Leibniz Centre for Agricultural Landscape Research (ZALF)

Developing a deep-learning standard for smallholder farm yield prediction

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Artificial Intelligence for Smart Agriculture
We offer AI-powered Nature-based Solutions

The Global Sustainability Challenges

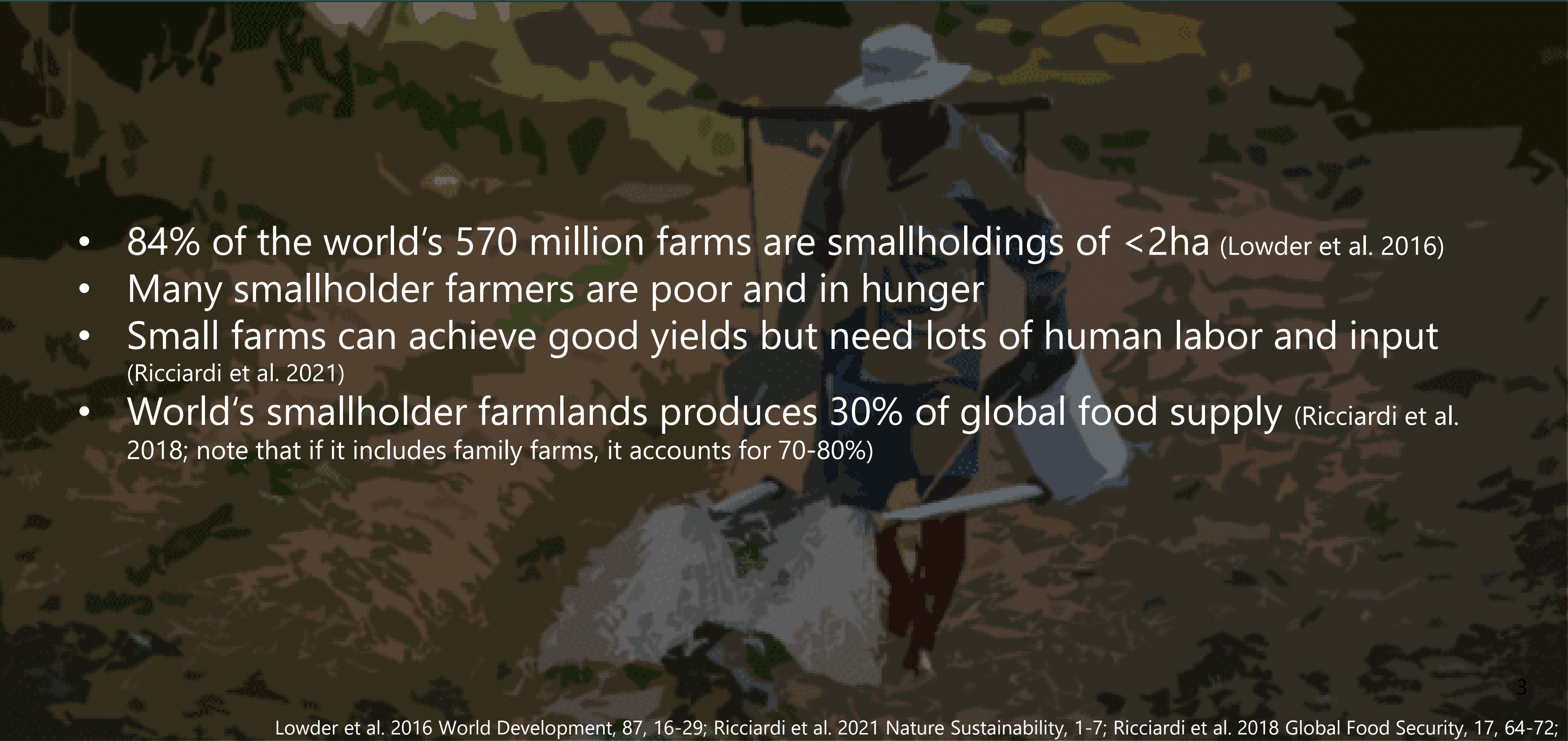
Improving agriculture & nature conservation is key!

