STØTTET AF
Promilleafgiftsfonden for landbrug

Halm til det hele
Revised models for prediction of straw yield components and straw yield by drone images

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Yield component estimation

Data

The dataset comprised high-resolution images collected from two primary sources: **Robotti images** for Spring Barley and Spring Wheat and **drone images** for Spring Barley, Spring Wheat, Winter Wheat, Winter Rye, and Winter Triticale. The data was annotated to support both head count and sepal count tasks, ensuring comprehensive coverage for multiple crops and enabling robust model training and evaluation.

Image Sources

- **Robotti Images:** Images of spring crops, including spring barley and spring wheat, were captured using Robotti ground-level imaging. These images provided high-resolution details, making them suitable for accurate sepal detection and segmentation.
- **Drone Images:** Images of spring crops including spring barley and spring wheat, and winter crops, including winter wheat, winter rye, and winter triticale, were captured using drones flying at different altitudes. Specifically, the dataset we used was from the heights:
  - **Drone 4m:** Images for winter wheat, winter rye, and winter triticale for head count.
  - **Drone 8m:** Images for spring barley, spring wheat, winter wheat, winter rye, and winter triticale for head and sepal count with segmentation.

Dataset Distribution

The dataset was divided into training and testing sets to ensure reliable model training and evaluation. Table 1 provides a detailed breakdown of the dataset distribution for head count and sepal count tasks across different crops.

Crop	Train (Head Count)	Test (Head Count)	Train (Sepal Count)	Test (Sepal Count)	Image Source
Spring Barley	68	5	419	43	Robotti + Drone (8m)
Spring Wheat	74	5	410	38	Robotti + Drone (8m)
Winter Wheat	65	5	25	3	Drone (4m & 8m)
Winter Rye	70	5	25	3	Drone (4m & 8m)
Winter Triticale	69	5	25	3	Drone (4m & 8m)

Table 1: Dataset Distribution for Head Count and Sepal Count across different crops, along with their respective image sources.

Annotation Process

The dataset was annotated using **Hasty**, an online AI-powered annotation platform designed for efficient and accurate labeling of images. Using Hasty's intuitive tools, we created bounding box annotations for head count tasks and mask annotations for sepal segmentation. The following steps were followed during annotation:

- **Bounding Boxes:** Used to mark and count the heads in both spring and winter crops.
- **Masks:** Created for segmenting sepals in images, ensuring precise detection of crop features.
- **Classes:** Each annotation was categorized into specific classes, such as sepals, heads, and background.

Dataset Applications

The dataset supported two primary tasks:

- **Head Count:** Detecting and counting the number of heads in crop images using bounding box annotations.
- **Sepal Count and Segmentation:** Identifying and segmenting sepals in crop images, providing detailed information about crop features for analysis.

The curated dataset, combined with its detailed annotations, serves as a robust foundation for training deep learning models and evaluating their performance.

Model Training and Implementation

For this study, two state-of-the-art deep learning models were used to address specific tasks in agricultural image analysis:

- **YOLOv10 for Head Count:** These models were employed for detecting and counting crop heads for each spring and winter crops. It was trained on drone images annotated with bounding boxes.
- **YOLOv11 for Sepal Count and Segmentation:** These models were employed for the task to include both detection and segmentation of sepals. It was trained on robotti and drone images annotated with bounding boxes and segmentation.

Results

Head Count Performance

Table 2 summarizes the performance of the YOLOv10 model for head count detection across different crops. The model achieved high precision and recall values, with notable performance for crops such as Winter Triticale, which demonstrated a precision of 0.948, recall of 0.860, and a mean Average Precision (mAP) of 0.947 at IoU 0.5. The model also performed robustly for Spring Wheat and Winter Rye, achieving mAP values of 0.803 and 0.911, respectively. These results highlight the capability of YOLOv10 in detecting crop heads under diverse conditions.

