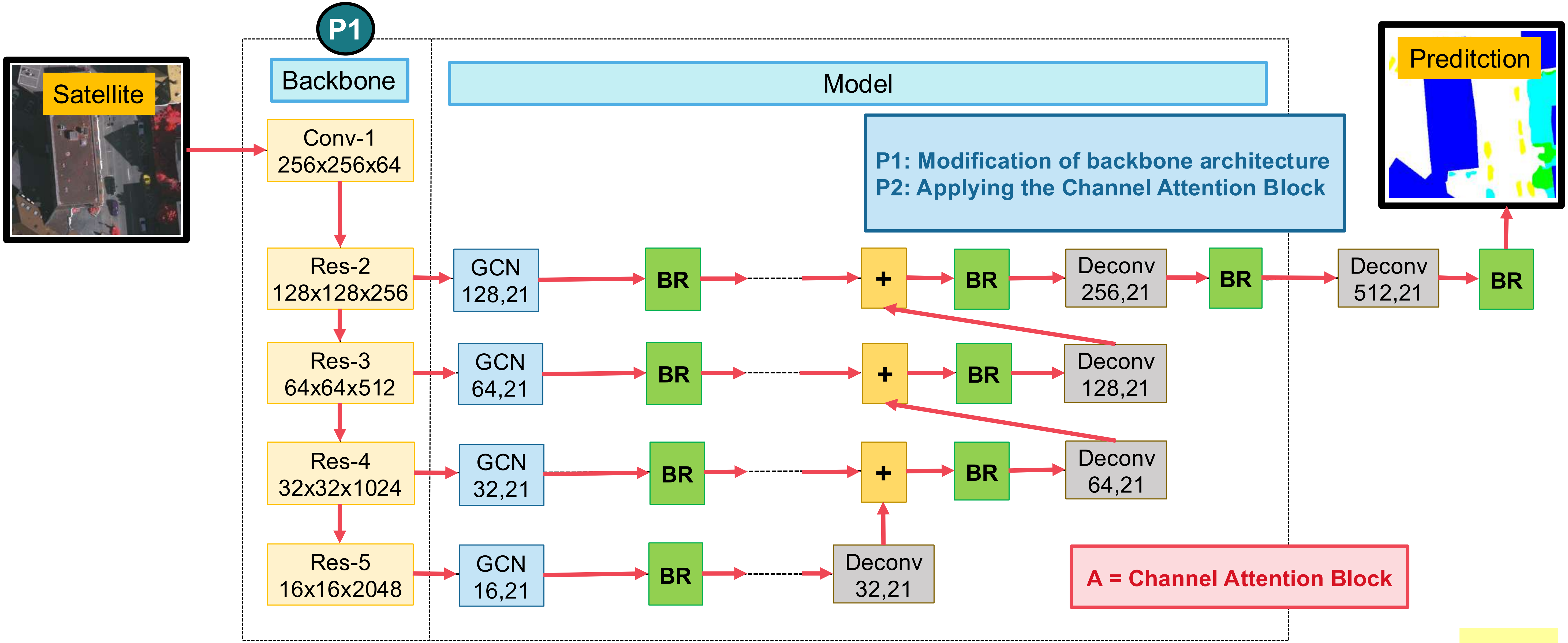


GCN = Global Conv Block

BR = Boundary Refinement Block

Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

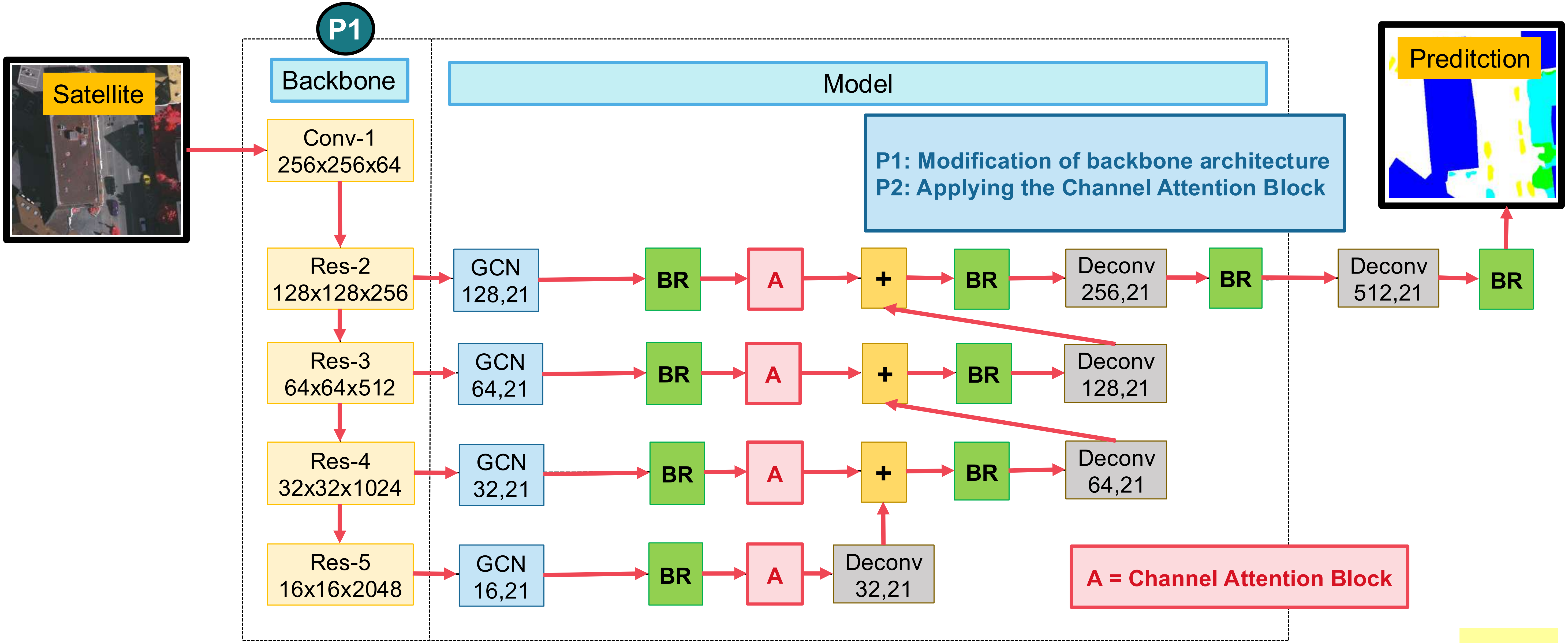


GCN = Global Conv Block

BR = Boundary Refinement Block

Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

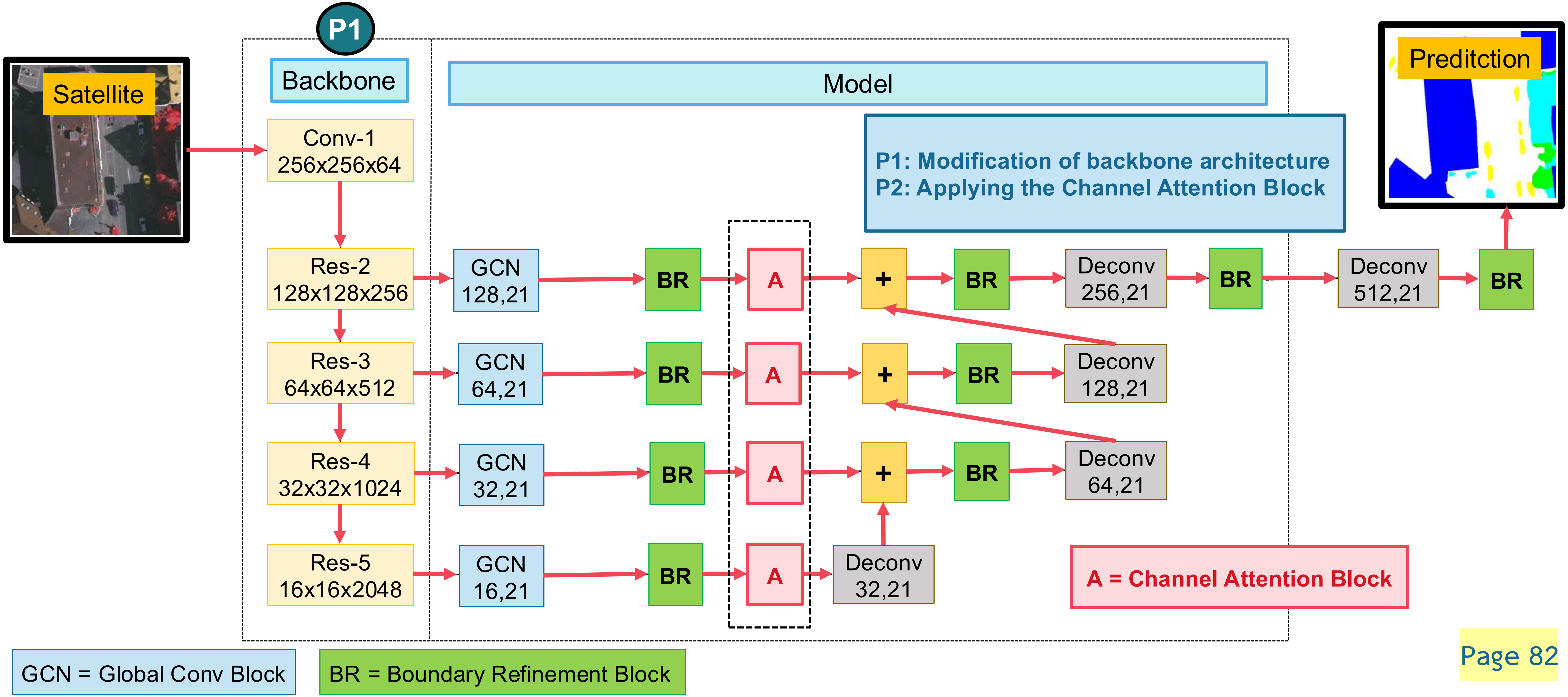


GCN = Global Conv Block

BR = Boundary Refinement Block

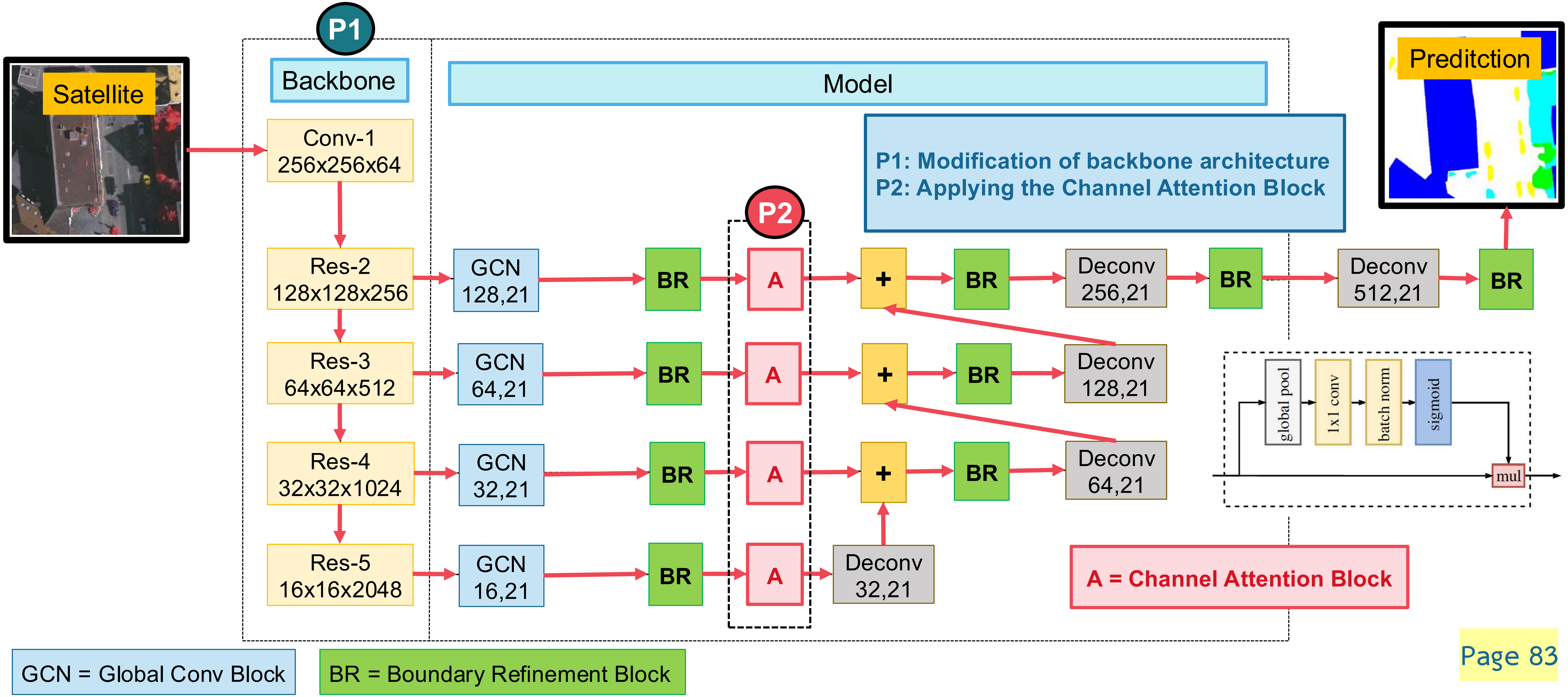
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



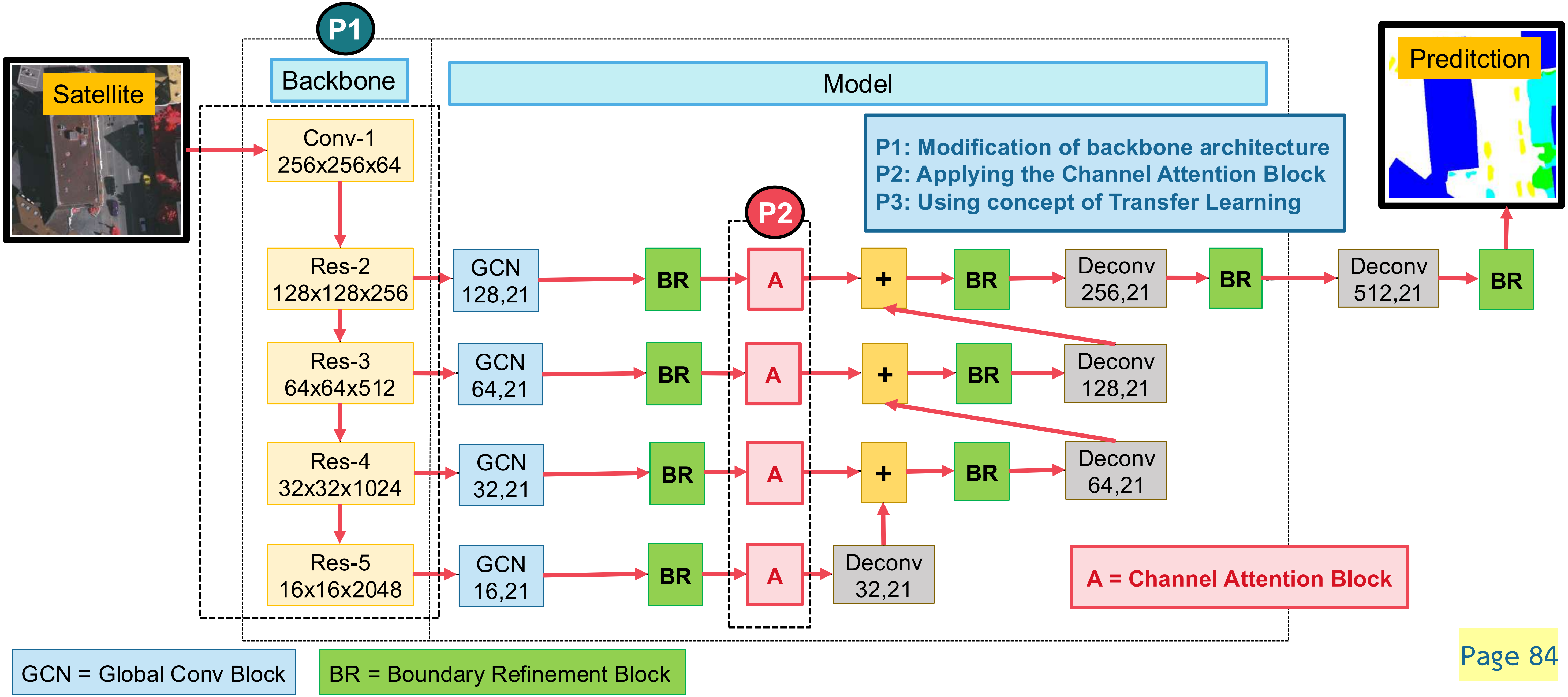
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



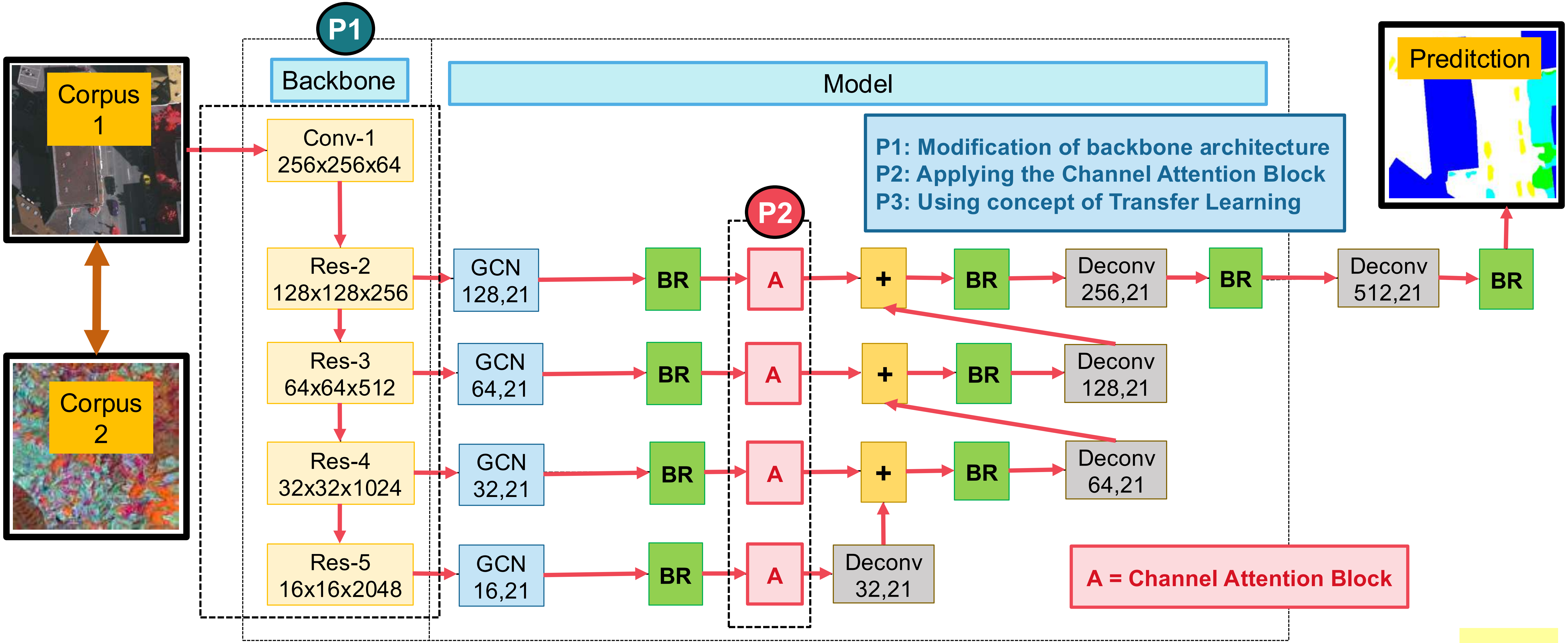
Proposed Method

P1 Backbone | P2 Attention (A) | P3 Transfer Learning (TL) | P4 Feature Fusion (FF) | P5 Depthwise Atrous (DA)



Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

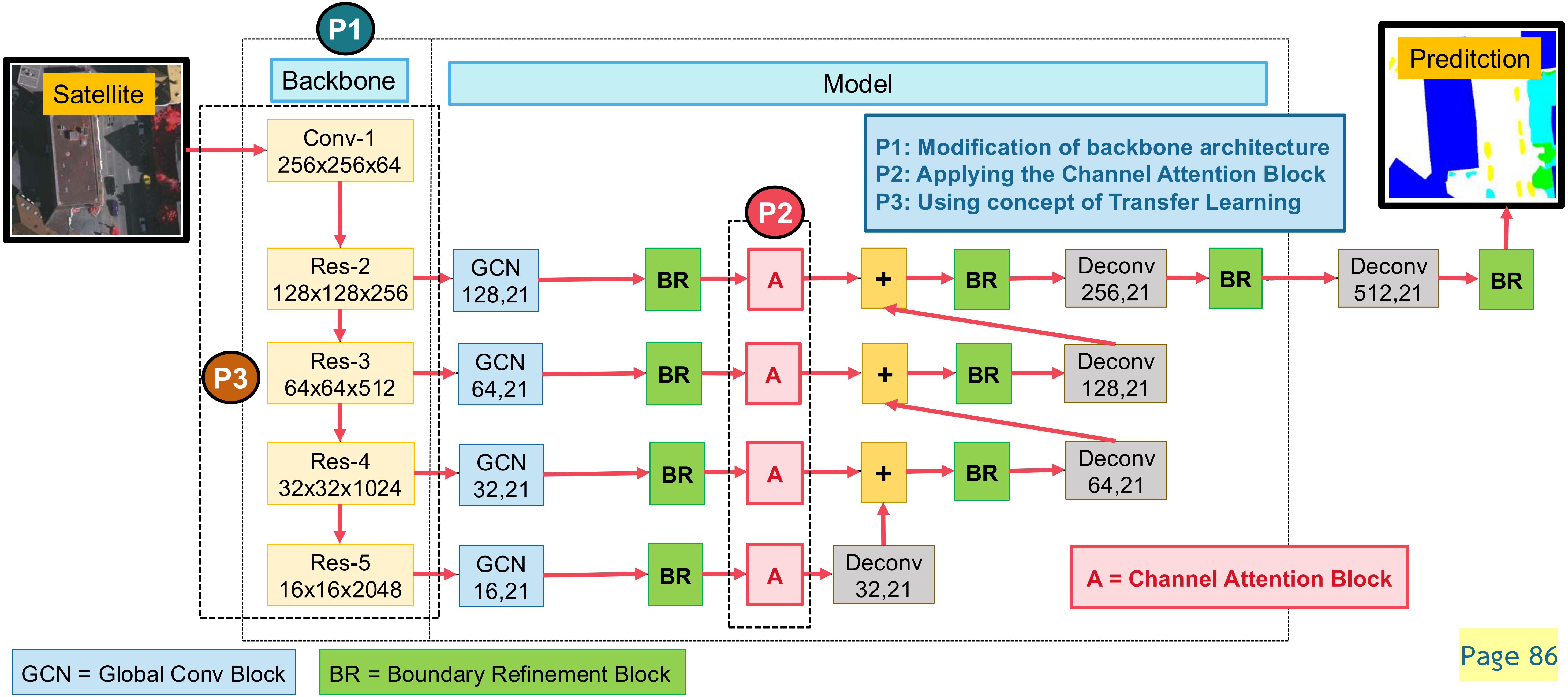


GCN = Global Conv Block

BR = Boundary Refinement Block

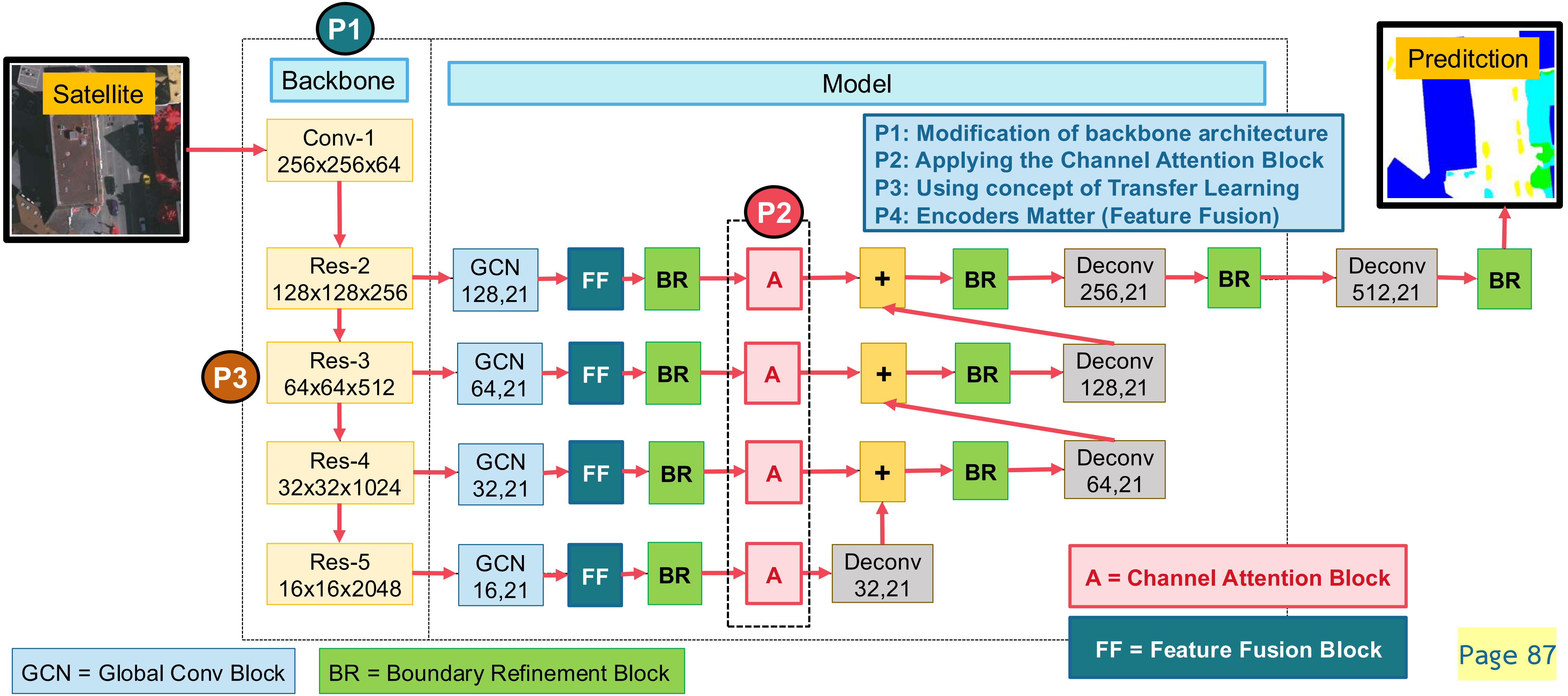
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



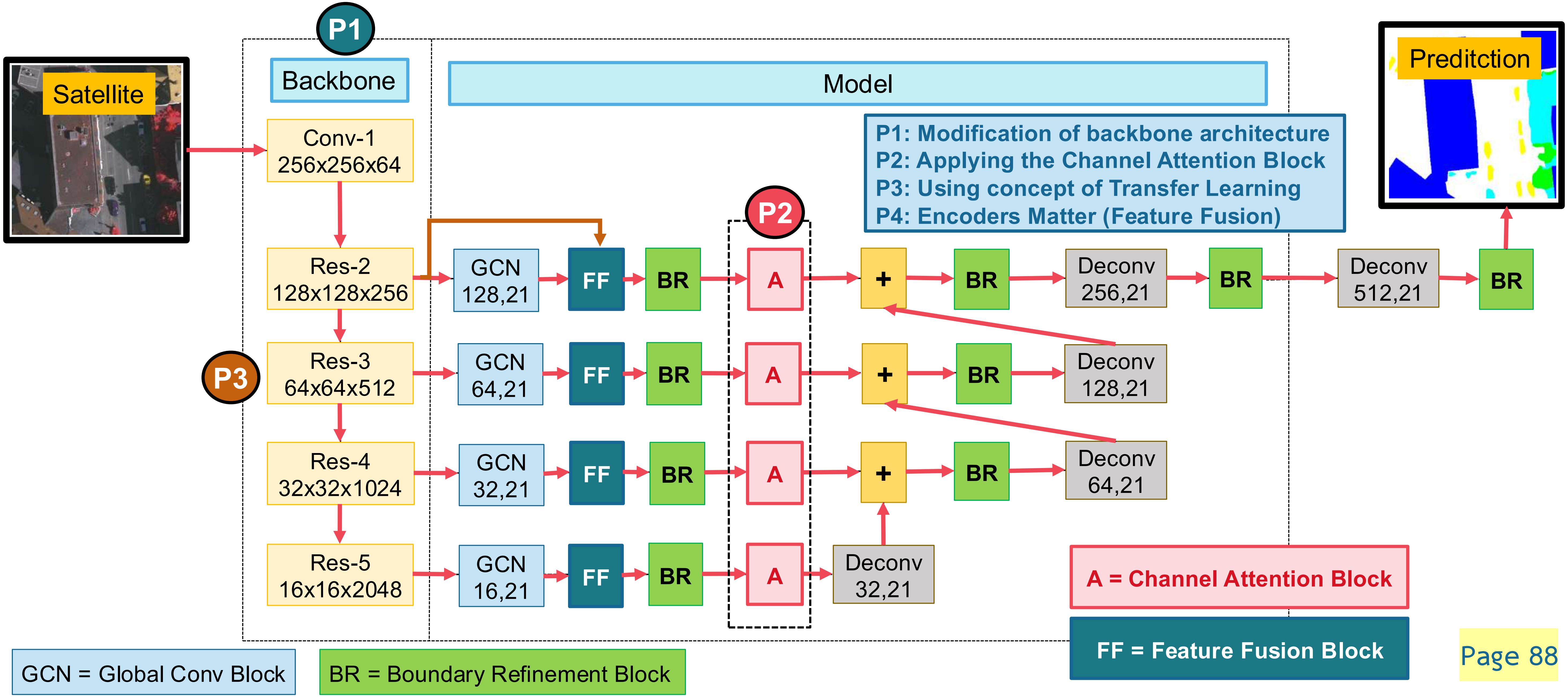
Proposed Method

P1	P2	P3	P4	P5
Backbone	Attention (A)	Transfer Learning (TL)	Feature Fusion (FF)	Depthwise Atrous (DA)



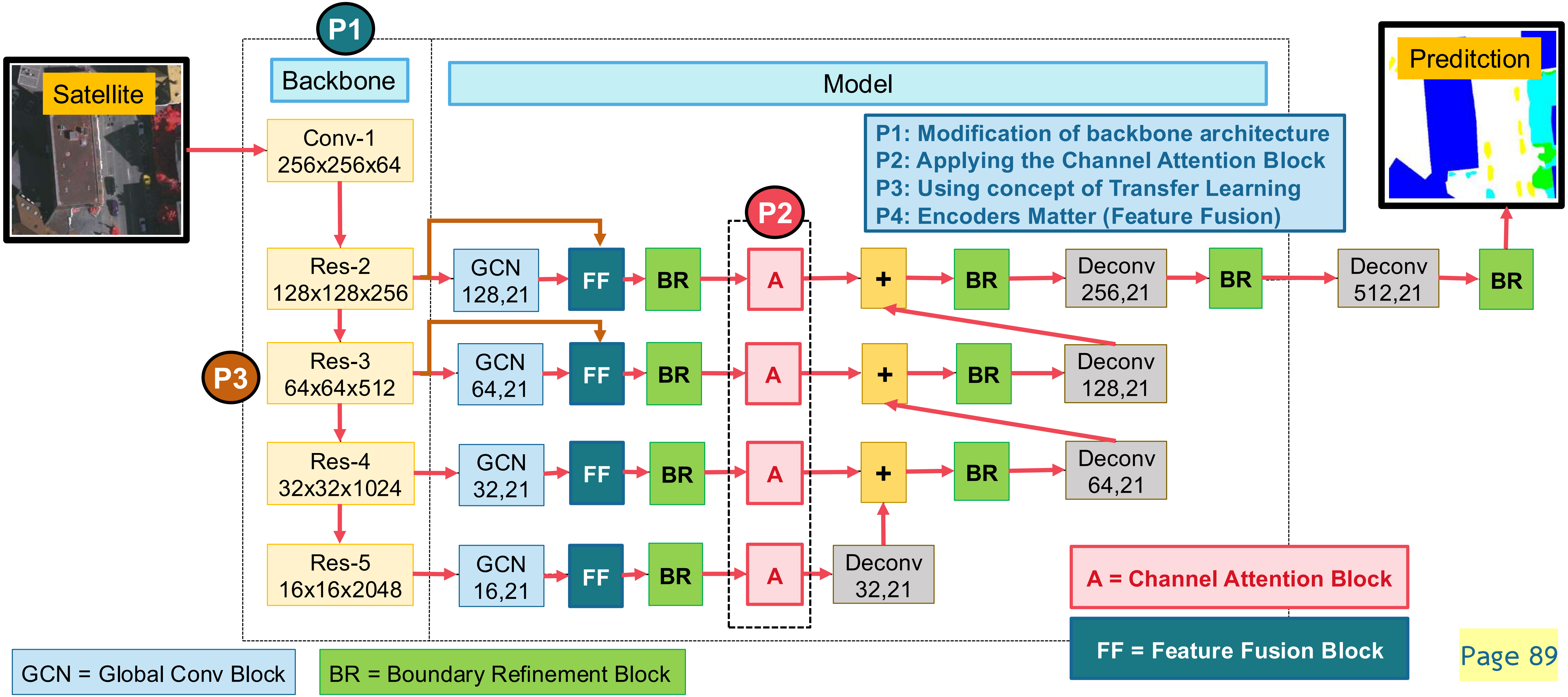
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



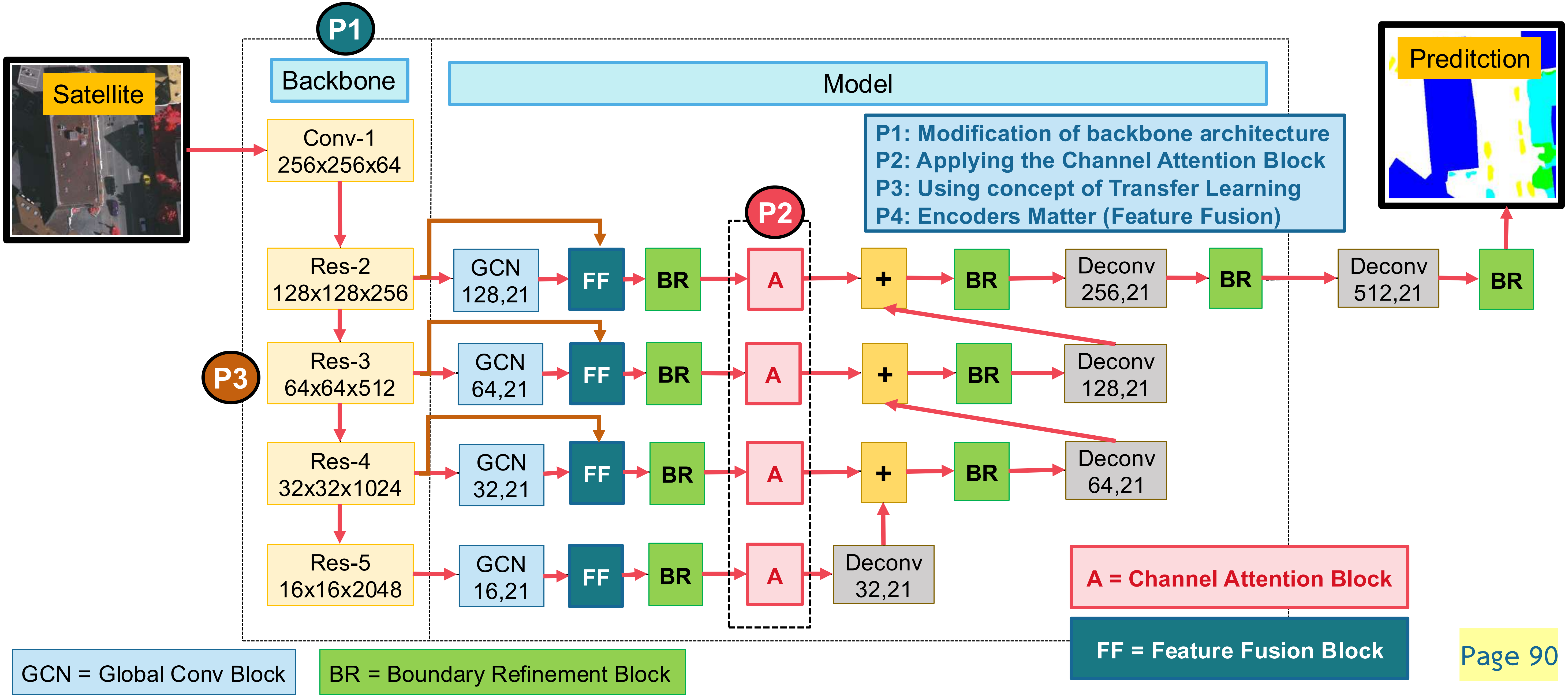
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



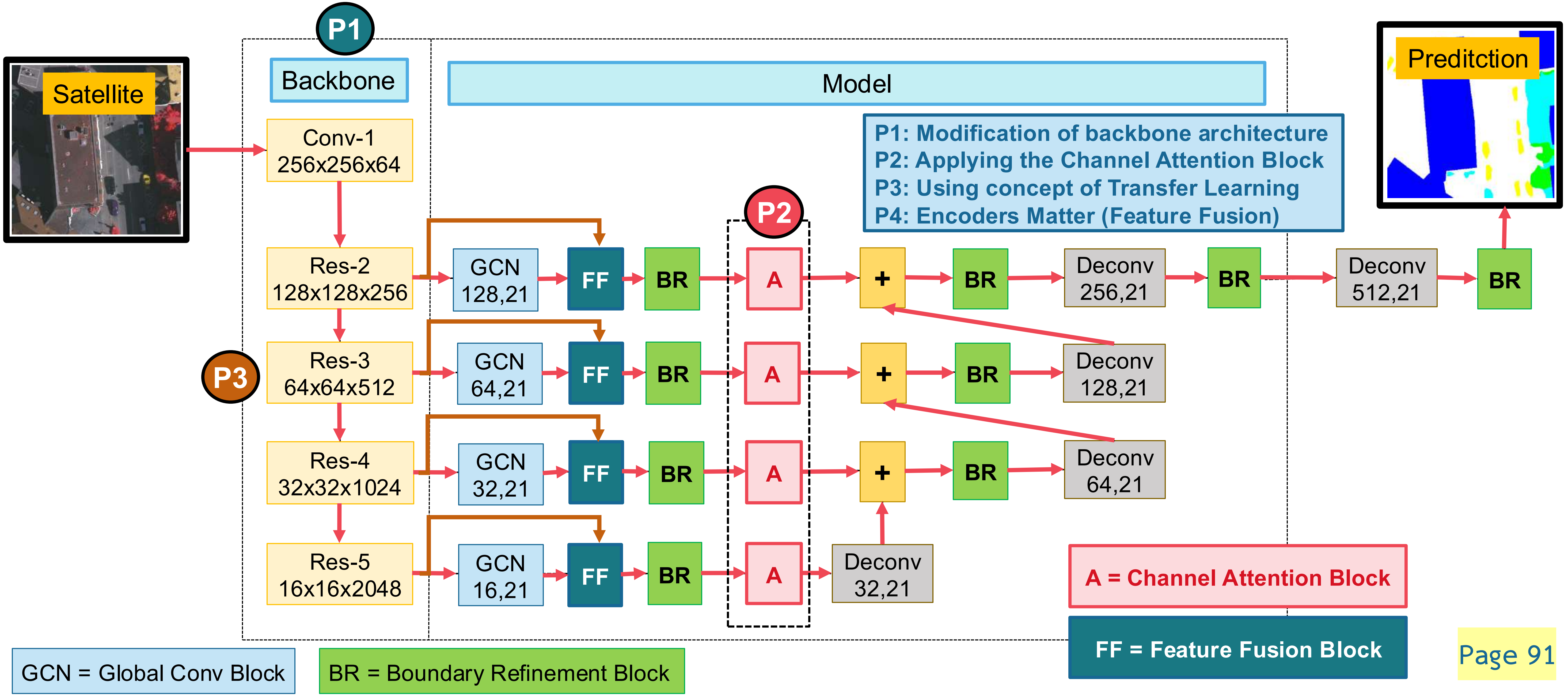
Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



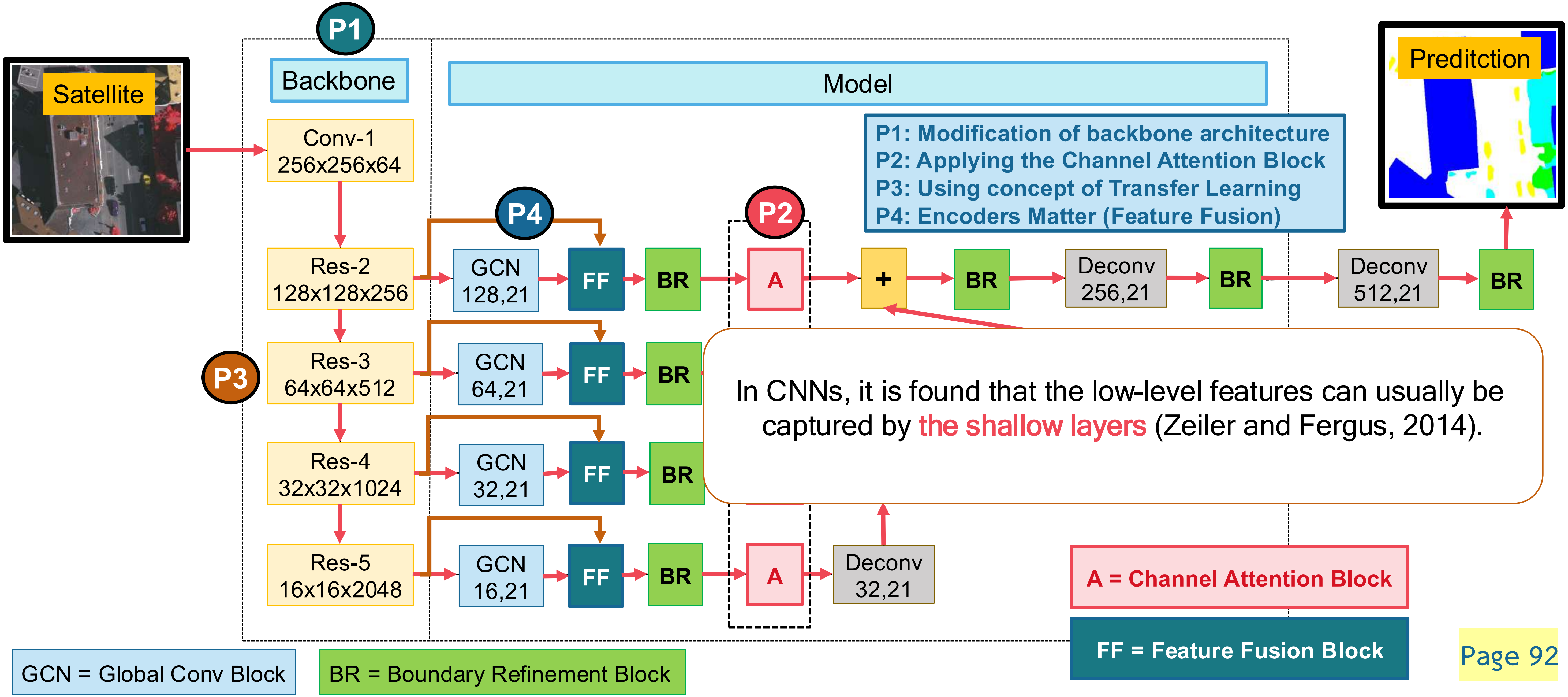
Proposed Method

P1 Backbone | P2 Attention (A) | P3 Transfer Learning (TL) | **P4 Feature Fusion (FF)** | P5 Depthwise Atrous (DA)



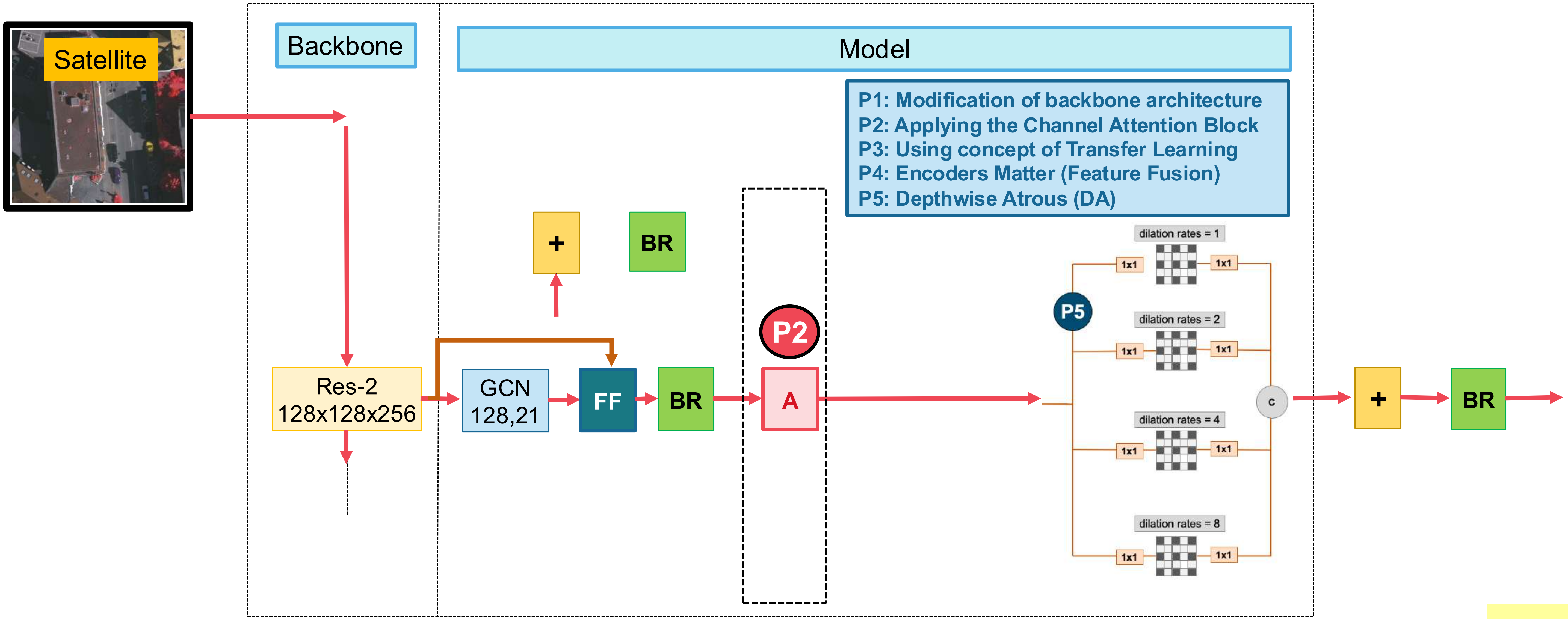
Proposed Method

P1 Backbone | P2 Attention (A) | P3 Transfer Learning (TL) | **P4 Feature Fusion (FF)** | P5 Depthwise Atrous (DA)



Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)



GCN = Global Conv Block

BR = Boundary Refinement Block

DA = Depthwise Atrous

Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

GCN = Global Conv Block

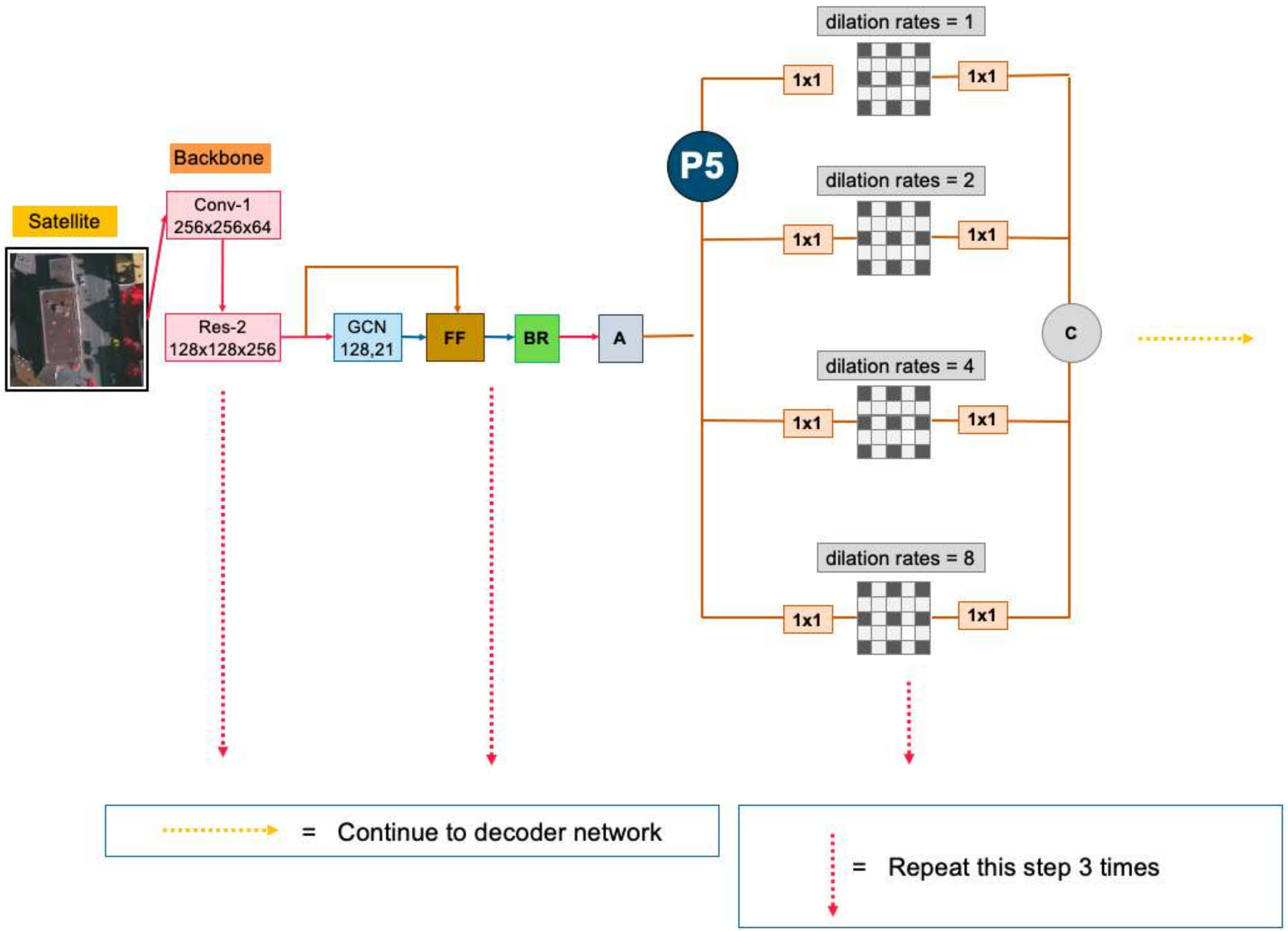
BR = Boundary Refinement Block

A = Channel Attention Block

TL = Transfer Learning

FF = Feature Fusion Block

DA = Depthwise Atrous



Proposed Method

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

GCN = Global Conv Block

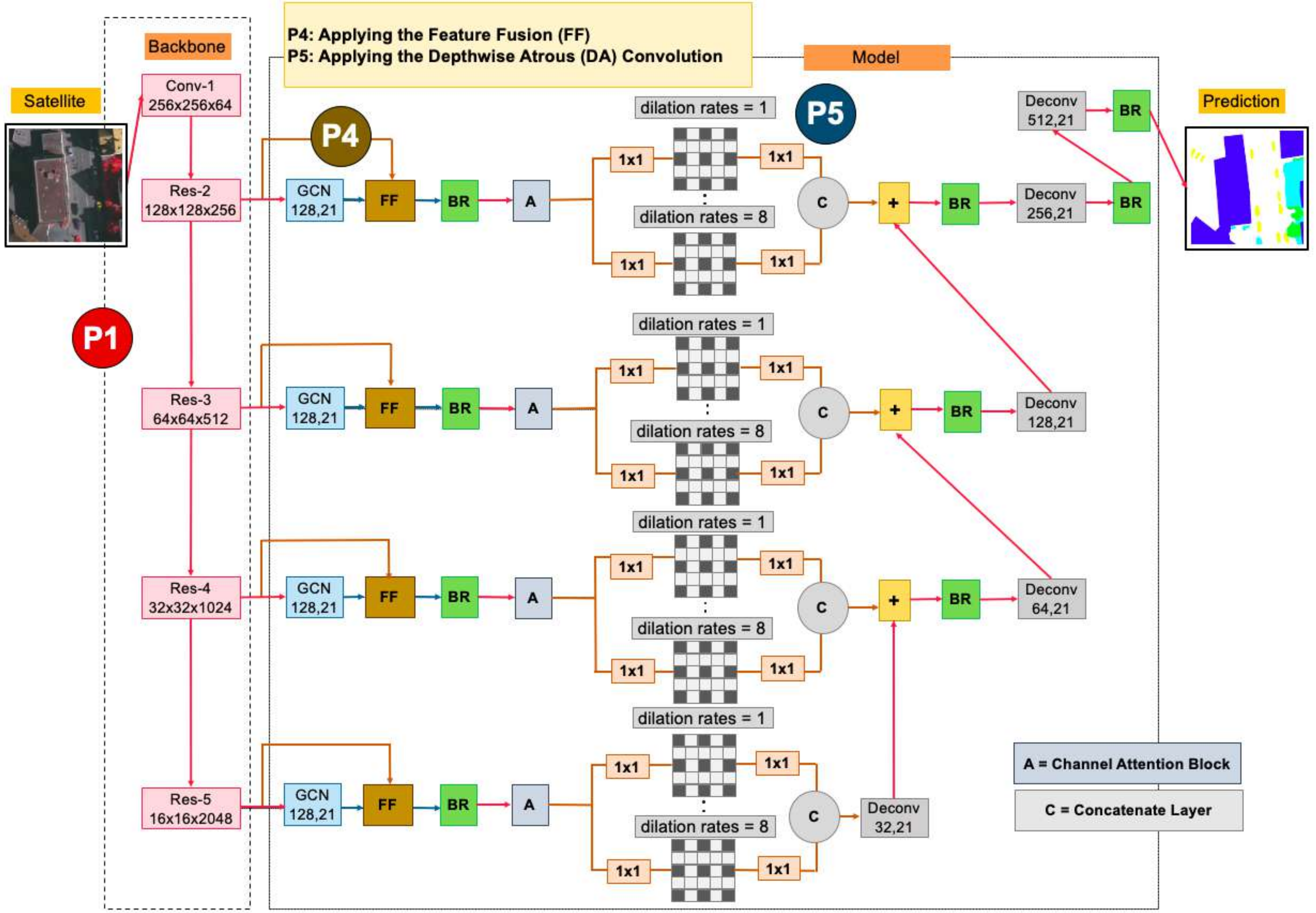
BR = Boundary Refinement Block

A = Channel Attention Block

TL = Transfer Learning

FF = Feature Fusion Block

DA = Depthwise Atrous



Proposed Method

P1 Backbone | P2 Attention (A) | P3 Transfer Learning (TL) | P4 Feature Fusion (FF) | P5 Depthwise Atrous (DA)

GCN = Global Conv Block

BR = Boundary Refinement Block

A = Channel Attention Block

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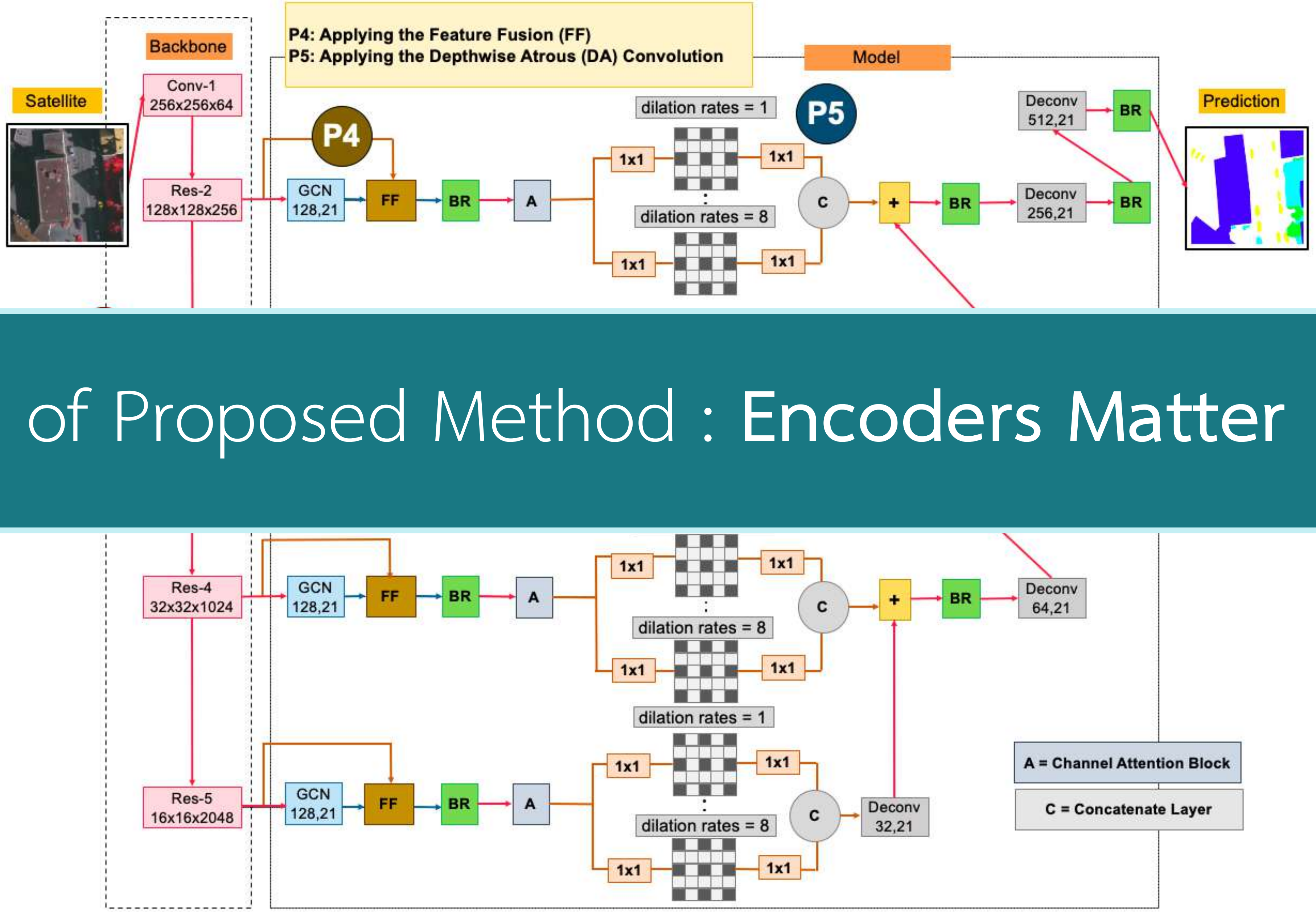
FF = Fe

DA = D

The Whole of Proposed Method : **Encoders Matter**



Outline | Experimental Results

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and Reference

Evaluation

Corpus 1
ISPRS Vaihingen

Corpus 2
Nan, Thailand

Corpus 3
Isan, Thailand

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
FF	Feature Fusion Module
DA	Depthwise Atrous Convolution

Abbreviations on our proposed deep learning methods

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

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

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

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

Performance Metrics

Recap: Each Methods from Proposed

GCN = Global Conv Block

A = Channel Attention Block

TL = Transfer Learning

FF = Feature Fusion Block

DA = Depthwise Atrous

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

- **Experiment 1:** How it impacts modern and over-deeper backbone?
- **Experiment 2:** Chanel Attention
- **Experiment 3:** Deep CNNs with Domain Specific Transfer Learning
- **Experiment 4:** Feature Fusion
- **Experiment 5:** Depthwise Atrous Convolution
- **Three data sets:** two private corpora from Landsat-8 satellite (Nan and Isan Region) and one public benchmark from the “ISPRS Vaihingen” challenge.

