Towards Global Crop Maps with Transfer Learning

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*Equal contribution

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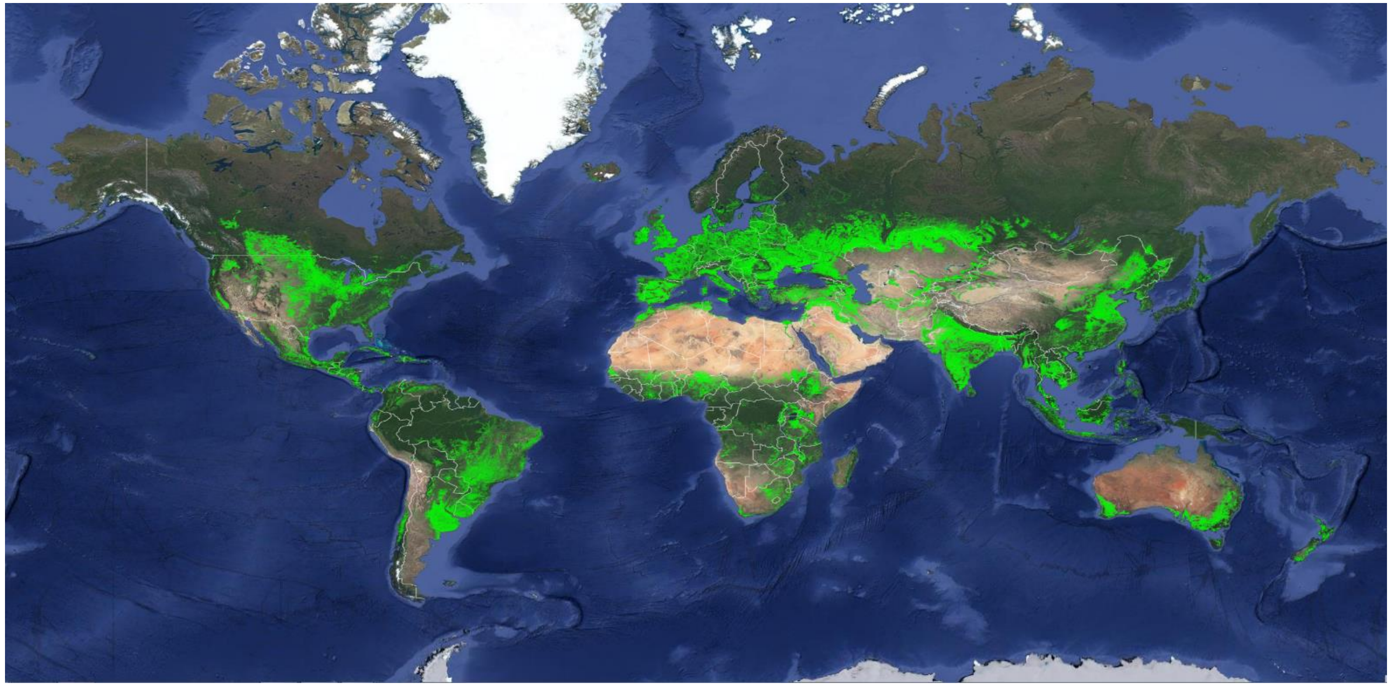
Motivation

Climate Change and Population Growth

Global Food Security

Global Crop Type Maps



Solution: Earth Observation

Limitation: Lack of annotated data

Introduction

01. Overview

Transfer learning for global crop mapping

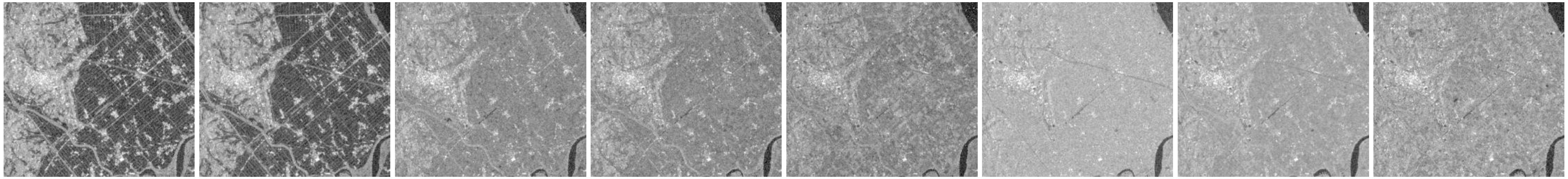
- Different areas: from South Korea to Europe (Spain, France, and the Netherlands)
- Different crop types: Rice to rice, rice to summer barley
- Different features: Sentinel-1 VH to VH and VV|VH

