



Making optimal use of limited field-scale data for crop yield forecasting using transfer learning and Sentinel-1 and 2 data

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ABSTRACT

Climate change increasingly threatens global agriculture, necessitating optimised resource management to ensure food security for an increasing population. Field-scale crop yield forecasts, using machine learning and Earth observation data, have great potential for adaptive farm management, but the development of such models is limited by the scarcity of field-scale training data. We evaluated a transfer learning (TL) approach, which entailed training and testing the model on different spatial domains, using artificial neural networks based on Sentinel-1 and 2 data to forecast crop yields in Austria and Czechia. We compared four model setups: training and testing both at the field scale (i), both at the regional scale (ii), TL with training on a regional scale and testing on a field scale with (iii) and without fine-tuning (iv). We calculated forecasts at four lead times (1–4 months) before harvest. The fine-tuned model demonstrated superior performance, achieving median R^2 of 0.52–0.69 at a one-month lead time for all crops while outperforming the model trained and applied at field scale by 0.05–0.12. TL required significantly less field-level data to achieve a performance comparable to the model trained only at the field level: 50% of the data for spring barley and maize, and only 25% for winter wheat. The model showed limitations in the leave-1-year-out cross-validation due to large differences between the years in the predictors and yields and the low number of years (6) available for training. Still, TL improved the efficiency of crop yield data utilisation and the performance of field-level forecasts.

1. Introduction

Population growth and the increasing frequency and intensity of extreme weather caused by climate change pose a key challenge in ensuring food security [78,41]. This requires immediate action, as envisaged by the Sustainable Development Goals of the United Nations (SDG-2 “End hunger, achieve food security and improved nutrition, and promote sustainable agriculture”) [77] and the European Green Deal “Farm to Fork Strategy” of the European Commission [21]. However, the initially mentioned factors of population growth and climate extremes have caused a deterioration in food security in recent years, which urgently requires further action [48]. Potential actions include improving agricultural productivity, technologies for food accessibility, precision agriculture, and early warning systems [76]. Near-real-time monitoring and forecasting of crop growth is at the heart of many of these: It is a part of precision agriculture [56] and can enhance agricultural productivity by supporting farmers in decisions for farm management practices

[3]. Crop yield forecasts provide key information for decision makers to guide import and export and thus ensure food accessibility [70]. Finally, it can be used to provide early warning of potential crop yield losses [6].

Crop yield forecasts are diverse. They differ in their characteristics (e.g., crop type, lead time, geographical scales), as well as in the models and input data that they are based on. Crop yield forecast systems have been developed, for example, for wheat [27,39], maize [13], barley [18], rice [40], cotton [54], and jujube [2]. Most forecasts have lead times of 1–2 months before harvest [13,27,35,64,69], but some can be up to 4 months before harvest [54,18,23]. Crop yield forecasts have been applied around the world [70] and on various levels: sub-field [64,61], field [49,27], farm [18], and regional scale [9,40]. Such models are usually process-based [2,37,55] or machine learning methods [18,27]. All models need various data sources either to calibrate (process-based) or train (machine learning) the model, and range from in situ [61], over Earth observation [27], meteorological [49], reanalysis data [14], to seasonal weather forecasts [9].

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EO data is a very important input to crop yield forecasting, both for process-based modelling, where they are used to fine-tuning the predictions via data assimilation or model calibration [15], and for machine learning methods, which use the EO data as predictors [13,18,35]. Most importantly, EO is the main source of data providing information on crop development over larger areas which otherwise would require extensive field surveying [52]. In addition to providing near-real-time global data, it is also globally consistent and provides key information, e.g., on crop and soil moisture conditions [25,30,70].

The potential of using EO data for machine learning-based field-scale crop yield forecasting is underlined by numerous studies in this field [13,18,23,27,39,40]. The satellites used can be categorised into solar-reflective, thermal, and microwave sensors. Sentinel-2 [18,39,49,64,73,1] and Landsat 5, 7, and 8 [13,54] are among the most frequently used solar-reflective sensors used for yield forecasting. Some studies use even higher resolution optical data, such as provided by WorldView3, Planetscope [69], and RapidEye [35], or medium-resolution MODIS data [10]. Thermal data is a good indicator of crop stress [17]. Thermal channels on Sentinel-3 [60], MODIS [63,81,65], and Advanced very-high-resolution radiometer [12] have been used for crop yield modelling. Among other microwave sensors, Sentinel-1 [58,27], TerraSAR-X, and Radarsat-2 [23] have been used. Furthermore, also sun-induced fluorescence (SIF) is often used for crop yield modelling and is typically estimated using near-infrared data at wavelengths around 750 nm [26]. Various studies have proven the value of SIF for crop yield modelling [33,86,83,43,88,82]. These studies mainly highlight the capability of SIF outperforming vegetation indices like Enhanced Vegetation and Normalized Difference Vegetation Index [83,88] and also highlight its effectiveness in years of severe drought since SIF is more sensitive to drought than the mentioned vegetation indices [83,43]. The main limitation of SIF products is the low spatial resolution of below 0.05° [86].

The performance of the forecasts in all studies using EO data is highly diverse and ranges between 0.35 [13] and 0.87 [27] explained variance one month before harvest, 0.89 at harvest time [53] and even 0.85 4 months before harvest [43]. However, the results are hardly comparable as they largely depend on the study area and validation technique. For example, forecasts in areas that are water-limited often lead to better forecasting scores than forecasts in areas that do not have one clear limiting factor [70]. Generally, most researchers agree, though, that the limited availability of field-scale crop yield data to train the models is a clear limitation to further improve and widen the use of such forecasts [70,57,40,18].

To overcome the issue of limited crop yield data availability, FAIR (Findable, Accessible, Interoperable, and Reusable) data sharing has become popular [28]. Also communities like AgML (Machine Learning for agricultural modelling) have collected and provided large databases for crop yield data [62]. Yet, for many countries, field-scale crop yield data remains scarce [70]. Regional-scale data is more readily accessible, as many countries collect and distribute this data. These datasets are typically available for longer time periods but usually represent yields only at large aggregation levels, such as counties or entire countries.

Transfer learning has a large potential to exploit the extensive availability of crop yield data on a regional level for field-level applications. Transfer learning is a machine learning approach where a model is trained on a certain domain and applied to another, related domain. These domains can be different geographical areas [47] or different tasks like using the image classification model Imagenet for remote sensing data [24]. In transfer learning, the model is trained on the original domain and retrained with samples of the target domain to adjust the model to this new domain [59]. The model can also be applied to a new domain without fine-tuning. However, this often leads to poorer results [46]. In the field of crop yield modelling, transfer learning has been tested to transfer between crop types [32], between regions [81,44,29,72], and to transfer a genotype model to a crop yield model [38]. The results of these studies are promising. For example, Khaki et al. [32] achieve correlations between forecasted and observed soy-

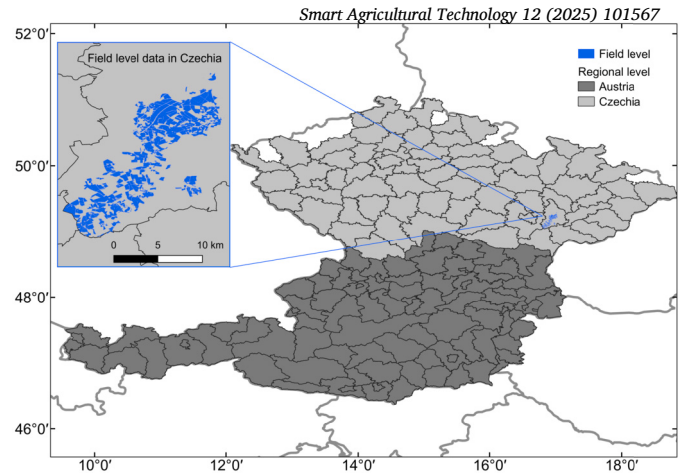


Fig. 1. Available crop yield data on a regional and field level.

