AI+ Remote Sensing:

Applying Deep Learning to Image Enhancement, Analytics, and its Business

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About Dr. Jui-Hsin(Larry) Lai

- Staff Research Scientist
  - US Research Lab of Ping An Technology in Silicon Valley
  - Lead the AI+ Remote Sensing team working on
    - Image enhancement for remote sensing imagery
    - Model generalization for object recognition and segmentation
    - Multi-modality for crop yield forecasting and natural disaster analysis

- Research Publications
  - Published 27+ IEEE/ACM papers on computer vision topics
  - Published 33+ US patents
  - More research demos, please visit http://www.larry-lai.com

About Ping An Group

- Primary business
  - Insurance
  - Banking
  - Financial services
  - Healthcare
  - Now, empowering each sector with technology

- The largest insurance company worldwide

Fortune Global 500 Rank

2020 **No.21**

2018 No.29
2016 No.41
2014 No,128
2012 No.242
2010 No.383
2008 No.462
1988 Established

- Ping An Finance Center(PAFC)
  - 115-story, skyscraper in Shenzhen, China

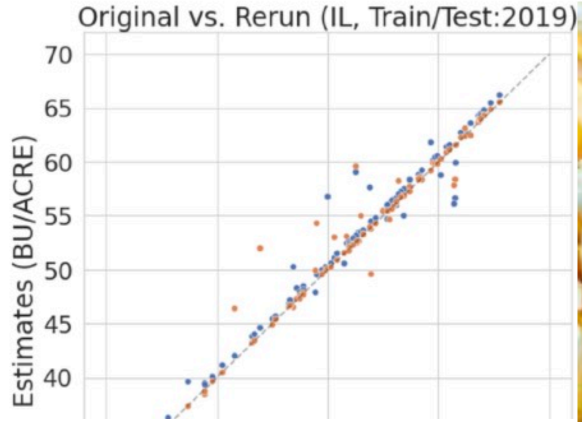
AI+ Remote Sensing in Ping An Group

- A close loop: Research Innovation <=> Business Applications

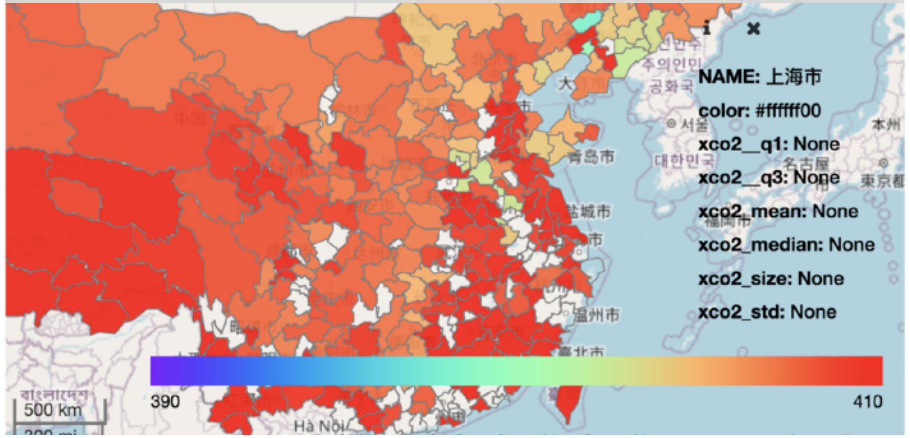
Agriculture Insurance

Smart City

Investment — Option Trading



Environment, Society, Government(ESG)



Outline

- PAII-SR Model:
  - 4X Super-Resolution Image Enhancement
  - The Proposed PAII-SR Dataset
- PAII-Haze Model
  - Haze Occlusion Removal
  - The Proposed PAII-Haze Dataset
- PAII-Crop Model
  - Parcel Detection Model
  - Crop Recognition Model
- More Analytics in Ping An Group

Image Resolution is a Key Limitation in Many Remote Sensing Analysis

Definition of **10m** resolution：
Each pixel size means 10-meter in ground distance

Some application like road or car detection needs **high-resolution** images

	Public(Free)	Commercial
Data Source	NASA(USA), ESA(European)	Planet Lab, NavInfo Co.
Resolution	10m, 30m, and above	0.5m, 1m, and 2m
Application	Greenfield detection, forest analysis	Road segmentation, crop recognition

Data Cost is the Entry Barrier in Remote Sensing Applications

ULTRA HIGH RESOLUTION Drone imagery	VERY HIGH RESOLUTION Satellite imagery	HIGH RESOLUTION Satellite imagery	MEDIUM RESOLUTION Satellite imagery	LOW RESOLUTION Satellite imagery
				
Resolution <0.05m	**Resolution** 0.3-1m	**Resolution** 1-5m	**Resolution** 5-10m	**Resolution** 10m+
Archive imagery **Not yet available**	**Archive imagery** From **$200** From $8 per Km^2	**Archive imagery** From **$100** From $4 per Km^2	**Archive imagery** **Contact us for quote** From $1 per Km^2	**Archive imagery** **FREE** When self-accessed
Custom tasked imagery From **$950** Up to 2 acres	**Custom tasked imagery** From **$900** From $15 per Km^2	**Custom tasked imagery** From **$800** From $8 per Km^2	**Custom tasked imagery** From **$710** From $1.42 per Km^2	**Custom tasked imagery** **Not applicable**

How Super-Resolution(SR) Model Enhances Image Detail?

How does the model reconstruct the missing information?

The Input for SR Model Training: (1) Spatial Pattern Correlations

Low-Resolution Image

V.S.

High-Resolution Image

The model learns the **pattern correlations** between low-resolution and high-resolution images.

The Input for SR Model Training: (2) Details under Temporal Changes

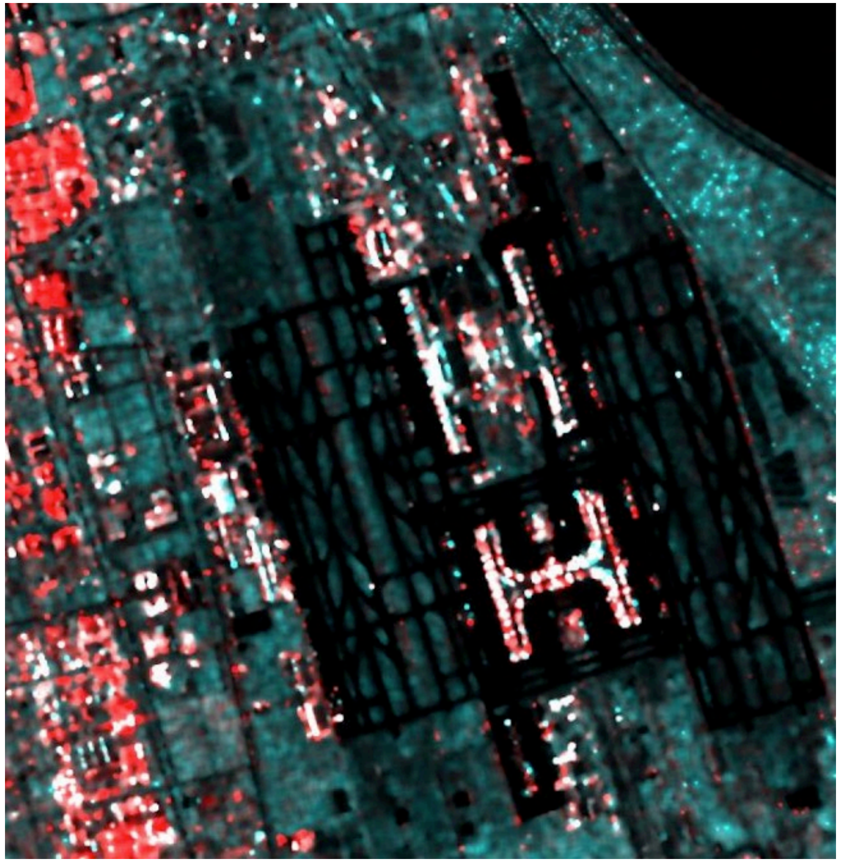
May 5, 2021

May 3, 2021

April 30, 2021

The model learns the details from **lighting changes, ground changes,** or **occlusions.**

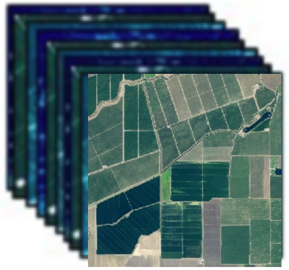
The Input for SR Model Training: (3) Attention from Other Sensors


Low-Resolution RGB Image + Synthetic Aperture Radar(SAR) = High-resolution RGB Image

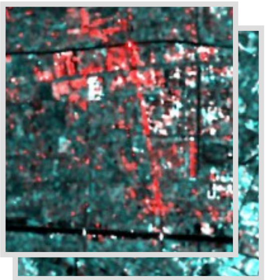
The model learns the **attention** from other sensors.

The Proposed PAII-SR Dataset



- 4 bands, BGRN
- 10m resolution
- 4 temporal captures
- Various terrain coverage

Sentinel-2
Multi-spectrum Imagery



- 2 bands, VV/VH
- 10m resolution
- 4 temporal captures
- Geolocation aligned with Sentinel-2

Sentinel-1
SAR Imagery

Input for Model Training

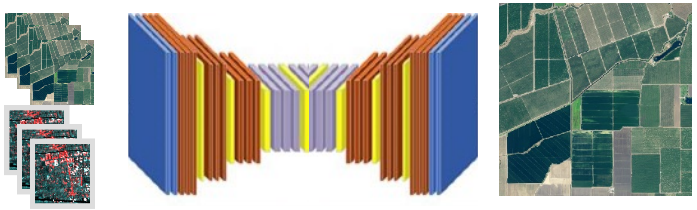
Geolocation aligned

Unmanned Aerial Vehicle (UAV)
BGRN Channels, 0.6m and 2.4m Resolutions

The Target of Model Output

The 4x Enhancement by PAII-SR Model

PAII-SR Model adapting the deep learning & GAN training
- Proposed the PAII-SR deep learning model with 4X Enhancement



Ground truth: **UAV 0.6m**

Bilinear 4X: 2.4m => 0.6m
PSNR: 34.5dB

PAII-SR 4X Model: 2.4m => 0.6m
Sharp details & PSNR: 34.2dB

The 4x Enhancement by PAII-SR Model

Test the PAII-SR Model Generalization

- Trained on Sentinel-2 10m => NAIP 2.5m
- Tested on Sentinel-2 40m => Sentinel-2 10m