SUSTAINABLE DEVELOPMENT GOALS

How food connects all the SDGs

Johan Rockström and Pavan Sukhdev present new way of viewing the Sustainable Development Goals and how they are all linked to food

Smallholder farmlands



- 84% of the world's 570 million farms are smallholdings of <2ha (Lowder et al. 2016)
- Many smallholder farmers are poor and in hunger
- Small farms can achieve good yields but need lots of human labor and input (Ricciardi et al. 2021)
- World's smallholder farmlands produces 30% of global food supply (Ricciardi et al. 2018; note that if it includes family farms, it accounts for 70-80%)

Lowder et al. 2016 World Development, 87, 16-29; Ricciardi et al. 2021 Nature Sustainability, 1-7; Ricciardi et al. 2018 Global Food Security, 17, 64-72;

Research objective

To develop a standardized framework for making deep learning prediction more reliable and applicable for smallholder farming

To capture an overview of potential technical challenges for deep learning implementation for smallholder yield prediction

→ *Small data with autocorrelation, explainability, and context-dependence*

Deep learning implementation flow

Data collection	Small data, observation bias and error
Data processing	Few response data/label
Deep learning model training	Sensitive to a change in data & strategy
Model evaluation	Overoptimistic report & black-box
Farmers' feedback	Lack of trust; not seeing benefit
App development & application	Low accuracy in new sites