Sepal Count and Segmentation Performance

The YOLOv11 model was employed for sepal count and segmentation tasks, and its performance is detailed in Table 3. The model demonstrated strong segmentation capabilities for Spring Barley and Spring Wheat, with mask mAP@50 values of 0.822 and 0.755, respectively. However, the performance for winter crops was comparatively lower, with Winter Wheat achieving a mask mAP@50 of 0.470 and Winter Triticale achieving 0.591. These results suggest the need for additional dataset annotations and further fine-tuning for winter crops.

Some test samples for both head count and sepal count are shown in Figure 1.

Crop	Images	Instances	Precision	Recall	mAP@50	mAP@50-95
Spring Barley	5	506	0.7495	0.7806	0.8341	0.4311
Spring Wheat	5	534	0.826	0.725	0.803	0.326
Wheat Wheat	5	393	0.926	0.918	0.963	0.581
Winter Rye	5	445	0.861	0.822	0.911	0.532
Winter Triticale	5	253	0.948	0.860	0.947	0.654

Table 2: Performance of Head Count YOLOv10 Model on Spring and Winter Crops

Crop	**Images**	**Instances**	**Mask (P)**	**Mask (R)**	**Mask (mAP@50)**	**Mask (mAP@50-95)**
Spring Barley	43	645	0.862	0.755	0.822	0.355
Spring Wheat	38	832	0.813	0.726	0.755	0.263
Winter Wheat	3	506	0.564	0.452	0.470	0.151
Winter Rye	3	229	0.685	0.655	0.699	0.228
Winter Triticale	3	564	0.654	0.541	0.591	0.183

Table 3: Performance of Sepal Count YOLOv11 Model on Spring and Winter Crops.

Web Interface for Model Interaction

We have developed a stable web platform to facilitate user interaction with our deep learning models. This platform provides an intuitive and user-friendly interface for testing crop images. The web platform currently consists of two dedicated pages:

- **Sepal Count Page**: This page allows users to upload images for sepal counting. The model processes the uploaded images and provides results, including the number of sepals and other elements such as weed thistle, monocot, dicot, and grass.
- **Head Count Page**: This page is designed for head count analysis across all crop types. Users can upload images, and the model detects and counts the crop heads, providing detailed metrics for evaluation.

The web platform supports all the crops included in this study and is currently operational on a local machine. Our objective is to make it accessible online for testing purposes, enabling breeders and researchers to utilize this tool remotely.

Figure 1: Models prediction for head detection (top row) and sepal segmentation (bottom row) across various crops, including spring barley, spring wheat, winter wheat, winter rye, and winter triticale.

Straw yield models

Methods

Straw yield models were based on linear regression models. Different sets of predictor variables were included in different models for comparisons. The included variables were digital height, RGB- and multispectral vegetation indices at different timings in the growth season, area under the vegetation index (AUVIC) for different RGB and multispectral vegetation indices, and grain yield.
Vegetation indices based on RGB imaging were:

$$\mathrm{RGBVI} = \frac{\mathrm{G}^2 - \mathrm{R} \cdot \mathrm{B}}{\mathrm{G}^2 + \mathrm{R} \cdot \mathrm{B}}$$

$$\mathrm{NEXG} = \frac{2 \cdot \mathrm{G} - \mathrm{R} - \mathrm{B}}{\mathrm{G} + \mathrm{R} + \mathrm{B}}$$

$$\mathrm{VARI} = \frac{\mathrm{G} - \mathrm{R}}{\mathrm{G} + \mathrm{R} - \mathrm{B}}$$

$$NGRDI = \frac{\mathrm{G} - \mathrm{R}}{\mathrm{G} + \mathrm{R}}$$

where R refers to the red, G to the green, and B to the blue band in the RGB images.
Vegetation indices based on multispectral imaging were:

$$\mathrm{NDVI} = \frac{\mathrm{NIR}_{860} - \mathrm{R}_{650}}{\mathrm{NIR}_{860} + \mathrm{R}_{650}}$$

$$\mathrm{GNDVI} = \frac{\mathrm{NIR}_{860} - \mathrm{G}_{560}}{\mathrm{NIR}_{860} + \mathrm{G}_{560}}$$

$$\mathrm{NDRE} = \frac{\mathrm{NIR}_{860} - \mathrm{RE}_{730}}{\mathrm{NIR}_{860} + \mathrm{RE}_{730}}$$