bean yields of 0.85 the month before harvest. They use a convolutional neural network in which only the last 4 layers are fine-tuned to maize and soybean (while the first 5 remain set). They also show that the root mean squared error (RMSE) decreases by 1-2 dt/ha compared to machine learning without transfer learning. The spatial transfers work for Huber et al. [29] and Ma et al. [44]. Huber et al. [29] improved the Argentinian crop yield estimation by an R^2 value of 39% by transferring a US trained model to Argentina while also Ma et al. [44] achieved promising results. They used a domain adaption algorithm to transfer a model trained in the US Eastern Temperate Forest to the US Great Plains for maize yield modelling and achieved an R^2 of around 0.75. However, Skobalski et al. [72] found limited improvement of crop yield forecasts using transfer learning. In their study, simply combining the datasets of Argentina and the US worked better than transferring trained models from one to the other region. Finally, Li et al. [38] showed that also models that are not trained on crop yield help to improve performance. They pretrained their model using genotype data and fine-tuned it using crop yield data and achieved increasing accuracies of 1.8 to 39.9% for wheat, maize and rice estimations. Still, transfer learning for crop yield forecasting is in its infancy and applications between different spatial scales are rare. Only one such application is known to the authors, which uses a deep learning framework trained on county-level data and applied to sub-field level with domain adaption to map maize, wheat, and soybean yields in the US [47]. This study showed room for improvement for all three crops with R^2 of 0.48, 0.32, and 0.39 for maize, soybean, and winter wheat, respectively. This is only slightly worse than a model trained on a field scale which requires significantly more labelled training data [47]. In general, these studies indicated some limitations that require further research. (1) Huber et al. [29] state that TL also needs to be tested in other countries with even less data to ensure generalisability - (2) Skobalski et al. [72] used UAV data which hinders a larger-scale application - and (3) Ma et al. [47] achieved remarkable results, but higher R^2 values than 0.32-0.48 need to be achieved to ensure usability of results. Thus, further studies are required to explore the full potential of transfer learning for field-scale crop yield forecasting.

In this study, we addressed these points and tested TL to tackle the problem of scarce field-scale crop yield data, which is the main limitation for field-scale crop yield modelling in most countries. Specifically, we tested this by training a model on a regional scale and transfer it to field scale. For this, we utilised regional-scale data from Austria and the Czech Republic to train our model, which is subsequently tested using field-scale data from a single farm in southern Czechia (Fig. 1). This approach was applied to three primary crops (winter wheat, spring barley, and maize) at four distinct lead times prior to harvest, ranging from 1 to 4 months. Our forecasting model employed artificial neural networks and incorporated backscatter data from Sentinel-1, and spectral vegetation indices from Sentinel-2. We conducted a comparative assessment

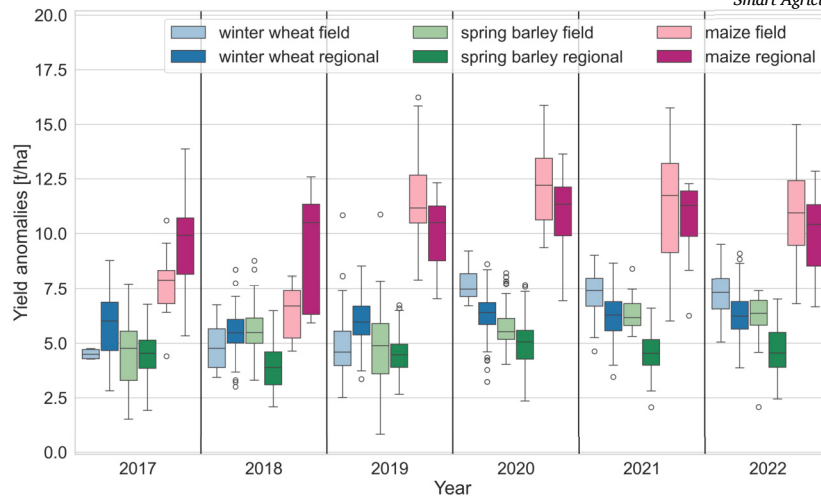


Fig. 2. Distribution of the crop yields per year.

between the transfer-learned forecasts and the crop yield predictions trained exclusively on field-scale data from the same area. This study addressed the critical issue of limited crop yield data availability at the field level.

2. Data and methods

2.1. Study area

The study area is located in Central Europe, specifically Austria and the Czech Republic (Czechia). We used regional-scale data from both these countries and field-scale data from southeastern Czechia (Fig. 1). Both countries are characterised by intensive agricultural land use [71, 7]. In Austria, agricultural activities are predominantly concentrated in the northern and eastern regions, with the remaining areas dominated by mountains and forests [71]. Around a third of the country is used as farmland [22]. In Czechia, around half of the country is used as farmland of which cereal production has the highest output value [22]. In both countries, winter wheat, spring barley, and maize are among the most cultivated crops. Thus, and due to data availability, we focused on these three crop types. The field-scale crop yield data originates from a farm near Brno, Czechia. It consists of 914 fields cultivating various crops. The study area is characterised by a warm temperate climate with hot summers, according to the Köppen-Geiger climate classification [34]. Mean annual precipitation is approximately 600-700 mm in Czechia's lowlands and 500-750 mm in eastern Austria where most agricultural production is located [8,84].

2.2. Crop yield data

We used crop yield data collected at both field and regional level (Fig. 1). Regional-scale data was sourced from the national statistical offices of Austria and Czechia, representing mean annual crop yields in tonnes per hectare cultivated land (t/ha) for each municipality. The dataset encompassed 94 administrative areas in Austria and 66 in Czechia, providing yield information for maize, winter wheat, and spring barley from 2016 to 2022. Field-scale data, directly obtained from farmers through harvesting machine records, covers the same crops across 914 fields within a 20 km × 25 km area from 2017 to 2022. The median field size is 9.4 ha, ranging from 0.03 to 107 ha. Fields smaller than 0.1 ha and very narrow fields were excluded to have sufficient EO pixels within a field. The total number of observations (crop yields per region and year) across crop types and scales is shown in Table 1. Since for most crops and regions we did not have yield data for every year, and maize yield data was in Czechia only available on NUTS3 instead of NUTS4 level, the number of observations was quite different

Table 1

Total observations per crop type and scale.

Crop	Regional	Field
Maize	282	338
Winter wheat	1097	222
Spring barley	747	281

between crops. Crop yields exhibited significant annual variation, typically ranging from 3 to 8 t/ha for winter wheat and spring barley, and 6 to 13 t/ha for maize at both field and regional levels (Fig. 2). The regional and field-scale data were often in a similar range for all crops and years. However, the mean winter wheat yields of field-scale data were consistently outside the interquartile range of regional yields. The same pattern was observed for spring barley in 2018, 2021, and 2022. Additionally, field-scale data exhibited increasing trends for all crops, while mean regional-level yields remained relatively constant over the years. This increasing trend is gradual and consistent for spring barley, but showed stepwise increases for maize (between 2018 and 2019) and winter wheat (between 2019 and 2020).