Ground truth: **Sentinel-2 10m**

Bilinear 4X: 40m => 10m

PAII-SR 4X Model: 40m => 10m
Model generalization seems working

The 4x Enhancement by PAII-SR Model

Test the PAII-SR Model Generalization

- Trained on Sentinel-2 10m => NAIP 2.5m
- Tested on Gaufen-2 4m => Gaufen-2 1m

Ground truth: **Gaufen-2 1m**

Bilinear 4X: 4m => 1m

PAII-SR 4X Model: 4m => 1m
Model generalization seems working

Quick Summary in SR Image Enhancement

- Image resolution is a key limitation in many remote sensing analytics
  - SR technique plays a critical role in translating free image source(low-resolution) into valuable imagery(high-resolution)
- Our PAII-SR Dataset
  - The largest remote sensing dataset for SR model training
  - Including 1.6M+ image pairs
  - Two 4x scaled imageries: (1) 10m => 2.5m, (2) 2.4m=>0.6m
  - Will release to public in Q4 2021
- Our PAII-SR 4x Enhancement Model
  - Achieve the average PSNR 34.19 dB
  - Effectively enhance the image details & preserve the consistent color tone
  - Model generalization to more resolutions(2.4m, 10m, 40m)
  - Model generalization to other satellites(Sentinel-2, Gaufen-2 satellites)

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  - **Haze Occlusion Removal**
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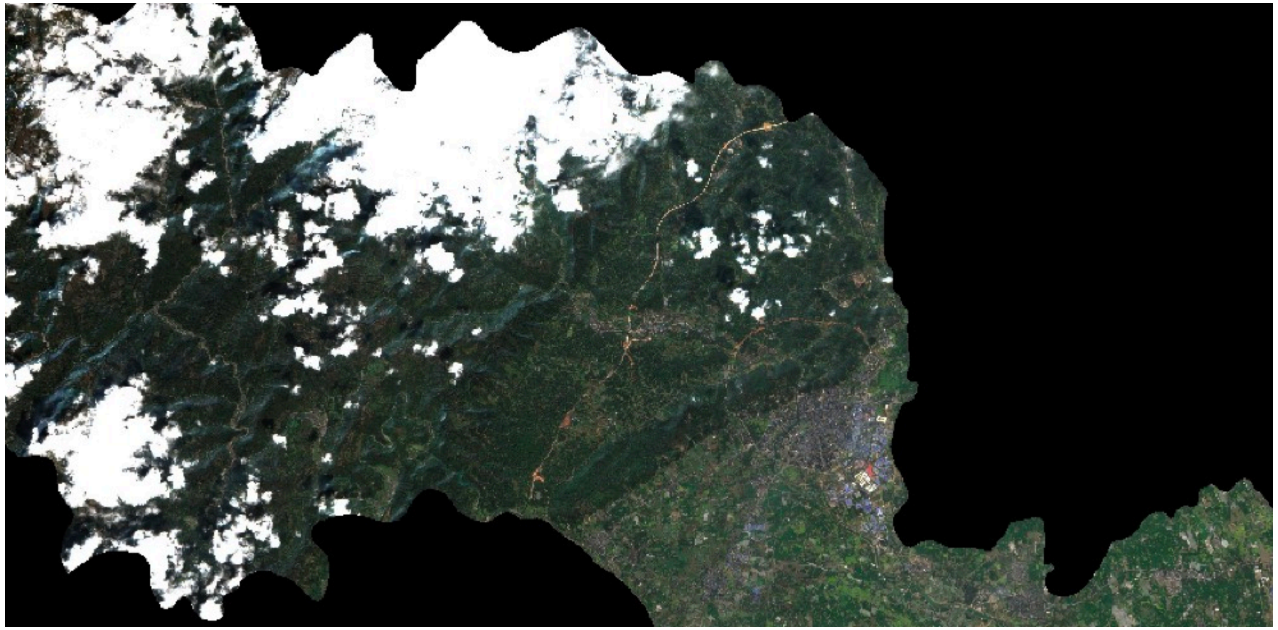
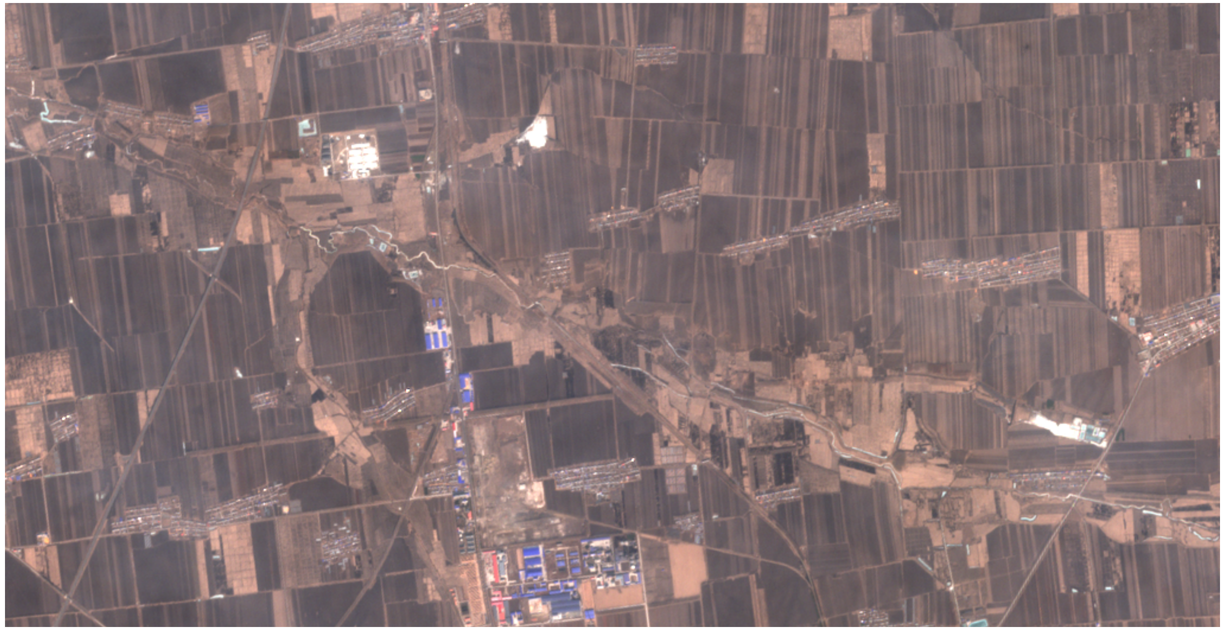
Cloud and Haze Occlusion in RS Images

Cloud occlusion is common in RS images.



Problems: Cannot see the ground activity.

Haze occlusion is more common than cloud but not easy to detect.



Problems: Cannot see the true ground reflectance. E.g., NDVI for growth monitoring.

Cloud Detection & Haze Removal in Sen2Cor

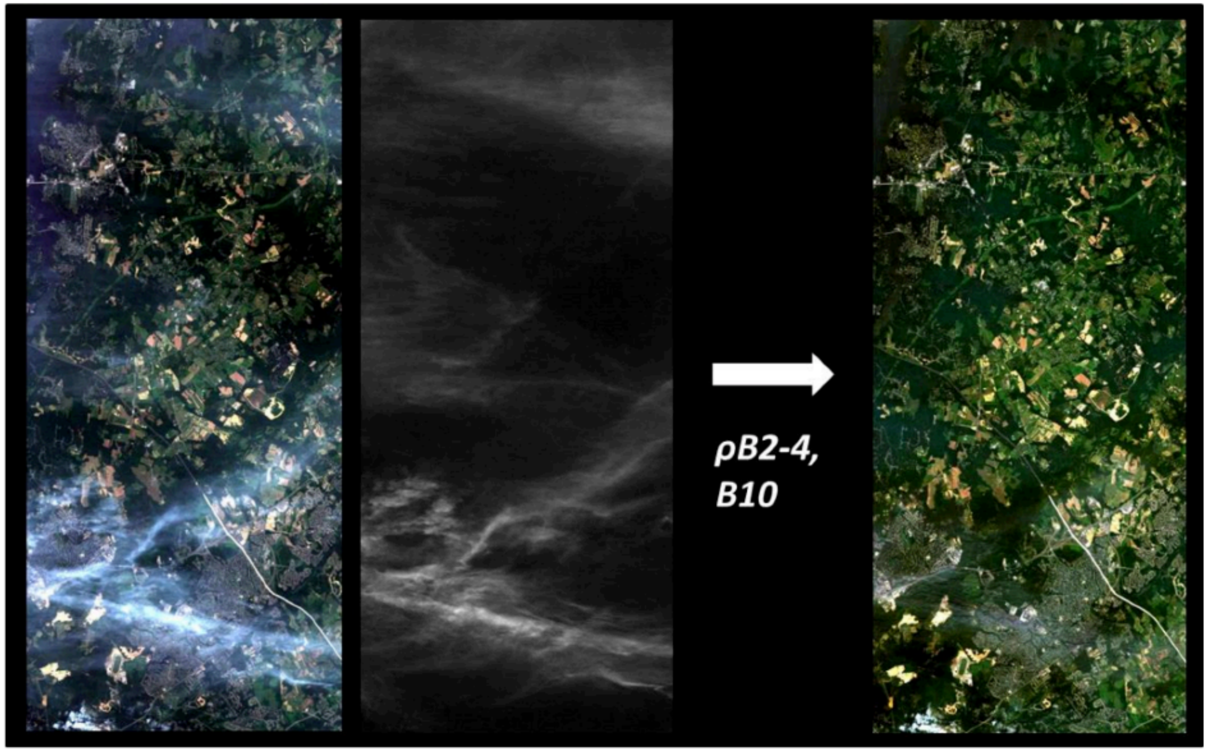


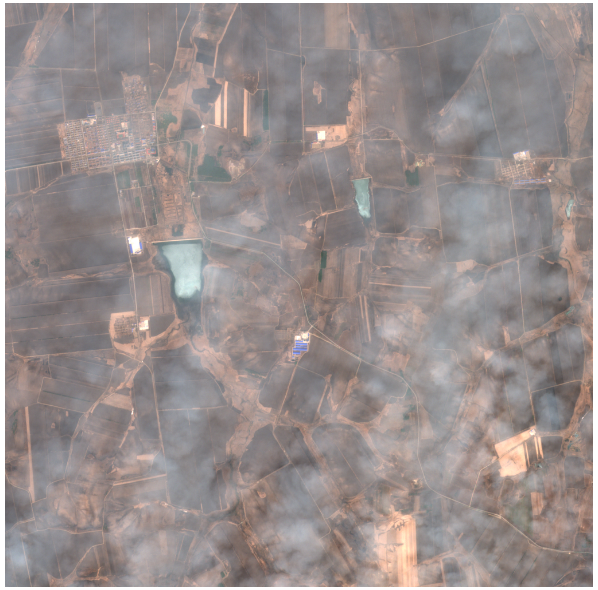
Figure 2-11 – Cirrus Correction, Bands 2-4 with Band 10

From Sen2Cor User Guide By ESA
Left: L1C RGB, Right: L2A RGB
Middle: Aerosol Optical Thickness (AOT) derived from B10

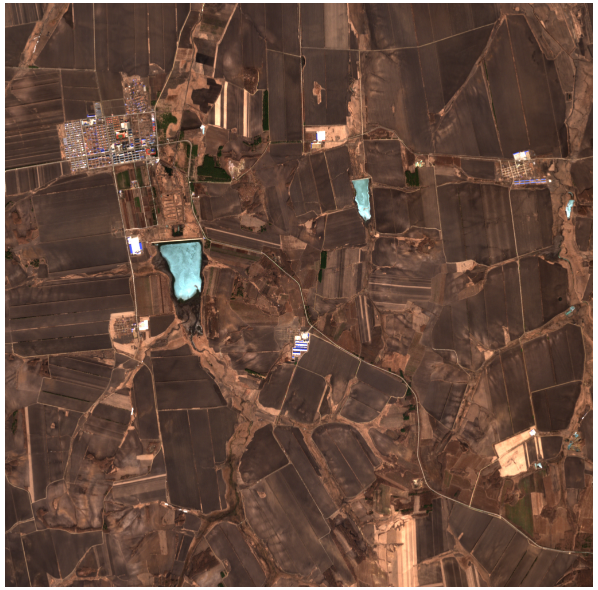
- Sentinel-2 L2A Product
  - The product after atmospheric correction
  - Should have accounted for the hazy/aerosol/cirrus
  - The cloud mask in L2A is highly accurate
  - But, **the haze is still an unsolved problem**

=> we need to correct the data that have already been corrected but not done in a good way.