where R_{650} refers to the red band, G_{560} to the green band, NIR_{860} to the near infrared band, and RE_{730} to the red edge band in the multispectral images. The numbers on the variables refer to the exact bands used in our camera.
Only models with a maximum of 4 predictor variables were included due to the limited size of the data set. Validation of the prediction models was based on 4- and 5-fold cross-validation. In the 4-fold cross-validation, the model was fitted to data from three blocks and evaluated in the last block. This was repeated four times, each time leaving out a new block, and the mean correlation between predicted and observed straw yield in the block left out (the test set) was found. In the 5-fold cross-validation, the model was fitted to data from four varieties and evaluated in the remaining variety. This was repeated five times, each time leaving out a new variety and the mean correlation between predicted and observed straw yield for the variety left out was found. The model with the highest cross-validated correlation across both cross validations were chosen as the best. The final model was obtained as a weighted average of the model trained on the different subsets of the data with weights according to the performance in the corresponding test sets. The final models were evaluated on the entire data sets and the results reported in terms of correlation between predicted and observed straw yield as well as the R^2.
For each crop different models are presented:

- The best model
- The best model based on RGB data only
- The best model excluding plots with full lodging
- The best model excluding plots with full lodging based on RGB data only
- The best model that does not include grain yield

Only the relevant non-identical models are presented for each crop. All analyses were made in R version 4.3.2.

Spring barley

For spring barley, the variety Halfdan was lodging early in the season and with complete lodging in all plots at harvest. Therefore, a model for all data and a model for non-lodging plots were found. Performance on the entire data set can be seen in Table 4 and the specific parameters for each model can be found in Table 9. The overall best model based on the cross validation results on the entire data set and without excluding any variables resulted in an $R^2 = 0.36$ (Table 4 and Figure 2). The models based on data excluding the plots with fully lodging performed much better ($R^2 = 0.48$) but overall the straw yield models for barley were not good.

Data	**Input**	**Variables in best model**	**Cor**	$\mathbf{R^2}$
All	All	$\text{GNDVI}_{\text{Booting}}$, $\text{Height}_{\text{Senescence}}$, $\text{NDRE}_{\text{Stem Elongation}}$, $\text{NDVI}_{\text{Booting}}$	0.60	0.36
All	RGB	$\text{NEXG}_{\text{Booting}}$, $\text{NEXG}_{\text{Fruit Development}}$, $\text{RGBVI}_{\text{Fruit Development}}$, $\text{VARI}_{\text{Fruit Development}}$	0.54	0.30
No lodging	All	$\text{GNDVI}_{\text{Booting}}$, $\text{NDVI}_{\text{Booting}}$, $\text{NEXG}_{\text{Leaf Development}}$, $\text{RGBVI}_{\text{Leaf Development}}$	0.69	0.48
No lodging	RGB	$\text{Height}_{\text{Booting}}$, $\text{NEXG}_{\text{Stem Elongation}}$, $\text{NEXG}_{\text{Tillering}}$, $\text{RGBVI}_{\text{Fruit Development}}$	0.67	0.44

Table 4: Variables included in the best models for straw yield in spring barley based on different data sets and sets of input variables as well as performance of the model on the entire data set.

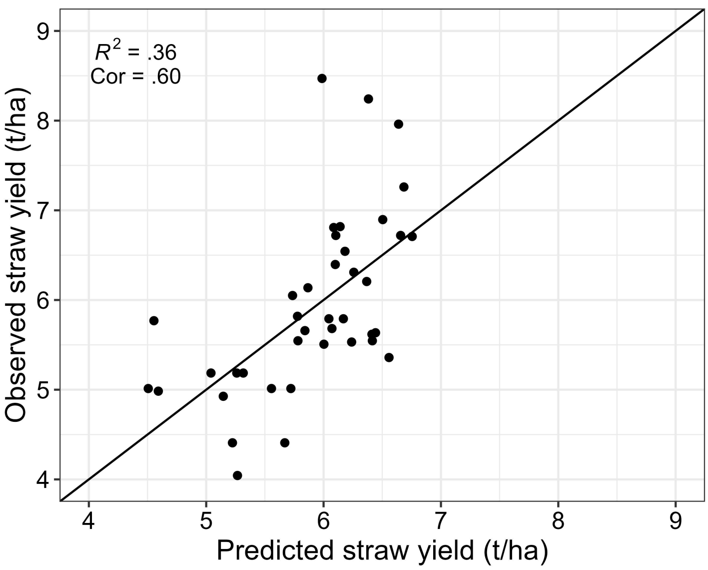

Figure 2: Observed vs predicted straw yield for spring barley based on all data.

