総合論文

Instant estimation of rice yield using ground–based RGB images and its potential applicability to UAV

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Rice (*Oryza sativa* L.) is one of the most important cereals, which provides 20% of the world's food energy. However, its productivity is poorly assessed especially in the global South. Here, we provide a first study to perform a deep learning-based approach for instantaneously estimating rice yield using RGB images. During ripening stage and at harvest, over 22,000 digital images were captured vertically downwards over the rice canopy from a distance of 0.8 to 0.9 m at 4,820 harvesting plots having the yield of 0.1 to 16.1 t ha^{-1} across six countries in Africa and Japan. A convolutional neural network (CNN) applied to these data at harvest predicted 68% variation in yield with a relative root mean square error (rRMSE) of 0.22. Even when the resolution of images was reduced (from 0.2 to 3.2 cm pixel^{-1} of ground sampling distance), the model could predict 57% variation in yield, implying that this approach can be scaled by use of unmanned aerial vehicles. Our work offers low-cost, hands-on, and rapid approach for high throughput phenotyping, and can lead to impact assessment of productivity-enhancing interventions, detection of fields where these are needed to sustainably increase crop production.

Key words : Rice (*Oryza sativa* L.), rough grain yield, convolutional neural network, RGB images, UAV

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Introduction

The global demand for staple crop products is expected to increase by 60% by 2,050, because of the increased population, per capita income growth, and use of biofuels[1]. As the conversion of carbon-rich and natural ecosystems to cropland exacerbates climate change and biodiversity loss, sustainable intensification of the existing cropland is needed to meet this estimated future demand by reducing yield gap as well as negative environmental impacts[2,3]. Despite the importance of these goals, crop productivity is poorly assessed, especially in the global South, where there is need to monitor agricultural productivity and evaluate the impact of productivity-enhancing interventions[4]. There are three well-known approaches for assessing crop yield, which include self-reporting, crop cutting, and remote sensing. However, self-reported data from smallholder farmers are often inaccurate[5] Crop cut, wherein a sub-section of a plot is physically harvested, is time- and labor-consuming, and difficult to scale to large areas with financial limitations. Remote sensing technologies such as satellites and unmanned aerial vehicles (UAVs) with specialized sensors have the capability to assess the crop productivity at scale, but they have not been fully utilized especially in the global South. The absence of reliable data on agriculture statistics is a serious constraint for both agricultural research and policy.

With recent advancement in computational technology, ground-based images captured by low-cost devices together with so called "machine learning" approaches have received great interest. Machine learning technology is one of the most remarkable innovations in the last decade[6,7]. Deep learning is categorized as supervised machine learning and mainly consists of convolutional neural network (CNN). A remarkable feature of CNN is its capability for image analysis. It has already been applied in various situations, which include language translation[8], protein structure prediction[9], board games[10], and agriculture[11,12]. Developing a practical CNN model requires a large-scale combination of images and supervising data. The desirable target objects or crop characteristics could be those that are relatively easy to be visually evaluated for massive data collection. For these reasons, many earlier studies applying CNNs to agriculture focused on the classification of crop biotic[13-15] and abiotic stresses[16], and estimation of crop growth-related traits such as biomass[17-20], leaf area index[21], grain number[22], and panicle density[23,24]. Recently, some studies demonstrated the direct estimation of crop growth status including yield in specific growth environments and cultivars[25,26]. However, to the best of our knowledge, no study has achieved the versatile estimation of crop yield covering wide range of genotypic and environmental diversity based on CNNs.

This study focuses on rice, which is by far the most important among the big three cereals in terms of human consumption in low- and lower-middle income countries and is mainly cultivated by smallholder farmers[27]. We established a database of ground-based digital images of rice taken during the ripening stage and at harvest, and the corresponding yields were collected from seven countries using a standardized data collection procedure. We then developed a CNN model that covered a wide range of yield levels, rice growing environments, cultivars, and crop management practices, such as crop establishment methods and fertilizer management. We assessed the robustness of the model under various conditions which potentially affected the yield estimation. We demonstrate that rice yield can be rapidly and effectively estimated at a low cost in diverse light environments at harvest and during the late ripening stage, without labor-intensive crop cuts or knowledge-intensive remote-sensing technologies.

Materials and Methods

Construction of database for rice canopy image and rough grain yield.