How to Design a Model to Remove Haze?



Haze Removal Model



How does the model outperform the Sen2Cor model?

How does the model know the output image is haze-free?

We Need to Index the Haze Density First!

- There is no universal standard for haze-level in industry or academy
  - We adapt the *Dark Channel Prior** to measure haze density
  - Observation: at least one color channel has very low intensity at some pixels

$$J^{dark}(\mathbf{x}) = \min_{c \in \{r,g,b\}} \left(\min_{\mathbf{y} \in \Omega(\mathbf{x})} (J^c(\mathbf{y})) \right),$$

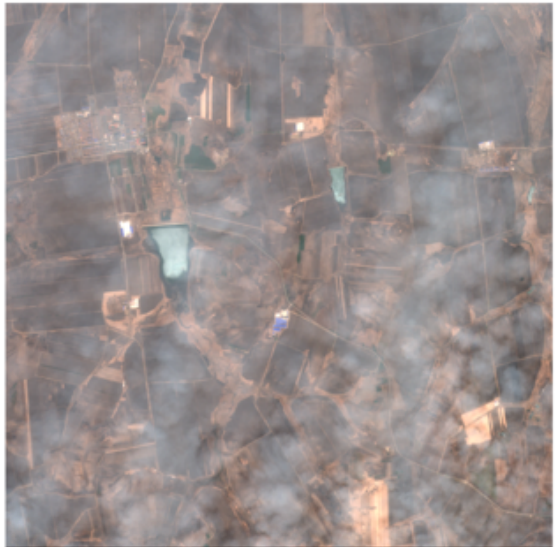
** He et al, Single Image Haze Removal Using Dark Channel Prior, CVPR 2009*

Haze Index Applying to Remote Sensing Imagery

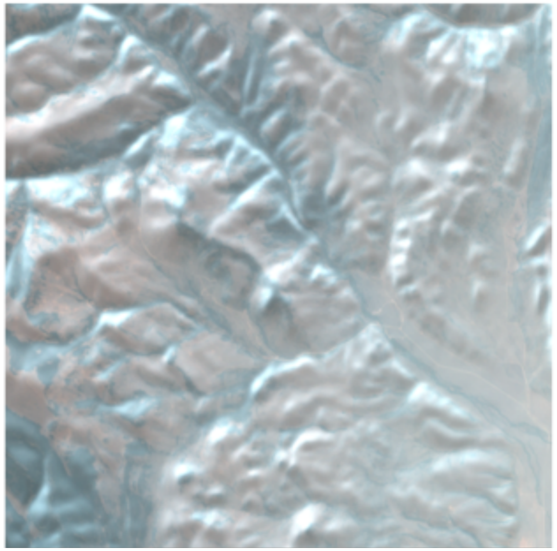
Below images are Sentinel-2 L2A product.
They should be "atmospheric correction", but you can easily see the haze occlusion.

DCP: 43

DCP: 58



DCP: 71



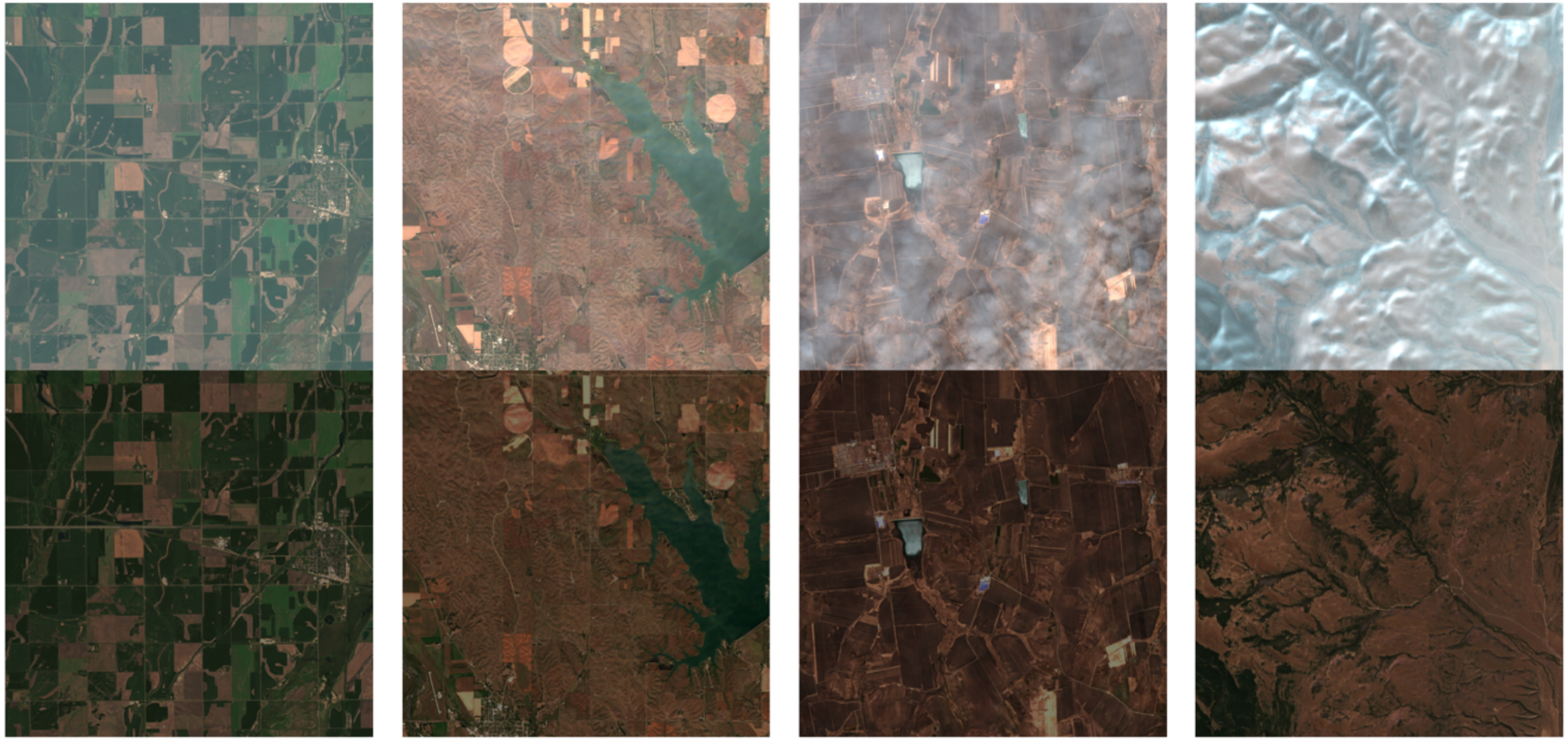
DCP: 88

- Dark Channel Prior(DCP)
  - The higher DCP value, the heavier haze level
  - The DCP level seems consistent to visual perception

The Proposed PAII-Haze Dataset

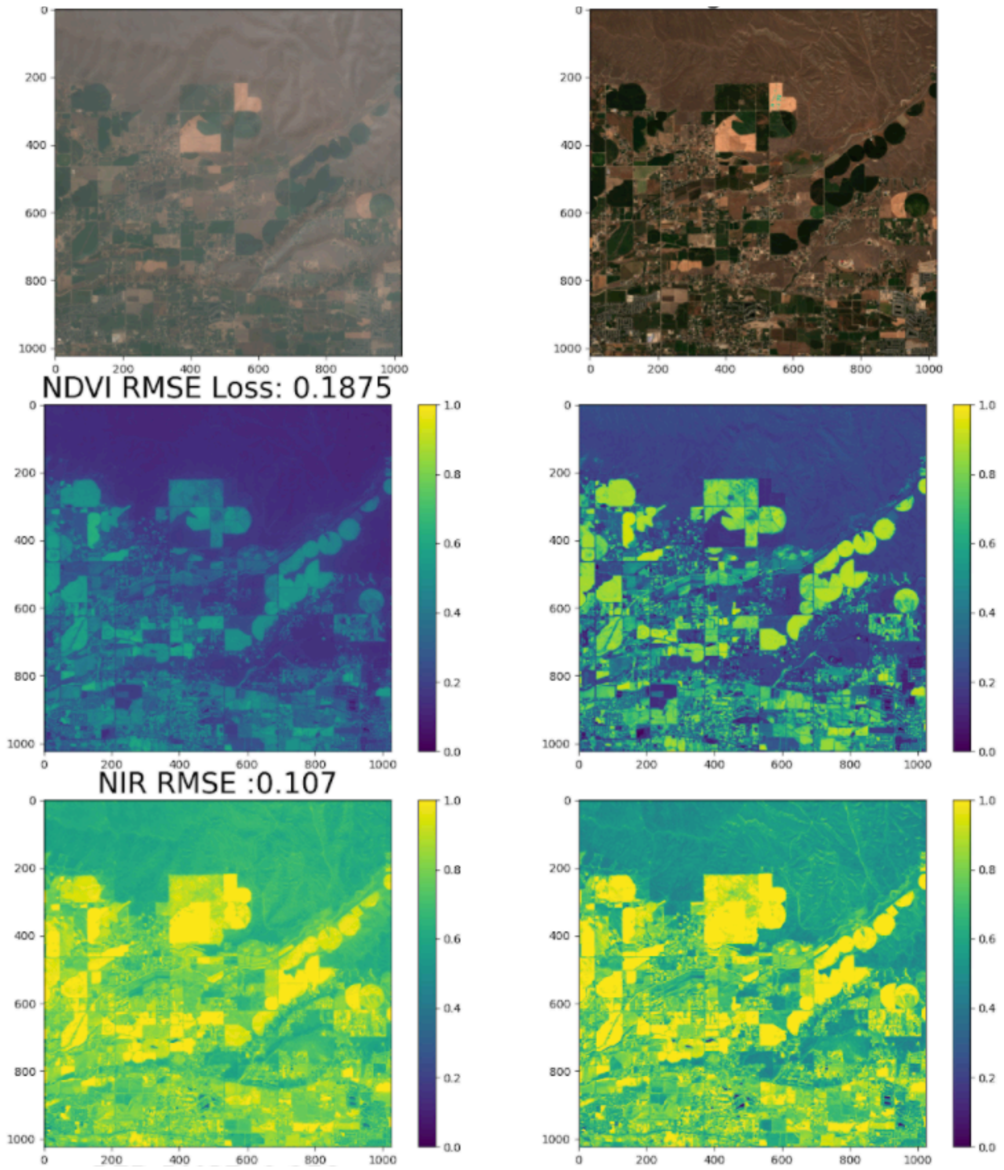
- Image pair on the same geo-location but having different haze-level
- Image pair captured within 5 days, to avoid ground change
- Various coverage of terrain types and seasons