2.3. Crop mask

For extracting the predictors on the regional level, we used information on crop cultivation locations. We utilised data from the Land Parcel Identification System (LPIS), which classifies agricultural parcels by the cultivated crop type per year. The LPIS data was collected by the respective Ministries of Agriculture or designated agencies [31]. The masks are provided in vector format and are available for all considered years of this study (2017-2022).

2.4. Predictor data

This study exclusively utilised Earth Observation (EO) data as predictors. EO data provides key information about crop growth and the conditions the crops are facing globally, with a high spatial resolution and in near-real-time. Moreover, EO data integrates the effects of other potential predictors, such as meteorology, crop management and disturbances (pests, hail, etc.). In addition, other potential predictors like seasonal weather forecasts, reanalysis, and in-situ data are not available on the high spatial and temporal resolution and spatial extent required for this study. Finally, it is generally advised to have at least ten times as many samples as predictors [89]. Since we had only 282 samples for maize, we should not have more than 28 features. We provided each variable over 4 lead times to the model (see subsection 2.5.1). For

lead time 1 we had already 4 observations (LT1, LT2, LT3, and LT4) per variable. Thus, we could use a maximum of 7 variables (which would provide 7 variables x 4 lead times = 28 predictors) for the model. We decided to use 3 per satellite to give each satellite equal weight.

Multispectral data from platforms such as Landsat 5, 7, and 8, and Sentinel-2 has consistently demonstrated its efficacy in crop yield forecasting [13,54,18,39]. However, relying solely on multispectral data presents challenges due to cloud interference [27] and its inability to directly measure soil moisture, a critical factor in crop development [85]. To address these limitations, we incorporated Sentinel-1 synthetic aperture radar (SAR) data, which provides crucial information on soil moisture [4] and canopy structure [79] and is unaffected by cloud cover. The synergistic use of multispectral and radar data showed remarkable potential in recent studies [27,23,90], offering a more comprehensive view of crop conditions. Our data sources, Sentinel-1 and Sentinel-2 ensure public accessibility and provide a good trade-off between spatial resolution and revisit time for our crop yield data spanning 2016-2022.

2.4.1. Sentinel-1

The Sentinel-1 mission was launched in 2014 by the European Space Agency. The two-satellite constellation provides global observation of C-Band Synthetic Aperture Radar operated at 5.5 cm wavelength [5]. It has a spatial sampling of 10 m and had a global revisit time of 6 days [75] until the failure of Sentinel-1B in December 2021 and of 12 days since [51]. The temporal resolution over Europe is significantly higher providing observations every 1.5 to 4 days until the failure of Sentinel-1B [50]. We pre-processed Sentinel-1 data for the years 2016-2023 using the software SNAP8 [20] and software packages developed at TU Wien as outlined in Wagner et al. [80] and applied in Reuß et al. [67]. The processing workflow consisted of the following steps:

1. Apply precise orbit data
2. Border-noise removal
3. Radiometric calibration
4. Radiometric terrain-flattening
5. Range-Doppler terrain correction

For steps 4) and 5) the 30 m Copernicus DEM (Digital Elevation Model) [36] was used. To extract time series on a field level from the pre-processed Sentinel-1 data, several further processing steps were performed to mitigate the impact of the viewing geometry and undesired objects within or near the fields. First, an incidence angle normalisation to 40° was performed, similar to [5]. Afterwards, all pixels below a standard deviation of 5 dB within one year were filtered out as they typically stem from radar shadow pixels or are not crop pixels. Finally, the cross-ratio (CR) was calculated by subtracting VV (vertical-vertical) and VH (vertical-horizontal) polarised backscatter. Hence, the final Sentinel-1 datasets included 3 variables: VV, VH, and CR.

2.4.2. Sentinel-2

The Sentinel-2 mission, launched in 2015 by the European Space Agency, provides optical data across 13 spectral bands from visible and near-infrared to short-wave infrared. Its spatial resolution ranges from 10 to 60 m depending on the band, with a revisit time of 5 days at the equator [16]. We accessed Sentinel-2 Level 2A (atmospherically corrected surface reflectance) data from the Microsoft Planetary Computer, retrieving bands 2, 4, 8, 11, 12, and the scene classification layer. The remaining bands were omitted, as they are not required for calculating the vegetation indices used in this study (see below). We considered all Sentinel-2 scenes from 2016 to 2022 with total cloud cover below 90%. The extracted data underwent two main post-processing steps: cloud masking and adjusting for the new dynamic range shift since January 2022. The cloud masking was done using the Sen2Cor scene classification layer [42], which categorises Sentinel-2 Level 2A images into various classes including clouds, cloud and topographic shadows, and vegetation. Only pixels classified as vegetation, non-vegetated, and wa-

ter were retained for further processing, and all others were masked. Water pixels were included to preserve information on extensively-irrigated fields, following the approach of Zhen et al. [87]. To address the dynamic range shift implemented on 25 January 2022, which resulted in a higher offset in the data, we subtracted an offset of 1000 digital numbers from all observations after this date to maintain consistency with earlier data [19]. Finally, we removed outliers to eliminate unrealistically high or low values that persisted after cloud masking. This was achieved by excluding all values below the 1st quartile - 2*interquartile range or above the 3rd quartile + 2*interquartile range of the values per field.

From the individual bands we calculated three indices to be used in the modelling: Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), and the Normalized Multiband Drought Index (NMDI). We focused on these three indices since these are often used for crop yield forecasting and complemented each other well, using different bands [64]. Further indices could have been used, but we wanted to keep a balance between Sentinel-1 and 2 based predictors. The formulas used for those are:

$$EVI = \frac{2.5 * (B8 - B4)}{(B8 + 6 * B4 - 7.5 * B2) + 1}$$

$$NDWI = \frac{B8 - B12}{B8 + B12}$$

$$NMDI = \frac{B8 - (B11 - B12)}{B8 + (B11 - B12)},$$

where B2 to B12 were the used Sentinel-2 Level 2A bands. I.e., B2 is blue (central wavelength = 490 nm), B4 red (665 nm), B8 is near-infrared (842 nm), B11 and B12 are shortwave infrared (1610 nm and 2190 nm) [42]. Taking these indices instead of the individual bands as predictors facilitated the interpretability of the predictors.

2.4.3. Satellite data preparation

The data preparation of the predictors followed a consistent workflow across all datasets. The datasets derived from Sentinel-1 and Sentinel-2 were accessed from a datacube (Sentinel-1 from EODC.eu and Sentinel-2 from the planetary computer) at their native spatial sampling. The data was extracted and resampled to the field polygons where we had crop data. For each field polygon, time step, and band, we calculated the median of all pixels of which the centre was located within the polygon. This resulted in a multivariate time series for each field (e.g., one per band for Sentinel-2 Level 2A). For the regional-scale datasets, we then calculated the median of all fields of a specific crop per region. The vegetation indices were calculated after this step. As a final step before modelling, the predictors were temporally resampled to monthly observations to reduce errors of individual observations. Starting from approximate harvest dates (20 July for Spring Barley, 25 July for Winter Wheat, and 10 October for Maize) the first lead time (LT1) included the last month before the harvest date. LT2 then included the month before that, and so on until LT4.