1st Corpus

Nan, Thailand (Medium Resolution Corpus)

Evaluation

Corpus 1
Nan, Thailand

Corpus 2
ISPRS Vaihingen

Corpus 3
Isan, Thailand

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.857	0.894	0.874
Proposed	-	Res50	**GCN**	0.881	0.872	0.875
	-	Res101	GCN	0.862	0.897	0.877
	-	Res152	GCN	0.892	0.878	0.884
	-	Res152	**GCN-A**	0.907	0.929	0.917
	TL	Res152	GCN-A	0.921	0.918	0.918
	TL	Res152	**GCN-A-FF**	0.930	0.924	0.927
	TL	Res152	**GCN-A-FF-DA**	**0.934**	**0.939**	**0.936**

Result: Our proposed method yields a higher F1 Score from baseline method at **6.2%**

Evaluation

Corpus 1
Nan, Thailand

Corpus 2
ISPRS Vaihingen

Corpus 3
Isan, Thailand

- Each class

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.982	0.962	0.763	0.854	0.725
Proposed	**GCN50**	0.967	0.948	0.817	0.881	0.792
	GCN101	0.976	0.929	0.685	0.929	0.785
	GCN152	0.976	0.950	0.823	0.913	0.797
	GCN152-A	0.984	0.944	0.882	0.899	0.822
	GCN152-TL-A	0.974	0.953	0.864	0.934	0.828
	GCN152-TL-A-FF	0.986	**0.982**	0.918	**0.956**	0.844
	GCN152-TL-A-FF-DA	**0.989**	0.957	**0.934**	0.949	**0.868**

Evaluation

Corpus 1
Nan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.857	0.894	**0.874**
Proposed	-	**Res50**	**GCN**	0.881	0.872	**0.875**
	-	**Res101**	GCN	0.862	0.897	0.877
	-	**Res152**	GCN	0.892	0.878	**0.884**

- Precision
- Recall
- F1-score

- GCN50 overcame DECD ~ 0.116 % F1
- GCN152 overcame DECD ~ 1.043 % F1

Evaluation

Corpus 1
Nan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	**0.982**	0.962	0.763	0.854	0.725
Proposed	GCN50	0.967	0.948	0.817	0.881	0.792
	GCN101	0.976	0.929	0.685	**0.929**	0.785
	GCN152	0.976	**0.950**	**0.823**	0.913	**0.797**

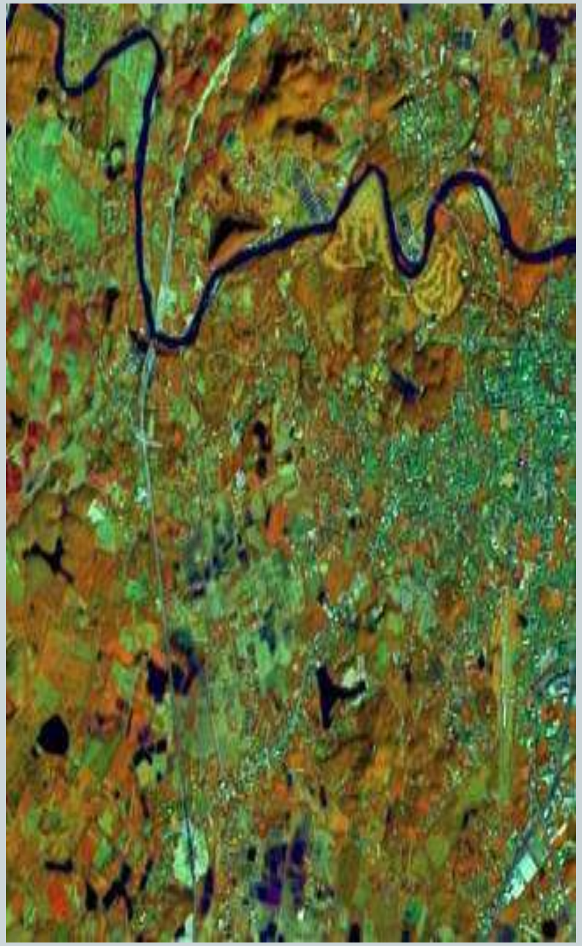
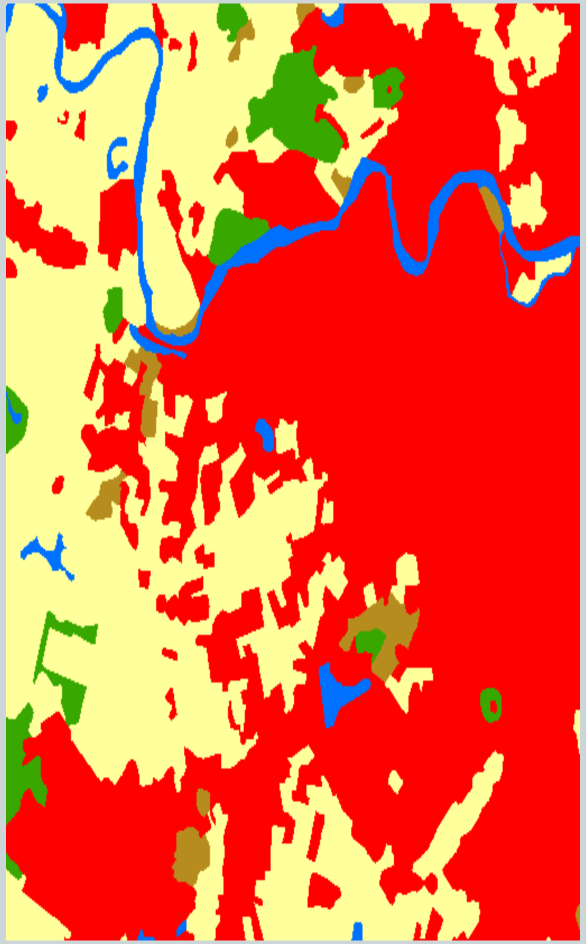
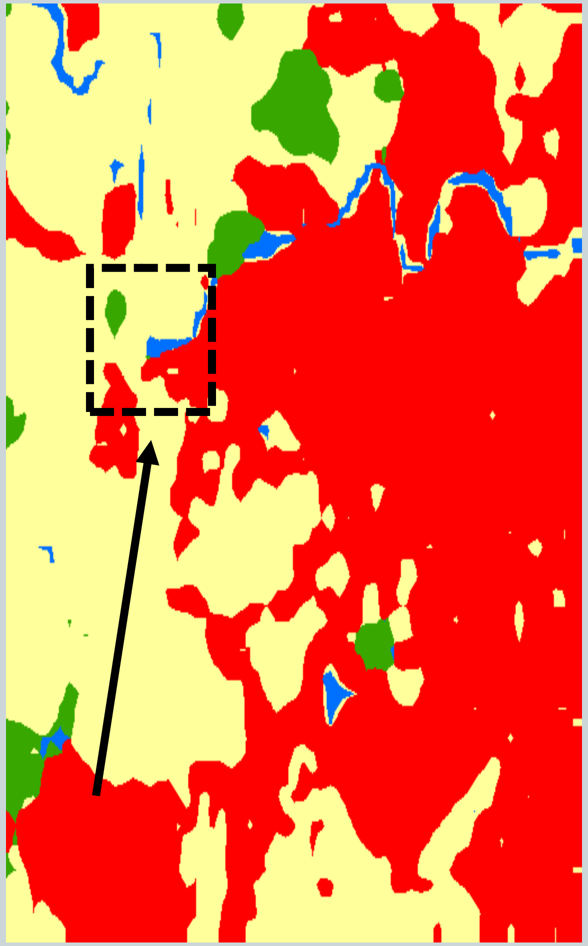
- Each class

- GCN Family won DECD 4 out of 5 classes

Evaluation

Corpus 1
Nan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

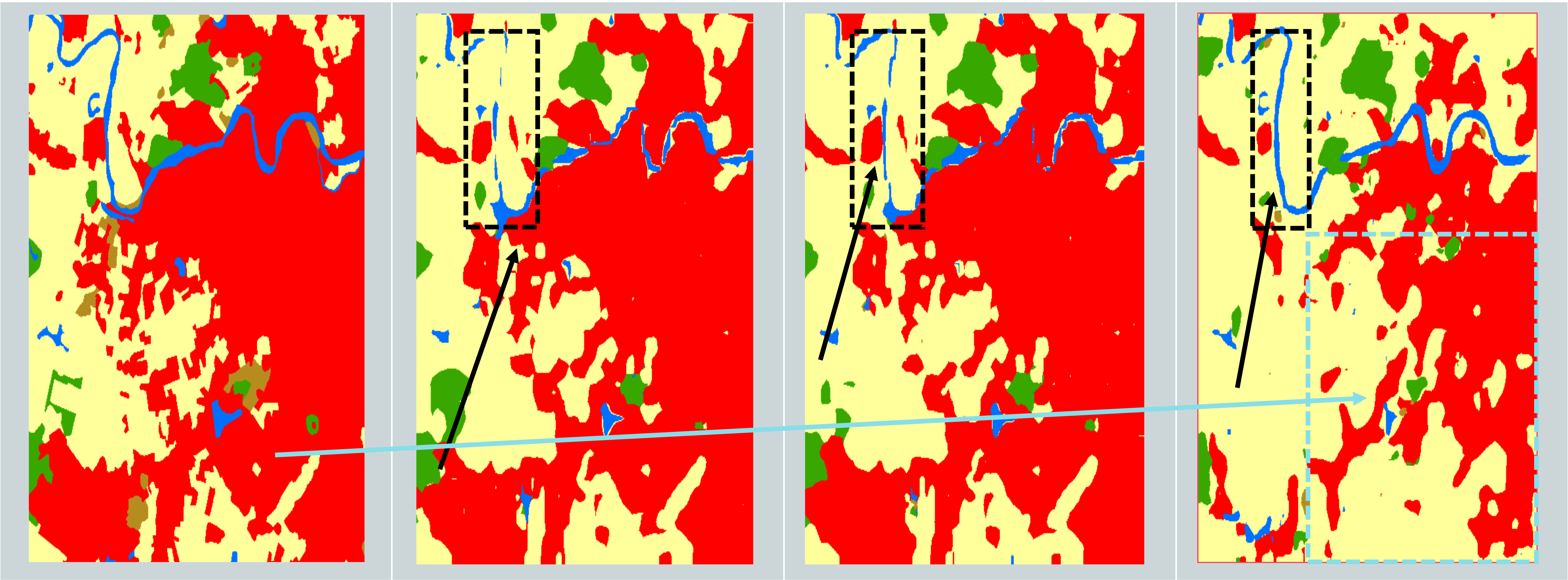
Input Image	Target Image	Baseline Method [10]	**GCN50**
			

Evaluation

Corpus 1
Nan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

Target Image	**GCN50**	GCN101	**GCN152**



Evaluation

Corpus 1
Nan, Thailand

Experiment 2:
Chanel Attention

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.857	0.894	0.874
Proposed	-	Res152	GCN	0.892	0.878	0.884
	-	Res152	GCN-A	0.907	0.929	0.917

- Precision
- Recall
- F1-score

- GCN152-A overcame DECD ~ 4.332 % F1
- GCN152-A overcame GCN152 ~ 3.288 % F1

Evaluation

Corpus 1
Nan, Thailand

Experiment 2:
Chanel Attention

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.982	**0.962**	0.763	0.854	0.725
Proposed	GCN152	0.976	0.950	0.823	**0.913**	0.797
	GCN152-A	**0.984**	0.944	**0.882**	0.899	**0.822**

- Each class

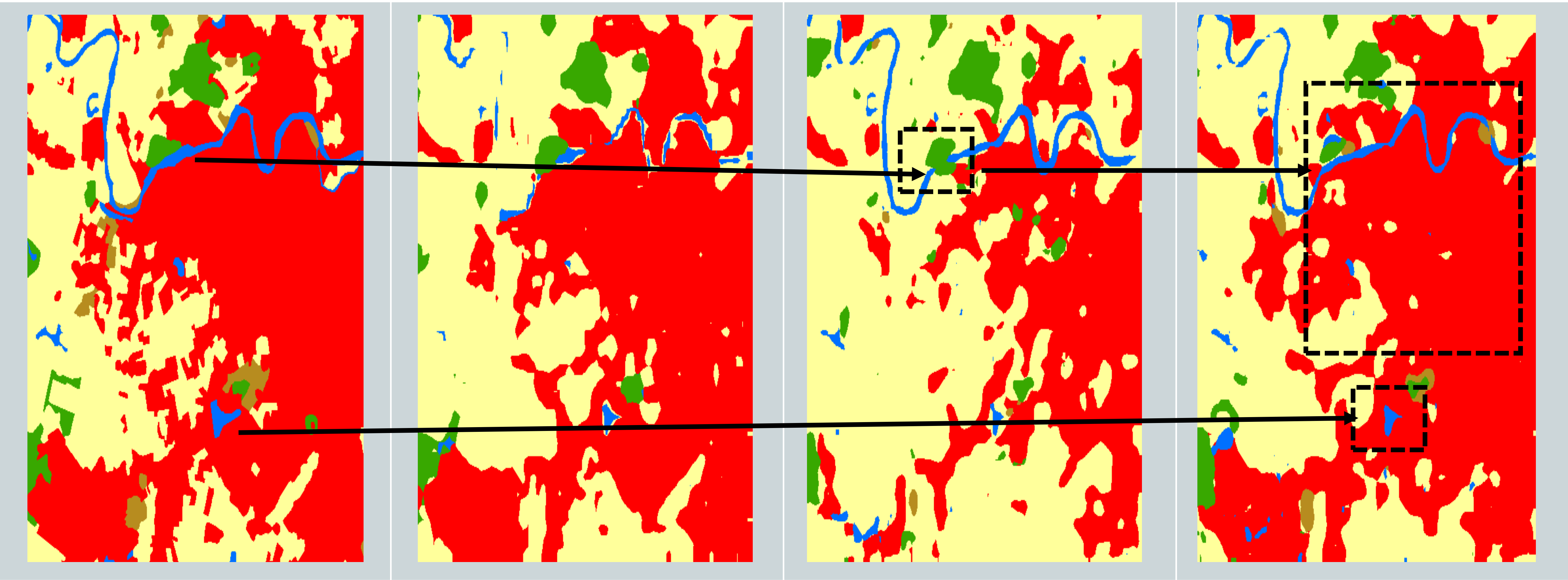
- Our Proposed won DECD 4 out of 5 classes

Evaluation

Corpus 1
Nan, Thailand

Experiment 2:
Chanel Attention

Target Image	Baseline Method [10	GCN152	GCN152-A



Evaluation

Corpus 1
Nan, Thailand

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.857	0.894	0.874
Proposed	-	Res152	GCN-A	0.907	0.929	0.917
	TL	Res152	GCN-A	0.921	0.918	0.918

- Precision
- Recall
- F1-score

- GCN152-A-TL overcame DECD ~ 4.446 % F1
- GCN152-A-TL overcame GCN152-A ~ 0.114 % F1

Evaluation

Corpus 1
Nan, Thailand

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.982	**0.962**	0.763	0.854	0.725
Proposed	GCN152-A	0.984	0.944	**0.882**	0.899	0.822
	GCN152-TL-A	**0.974**	0.953	0.864	**0.934**	**0.828**

- Each class

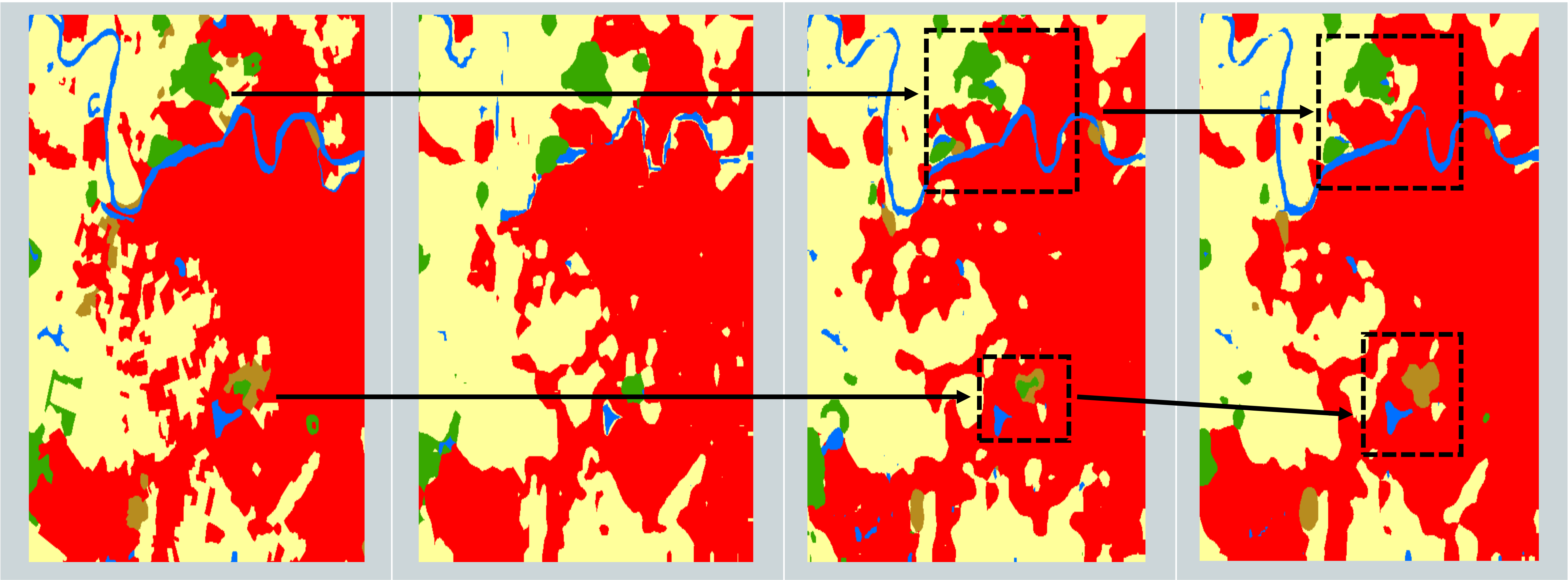
- Our Proposed won DECD 4 out of 5 classes

Evaluation

Corpus 1
Nan, Thailand

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Target Image	Baseline Method [10	GCN152-A	GCN152-A-TL



Evaluation

Corpus 1
Nan, Thailand

Experiment 4:
Feature Fusion

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.857	0.894	0.874
Proposed	TL	Res152	GCN-A	0.921	0.918	0.918
	TL	Res152	GCN-A-FF	0.930	0.924	0.927

- GCN152-A-TL-FF overcame DECD ~ 5.288 % F1
- GCN152-A-TL-FF overcame GCN152-A-TL ~ 0.843 % F1

Evaluation

Corpus 1
Nan, Thailand

Experiment 4:
Feature Fusion

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.982	0.962	0.763	0.854	0.725
Proposed	GCN152-TL-A	0.974	0.953	0.864	0.934	0.828
	GCN152-TL-A-FF	**0.986**	**0.982**	**0.918**	**0.956**	**0.844**

- Each class

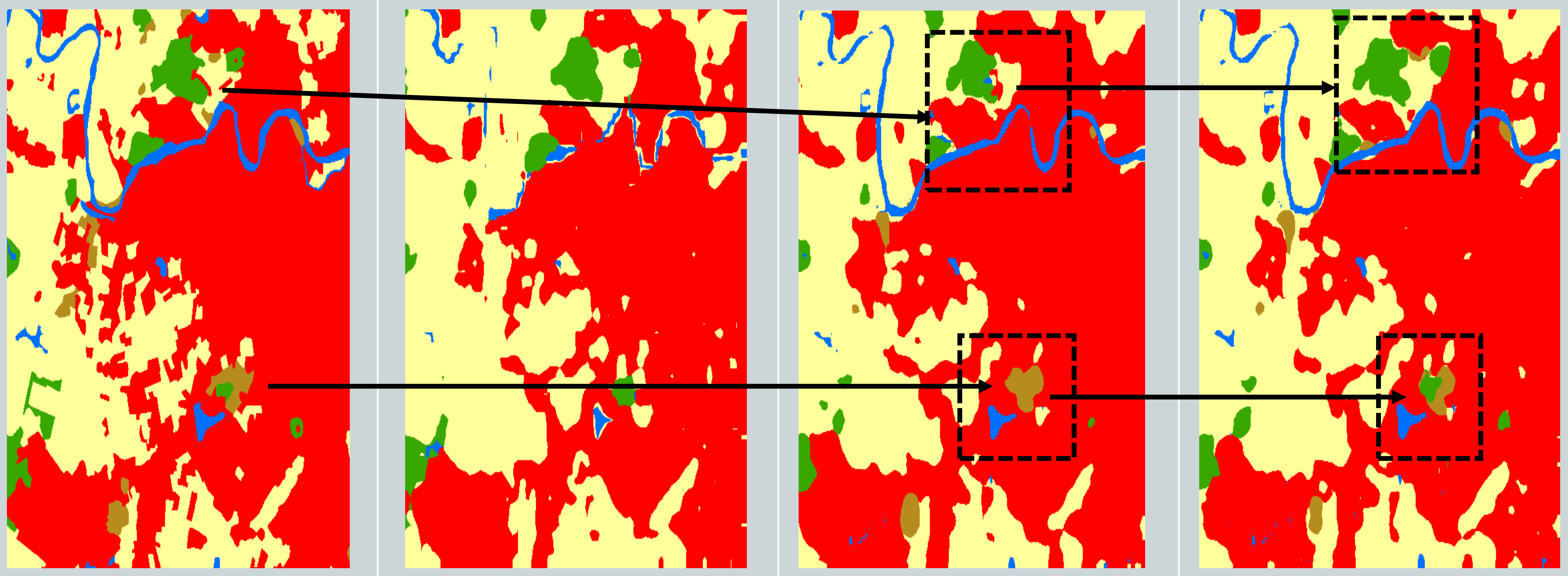
- Our Proposed won DECD 5 out of 5 classes

Evaluation

Corpus 1
Nan, Thailand

Experiment 4:
Feature Fusion

Target Image	Baseline Method [10	GCN152-A-TL	GCN152-A-TL-FF



Evaluation

Corpus 1
Nan, Thailand

Experiment 5:
Depthwise Atrous Convolution

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.857	0.894	0.874
Proposed	TL	Res152	GCN-A-FF	0.930	0.924	0.927
	TL	Res152	GCN-A-FF-DA	**0.934**	**0.939**	**0.936**

- GCN152-A-TL-FF-DA overcame DECD ~ 6.221 % F1
- GCN152-A-TL-FF-DA overcame GCN152-A-TL-FF ~ 0.933 % F1

Evaluation

Corpus 1
Nan, Thailand

Experiment 5:
Depthwise Atrous Convolution

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.982	0.962	0.763	0.854	0.725
Proposed	GCN152-TL-A-FF	0.986	**0.982**	0.918	**0.956**	0.844
	GCN152-TL-A-FF-DA	**0.989**	0.957	**0.934**	0.949	**0.868**

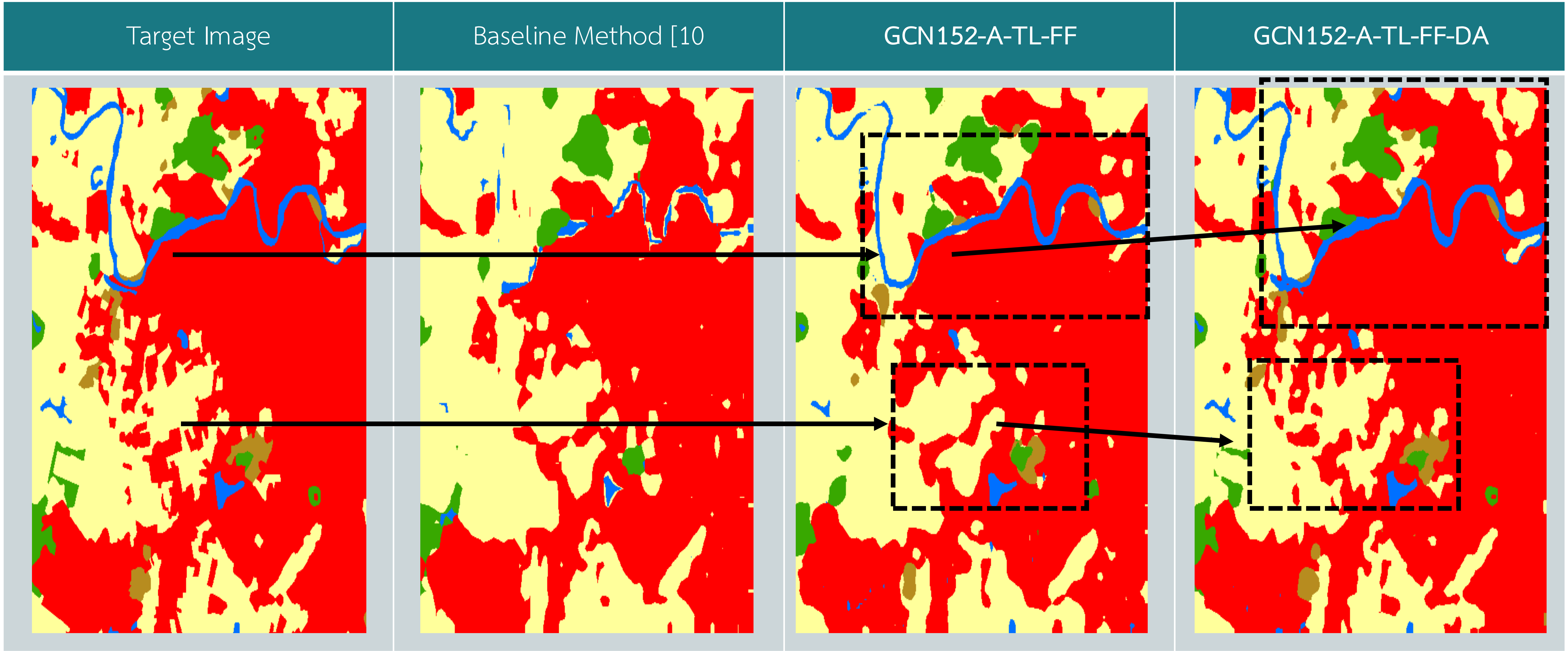
- Each class

- Our Proposed won DECD 5 out of 5 classes

Evaluation

Corpus 1
Nan, Thailand

Experiment 5:
Depthwise Atrous Convolution



Evaluation

Corpus 1
Nan, Thailand

Summary

Method	Model	F1 Score	Increase
Baseline	DCED	0.874	
P1	Enhanced GCN + Deeper Head Network	0.884	1.043 %
P2	+ Attention	0.917	3.288 %
P3	+ Transfer Learning	0.918	0.114 %
P4	+ Feature Fusion	0.927	0.843 %
P5	+ Depthwise Atrous Convolution	0.936	0.933%

The most impactful method:

Channel Attention

2nd Corpus

ISPRS Vaihingen

Evaluation

Corpus 1
Nan, Thailand

Corpus 2
ISPRS Vaihingen

Corpus 3
Isan, Thailand

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.867	0.849	0.854
Proposed	-	**Res50**	**GCN**	0.872	0.852	0.858
	-	**Res101**	GCN	0.850	0.854	0.866
	-	**Res152**	GCN	0.873	0.864	0.868
	-	**Res152**	**GCN-A**	0.875	0.869	0.874
	TL	**Res152**	GCN-A	0.897	0.877	0.881
	TL	**Res152**	**GCN-A-FF**	0.896	**0.904**	0.905
	TL	**Res152**	**GCN-A-FF-DA**	**0.923**	0.900	**0.911**

Result: Our proposed method yields a higher F1 Score from baseline method at **5.7%**

Evaluation

Corpus 1
Nan, Thailand

Corpus 2
ISPRS Vaihingen

Corpus 3
Isan, Thailand

- Each class

Method	Model	Imps	Building	Low veg	Tree	Car
Baseline	DCED	0.872	0.893	0.841	0.914	0.815
Proposed	GCN50	0.876	0.873	0.857	0.953	0.803
	GCN101	**0.941**	0.913	0.742	0.904	0.699
	GCN152	0.810	0.963	0.895	0.912	0.806
	GCN152-A	0.886	0.928	0.811	0.895	0.820
	GCN152-TL-A	0.871	0.916	0.890	0.918	0.874
	GCN152-TL-A-FF	0.928	0.976	0.926	0.968	0.898
	GCN152-TL-A-FF-DA	0.907	**0.979**	**0.927**	**0.972**	**0.910**

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 1:
How it impacts modern and over-deeper backbone?

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.867	0.849	**0.854**
Proposed	-	Res50	GCN	0.872	0.852	**0.858**
	-	Res101	GCN	0.850	0.854	0.866
	-	Res152	GCN	0.873	0.864	**0.868**

- Precision
- Recall
- F1-score

- GCN50 overcame DECD ~ 0.386 % F1
- GCN152 overcame DECD ~ 1.366 % F1

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 1:
How it impacts modern and over-deeper backbone?

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.872	0.893	0.841	0.914	0.815
Proposed	GCN50	0.876	0.873	0.857	**0.953**	0.803
	GCN101	**0.941**	0.913	0.742	0.904	0.699
	GCN152	0.810	**0.963**	**0.895**	0.912	**0.806**

- Each class

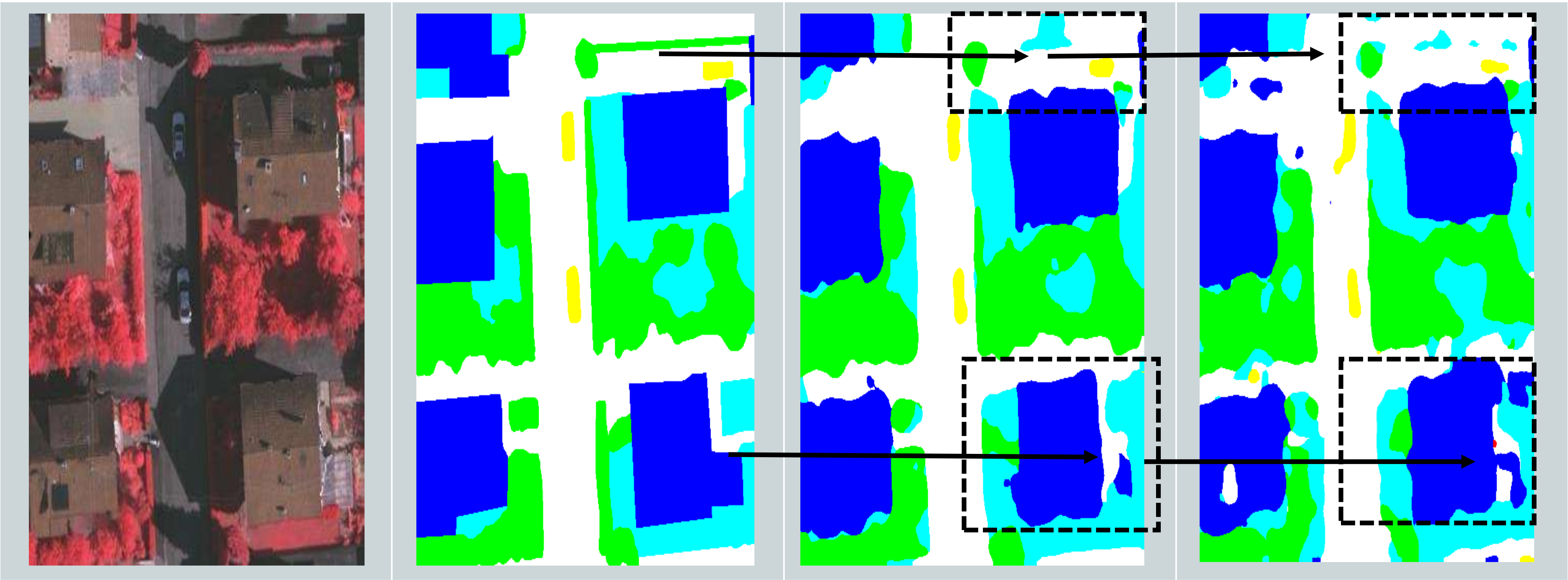
- GCN Family won DECD 5 out of 5 classes

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 1:
How it impacts modern and over-deeper backbone?

Input Image	Target Image	Baseline Method [10]	**GCN50**

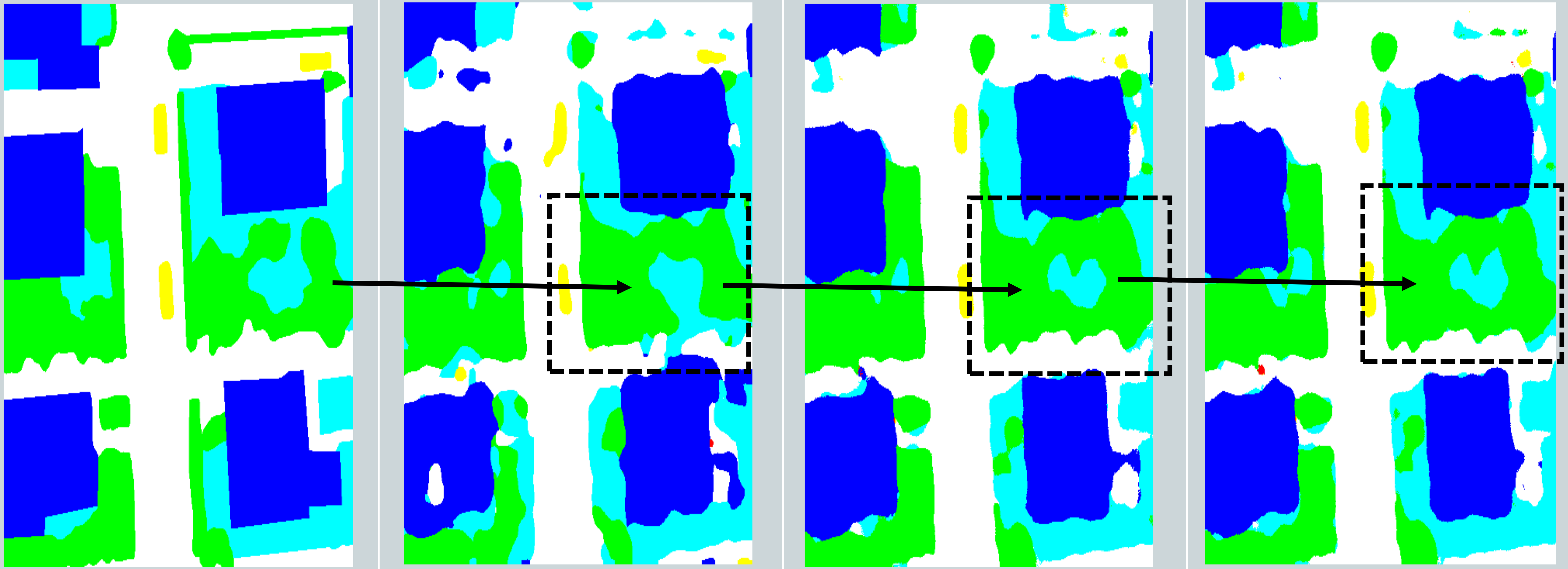


Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 1:
How it impacts modern and over-deeper backbone?

Target Image	**GCN50**	GCN101	**GCN152**



Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 2:
Chanel Attention

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.867	0.849	0.854
Proposed	-	Res152	GCN	0.873	0.864	0.868
	-	Res152	GCN-A	0.875	0.869	**0.874**

- Precision
- Recall
- F1-score

- GCN152-A overcame DECD ~ 1.916 % F1
- GCN152-A overcame GCN152 ~ 0.55 % F1

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 2:
Chanel Attention

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.872	0.893	0.841	**0.914**	0.815
Proposed	GCN152	0.810	**0.963**	**0.895**	0.912	0.806
	GCN152-A	**0.886**	0.928	0.811	0.895	**0.820**

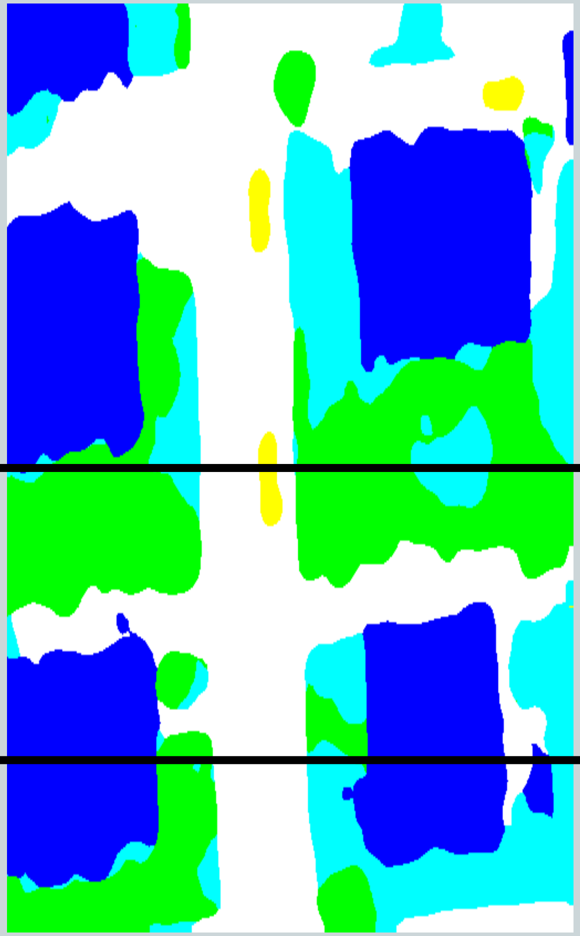
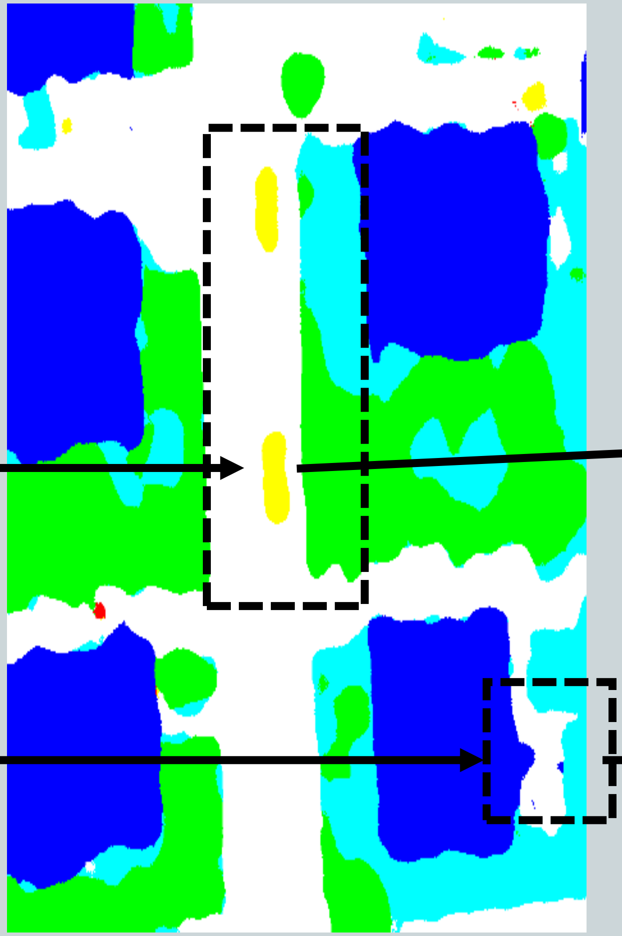
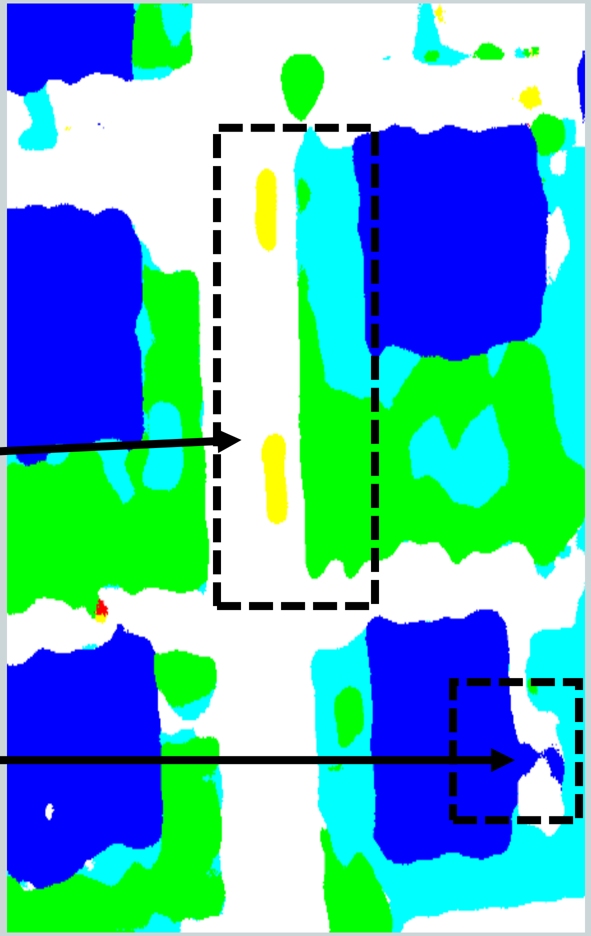
- Each class

- Our Proposed won DECD 4 out of 5 classes

Evaluation

Corpus 1
Nan, Thailand

Experiment 2:
Chanel Attention

Target Image	Baseline Method [10	GCN152	GCN152-A
			

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.867	0.849	0.854
Proposed	-	Res152	GCN-A	0.875	0.869	0.874
	TL	Res152	GCN-A	0.897	0.877	**0.881**

- Precision
- Recall
- F1-score

- GCN152-A-TL overcame DECD ~ 2.642 % F1
- GCN152-A-TL overcame GCN152-A ~ 0.726 % F1

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.872	0.893	0.841	0.914	0.815
Proposed	GCN152-A	**0.886**	**0.928**	0.811	0.895	0.820
	GCN152-TL-A	0.871	0.916	**0.890**	**0.918**	**0.874**

- Each class

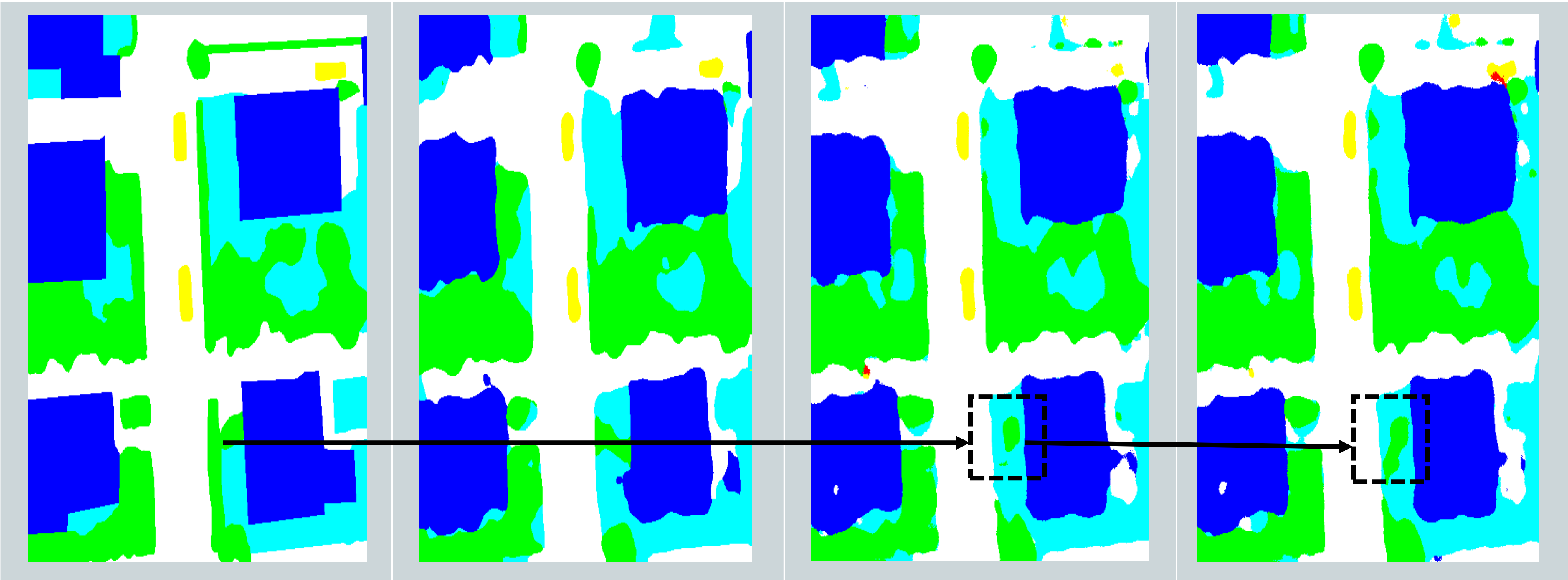
- Our Proposed won DECD 5 out of 5 classes

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Target Image	Baseline Method [10	GCN152-A	GCN152-A-TL



Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 4:
Feature Fusion

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.867	0.849	0.854
Proposed	TL	Res152	GCN-A	0.897	0.877	0.881
	TL	Res152	GCN-A-FF	0.896	0.904	**0.905**

- GCN152-A-TL-FF overcame DECD ~ 5.097 % F1
- GCN152-A-TL-FF overcame GCN152-A-TL ~ 2.455 % F1

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 4:
Feature Fusion

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.872	0.893	0.841	0.914	0.815
Proposed	GCN152-TL-A	0.871	0.916	0.890	0.918	0.874
	GCN152-TL-A-FF	**0.928**	**0.976**	**0.926**	**0.968**	**0.898**