Datasets

01. Time Series Sentinel-1 Data

- 2560 m x 2560 m patches with the pixels of 10 m resolution (≈ 6.55 km^2)
- Time series Sentinel -1 (VV|VH) images were composited in 8 period (Rice: 20 days interval, 2 of each 4 phenological stage; Barley: Monthly)

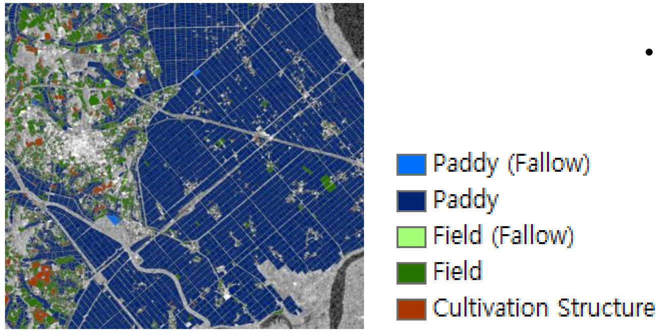
	Planting		Tillering		Booting		Ripening	



Korea Rice	May 10 – May 31	Jun 1 – Jun 20	Jun 21 – Jul 10	Jul 11 – Jul 31	Aug 1 – Aug 20	Aug 21 – Sep 10	Sep 11 – Sep 30	Oct 1 – Oct 20
Europe Rice	From Apr 20 to Sep 30 (-20 d)							

02. Labeling (CALLISTO Dataset Collection: https://github.com/Agri-Hub/Callisto-Dataset-Collection)

South Korea: Farm map (MAFRA)



- Korean Ministry of Agriculture, Food and Rural Affairs (MAFRA) provides farm map, which was produced by a visual interpretation on aerial photos and satellite images referencing the parcel boundaries at national GIS data.

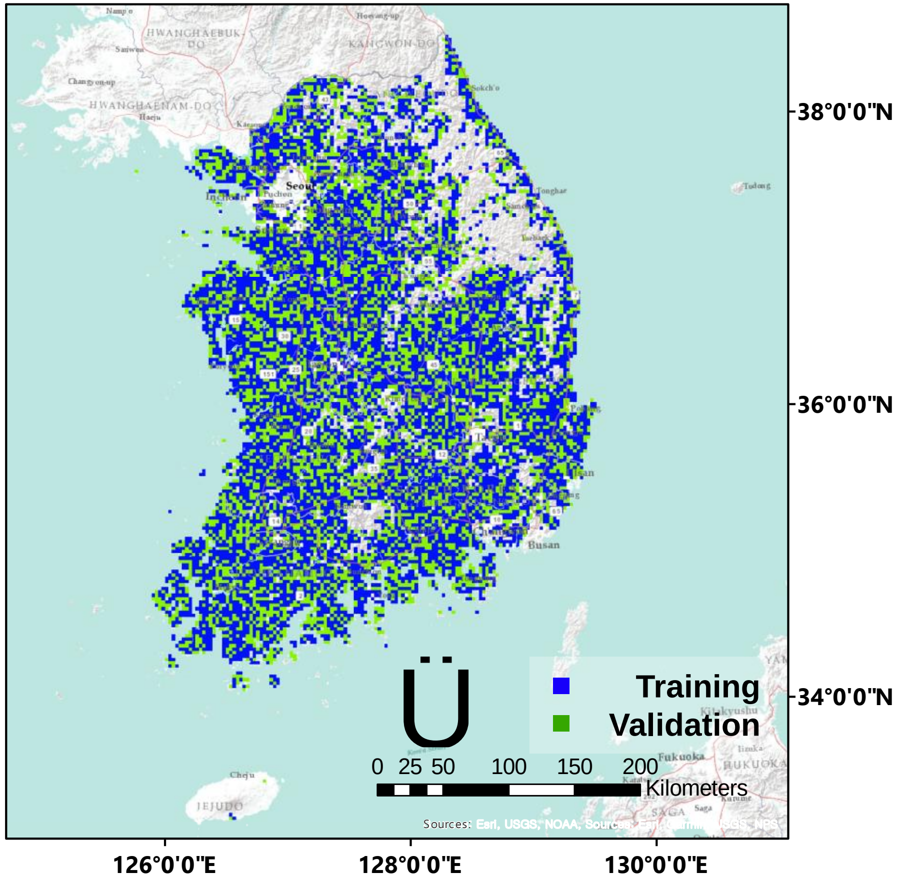
Europe:

- **Catalonia**: The Department of Climate Action, Agriculture and Rural Agenda of Catalonia (DACC)
- **France:** A geographical database serving as a reference for the instruction of the aids of the common agricultural policy (CAP)
- **The Netherlands:** National GeoRegistry of The Netherlands

Study Area

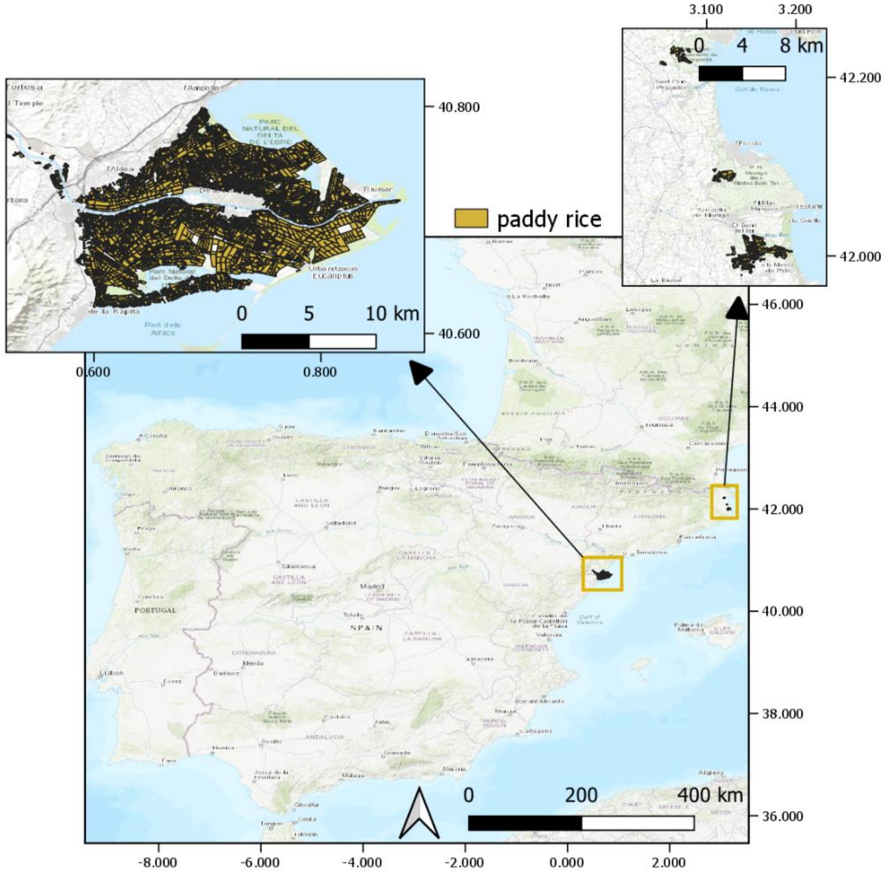
01. South Korea

- Approximately **780,000 ha of paddy rice** through the entire country
- 12,942 patches (Randomly selected - Training: 7,762; Validation: 5,180)