Field campaigns were conducted in 2019 and 2020 at 20 locations in seven countries (Côte d'Ivoire, Senegal, Japan, Kenya, Madagascar, Nigeria, and Tanzania). Data on rice growth traits and digital images were collected in seed production plots as well as experimental fields at research stations and farmers' fields. At maturity, the RGB images were captured vertically downwards over the rice canopy from a distance of 0.8 to 0.9 m using a digital camera. The camera was set to automatic mode. The focal length and aspect ratio were set to 28 mm and 4 : 3 or 16 : 9, respectively. All the images were saved as jpg files. The digital cameras used in this study are listed in Table S1. The rice canopy images covered 1 m^2, which correspond to the harvesting area proposed by Food and Agriculture Organization (FAO) and used by Japan for agricultural statistics[28]. Rough grain yield that contained filled and unfilled grains was measured at the corresponding plot or larger plots, where yield data were collected based on field experiments. Rice yields were reported as 14% moisture content. The aboveground total dry weight and filled grain weight were also recorded in most studies, but not used for the CNN-based estimation because of the lack of data in some cases. For the training, validation, and test data, a single image per plot was recorded. These three categories are the main part of the database and randomly split by a ratio of 5 : 1 : 1. After splitting the data, the images categorized in the training data were augmented 4-fold by flipping horizontally, vertically, and their combination, which resulted in 17,764 images for training data. In total, 4,820 yield data and 22,067 images of 462 rice cultivars were used in this study.

Image processing and development of convolutional neural network model

The RGB images of the rice canopy were recorded with an aspect ratio of 4 : 3 or 16 : 9. For the images recorded at 16 : 9, the edge of the long side was trimmed to a ratio of 4 : 3. The images were then resized to 600 × 450 pixels for recording in the database. A bilinear algorithm was used to resize the images. This resize was to eliminate the difference in pixel sizes of images from various cameras, while keeping the aspect ratio and ground sampling distance (GSD). The images used for the analyses have a GSD of 0.2 cm pixel^{-1}. The images were again resized to a square of 512 × 512 pixels in 8-bit PNG format as inputs for the CNN model. The brightness values of each channel of RGB were divided by 255 to scale from 0 to 1. These values were then standardized using the mean and variance calculated from all images categorized in the training dataset. The mean and variance of the RGB channel for the training dataset were [R, G, B] = [0.490, 0.488, 0.281] and [0.230, 0.232, 0.182], respectively. The structure of the CNN was developed by Neural Network Console software version 1.5 (Sony Network Communications Inc., Japan, https://dl.sony.com/). The Neural Network Console is a GUI-based software for Windows OS to design the structure of CNN and perform the training of the model. The database of the RGB images and rough grain yield was imported to the Neural Network Console, and the optimal structure showing the lowest validation error was determined by the CNN structural search function of the software. During the structural search, the loss function and optimizer were defined by the mean absolute error and Adam optimizer, respectively. The batch size, learning rate and epoch number were set to 32, 0.001 and 50, respectively. The determined CNN structure, loss function and optimizer were then deployed using Python language (version 3.7) with Pytorch framework (version 1.7). The optimal learning rate and batch size were determined by changing the combination of these hyper-parameters. Batch sizes of 16, 32, 64, 128, and learning rates of 0.0001, 0.0002, 0.0005, 0.0008, and 0.001 were combined, and the learning process was replicated 10 times for each combination. The epoch number was set to 100, and the learning process was conducted by minimizing the loss of estimated and observed yields in the training dataset. The validation loss was also calculated for every epoch, and the model showing the least loss for validation was recorded. The rRMSE for the test dataset was calculated for models with all combinations of the hyper-parameters, and averaged across 10 replications. The best combination of batch size and learning rate was determined, and the recorded model was used in the present study.

To evaluate the model accuracy with the images of lower resolutions, we additionally developed the sets of training, validation and test images with GSD of 0.4, 0.8, 1.6, and 3.2 cm pixel^{-1}. The CNN models were trained by using images having these lower resolutions. The framework, optimizer and the epoch number were identical with the establishment of the default model. Based on the optimization for the default model, the batch size and learning rate were set to 32 and 0.0001, respectively. The learning process was replicated 5 times for each GSD condition. The validation loss was also calculated for every epoch, and the model showing the least loss for validation was recorded. The R^2 value for validation and test dataset was calculated for each selected model, and averaged across 5 replications. The altitude of the UAV and the single image footprint which gives the specific GSD was calculated by assuming the camera spec with a focal length = 10 mm, image sensor size = 1 inch and pixel size = 20M.