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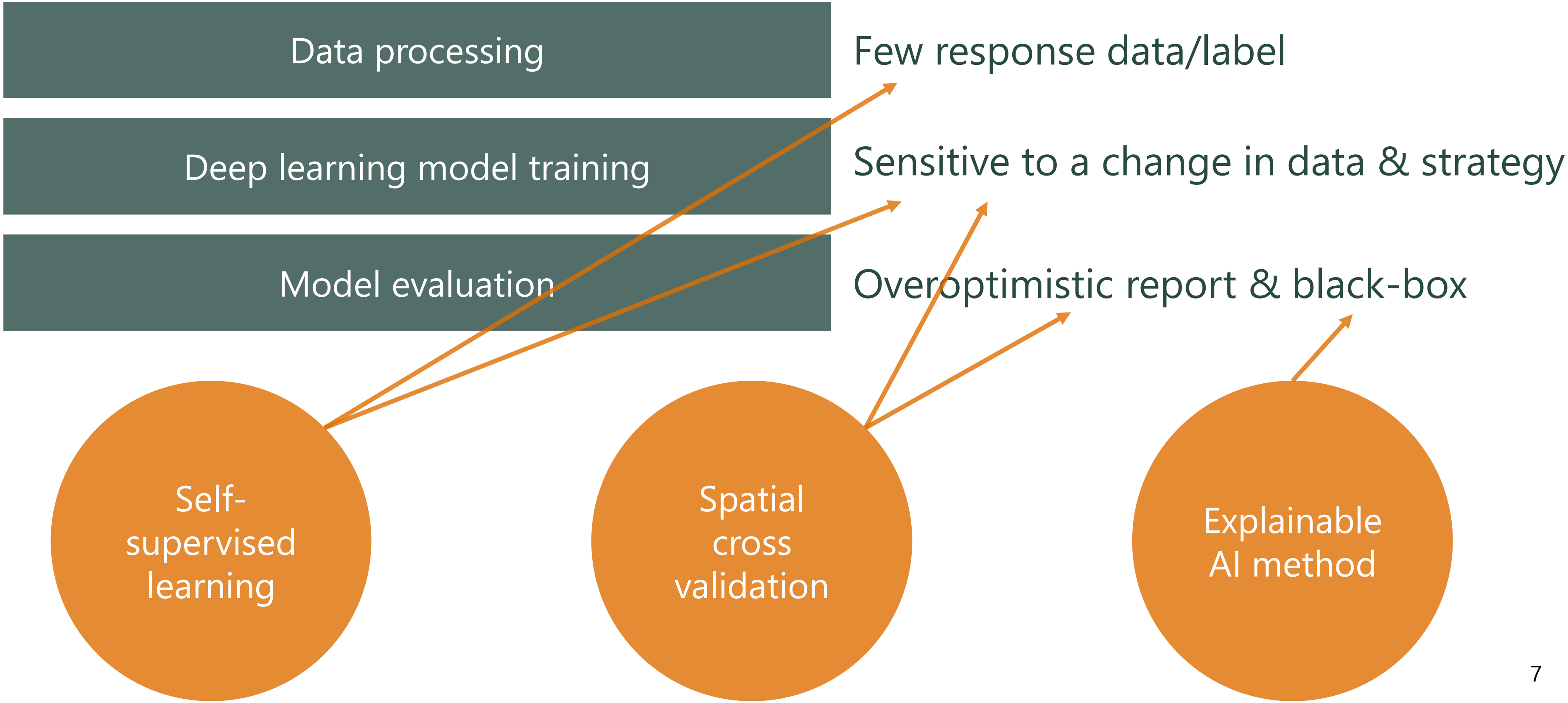
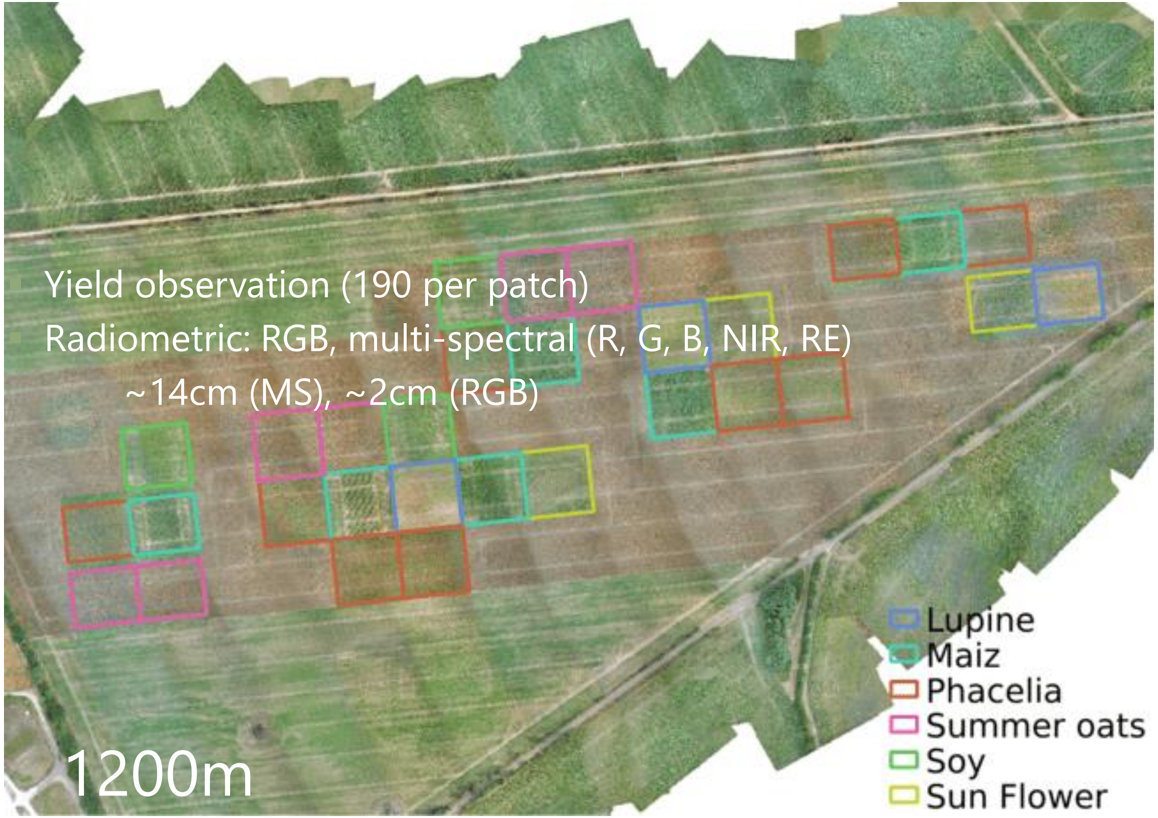
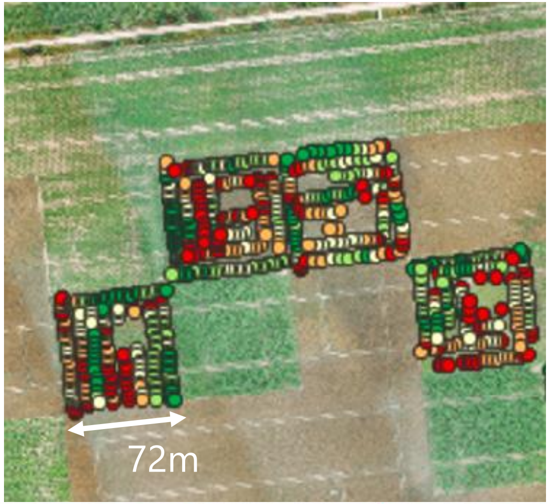