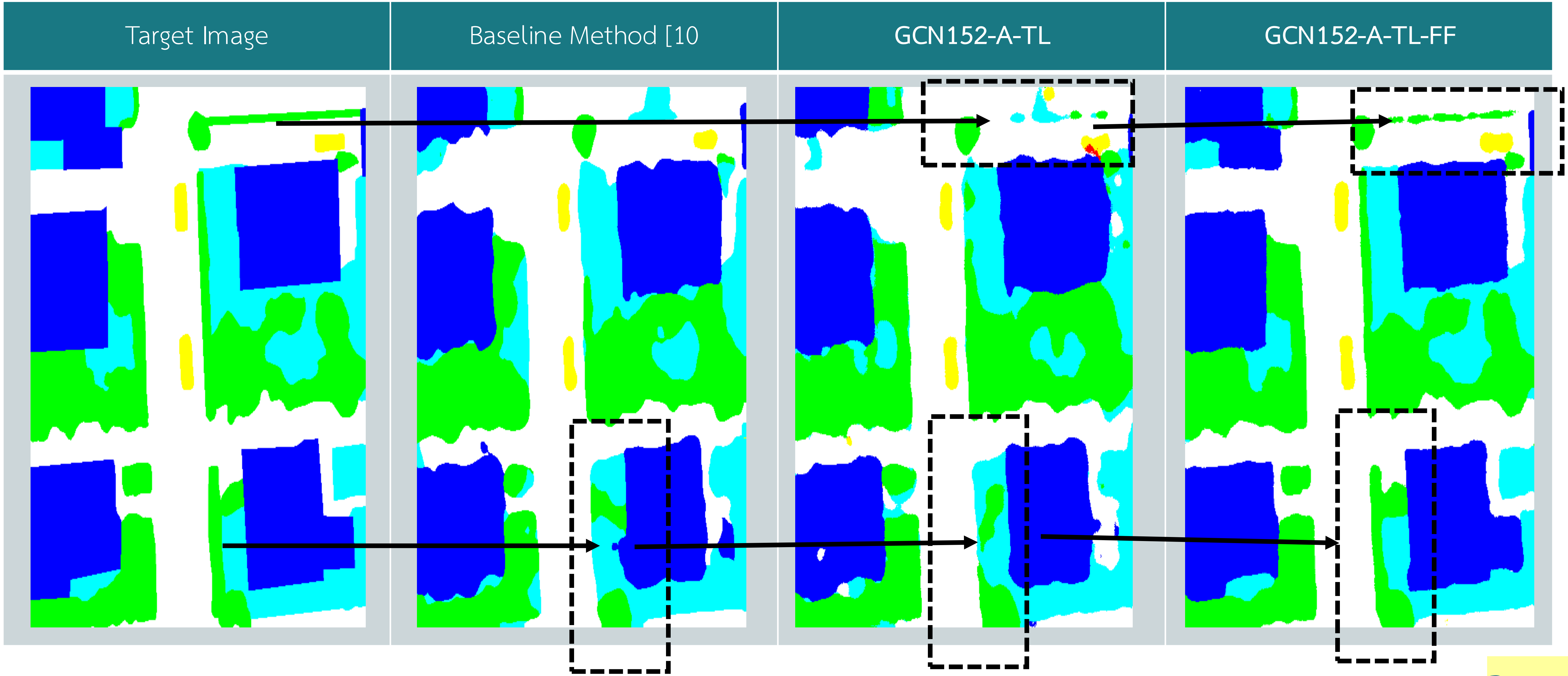
- Each class

- Our Proposed won DECD 5 out of 5 classes

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 4:
Feature Fusion



Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 5:
Depthwise Atrous Convolution

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.867	0.849	0.854
Proposed	TL	Res152	GCN-A-FF	0.896	0.904	0.905
	TL	Res152	GCN-A-FF-DA	0.923	0.900	**0.911**

- GCN152-A-TL-FF-DA overcame DECD ~ 5.67 % F1
- GCN152-A-TL-FF-DA overcame GCN152-A-TL-FF ~ 0.573 % F1

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 5:
Depthwise Atrous Convolution

Method	Model	Agri	Forest	Misc	Urban	Water
Baseline	DCED	0.872	0.893	0.841	0.914	0.815
Proposed	GCN152-TL-A-FF	**0.928**	0.976	0.926	0.968	0.898
	GCN152-TL-A-FF-DA	0.907	**0.979**	**0.927**	**0.972**	**0.910**

- Each class

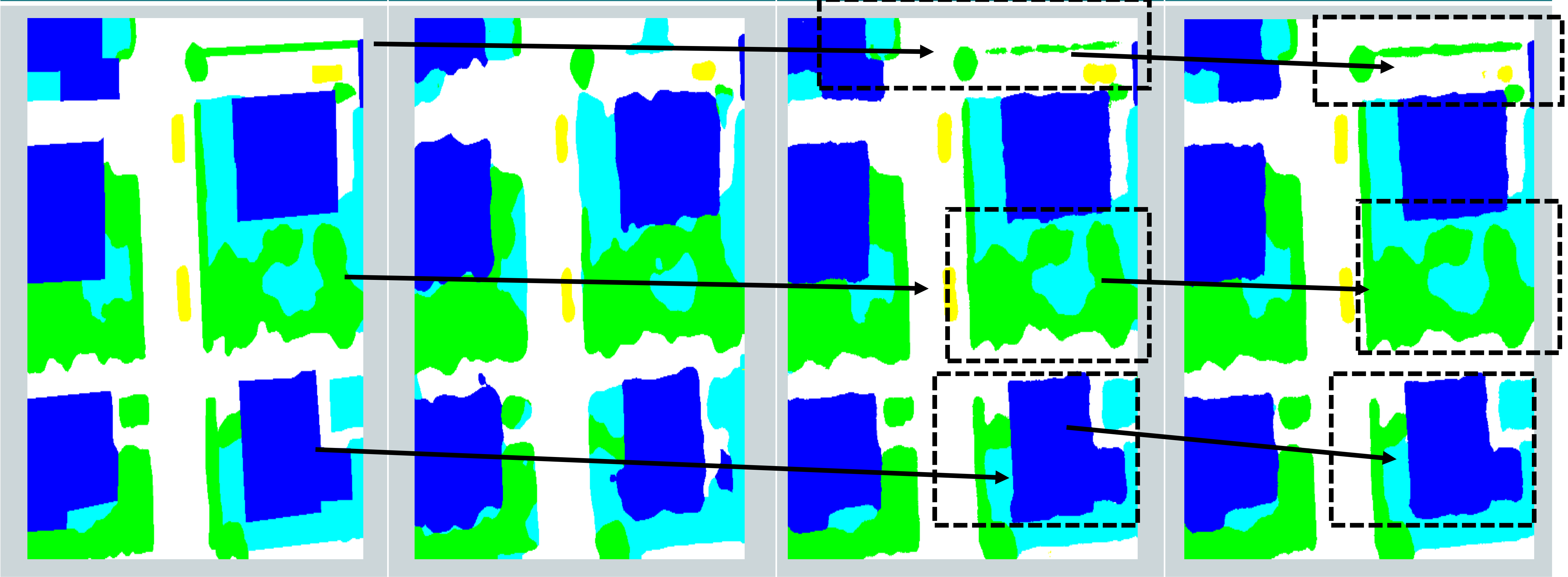
- Our Proposed won DECD 5 out of 5 classes

Evaluation

Corpus 2
ISPRS Vaihingen

Experiment 5:
Depthwise Atrous Convolution

Target Image	Baseline Method [10	GCN152-A-TL-FF	GCN152-A-TL-FF-DA



Evaluation

Corpus 2
ISPRS Vaihingen

Summary

Method	Model	F1 Score	Increase
Baseline	DCED	0.854	
P1	Enhanced GCN + Deeper Head Network	0.868	1.366 %
P2	+ Attention	0.874	0.550 %
P3	+ Transfer Learning	0.881	0.726 %
P4	+ Feature Fusion	0.905	2.455 %
P5	+ Depthwise Atrous Convolution	0.911	0.573 %

The most impactful method:

Feature Fusion

3rd Corpus

Isan, Thailand (Medium Resolution Corpus)

Evaluation

Corpus 1
Nan, Thailand

Corpus 2
ISPRS Vaihingen

Corpus 3
Isan, Thailand

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.861	0.782	0.810
Proposed	-	Res50	GCN	0.873	0.872	0.872
	-	Res101	GCN	0.865	0.884	0.874
	-	Res152	GCN	0.860	0.898	0.876
	-	Res152	GCN-A	0.865	0.891	0.877
	TL	Res152	GCN-A	0.890	0.923	0.899
	TL	Res152	GCN-A-FF	0.919	0.934	0.929
	TL	Res152	GCN-A-FF-DA	**0.945**	**0.938**	**0.947**

Result: Our proposed method yields a higher F1 Score from baseline method at **13.7%**

Evaluation

Corpus 1
Nan, Thailand

Corpus 2
ISPRS Vaihingen

Corpus 3
Isan, Thailand

- Each class

Method	Model	Corn	Pineapple	Pararubber
Baseline	DCED	0.905	0.815	0.820
Proposed	GCN50	0.933	0.778	0.888
	GCN101	0.837	0.815	0.862
	GCN152	0.910	0.721	0.879
	GCN152-A	0.858	0.768	0.854
	GCN152-TL-A	0.919	0.899	0.919
	GCN152-TL-A-FF	0.952	0.925	0.931
	GCN152-TL-A-FF-DA	**0.969**	**0.948**	**0.938**

Evaluation

Corpus 3
Isan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.861	0.782	0.810
Proposed	-	Res50	GCN	0.873	0.872	0.872
	-	Res101	GCN	0.865	0.884	0.874
	-	Res152	GCN	0.860	0.898	0.876

- Precision
- Recall
- F1-score

- GCN50 overcame DECD ~ 6.145 % F1
- GCN152 overcame DECD ~ 6.601 % F1

Evaluation

Corpus 3
Isan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

Method	Model	Corn	Pineapple	Pararubber
Baseline	DCED	0.905	**0.815**	0.820
Proposed	GCN50	**0.933**	0.778	**0.888**
	GCN101	0.837	**0.815**	0.862
	GCN152	0.910	0.721	0.879

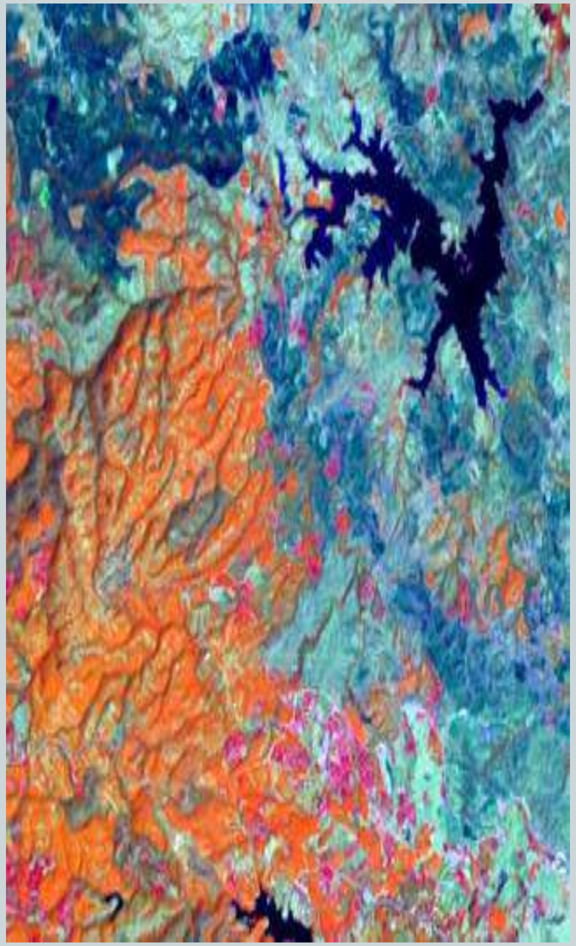
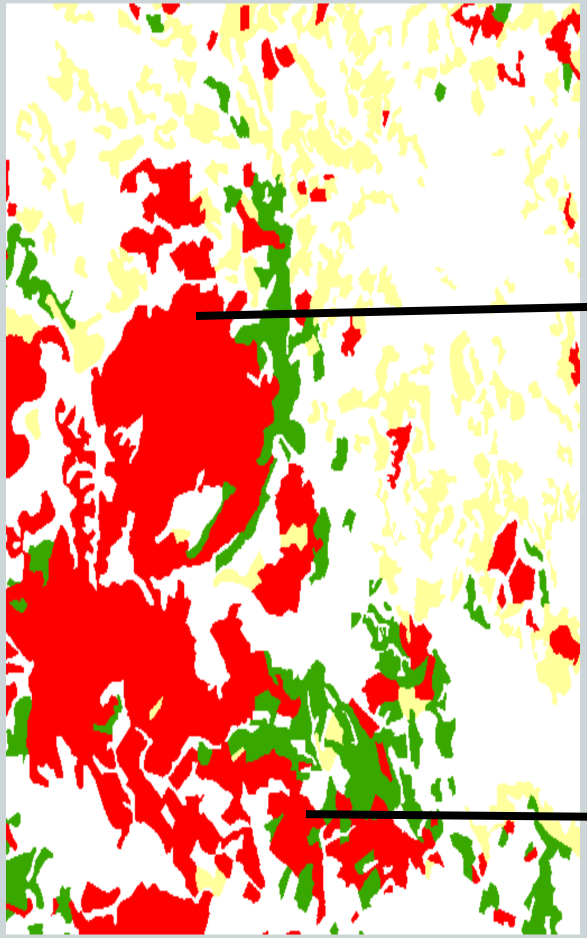
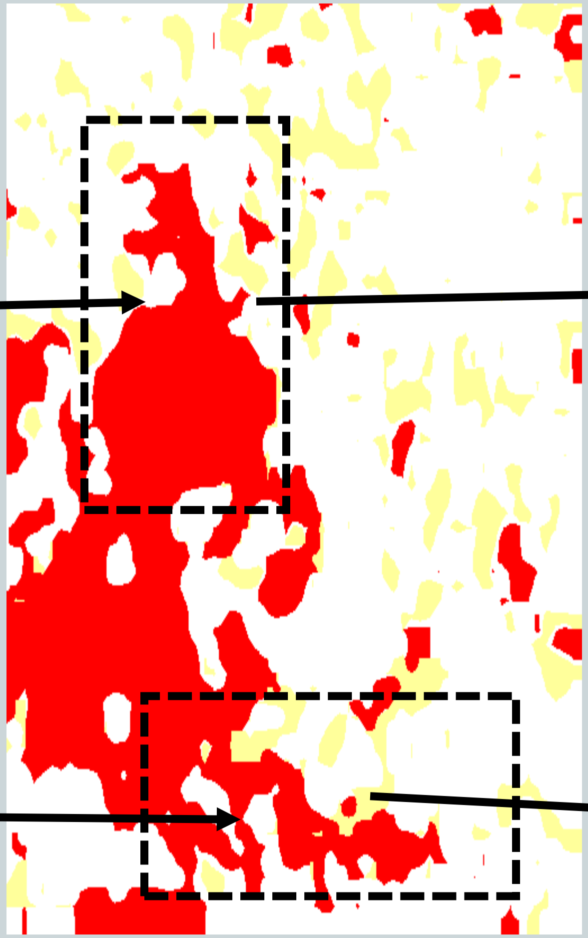
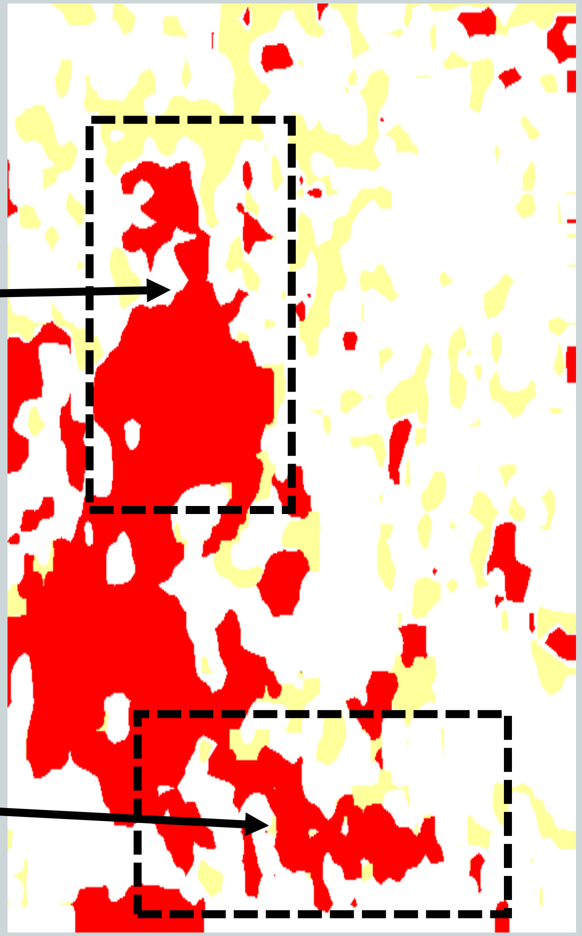
- Each class

- GCN Family won DECD 3 out of 3 classes

Evaluation

Corpus 3
Isan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

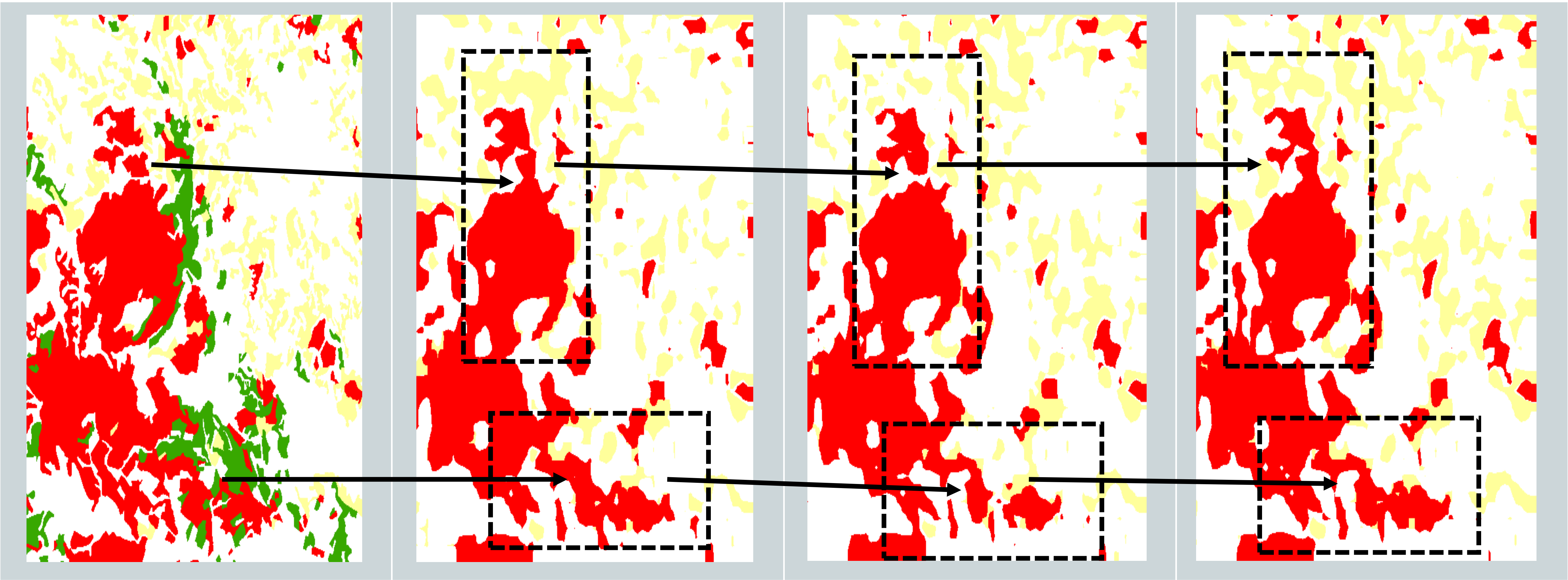
Input Image	Target Image	Baseline Method [10]	**GCN50**
			

Evaluation

Corpus 3
Isan, Thailand

Experiment 1:
How it impacts modern and over-deeper backbone?

Target Image	GCN50	GCN101	GCN152



Evaluation

Corpus 3
Isan, Thailand

Experiment 2:
Chanel Attention

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.861	0.782	0.810
Proposed	-	Res152	GCN	0.860	0.898	0.876
	-	**Res152**	**GCN-A**	0.865	0.891	**0.877**

- Precision
- Recall
- F1-score

- GCN152-A overcame DECD ~ 6.681 % F1
- GCN152-A overcame GCN152 ~ 0.081 % F1

Evaluation

Corpus 3
Isan, Thailand

Experiment 2:
Chanel Attention

Method	Model	Corn	Pineapple	Pararubber
Baseline	DCED	0.905	**0.815**	0.820
Proposed	GCN152	**0.910**	0.721	0.879
	GCN152-A	0.858	0.768	**0.854**

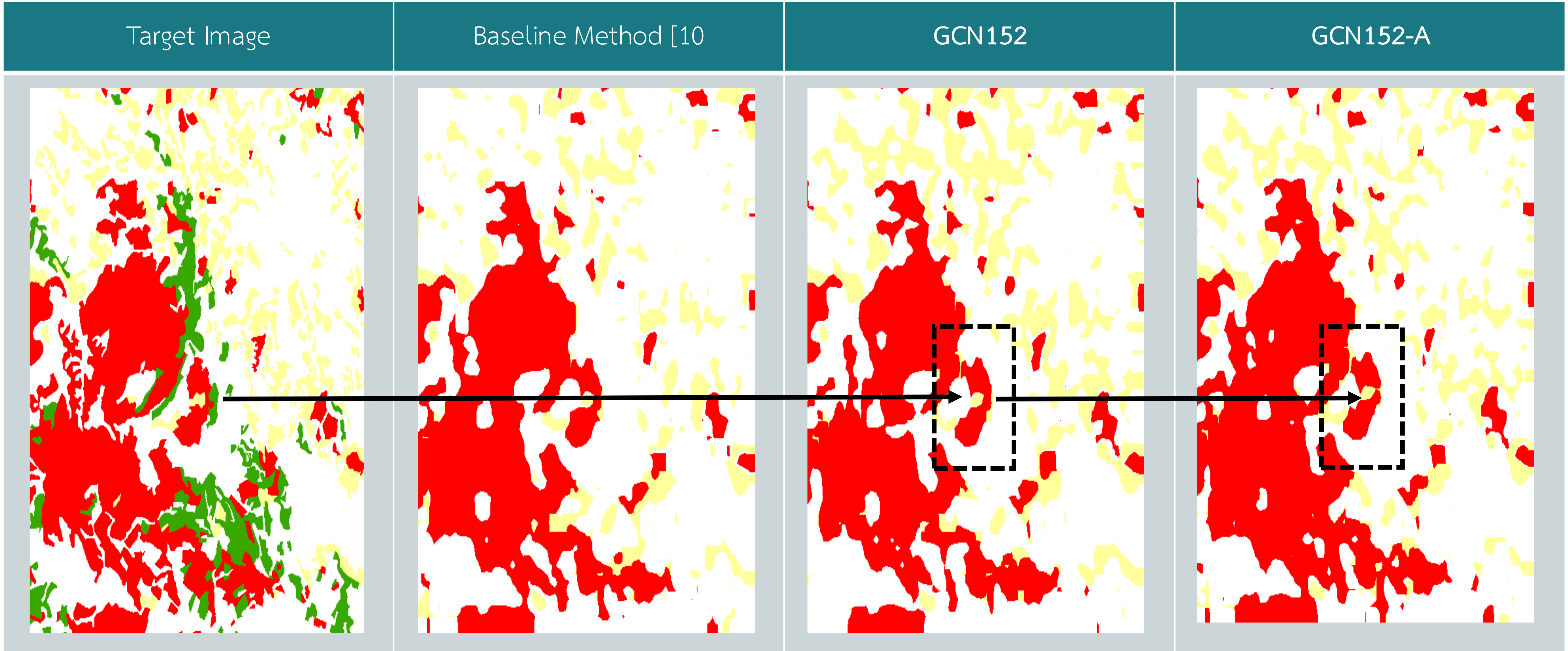
- Each class

- Our Proposed won DECD 2 out of 3 classes

Evaluation

Corpus 3
Isan, Thailand

Experiment 2:
Chanel Attention



Evaluation

Corpus 3
Isan, Thailand

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.861	0.782	0.810
Proposed	-	Res152	GCN-A	0.865	0.891	0.877
	TL	Res152	GCN-A	0.890	0.923	0.899

- Precision
- Recall
- F1-score

- GCN152-A-TL overcame DECD ~ 8.875 % F1
- GCN152-A-TL overcame GCN152-A ~ 2.194 % F1

Evaluation

Corpus 3
Isan, Thailand

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning

Method	Model	Corn	Pineapple	Pararubber
Baseline	DCED	0.905	0.815	0.820
Proposed	GCN152-A	0.858	0.768	0.854
	GCN152-TL-A	**0.919**	**0.899**	**0.919**

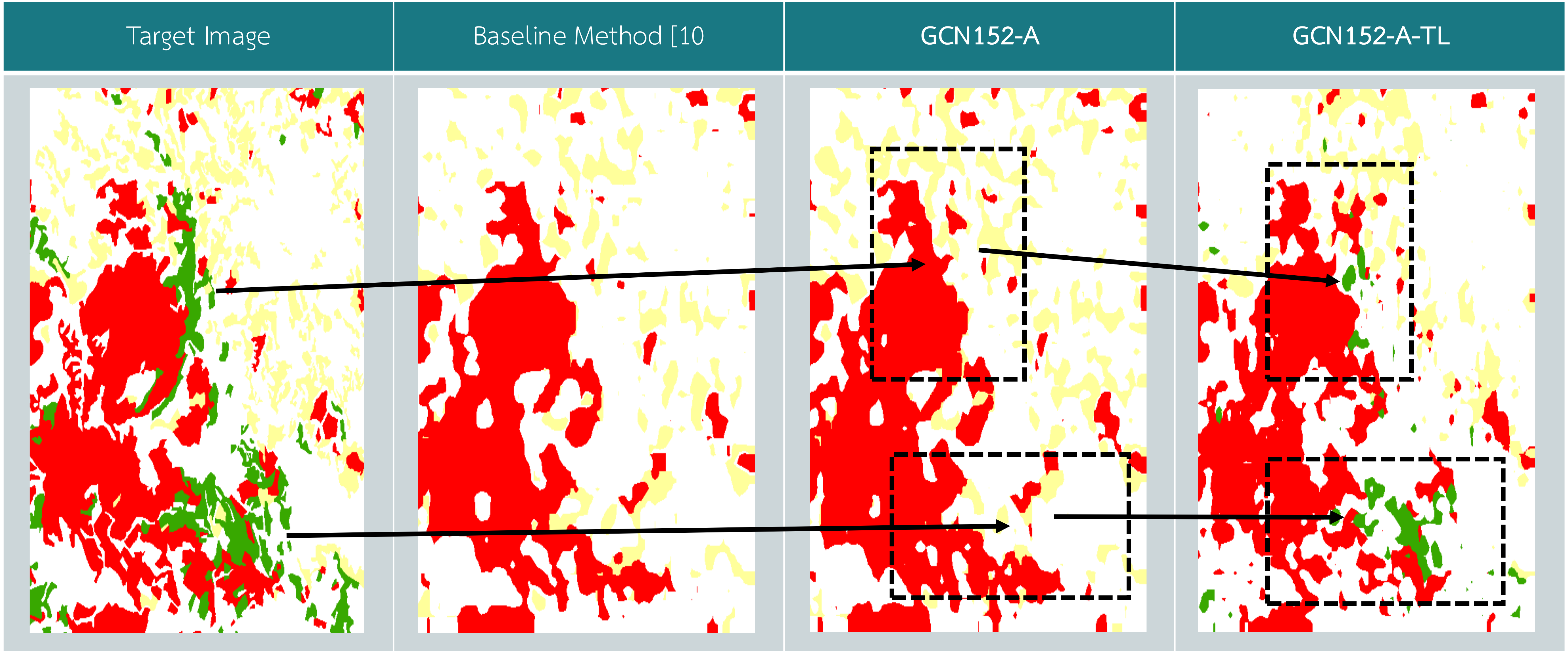
- Each class

- Our Proposed won DECD 3 out of 3 classes

Evaluation

Corpus 3
Isan, Thailand

Experiment 3:
Deep CNNs with Domain Specific Transfer Learning



Evaluation

Corpus 3
Isan, Thailand

Experiment 4:
Feature Fusion

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.861	0.782	0.810
Proposed	TL	Res152	GCN-A	0.890	0.923	0.899
	TL	Res152	GCN-A-FF	0.919	0.934	**0.929**

- GCN152-A-TL-FF overcame DECD ~ 11.829 % F1
- GCN152-A-TL-FF overcame GCN152-A-TL ~ 2.954 % F1

Evaluation

Corpus 3
Isan, Thailand

Experiment 4:
Feature Fusion

Method	Model	Corn	Pineapple	Pararubber
Baseline	DCED	0.905	0.815	0.820
Proposed	GCN152-TL-A	0.919	0.899	0.919
	GCN152-TL-A-FF	**0.952**	**0.925**	**0.931**

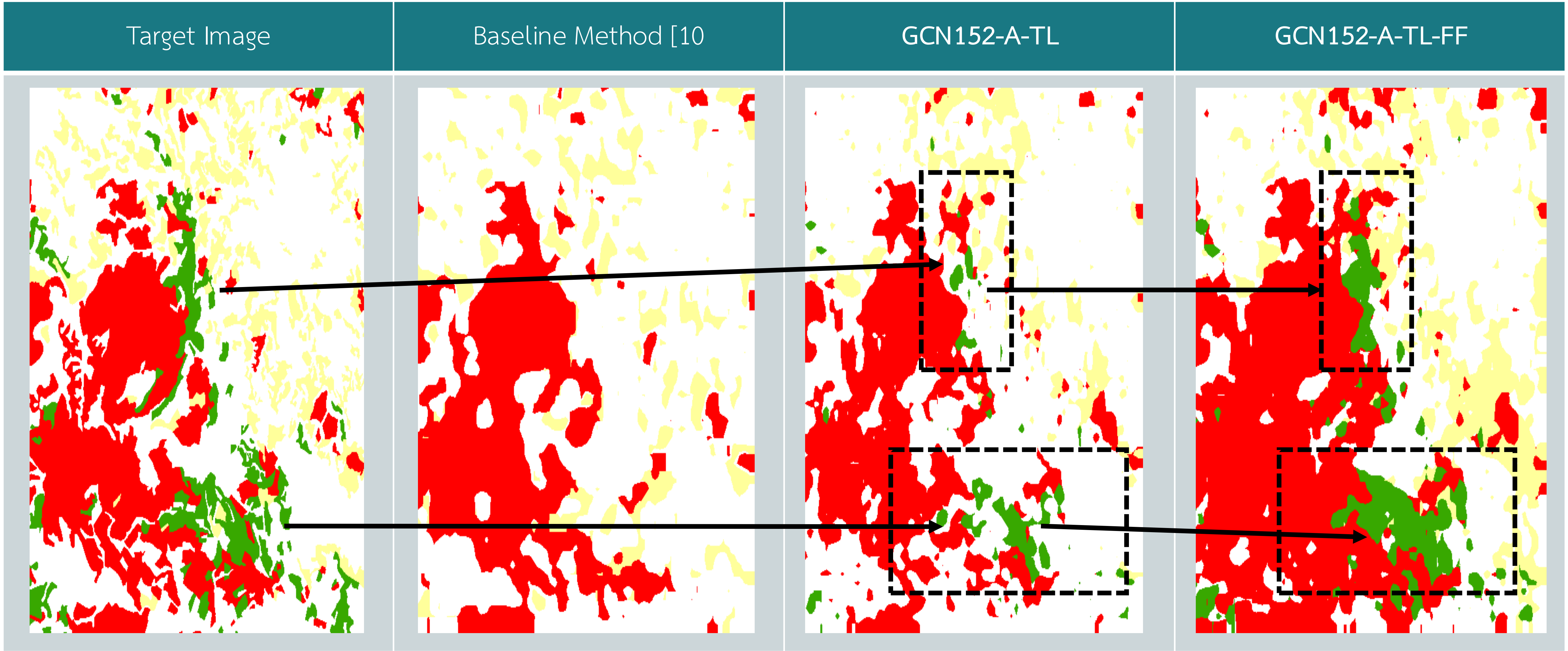
- Each class

- Our Proposed won DECD 3 out of 3 classes

Evaluation

Corpus 3
Isan, Thailand

Experiment 4:
Feature Fusion



Evaluation

Corpus 3
Isan, Thailand

Experiment 5:
Depthwise Atrous Convolution

- Precision
- Recall
- F1-score

Method	Pretrained	Backbone	Model	Precision	Recall	F1 Score
Baseline	-	-	DCED	0.861	0.782	0.810
Proposed	TL	Res152	GCN-A-FF	0.919	0.934	0.929
	TL	Res152	GCN-A-FF-DA	0.945	0.938	**0.947**

- GCN152-A-TL-FF-DA overcame DECD ~ 13.701 % F1
- GCN152-A-TL-FF-DA overcame GCN152-A-TL-FF ~ 1.872 % F1

Evaluation

Corpus 3
Isan, Thailand

Experiment 5:
Depthwise Atrous Convolution

Method	Model	Corn	Pineapple	Pararubber
Baseline	DCED	0.905	0.815	0.820
Proposed	GCN152-TL-A-FF	0.952	0.925	0.931
	GCN152-TL-A-FF-DA	**0.969**	**0.948**	**0.938**

- Each class

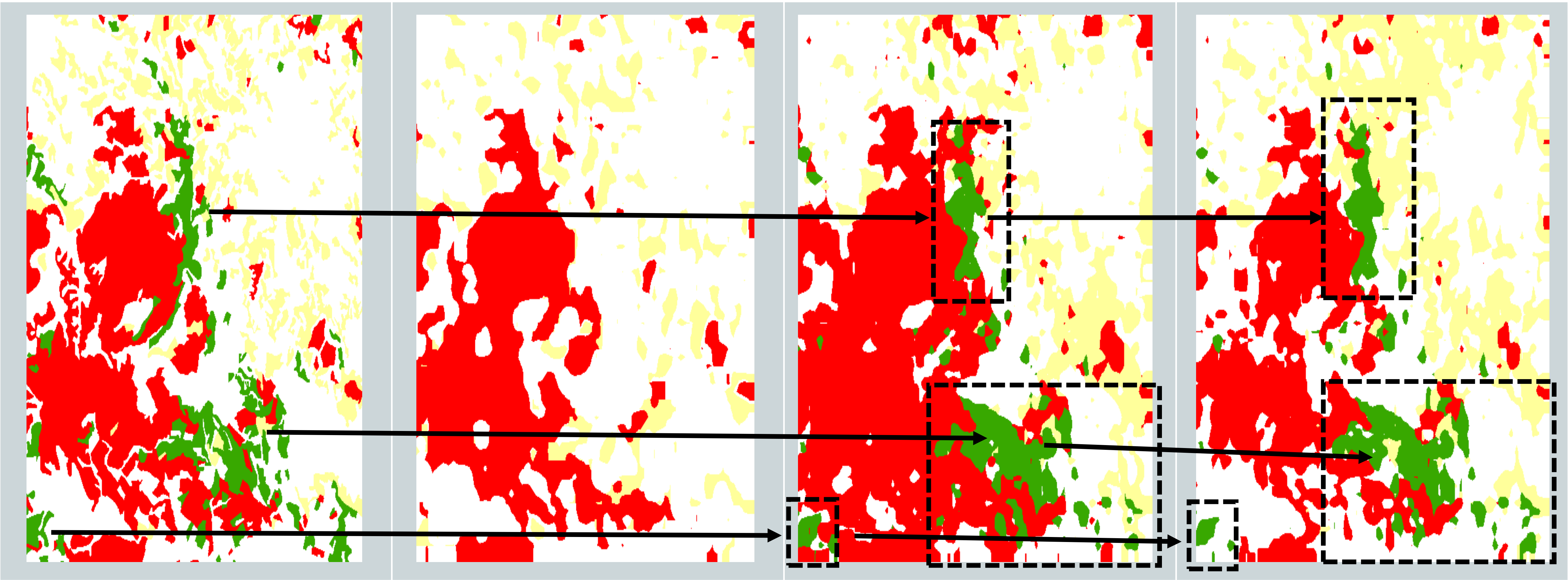
- Our Proposed won DECD 3 out of 3 classes

Evaluation

Corpus 3
Isan, Thailand

Experiment 5:
Depthwise Atrous Convolution

Target Image	Baseline Method [10	GCN152-A-TL-FF	GCN152-A-TL-FF-DA



Evaluation

Corpus 3
Isan, Thailand

Summary

Method	Model	F1 Score	Increase
Baseline	DCED	0.810	
P1	Enhanced GCN + Deeper Head Network	0.876	6.601 %
P2	+ Attention	0.877	0.081 %
P3	+ Transfer Learning	0.899	2.194 %
P4	+ Feature Fusion	0.929	2.954 %
P5	+ Depthwise Atrous Convolution	0.947	1.872 %

The most impactful method:

Feature Fusion

And Transfer Learning

(from Nan Corpus)

Recap: The Results (Summary)

GCN = Global Conv Block

A = Channel Attention Block

TL = Transfer Learning

FF = Feature Fusion Block

DA = Depthwise Atrous

P1 Backbone	P2 Attention (A)	P3 Transfer Learning (TL)	P4 Feature Fusion (FF)	P5 Depthwise Atrous (DA)

- **Corpus 1:** Nan Province (Medium Resolution Corpus)
  - GCN152-A-TL-FF-DA overcame DECD ~ **6.221 % F1**
  - The most impactful method: **Channel Attention**
- **Corpus 2:** ISPRS Vaihingen (Very-High Resolution Corpus)
  - GCN152-A-TL-FF-DA overcame DECD ~ **5.67 % F1**
  - The most impactful method: **Feature Fusion**
- **Corpus 3: Isan Region** (Medium Resolution Corpus)
  - GCN152-A-TL-FF-DA overcame DECD ~ **13.701 % F1**
  - The most impactful method: Feature Fusion and **Transfer Learning from Nan**

Outline | Objective and Procedure

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- **Objectives and Procedure**
- Conclusions
- Publication and Reference

Objective

Objective of research

The objectives of this research are as follows:

1. To propose a **new deep learning architecture** to segment **multi-objects** from **aerial and satellite images (remote sensing corpora)**
2. To **explore the effectiveness** of **proposing new deep learning techniques** for semantic segmentation particularly on remote sensing corpora

Objective

Scope of research

1. Evaluate the proposed new deep learning on ISPRS Vaihingen corpus (a city district of Stuttgart, Germany) and GISTDA corpora (GISTDA Nan province and Isan zone corpora) with Encoder-Decoder baseline model
   - Nan province corpora have **five classes:** agriculture, forest, miscellaneous, urban, and water
   - Isan zone corpora have **three classes:** corn, pineapple, and rubber tree
2. Evaluate the proposed deep learning on reliable measurements such as **Precision, Recall, and F1-score**

Procedure

Procedure

Research Planning	S1/2017	S2/2017	S1/2018	S2/2018	S1/2019	S2/2019
1. Research modern deep learning techniques						
2. Research deep learning on remote sensing images						
3. Literature review						
4. Request and collect data sets from ISPRS corpus and private corpus (GISTDA)						
5. Design and implement the proposed and baseline deep learning.						
6. Conclude and prepare for 1st ISI journal						
7. Write and thesis proposal examination						
8. Evaluate and improve my new deep learning architecture						
9. Conclude and prepare for 2nd ISI journal						
10. Write and defend the dissertation						

Outline | Conclusions

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and Reference

Conclusions

Title: Semantic Segmentation on Remotely Sensed Images Using Deep Convolutional Encoder-Decoder Neural Network

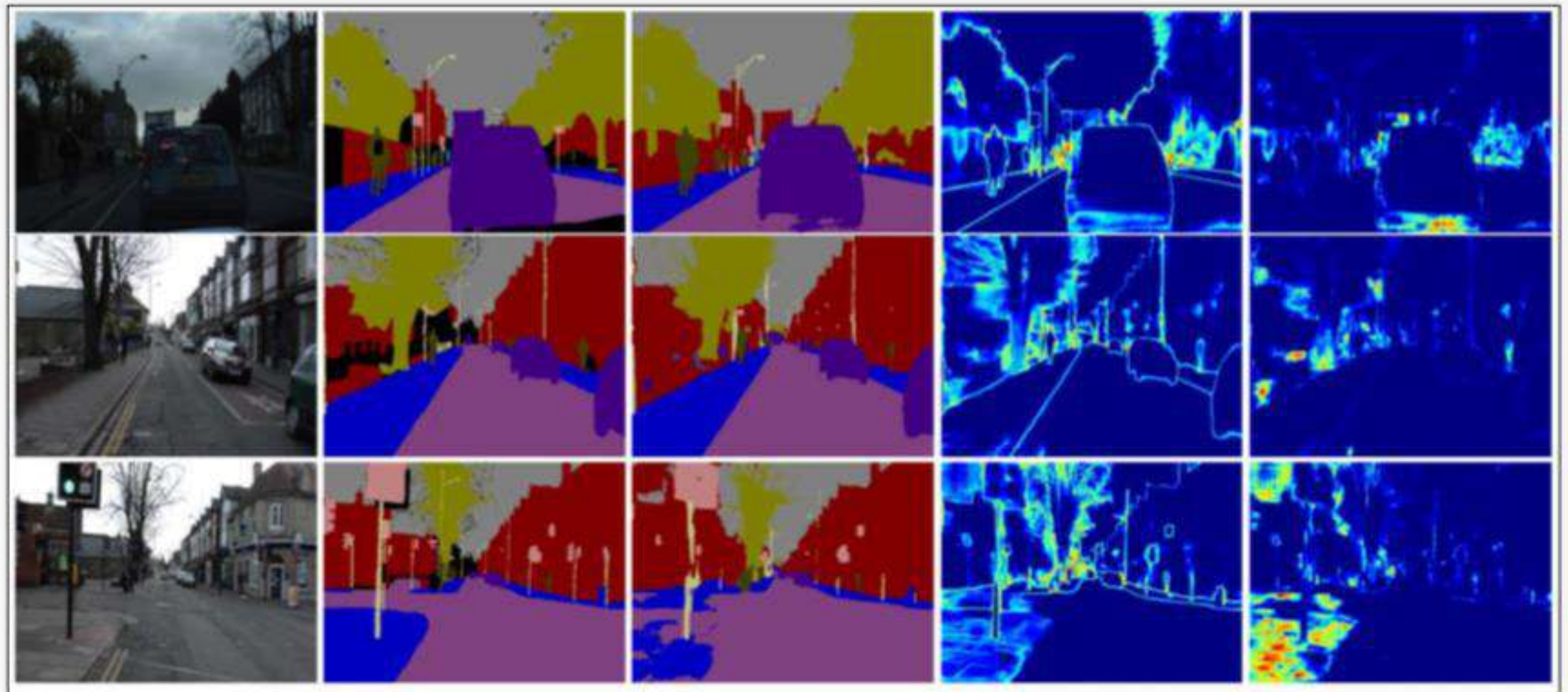
- **What:** Semantic Segmentation on Remotely Sensed Corpora
- **Why:** The previous methods suffer from accuracy performance
- **How:** Deep Convolutional Encoder-Decoder Neural Network
- **Proposed Methods (What's New):**
  - (1) Varying Backbones (2) Channel Attention (3) Domain-specific Transfer Learning (4) Feature Fusion (5) Depthwise Atrous Conv
- **Result:**
  - The results demonstrate that the "GCN152-TL-A-FF-DA" model significantly exceeds all baselines. It is the victor in all data sets and exceeds more than 90% of F1: 0.9114, 0.9362, and 0.9111 of the Landsat-8w3c, Landsat-8w5c, and ISPRS Vaihingen.
  - Moreover, it reaches an accuracy surpassing 90% in almost all classes.
- **Future Plan:**
  - Efficient Uncertainty Estimation for Semantic Segmentation (Aleatoric and Epistemic) | Explainable AI

Efficient Uncertainty Estimation for Semantic Segmentation (Aleatoric and Epistemic)

Future Plan: Huang, Po-Yu, et al. "Efficient uncertainty estimation for semantic segmentation in videos." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

What kind of uncertainty can we model?

Epistemic uncertainty is *modeling* uncertainty
Aleatoric uncertainty is *sensing* uncertainty



(a) Input Image (b) Ground Truth (c) Semantic Segmentation (d) Aleatoric Uncertainty (e) Epistemic Uncertainty

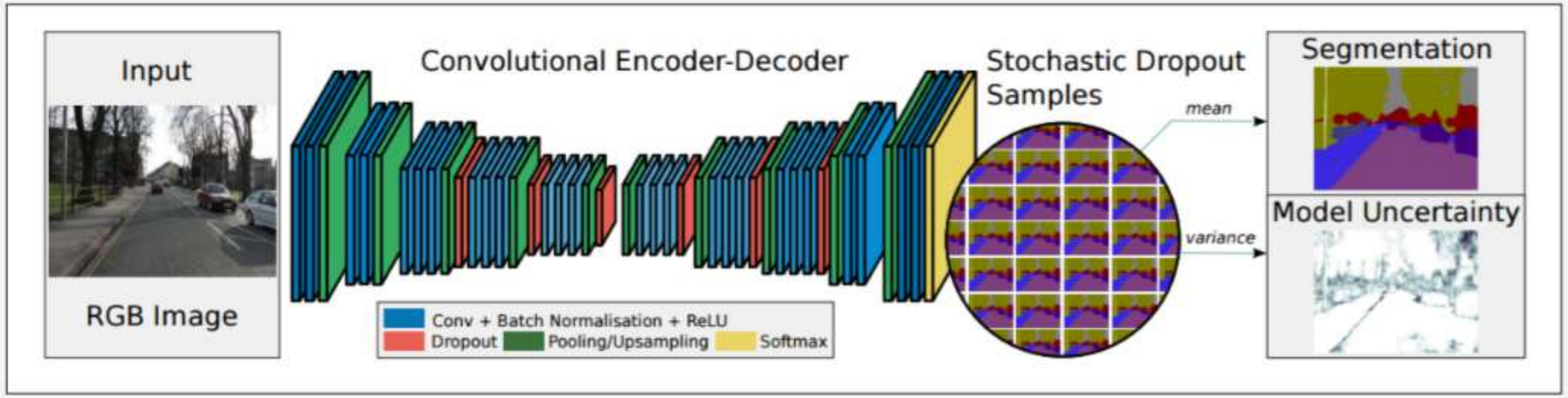
Efficient Uncertainty Estimation for Semantic Segmentation (Aleatoric and Epistemic)

Future Plan: Huang, Po-Yu, et al. "Efficient uncertainty estimation for semantic segmentation in videos." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

Modeling Epistemic Uncertainty with Bayesian Deep Learning

We can **model epistemic uncertainty** in deep learning models using Monte Carlo **dropout sampling** at test time.

Dropout sampling can be interpreted as **sampling from a distribution over models**.



Alex Kendall, Vijay Badrinarayanan and Roberto Cipolla **Bayesian SegNet: Model Uncertainty in Deep Convolutional Encoder-Decoder Architectures for Scene Understanding**. arXiv preprint arXiv:1511.02680, 2015.

Efficient Uncertainty Estimation for Semantic Segmentation (Aleatoric and Epistemic)

Future Plan: Huang, Po-Yu, et al. "Efficient uncertainty estimation for semantic segmentation in videos." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

Modeling Aleatoric Uncertainty with Probabilistic Deep Learning

	Deep Learning	Probabilistic Deep Learning
Model	$[\hat{y}] = f(x)$	$[\hat{y}, \hat{\sigma}^2] = f(x)$
Regression	$Loss = \lVert y - \hat{y} \rVert^2$	$Loss = \frac{\lVert y - \hat{y} \rVert^2}{2\hat{\sigma}^2} + \log \hat{\sigma}^2$
Classification	$Loss = SoftmaxCrossEntropy(\hat{y}_t)$	$\hat{y}_t = \hat{y} + \epsilon_t \quad \epsilon_t \sim N(0, \hat{\sigma}^2)$ $Loss = \frac{1}{T} \sum_t SoftmaxCrossEntropy(\hat{y}_t)$

Alex Kendall and Yarin Gal. **What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?** arXiv preprint 1703.04977, 2017.

Outline | Conclusions

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and Reference

1st Publication (Q1-Tier1, ISI Journal, 2019)

Title: Semantic Segmentation on Remotely Sensed Images Using an Enhanced Global Convolutional Network with Channel Attention and Domain Specific Transfer Learning, 2019

- Panboonyuen, T.; Jitkajornwanich, K.; Lawawirojwong, S.; Srestasathiern, P.; Vateekul, P. Semantic Segmentation on Remotely Sensed Images Using an Enhanced Global Convolutional Network with Channel Attention and Domain Specific Transfer Learning. *Remote Sens.* **2019**, *11*, 83.

- https://www.mdpi.com/2072-4292/11/1/83

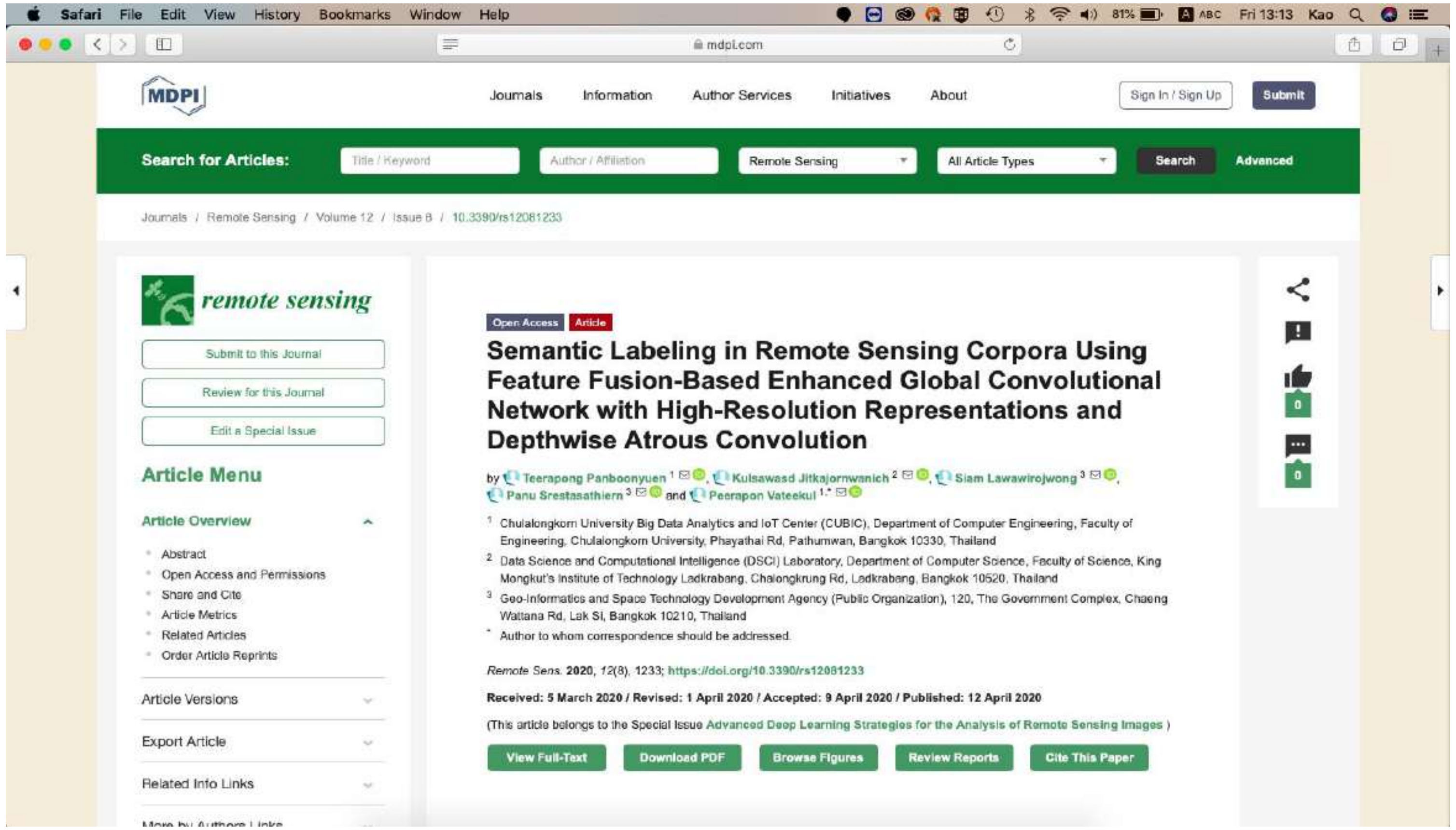
Remote Sens. **2019**, *11*(1), 83; https://doi.org/10.3390/rs11010083

Received: 5 December 2018 / Revised: 25 December 2018 / Accepted: 1 January 2019 / Published: 4 January 2019

2nd Publication (Q1-Tier1, ISI Journal, 2020)

Title: Semantic Labeling in Remote Sensing Corpora Using Feature Fusion-Based Enhanced Global Convolutional Network with High-Resolution Representations and Depthwise Atrous Convolution, 2020

- Panboonyuen, T.; Jitkajornwanich, K.; Lawawirojwong, S.; Srestasathiern, P.; Vateekul, P. Semantic Labeling in Remote Sensing Corpora Using Feature Fusion-Based Enhanced Global Convolutional Network with High-Resolution Representations and Depthwise Atrous Convolution. Remote Sens. **2020**, 12, 1233.



- https://www.mdpi.com/2072-4292/12/8/1233

Remote Sens. 2020, 12(8), 1233; https://doi.org/10.3390/rs12081233

Received: 5 December 2018 / Revised: 25 December 2018 / Accepted: 1 January 2019 / Published: 4 January 2019

Outline | Publication and Reference

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and **Reference**

Reference (based-modern deep learning)

- [1] Zhao, H., Shi, J., Qi, X., Wang, X., & Jia, J. (2017). Pyramid scene parsing network. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2881-2890).
- [2] Jégou, S., Drozdzal, M., Vazquez, D., Romero, A., & Bengio, Y. (2017). The one hundred layers tiramisu: Fully convolutional densenets for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 11-19).
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Reference (based-deep learning on Remote Sensing)

- [6] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).
- [7] Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). Segnet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE transactions on pattern analysis and machine intelligence, 39(12), 2481-2495.
- [8] Noh, H., Hong, S., & Han, B. (2015). Learning deconvolution network for semantic segmentation. In Proceedings of the IEEE international conference on computer vision (pp. 1520-1528).
- [9] Wang, H., Wang, Y., Zhang, Q., Xiang, S., & Pan, C. (2017). Gated convolutional neural network for semantic segmentation in high-resolution images. Remote Sensing, 9(5), 446.
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- etc.