Statistical analyses, data summarizing, and code availability

The 4,820 observations of rough grain yield data were summarized by calculating the average, maximum, and minimum yields. The data were categorized according to the collected country, and the average yield in each country was calculated. The R2 and rRMSE were calculated to evaluate the model performance in each analysis. The rRMSE is defined as follows :

$$\frac{1}{\bar{y}}\sqrt{\frac{1}{n}\sum_{k=1}^{n}(f_i - y_i)^2} \qquad (1)$$

where, y is the average of the observed yield, n is the size of the data, and fi and yi are the individual estimations and observations of the yield.

All analyses in the present study were conducted using Microsoft Excel (Microsoft, Redmond, WA, USA), Neural Network Console software (Sony Network Communications Inc., Japan), and Python language version 3.7 (http://www.python.org) with Pytorch framework version 1.7 (https://pytorch.org/). The code to run the developed CNN model is available at https://github.com/r1wtn/rice_yield_CNN.

Results

Database on rice canopy image and grain yield

The multinational dataset of rice canopy images and corresponding rough and filled grain yields, and aboveground dry weight were established with a standardized data collection procedure for 4,820 harvested plots and 22,067 images across 20 locations in seven countries (Fig. 1a). Côte d'Ivoire, Senegal, and Japan accounted for 56%, 32%, and 5% of total plots, respectively. The dataset covers both lowland and upland rice production systems containing 462 rice cultivars, and includes two crop establishment methods (direct seeding and transplanting). N–P–K fertilizer application ranged from 0 to 200 kg N ha^{-1}, 0 to 120 kg P_2O_5 ha^{-1}, and 0 to 120 K_2O kg ha^{-1}, respectively. The observed rough grain yield ranged from 0.1 to 16.1 t ha^{-1} (Fig. 1b–c) with an average of 5.8 t ha^{-1} and showed a normal distribution (Fig. 1a). As rough and filled grain yields, and aboveground dry weight were highly correlated with each other, further data analyses using the CNN model focused only on rough grain yield.

A CNN model to estimate rough grain yield from canopy image

The determined CNN structure had five convolutional layers in the main stream, and the four convolutional layers in the branching stream. The pooling layers included both of Average Pooling and Max Pooling. The ReLU was mainly chosen as the activation function, but the ELU and LeakyReLU were also used in some parts. In the head part of CNN, the information from the two streams was fully connected, followed by the last ReLU