02. Spain

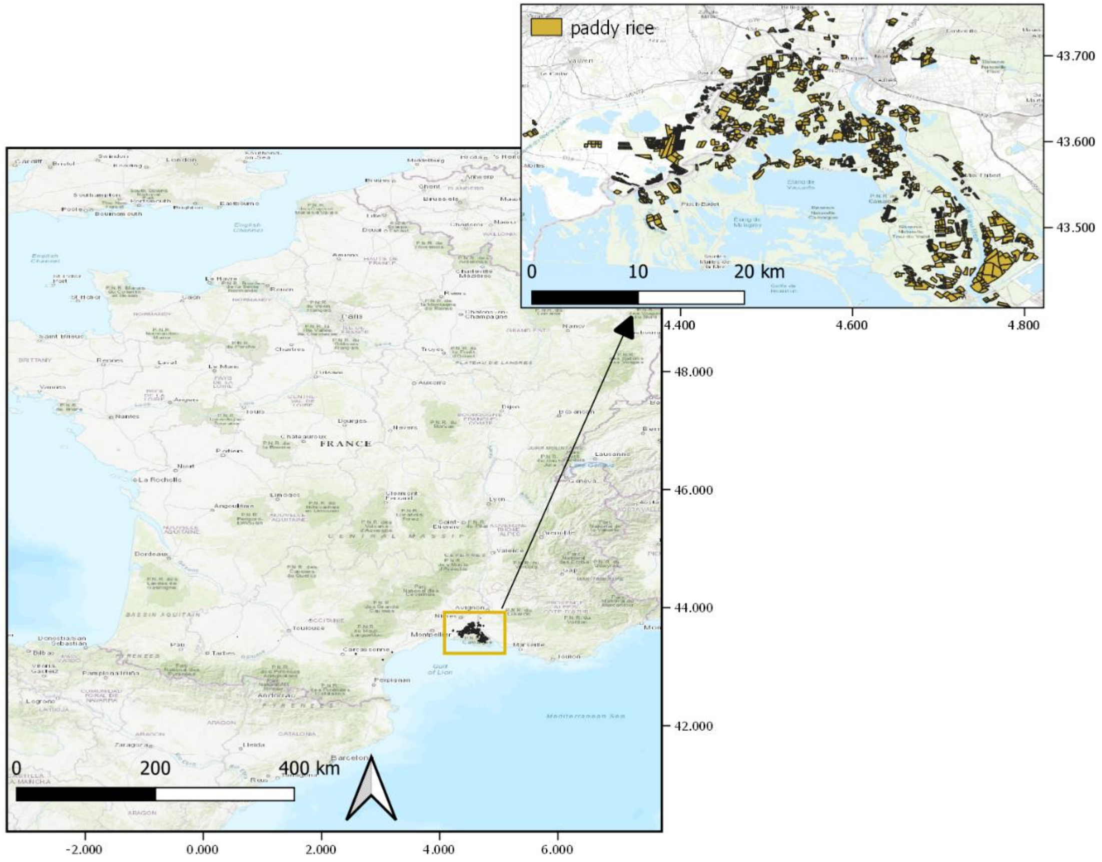
- Approximately **20,600 ha of paddy rice** in the area of Catalonia
- 88 patches (6,312 parcels)