2.5. Modelling

2.5.1. Model setup

We considered three crop types: winter wheat, spring barley, and maize. We chose these crops since they are among the most cultivated in the area [9] and consequently provided the most solid data basis. For each crop, we established four monthly forecasts. The first forecast was made approximately 4 months before harvest. For the first forecast, the model used only the observations of the predictors from LT4. Each successive month, new observations of the predictors were added to the model, and the model was retrained. For example, the model run of LT1 incorporated four monthly values (LT4 to LT1) of each predictor. Given the 3 variables from Sentinel-1 and the 3 variables from Sentinel-2 data, this summed up to 24 predictors for the LT1 forecast. Finally, we considered two different spatial scales: regional and field.

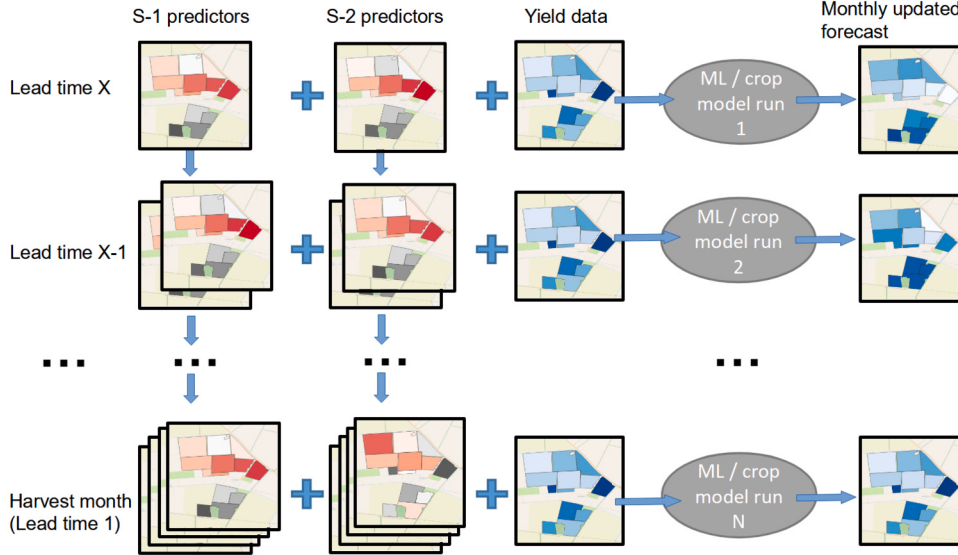


Fig. 3. Model setup of the crop yield forecasting system.

Table 2
Model setups used in this study.

Name	Training	Fine-tuning	Testing
reg2reg	80% regional samples	-	20% regional samples
fld2fld	80% field samples	-	20% field samples
reg2fld	80% regional samples	-	20% field samples
reg2fld_ft	80% regional samples	80% field samples	20% field samples
xgb_fld	80% field samples	-	20% field samples

In this study, we evaluated the potential of transfer learning from regional to field-scale. Hence, we established five model setups (Table 2). The first two approaches were traditional ANN approaches without fine-tuning, used as a baseline to assess the performance of the transfer learning approaches. The last approach was a classical machine learning approach as reference on how well this performs compared to ANNs.

In summary, the reg2reg, fld2fld, and xgb_fld used only training and testing data from one scale, either regional or field scale. Only in the case of reg2fld and reg2fld_ft the two scales were mixed by using regional-scale data for training and field-scale data for fine-tuning (in the case of reg2fld_ft) and testing.

2.5.2. Machine learning

The crop yield forecasts were established using an artificial neural network (ANN) with 2 hidden layers. Each hidden layer had 50 neurons while the input layer had 100 neurons and the output layer only 1. For the fine-tuning of the transfer learning, we only retrained the last layer and left the remaining ones unchanged. In other words, the model was first fully trained to define the weights of all neurons. These weights were then fixed, and during fine-tuning, the model was fitted again to adjust only the weights of the last layer.

The model architecture was obtained by manually testing various setups during hyperparameter tuning. We experimented with different numbers of hidden layers (1-4), nodes per layer (10-100), and number of retrained layers (1-3) for fine-tuning. We tested this on spring barley only, using 60% of the data for training and 20% for validation during hyperparameter tuning. The remaining 20% was reserved for final testing. Since we experienced severe overfitting after initial model training, we added two more parameters: we set the *dropout percentage* to 40% and set the *early stopping patience* to 2. Dropout is an effective method for reducing overfitting by randomly dropping units of the network during training [74]. Similarly, early stopping can be used to increase generalisation by stopping the training after a specified number of epochs where

the model has not improved. In our case, the early stopping patience of 2 means that training stopped if there was no improvement in validation performance for two consecutive epochs [66]. Based on these experiments, we determined that retraining only the last layer during fine-tuning yielded the best results. The final model was trained individually for each lead time (LT) (Fig. 3).

The feature importance of the model was estimated using permutation importance. This technique randomly shuffled single feature values and assessed the degradation of the model after doing so. The permutation importance was assessed in a 30-fold cross-validation to analyse how the feature importance changed in different training runs.

The xgb_fld model was established using Extreme Gradient Boosting (XGB) [11]. This model was chosen to check if classical machine learning models provided better results than ANN approaches given the limited amount of training data.

2.5.3. Model validation

The models were validated using a random 30-fold cross-validation and a leave-one-year-out cross-validation (LIYOCV). We decided to focus on two different validation methods to provide a thorough validation of our results. The LIYOCV provides a realistic estimation of the model performance, as it simulates the conditions of an operational crop yield forecasting system. In such a system, forecasts are made for the current year, for which no yield data is yet available. In our study, the limited number of years available with crop yield data - combined with the high variability in yields between these years (Fig. 2) - presented challenges for training a model effectively in a leave-one-year-out cross-validation setup. In this setup, entire portions of the predictor space could be lost in the training dataset [68]. This is not the case in a random cross-validation where the sampling of the training, fine-tuning, and testing data was done randomly independent of locations and years, yielding more similar test and train spaces. Hence, using a random cross-validation, we could better compare transfer learning to classical machine learning approaches without necessitating a large number of years available for training data.

The different train, fine-tune, and test model setups are described in subsection 2.5.1. An additional validation setup was implemented to compare fld2fld and reg2fld_ft in more detail. This validation setup was chosen to assess how the model performance of the reg2fld_ft and the fld2fld model approaches changed with varying numbers of observations used for training and fine-tuning, respectively. For this analysis, we again randomly selected 20% of the field observations for testing but