Spring wheat

No lodging was observed for spring wheat. Performance for different models on the entire data set can be seen in Table 5 and the specific parameters for each model can be found in Table 9. The overall best model based on the cross validation results on the entire data set and without excluding any variables resulted in an $R^2 = 0.54$ (Table 5 and Figure 3).

Data	Input	Variables in best model	Cor	R^2
All	All	GrainDW, $\text{NDRE}_{\text{Stem Elongation}}$, $\text{NDVI}_{\text{Ripening}}$, $\text{RGBVI}_{\text{Leaf Development}}$	0.73	0.54
All	RGB	GrainDW, $\text{Height}_{\text{Flowering}}$, $\text{Height}_{\text{Senescence}}$, $\text{VARI}_{\text{Flowering}}$	0.69	0.48
All	No Grain DW	$\text{NDRE}_{\text{Flowering}}$, $\text{NDVI}_{\text{Ripening}}$, $\text{NEXG}_{\text{AUVIC To Flowering}}$, $\text{RGBVI}_{\text{AUVIC}}$	0.76	0.58
All	No Grain DW, RGB	$\text{Height}_{\text{Flowering}}$, $\text{NEXG}_{\text{AUVIC}}$, $\text{RGBVI}_{\text{AUVIC}}$	0.60	0.37

Table 5: Variables included in the best models for straw yield in spring wheat based on different data sets and sets of input variables as well as performance of the model on the entire data set.

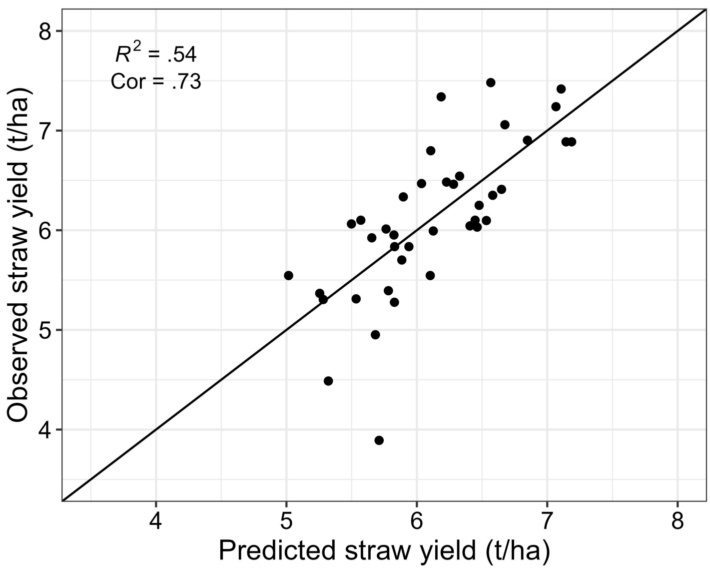

Figure 3: Observed vs predicted straw yield for spring wheat based on all data.

Winter wheat

No lodging was observed for winter wheat. Performance for different models on the entire data set can be seen in Table 6 and the specific parameters for each model can be found in Table 9. For winter wheat, the overall best model only contained variables obtained from the RGB camera (Table 6) resulting in an $R^2 = 0.63$ (Table 6 and Figure 4).