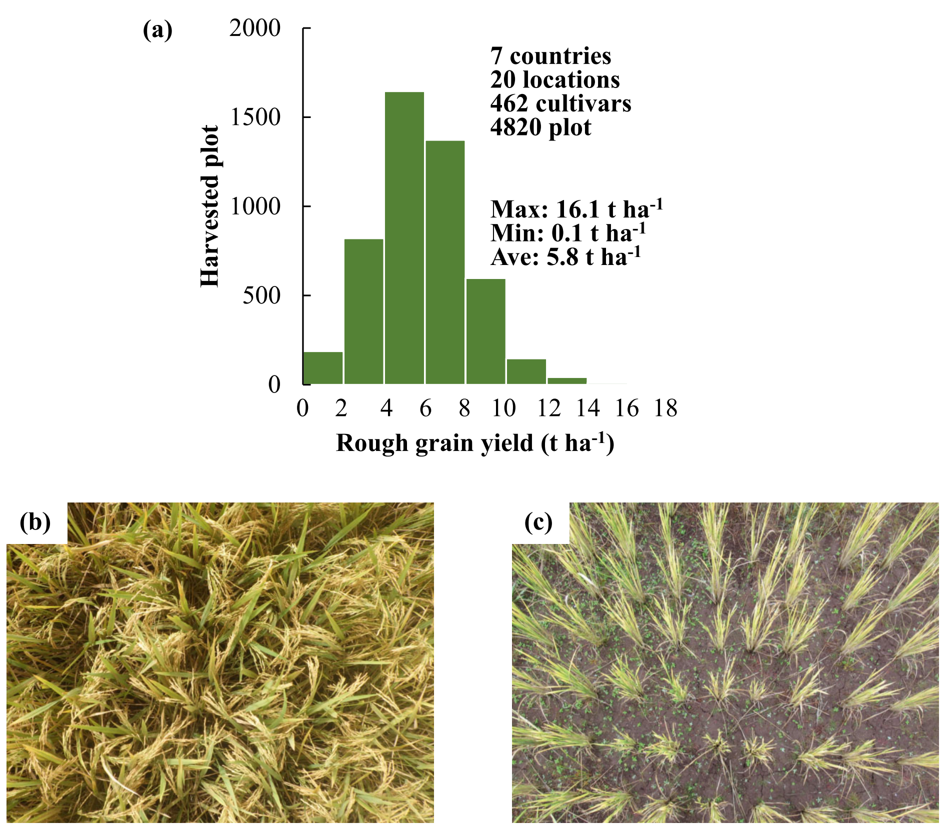

Fig.1　The global database of the rice canopy image and corresponding rough grain yield.
(a) Bar plot depicting the frequency distribution of observed rough grain yield in the database collected at 7 countries. (b-c) Images of the rice canopy showing the highest (b) and the lowest (c) rough grain yield, which is collected in Senegal and Madagascar, respectively.

layer to output the estimated yield. The total number of parameters of the structure was 41,017. The learning rate and batch size during the learning process were optimized with 10 replications and identified the best combination at 0.0001 and 32, respectively, for the test dataset. With this combination, the best model of the learning process was generated at epoch = 61, and the model was used for all of the following analyses (Fig. 2a), except for the test of greater GSD images. The developed CNN model could explain 69 and 68% of the variation in yield for validation and test data, respectively, with a relative root mean square error (rRMSE) of 0.22 for both (Fig. 2b–c). The relationship between the observed and estimated yields fit well with the 1 : 1 line for both datasets. The deviation between the estimated and observed yields of individual cultivars in the test dataset was plotted against the number of harvested plots in the training dataset (Fig. 2d). The cultivars with more than 25 harvesting plots in the training dataset tended to have less than 1.5 t ha^{-1} deviation. The empirical relationships illustrated as upper and lower boundary curves in Fig. 2d indicate that increasing the number of plots by 10 times can reduce the error of the yield estimation by 50%.

The applicability of the CNN to the images with greater GSD was then evaluated by comparing the models