Q&A

Teerapong Panboonyuen (Kao)

ธีรพงศ์ ปานบุญยืน (เก้า)

https://kaopanboonyuen.github.io/

Appendix

1st Publication (Q1-Tier1, ISI Journal, 2019)

Title: Semantic Segmentation on Remotely Sensed Images Using an Enhanced Global Convolutional Network with Channel Attention and Domain Specific Transfer Learning, 2019

- Panboonyuen, T.; Jitkajornwanich, K.; Lawawirojwong, S.; Srestasathiern, P.; Vateekul, P. Semantic Segmentation on Remotely Sensed Images Using an Enhanced Global Convolutional Network with Channel Attention and Domain Specific Transfer Learning. *Remote Sens.* **2019**, *11*, 83.

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- https://www.mdpi.com/2072-4292/11/1/83

Remote Sens. **2019**, *11*(1), 83; https://doi.org/10.3390/rs11010083

Received: 5 December 2018 / Revised: 25 December 2018 / Accepted: 1 January 2019 / Published: 4 January 2019

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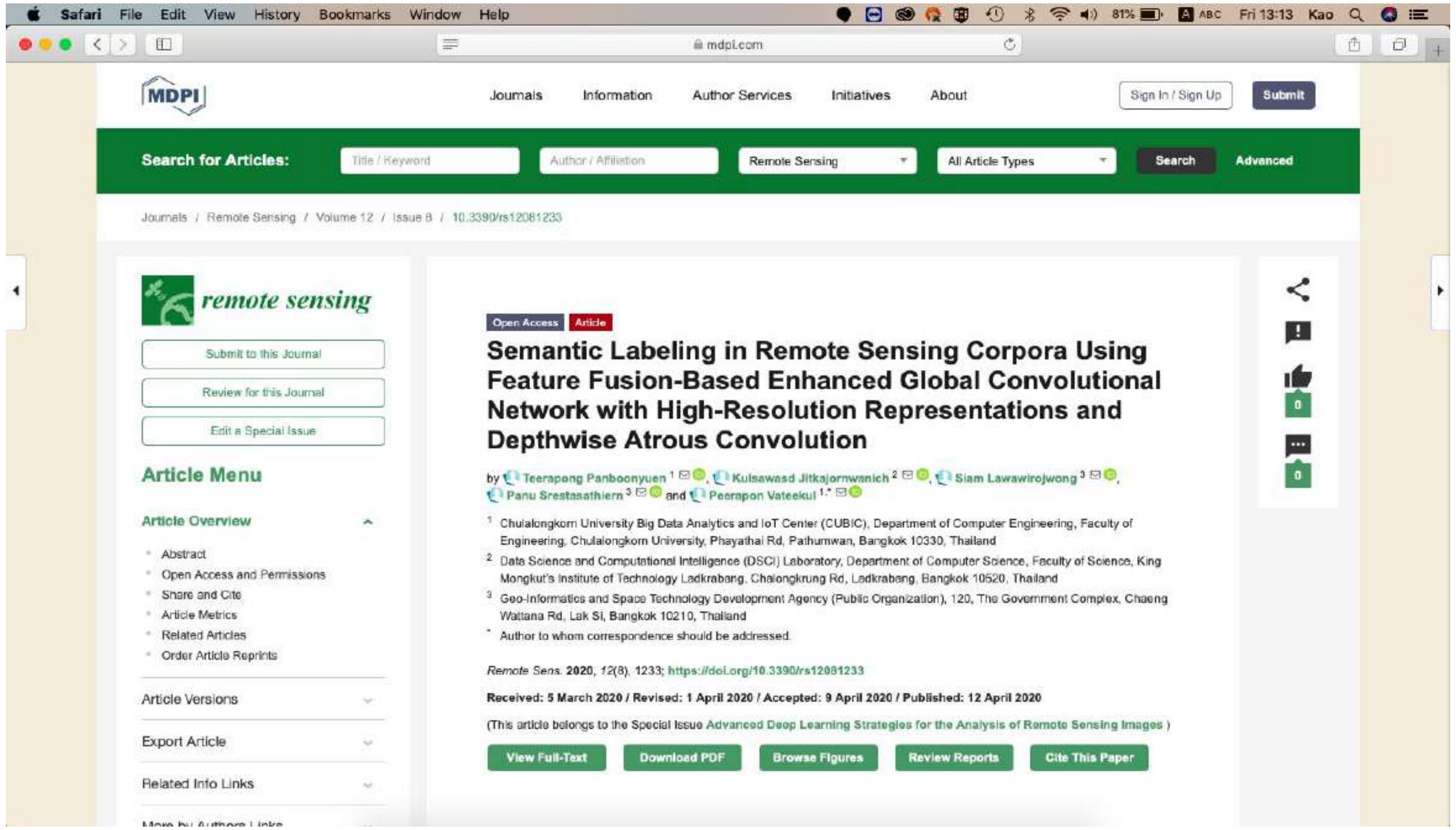


- https://www.mdpi.com/2072-4292/12/8/1233

Remote Sens. 2020, 12(8), 1233; https://doi.org/10.3390/rs12081233

Received: 5 December 2018 / Revised: 25 December 2018 / Accepted: 1 January 2019 / Published: 4 January 2019

Detail of All Corpora (1) Support Value

ISPRS			
		Support	
Class	0	778361	**Impervious Surfaces**
Class	1	920658	**Buildings**
Class	2	332791	**Low Vegetation**
Class	3	393875	**Tree**
Class	4	32939	**Car**

ISAN	LC129048		
		Support	
Class	0	333917	Miscellaneous
Class	1	892808	Para Rubber
Class	2	32180	Pine Apple
Class	3	523588	Corn

NAN			
		Support	
Class	0	443917	**Agriculture**
Class	1	1022641	**Forest**
Class	2	20039	**Miscellaneous**
Class	3	61773	**Urban**
Class	4	7086	**Water**

Detail of All Corpora (2) Training Size

Public Data Set: 2D Semantic Labeling - Vaihingen

- **Training Set:** 512x512 (210 Images)
- **Validation Set:** 512x512 (30 Images)
- **Testing Set:** 512x512 (30 Images)

Private Data Set: GISTDA Nan Province Corpus

- **Training Set:** 512x512 (1,770 Images)
- **Validation Set:** 512x512 (49 Images)
- **Testing Set:** 512x512 (100 Images)

Private Data Set: GISTDA ISAN zone Corpus

- **Training Set:** 512x512 (2,115 Images)
- **Validation Set:** 512x512 (49 Images)
- **Testing Set:** 512x512 (100 Images)

NAN			
		Support	
Class	0	443917	**Agriculture**
Class	1	1022641	**Forest**
Class	2	20039	**Miscellaneous**
Class	3	61773	**Urban**
Class	4	7086	**Water**

ISAN	LC129048		
		Support	
Class	0	333917	Miscellaneous
Class	1	892808	Para Rubber
Class	2	32180	Pine Apple
Class	3	523588	Corn

ResNet - Architecture

ResNet-50
PRETRAINED MODEL

P1

Satellite

ResNet 50

ResNet 101

ResNet 152

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Problem Solve: Unbalanced Class

Zerphed commented on May 30, 2017

@JeffKo427 Thanks! This is in fact what I am using right now. The losses seem quite bit, but I guess that was to be expected:

```
def weighted_pixelwise_crossentropy(class_weights):

    def loss(y_true, y_pred):
        epsilon = _to_tensor(_EPSILON, y_pred.dtype.base_dtype)
        y_pred = tf.clip_by_value(y_pred, epsilon, 1. - epsilon)
        return - tf.reduce_sum(tf.multiply(y_true * tf.log(y_pred), class_weights))

    return loss
```

👍 5

https://github.com/keras-team/keras/issues/6261

How does mean image subtraction work?

2 Answers

active oldest votes

7

In deep learning, there are in fact different practices as to how to subtract the mean image.

Subtract mean image

The first way is to subtract mean image as @lejlot described. But there is an issue if your dataset images are not the same size. You need to make sure all dataset images are in the same size before using this method (e.g., resize original image and crop patch of same size from original image). It is used in original ResNet paper, see reference here.

Subtract the per-channel mean

The second way is to subtract per-channel mean from the original image, which is more popular. In this way, you do not need to resize or crop the original image. You can just calculate the per-channel mean from the training set. This is used widely in deep learning, e.g, Caffe: here and here. Keras: here. PyTorch: here. (PyTorch also divide the per-channel value by standard deviation.)

share improve this answer

edited Dec 6 '17 at 1:18

answered Dec 5 '17 at 9:49

jdhao

5,760 ●2 ●36 ●60

add a comment

https://stackoverflow.com/questions/44788133/how-does-mean-image-subtraction-work

Other Layers

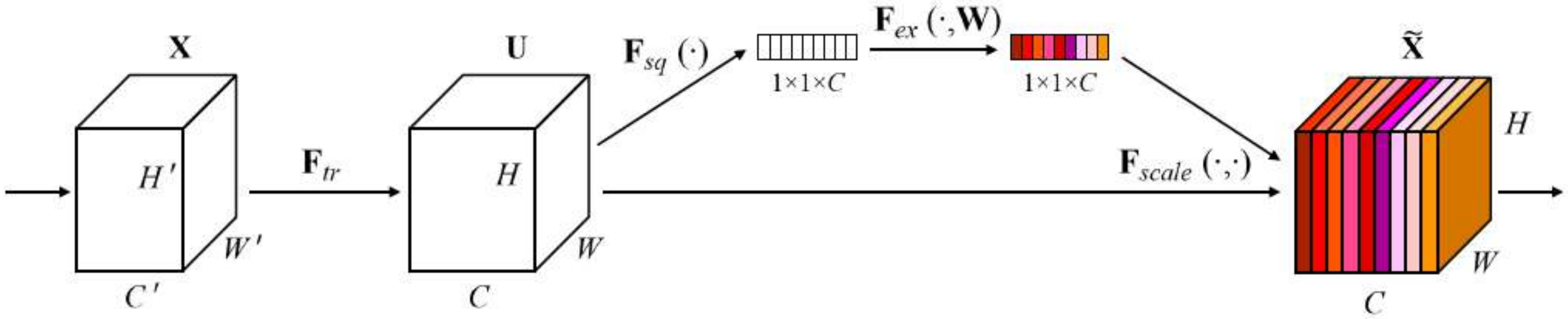
- Interpolation Layer: Interpolation layer
  - performs resizing operation along the spatial dimension.
  - In our network, we use bilinear interpolation.
- Elementwise Layer: Elementwise layer
  - performs elementwise operations on two or more previous layers, in which the feature maps must be of the same number of channels and the same size.
  - There are three kinds of elementwise operations:
    - product, sum, max.
    - In our network, we use sum operation.

Related Theory

Attention

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- **(4) Channel Attention**
- (5) Feature Fusion
- (6) Design CNNs
- (7) Depthwise Atrous

- Attention is helpful to focus on what we want
- We utilize channel attention to select the important features



One word "attends" to other words in the same sentence differently.

Refers to Squeeze-and-Excitation Networks and BiseNet

Related Theory

Attention

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- **(4) Channel Attention**
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- (6) Design CNNs
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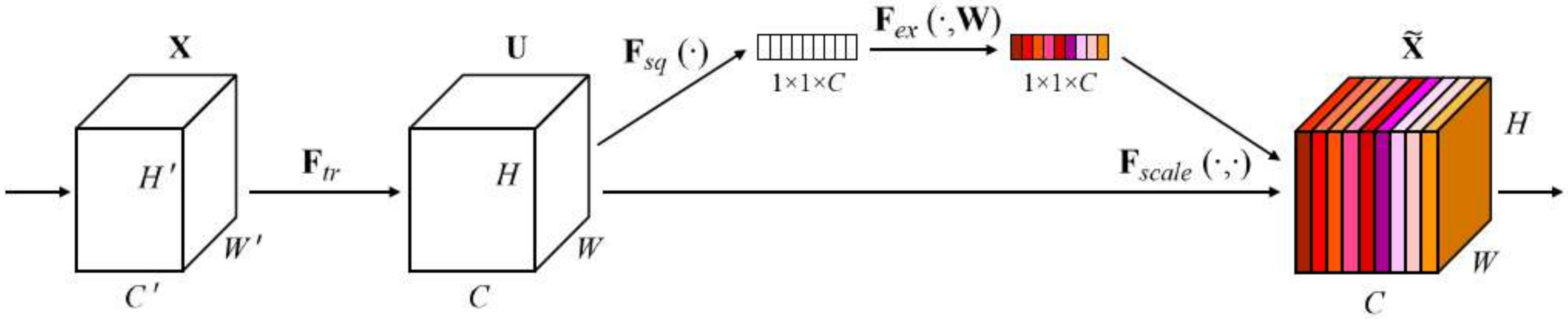

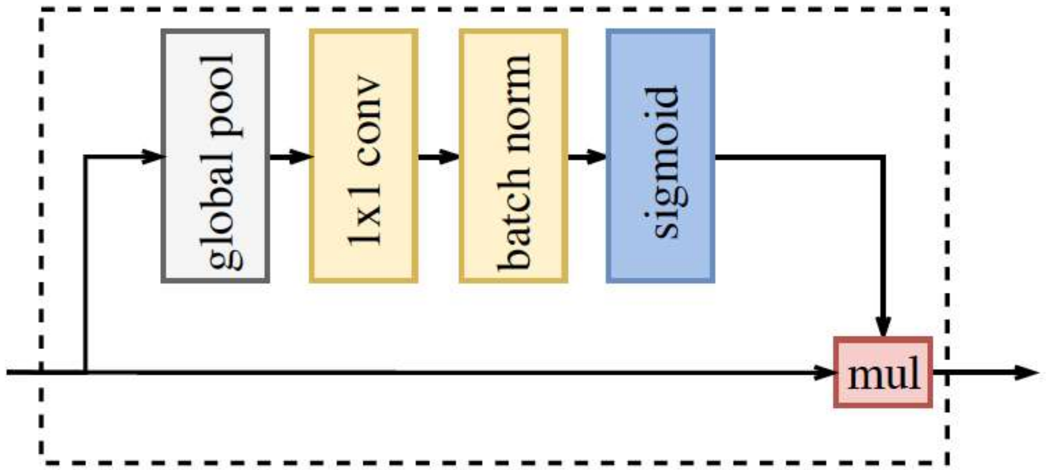

Refers to Squeeze-and-Excitation Networks and BiseNet

Related Theory

Attention

- (1) Computer Vision Tasks
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  - Traditional CNNs
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- **(4) Channel Attention**
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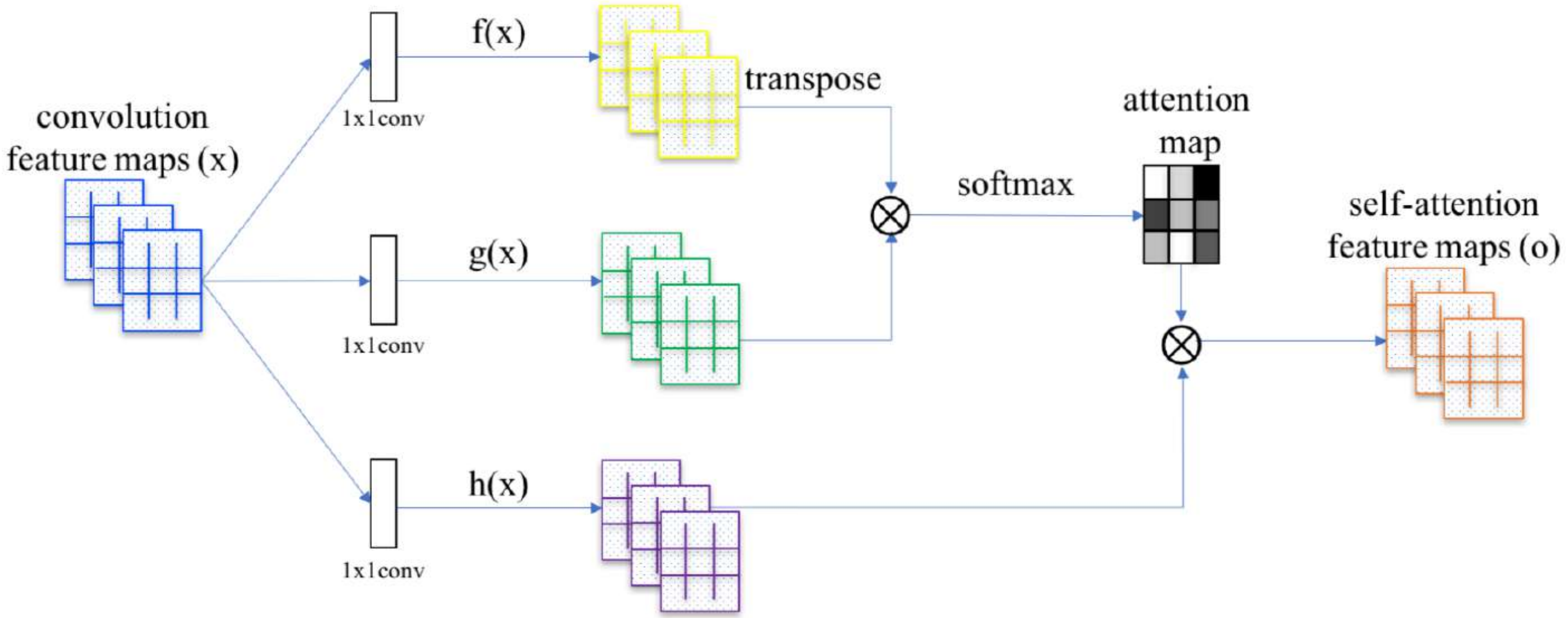


https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

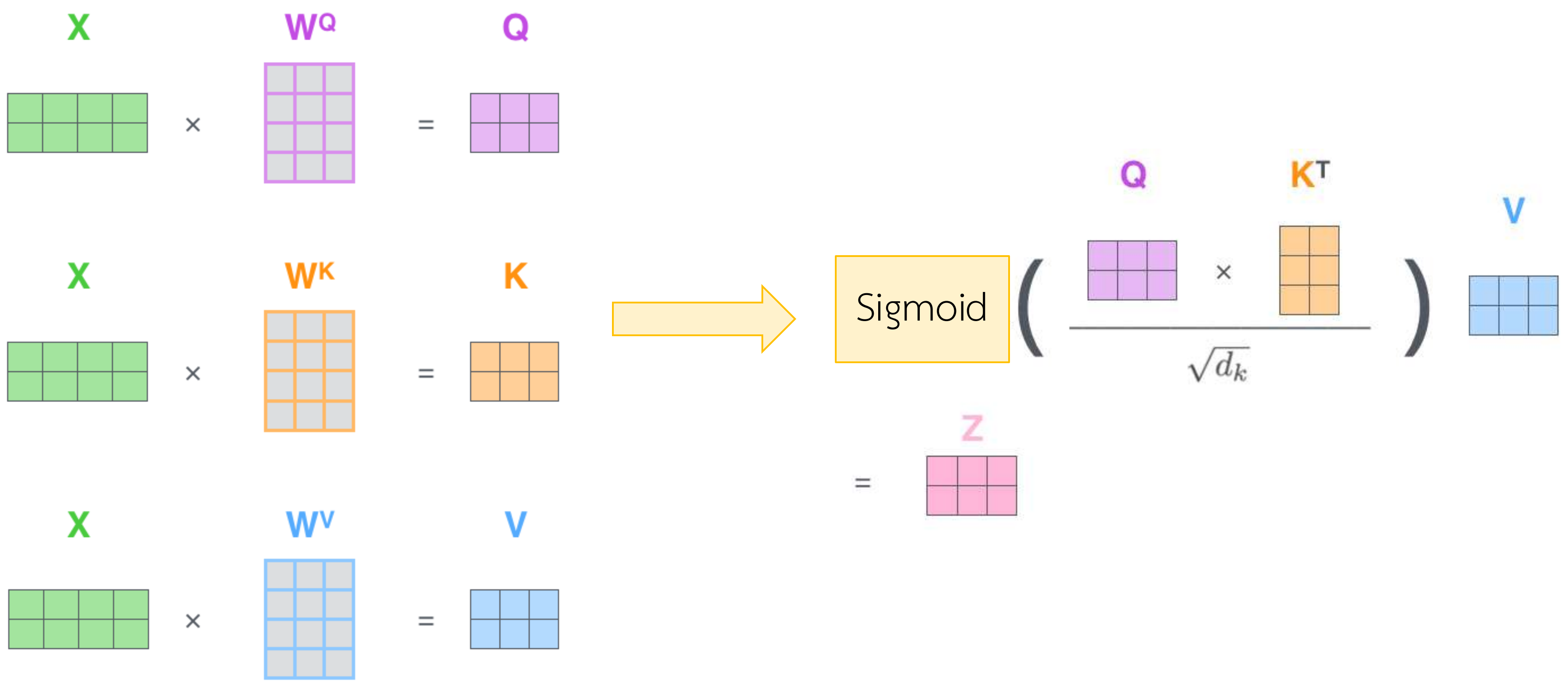
Related Theory

Attention

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- **(4) Channel Attention**
- (5) Feature Fusion
- (6) Design CNNs
- (7) Depthwise Atrous

Matrix Calculation of Self-Attention

- The first step is to calculate the Query, Key, and Value matrices.
- We do that by packing our embeddings into a matrix X, and multiplying it by the weight matrices we've trained (WQ, WK, WV).



Related Theory

ResNet

- (1) Computer Vision Tasks
- (2) CNNs
  - **Traditional CNNs**
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs
- (7) Depthwise Atrous

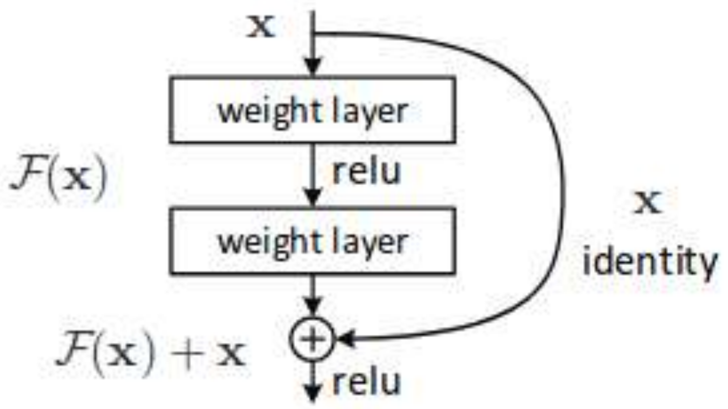


Figure 2. Residual learning: a building block.

1. The identity shortcuts (x) can be directly used when the input and output are of the same dimensions.

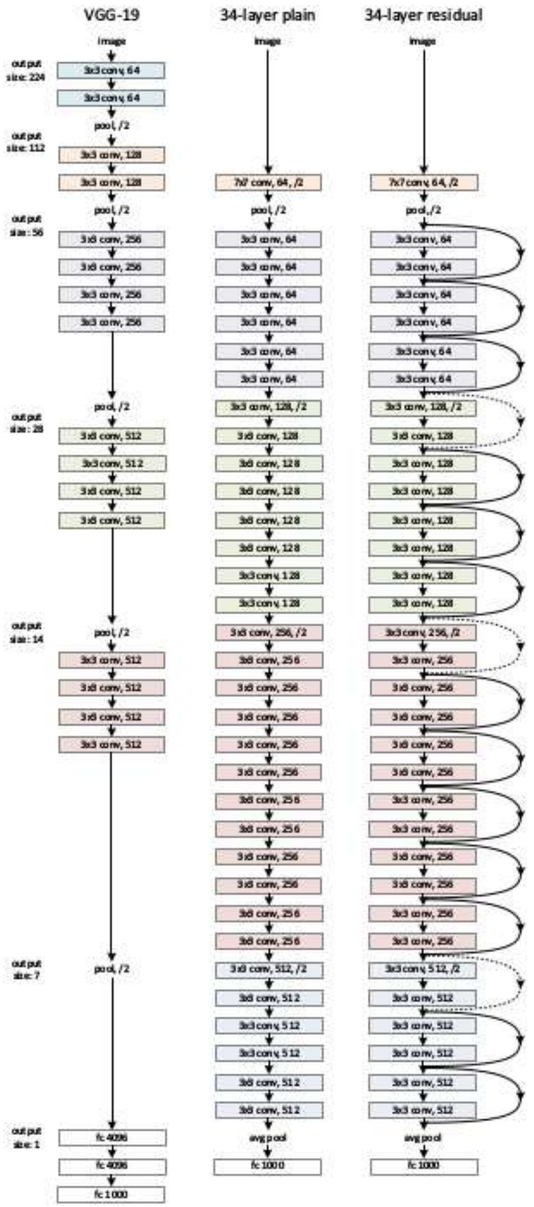
$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + \mathbf{x}. \quad (1)$$

Residual block function when input and output dimensions are same

2. When the dimensions change, A) The shortcut still performs identity mapping, with extra zero entries padded with the increased dimension. B) The projection shortcut is used to match the dimension (done by 1*1 conv) using the following formula

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + W_s\mathbf{x}. \quad (2)$$

Residual block function when the input and output dimensions are not same.



Evaluation

```
>>> from sklearn.metrics import f1_score
>>> y_true = [0, 1, 2, 0, 1, 2]
>>> y_pred = [0, 2, 1, 0, 0, 1]
>>> f1_score(y_true, y_pred, average='macro')
0.26...
>>> f1_score(y_true, y_pred, average='micro')
0.33...
>>> f1_score(y_true, y_pred, average='weighted')
0.26...
>>> f1_score(y_true, y_pred, average=None)
array([0.8, 0. , 0. ])
```

4.4. Evaluation metrics

To assess the quantitative performance, two overall benchmark metrics are used, i.e., *F1 score* (F1) and *intersection over union* (IoU). F1 is defined as

$$\mathrm{F1} = 2\frac{\mathrm{Pre}\times\mathrm{Rec}}{\mathrm{Pre}+\mathrm{Rec}},\ \mathrm{Pre} = \frac{tp}{tp+fp},\ \mathrm{Rec} = \frac{tp}{tp+fn}. \tag{9}$$

Here, tp, fp and fn are the number of true positives, false positives and false negatives, respectively.

IoU is defined as:

$$\mathrm{IoU}(\mathcal{P}_m, \mathcal{P}_{gt}) = \frac{|\mathcal{P}_m \cap \mathcal{P}_{gt}|}{|\mathcal{P}_m \cup \mathcal{P}_{gt}|}, \tag{10}$$

where $\mathcal{P}_{gt}$ is the set of ground truth pixels and $\mathcal{P}_m$ is the set of prediction pixels, '∩' and '∪' denote *intersection* and *union* operations,

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

Evaluation

```
>>> from sklearn.metrics import f1_score
>>> y_true = [0, 1, 2, 0, 1, 2]
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0.33...
>>> f1_score(y_true, y_pred, average='weighted')
0.26...
>>> f1_score(y_true, y_pred, average=None)
array([0.8, 0. , 0. ])
```

1. Micro-average Method

In Micro-average method, you sum up the individual true positives, false positives, and false negatives of the system for different sets and the apply them to get the statistics. For example, for a set of data, the system's

```
True positive (TP1)  = 12
False positive (FP1) = 9
False negative (FN1) = 3
```

Then precision (P1) and recall (R1) will be $57.14\% = \frac{TP1}{TP1+FP1}$ and $80\% = \frac{TP1}{TP1+FN1}$

and for a different set of data, the system's

```
True positive (TP2)  = 50
False positive (FP2) = 23
False negative (FN2) = 9
```

Then precision (P2) and recall (R2) will be 68.49 and 84.75

Now, the average precision and recall of the system using the Micro-average method is

$$\text{Micro-average of precision} = \frac{TP1+TP2}{TP1+TP2+FP1+FP2} = \frac{12+50}{12+50+9+23} = 65.96$$

$$\text{Micro-average of recall} = \frac{TP1+TP2}{TP1+TP2+FN1+FN2} = \frac{12+50}{12+50+3+9} = 83.78$$

The Micro-average F-Score will be simply the harmonic mean of these two figures.

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

Evaluation

```
>>> from sklearn.metrics import f1_score
>>> y_true = [0, 1, 2, 0, 1, 2]
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0.33...
>>> f1_score(y_true, y_pred, average='weighted')
0.26...
>>> f1_score(y_true, y_pred, average=None)
array([0.8, 0. , 0. ])
```

2. Macro-average Method

The method is straight forward. Just take the average of the precision and recall of the system on different sets. For example, the macro-average precision and recall of the system for the given example is

$$\text{Macro-average precision} = \frac{P1+P2}{2} = \frac{57.14+68.49}{2} = 62.82$$
$$\text{Macro-average recall} = \frac{R1+R2}{2} = \frac{80+84.75}{2} = 82.25$$

The Macro-average F-Score will be simply the harmonic mean of these two figures.

Suitability Macro-average method can be used when you want to know how the system performs overall across the sets of data. You should not come up with any specific decision with this average.

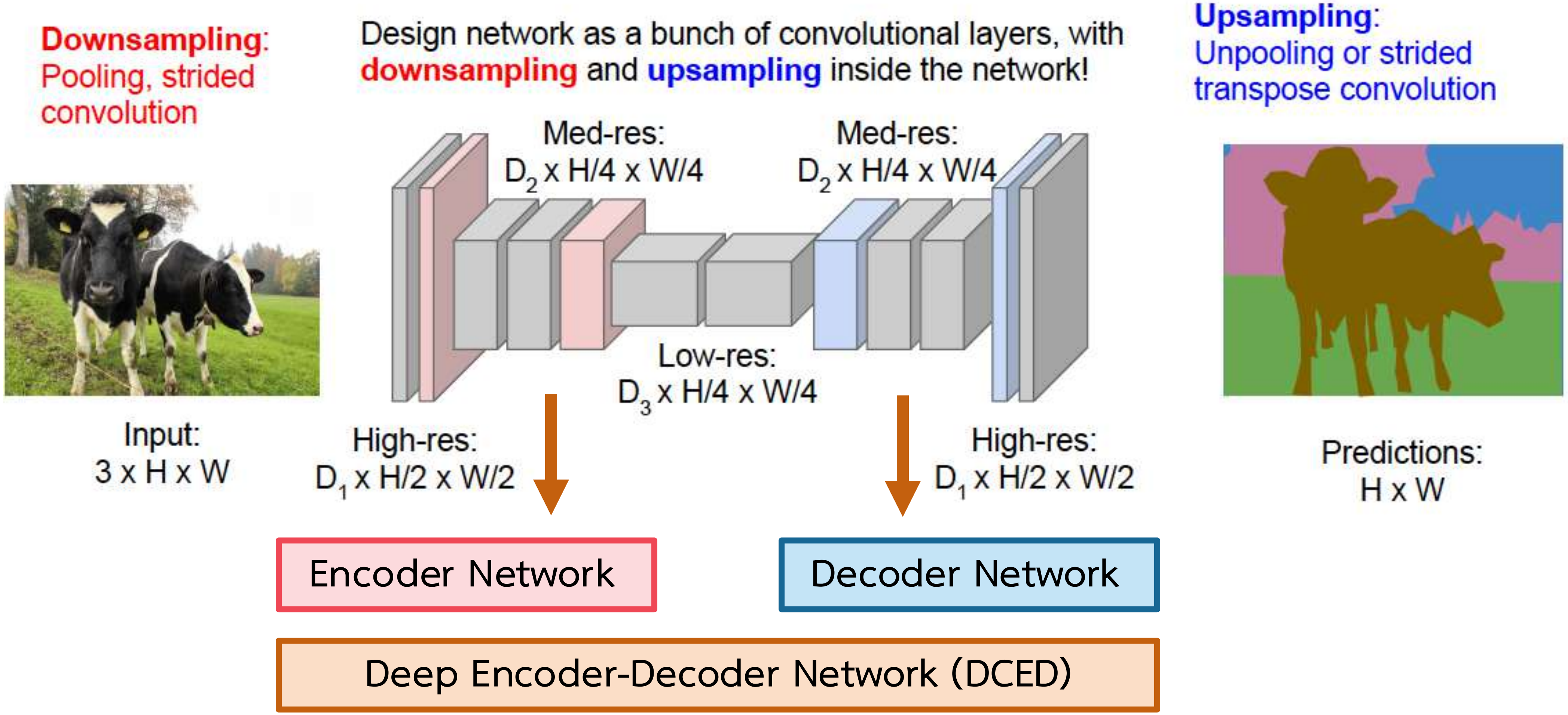
On the other hand, micro-average can be a useful measure when your dataset varies in size.

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

Related Theory

Traditional Image Segmentation Network

- (1) Computer Vision Tasks
- **(2) CNNs**
    - **Traditional CNNs**
    - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs



Related Theory

Traditional Image Segmentation Network: Sample (1)

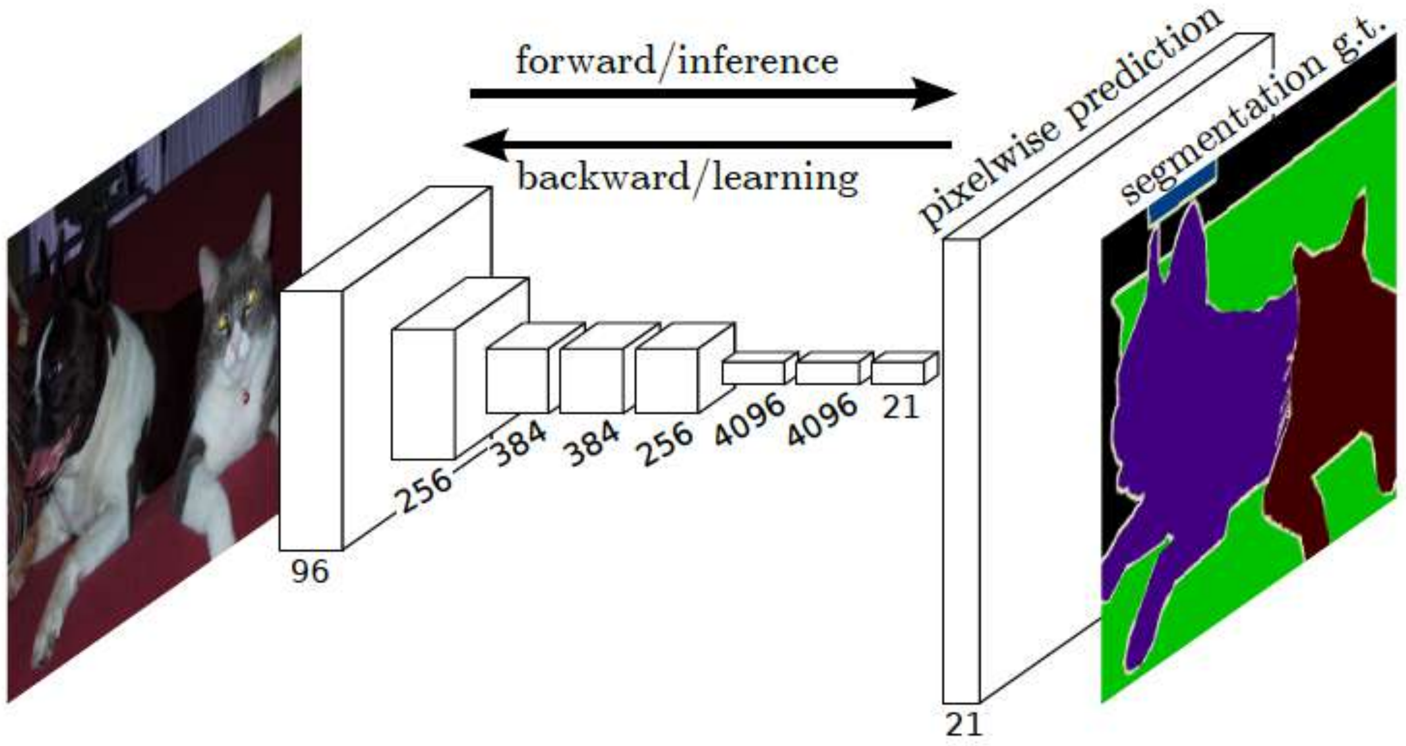
- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs

FCN

Encoder Network

Decoder Network

Deep Encoder-Decoder Network (DCED)



http://cs231n.stanford.edu/

Related Theory

Traditional Image Segmentation Network: Sample (2)

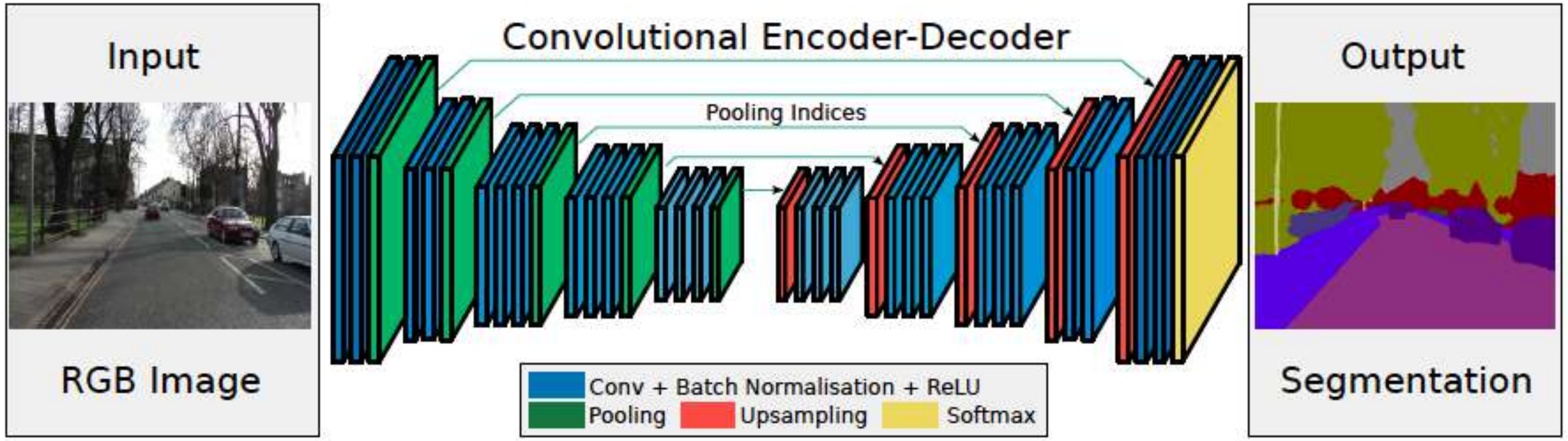
- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs

SegNet

Encoder Network

Decoder Network

Deep Encoder-Decoder Network (DCED)



Related Theory

Traditional Image Segmentation Network: Sample (3)

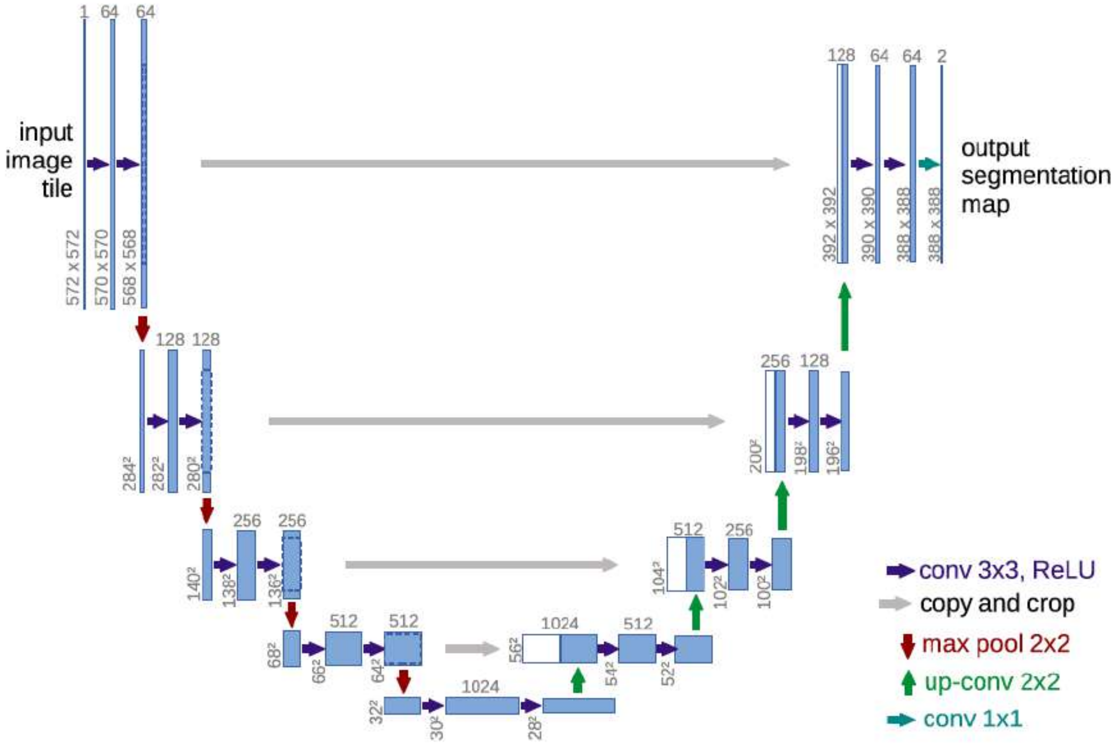
- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs

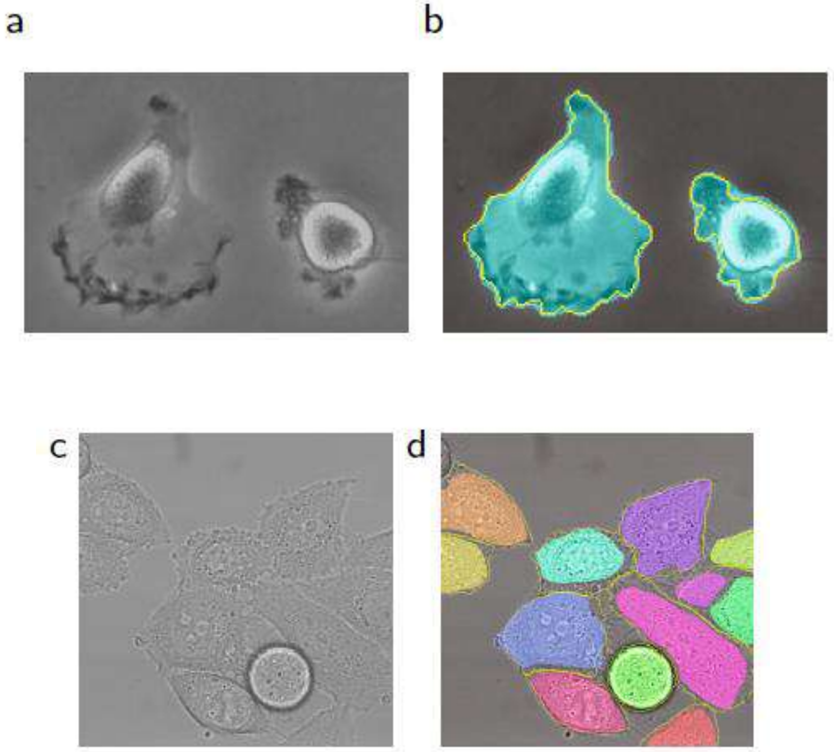
UNet

Encoder Network

Decoder Network

Deep Encoder-Decoder Network (DCED)





Related Theory

Traditional Image Segmentation Network: Sample (4)

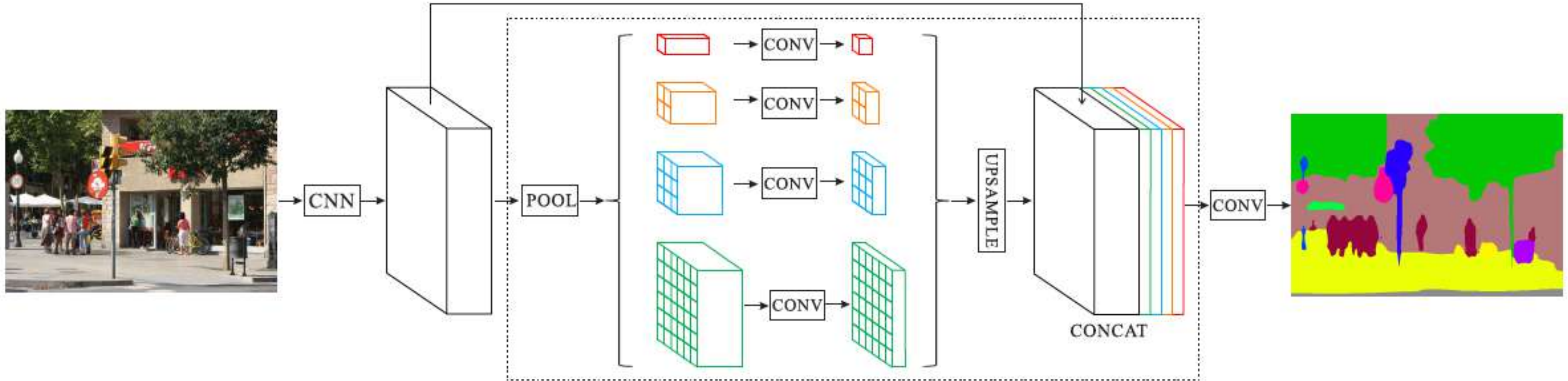
- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs

PSPNet

Encoder Network

Decoder Network

Deep Encoder-Decoder Network (DCED)



(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

Related Theory

Traditional Image Segmentation Network: Sample (5)

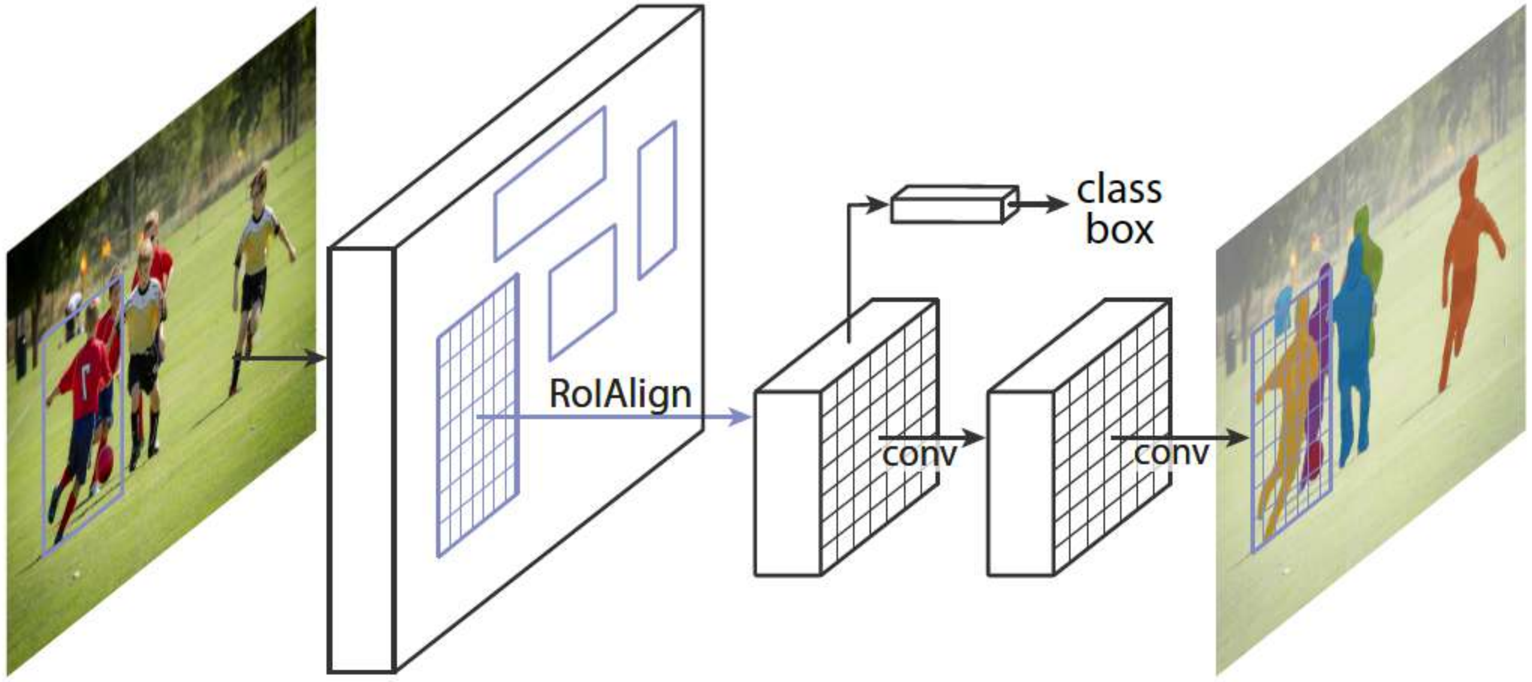
- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs

Mask R-CNN

Encoder Network

Decoder Network

Deep Encoder-Decoder Network (DCED)



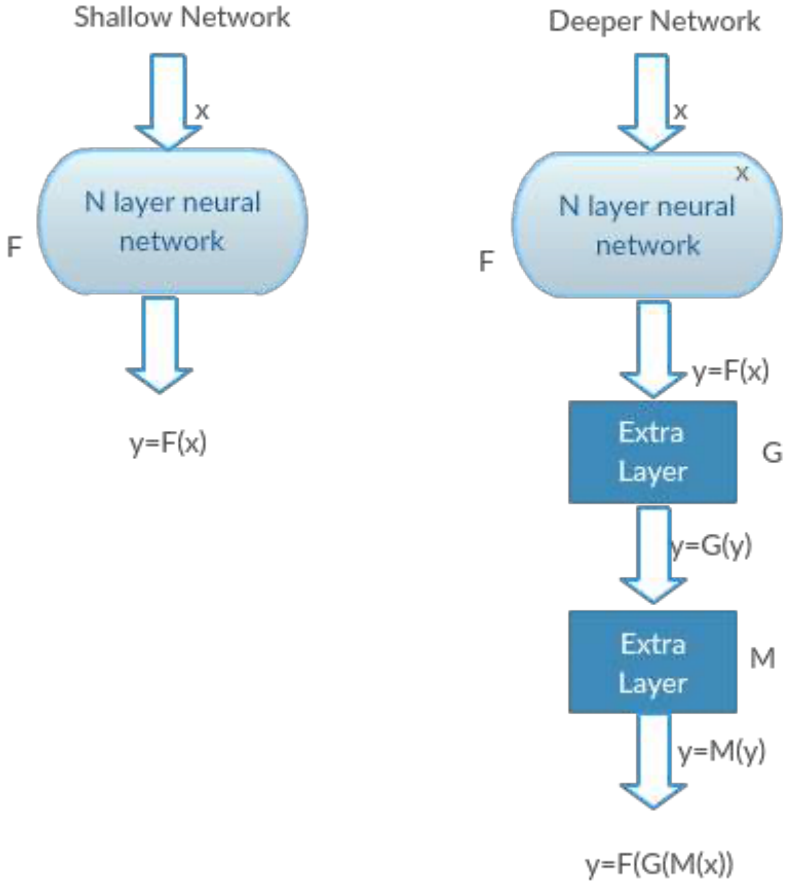
http://cs231n.stanford.edu/

Facebook AI Research (FAIR)

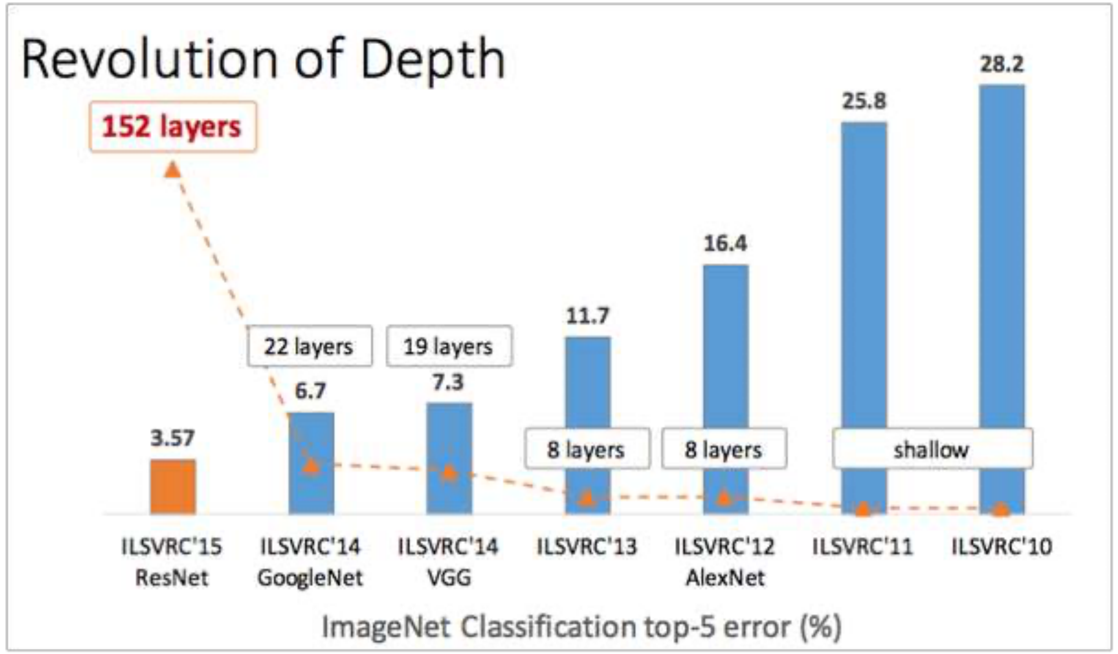
Related Theory

ResNet (Microsoft)

- (1) Computer Vision Tasks
- (2) CNNs
    - Traditional CNNs
    - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs



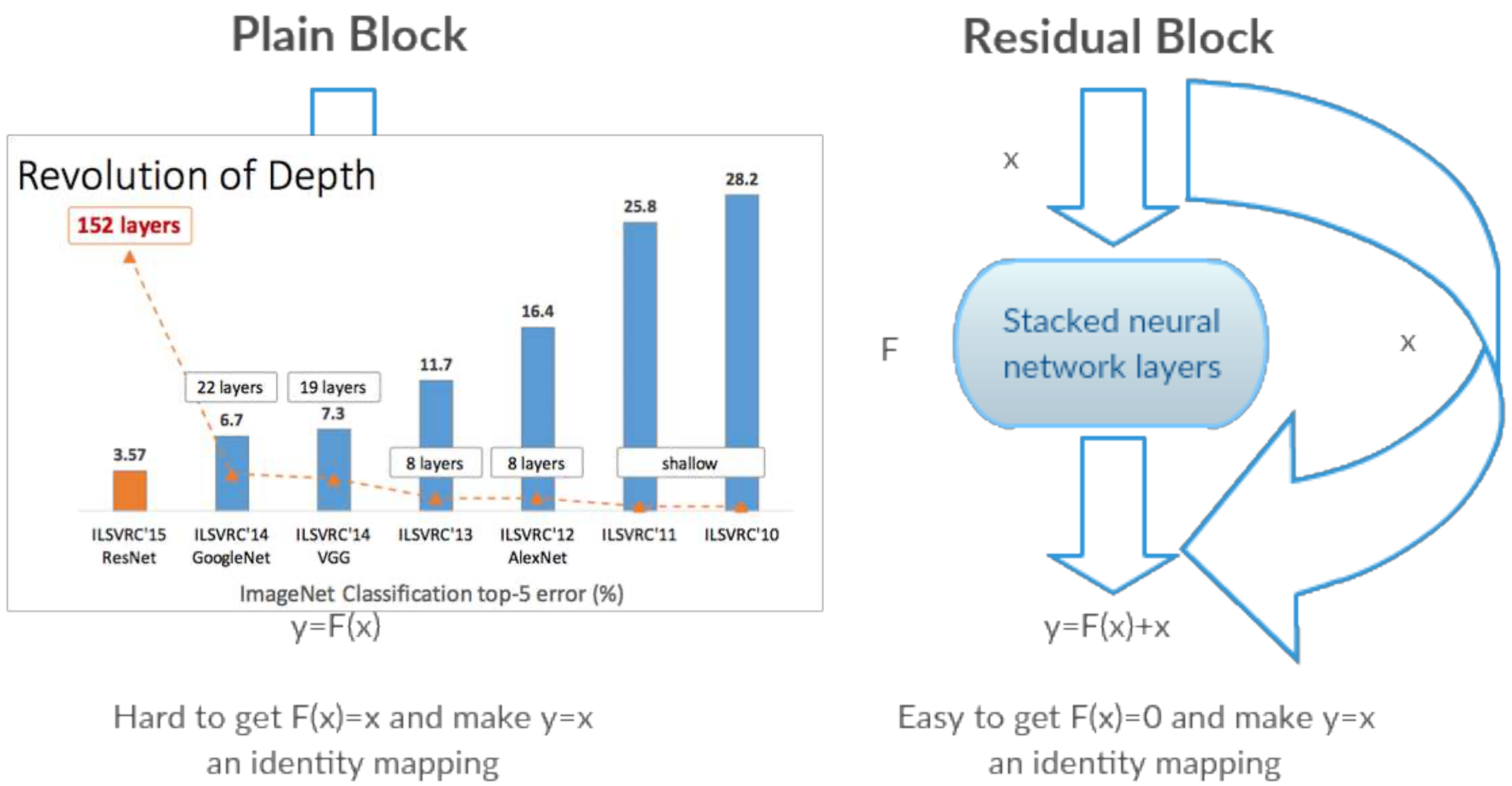
G and M act as Identity Functions. Both the Networks Give same output



Related Theory

ResNet (Microsoft)

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs



Encoder Network (VGG (Residual) Style)

https://medium.com/@14prakash/

Related Theory

ResNet (Microsoft)

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Design CNNs

- More layers is better
  - but because of the vanishing gradient problem
  - model weights of the first layers can not be updated correctly through the backpropagation of the error gradient
  - the chain rule multiplies error gradient values lower than one and then, when the gradient error comes to the first layers, its value goes to zero
- Objective of Resnet is preserve the gradient

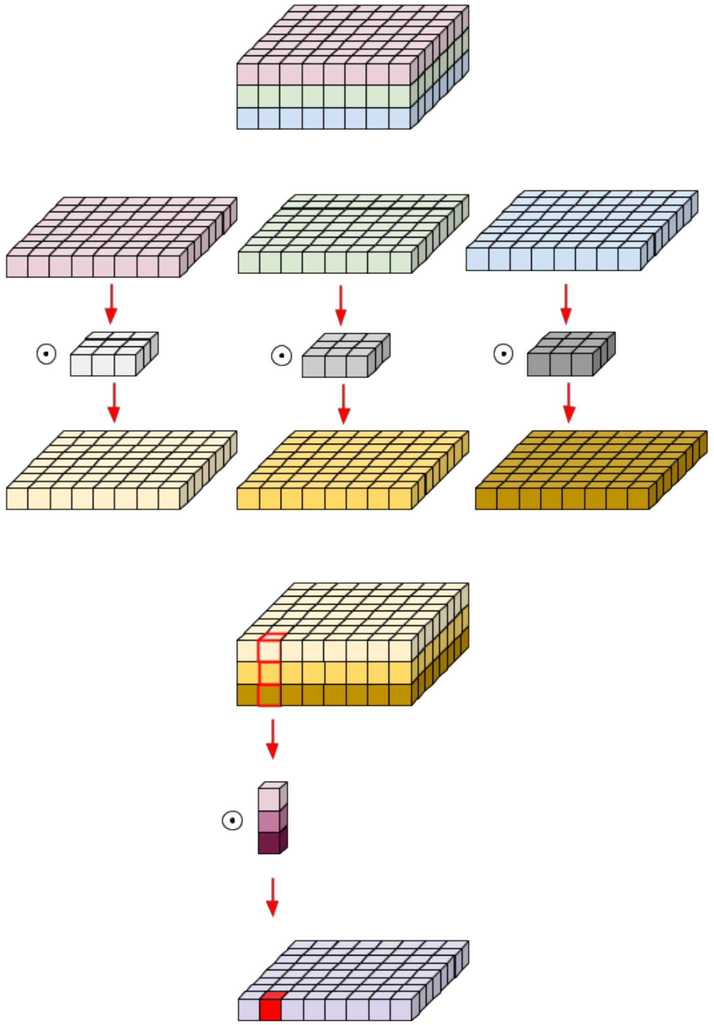
$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + \mathbf{x}.$$

https://medium.com/@14prakash/

Related Theory

Depth-wise Separable Convolution

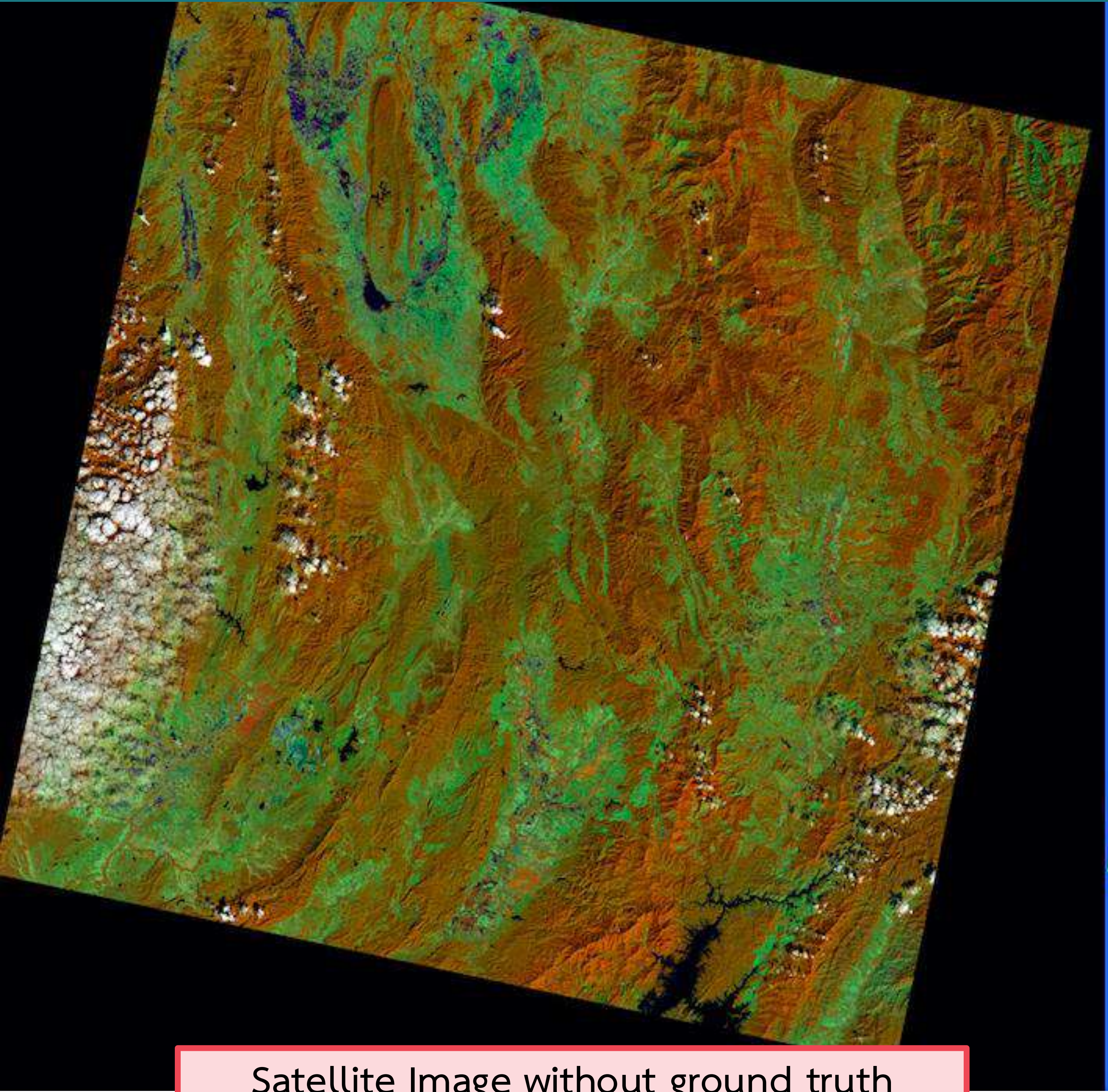
- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- **(6) Depthwise Convolution**
- (7) Design CNNs



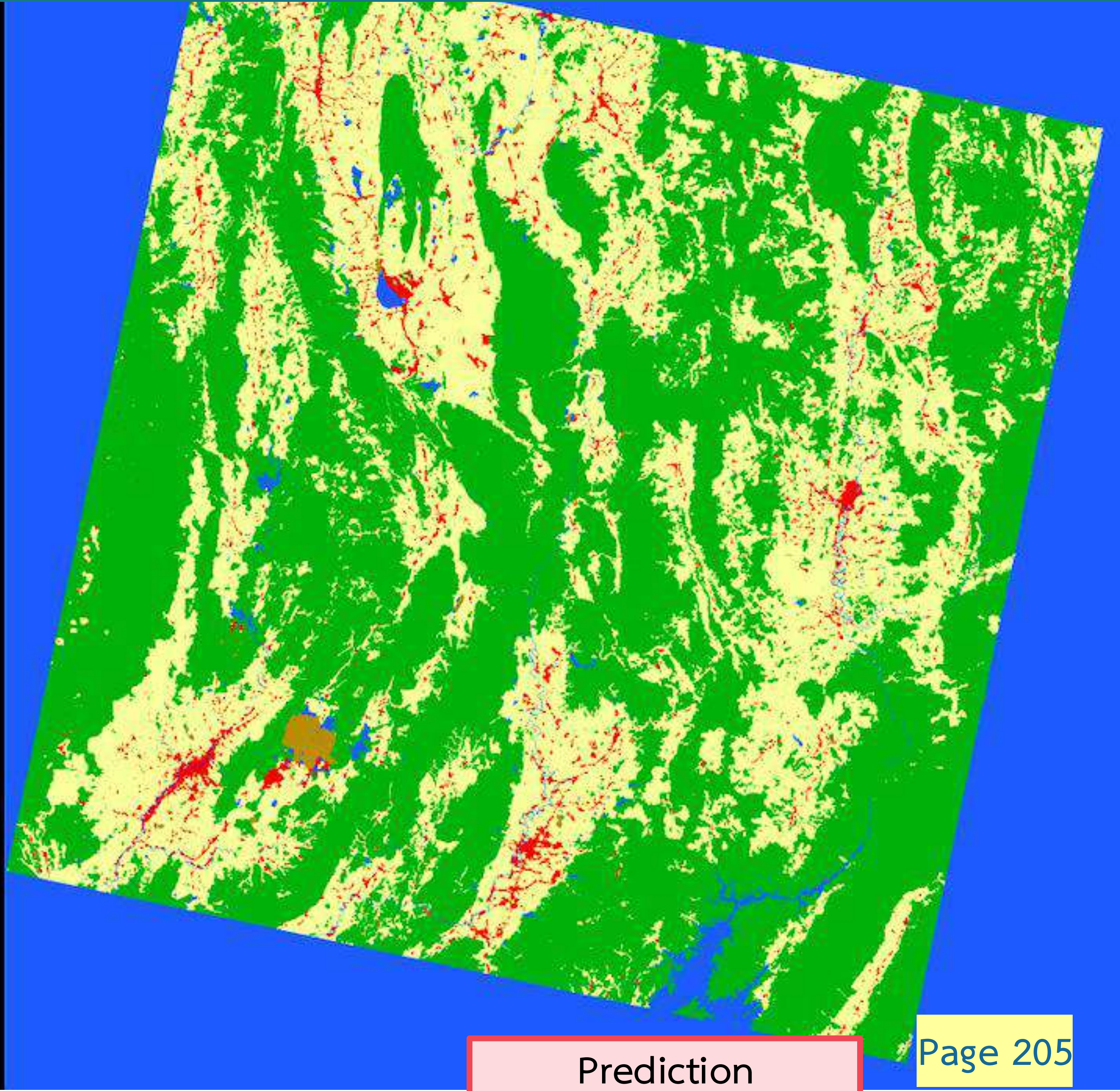
https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC123047



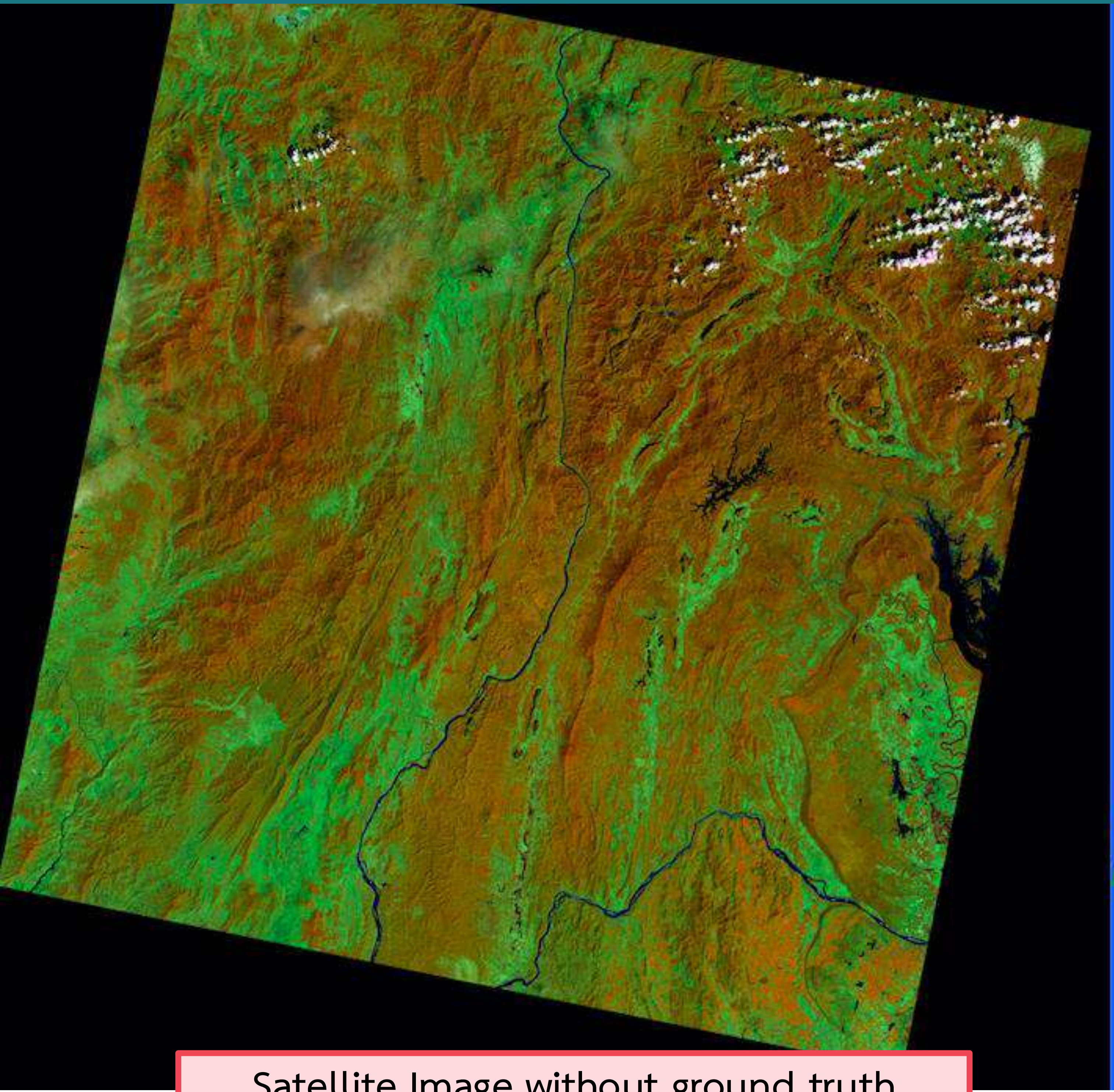
Satellite Image without ground truth



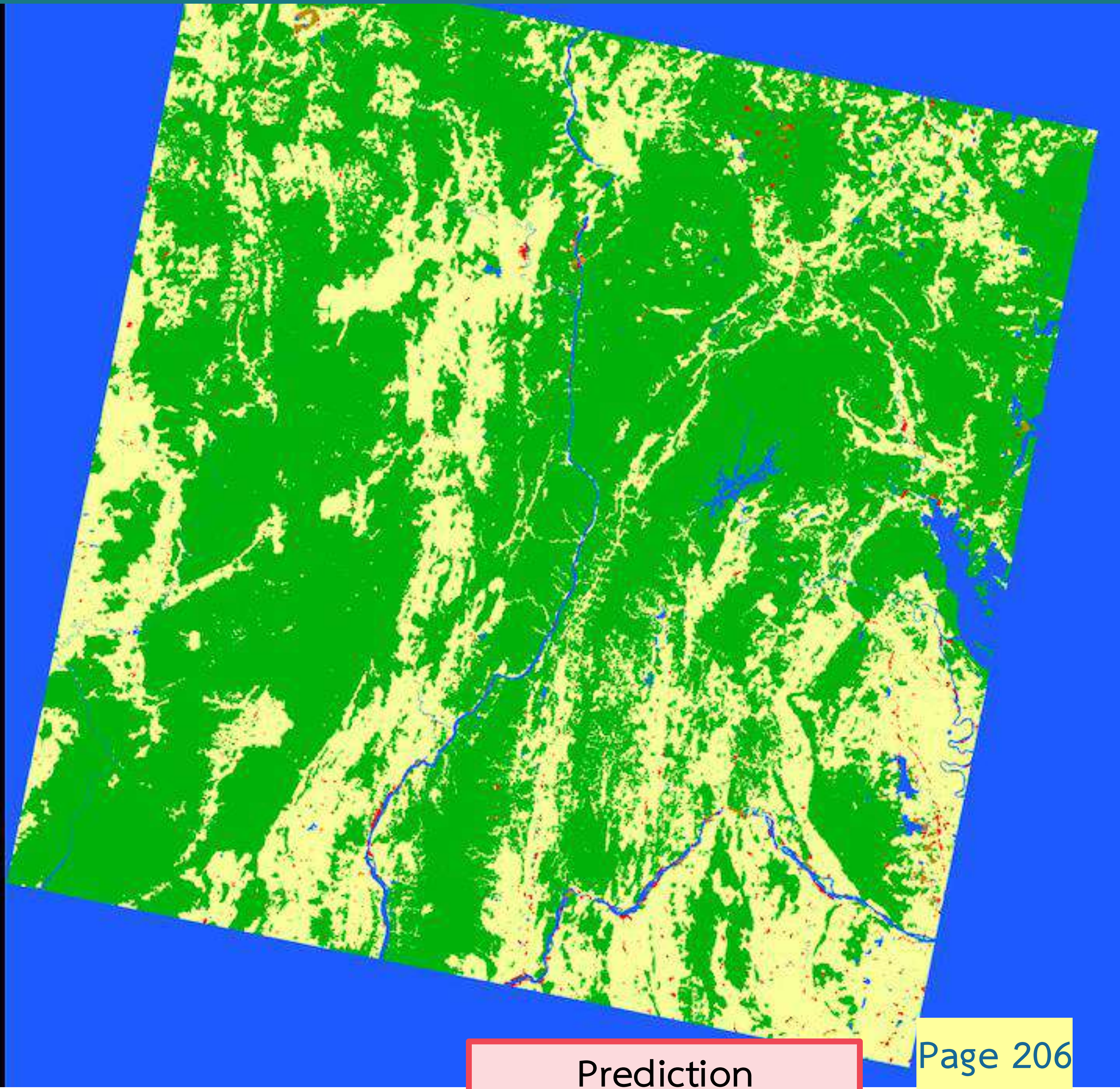
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC129047



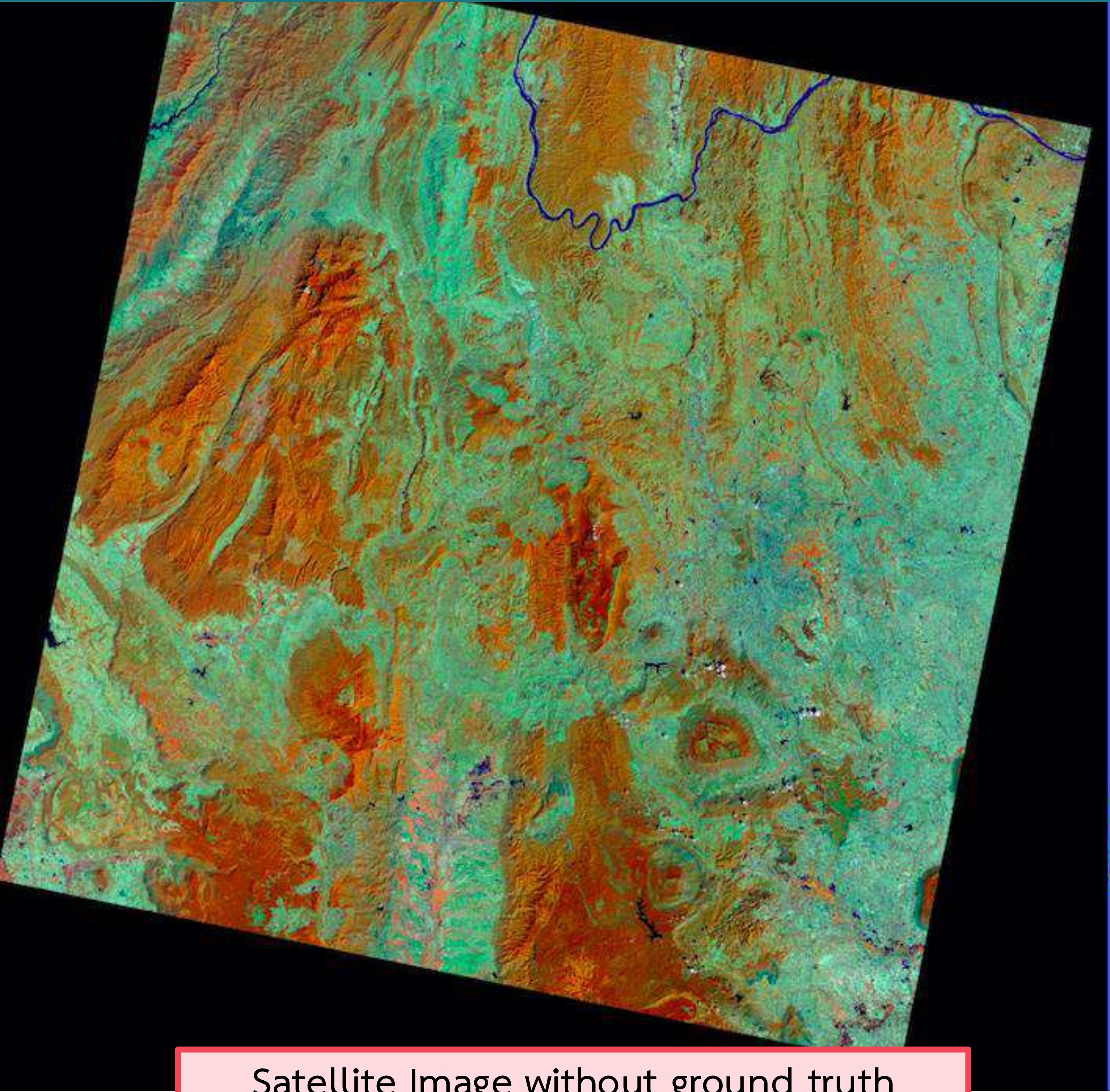
Satellite Image without ground truth



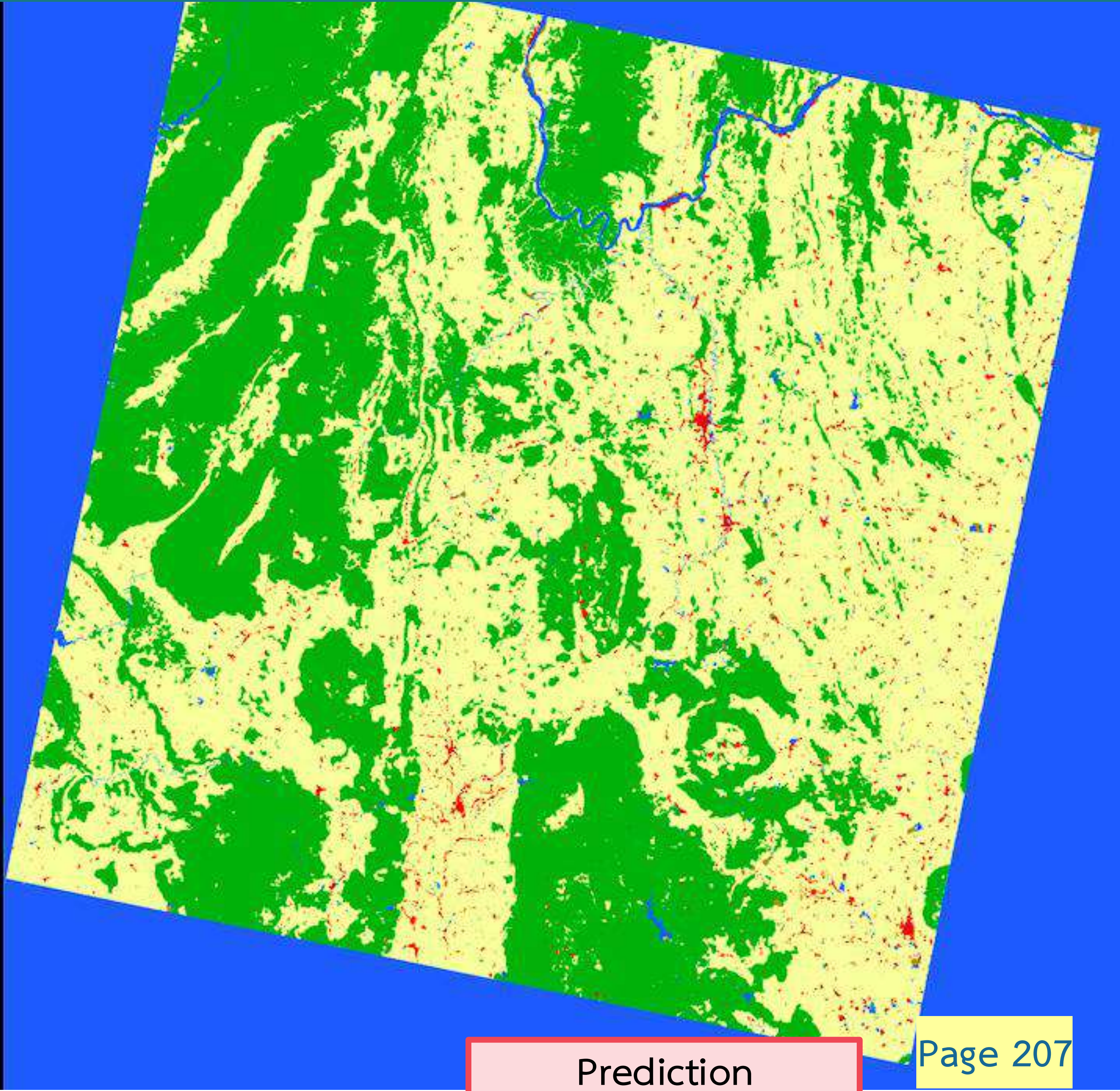
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC129048



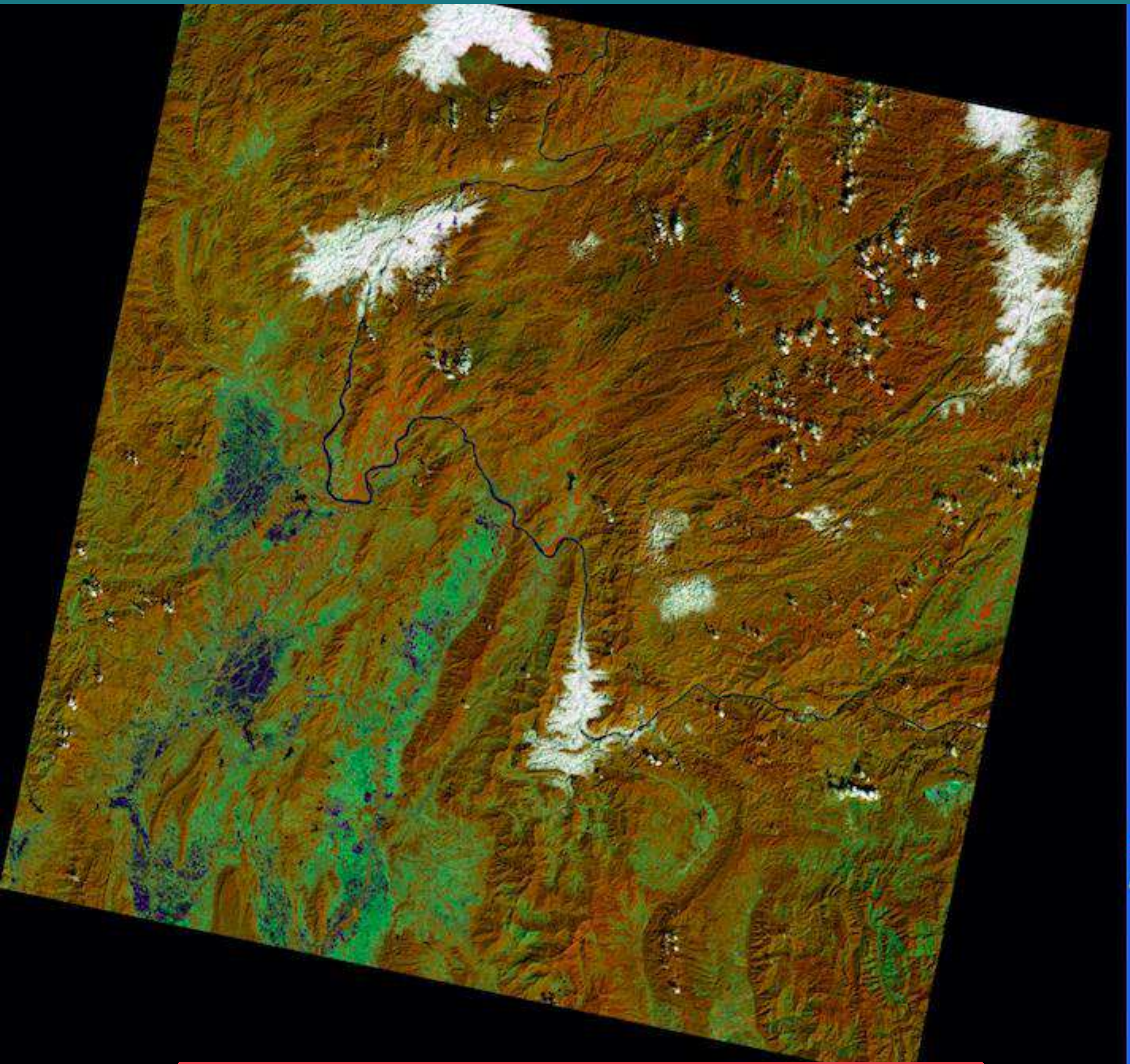
Satellite Image without ground truth



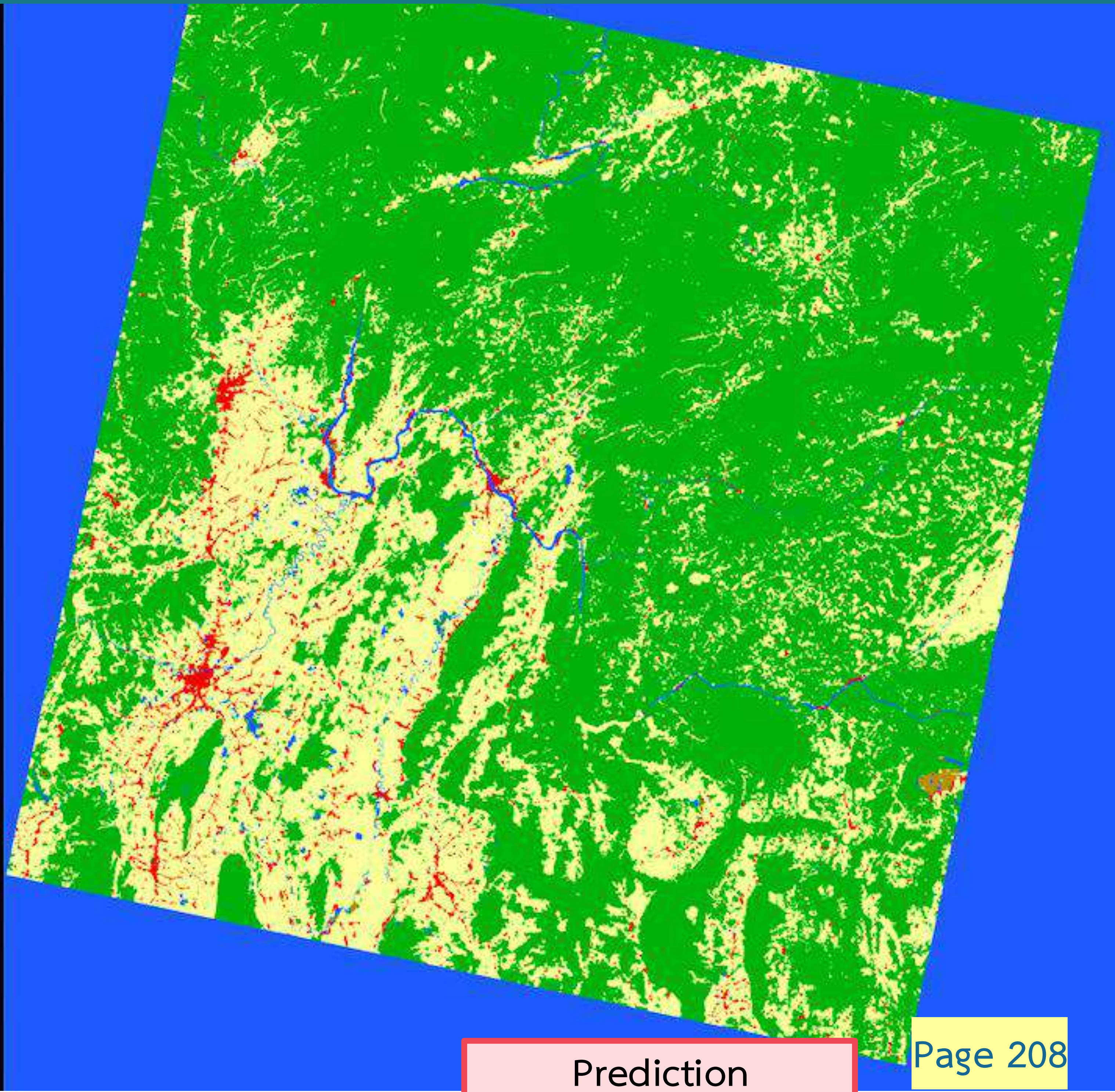
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC130046



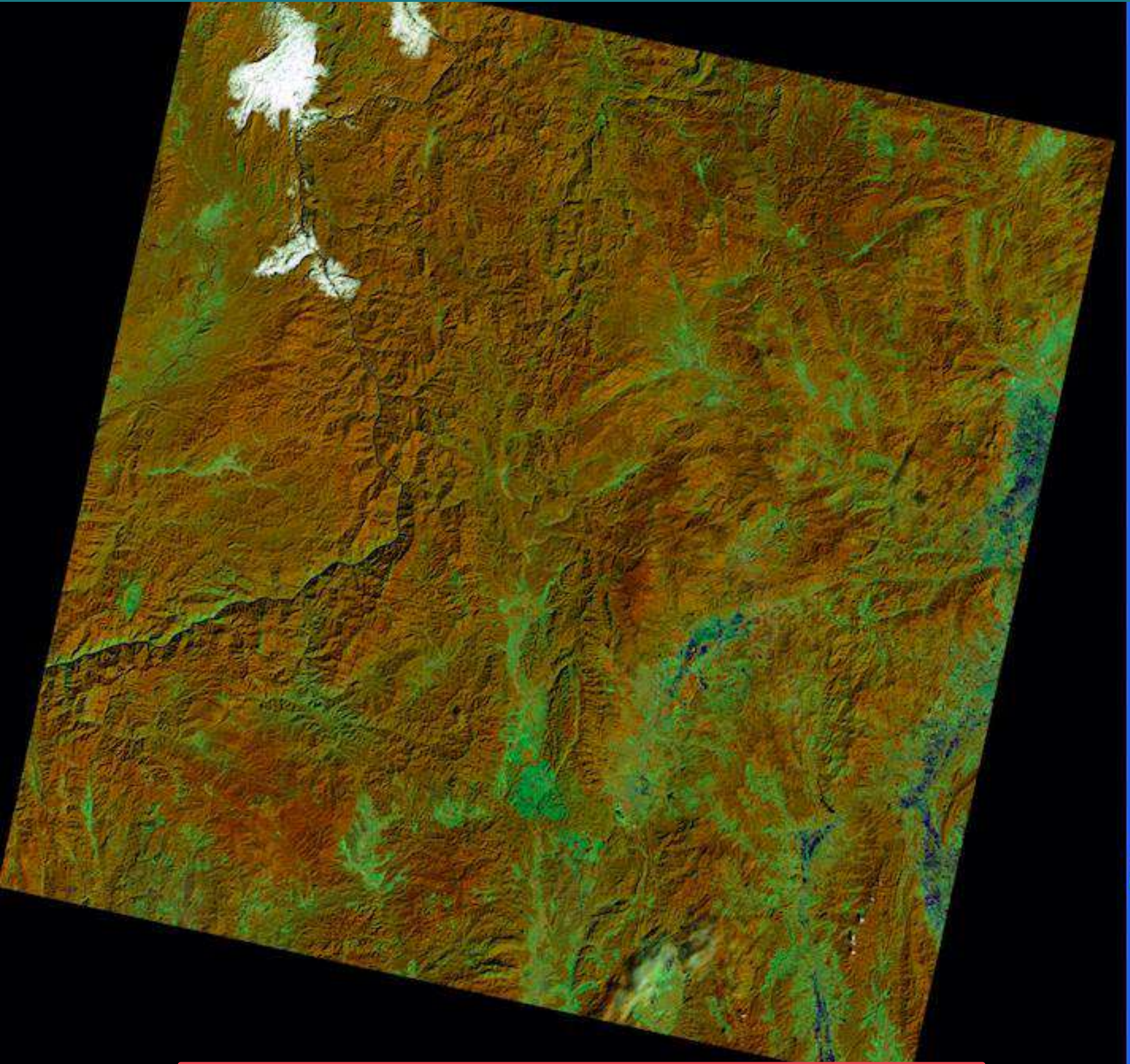
Satellite Image without ground truth



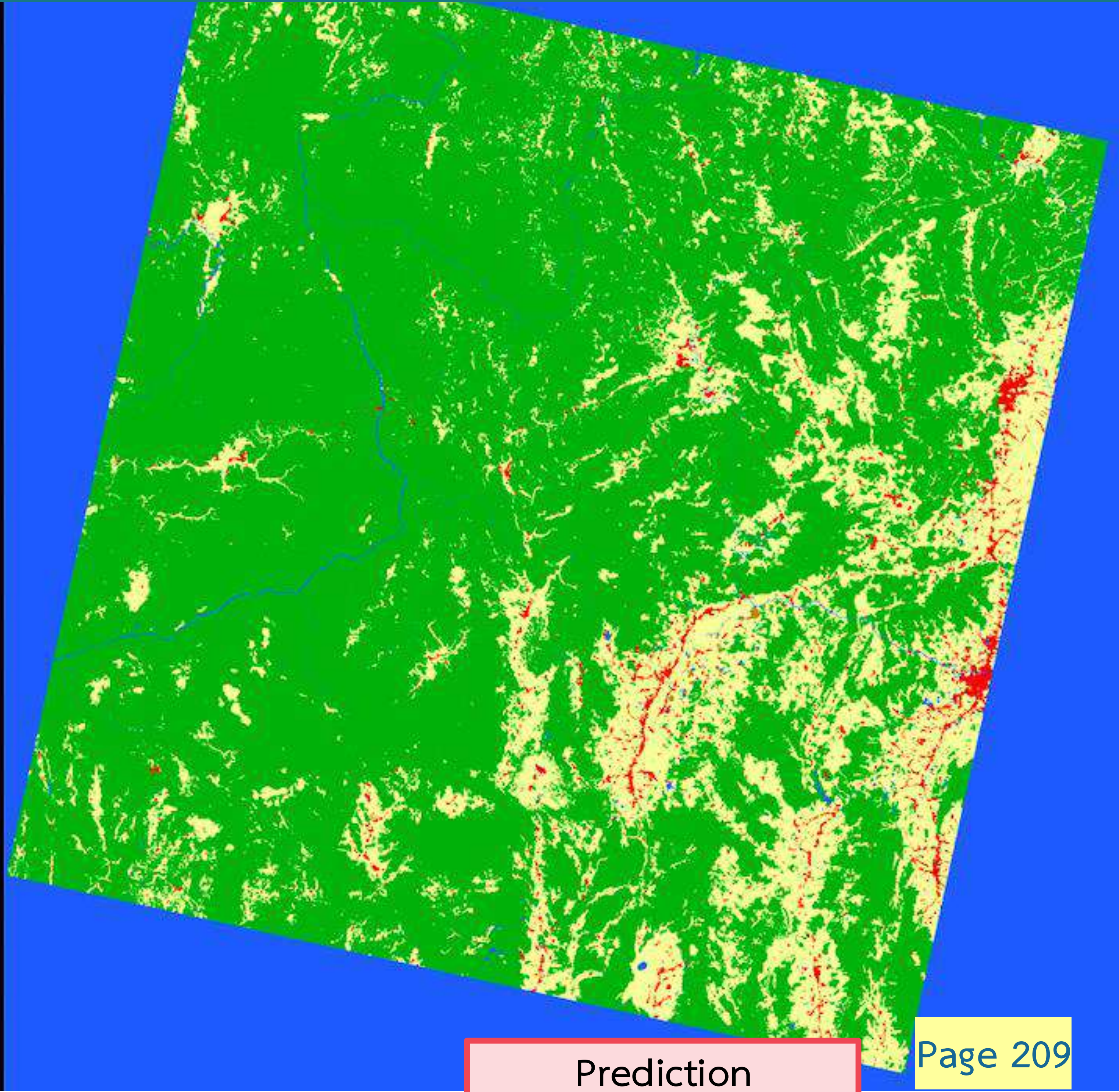
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC131046



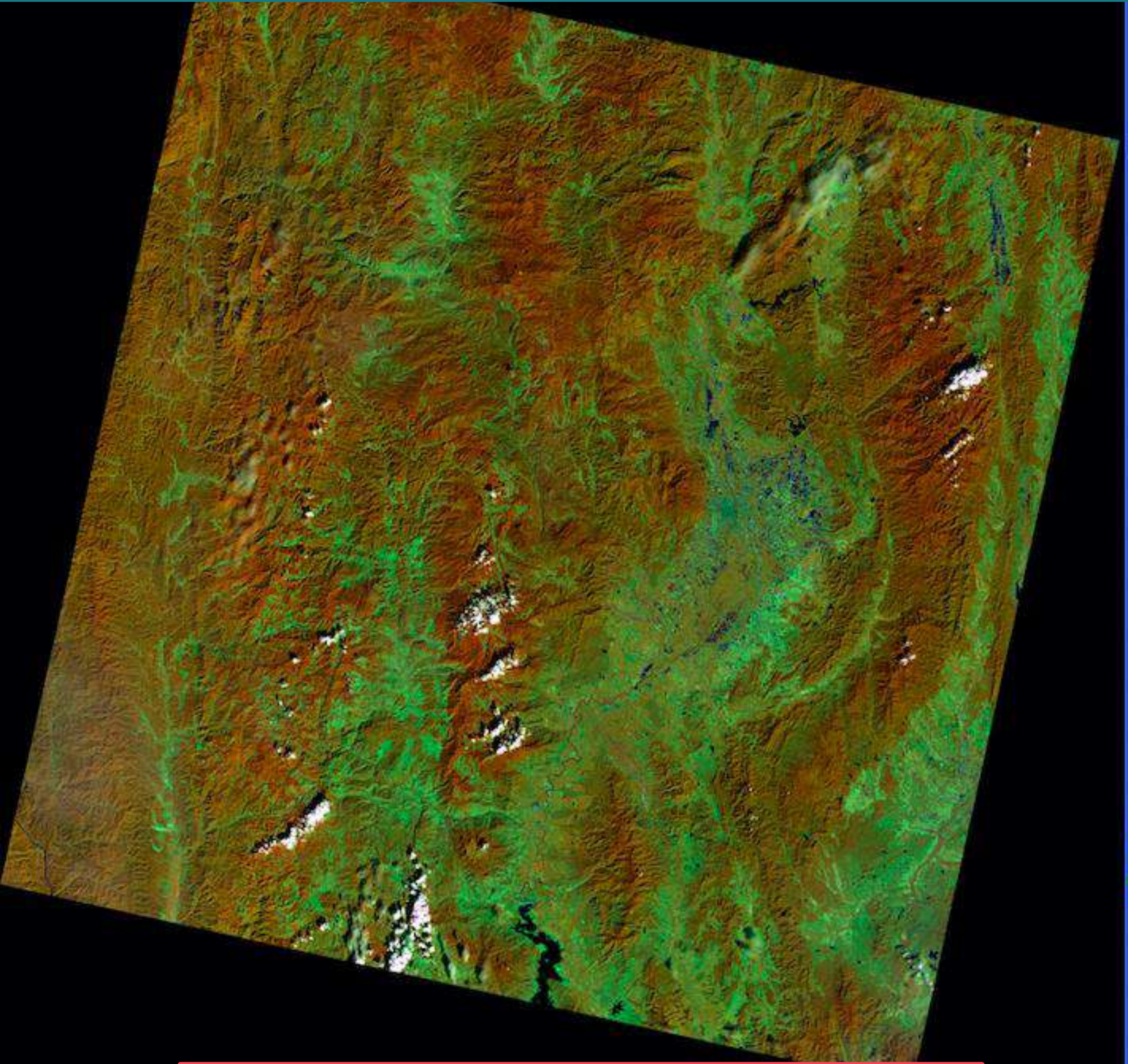
Satellite Image without ground truth



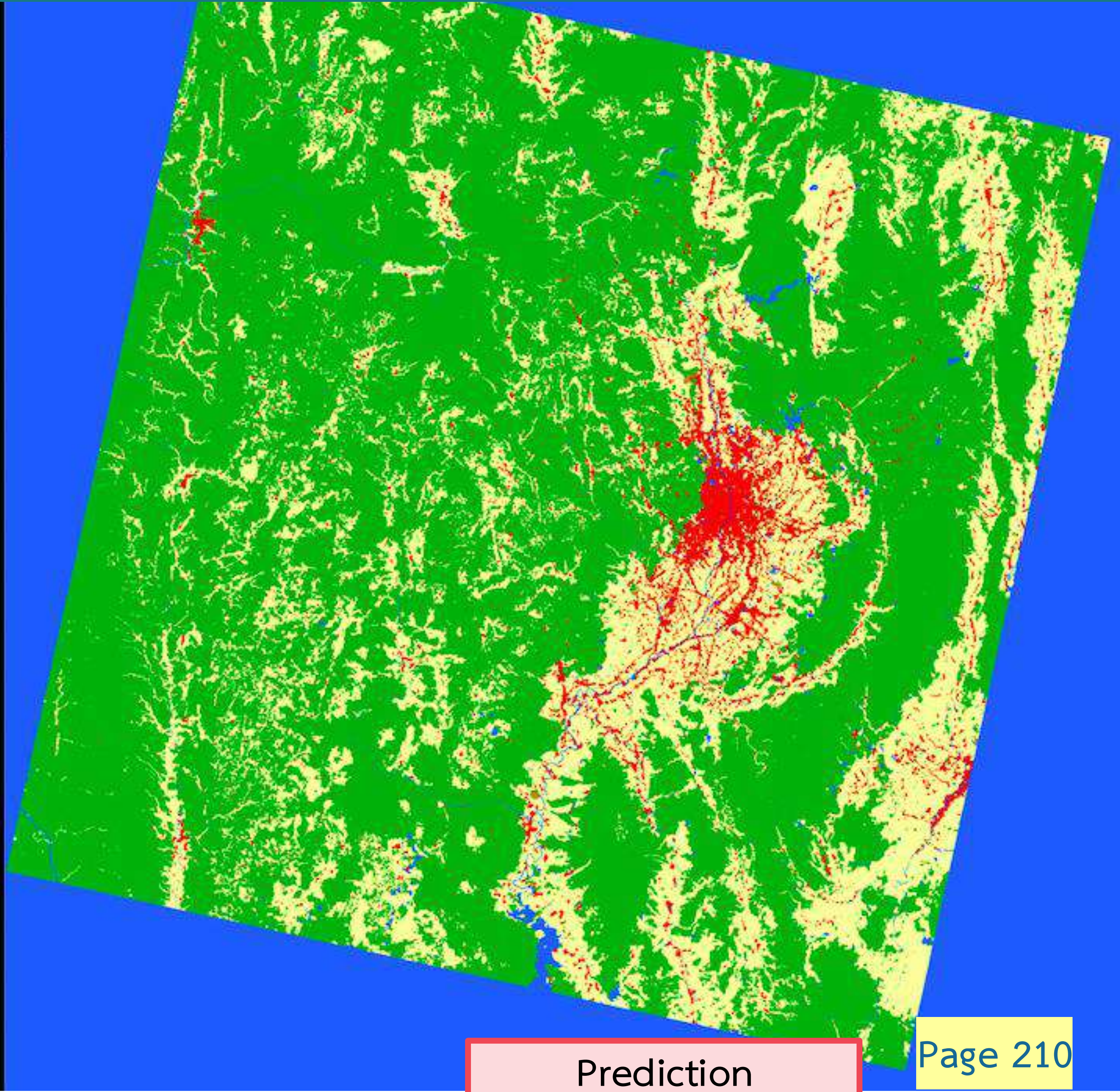
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC131047