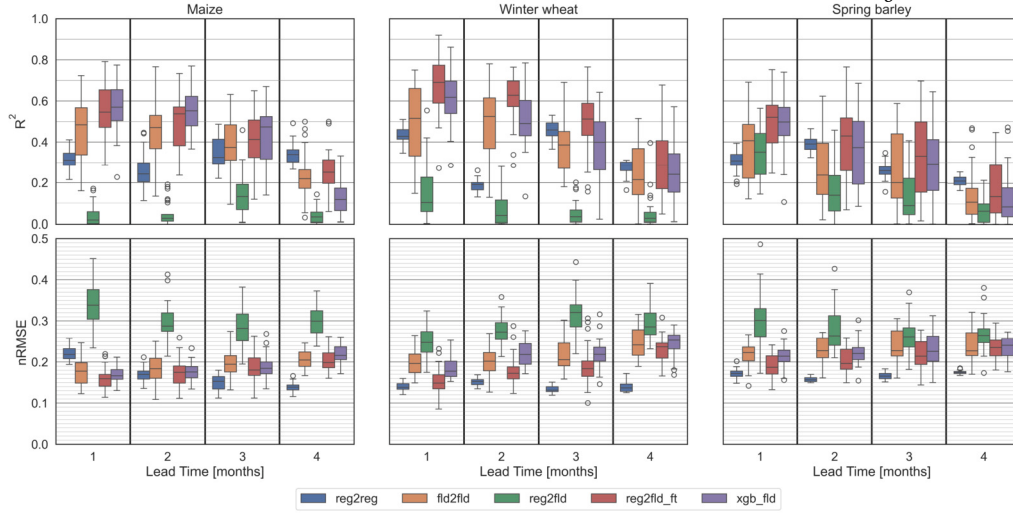


Fig. 4. Validation of forecasts for the five different training and validation setups: (1) reg2reg represents a model trained and tested on the regional level (2) fld2fld represents a model trained and tested on field level (3) reg2fld was trained on regional-scale data and tested on field-scale data (4) reg2fld_ft was trained on a regional-scale, fine-tuned using field-scale data and tested on field data only (5) xgb_fld is like fld2fld but using XGBoost instead of an ANN. All five models were tested using 30-fold random cross-validation. All models except for model 1 (reg2reg) were tested on a field scale.

used only 10-80% of the field data for training or fine-tuning the model. This assessment was also based on a random 30-fold cross-validation.

For the L1YOCV, we tested the model for each year individually while training the models with the remaining years. In the case of the fine-tuning model (reg2fld_ft), we trained the model with all regional scale data except for one year, fine-tuned it with all field-scale data except for data from the same year, and tested it with the field data from that year. As pointed out above, differences in the performance metrics between the random test-train split and the L1YOCV could be caused by different distributions of the training and testing sets in the predictor and the yield datasets. We analysed these differences by comparing the distributions of the predictors and yields in the train and test domain (Fig. 8). For simplicity, only two predictors were analysed, which were EVI and Sig40 CR of LT1.

As validation metrics for the model performance, we used R^2 and nRMSE as defined below. These metrics were chosen for their complementary strengths in assessing model performance, i.e., R^2 provides a measure that is easily comparable between different models, while nRMSE offers an easily interpretable standardised error, indicating the model's accuracy relative to the mean crop yield.

$$R^2 = \left(\frac{\sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2}} \right)^2$$

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}}{\bar{y}},$$

with n being the number of samples, y_i and $\hat{y}_i$ the i -th observed and forecasted value of the dependent variable, and $\bar{y}$ and $\bar{\hat{y}}$ the mean of the observed and forecasted values.

3. Results

3.1. General performance of the models

Fig. 4 shows the performance of the models at the four lead times. The performances of the models varied considerably, with median R^2 (median nRMSE) from 0 (37%) for the reg2fld winter wheat model at LT3 and LT4 to 0.69 (15%) for reg2fld_ft winter wheat at LT1. Generally, the performance increased from LT4 to LT1 for most models

and crops. The two performance metrics showed similar patterns, except for the reg2reg model, which on average had the lowest nRMSE but was often outperformed by fld2fld and reg2fld_ft according to R^2 . Also, the reg2reg model performance had a lower spread than the other models and showed very low variation between the 30 folds of the cross-validation, especially for winter wheat. The fine-tuned model (reg2fld_ft) overall showed best results, with median R^2 (median nRMSE) ranging from 0.41-0.55 (16-18%) for LT3 to LT1 for maize, 0.51-0.69 (15-18%) for winter wheat, and 0.33-0.52 (19-21%) spring barley. Only in the case of maize, a better performance was achieved using XGB for LT1 to LT3.

3.2. Comparison of the training approaches

The performance of the models varied significantly depending on the used training approach (Fig. 4). Training the model only on a regional scale was insufficient for achieving high forecasting performance at the field-scale (reg2fld). This limitation was particularly evident for maize and winter wheat, where this approach showed low R^2 (<0.14) and high nRMSE values ($>25\%$) between forecasted and observed crop yields. Spring barley showed slightly better results for reg2fld, with LT1 performance approaching that of the field-data-trained model (fld2fld). Models incorporating field-level data for training or fine-tuning (fld2fld, reg2fld_ft, xgb_fld) consistently outperformed the reg2fld model across all LTs and crops. Of these three models, reg2fld_ft demonstrated superior performance in all scenarios except for maize LT1 to LT3. Compared to the field level trained models (fld2fld and xgb_fld), reg2fld_ft increased median R^2 (decreased nRMSE) by 0.04-0.11 (1-4 percentage points) for winter wheat, and 0.03-0.07 (0-3 percentage points) for spring barley. The xgb_fld model increased median R^2 by 0.02-0.07 over the other two approaches (fld2fld and reg2fld_ft) with nRMSE being in a similar range. A comparison between the models tested on a field scale and reg2reg was not straightforward since reg2reg showed often lower nRMSE than the other models but also lower R^2 values.

3.3. How much data is required for fine-tuning?

The initial results demonstrated that transfer learning with fine-tuning (reg2fld_ft) outperforms the model trained solely on field data (fld2fld). Therefore, we then investigated how much data was required for fine-tuning to achieve better results than training the model on field-level data alone. This is illustrated in Fig. 5 for the models with LT1. The

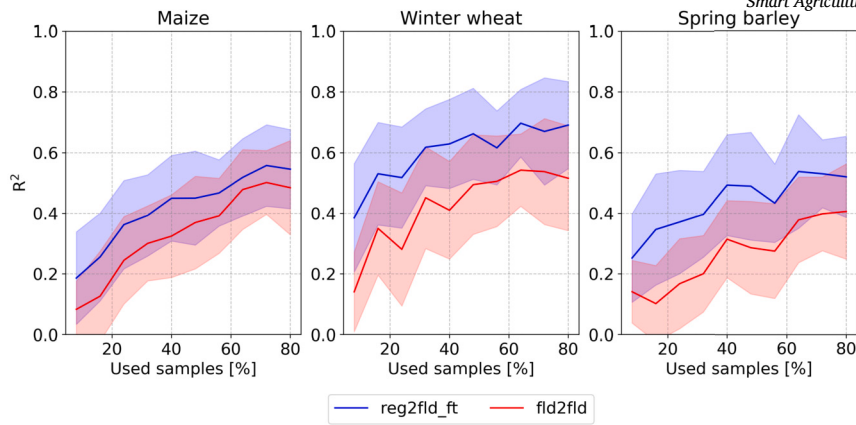


Fig. 5. Validation of the LT1 forecasts comparing the performance of the transfer-learned model vs the model trained on field-scale by using varying amounts of training samples. The errors show the median +/- the standard deviation of the 30-fold cross-validation.