Data	Input	Variables in best model	Cor	R^2
All	All	GrainDW, $\text{Height}_{\text{Booting}}$, $\text{Height}_{\text{Flowering}}$, $\text{NEXG}_{\text{Booting}}$	0.79	0.63
All	RGB	GrainDW, $\text{Height}_{\text{Booting}}$, $\text{Height}_{\text{Flowering}}$, $\text{NEXG}_{\text{Booting}}$	0.79	0.63
All	No Grain DW	$\text{Height}_{\text{Booting}}$, $\text{Height}_{\text{Senescence}}$, $\text{NDRE}_{\text{Heading}}$, $\text{NDRE}_{\text{Tillering}}$	0.74	0.55
All	No Grain DW, RGB	$\text{NEXG}_{\text{Stem Elongation}}$, $\text{RGBVI}_{\text{Ripening}}$, $\text{VARI}_{\text{Booting}}$, $\text{VARI}_{\text{Heading}}$	0.73	0.53

Table 6: Variables included in the best models for straw yield in winter wheat based on different data sets and sets of input variables as well as performance of the model on the entire data set.

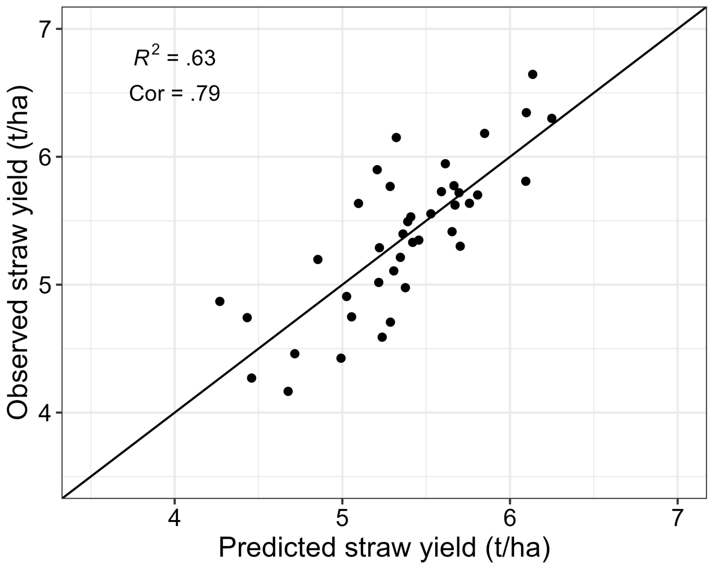

Figure 4: Observed vs predicted straw yield for winter wheat based on all data.

Winter triticale

No lodging was observed for winter triticale. The best model resulting in $R^2 = 0.67$ was based on RGB data only (Table 7 and Figure 5). The specific parameters for the model can be found in Table 9.

Data	Input	Variables in best model	Cor	R^2
All	All	$\text{RGBVI}_{\text{Senescence}}$, $\text{VARI}_{\text{Heading}}$, $\text{VARI}_{\text{Ripening}}$, $\text{VARI}_{\text{Stem Elongation}}$	0.82	0.67

Table 7: Variables included in the best models for straw yield in winter triticale based on different data sets and sets of input variables as well as performance of the model on the entire data set.

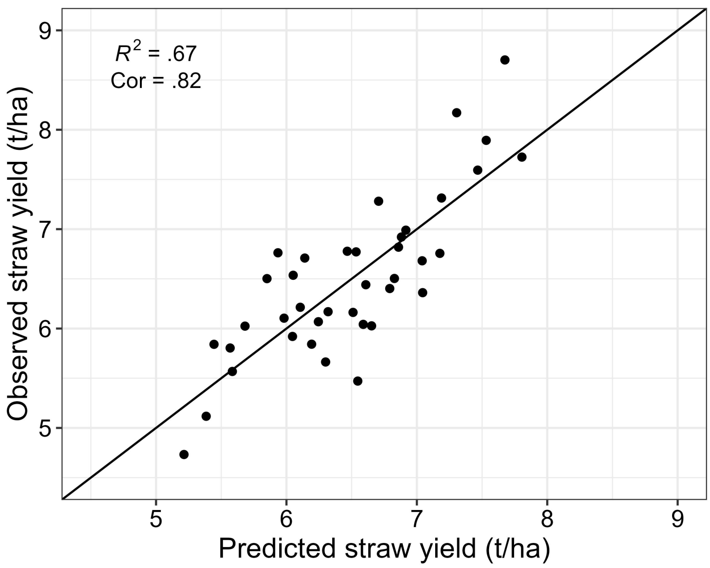

Figure 5: Observed vs predicted straw yield for winter triticale based on all data.