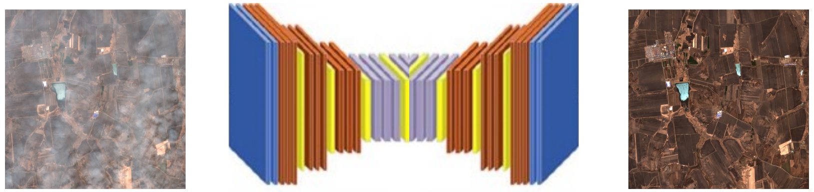
DCP: 43 DCP: 58 DCP: 71 DCP: 88



DCP: 25 DCP: 26 DCP: 21 DCP: 25

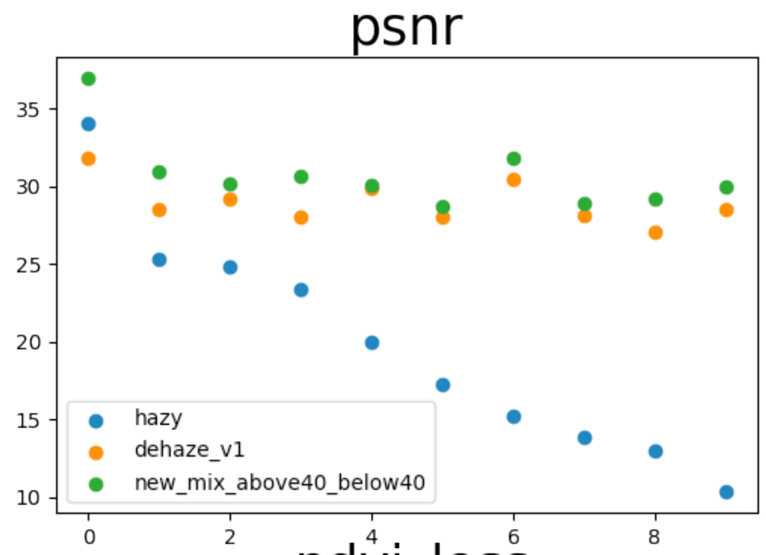
The Proposed Deep Learning PAII-Haze Model

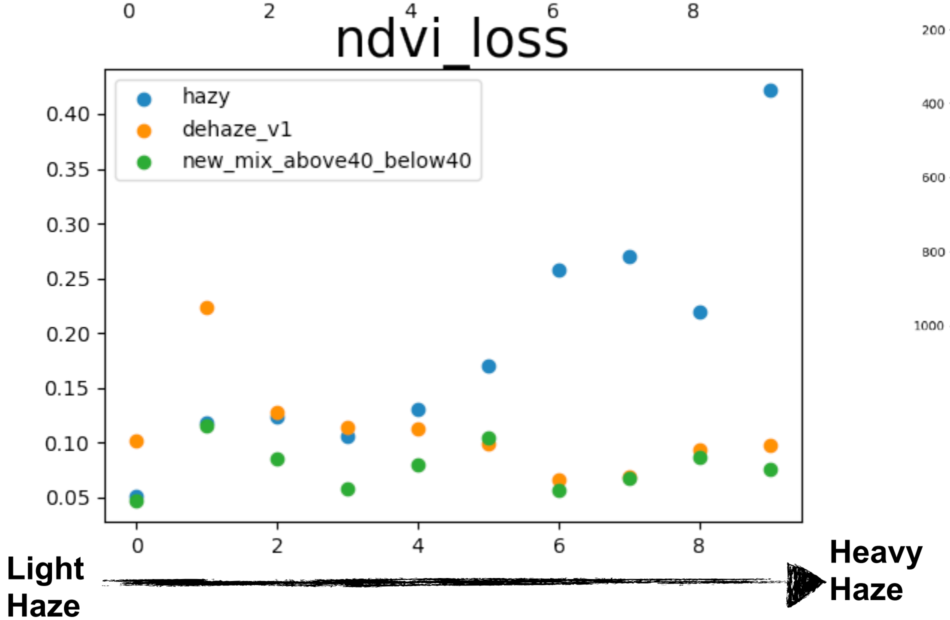


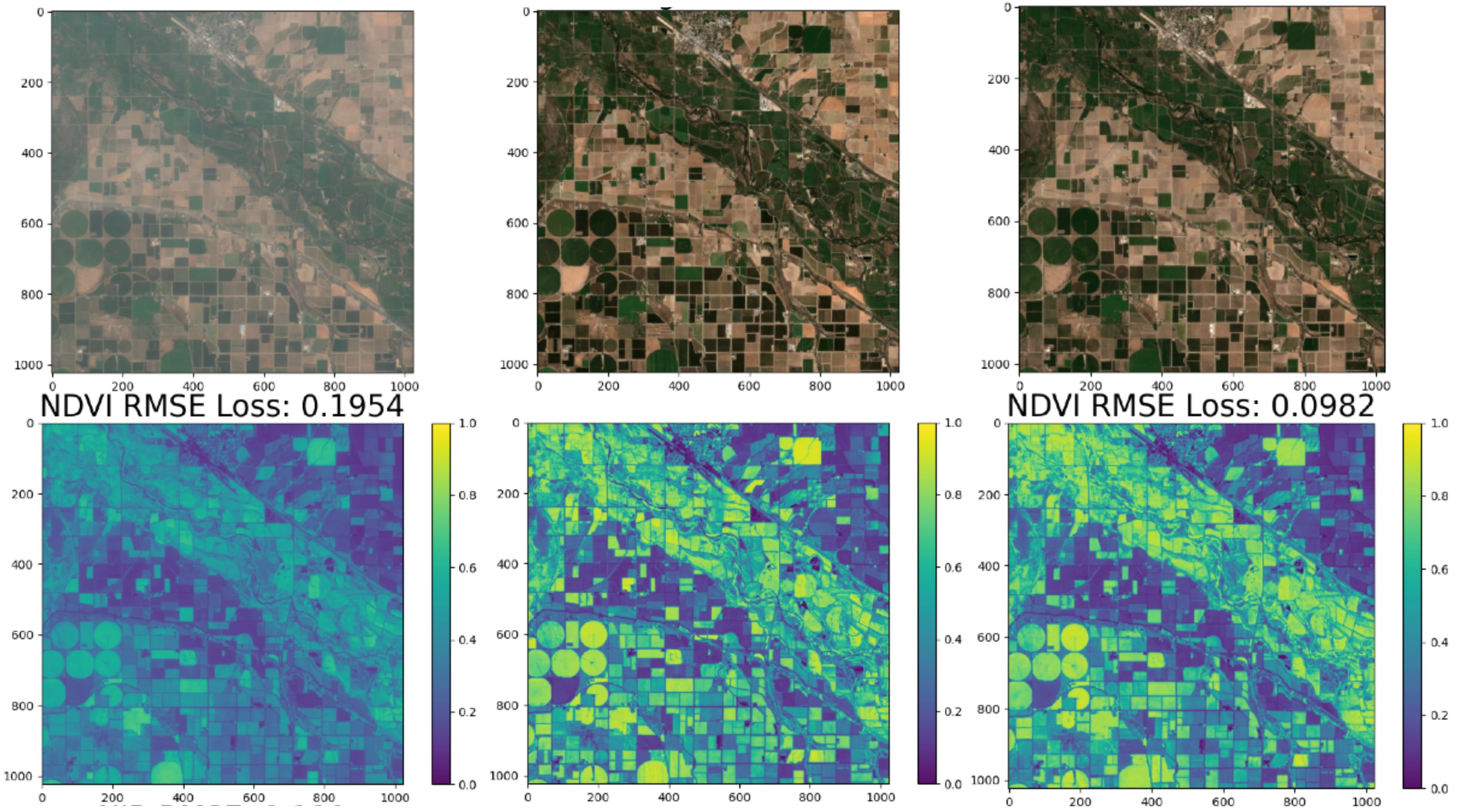


PAII-Haze Model
- BGRN 4-Channel Deep Learning model
- Model loss: L1-loss of RGB & N & NDVI
- We Highlight the NDVI accuracy
- Single model trained on various haze levels

Evaluation of PAII-Haze Model







Hazy image　　GT image　　Haze removal image

The PAII-Haze Model can cope with various haze density

- Average PSNR: 30.5 dB
- Subjective evaluation shows dramatic improvement

Quick Summary in Haze Removal

- Over 90% remote sensing images are covered with haze-level over 30+ DCP
  - We can NOT see the true ground reflectance, e.g., the NDVI for crop growth monitoring
- Our PAII-Haze Dataset
  - The largest remote sensing dataset for Haze-Removal model
  - Including 800K+ image pairs
  - Each image with BGRN 4-channel and 512x512 pixel-size
  - Will release to public in Q4 2021
- Our PAII-Haze Model
  - Effectively remove haze under various haze-level
  - Achieve the average PSNR 30.5 dB
  - Subjective evaluation shows dramatic improvement