Study Area

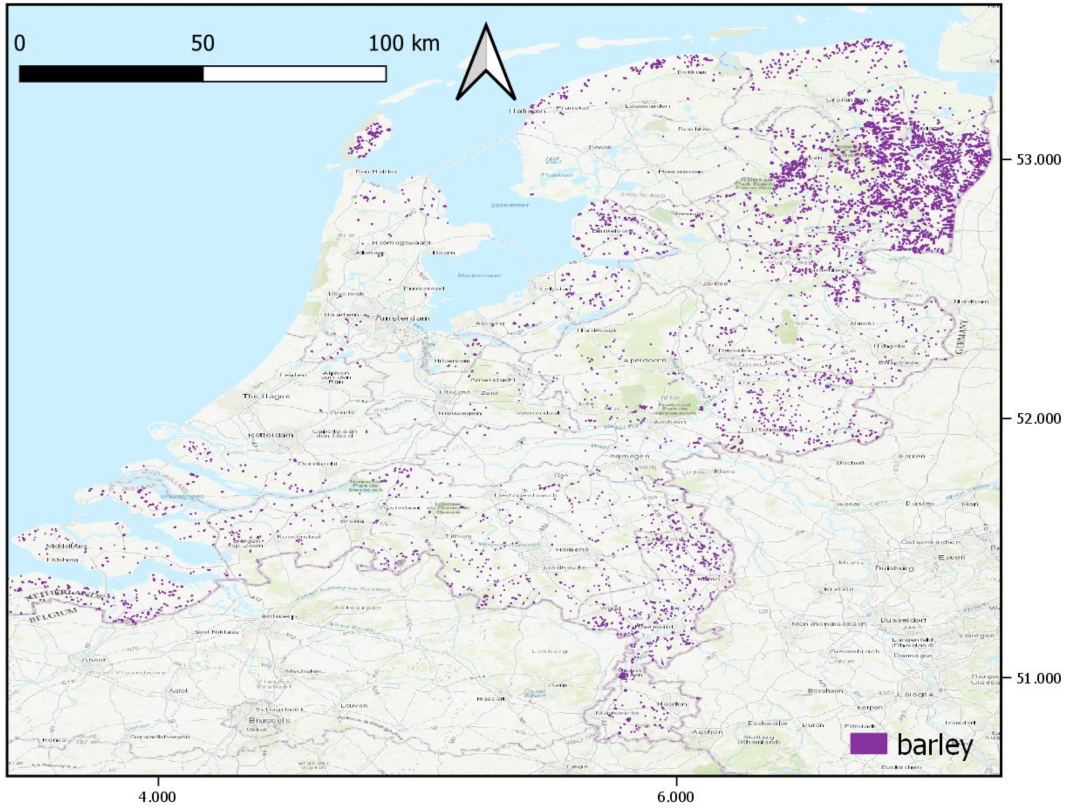
03. France

- Approximately **14,500 ha of paddy rice**
- 134 patches (1,697 parcels)



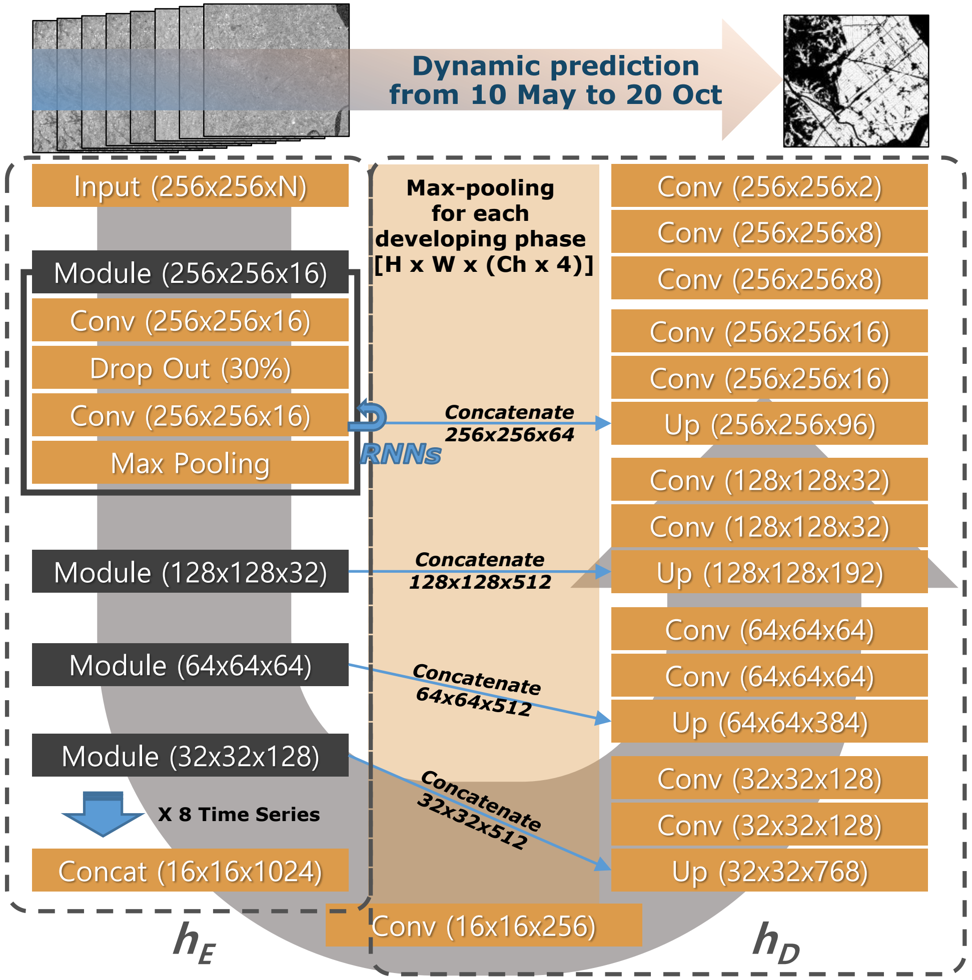
04. The Netherlands

- Approximately **22,545 ha of summer barley**
- 2,280 patches (6,660 parcels)