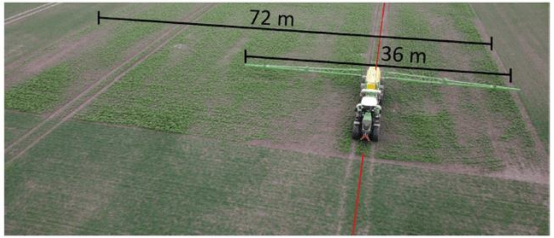
Target fields

Case study 1: Within-field yield variability

- Yield observation (190 per patch)
- Radiometric: RGB, multi-spectral (R, G, B, NIR, RE)
  ~14cm (MS), ~2cm (RGB)



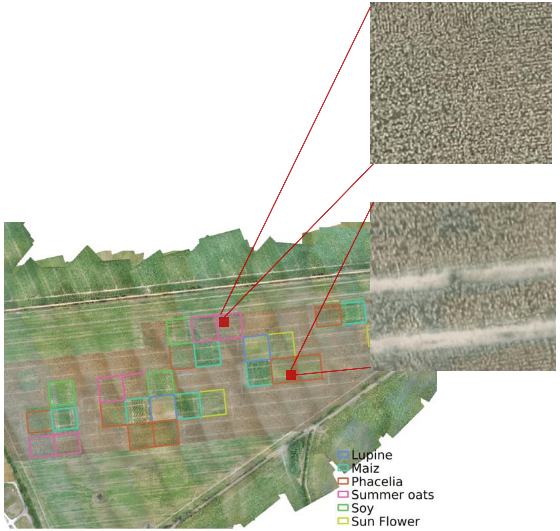


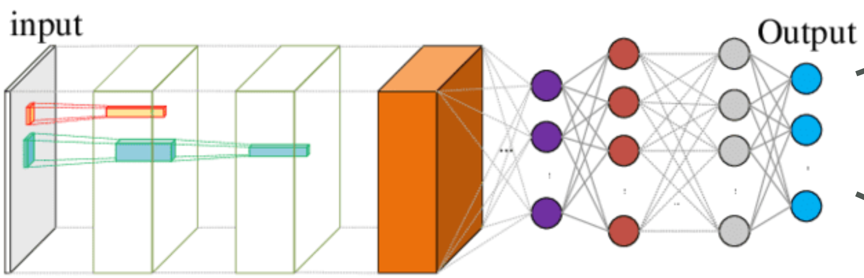


PatchCROP *(Grahmann et al. 2021)*

Deep Learning
(black-box model)

Input **Deep Learning** **Prediction**





10 dt/ha

4 dt/ha

Crop yield [dt/ha] regressed using Convolutional Neural Network (*LeCun et al. 1999*) with 6 convolutional layers with 5 fully connected layers; pytorch library

Modeling strategy

Comparing multiple modeling strategies:

1) Learning from the data (baseline)
2) Fine-tuning a pre-trained model: Transfer learning with a big dataset
3) Fine-tuning a pre-trained model: Self-supervised learning

Our hypothesis: #3 > #1 > #2
→ "transfer learning" from a big dataset is not a clever solution

Modeling strategy: Transfer learning with a large generic dataset

14M images; 21000+ classes (ResNet50)