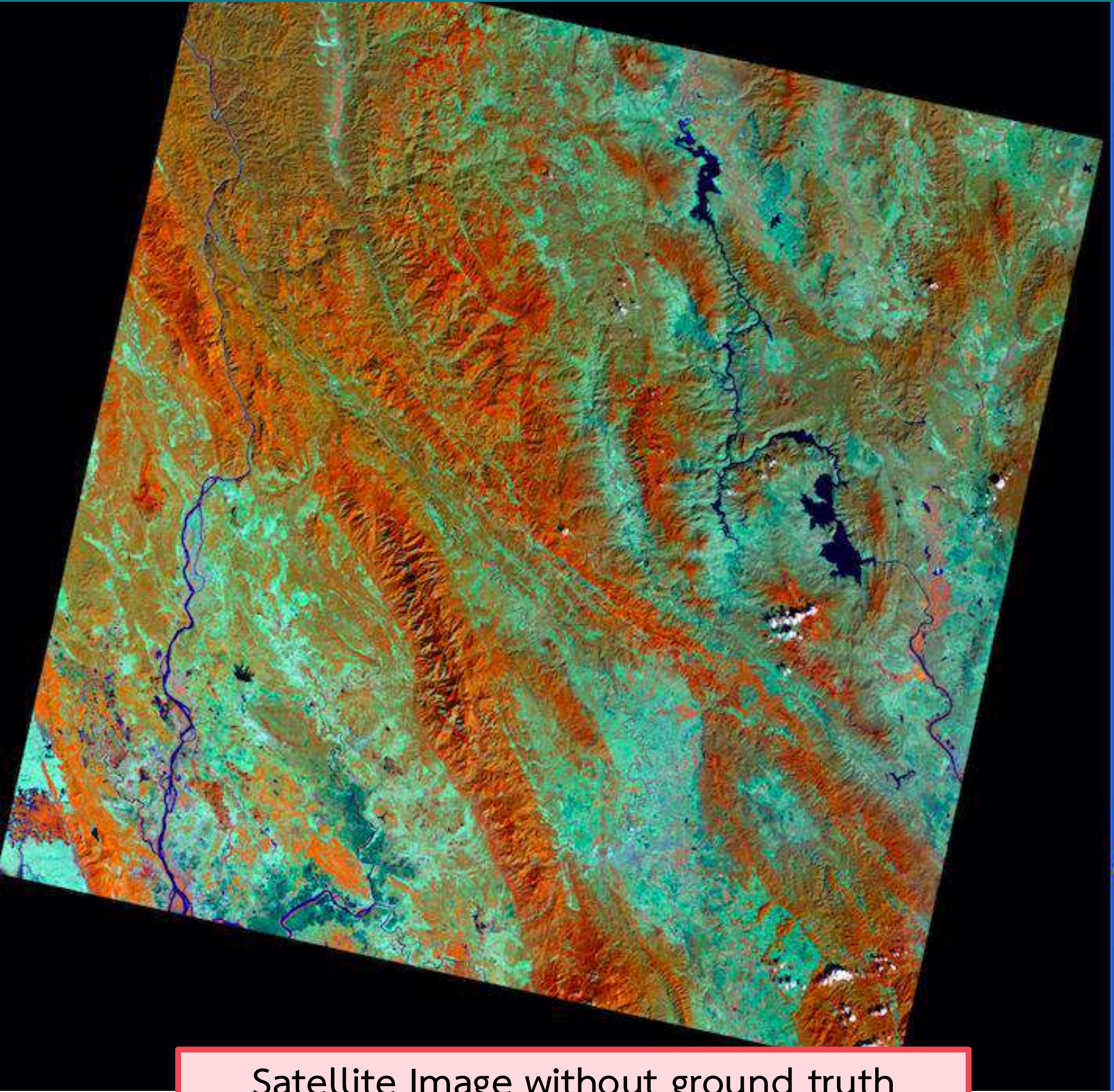
Satellite Image without ground truth



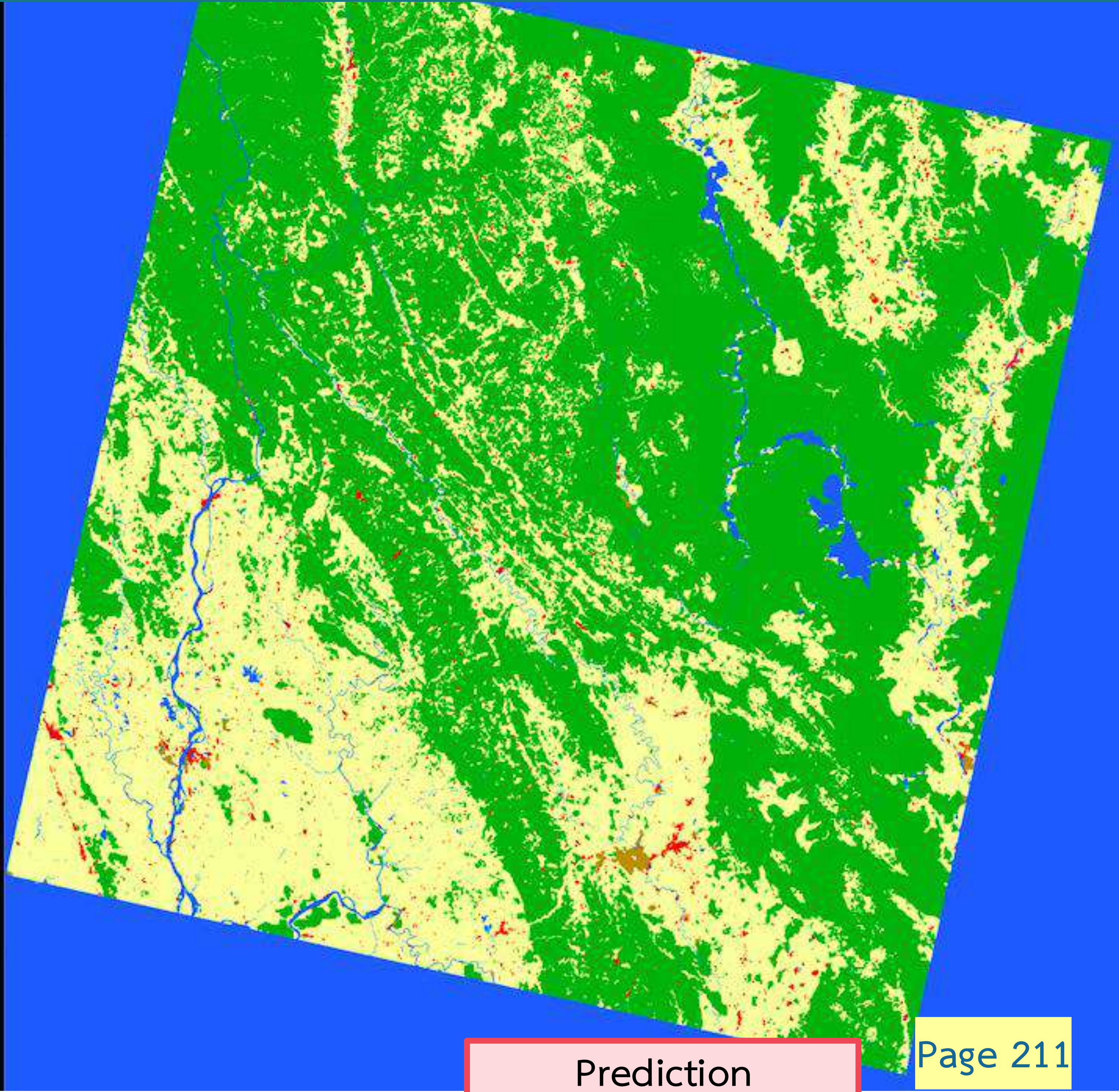
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC131048



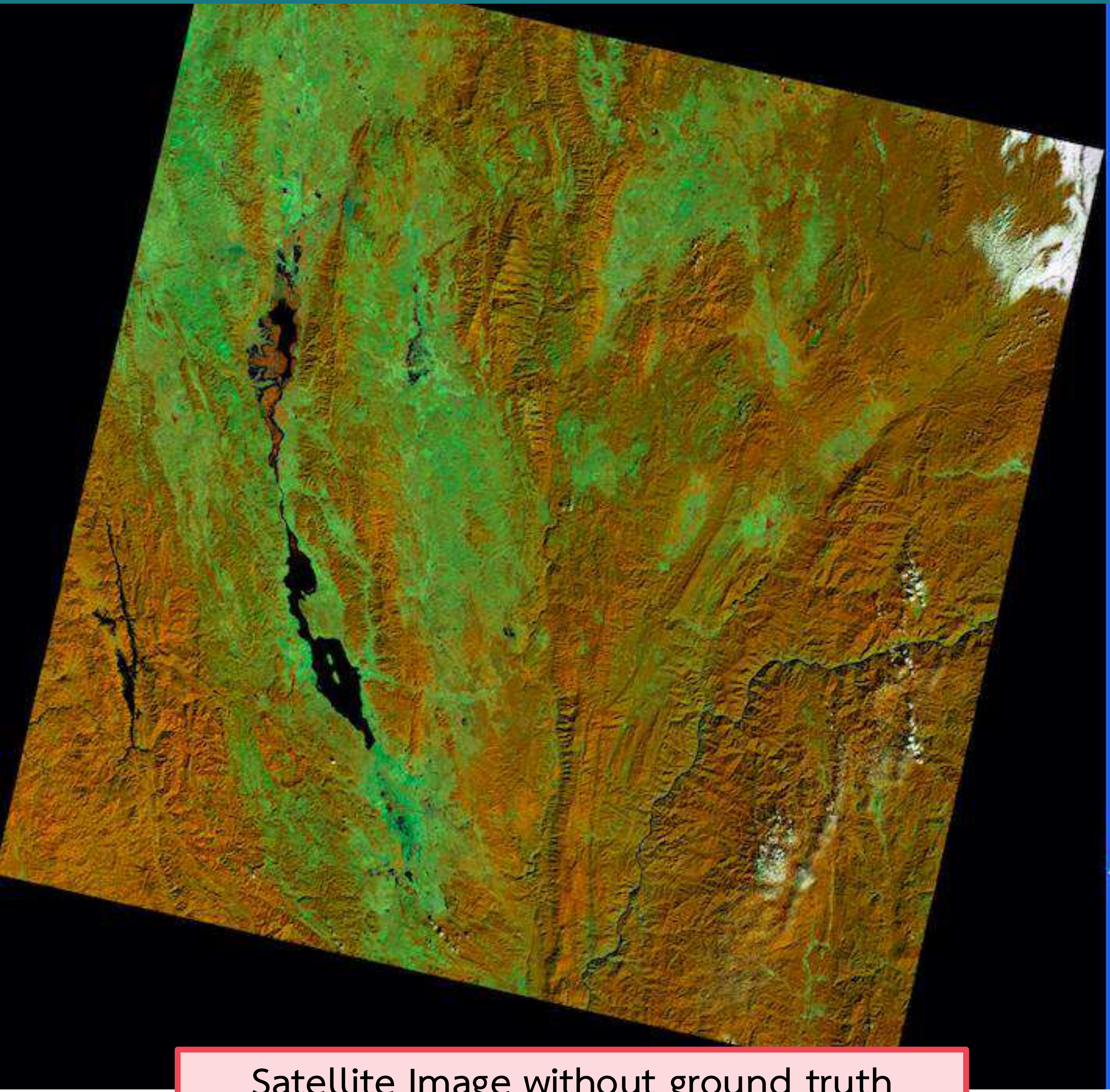
Satellite Image without ground truth



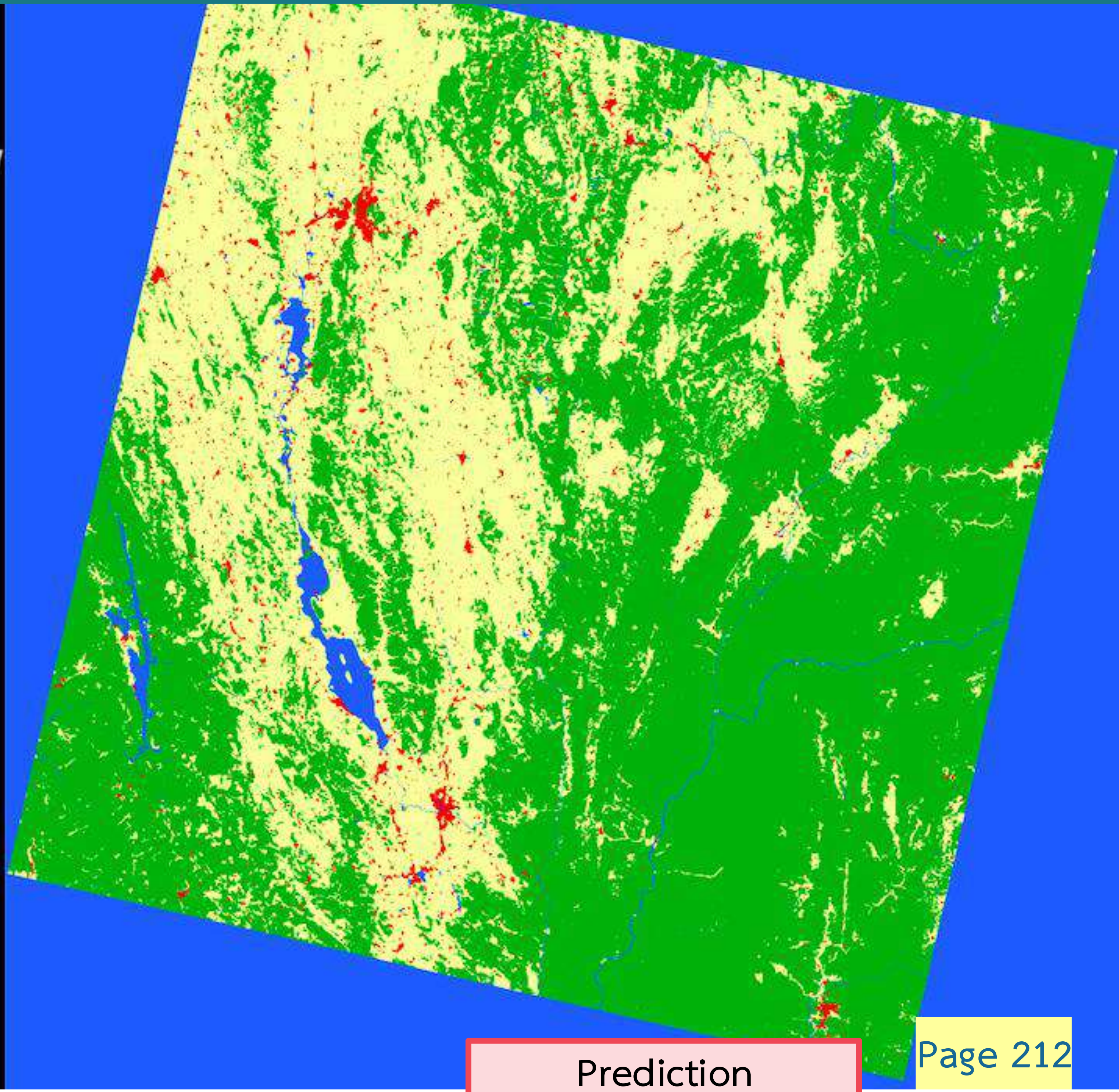
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC132046



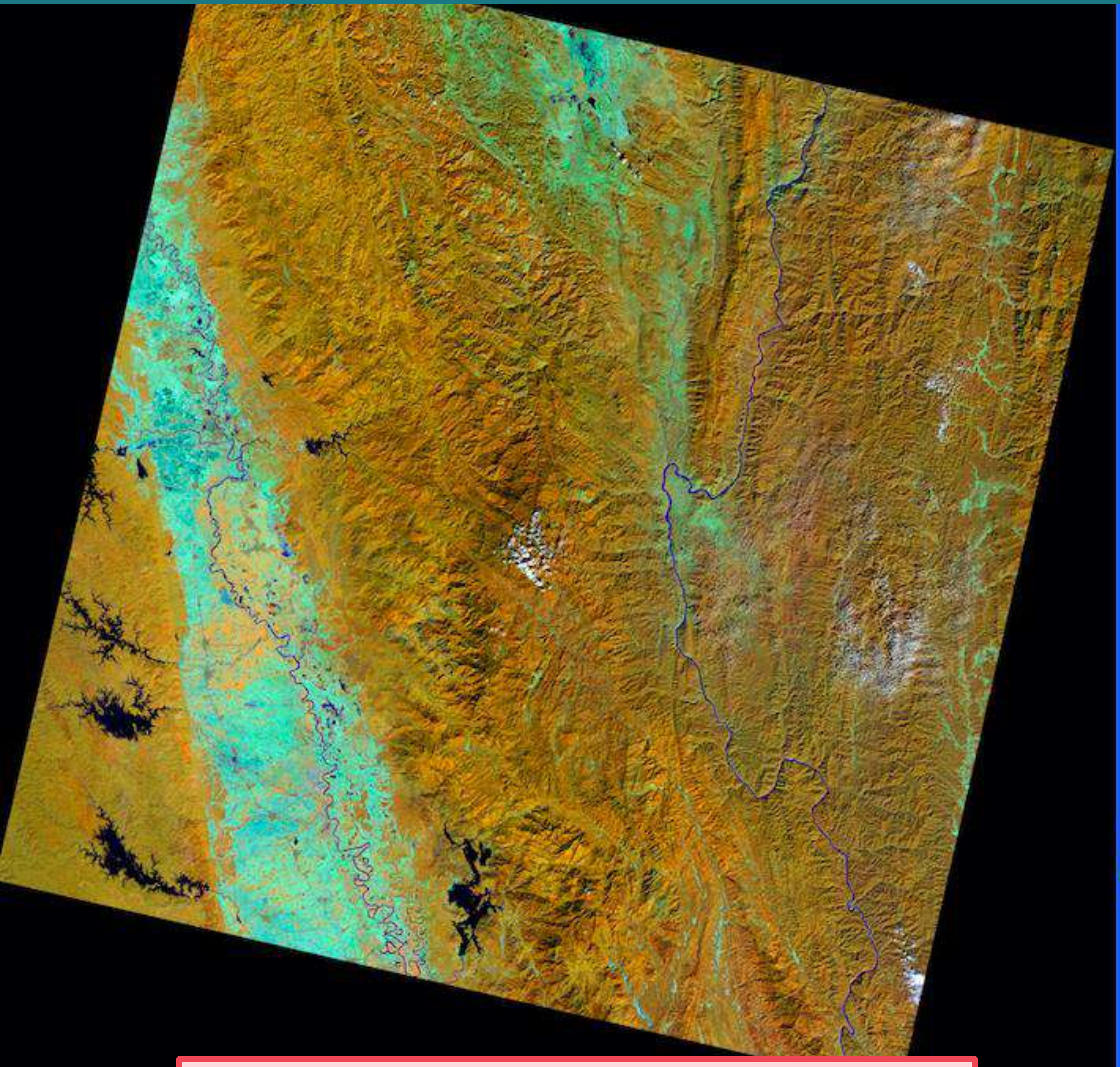
Satellite Image without ground truth



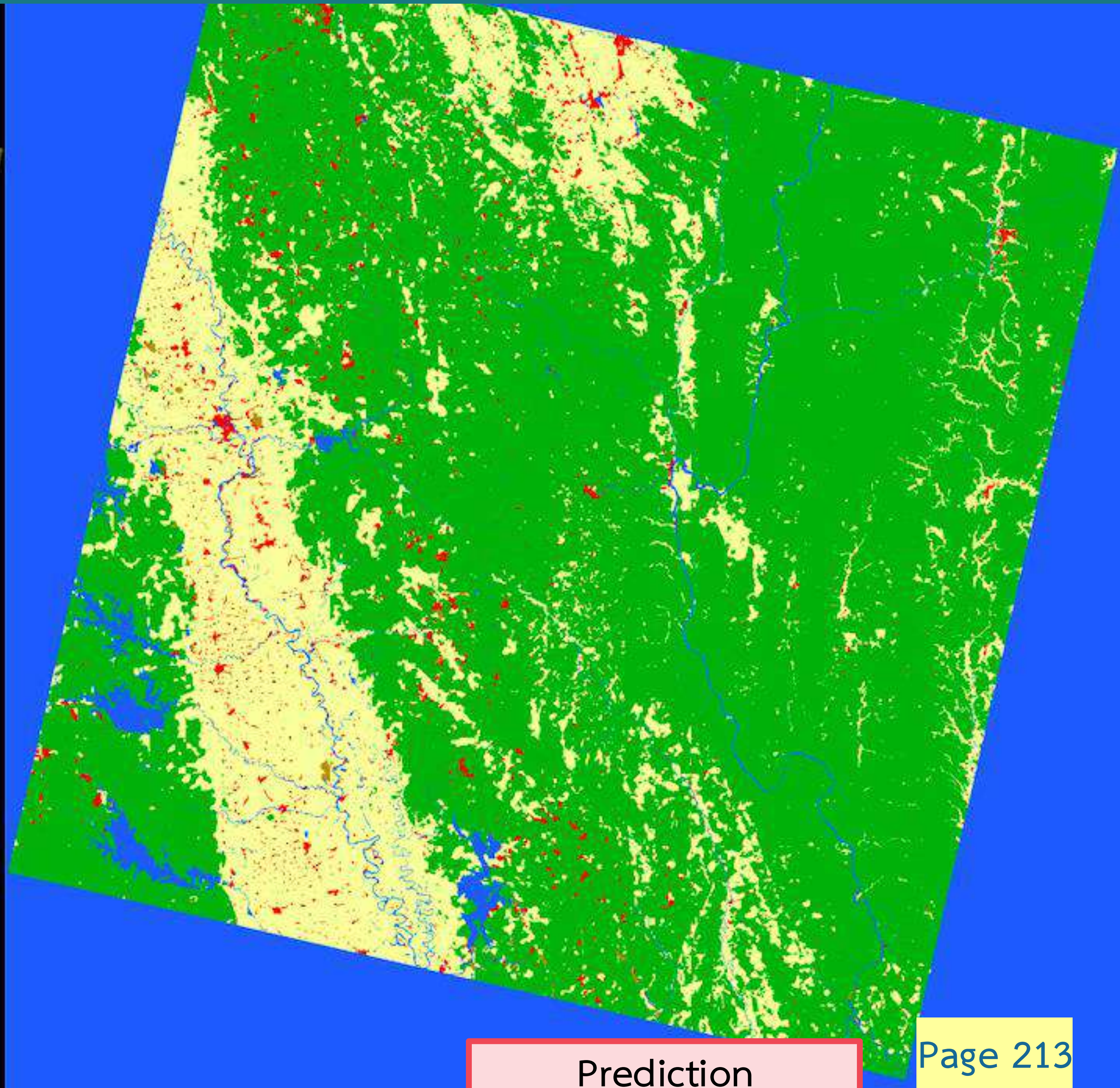
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC132047



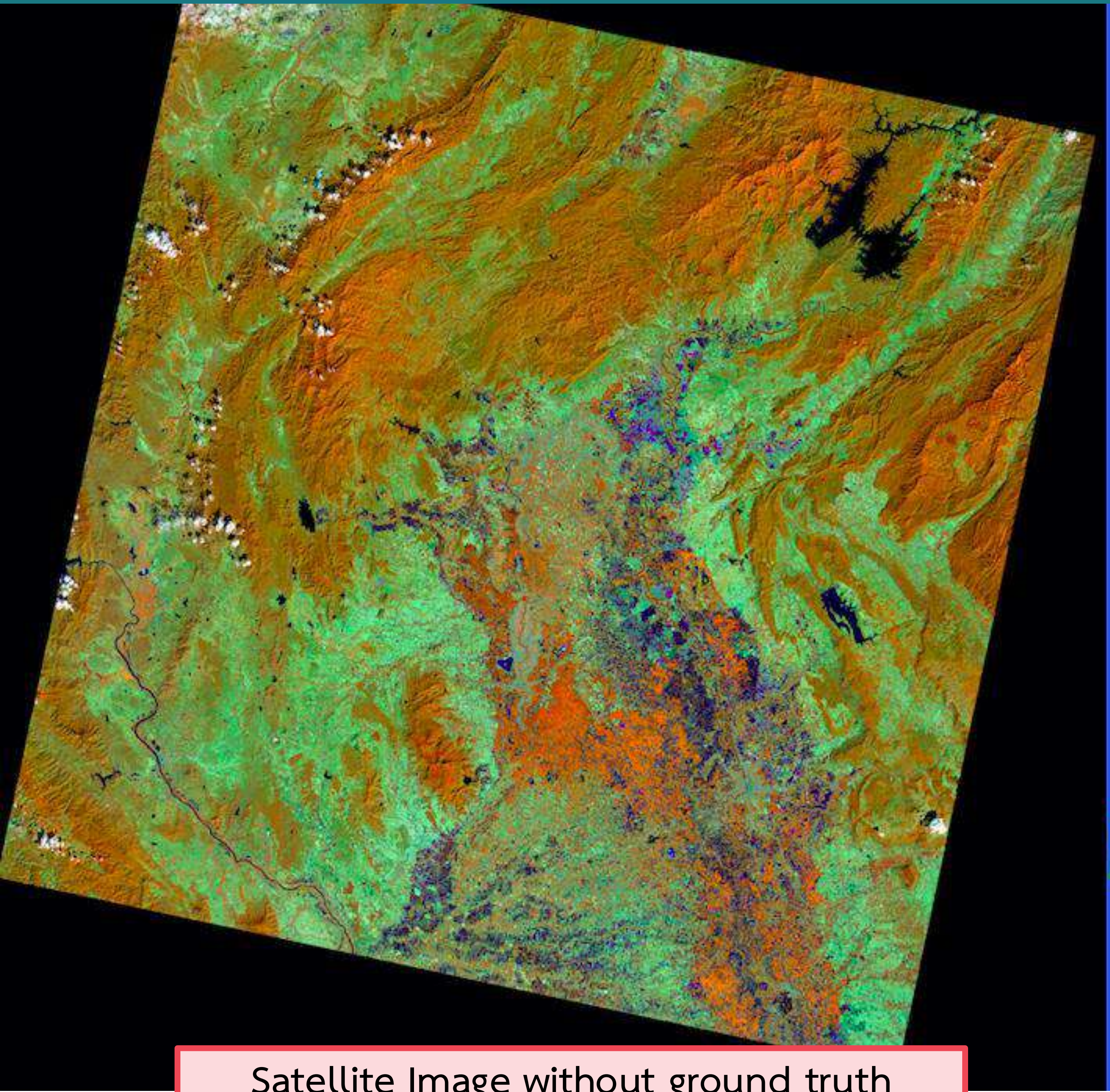
Satellite Image without ground truth



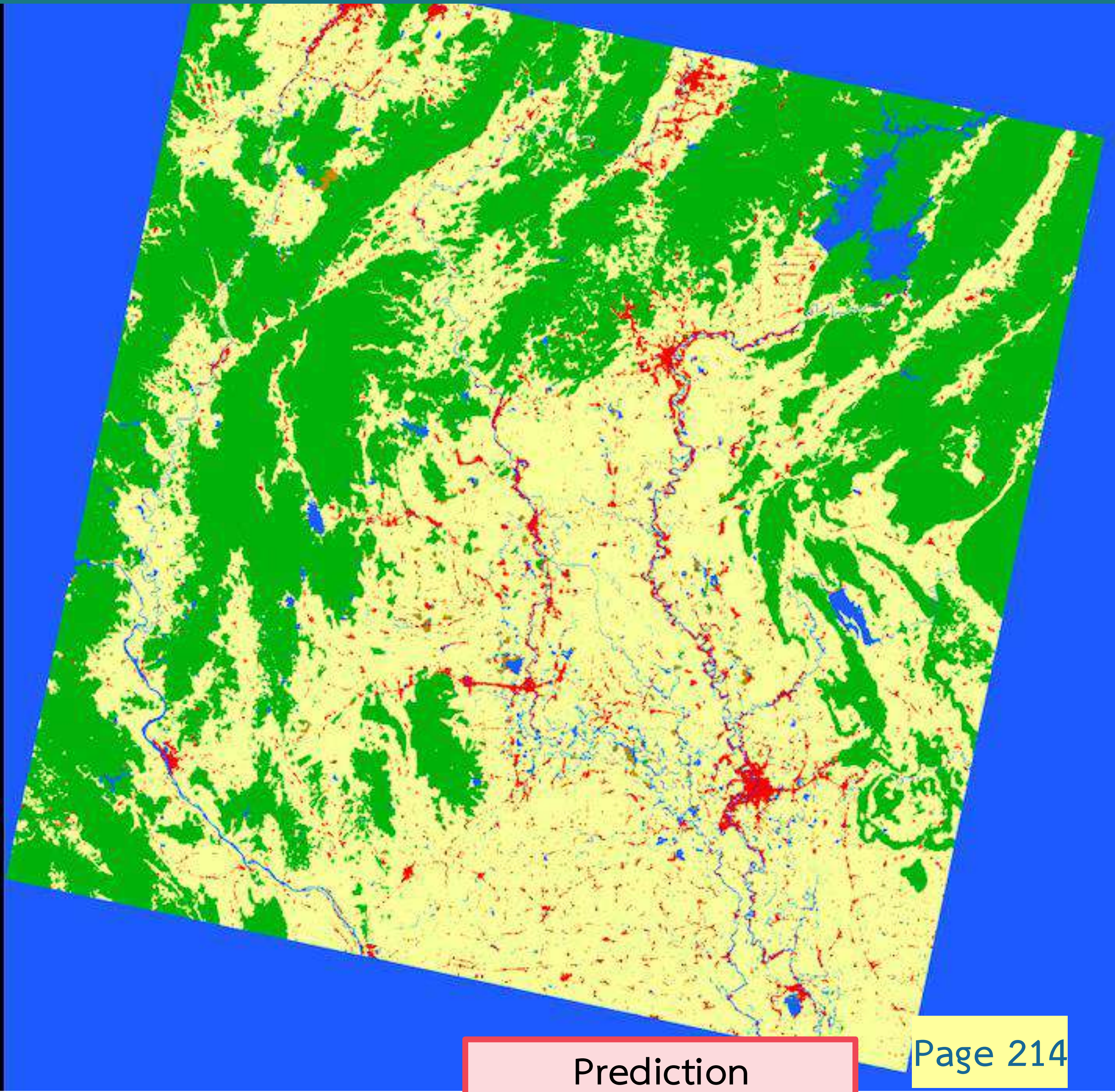
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC132048



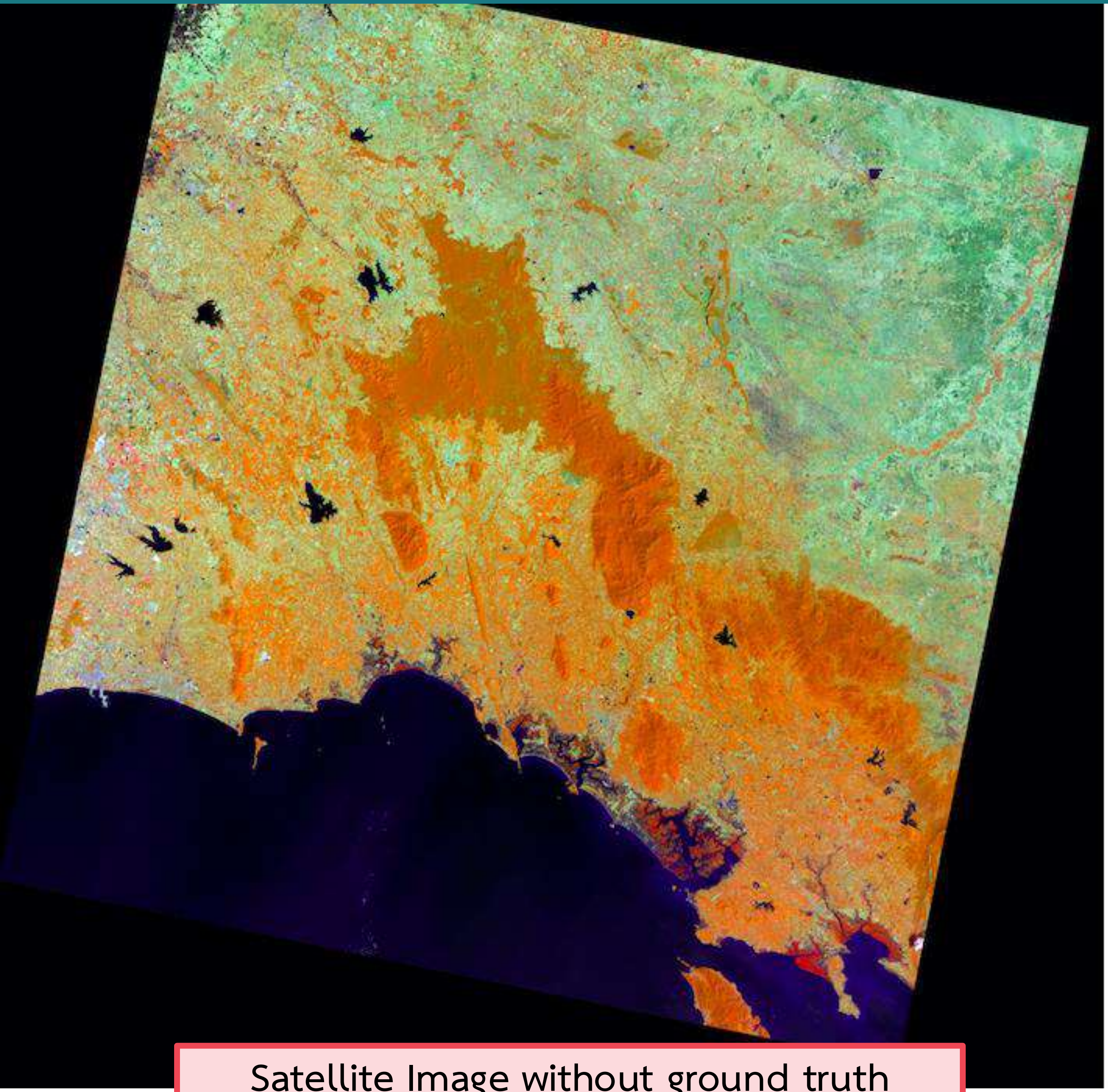
Satellite Image without ground truth



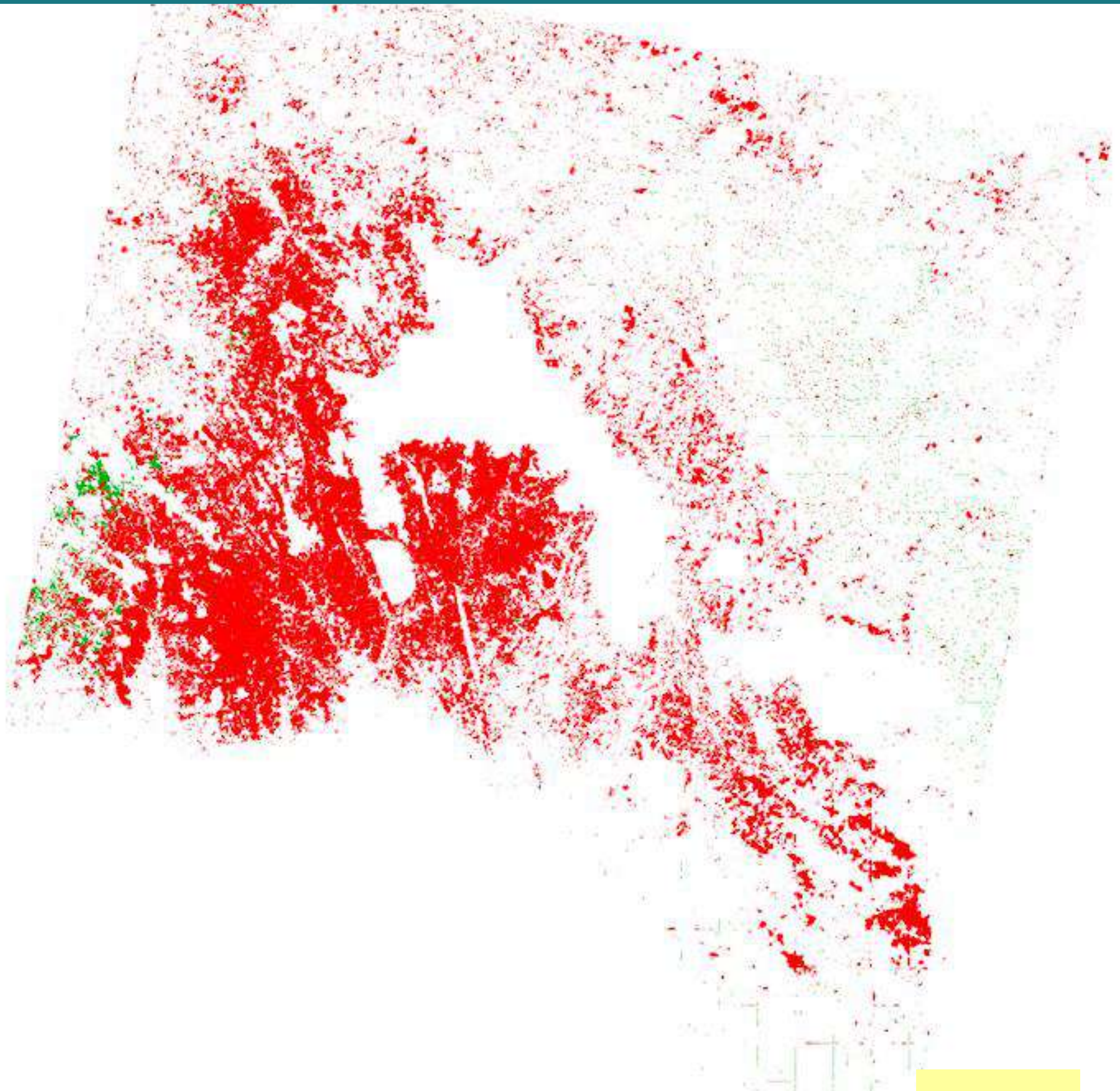
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC128051



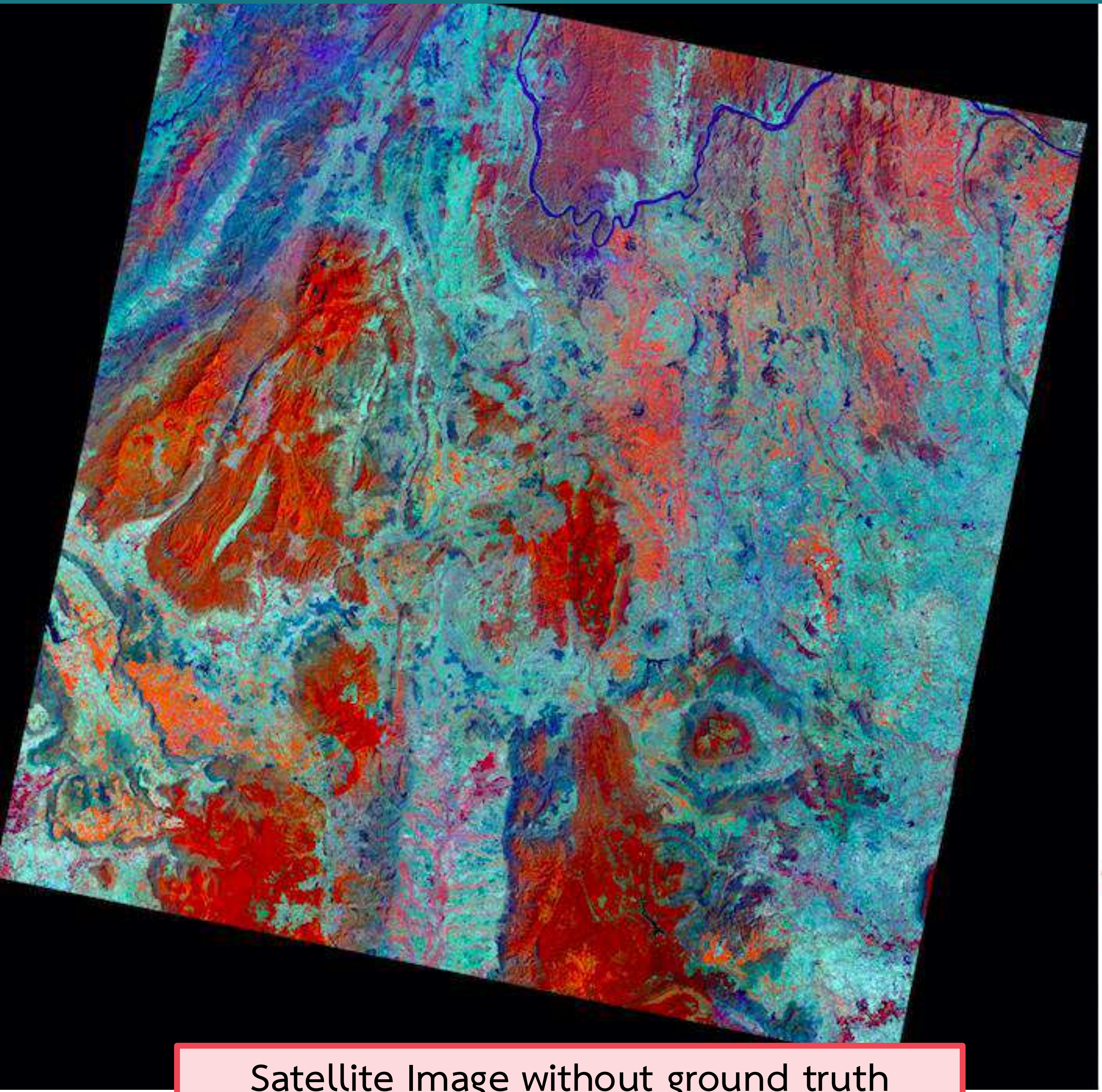
Satellite Image without ground truth



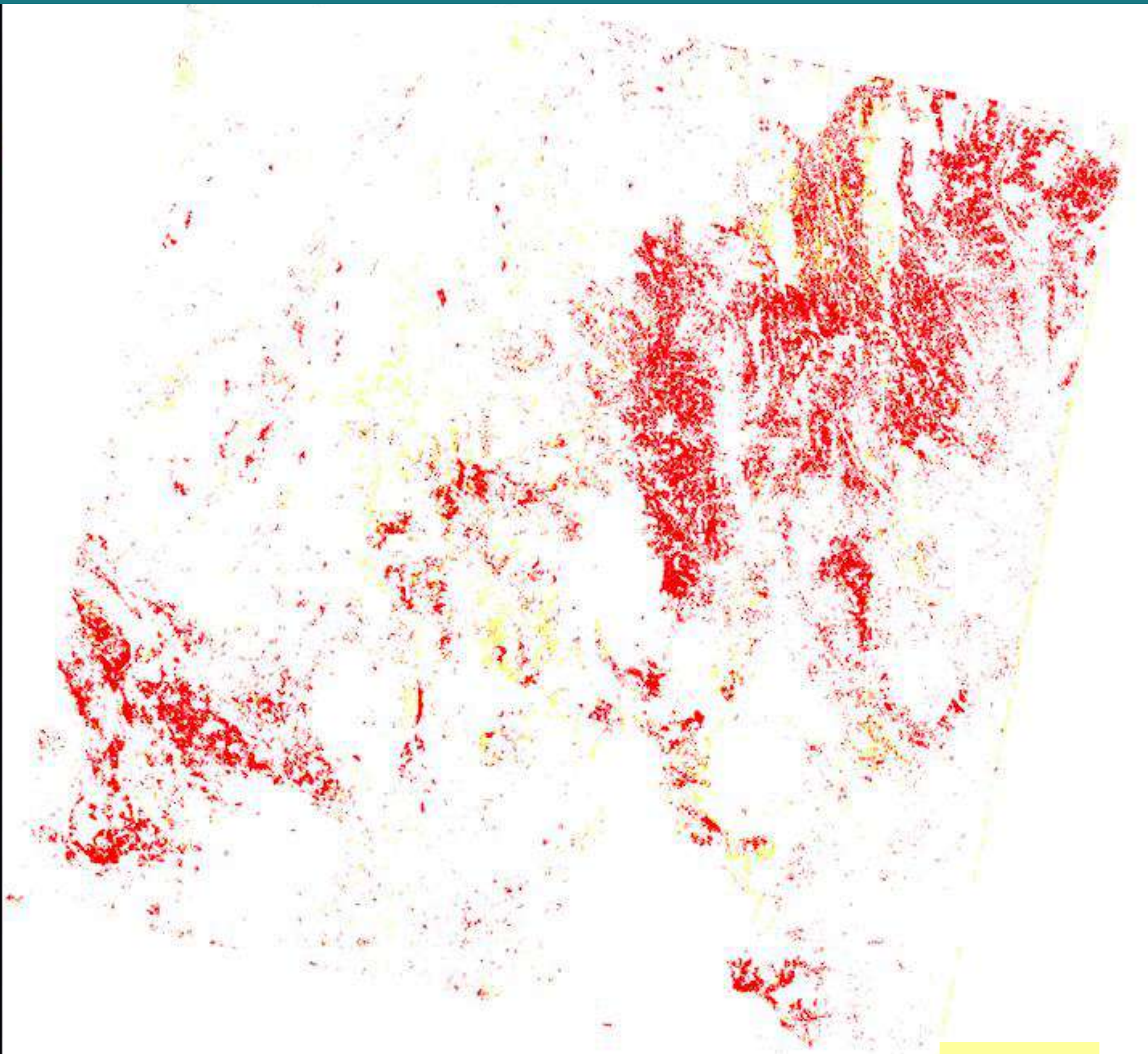
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC129048



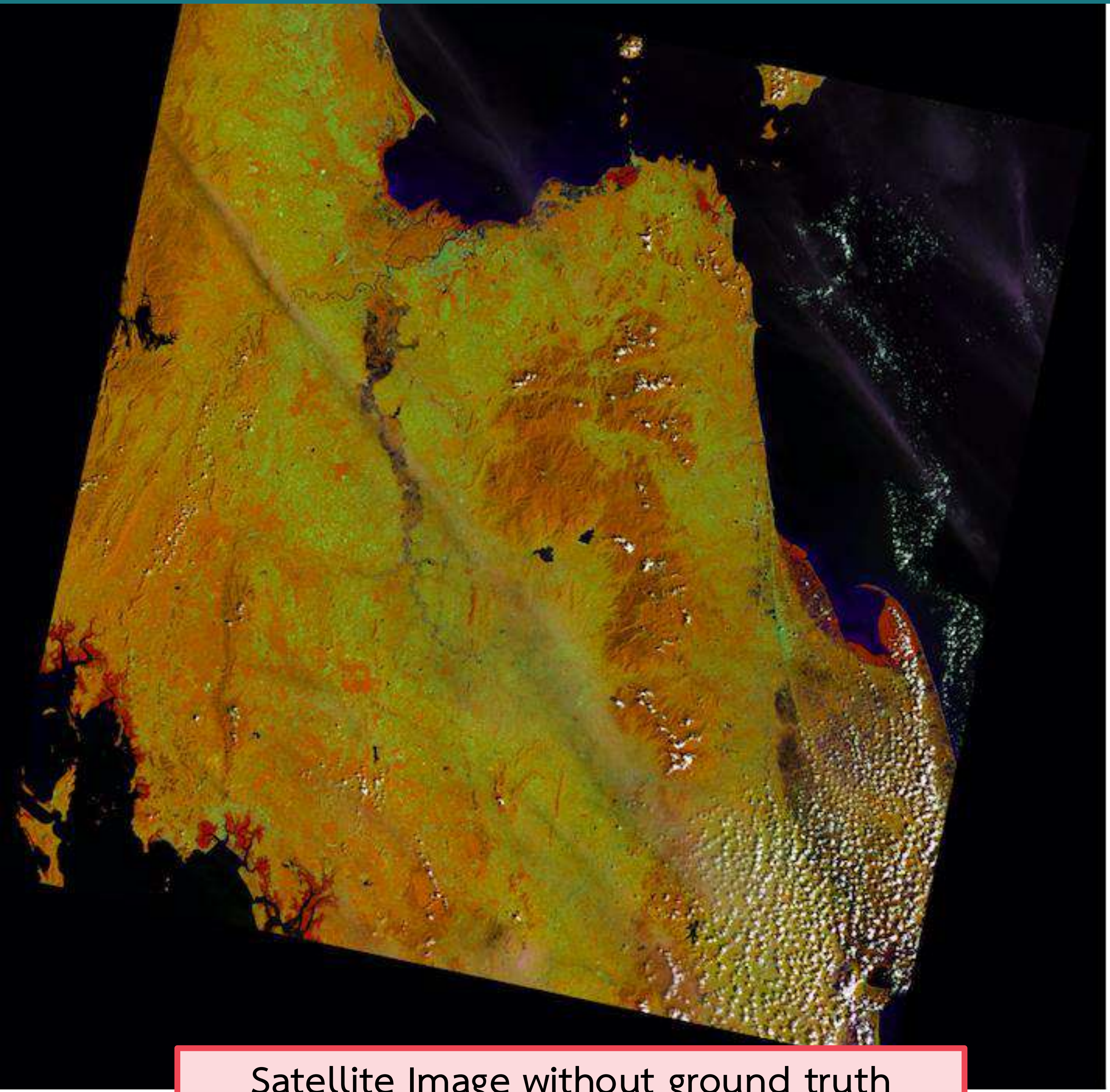
Satellite Image without ground truth



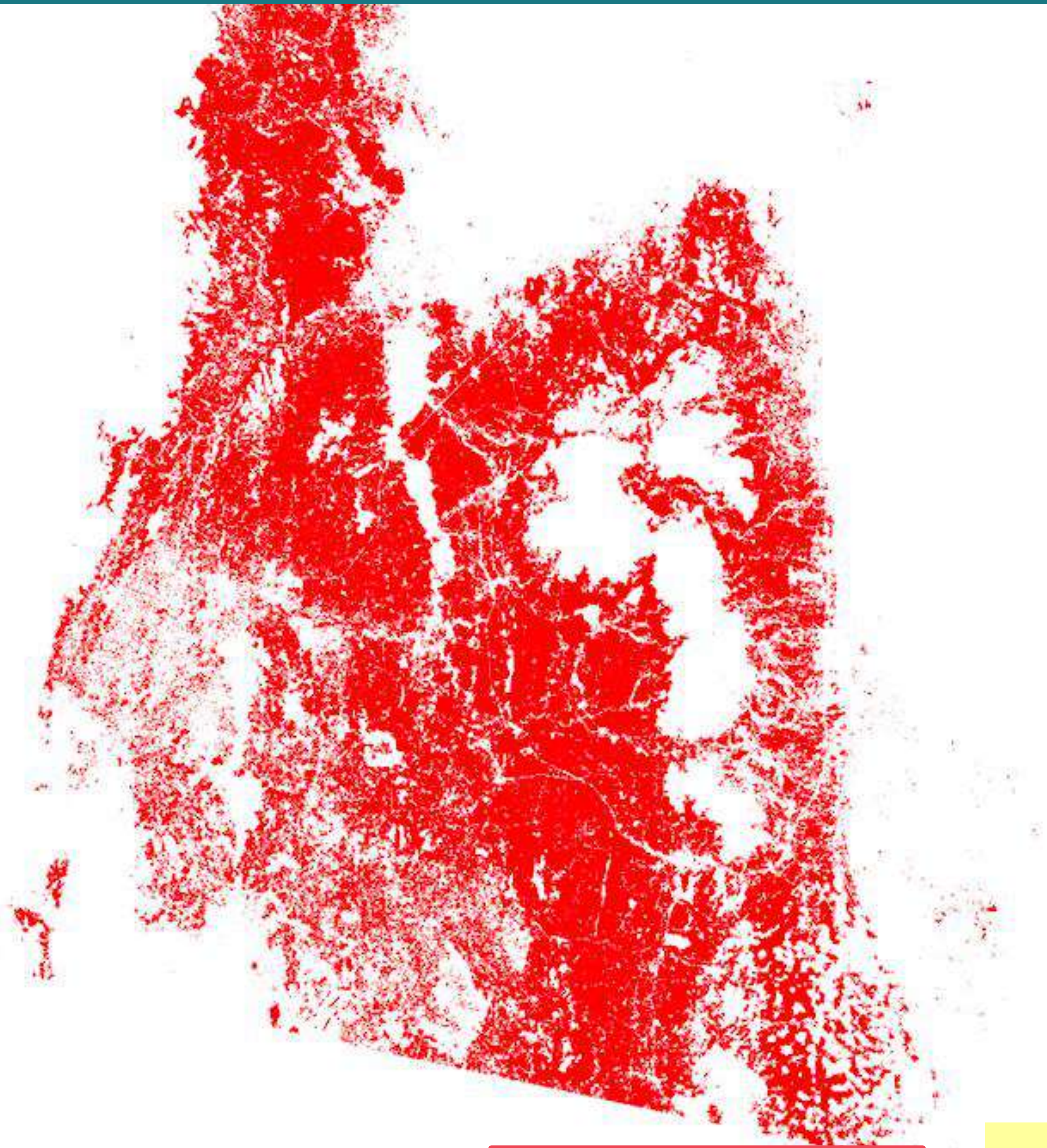
Prediction

Experimental Results with Full Proposed Method (GCN152-TL-A-FF-DA)

Path: LC129054

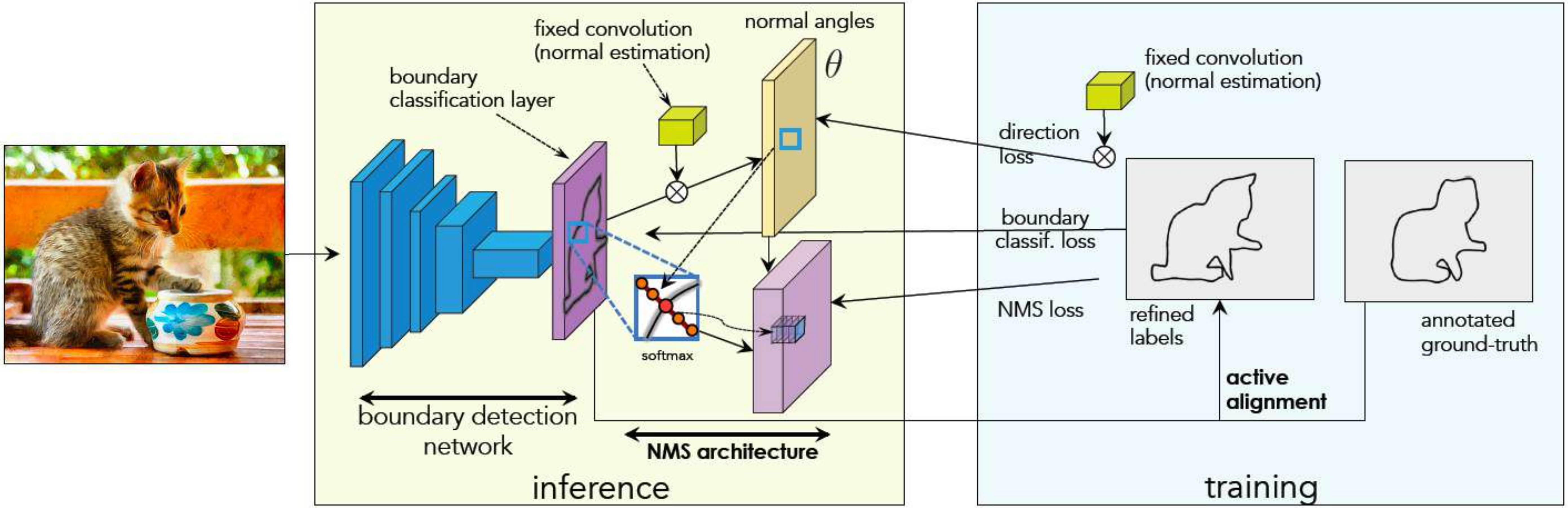


Satellite Image without ground truth



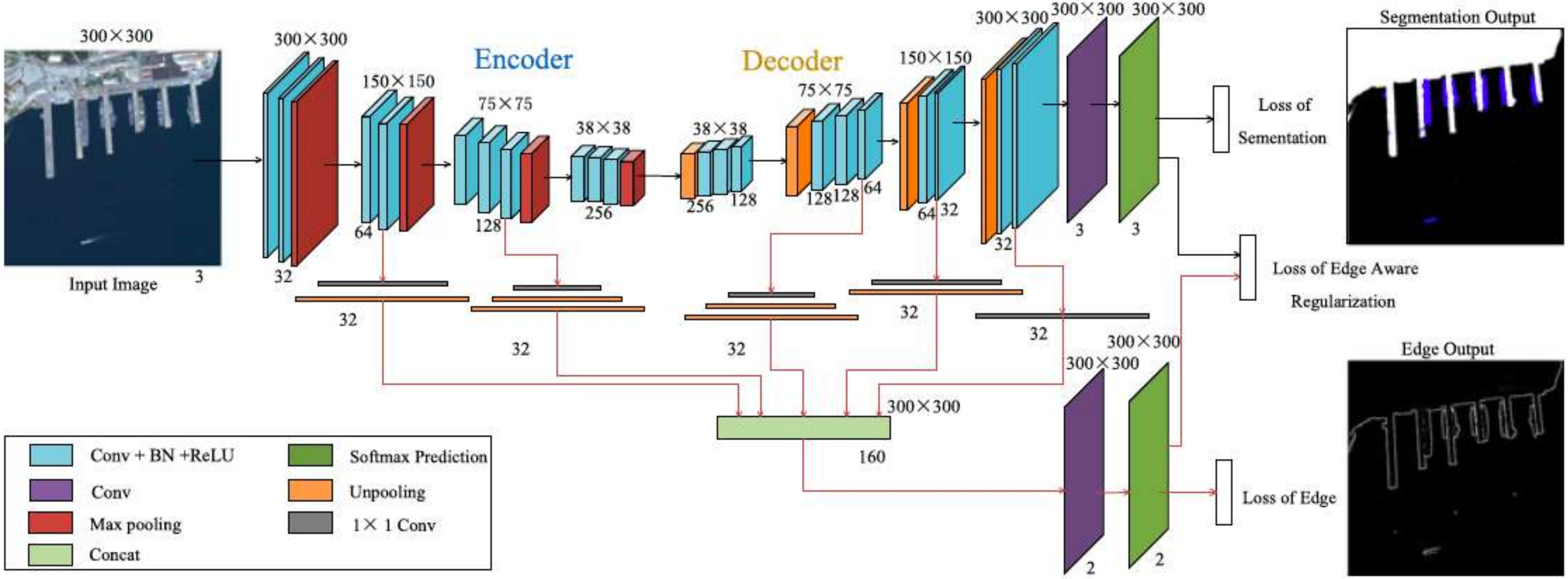
Prediction

New Idea (1)



Acuna, David, Amlan Kar, and Sanja Fidler. "Devil is in the edges: Learning semantic boundaries from noisy annotations." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019.