Winter rye

Lodging was observed at harvest for some plots in the winter rye experiment, especially for the variety KWS Rotor. Accordingly, models are presented for all data and excluding plots with complete lodging at harvest. Performance for different models on the entire data set and the smaller data set can be seen in Table 8 and the specific parameters for each model can be found in Table 9. The overall best model based on the cross validation results on the entire data set and without excluding any variables resulted in an $R^2 = 0.72$ (Table 8 and Figure 6).

Data	**Input**	**Variables in best model**	**Cor**	**R^2**
All	All	$\mathrm{GrainDW}, \mathrm{NDRE}_{\mathrm{Ripening}}, \mathrm{NDRE}_{\mathrm{Senescence}}, \mathrm{VARI}_{\mathrm{Fruit\ Development}}$	0.85	0.72
All	RGB	$\mathrm{GrainDW}, \mathrm{NEXG}_{\mathrm{Ripening}}, \mathrm{VARI}_{\mathrm{Fruit\ Development}}, \mathrm{VARI}_{\mathrm{Senescence}}$	0.85	0.72
All	No Grain DW	$\mathrm{Height}_{\mathrm{Fruit\ Development}}, \mathrm{NDRE}_{\mathrm{Fruit\ Development}}, \mathrm{NDRE}_{\mathrm{Senescence}}, \mathrm{NEXG}_{\mathrm{Senescence}}$	0.91	0.82
All	No Grain DW, RGB	$\mathrm{Height}_{\mathrm{Fruit\ Development}}, \mathrm{Height}_{\mathrm{Senescence}}, \mathrm{NEXG}_{\mathrm{Senescence}}$	0.88	0.77
No lodging	All	$\mathrm{Height}_{\mathrm{Fruit\ Development}}, \mathrm{NDRE}_{\mathrm{Senescence}}, \mathrm{NEXG}_{\mathrm{Heading}}, \mathrm{NEXG}_{\mathrm{Senescence}}$	0.94	0.86
No lodging	RGB	$\mathrm{GrainDW}, \mathrm{Height}_{\mathrm{FruitDevelopment}}, \mathrm{NEXG}_{\mathrm{Senescence}}, \mathrm{VARI}_{\mathrm{AUVIC}}$	0.94	0.86
No lodging	No Grain DW, RGB	$\mathrm{Height}_{\mathrm{Fruit\ Development}}, \mathrm{NEXG}_{\mathrm{Senescence}}, \mathrm{VARI}_{\mathrm{Booting}}, \mathrm{VARI}_{\mathrm{Heading}}$	0.93	0.87

Table 8: Variables included in the best models for straw yield in winter rye based on different data sets and sets of input variables as well as performance of the model on the entire data set.

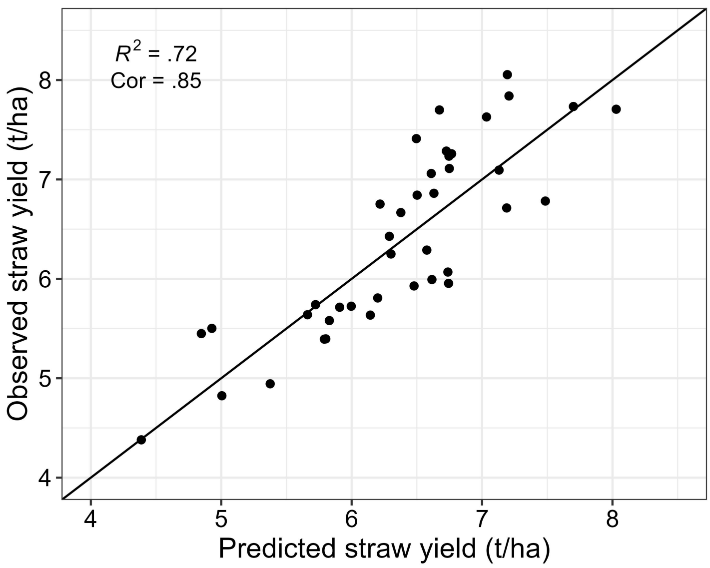

Figure 6: Observed vs predicted straw yield for winter rye based on all data.