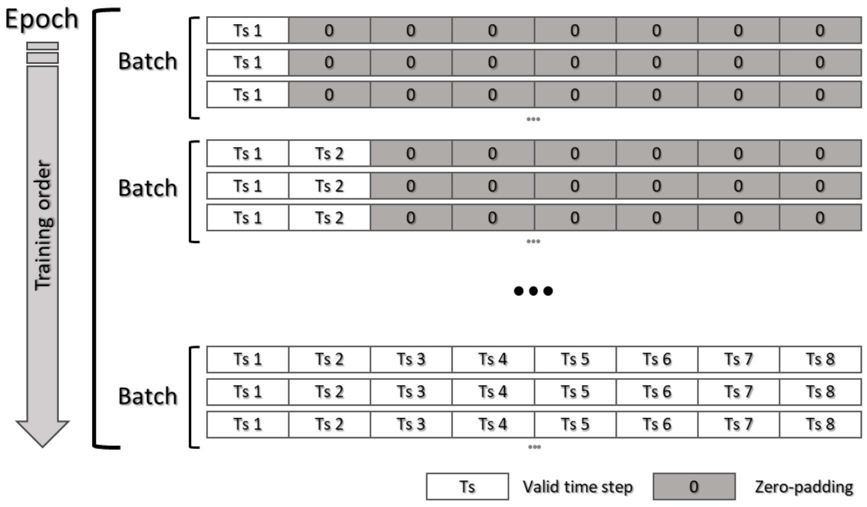


Deep-learning Architecture

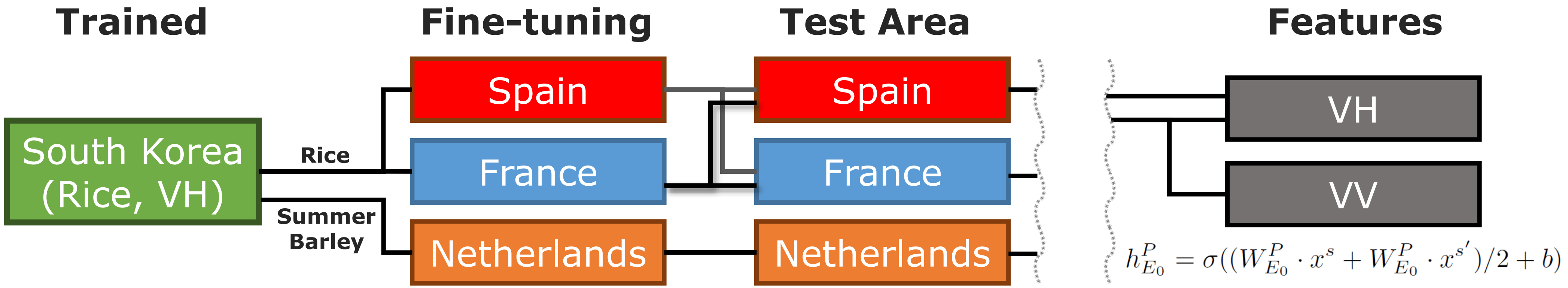
01. Recurrent U-net



- **Recurrent U-Net** architecture for extracting both spatial and temporal features of crop
- Weighted features are added to the next time step in the recurrent modules
- **Chronological batch training**: update parameters gradually, with an additional time step after every new batch type, which is more likely to preserve the knowledge gained from the values of each new time step



Transfer Learning



01. Random Forest as a Baseline (RF)

- Pixel-based
- Locally trained and fine-tuned models in each area

02. Random Initialization (RI)

- $RI = f(h_E \cdot h_D)$
- Transfer only the architecture
- Randomly initialize weights

03. Fine Tuning All Layers (FT)

- $FT = f(h^P_E \cdot h^P_D)$
- Initialize with the pre-trained weights (W^P)
- Fine-tune the entire weights

04. Fine Tuning Encoder (FT_E)

- $FT = f(h^P_E) \cdot h^P_D$
- Initialize with the pre-trained weights (W^P)
- Freeze the decoder part (h_D) and Fine-tune only the encoder part (h_E)

Results

Intersection over Union (IoU)