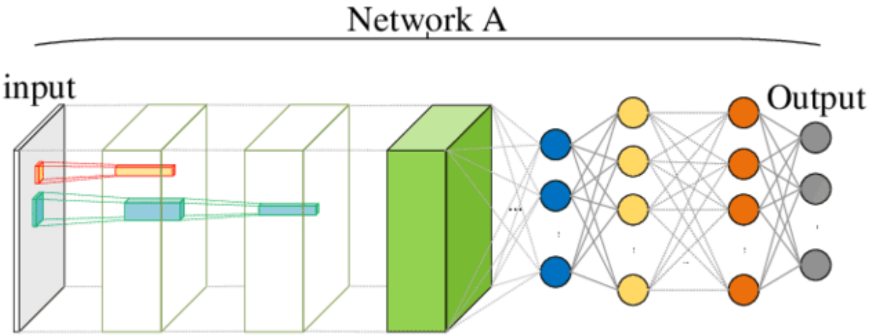
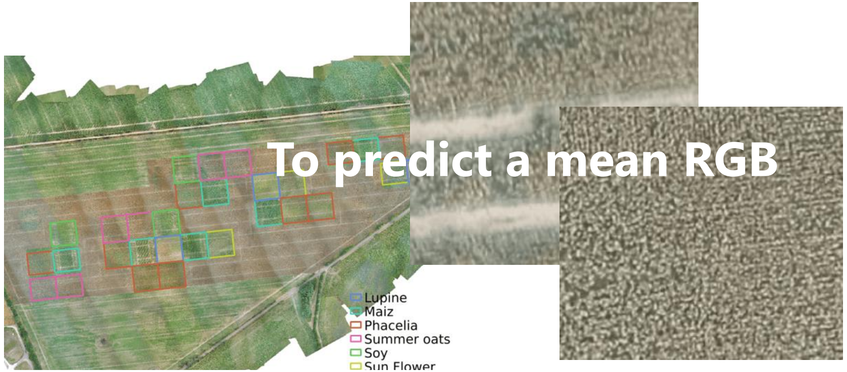


Image modified from Lemley et al. 2017

Modeling strategy: Transfer learning with the same dataset



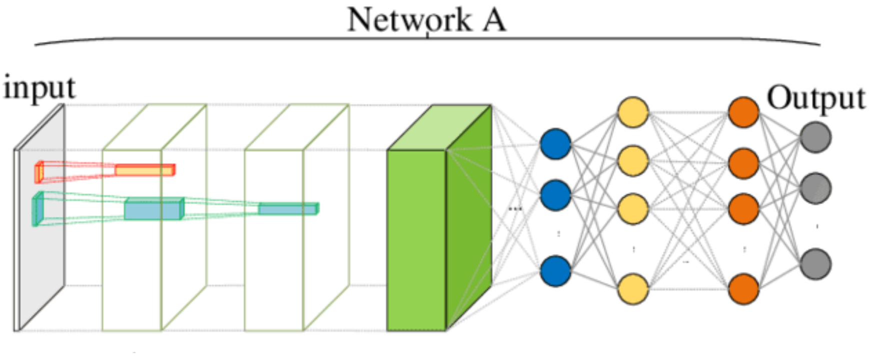


Image modified from Lemley et al. 2017

Validation strategy

Comparing two validation strategies:

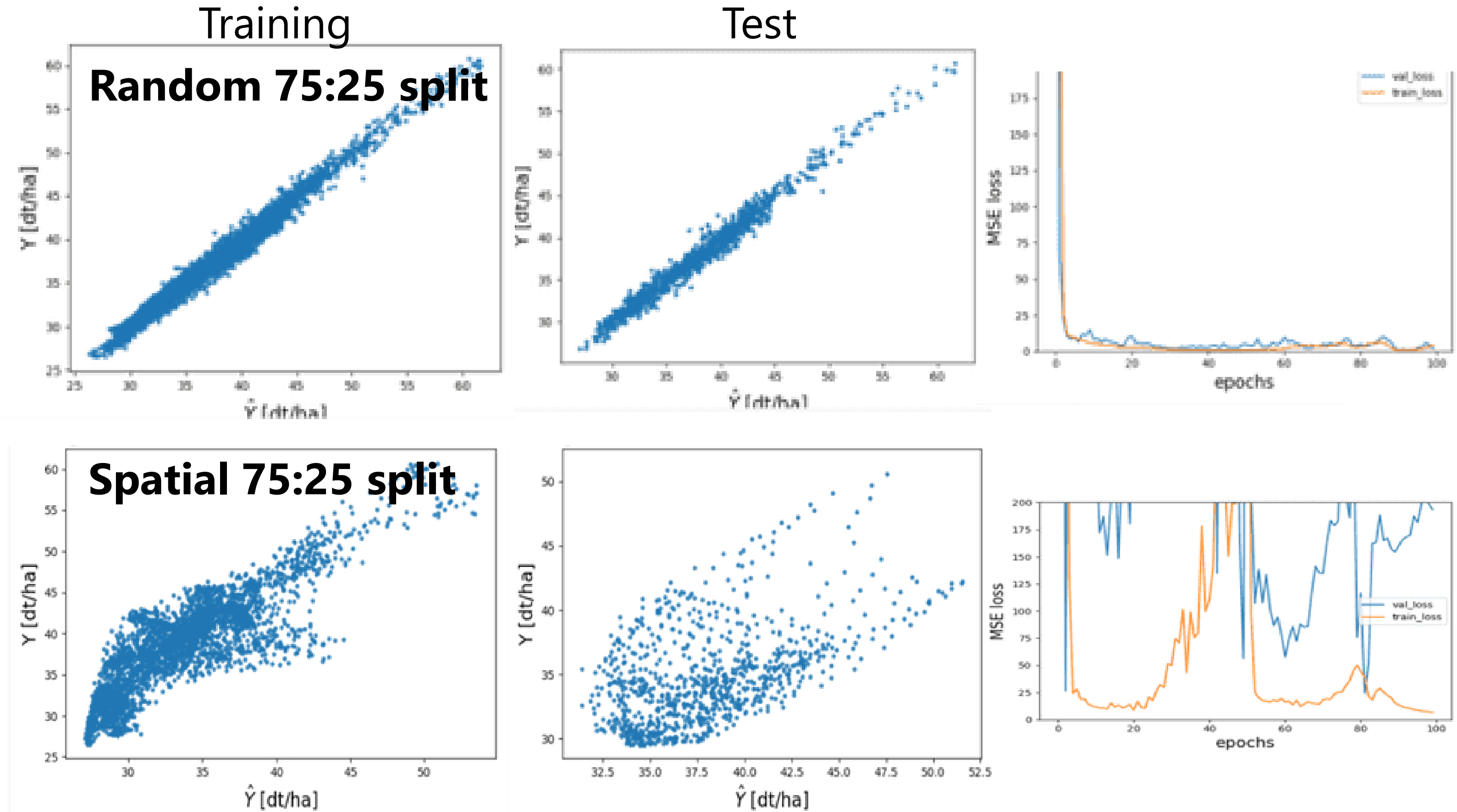
1) Random 75:25 split cross validation
2) Spatially structured 75:25 split cross validation

Our hypothesis: #2 is more honest, although #1 is often employed
→ Spatial autocorrelation in the data is quite overlooked in DL applications

Spatial cross validation vs random sampling

https://towardsdatascience.com/spatial-cross-validation-using-scikit-learn-74cb8ffe0ab9