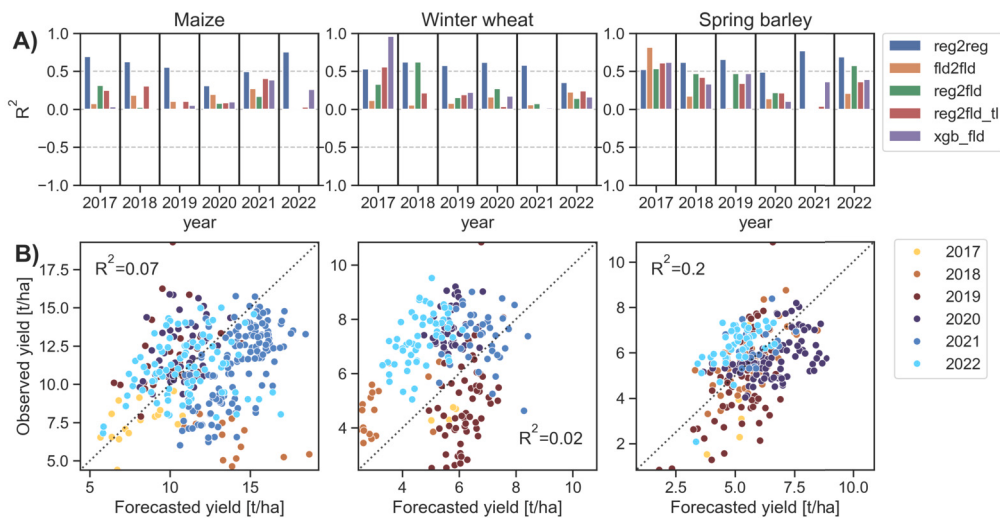


Fig. 6. Leave-one-year-out cross-validation showing R^2 of the LT1 models in A and the scatterplot of the results of reg2fld_ft in B.

models were clearly improving with increasing amounts of field-level training or fine-tuning data. We could also observe that reg2fld_ft consistently outperformed the fld2fld model when using the same amount of field training and fine-tuning data. Conversely, this means that the reg2fld_ft model required much less training data to achieve the same performance as for fld2fld.

For maize, reg2fld_ft required only half the data to obtain the same performance as the field model. For spring barley, it needed around a third, and for winter wheat, the reg2fld_ft model achieved the same R^2 as the field model with just a quarter of the data. Hence, transfer learning significantly reduced the required amount of field-scale data for crop yield forecasting. With only 22 field observations (10% of 222) of winter wheat used for fine-tuning the model, an R^2 of above 0.4 was achieved while 67 observations (30% of 222) led to R^2 above 0.6. For the other two crops, more samples were required to obtain good results. For the maize model, 203 samples (60% of 338) were required for an R^2 above 0.5. For spring barley, 112 samples (40% of 281) were needed to achieve an R^2 above 0.5.

Another point to mention is that the amount of regional level data used for training impacted the performance after fine-tuning as well. The highest performance gain of reg2fld_ft over fld2fld was seen for winter wheat, where we had 1097 regional samples and not much data was required for fine-tuning. Also for spring barley, with 747 regional samples, we had a considerable difference between reg2fld_ft and fld2fld.

Finally, for maize, with only 282 regional samples, the added value of reg2fld_ft over fld2fld was less pronounced.

3.4. Leave-1-year-out cross-validation

The L1YOCV demonstrated reasonable results for the reg2reg model, with R^2 exceeding 0.5 for almost all years and crops (Fig. 6A). For spring barley and maize, R^2 even exceeded 0.6 in numerous years. However, models tested at the field scale did not show satisfactory performance. For maize, all years and field models (fld2fld, reg2fld, and reg2fld_ft) showed R^2 values below 0.55, occasionally approaching 0. Spring barley models showed slightly better performances than winter wheat, which in turn were better than maize. The four field-scale models (fld2fld, reg2fld, and reg2fld_ft, xgb_fld) often showed similarly low performance, with different models performing best for different crop types: fld2fld frequently excelled for maize, reg2fld_ft for winter wheat, and reg2fld for spring barley, and an outlier for xgb_fld for winter wheat in 2017. Examining all data points did not improve the overall impression (Fig. 6B). The model struggled to distinguish the different years effectively. For instance, 2018 showed very low maize yields (<10t/ha) yet the model still forecasted high yields of 10-14 t/ha. Also a spatial visualisation of the 2022 results (Fig. 7) indicated a similar pattern: the range of forecasted and observed yields did not agree well. In addition, the model was not able to clearly differentiate yields of the different fields. In some cases, when there were clearly different yields of two

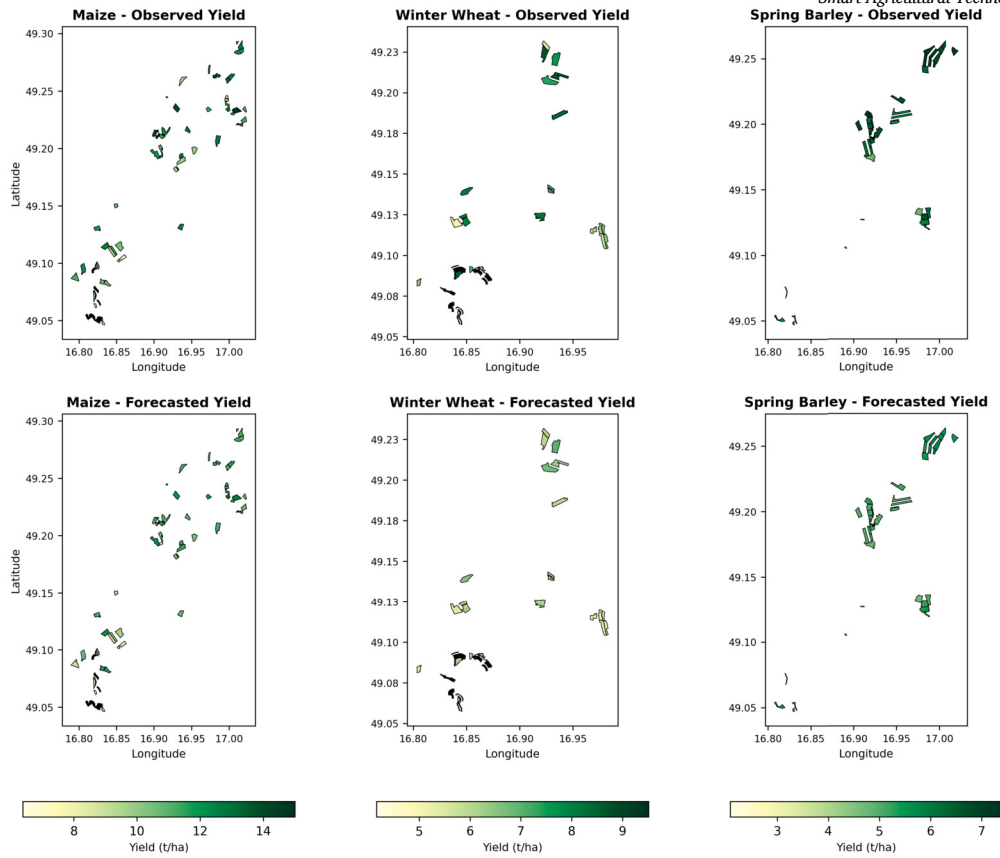


Fig. 7. Spatial comparison of the observed and forecasted yields of reg2fld_ft LT1 in 2022 for the three crops.