Fine-tuning	Spain				France				The Netherlands	
Test	Spain		France		France		Spain		The Netherlands	
Feature	VH	VH|VV	VH	VH|VV	VH	VH|VV	VH	VH|VV	VH	VH|VV
RF	0.87	**0.90**	**0.63**	**0.66**	0.76	0.84	0.77	0.78	0.26	0.40
RI	0.86	0.69	0.52	0.36	0.76	0.74	0.70	0.73	0.31	0
FT	0.89	**0.90**	0.57	0.63	0.82	0.83	**0.82**	0.83	0.40	0.45
FT_E	**0.90**	**0.90**	**0.63**	**0.66**	**0.86**	**0.86**	0.79	**0.84**	**0.42**	**0.54**

- RI: Poor performance in most cases, especially when using both VV|VH features.
- FT & FT_E: Works very well for paddy rice mapping. Fine-tuning and testing in the same area performed better.
- RF: Works also very well, especially when fine-tuned in Spain.
- Transferring the paddy rice model to predict summer barley yields promising results

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- Significant drop in IoU from Spain to France

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Visual Maps

Spain

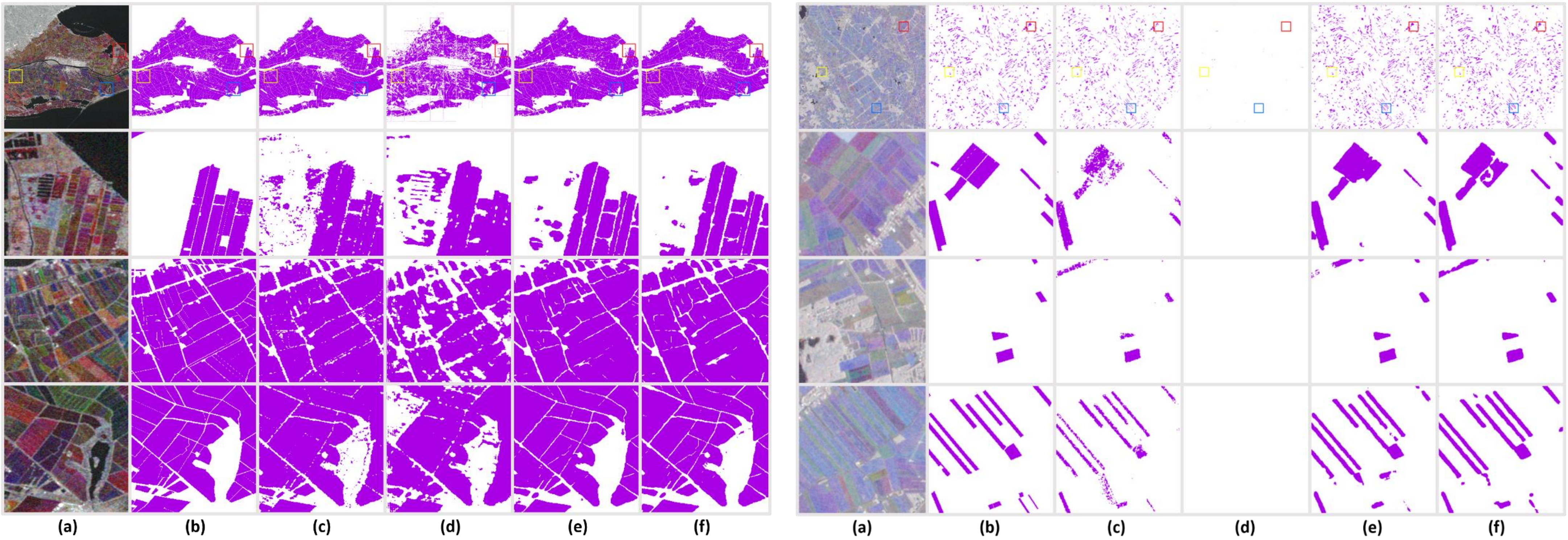
The Netherlands

Entire area

Site 1

Site 2

Site 3



(a) Composited of the first three Sentinel-1 VH images (b) Ground truth labels
(c) RF predictions (d) RI predictions (e) FT predictions (f) FT predictions

Conclusion

- TL for paddy rice mapping yielded excellent results and fine-tuning the encoder works slightly better.
- TL for barley in the Netherlands exhibits promising results and significantly outperforms the RF baseline model.
- Additional input (i.e. VV backscatter) can enhance the predictive performance of TL

Thank you!

National Research Foundation of Korea

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