Supplementary material for the paper:

Predicting potato plant vigor from the seed tuber properties

Quantification of Potato Plant Vigor in Field Trials

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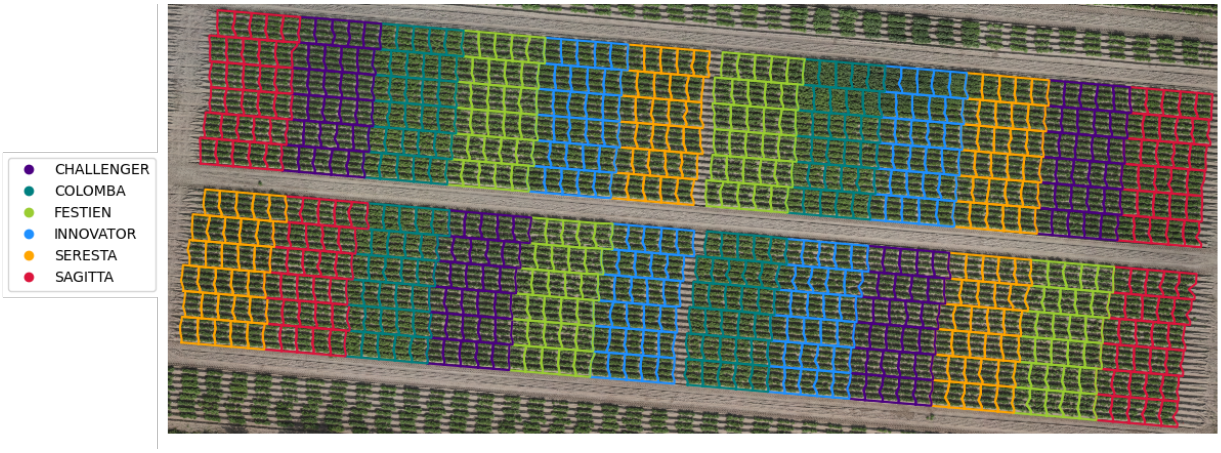

Figure 1: Complete randomized block design in the Veenklooster trial field in 2021. Each genotype is repeated four times as four randomly located compact blocks. Each batch has one plot inside the corresponding genotype block (small polygon), i.e., there are four plots of each batch in total.

Abstract

This document describes the field trials for measuring the vitality of potato plants conducted in 2019, 2020, and 2021, as well as the methods and techniques pertaining to the extraction and spatial correction of the vitality data. This document expands on the protocol in [2], with respect to which the polygonal boundaries for Montfrin 2020 have been improved, the color segmentation has been redone according to new parameters for all measurements, and additionally the measurements in the experimental year 2021 are also present.

1 Field trials and available data

The field trials for measuring the vitality of potato plants have been conducted during three consecutive years, 2019, 2020, and 2021, in the same three geographical locations:

- Montfrin (M), in the South of France (54.4980 N, 5.1090 E)
- Kollumerwaard-SPNA (S), in the North of the Netherlands (ca. 70.4325 N, 6.9825 E)
- Veenklooster (V), in the North of the Netherlands (70.3935 N, 6.7080 E)

Each year the experiments involved 180 batches belonging to 6 varieties (30 batches per variety). Although the same 6 genotypes were studied in all years, the seed tuber batches that represented these genotypes had a different production origin among the years. Observing and explaining the differences between the batches were the main goals of this project.

From each batch of potato seed tubers, 96 tubers were randomly selected for a field trial and planted in four different plots of 24 plants. Thus, with 180 batches, this resulted in 720 plots distributed over the trial field according to a complete randomized block design. For example, the experimental design realized in the Veenklooster test field is shown in Figure 1.

The development of potato plants was documented with images of the complete field taken by a drone mounted camera at certain moments after the planting of the seed tubers up until (and sometimes also after) the canopy closure, i.e., the moment when the leaf canopies of the neighboring plants begin to overlap. The exact dates of the drone images per year and field can be found in Table 1 and Table 2.

The next sections of this document detail our methodology of measuring the plant vitality, with particular emphasis on the following stages:

1. RGB image post-processing and plot localization
2. image segmentation and raw canopy area estimation
3. spatial effect removal
4. choice of the vitality measure
5. correlations in vitality across test fields

Field	Date	DAP	zero plots (%)
M	2019-04-10	36	626 (86.9%)
M	2019-04-19	45	20 (2.78 %)
M	2019-04-26	52	0 (0.0 %)
V	2019-05-24	36	44 (6.1 %)
V	2019-05-29	41	0 (0.0 %)
V	2019-06-07	50	0 (0.0 %)
S	2019-06-07	36	4 (0.56 %)
S	2019-06-19	48	0 (0.0 %)

Field	Date	DAP	zero plots (%)
M	2020-04-10	35	discarded
M	2020-04-13	38	199 (27.6 %)
M	2020-04-16	41	38 (5.3 %)
M	2020-04-18	43	13 (1.8 %)
M	2020-04-22	47	0 (0.0 %)
M	2020-04-25	50	0 (0.0 %)
V	2020-05-27	35	1 (0.14 %)
V	2020-05-30	38	0 (0.0 %)
V	2020-06-07	46	0 (0.0 %)
V	2020-06-10	49	0 (0.0 %)
V	2020-06-12	51	0 (0.0 %)
S	2020-06-03	35	7 (0.97 %)
S	2020-06-10	42	0 (0.0 %)
S	2020-06-12	44	0 (0.0 %)
S	2020-06-15	47	0 (0.0 %)
S	2020-06-19	51	0 (0.0 %)

Table 1: The dates (year-month-day) of the drone images of the three test fields (M, V, and S) in 2019 (top table) and in 2020 (bottom table). The 'DAP' column shows the time of the drone image in Days After Planting (DAP). The column 'zero plots (%)' gives the number of plots with no measurable canopy and their fraction among all plots in the field. We discarded the measurement at 35 DAP in Montfrin 2020 due to unreliable segmentation.