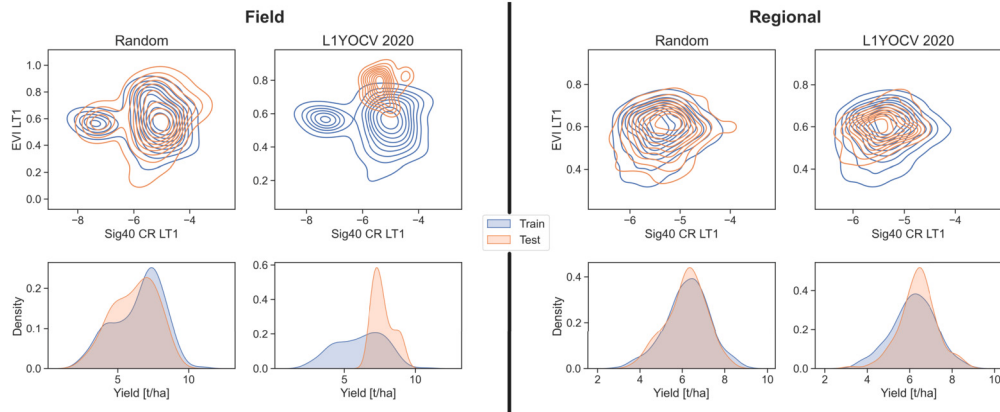


Fig. 8. Distribution of the test and train split for random and L1YOCV for the datasets field and regional for winter wheat at LT1. The predictors and crop yields are shown as the original values before standardisation.

adjacent fields (e.g. the northernmost winter wheat fields in Fig. 7) the model forecasted more or less the same yield for both fields. Also the contrary occurred, when two fields had almost the same observed yields, but the model forecasted clear differences (e.g. the westernmost maize fields in Fig. 7).

We also analysed how the distribution of predictors and yields differed in the test and train dataset of the random split and the L1YOCV (Fig. 8), to analyse if this had an impact on the model performance for the two validation setups. As expected, it showed that the random test-train split led to similar distributions of the two predictors and yields in the train and test domains. In the L1YOCV setup, the regional dataset still showed a similar distribution of the predictors and yield in the train and test data. However, on the field scale, there were significant differences between the yields and the predictors of the train and test data,

with especially EVI LT1 being significantly higher in the test domain. A similar tendency could be seen in Fig. 2. While the distribution of the crop yields were similar between the years for the regional datasets, there were significant differences between the years in the crop yields on a field scale.

3.5. Feature importance

The feature importance analysis showed different aspects of the model: (1) the 30-fold cross-validation of the model showed that the feature importance was for every model training quite different, with other predictors being the most important ones. This could be seen in the large error bars in Fig. 9. However, we could still see some general trends: (2) the 3 Sentinel-2-based predictors (NMDI, NDWI, and EVI)

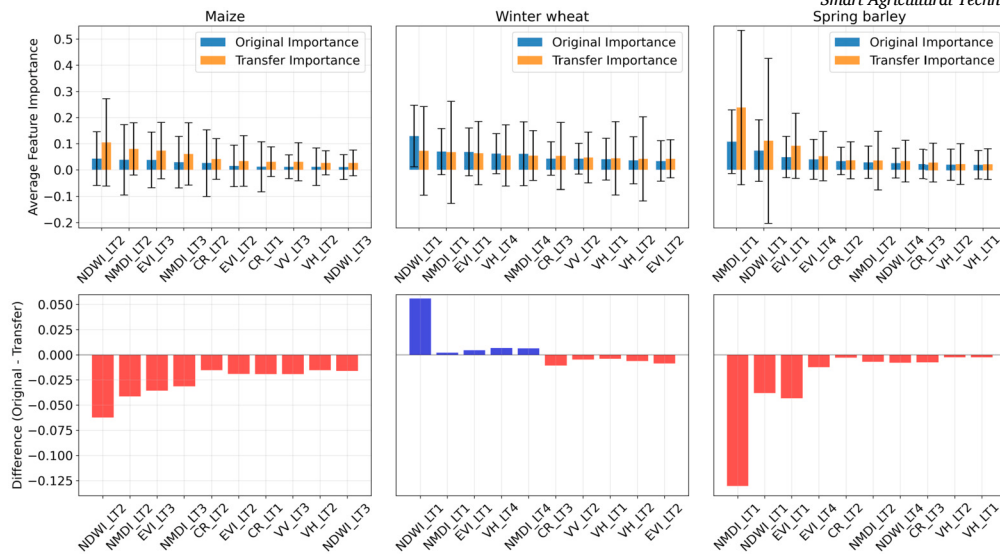


Fig. 9. Feature importance of the forecasting model before and after fine-tuning (reg2fld and reg2fld_ft). The error bars show the standard deviation of the 30-fold cross validation. For simplicity, this plot only shows the 10 most important features.

were more important than the ones from Sentinel-1 (VV, VH, and CR). Still, Sentinel-1 added value, being for all crops the fourth or fifth most important predictor. (3) the Sentinel-2-based predictors from lower lead times had a bigger impact on the model. For maize mainly the ones from LT2 and for winter wheat and spring barley LT1. For Sentinel-1 based predictors this was less obvious: while for maize the most important Sentinel-1-based predictors were CR from LT2 and LT1, for spring barley LT2 and LT3 were the most important and for winter wheat even LT4 of VH was the most important followed by CR of LT3. (4) most of the features had a larger importance after fine-tuning, while the ranking of the features remained similar. For two crops (maize and spring barley), only higher feature importances were observed after fine-tuning of the 10 most important features shown in Fig. 9. Thus, the model specialised more on a smaller amount of features after fine-tuning.

4. Discussion

The reg2reg model had rather lower performance than the other model setups in the random CV considering R^2 (Fig. 4) but clearly outperformed the other models in the L1YOCV (Fig. 6). Looking at the nRMSE this was not the case, but this was mainly related to the higher mean yield of the regional-scale data. The reg2reg model even had a higher R^2 in the L1YOCV setup than in the random CV which is unusual and not the case for the other models. The distribution of the predictors and yields (Fig. 8) did not provide a clear explanation why this was the case. The train and test space overlapped slightly better for the 2020 L1YOCV setup for winter wheat, but not to an extent that would explain the much worse performance of the random CV.

Transfer learning showed promising results. The reg2fld_ft model outperformed fld2fld for all crops and LTs and also XGB for winter wheat and spring barley (Fig. 4). Hence, the model appeared to learn substantially from regional-scale data when sufficiently fine-tuned. This use of transfer learning provides useful crop yield forecasts at the field level and can significantly reduce the required amount of field-level data (Fig. 5). The better performance of TL over field-trained models showed the advantage of TL: it learned key relationships between predictors and crop yields at a regional level. E.g., which EVI and backscatter values were beneficial for crop growth at which stages. Since these key relationships were already learned by the model, the fine-tuning only needed to make sure to adapt to local conditions, while the field-trained model first needed to learn all these relationships from scratch. This efficient use of field-scale crop yield data opens new opportunities to enhance

field-level crop yield forecasting without intensive field-level data collection. Considering the vast amount of regional-scale crop yield data available in Europe and the US (<https://cybench.agml.org/>), there is enormous potential. We showed that using a larger amount of regional-level data for training also improved the performance gain of reg2fld_ft over fld2fld and xgb_fld. Hence, a sufficiently well pretrained model can make much use of limited field-scale data with transfer learning. While this study used only pretraining data from two countries (Austria and Czechia), it is likely that incorporating other countries for training for a larger diversity and potentially other predictor datasets, such as ERA5-Land or seasonal weather forecasts, will further improve crop yield forecasts.

The training and target domain in this study - i.e. regional- and field-scale data of this study - may seem closely related, since they were from the same geographical area. Especially compared to other studies, where TL was used to transfer crop yield estimations to different continents [72,29]. However, we showed that the two domains were still quite different since a direct application of regional trained models was not possible (reg2fld in Fig. 4). This can be explained by the complex topography of the study area. This leads to very diverse climatic conditions and management practices over the regional-scale data. I.e., agriculture in mountainous areas is different from the lowlands. This leads to heterogeneous field data which is in strong contrast to agriculture in other areas such as the US with its large-scale and rather homogeneous fields. This heterogeneity and complex field-structure was also evident in the field-scale data of this study and its complex field shapes (Fig. 7). Hence, the diversity of fields in the training domain may have led to not having sufficient data that is closely related to the target domain for a direct application without fine-tuning.