Validation method comparison



Target fields

Yield estimate with object detection

YOLO: Object detection algorithm for explainability

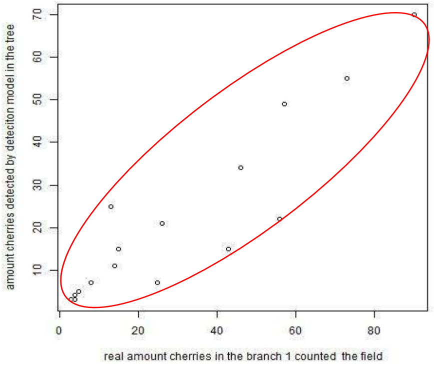
C_2 C_4

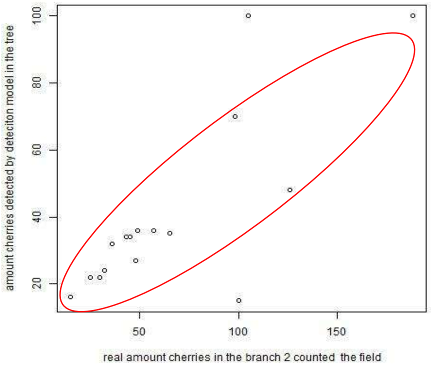
C_1 C_3

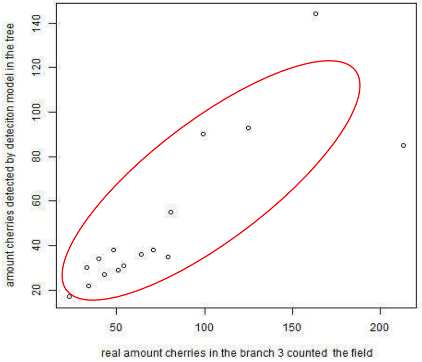
Model Detection

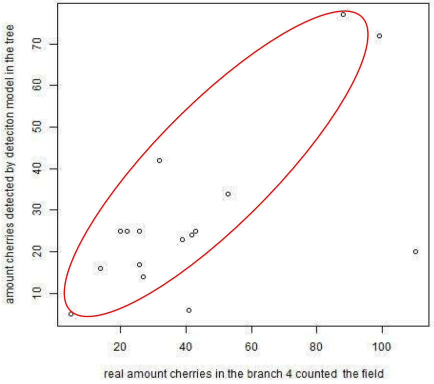
Redmon et al. 2016 You Only Look Once *https://arxiv.org/abs/1506.02640*

Yield prediction





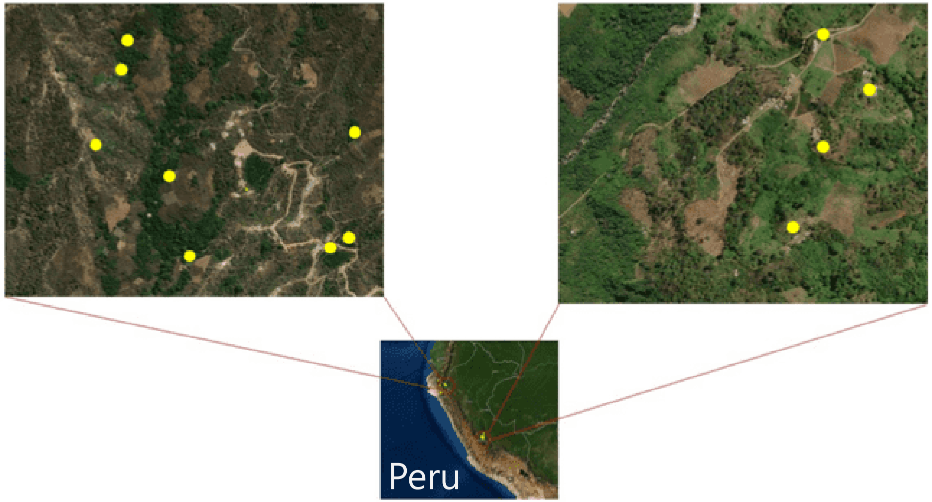




Yield estimate with object detection

Can the model performance
Improve by considering…

1) The local soil condition
2) The surrounding landscape
3) The climate condition



Take-home message

A standardized framework is needed for making deep learning prediction truly applicable for smallholder farmers

- self-supervised learning, autocorrelation data by employing spatial cross validation method,
- multi-scale influence by combining remote sensing and mobile phone-taken images
- increasing explainability by employing explainable artificial intelligence (XAI) methods.

Data collection (timing, distribution etc.)

Data processing (labelling, curating etc.)

Deep learning model training

Model evaluation (validation & test)

Farmers’ feedback

App development & application

Thank you for your attention.

Leibniz Centre for
Agricultural Landscape Research
(ZALF)

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