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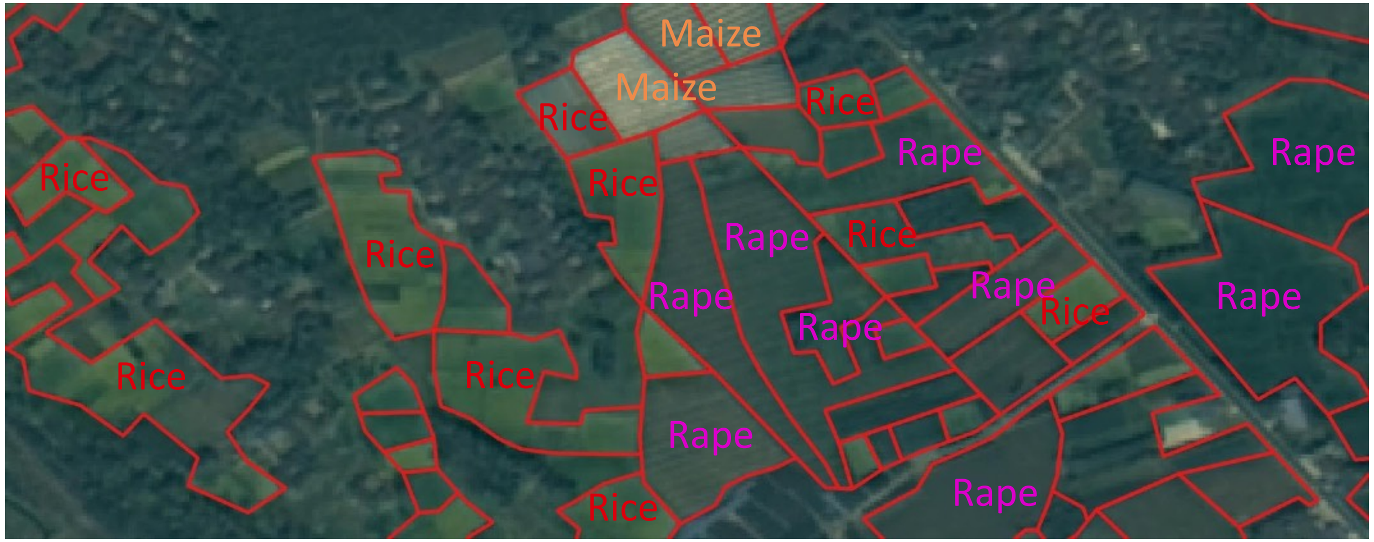
- More Analytics in Ping An Group

Remote Sensing Recognition is Not Easy to Machine, Even to Human

- The tasks under crop recognition
  - Cropland segmentation
  - Parcel detection
  - Crop recognition

- Each task is challenging
  - Cropland and forest look similar
  - Parcel shapes are irregular
  - Crop recognition cannot be done based on a single image
  - And …

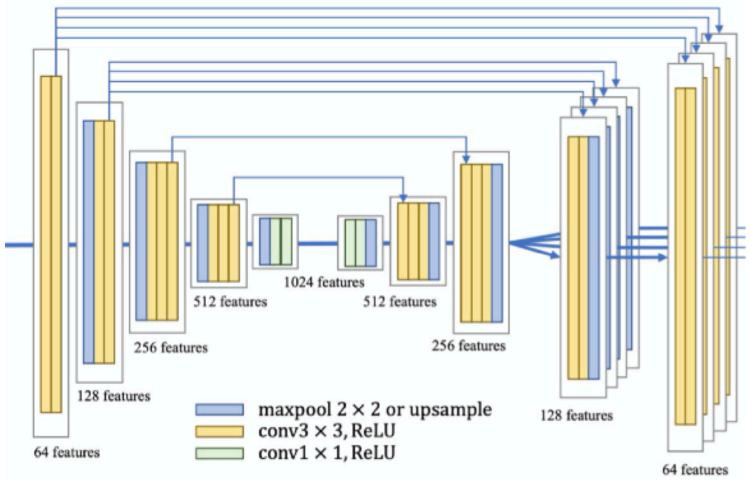


In 2019, We Proposed a Framework — Cropland & Parcel & Crop Models

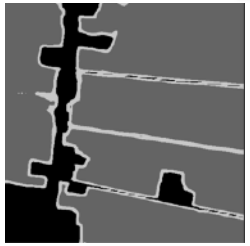
Input Data	Ridge/Cropland/Non-Cropland Segmentation	Topology	Post-Processing

Multi-spectral & Multi-temporal satellite images

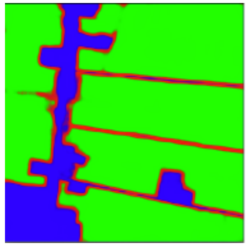
PAII-Cropland Model



Cropland Segmentation Result



Segmentation



Probabilities

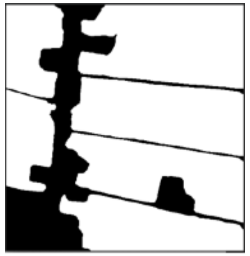
Graph-based Topology Connecting Model

Topology Connecting Result

Topology connected graph

Post-processing (morphological operation)

Segmentation Result



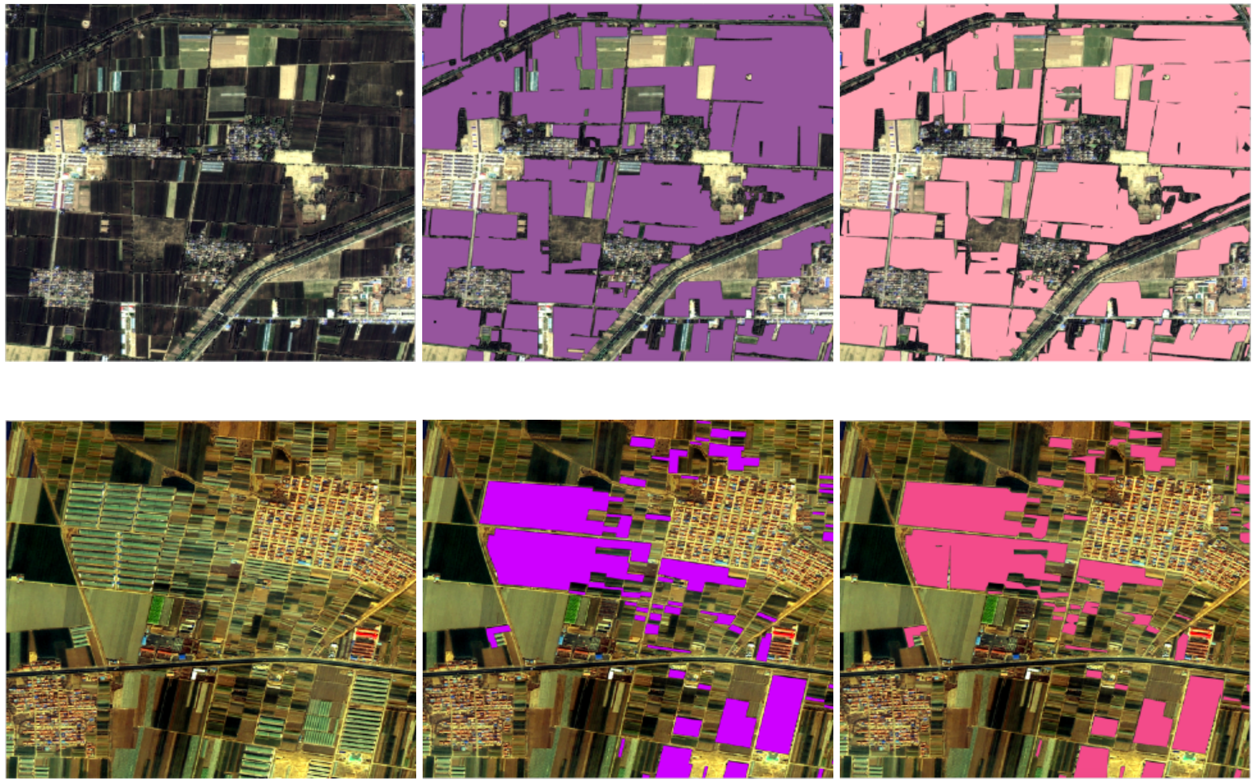
Cropland segments

*The topology model connects the broken ridges.

In 2019, We Did a Good Job on Prove of Concept(PoC) Counties

Corn in Caoxian County

Greenhouse in Shouguang County



Satellite Image Annotation Prediction

- Train 5 different models for 5 different crop types
- Testing on 9 PoC counties
- Average recall/precision are high

Crop Type	Precision/Recall
Rice	0.85/0.86
Wheat	0.88/0.86
Corn	0.87/0.83
Cotton	0.92/0.82
Greenhouse	0.93/0.90

In 2020, We Marched Quickly and Broadly!

From PoC to massive area production, the wheat detection on the mainland China in March 2020

图1 9个小麦主产县区地理分布

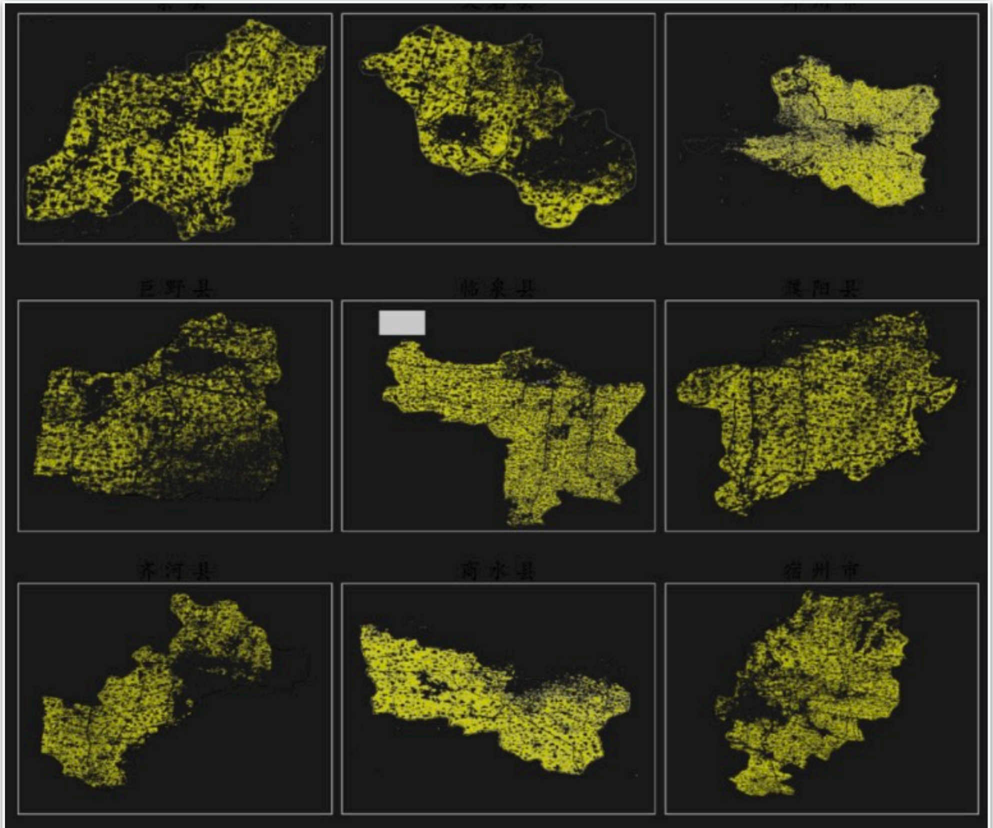
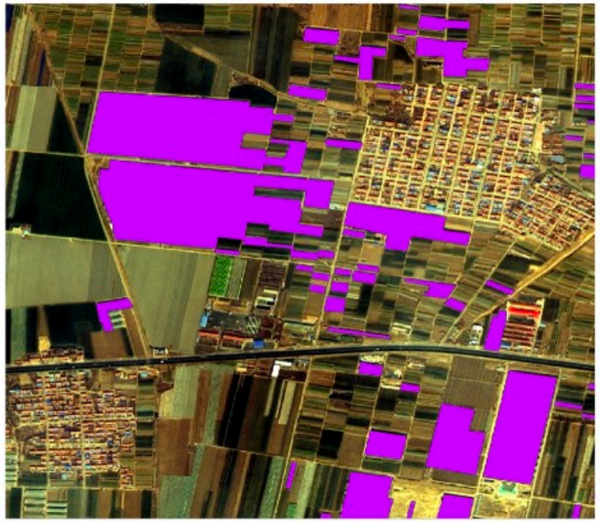


图2 9个县市遥感识别2020年小麦分布结果

However, the challenges between the PoC and massive production are totally different scales.