Conclusion

Using YOLOv10 for head count detection, we achieved promising results, demonstrating robust performance across various crops, including barley, wheat, and rye, under diverse imaging conditions such as drone and Robotti images. Conversely, YOLOv11 for sepal detection and segmentation revealed challenges in achieving accurate predictions, indicating the need for further improvements in model design and dataset quality. Straw yield models for winter crops performed better than the models for the spring crops, with especially the models for spring barley not being satisfactory. Results are still based on data from one season only, which may have a high impact on the different coefficients in the presented prediction models.

Crop	Data	Variables	Best model
Spring barley	All	All	$\text{Straw yield} = -16.29 + -86.51 \cdot \text{GNDVI}_{\text{Booting}} + 2.27 \cdot \text{Height}_{\text{Senescence}} + 12.93 \cdot \text{NDRE}_{\text{Stem Elongation}} + 93.35 \cdot \text{NDVI}_{\text{Booting}}$
	All	RGB	$\text{Straw yield} = 4.49 + 9.89 \cdot \text{NEXG}_{\text{Booting}} - 384.53 \cdot \text{NEXG}_{\text{Fruit Development}} + 217.46 \cdot \text{RGBVI}_{\text{Fruit Development}} + 175.66 \cdot \text{VARI}_{\text{Fruit Development}}$
	No lodging	All	$\text{Straw yield} = -7.06 - 95.59 \cdot \text{GNDVI}_{\text{Booting}} + 94.46 \cdot \text{NDVI}_{\text{Booting}} - 1024.16 \cdot \text{NEXG}_{\text{Leaf Development}} + 699.09 \cdot \text{RGBVI}_{\text{Leaf Development}}$
	No lodging	RGB	$\text{Straw yield} = -16.95 + 21.52 \cdot \text{Height}_{\text{Booting}} + 31.65 \cdot \text{NEXG}_{\text{Stem Elongation}} + -27.19 \cdot \text{NEXG}_{\text{Tillering}} + 12.04 \cdot \text{RGBVI}_{\text{Fruit Development}}$
Spring wheat	All	All	$\text{Straw yield} = -9.95 + 0.57 \cdot \text{GrainDW} + 20.3 \cdot \text{NDRE}_{\text{Stem Elongation}} + 11.88 \cdot \text{NDVI}_{\text{Ripening}} - 26.12 \cdot \text{RGBVI}_{\text{Leaf Development}}$
	All	RGB	$\text{Straw yield} = 0.93 + 0.7 \cdot \text{GrainDW} + 9.66 \cdot \text{Height}_{\text{Flowering}} - 10.37 \cdot \text{Height}_{\text{Senescence}} + 6.83 \cdot \text{VARI}_{\text{Flowering}}$
	All	No Grain DW	$\text{Straw yield} = -3.8 - 9.49 \cdot \text{NDRE}_{\text{Flowering}} + 19.52 \cdot \text{NDVI}_{\text{Ripening}} + 0.84 \cdot \text{NEXG}_{\text{AUVIC To Flowering}} - 0.48 \cdot \text{RGBVI}_{\text{AUVIC}}$
	All	No Grain DW, RGB	$\text{Straw yield} = -0.38 + 6.72 \cdot \text{Height}_{\text{Flowering}} + 1.08 \cdot \text{NEXG}_{\text{AUVIC}} - 0.75 \cdot \text{RGBVI}_{\text{AUVIC}}$
Winter wheat	All	All	$\text{Straw yield} = -4.18 + 0.78 \cdot \text{GrainDW} - 11.43 \cdot \text{Height}_{\text{Booting}} + 9.52 \cdot \text{Height}_{\text{Flowering}} - 3.29 \cdot \text{NEXG}_{\text{Booting}}$