New Idea (1)



Acuna, David, Amlan Kar, and Sanja Fidler. "Devil is in the edges: Learning semantic boundaries from noisy annotations." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019.

Outline | Related Theory

- Introduction
- Related Theory
- Related Works
- Methodology (Proposed Method)
- Experimental Results
- Objectives and Procedure
- Conclusions
- Publication and Reference

Related Theory

- (1) Computer Vision Tasks
- (2) Deep Convolutional Neural Networks (CNNs)
    - Traditional CNNs
    - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Depthwise Convolution
- (7) Design CNNs

Related Theory

- **(1) Computer Vision Tasks**
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  - Traditional CNNs
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- (3) Transfer Learning
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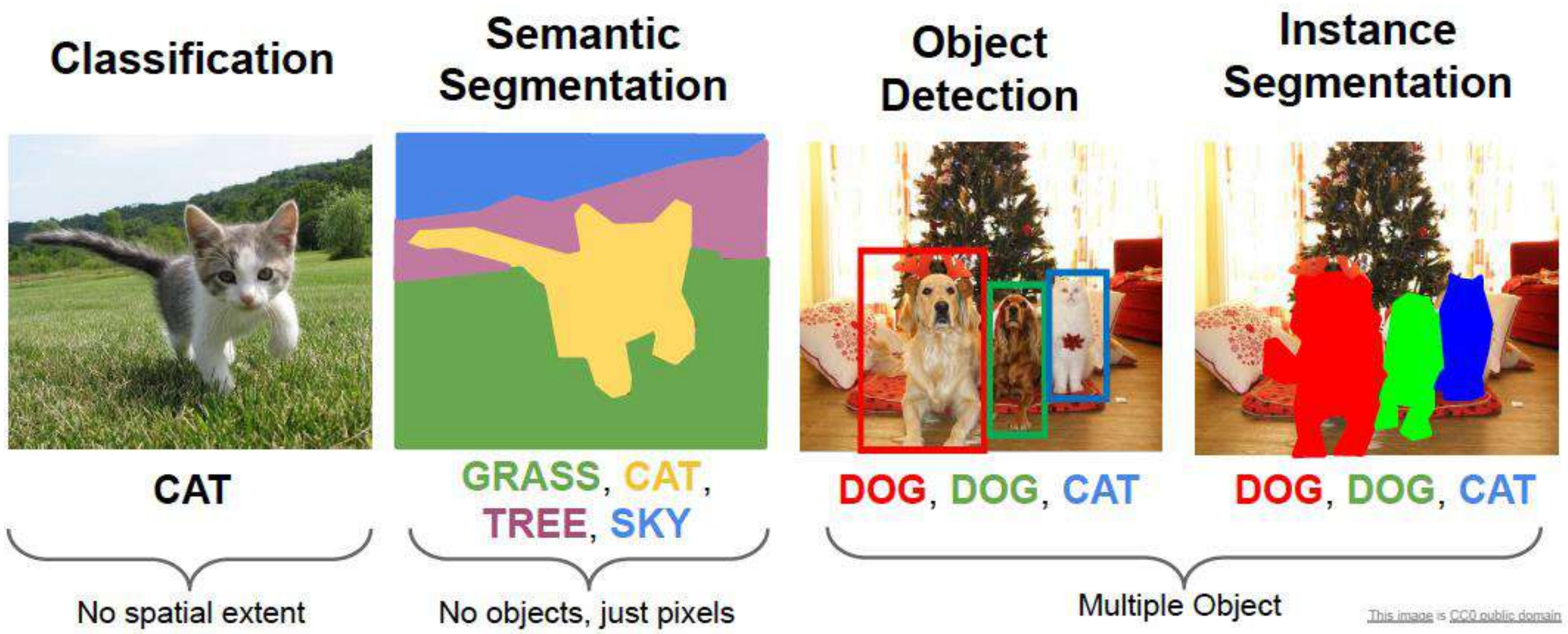

Related Theory

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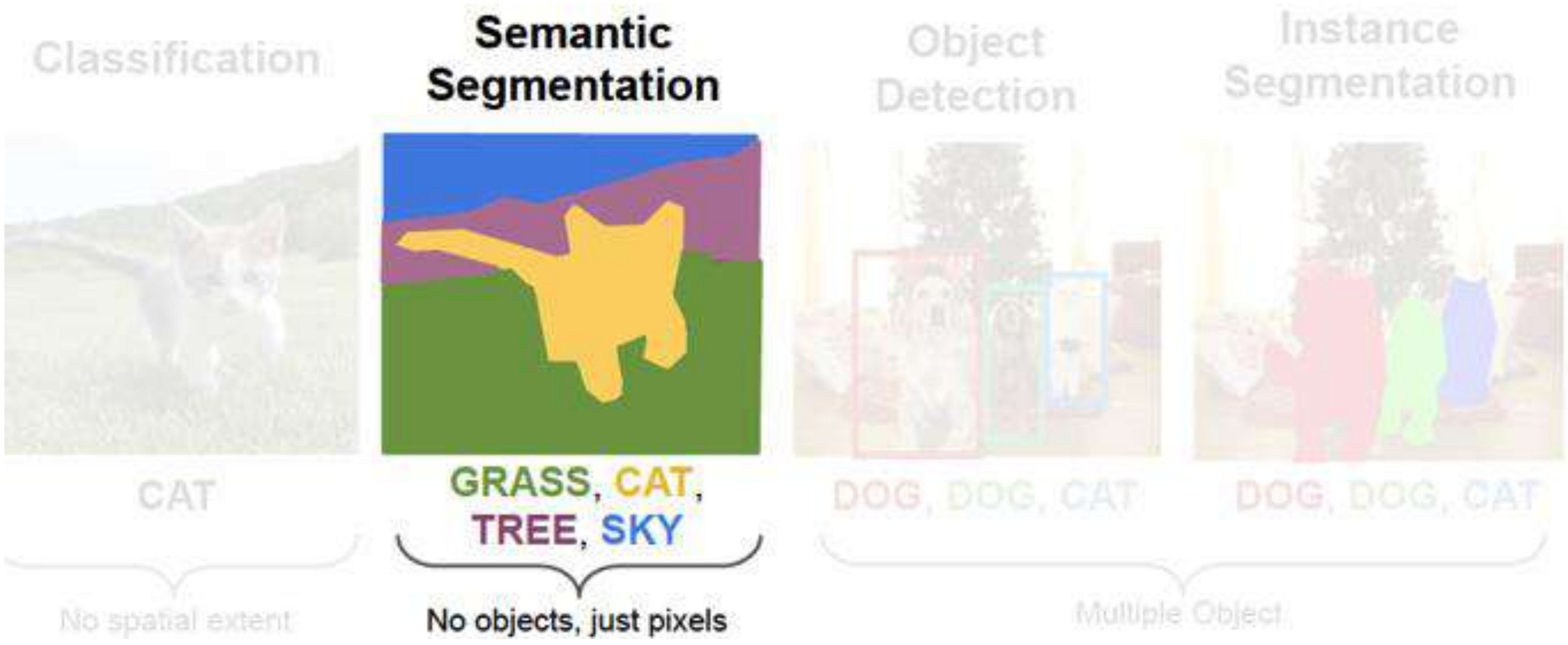

http://cs231n.stanford.edu/

Related Theory

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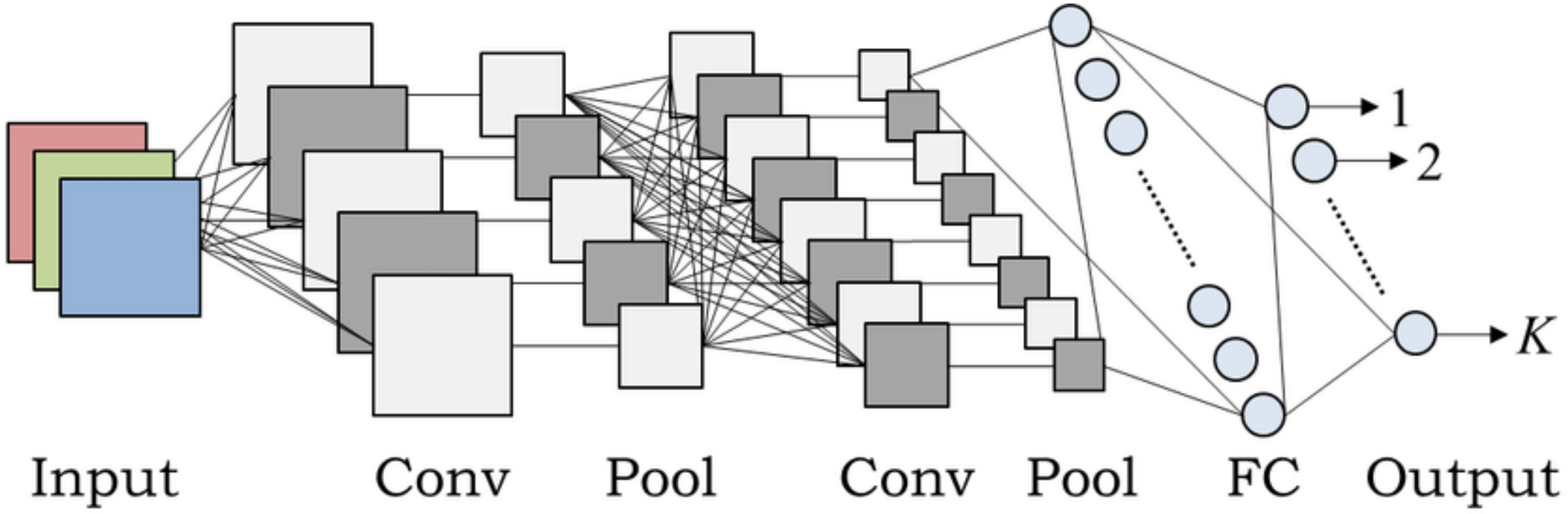


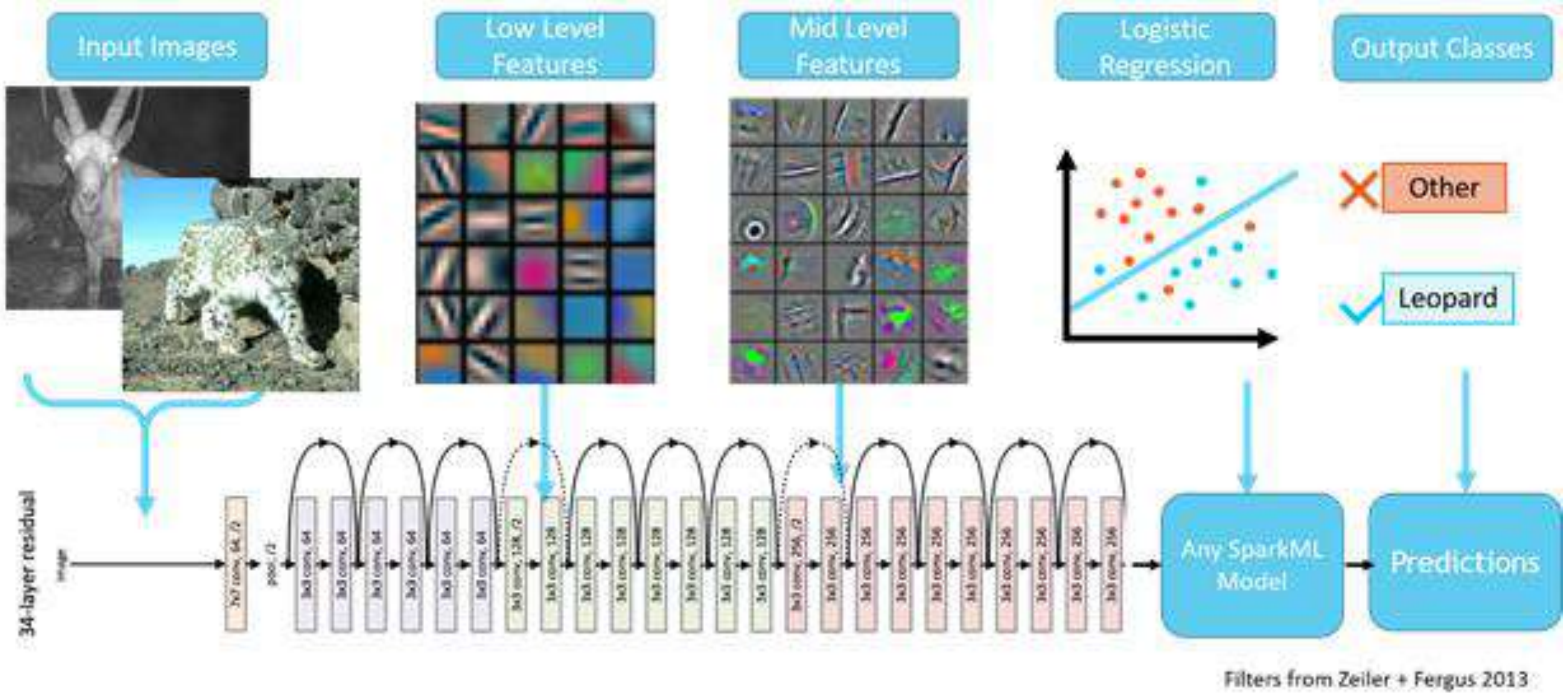
Encoder Network (VGG Style)

Related Theory

- (1) Computer Vision Tasks
- (2) CNNs
    - Traditional CNNs
    - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Depthwise Convolution
- (7) Design CNNs

Low Level Features

Mid and High Level Features



https://blogs.technet.microsoft.com/machinelearning/2018/10/03/deep-learning-without-labels/

Related Theory

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
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- (3) Transfer Learning
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- (5) Feature Fusion
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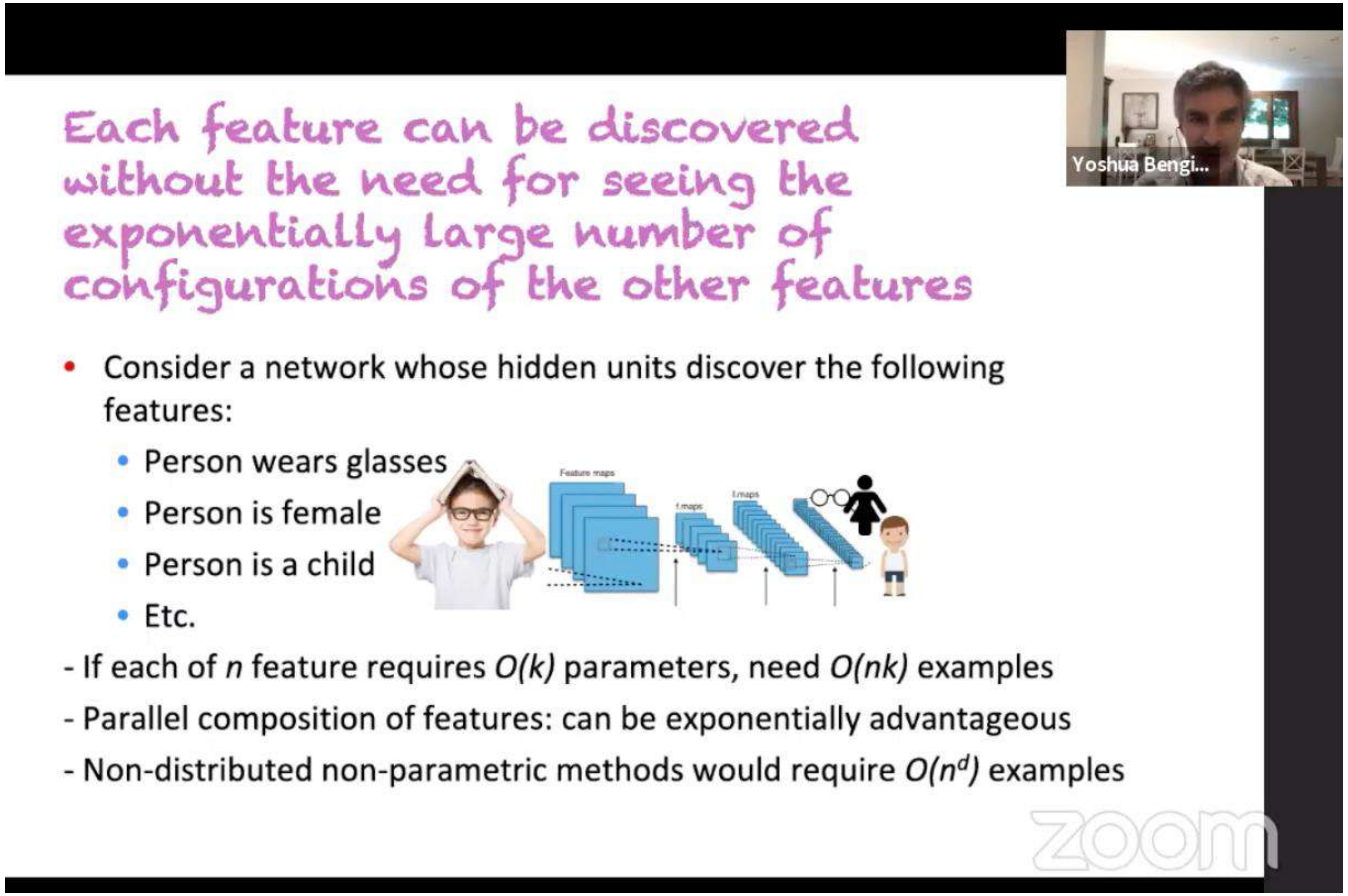

Credit: Prof Yoshua Bengio

Related Theory

- (1) Computer Vision Tasks
- **(2) CNNs**
  - **Traditional CNNs**
  - Deep Learning Layers
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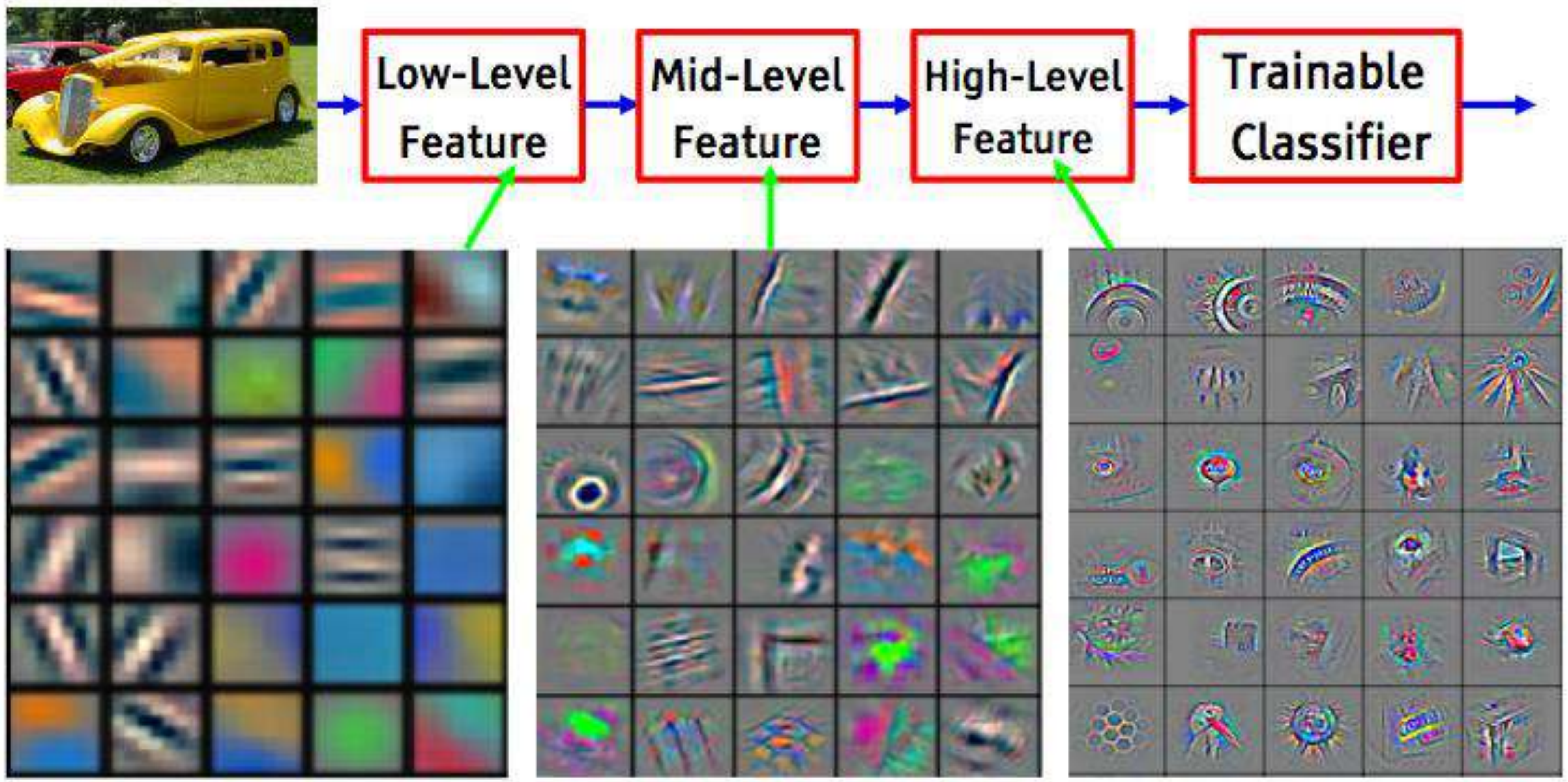
- (5) Feature Fusion
- (6) Depthwise Convolution
- (7) Design CNNs



https://machinelearningmastery.com/what-is-deep-learning/

Related Theory

Traditional Image Segmentation Network

- (1) Computer Vision Tasks
- **(2) CNNs**
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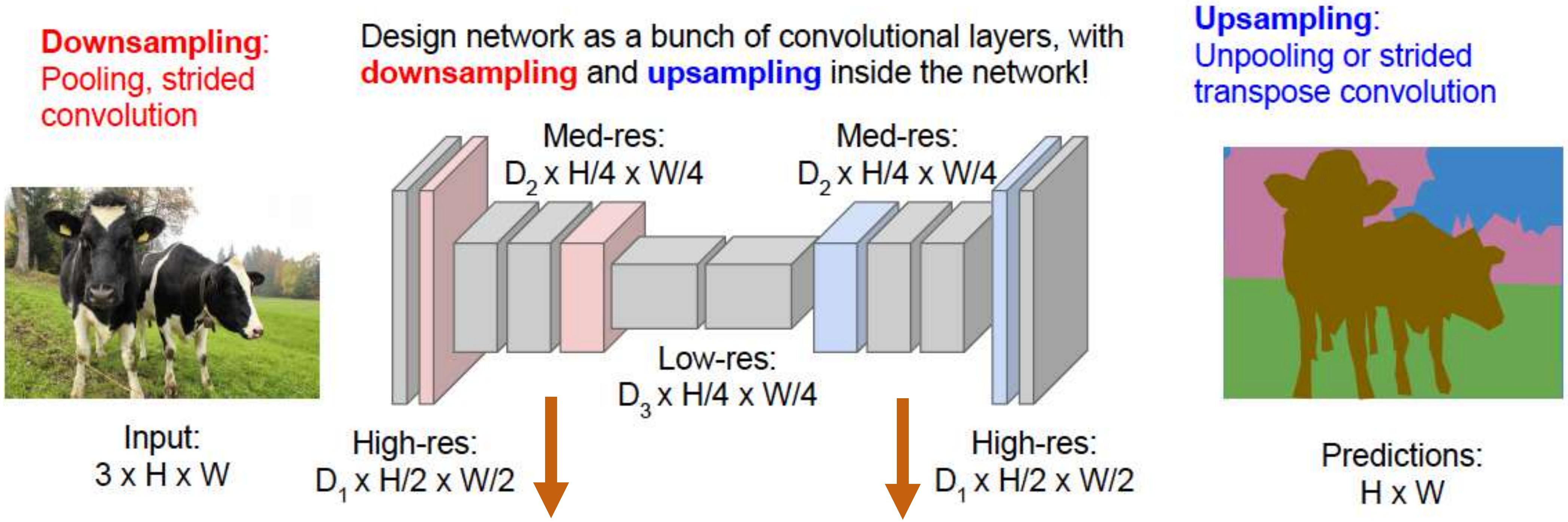
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Depthwise Convolution
- (7) Design CNNs



Encoder Network

Decoder Network

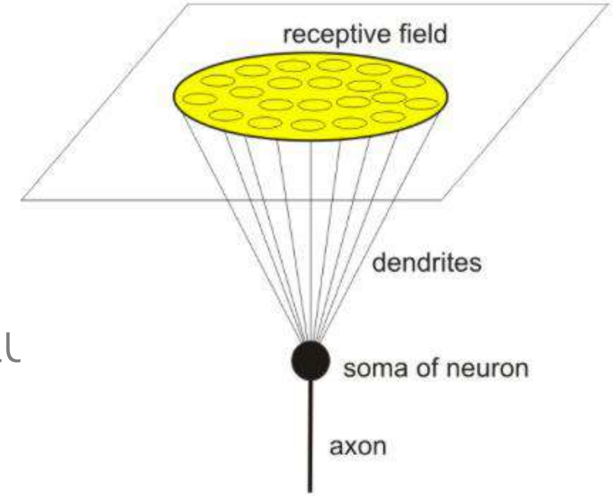
Deep Encoder-Decoder Network (DCED)

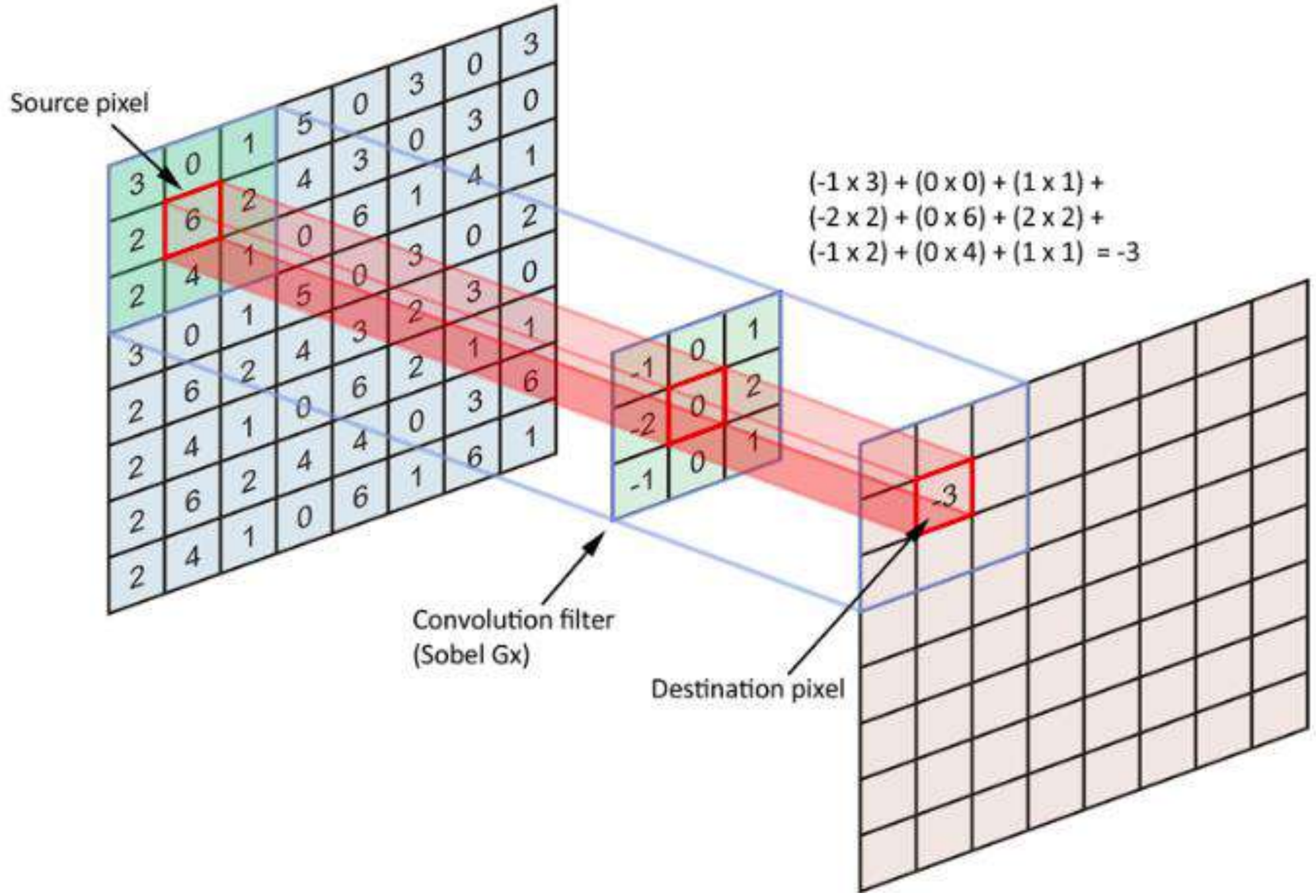
http://cs231n.stanford.edu/

Related Theory

Convolution Layer

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Depthwise Convolu
- (7) Design CNNs





https://www.freecodecamp.org/news/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050/

Related Theory

ResNet (Microsoft)

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
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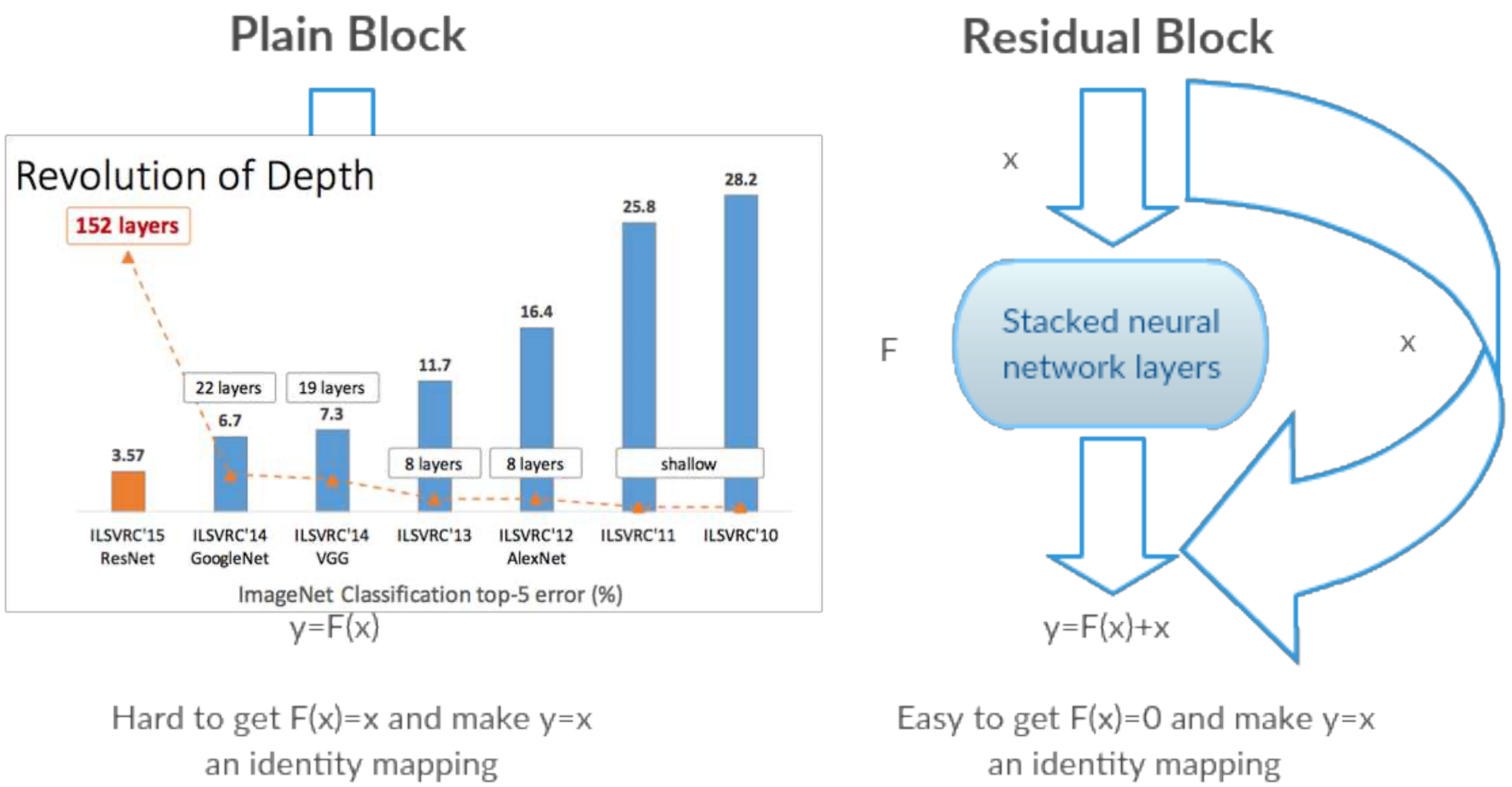
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Depthwise Convolution
- (7) Design CNNs



Encoder Network (VGG (Residual) Style)

Related Theory

Max-Pooling and Max-Unpooling Layer

- (1) Computer Vision Tasks
- **(2) CNNs**
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  - **Deep Learning Layers**
- (3) Transfer Learning
- (4) Channel Attention
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- (7) Design CNNs

Max Pooling
Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

→ . . . → Rest of the network

Max Unpooling
Use positions from pooling layer

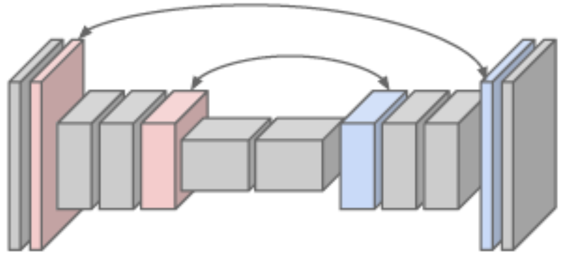
1	2
3	4

Input: 2 x 2

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

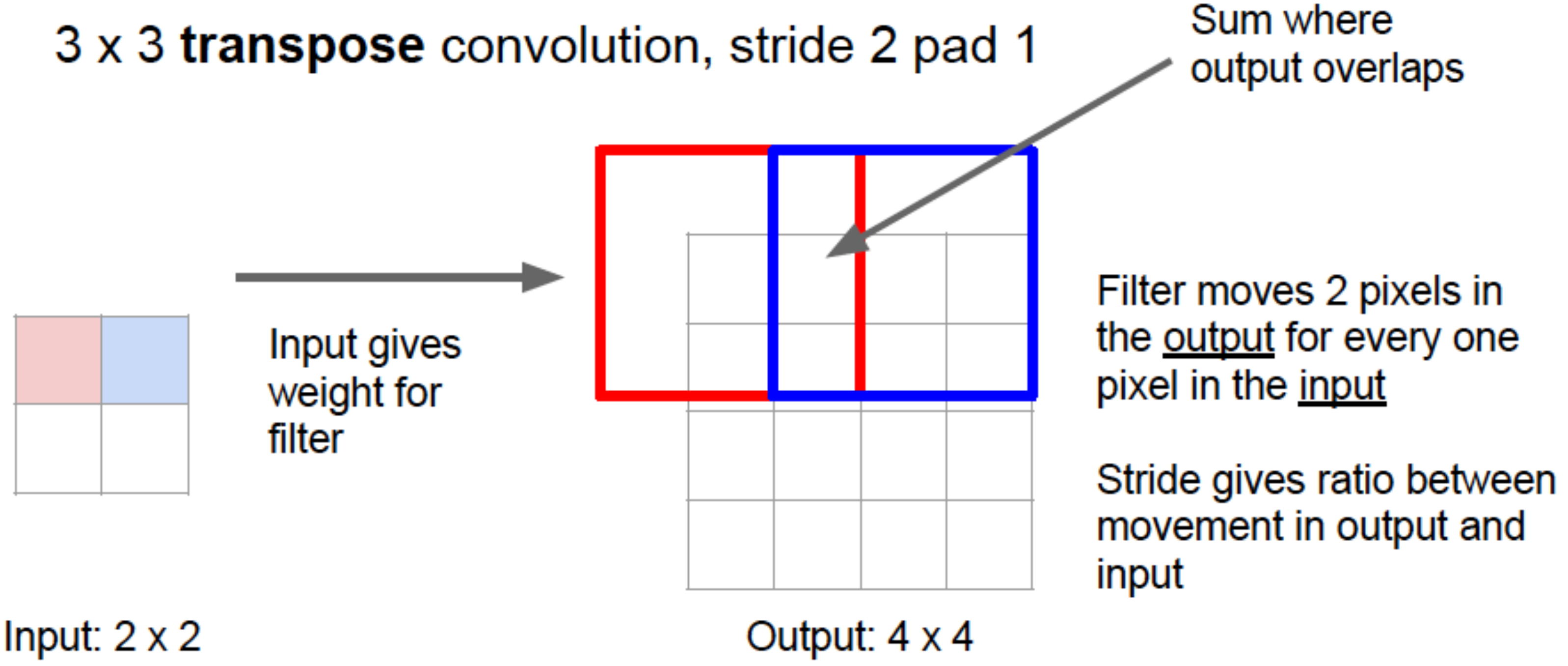


Related Theory

Learnable Up-sampling: Transpose Convolution

- (1) Computer Vision Tasks
- (2) CNNs
  - Traditional CNNs
  - Deep Learning Layers
- (3) Transfer Learning
- (4) Channel Attention
- (5) Feature Fusion
- (6) Depthwise Convolution
- (7) Design CNNs

Other names:
-Deconvolution (bad)
-Upconvolution
-Fractionally strided convolution
-Backward strided convolution



Related Theory

Learnable Up-sampling: Transpose Convolution

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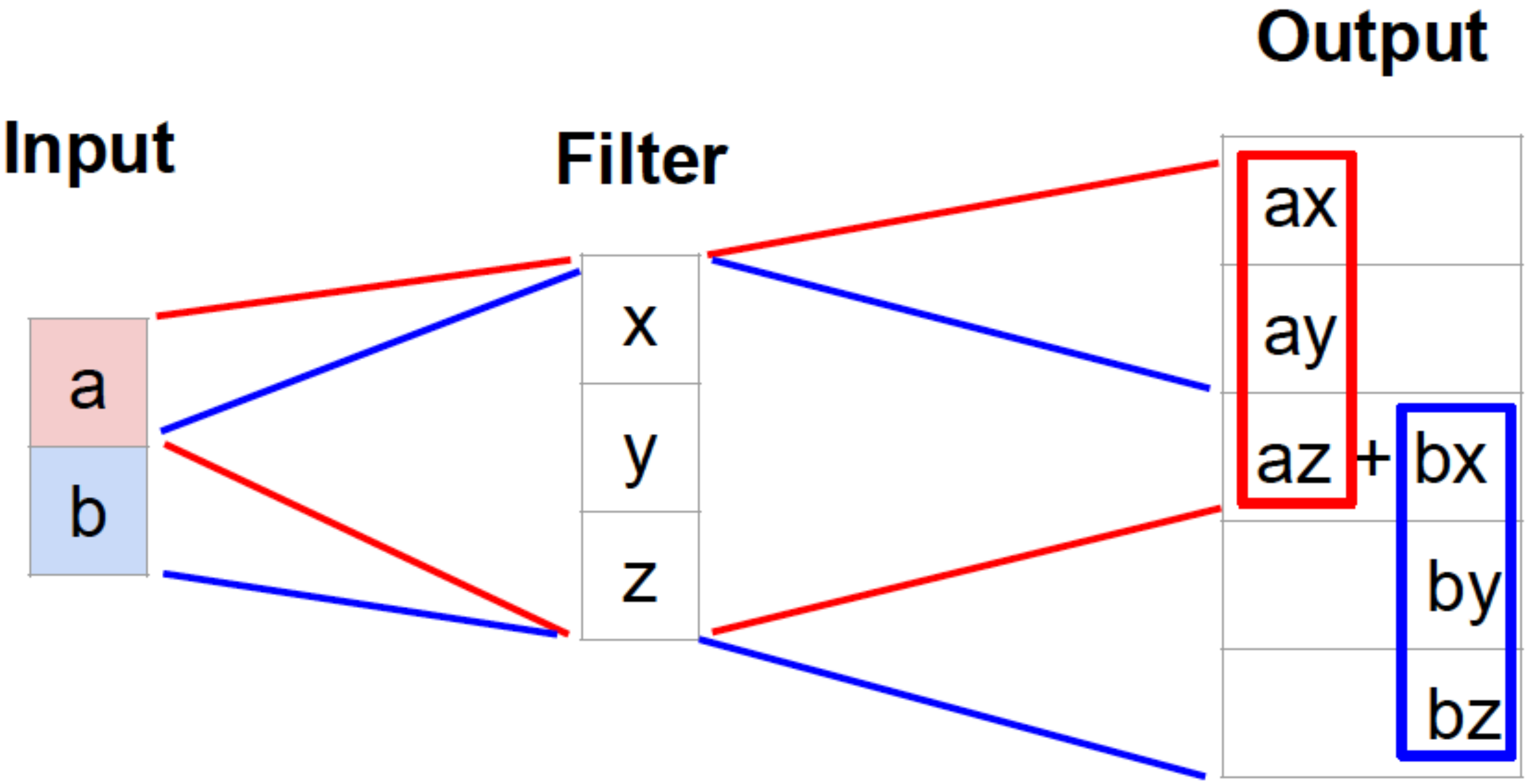

Related Theory

Other Layers

- (1) Computer Vision Tasks
- **(2) CNNs**
  - Traditional CNNs
  - **Deep Learning Layers**
- (3) Transfer Learning
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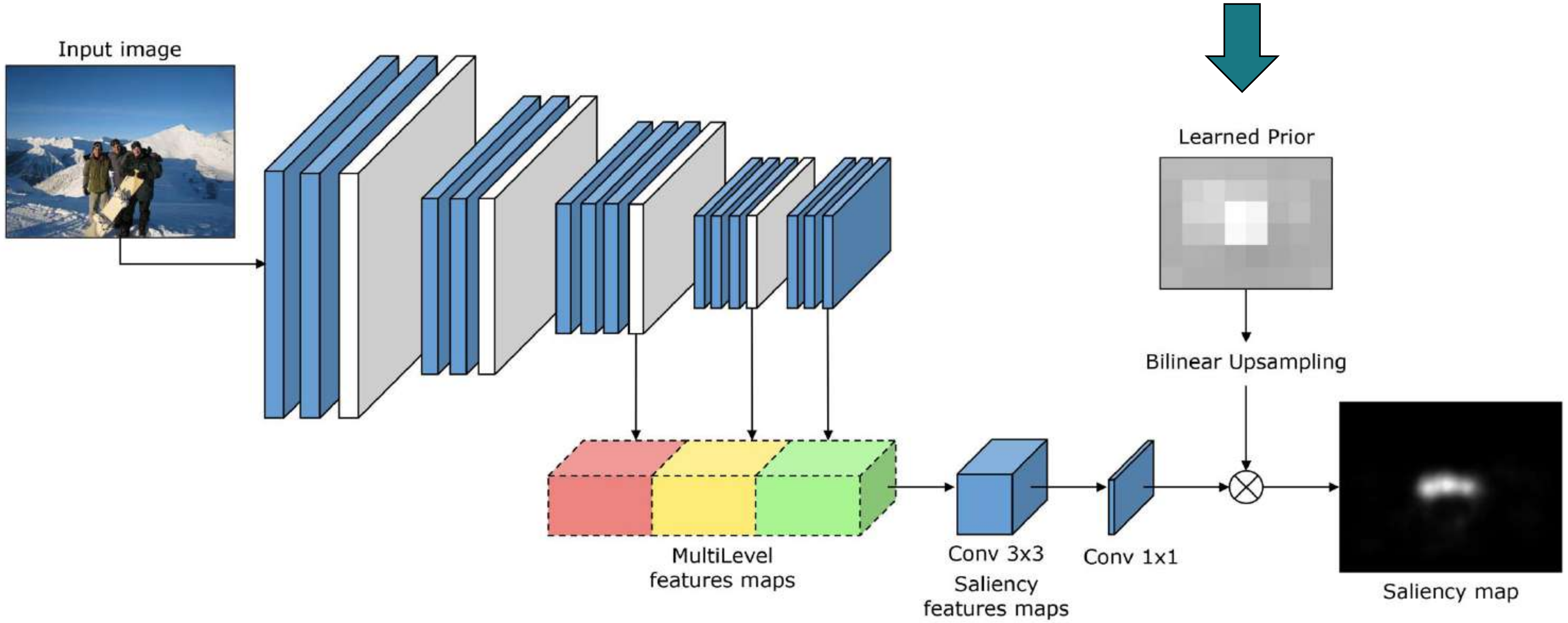
- Interpolation Layer: Interpolation layer
  - performs resizing operation along the spatial dimension.
  - In our network, we use bilinear interpolation.



Related Theory

Other Layers

- (1) Computer Vision Tasks
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- Elementwise Layer: Elementwise layer
  - performs elementwise operations on two or more previous layers, in which the feature maps must be of the same number of channels and the same size.
  - There are three kinds of elementwise operations:
    - product, add (sum), max.
    - In our network, we use add operation.

Related Theory

Other Layers

- (1) Computer Vision Tasks
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- ReLU Layer: The rectified linear unit (ReLU) (Hinton, 2010)
  - It is usually chosen as the nonlinearity layer
  - It thresholds the non-positive value as zero and keeps the positive value unchanged
  - It can achieve a considerable reduction in training time
- Batch Normalization Layer:
  - It normalizes layer inputs to a Gaussian distribution with zero-mean and unit variance.
  - Aiming at addressing the problem of internal covariate shift
- Softmax Layer: The softmax nonlinearity (Bridle, 1989)
  - It is applied to the output layer in the case of multiclass classification
  - It outputs the posterior probabilities over each category

Related Theory

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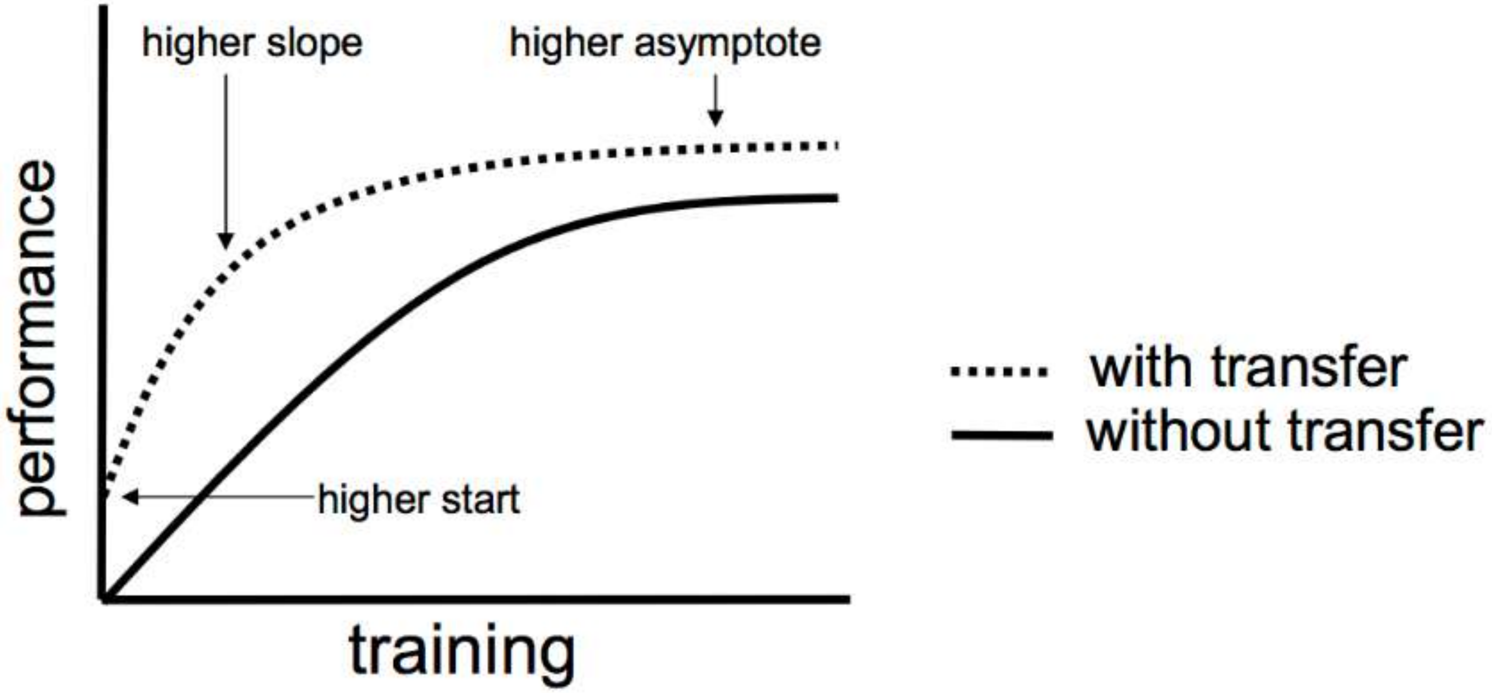
"Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned."



https://machinelearningmastery.com/transfer-learning-for-deep-learning/

Related Theory

Attention

- (1) Computer Vision Tasks
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- (3) Transfer Learning
- **(4) Channel Attention**
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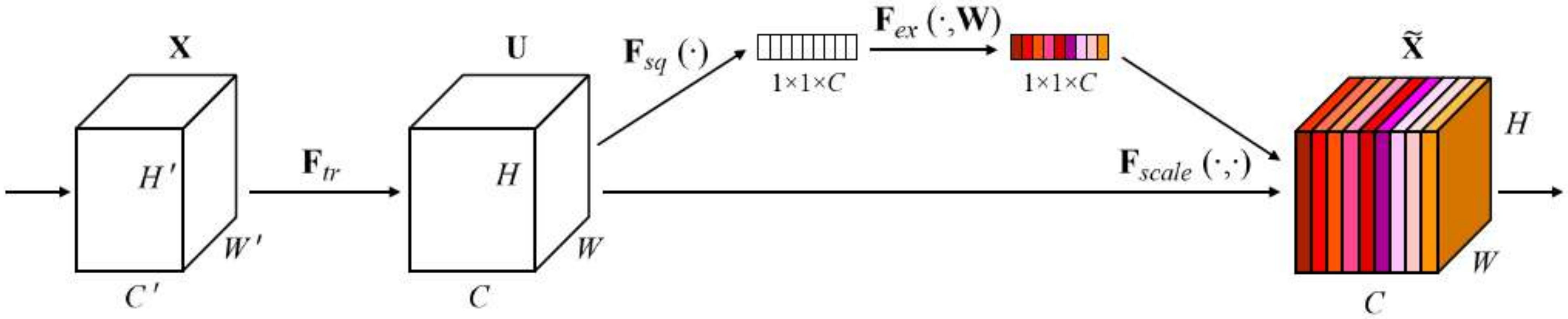
- (7) Design CNNs

- Attention is helpful to focus on what we want
- We utilize channel attention to select the important features



One word “attends” to other words in the same sentence differently.