On the downside, regional-scale crop yield data alone was insufficient to train the model. Crop classification maps were also required, which can be more challenging to obtain. Additionally, in countries outside Europe and the US, where even regional data is scarce, the transfer learning approach offers limited benefits. To address this, it would be valuable to explore the geographical limits of transfer learning. Thus, more research on intercontinental transferability of crop yield models is required.

Another, more significant limitation was shown in Fig. 6. The models struggled to clearly distinguish crop yields of different fields within individual years and all field-scale models had low R^2 values. The fact that for each year and crop another field-model was performing best showed that no model was able to clearly differentiate the fields. It was rather by coincidence that a certain model reached acceptable R^2 val-

ues for some years (e.g. xgb_fld winter wheat 2017, reg2fld winter wheat 2018 and all models for spring barley 2017) since the mean R^2 over all years was low for all of them. This limitation is problematic if we intend to use a model developed from past observations as an advisory tool for the current year. For example, if farmers do not receive information on expected lower yields, they cannot adjust their management practices based on this forecast. The low performance in the L1YOCV could be partially explained by the distributions of crop yields across different years (Fig. 2). The field-level data distribution presented several challenges for accurate forecasting: (1) field-level maize and winter wheat yields both showed two clusters: in the initial years (2017 and 2018 for maize, 2017–2019 for winter wheat), yields were significantly lower than in subsequent years; (2) For maize, even the first two years differed markedly from each other, making prediction difficult due to insufficient data in that value range for the model to learn from. The last four years (three years for winter wheat) had at least a similar yield value range. However, even within this range, the L1YOCV did not show satisfying results. (3) Finally, there was also a linear trend in the spring barley field-scale data. All these issues were much less pronounced in the regional-scale dataset, which exhibited more uniform distributions over different years without notable trends or significant interannual changes in the variability. At this coarse spatial scale, possible large inter-annual variability for individual fields was likely dampened when computing yield ensembles over many fields. Consequently, the reg2reg model demonstrated a much higher performance for the L1YOCV than the models tested at the field-scale. In addition to the yield values, also the predictors (i.e. EVI and Sig40 CR at LT1) were significantly different between the train and the test dataset (Fig. 8). This hindered the model's ability to generalise well enough into predictor spaces that it had not been trained on [68]. These reasons make it hard for any model to generalise well. Thus, we expect that only major improvements of L1YOCV model performance can be achieved by having more years available with crop yield data to include a wider range of yield and predictor data in training. It would need to be tested again whether it is sufficient to have this data only on regional level, or if it is required for the fine-tuning step too. The assumption that more years of data will help is based on the observation that the impact of the differences in the annual crop yields and predictors on a field level on model performance was considerably smaller for a random test-train split, as the training and testing data were in a similar value range. Another approach to address this challenge could again involve transfer learning. In an operational system, the model would be trained solely on data from previous years. This model could then be fine-tuned in-season by incorporating expert-based forecasts of crop yields for individual fields. For instance, farmers could provide estimates of expected yields for some fields, which could be fed into the model, potentially improving the performance of the forecasts.

Overall, the results presented here align with previous studies on transfer learning for crop yield modelling. Khaki et al. [32] demonstrated that maize and soybean forecasts can utilise the same weights for 5 of 9 hidden layers in their convolutional neural network. They achieved correlations between forecasted and observed crop yields of 0.80 for maize with a lead time of four months and 0.88 for one month before harvest, and 0.71 (LT4) to 0.83 (LT1) for soybean, respectively. These correlations are slightly higher than our model, likely due to their use of many more samples for training (approximately 1000 counties over 15 years), but also the different environmental and geographical conditions played a role. Wang et al. [81] showed that combining datasets from Argentina and Brazil with transfer learning improved the median R^2 by 0.1 at LT1 compared to a model trained only with data from Brazil. Similarly, Ma et al. [45] demonstrated that using domain adaptation enhanced prediction performance when testing the model in a different ecological zone than the one it was trained for. They achieved an R^2 of 0.76 at LT1 in two different regions in the US, which was approximately 0.08 higher than the models they used without domain adjustments. All three of these studies utilised mainly reflectance and land surface temperature imagery from MODIS as predictors. In addition,

we addressed the three limitations stated in the introduction and increased generalisability of successful TL implementation stated by Huber et al. [29] by only using globally available Earth observation data. Finally, we also achieved some performance gain over the most closely related study by Ma et al. [47], although, a comparison of the studies is hardly possible due to the very different agricultural and climatic conditions and validation setups. They use Landsat and Gridmet data along with Quantile loss Domain Adversarial Neural Networks to map subfield level crop yields based on regional-scale models. They achieved nRMSE of 20% for maize and 34% for winter wheat at LT1, which is lower than our results (16% for maize and winter wheat). In general, all studies proved the large potential of transfer learning for crop yield modelling.

5. Conclusion

Crop yield forecasting is a crucial tool for ensuring food security in a changing climate. Machine learning and remote sensing offer flexible approaches to provide such forecasts. However, machine learning tools require substantial training data, which is challenging to gather, especially at the field scale. In this study, we demonstrated how transfer learning can address this issue. By training a model at the regional scale and fine-tuning it at the field scale, we shifted the problem of obtaining sufficient data from the field to the regional level, where data is typically more accessible. Using this approach, we showed that transfer learning better dealt with limited data as long as the model is sufficiently pretrained. In that case, it outperformed classical machine learning and ANNs for field-scale crop yield forecasting. This confirmed findings of other studies that TL is a key tool to tackle data scarcity. In addition, we showed for the first time how well this works for field-scale crop yield forecasting in a highly complex region with small-scale farms and training data from topographically complex regions.

This methodology opens up possibilities for improving crop yield forecasting across scales. Further research is needed to determine the extent to which such a pre-trained model can be transferred across dissimilar environmental conditions (e.g., between different climatic zones or different agricultural practices). It is possible that one well-trained model per climate zone could be sufficient, which could then be applied to many regions using transfer learning. Additionally, the performance of in-season crop yield forecasts may be enhanced by incorporating expert estimations of crop yields into the model for the current year. The results presented in this paper provide a solid baseline for further exploration of transfer learning in crop yield forecasting using Earth observation data.

CRedit authorship contribution statement

Bueechi E.: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Reuß F.:** Writing – review & editing, Data curation. **Píkl M.:** Writing – review & editing, Data curation. **Homolova L.:** Writing – review & editing, Data curation. **Lukas V.:** Writing – review & editing, Data curation. **Trnka M.:** Writing – review & editing, Funding acquisition, Data curation. **Dorigo W.:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization.

Data and code

The crop yield data used in this paper is shared on <https://features.dev.services.eodc.eu/collections>, where publicly available. Unfortunately, the field-scale data cannot be shared due to privacy agreement with the farmers who shared the data with us. The regional-scale data can be acquired on <https://www.statistik.at/en> for Austria and was obtained from <https://www.akcr.cz/> for Czechia.

The Python code used for the data preparation and crop yield forecasting is available upon request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used perplexity.ai and claude.ai in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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