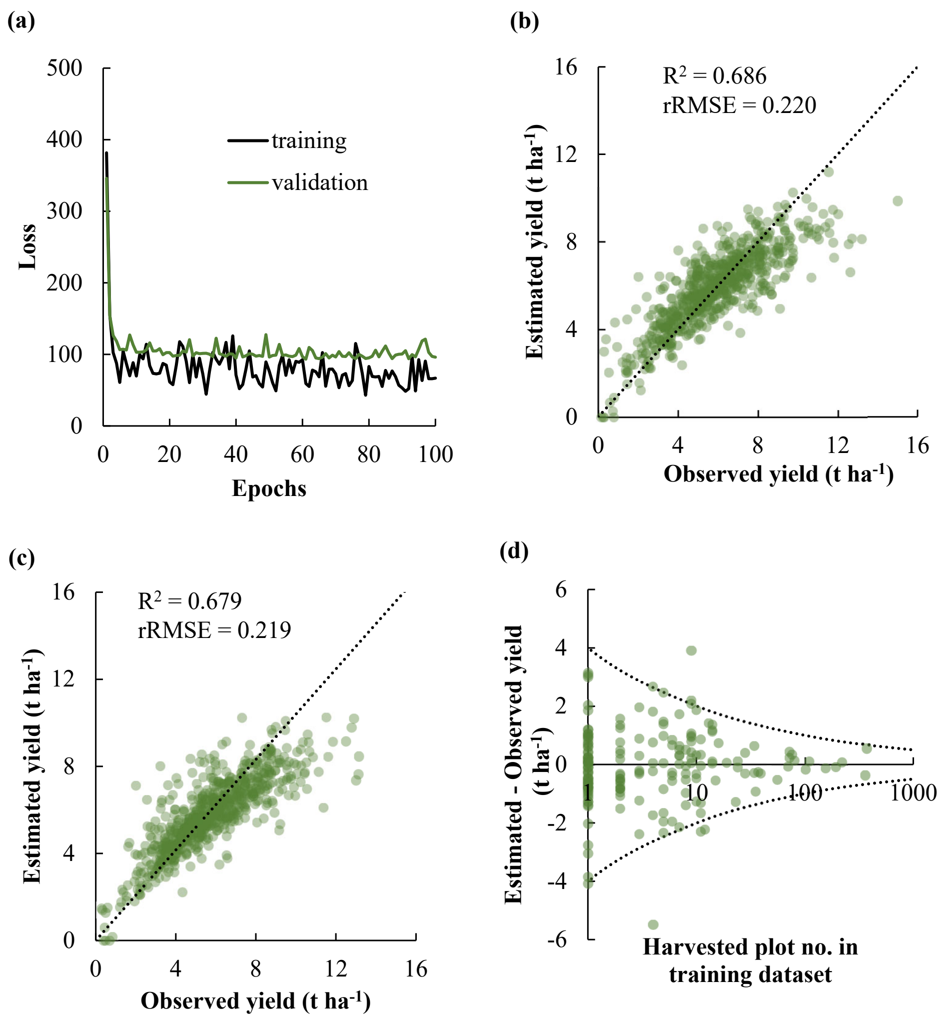

Fig.2 Development of the deep learning-based model to estimate the rough grain yield of rice.
(a) Graph illustrating the learning curve for the training and validation dataset. The minimum loss for the validation dataset was recorded at epoch = 61, and the model was used for all the analyses in the present study. (b-c) Scatter plots depicting the estimation of the rough grain yield in the validation (b) and the test (c) dataset. The dotted line represents the 1 : 1 relationship. rRMSE represents the relative root mean square error. (d) Scatter plot showing the difference between estimated and observed yield of each cultivar in test dataset plotted against the number of harvested plots in training dataset.

The dotted line represents $y = 4 \cdot \left(\frac{1}{2}\right)^{\log_{10} x}$

developed by the various resolutions of the image dataset. Compared with the default model (GSD = 0.2 cm pixel^{-1}), the model based on the greater GSD showed a lower accuracy both with the validation and test dataset (Fig. 3a). The R2 value for the test dataset was, however, greater than 0.55 even when the model was trained by the images with GSD = 3.2 cm pixel^{-1}. When assuming the typical camera specs of UAV, this GSD corresponds with altitude of 134 m, and single image footprint of 2.06 ha (Fig. 3a).

Discussion

This is the first study to develop a versatile CNN model to predict rice yield accurately only by using ground-based RGB images. In the previous attempts [25,26], the application of the CNN model was tested in the specific growing environments and cultivars. Our model was able to estimate rice yield with satisfactory precision in the to date most comprehensive and international dataset in terms of the growing environments, management practices, number of cultivars, camera angles and time of days. The accuracy of estimation in the test dataset was comparable to or even higher than those shown in earlier studies, that used satellite data, or in combination with other data and models, or UAVs equipped with various sensors for estimating crop growth-related traits such as aboveground biomass and leaf area index, or indirectly predicting crop yield in farmers' fields[26,29-35]. Dry weight-based evaluation of the rough grain yield needs at least 48 to 72 hr oven-drying[28]. In addition to that, crop cut, threshing and other processes requires additional time and labor inputs. In contrast with this conventional method, the CNN-based estimation is instantaneous, and shooting an image requires a few seconds. Our model can be applied to the high-throughput phenotyping for on-station agronomic experiments.

Our analyses showed a negative relationship between the model accuracy and GSD of the images used for the model development. This was because the lower resolutions led to the loss of the leaf and panicle architecture (Fig. 3b-c). However, the CNN model trained with the images of GSD = 3.2 cm pixel^{-1} still shows sufficient