Refers to Squeeze-and-Excitation Networks and BiseNet

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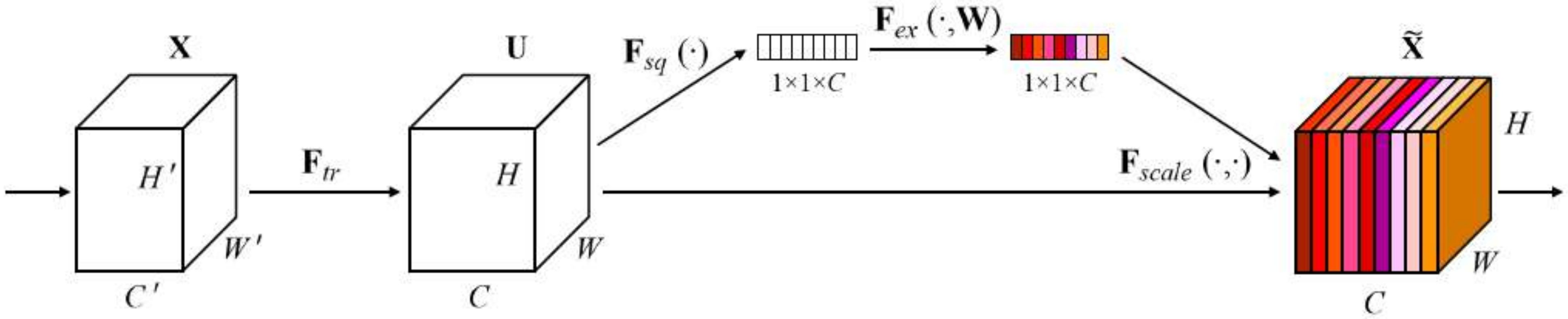

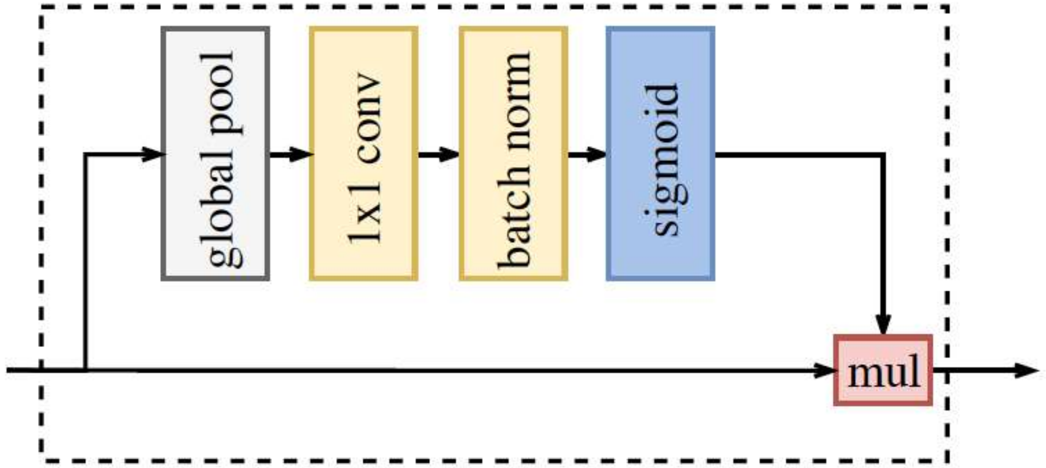

Refers to Squeeze-and-Excitation Networks and BiseNet

Related Theory

Attention

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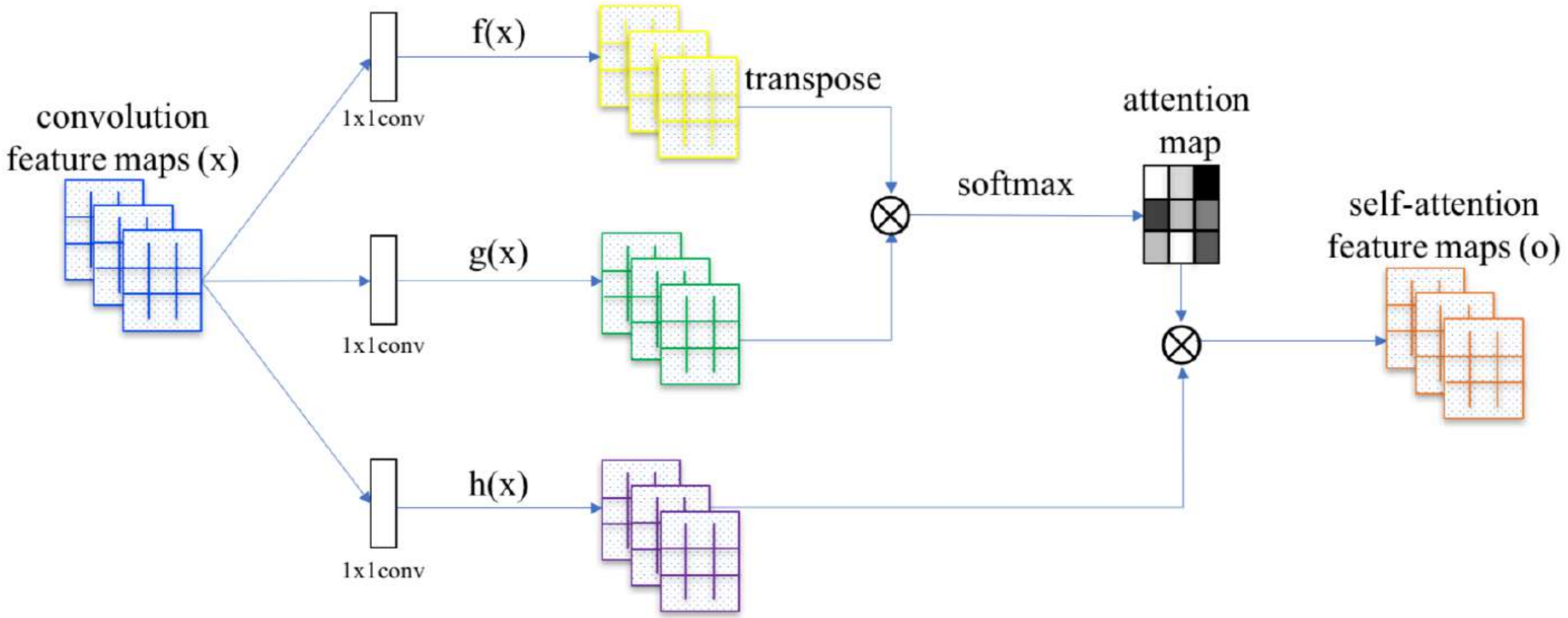

https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

Related Theory

Feature Fusion (1)

- (1) Computer Vision Tasks
- (2) CNNs
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- (3) Transfer Learning
- (4) Channel Attention
- **(5) Feature Fusion**
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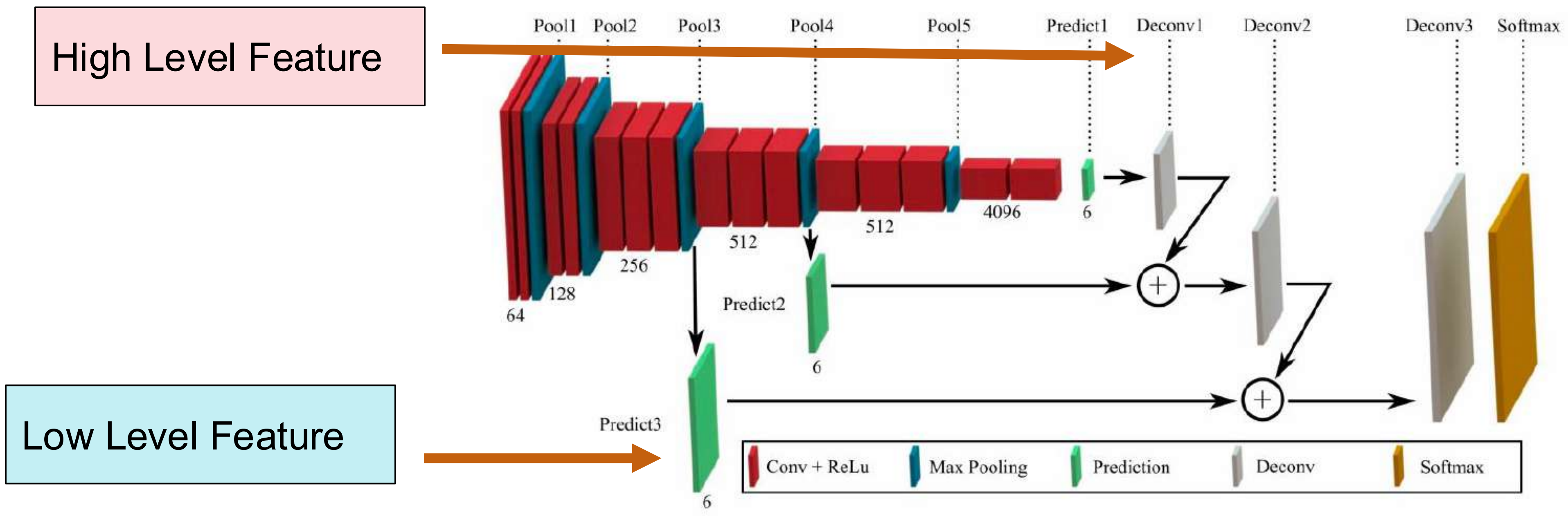
- (7) Design CNNs

- The features of the two paths are different in level of feature representation
- Simply sum up low and high features
  - Utilization of low-level features for objects refinement



Tai, Lei, et al. "PCA-aided fully convolutional networks for semantic segmentation of multi-channel fMRI." 2017 18th International Conference on Advanced Robotics (ICAR). IEEE, 2017.

- (1) Computer Vision Tasks
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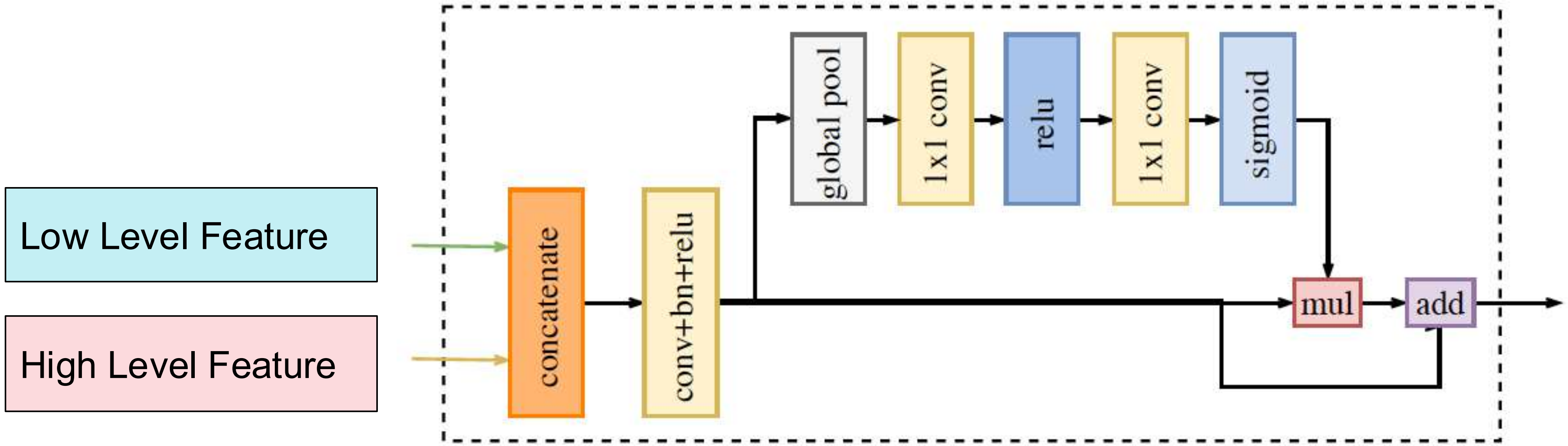
- The features of the two paths are different in level of feature representation
- Fuse spatial path (low level features) and context path (high level feature) together



(c) Feature Fusion Module

Yu, C., Wang, J., Peng, C., Gao, C., Yu, G., & Sang, N. (2018). Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 325-341).

Related Theory

Depth-wise Convolution

- (1) Computer Vision Tasks
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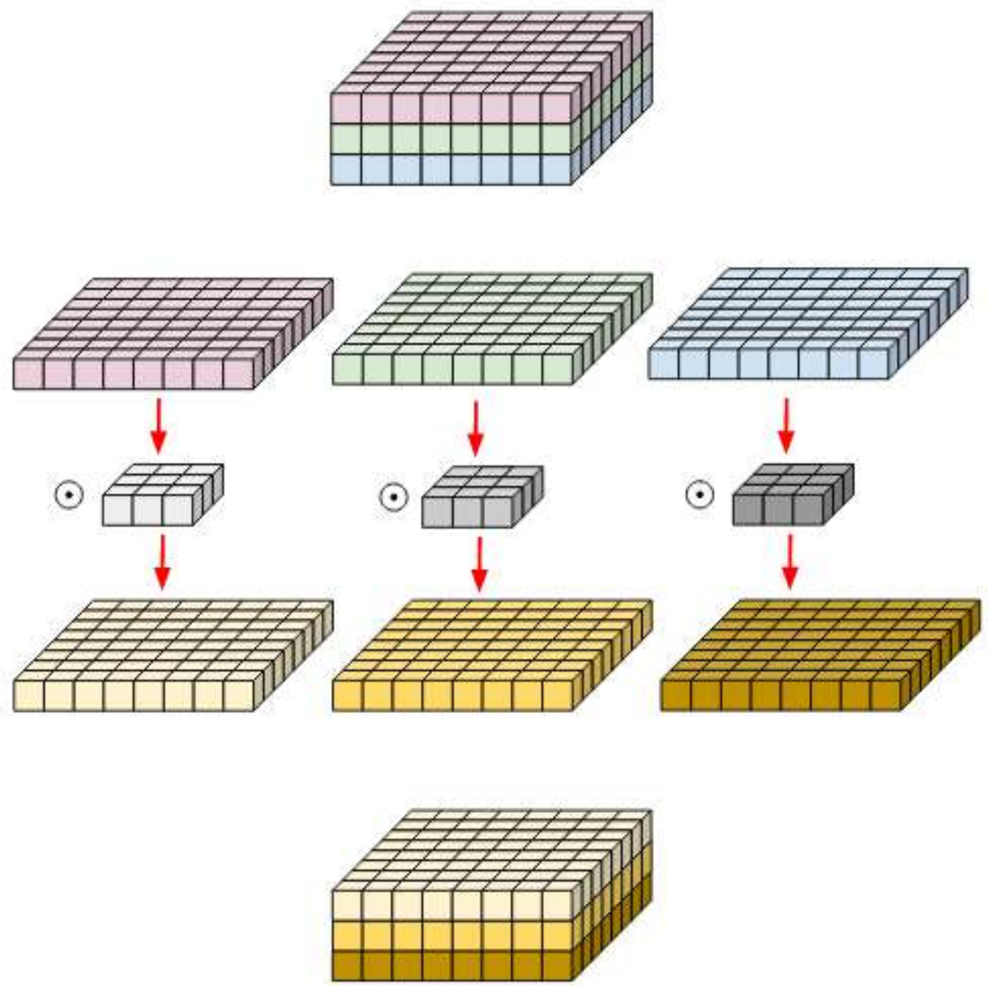
- Filters and image **have been broken into three different channels** and then convolved separately and stacked thereafter



https://medium.com/@zurister/depth-wise-convolution-and-depth-wise-separable-convolution-37346565d4ec

Related Theory

Depth-wise Convolution

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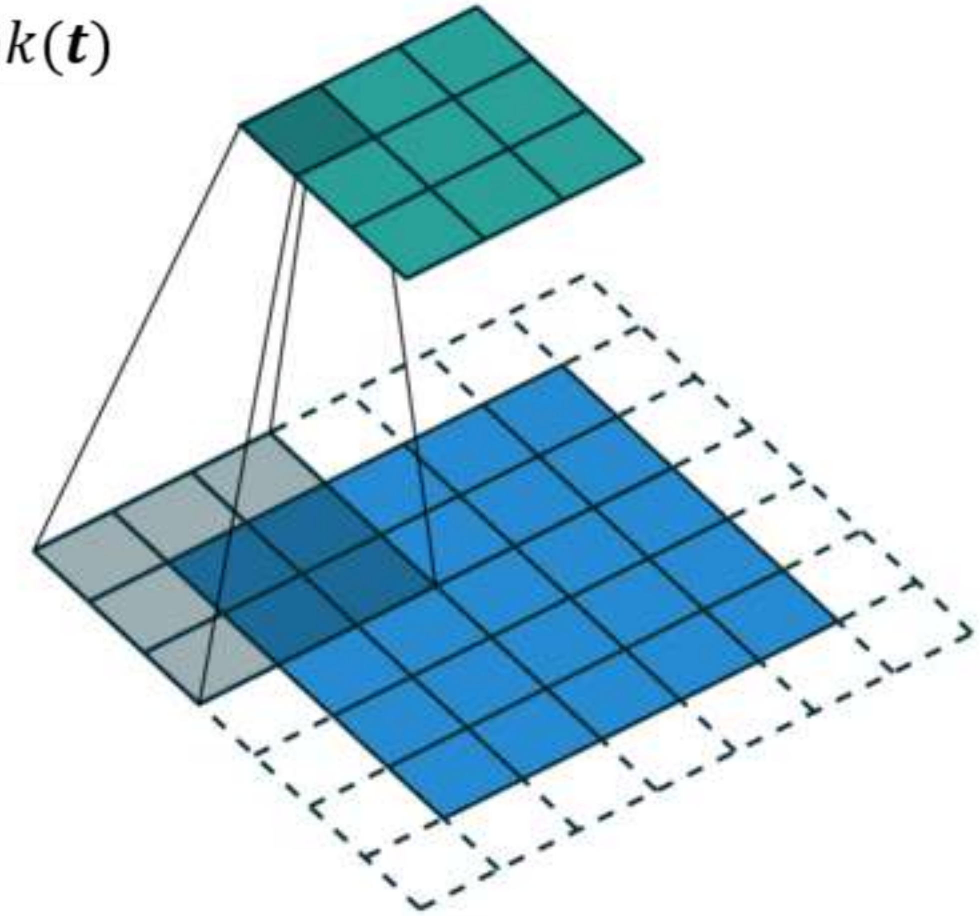
This is the standard discrete convolution:

$$(F * k)(\mathbf{p}) = \sum_{\mathbf{s}+\mathbf{t}=\mathbf{p}} F(\mathbf{s})k(\mathbf{t})$$



https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Related Theory

Dilated Convolution (Atrous Convolution)

- (1) Computer Vision Tasks
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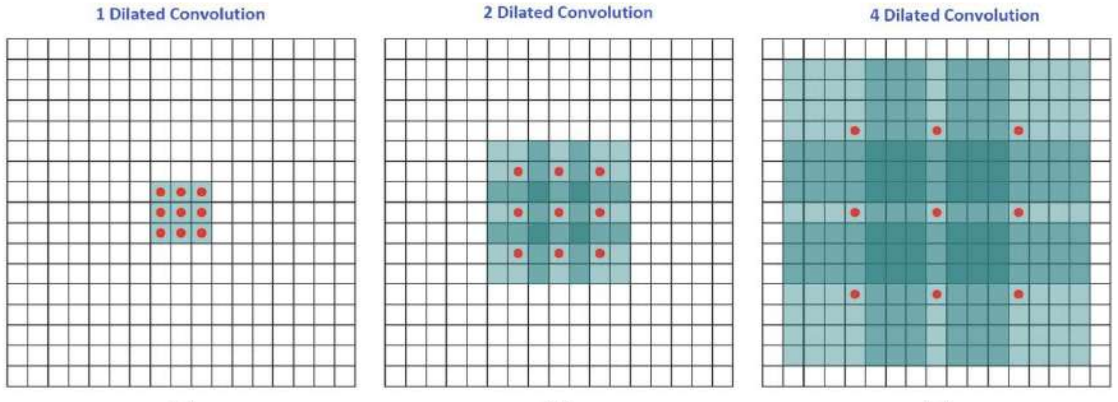
- **Multi-scale context aggregation** by dilated convolutions

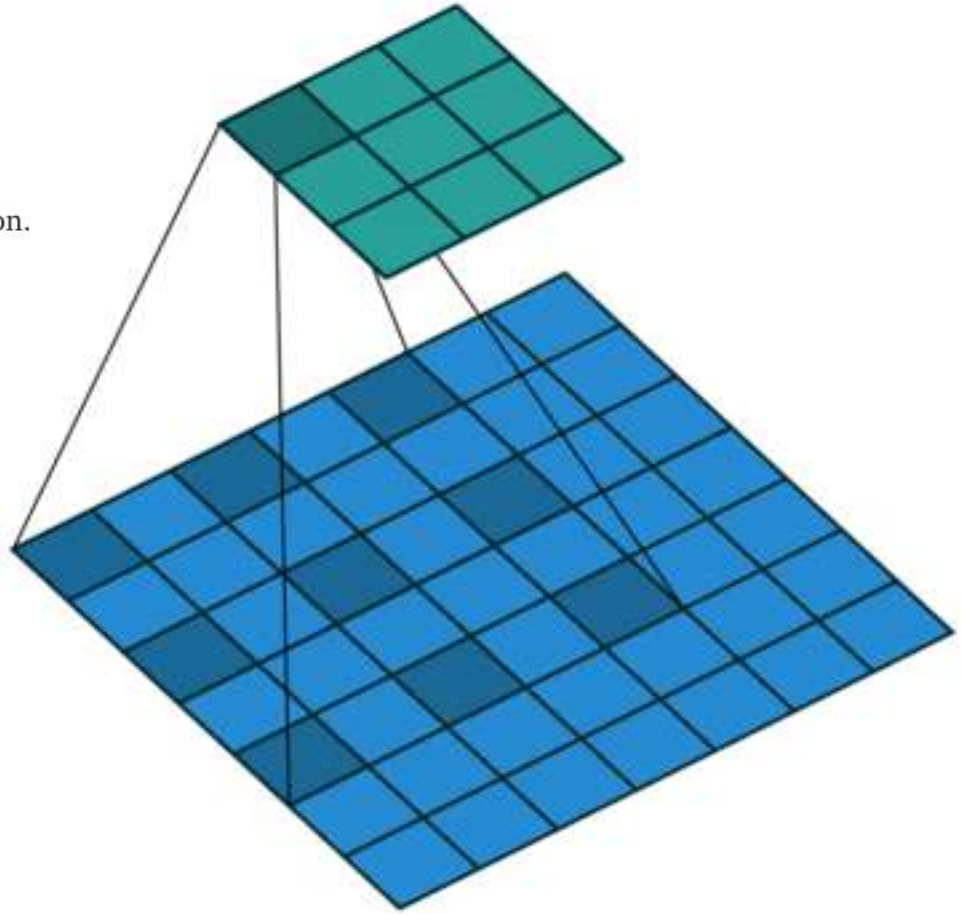
The dilated convolution follows:

$$(F *_l k)(\boldsymbol{p}) = \sum_{\boldsymbol{s}+l\boldsymbol{t}=\boldsymbol{p}} F(\boldsymbol{s})k(\boldsymbol{t})$$

When $l = 1$, the dilated convolution becomes as the standard convolution.



(a) (b) (c)



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Dilated Convolution (Atrous Convolution)

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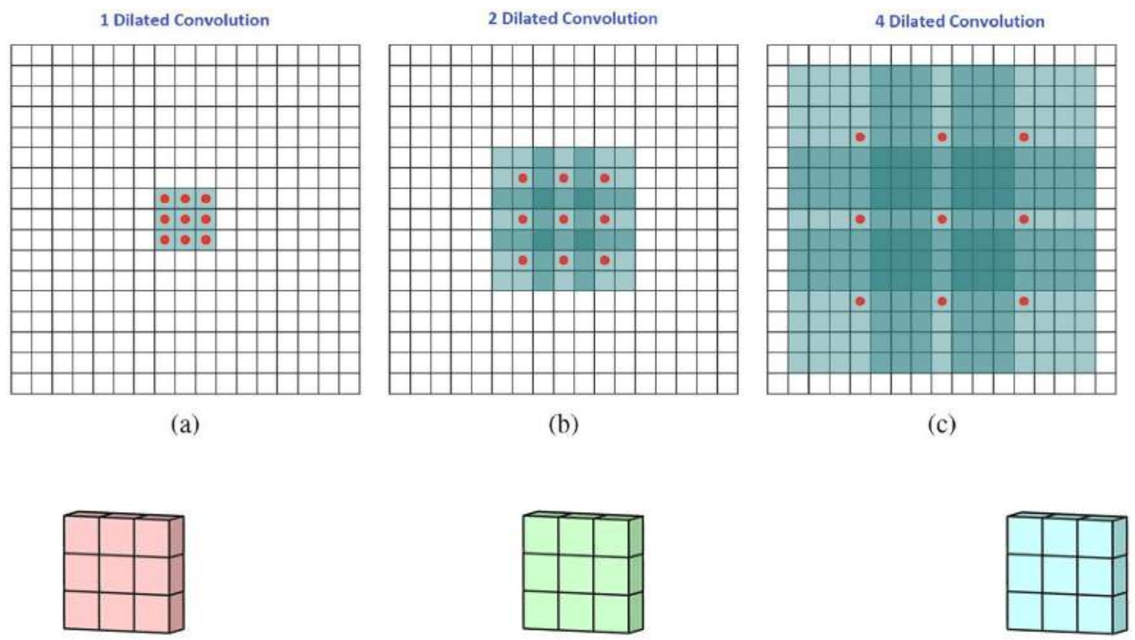
- **Multi-scale context aggregation** by dilated convolutions

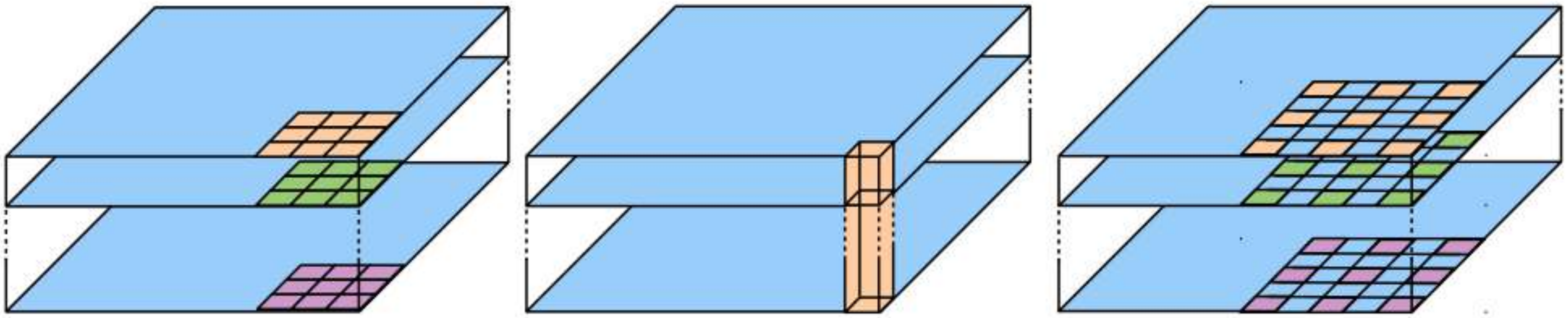


Related Theory

Dilated Convolution (Atrous Convolution)

- (6) Depthwise Convolution

- **Multi-scale context aggregation** by dilated convolutions
- 3x3 Depthwise separable convolution decomposes a standard convolution into (a) a depthwise convolution (applying a single filter for each input channel) and (b) a pointwise convolution (combining the outputs from depthwise convolution across channels). In this work, we explore atrous separable convolution where atrous convolution is adopted in the depthwise convolution, as shown in (c) with rate = 2.



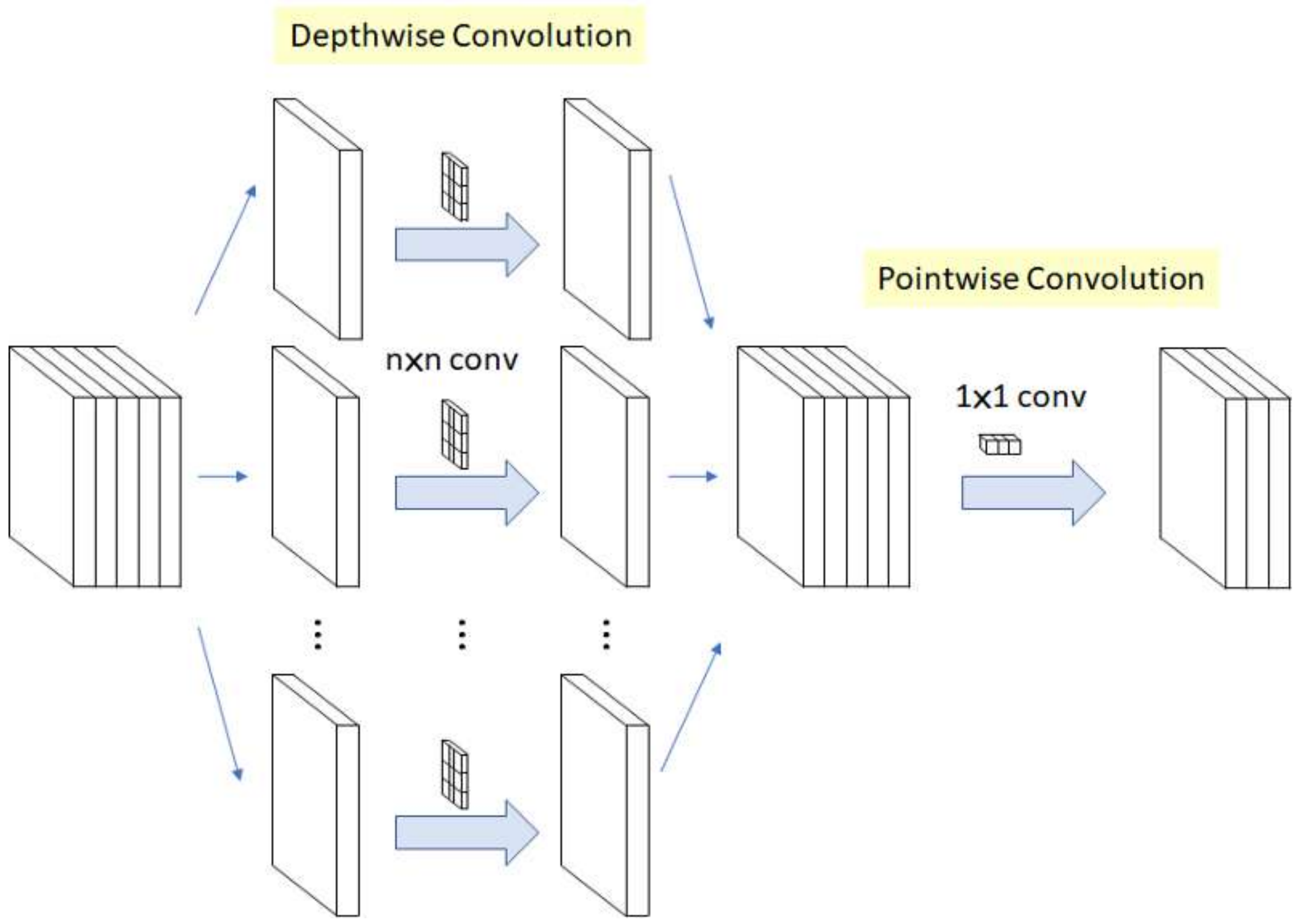
(a) Depthwise conv. (b) Pointwise conv. (c) Atrous depthwise conv.

https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

Related Theory

Dilated Convolution (Atrous Convolution)

- (6) Depthwise Convolution vs Pointwise Convolution



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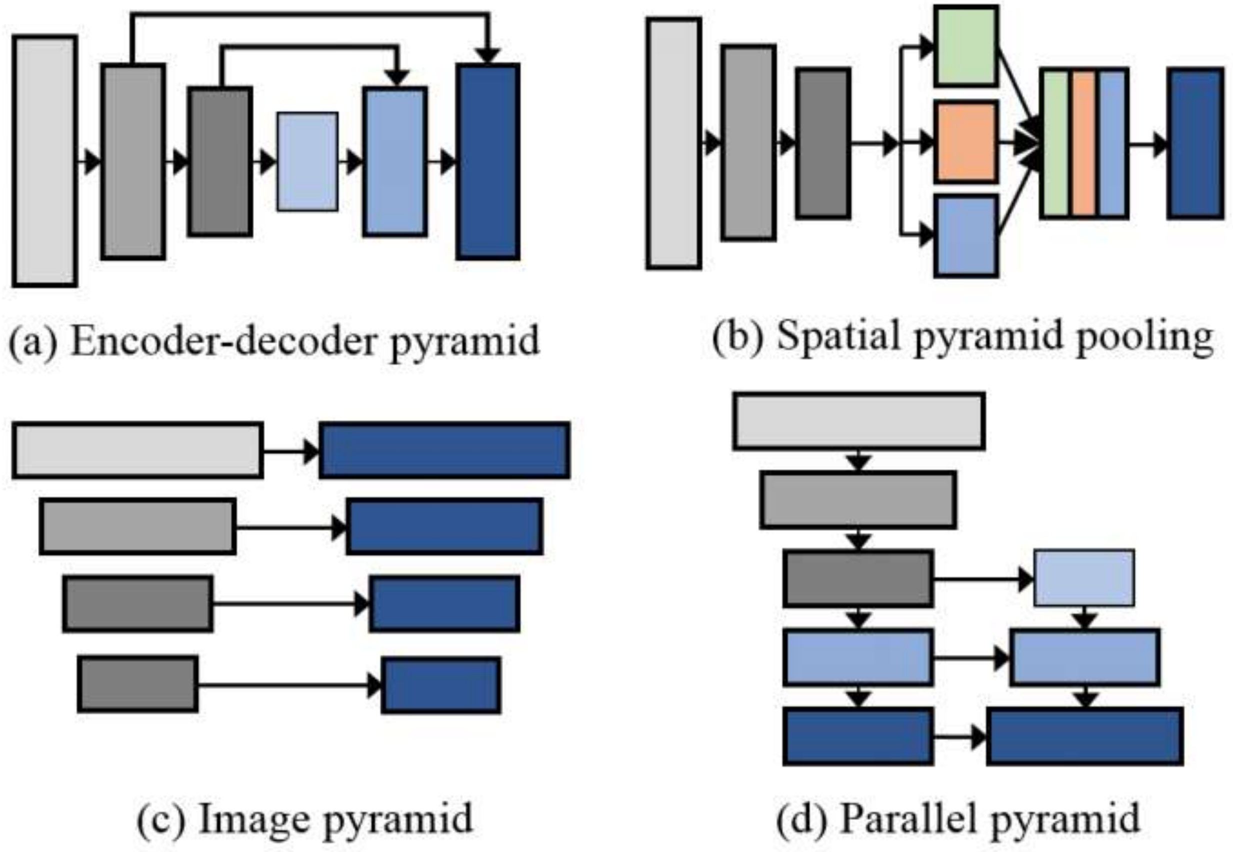


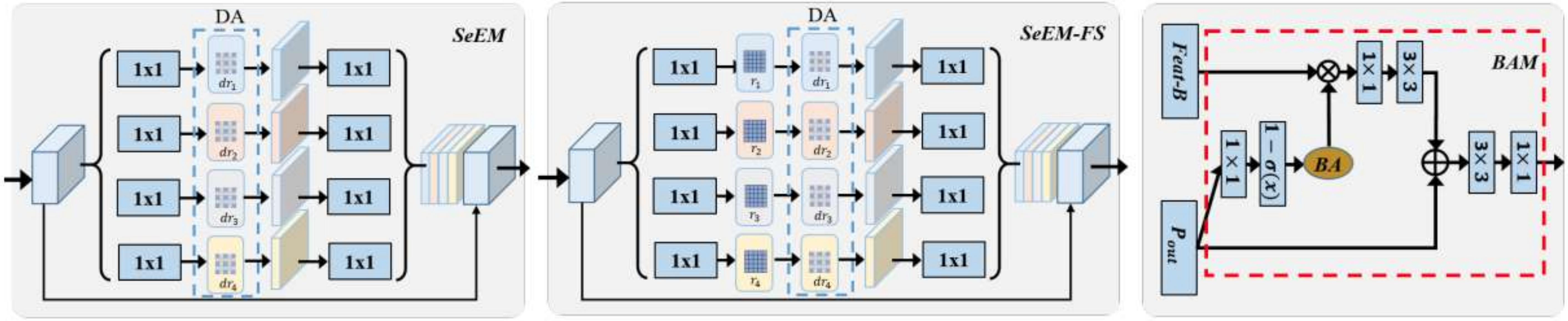
Figure 2. Different pyramids for capturing multi-scale features.

Pang, Y.; Li, Y.; Shen, J.; Shao, L. Towards bridging semantic gap to improve semantic segmentation. In Proceedings of the IEEE International Conference on Computer Vision, Seoul, Korea, 27 October–2 November 2019; pp. 4230–4239.

Related Theory

Dilated Convolution (Atrous Convolution)

- **Multi-scale context aggregation** by dilated convolutions



(a) Semantic Enhancement Module (b) Semantic Enhancement Module with full sampling (c) Boundary Attention Module

Figure 4. Semantic Modules in the proposed parallel pyramid method for improving feature fusion. We introduce semantic enhancement modules (a) and (b) to enhance the semantics of shallow features, and propose a boundary attention module (c) to extract complementary information from very shallow features and enhance the deep features. 'DA' represents depthwise atrous convolution. 'dr_i' represents the dilation rate. 'r_i' represents the kernel size of convolutional layer. 'BA' represents boundary attention.

Pang, Y.; Li, Y.; Shen, J.; Shao, L. Towards bridging semantic gap to improve semantic segmentation. In Proceedings of the IEEE International Conference on Computer Vision, Seoul, Korea, 27 October–2 November 2019; pp. 4230–4239.

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- **Multi-scale context aggregation** by dilated convolutions

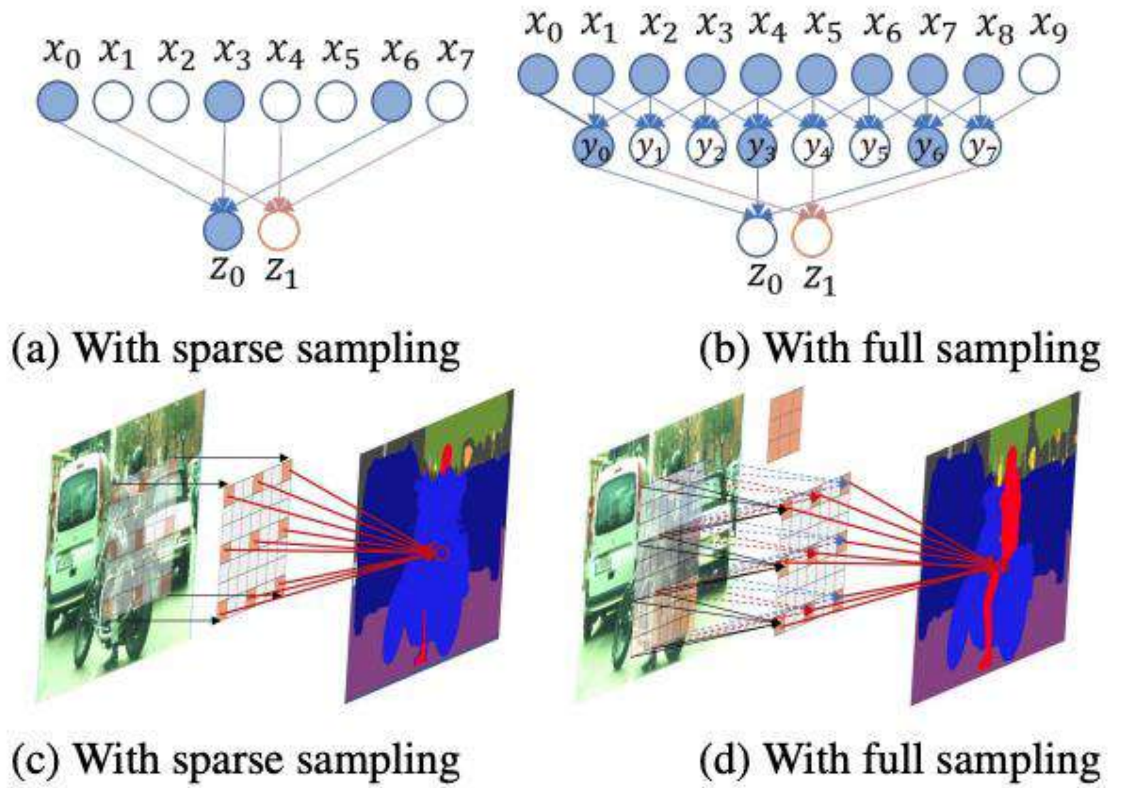

Figure 5. Atrous convolution with sparse sampling in SeEM and full sampling in SeEM-FS.

Pang, Y.; Li, Y.; Shen, J.; Shao, L. Towards bridging semantic gap to improve semantic segmentation. In Proceedings of the IEEE International Conference on Computer Vision, Seoul, Korea, 27 October–2 November 2019; pp. 4230–4239.

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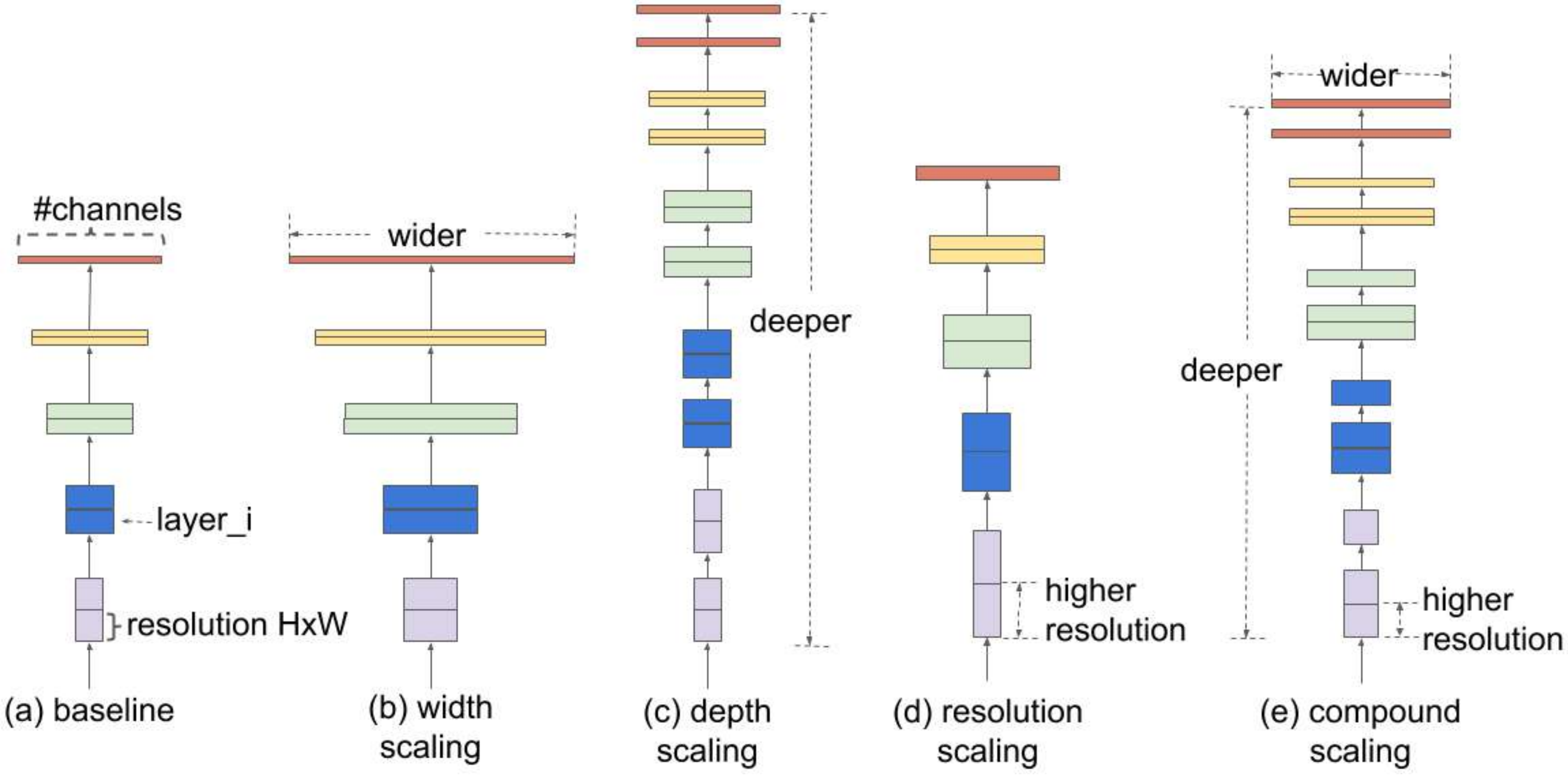

EfficientNet: Improving Accuracy and Efficiency through AutoML and Model Scaling

https://ai.googleblog.com/2019/05/efficientnet-improving-accuracy-and.html

Related Theory

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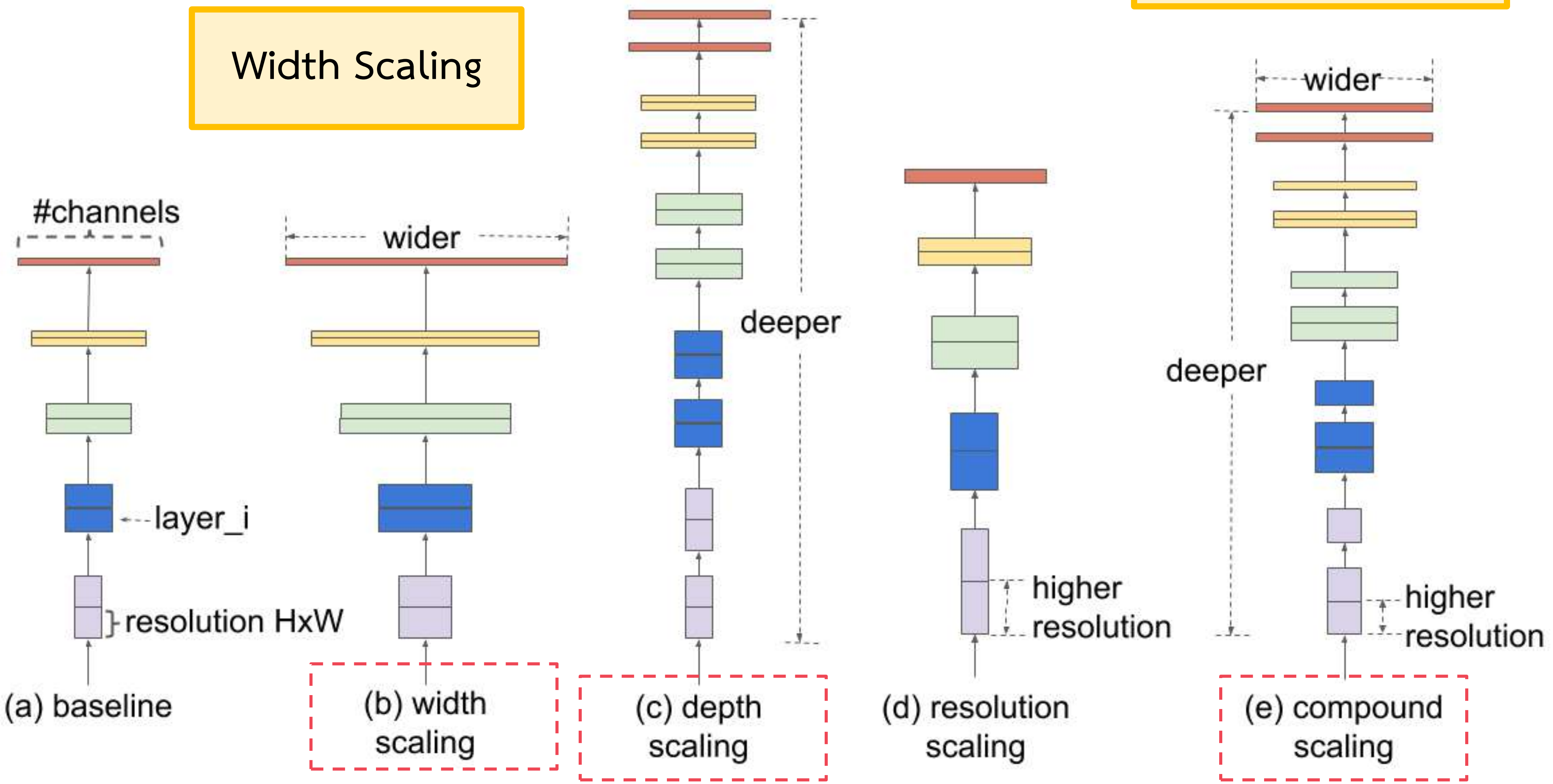
Depth Scaling

Compound Scaling

Width Scaling



EfficientNet: Improving Accuracy and Efficiency through AutoML and Model Scaling

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Related Theory

Dept Scaling

Width Scaling

Compound Scaling

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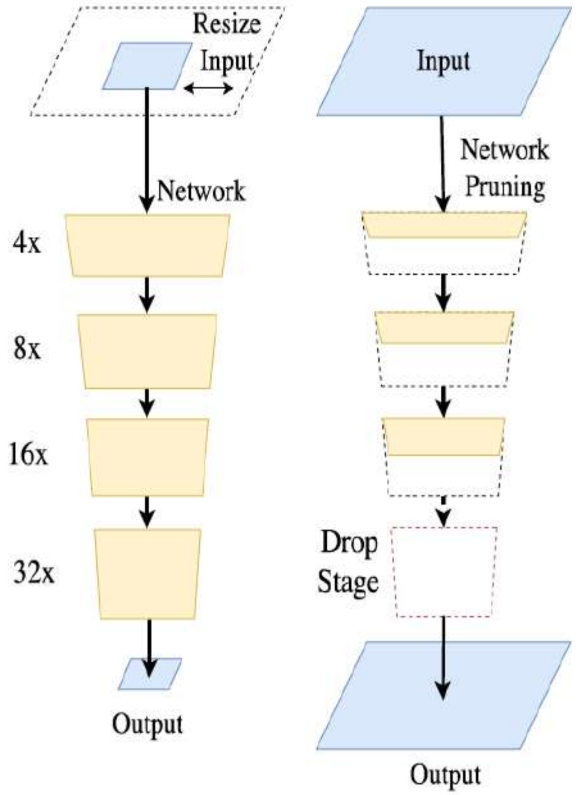
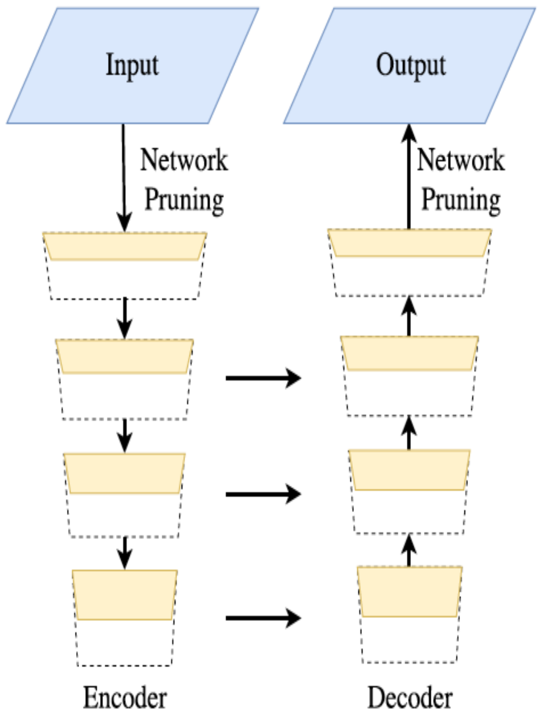
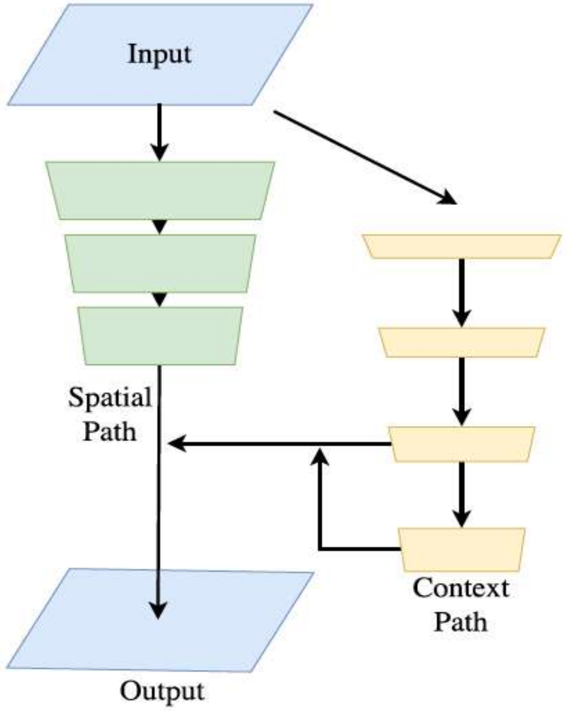
VGG Style (Depth Scaling)	U-Shape Style (Width Scaling)	Context Path Style (Compound Scaling)







Yu, C., Wang, J., Peng, C., Gao, C., Yu, G., & Sang, N. (2018). Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 325-341).