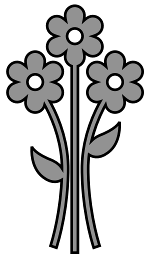
In 2020, Challenges in Data labeling & Model Generalization

Need huge training data, high labeling cost



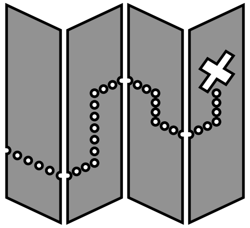
Labeling cost for crop recognition: $12 USD/$KM^2$

Model generalization is difficult.



Different crop seeds

Different satellite imaging



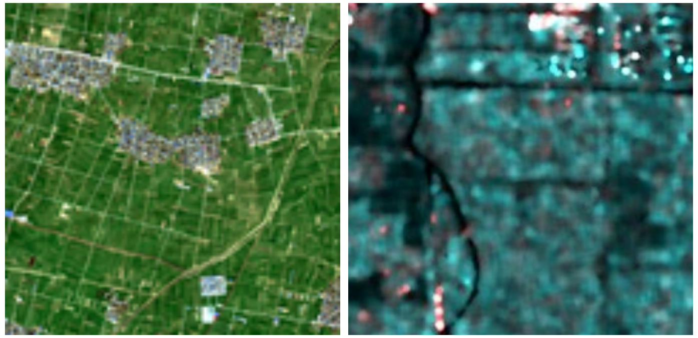
Various lighting conditions
under log/lat coordinates

How the model to cope with various geo-locations, crop types, and satellite imageries?

In 2021, We Think Out of the Box — Semi-Supervised Parcel Detection

- Core ideas
  - Reduce the dependency of supervised training data
  - Adapt machine learning and reduce model parameters
  - Adapt semi-supervised learning trained from general tasks
  - Leverage other sensors, attention map from SAR

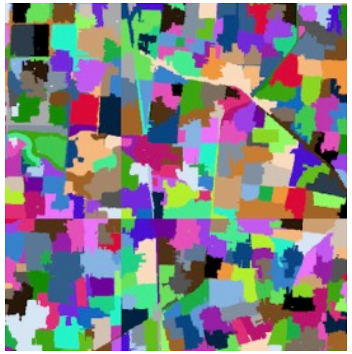
Multi-spectrum & SAR images



The **PAII-Parcel** Model

Pixel clustering model

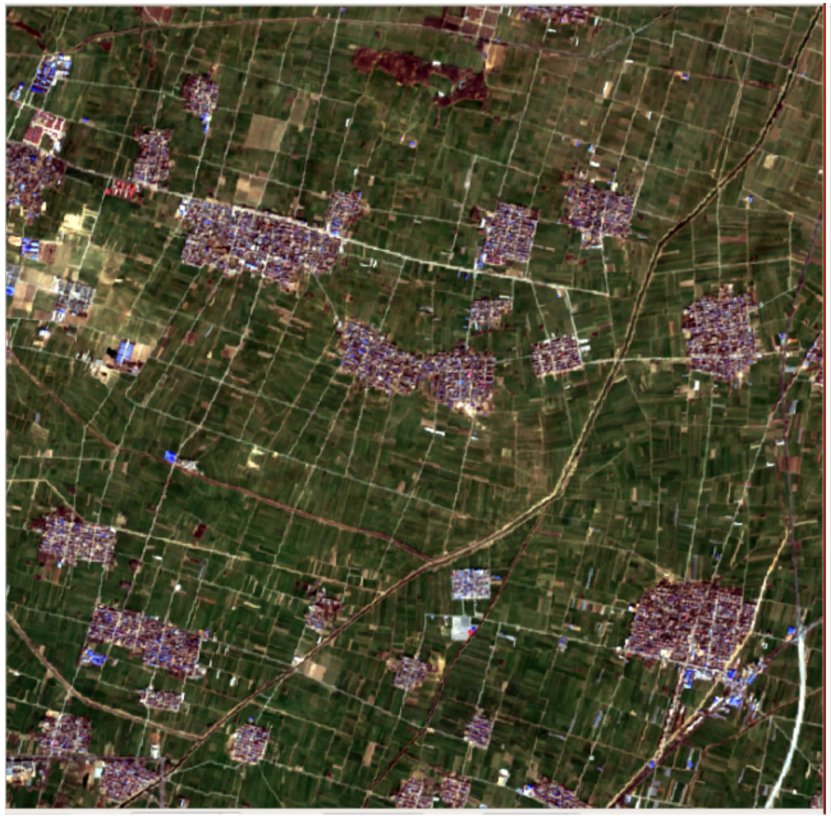
Semi-supervised learning for boundary refinement



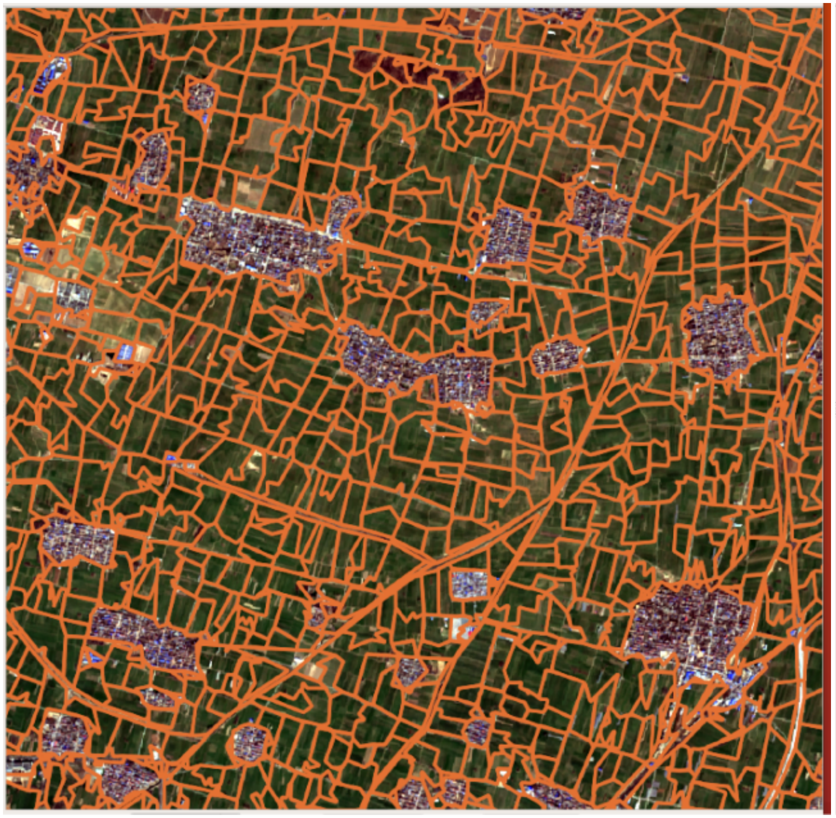
Results of parcel detection

Results of PAII-Parcel Model

The PAII-Parcel Model is trained from a universal dataset, and it can output multiple levels of parcel sizes.



Input Image



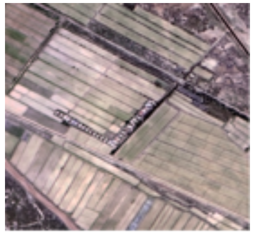
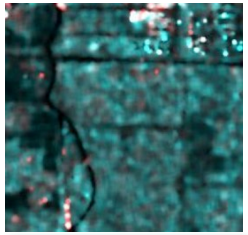
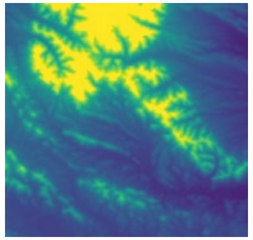
Output: **fine-grain** parcel detection

Output: **coarse-grain** parcel detection

In 2021, We Think Out of the Box — Few-Shot Learning Crop Recognition System

- Core ideas
  - Adapt the Expert Knowledge Dataset, e.g., local crop history, growth period, terrain conditions.
  - Introduce the interactive UI system to collect training labels for few-shot learning
  - Leverage SAR imagery to get ground reflectance e.g., water detection for rice
  - Leverage DEM imagery to get terrain slop and hill shade

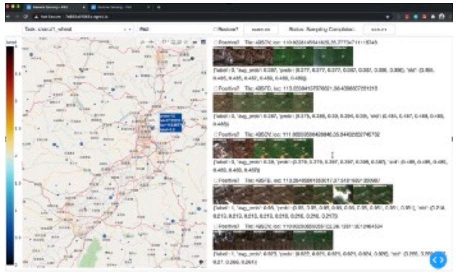
Multi-inputs

Expert Knowledge Dataset

PAII-Crop Model: time-series crop recognition model with few-shot learning

UI for collecting training labels



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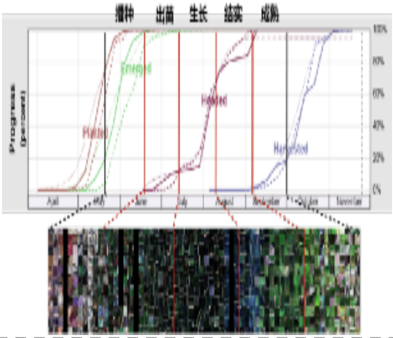
Time series of crop growth analysis