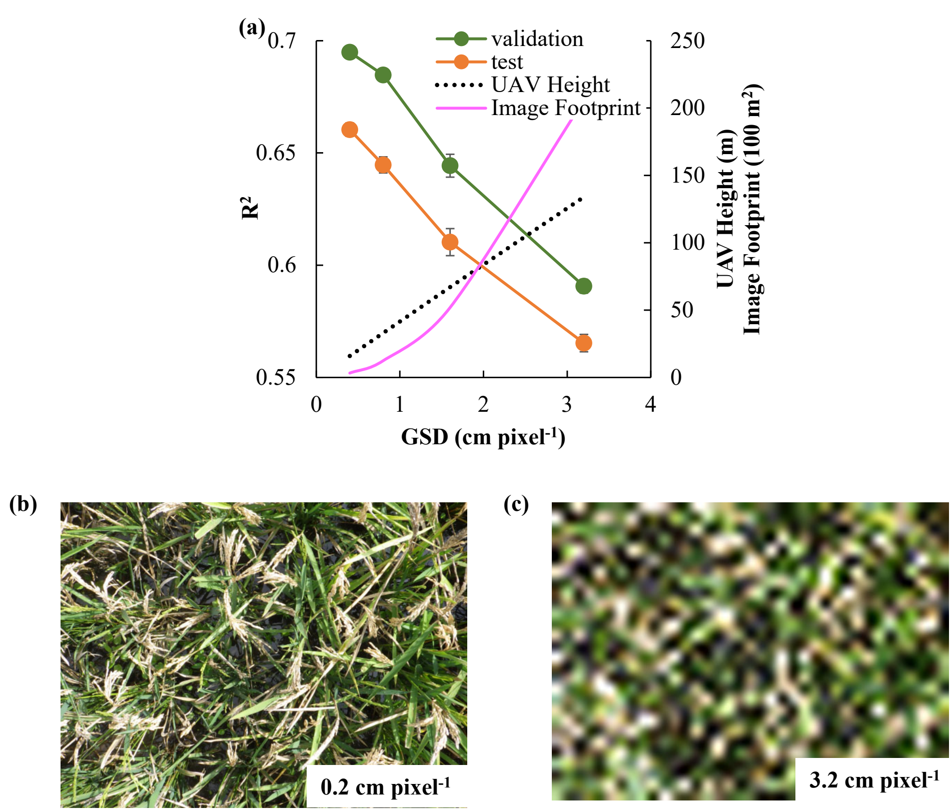

Fig.3　The accuracy of the yield estimation by the models established by using various resolutions of the images.
(a) The relationship between R2 values of the models and ground sampling distance (GSD) in the validation and test dataset. The dotted line represents the corresponding height of the camera when assuming the UAV with focal length = 10 mm, image sensor size = 1 inch and pixel size = 20M. (b) Scatter plots depicting the estimation of the rough grain yield in the test dataset with images of 3.2 cm pixel^{-1}. (c-d) An example of the image with GSD of 0.2 cm pixel^{-1} (original) and 3.2 cm pixel^{-1}, respectively.

estimation accuracy (Fig. 3a). This GSD level is easily achieved by the UAV altitude greater than 100 m, if a commercial RGB camera is used. These results suggest that the CNN model can potentially use the images captured by the UAV for yield estimation. The CNN-based estimation of rice yield and its spatial variation at field level can be a powerful solution for monitoring the rice productivity in the regional scale in the future.

Unexpected conditions causing the poor or moderate estimations of the CNN model should always be assumed when considering the scale and diversity of on-farm rice cropping systems globally. For instance, the dataset does not include the canopy affected by severe lodging, pests, insects, weeds, or abiotic stresses such as heat, drought, and flooding. Most of the data are from on-station irrigated lowland rice fields with relatively higher yields, and data from farmers' fields are limited. Thus, further research should especially focus on low-yielding and rain fed environments, and assessment of the potential use of the model for stressed or injured rice plants is warranted. The most practical solution to adapt the model to these conditions would be to add these new data to the database and develop a new model. The results in Fig. 2d suggest that better accuracy can be achieved with more harvesting plots, indicating the extensibility of the CNN model. As a criterion, 25 harvesting plots are needed for adaptation to new conditions with practical accuracy (error < 1.5 t ha^{-1}) , which should be validated for developing a sampling framework for improving and adapting the model to new conditions.

The CNN structure used in this study has several convolutional layers, and is much smaller than the CNN used in the previous study for rice yield estimation[26], or representative structures for image recognition[37]. This implies that the developed model can be easily transferred to mobile devices such as smartphones. The model does not require any type of color checker. A model having sufficient accuracy could be developed with images of lower resolution, and our approach can be potentially combined with UAV-based imagery. The present study leads to high throughput phenotyping, impact assessment of productivity-enhancing interventions, and identifying fields where these are needed to sustainably increase crop production[38].

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