	All	RGB	$\text{Straw yield} = -4.18 + 0.78 \cdot \text{GrainDW} - 11.43 \cdot \text{Height}_{\text{Booting}} + 9.52 \cdot \text{Height}_{\text{Flowering}} - 3.29 \cdot \text{NEXG}_{\text{Booting}}$
	All	No Grain DW	$\text{Straw yield} = -5.62 - 5.97 \cdot \text{Height}_{\text{Booting}} + 6.6 \cdot \text{Height}_{\text{Senescence}} + 13.79 \cdot \text{NDRE}_{\text{Heading}} + 24.24 \cdot \text{NDRE}_{\text{Tillering}}$
	All	No Grain DW, RGB	$\text{Straw yield} = 1.56 + 6.34 \cdot \text{NEXG}_{\text{Stem Elongation}} + 6.16 \cdot \text{RGBVI}_{\text{Ripening}} - 4.81 \cdot \text{VARI}_{\text{Booting}} + 9.29 \cdot \text{VARI}_{\text{Heading}}$
Winter triticale	All	All	$\text{Straw yield} = 10.26 - 46.13 \cdot \text{RGBVI}_{\text{Senescence}} - 19.35 \cdot \text{VARI}_{\text{Heading}} + 28.2 \cdot \text{VARI}_{\text{Ripening}} + 29.89 \cdot \text{VARI}_{\text{Stem Elongation}}$
	All	RGB	$\text{Straw yield} = 10.26 - 46.13 \cdot \text{RGBVI}_{\text{Senescence}} - 19.35 \cdot \text{VARI}_{\text{Heading}} + 28.2 \cdot \text{VARI}_{\text{Ripening}} + 29.89 \cdot \text{VARI}_{\text{Stem Elongation}}$
Winter rye	All	All	$\text{Straw yield} = 4.11 + 0.42 \cdot \text{GrainDW} - 27.33 \cdot \text{NDRE}_{\text{Ripening}} + 13.71 \cdot \text{NDRE}_{\text{Senescence}} + 9.43 \cdot \text{VARI}_{\text{Fruit Development}}$
	All	RGB	$\text{Straw yield} = 2.44 + 0.21 \cdot \text{GrainDW} - 3.3 \cdot \text{NEXG}_{\text{Ripening}} + 6.61 \cdot \text{VARI}_{\text{Fruit Development}} - 21.76 \cdot \text{VARI}_{\text{Senescence}}$
	All	No Grain DW	$\text{Straw yield} = -2.61 + 5.93 \cdot \text{Height}_{\text{Fruit Development}} + 5.61 \cdot \text{NDRE}_{\text{Fruit Development}} + 14.86 \cdot \text{NDRE}_{\text{Senescence}} - 17.48 \cdot \text{NEXG}_{\text{Senescence}}$
	All	No Grain DW, RGB	$\text{Straw yield} = 2.14 + 6.13 \cdot \text{Height}_{\text{Fruit Development}} + 0.11 \cdot \text{Height}_{\text{Senescence}} - 34.34 \cdot \text{NEXG}_{\text{Senescence}}$
	No lodging	All	$\text{Straw yield} = -1.19 + 7.88 \cdot \text{Height}_{\text{Fruit Development}} + 15.71 \cdot \text{NDRE}_{\text{Senescence}} - 5.15 \cdot \text{NEXG}_{\text{Heading}} - 31.48 \cdot \text{NEXG}_{\text{Senescence}}$
	No lodging	RGB	$\text{Straw yield} = 0.02 + 0.31 \cdot \text{GrainDW} + 6.27 \cdot \text{Height}_{\text{FruitDevelopment}} - 32.41 \cdot \text{NEXG}_{\text{Senescence}} - 0.12 \cdot \text{VARI}_{\text{AUVIC}}$
	No lodging	No Grain DW, RGB	$\text{Straw yield} = 2.77 + 7.66 \cdot \text{Height}_{\text{Fruit Development}} - 48.9 \cdot \text{NEXG}_{\text{Senescence}} + 0.53 \cdot \text{VARI}_{\text{Booting}} - 7.15 \cdot \text{VARI}_{\text{Heading}}$

Table 9: Final models for straw yield for each crop.