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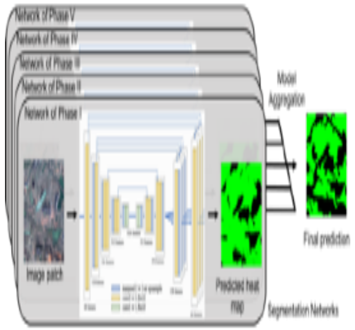
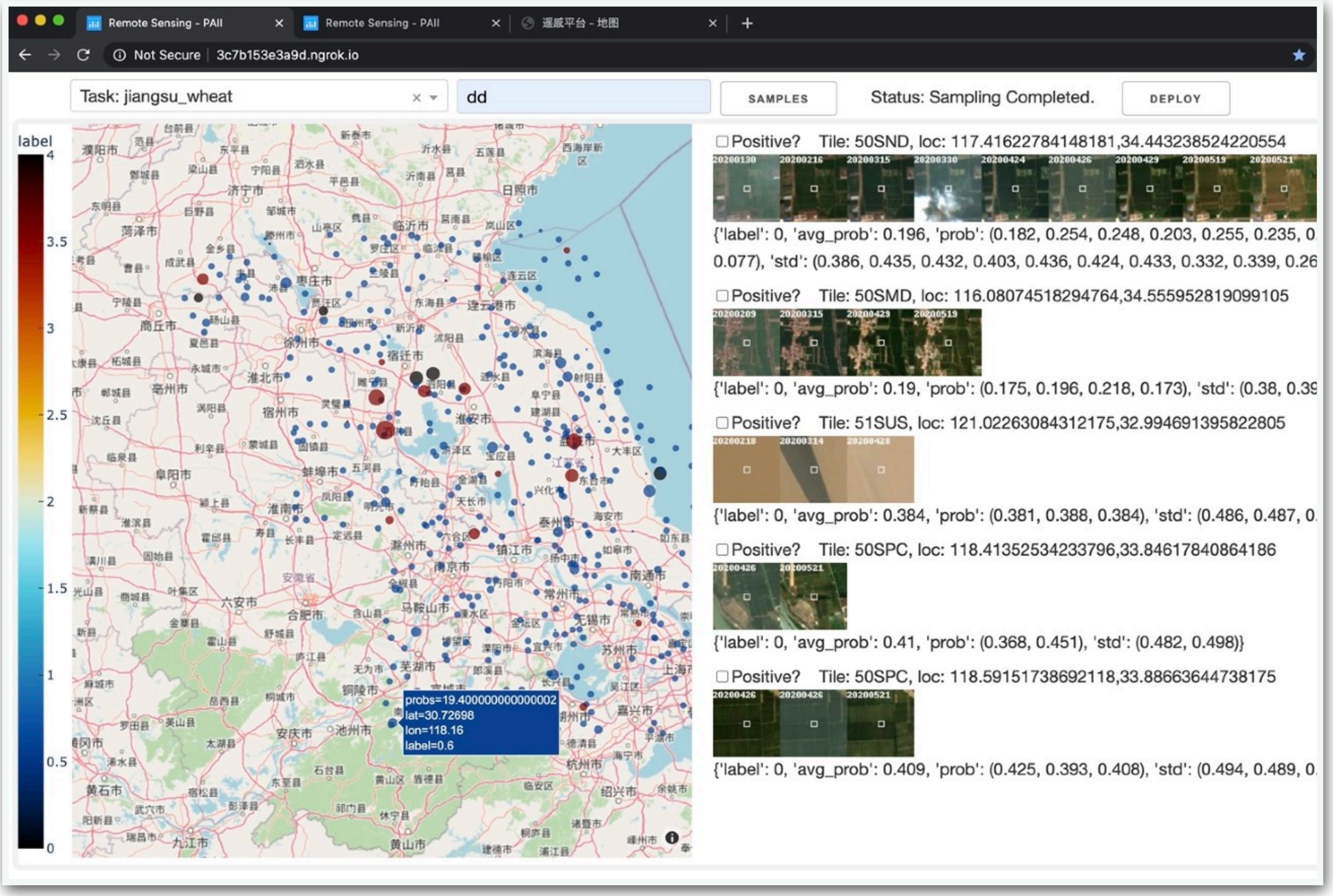
Multi-stage & light-weight recognition model



Recognition results

System of PAII-Crop Labeling, Model Training, and Model Deployment

- A real-time and interactive labeling system with few-shot learning model



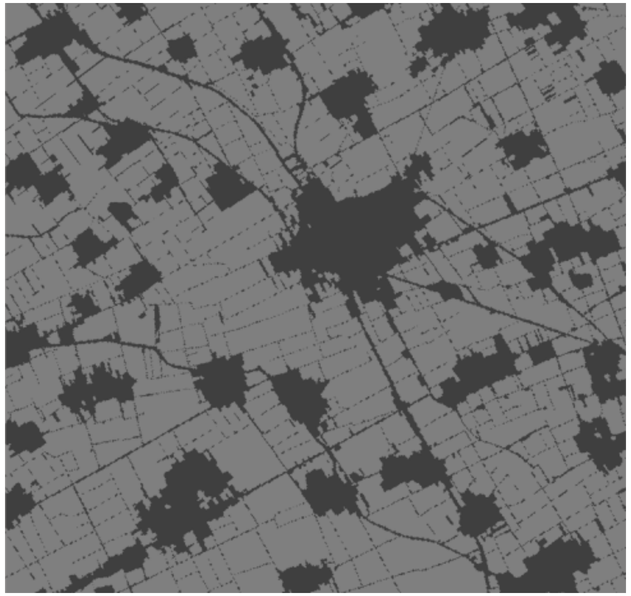
Recognition Results of PAII-Crop Model

Few-Shot Learning for PAII-Crop Model:
40 labels/10,000 KM^2 collecting from the interactive UI

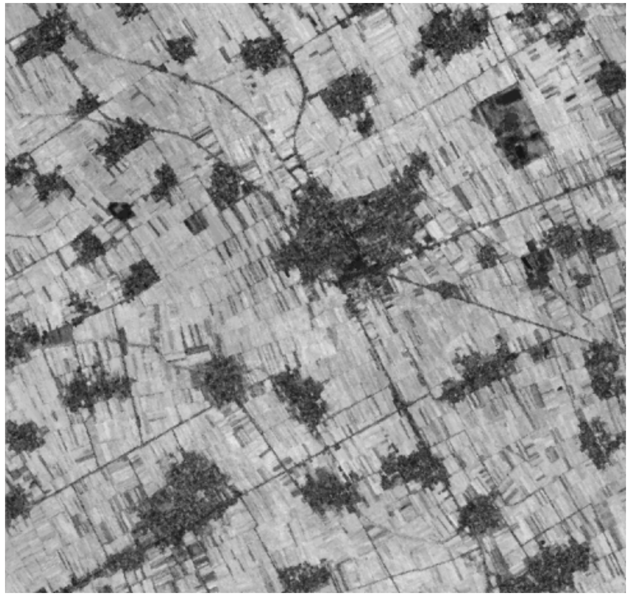
Massive Deployment for **PAII-Crop Model**:
Test the system running on massive area

Category	Province	Precision	Recall
Almond	CA, US	72.420	76.036
Corn	Henan, China	89.445	88.431
Cropland	Henan, China	91.128	92.554
Cropland	Hubei, China	91.974	93.946
Wheat	Hubei, China	80.927	92.318
Cropland	Jilin, China	93.327	91.179

Ground Truth:
Cropland in Henan Province



Model Output:
Gray-scale [0-1] probability



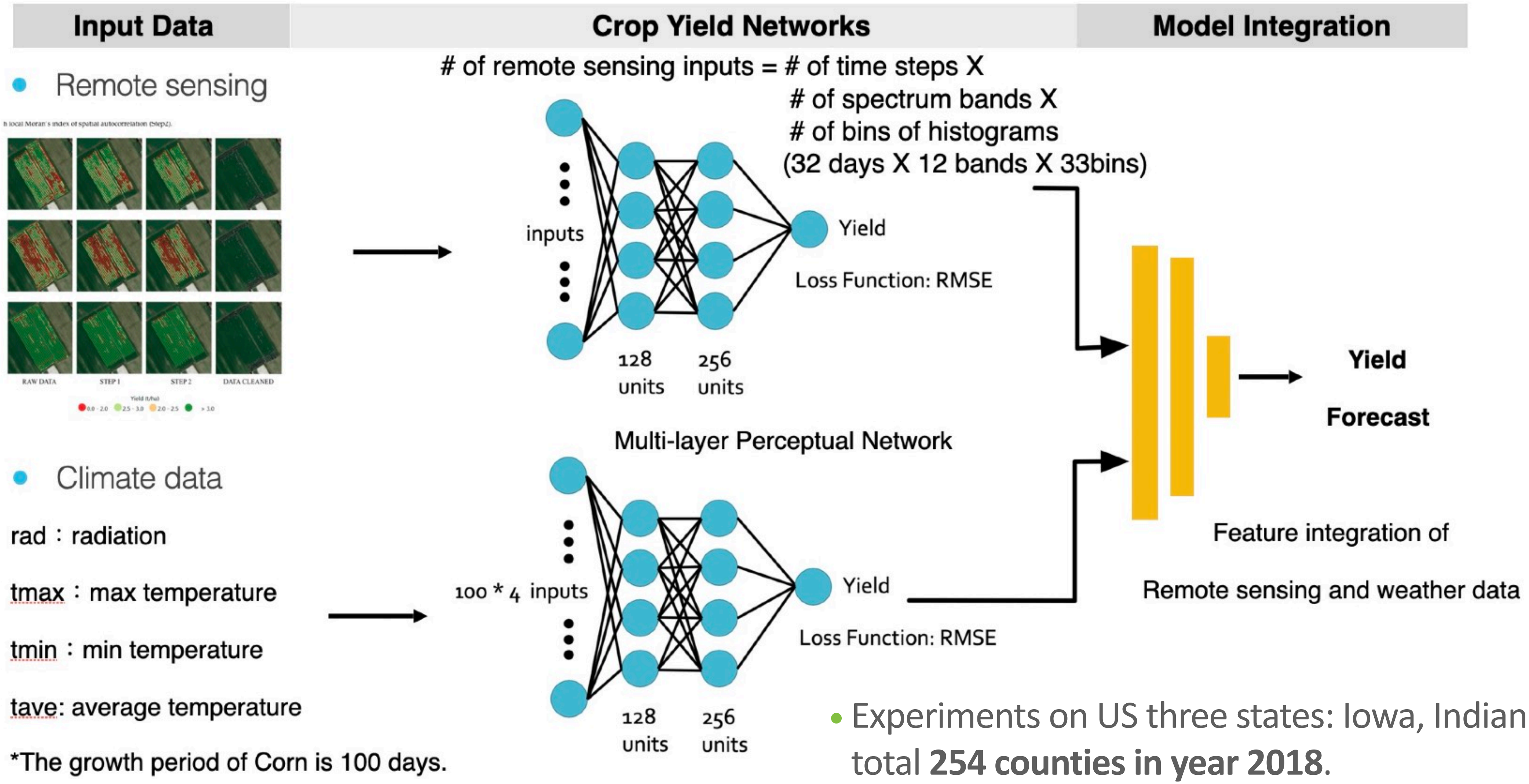
Quick Summary in Crop Recognition

- Crop recognition is one of the core agriculture applications
  - A combination of cropland segmentation, parcel detection, and recognition
- Our PAII-Parcel Model
  - Abandon the requirement of huge label data
  - Proposed the semi-supervised learning for pixel clustering and boundary refinement
  - Trained from a universal dataset and output multiple levels of parcel sizes
- Our PAII-Crop Model
  - Abandon the requirement of huge training data
  - Introduce the interactive UI system to collect training labels for few-shot learning
  - Synergy of the Expert Knowledge Dataset, multi-spectrum, SAR, and DEM imageries
  - Test the system running on province-level and its performance precision over 80%, recall 80%

Outline

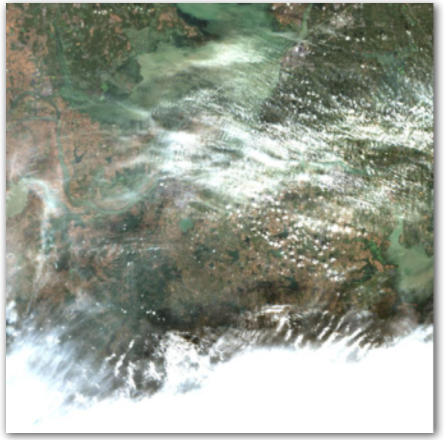
- PAII-SR Model:
  - 4X Super-Resolution Image Enhancement
  - The Proposed PAII-SR Dataset
- PAII-Haze Model
  - Haze Occlusion Removal
  - The Proposed PAII-Haze Dataset
- PAII-Crop Model
  - Parcel Detection Model
  - Crop Recognition Model
- **More Analytics in Ping An Group**

Crop Yield Forecasting for Investment Business

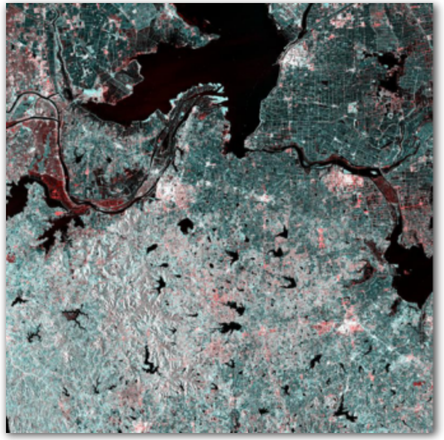


- Experiments on US three states: Iowa, Indiana, and Illinois, total **254 counties in year 2018**.
- The average precision rate for testing counties: **90.3%**

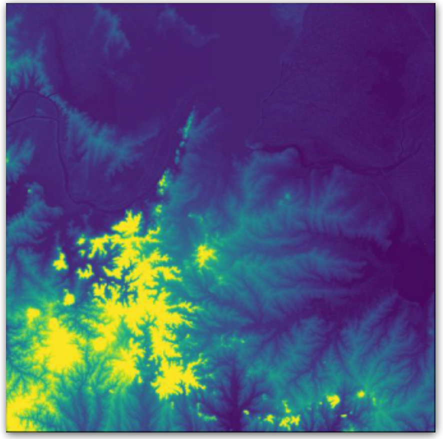
Flooding and Natural Damage Analysis for Smart City



Multi-spectrum Image



SAR Image

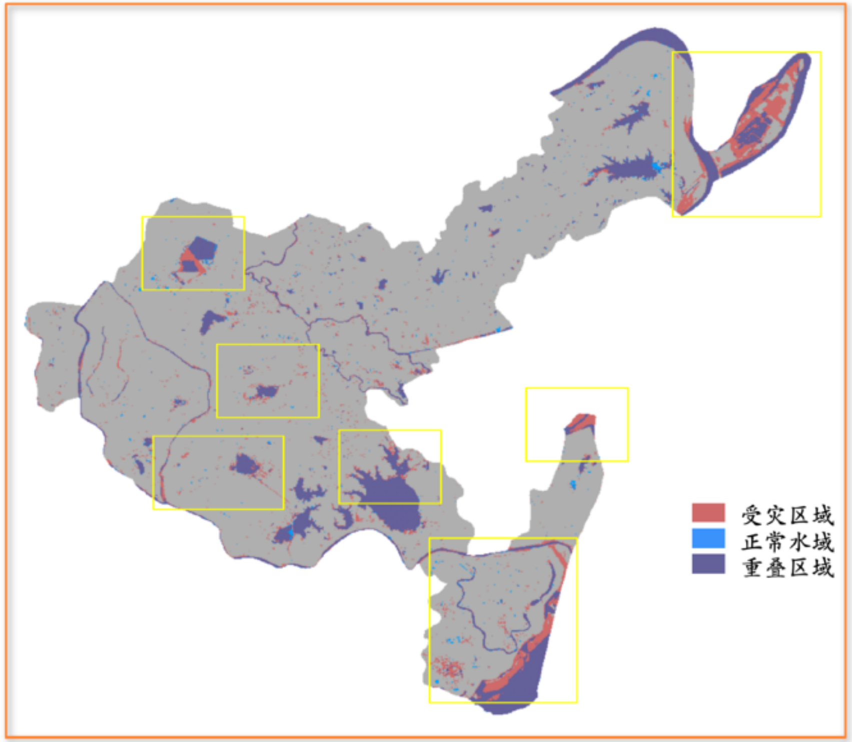


Elevation(DEM) Image

July 2020 Hubei Province, Flooding detection

水淹后（2020年7月18日）

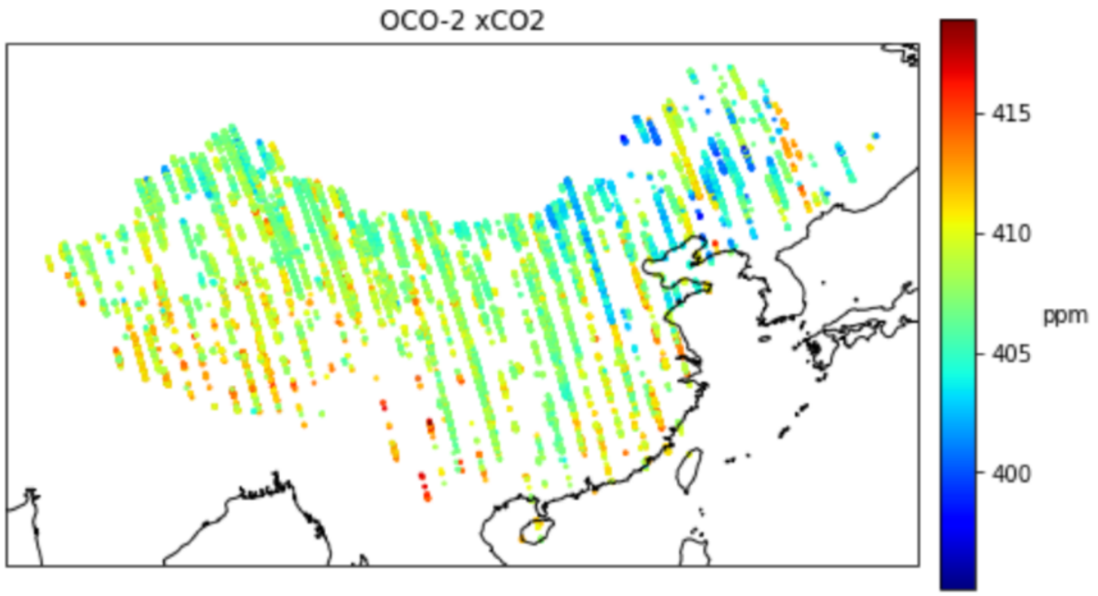
水淹前（2019年8月17）



两时间点比较图

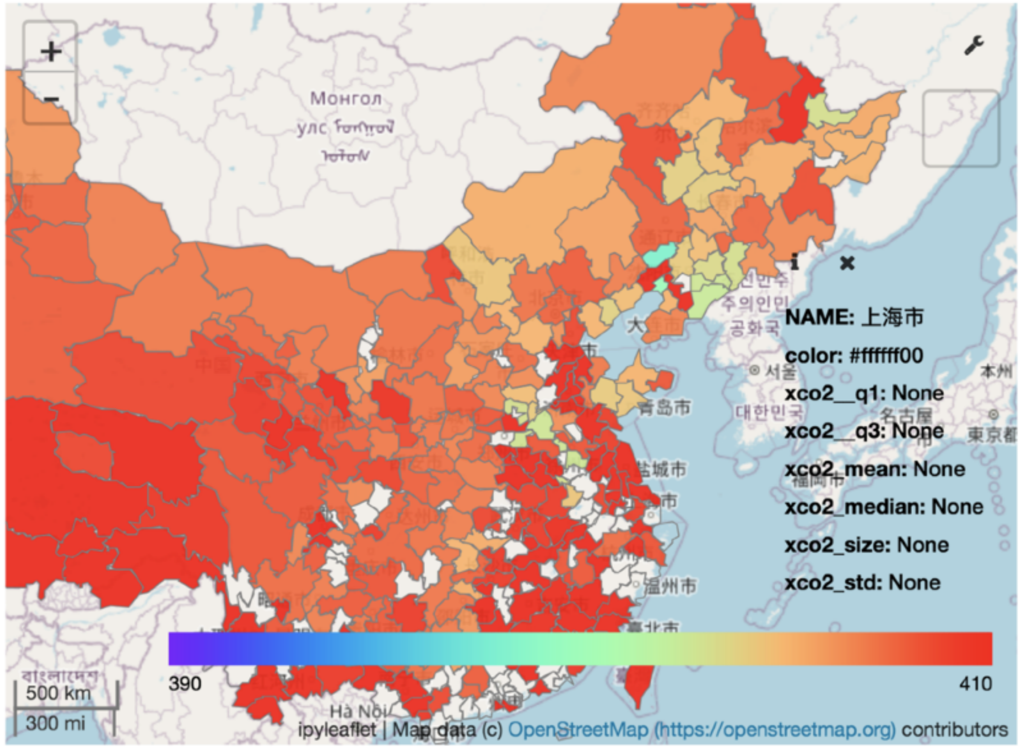
Carbon Emission Analysis for Environment, Society, and Government(ESG)

CO_2 Data processing for OCO-2 Satellite.



2019/06/01 - 2019/09/01

PAII-Carbon Analysis for **global** county-level CO_2 emission. We are working on data enhancement for **high-temporal** and **high-spatial** resolution emission analysis.



2019/06/01 - 2019/09/01

Thank You!