Field	Date	DAP	zero plots (%)
M	2021-04-02	24	26 (3.61 %)
M	2021-04-07	29	7 (0.97 %)
M	2021-04-08	30	3 (0.42 %)
M	2021-04-16	38	29 (4.03 %)
M	2021-04-19	41	3 (0.42 %)
M	2021-04-22	44	1 (0.14 %)
M	2021-04-26	48	0 (0.00 %)
M	2021-05-02	54	0 (0.00%)
M	2021-05-04	56	0 (0.00%)
M	2021-05-08	60	0 (0.00%)
M	2021-05-11	63	0 (0.00%)
M	2021-05-14	66	0 (0.00%)
M	2021-05-19	71	0 (0.00%)
V	2021-05-20	29	13 (1.81%)
V	2021-05-24	33	5 (0.69%)
V	2021-05-28	37	0 (0.0 %)
V	2021-05-31	40	0 (0.0%)
V	2021-06-04	44	0 (0.0%)
V	2021-06-07	47	0 (0.0%)
V	2021-06-11	51	0 (0.0%)
V	2021-06-18	58	0 (0.0%)
V	2021-06-23	63	0 (0.0%)
S	2021-06-18	15	653 (90.69%)
S	2021-06-23	20	31 (4.31 %)
S	2021-06-28	25	0 (0.0 %)
S	2021-07-03	30	0 (0.00%)
S	2021-07-05	32	0 (0.00%)
S	2021-07-08	35	0 (0.00%)
S	2021-07-14	41	0 (0.00%)
S	2021-07-16	43	0 (0.00%)

Table 2: The dates (year-month-day) of the drone images of the three test fields (M, V, and S) in 2021. The 'DAP' column shows the time of the drone image in Days After Planting (DAP). The column 'zero plots (%)' gives the number of plots with no measurable canopy and their fraction among all plots in the field.

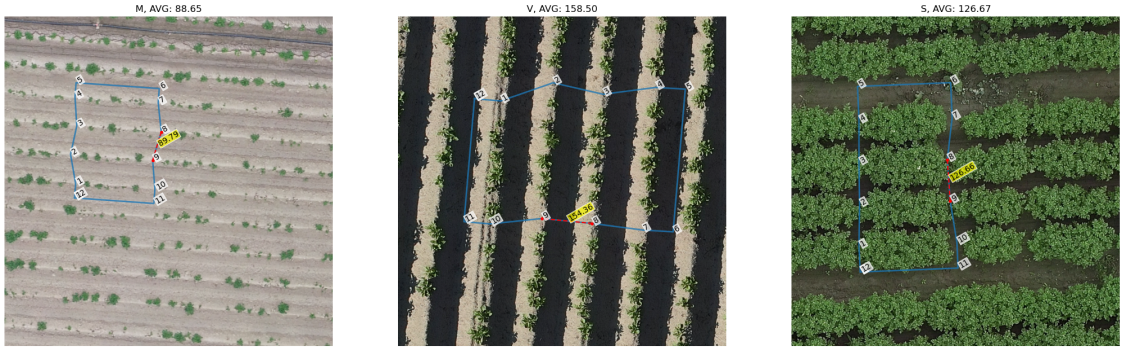

Figure 2: Examples of polygon boundary vertices found in different fields at different times throughout the season with vertex labels. Numbers inside yellow rectangles are the distances between the two vertices in pixels. Image titles show the field average of the inter-ridge distance in pixels, which is subsequently used for the conversion of the canopy area measurements to cm^2.

2 RGB image post-processing and canopy measurement

2.1 Plot localization

Due to the relatively large scale of the trials and the chosen planting technique, the trial fields did not exhibit the usual regular structure with easily identifiable rows and columns of plots. Therefore, we have developed an in-house standardized procedure with minimal manual interaction to detect and identify plots in the trial fields' images. The main steps of the plot-detection algorithm are:

1. From the provided row-column plot labeling and schematics, the expected number N of plots along the ridges of the trial fields is identified
2. The field image where the canopy size allows to detect the gaps between the plots along the ridges is selected from the available images of the trial field. Such an image is usually found towards the end of the canopy growth season, where canopies inside a plot are touching, but have not yet grown as to bridge the gaps to neighbouring plots
3. The beginning and the end of the trial field along each ridge is interactively determined in the selected image
4. The expected number of $N - 1$ inter-plot gaps is automatically detected in the images along each ridge. To this end:
   (a) The field image is binarized using a strict green filter such that decidedly green regions will be white and soil will be black in the resulting image. Since the purpose is to find gaps between lots the use of a strict filter is not detrimental in this case
   (b) The morphological operation of closure is applied to the binarized image to discard possible noise left over from the binarization procedure
   (c) Each ridge is uniformly divided into N sub-intervals
   (d) Image intensity is extracted along three lines parallel and in the neighborhood of the mid-ridge line
   (e) The regions for which the intensity along all three lines is zero (black, i.e. soil in our binarization) are considered the inter-plot gaps and the image coordinates of the midpoint of these regions is saved for further processing
5. The detected plot polygons are displayed and inspected for eventual remaining inaccuracies and distortions and the wrongly identified plot boundary points are corrected interactively
6. For each plot a set of image coordinates of the plot polygonal boundary is saved

Examples of detected inter-plot gaps along the ridges can be found in Figure 2. The four plots of the same batch detected in a trial field are shown in Figure 3.

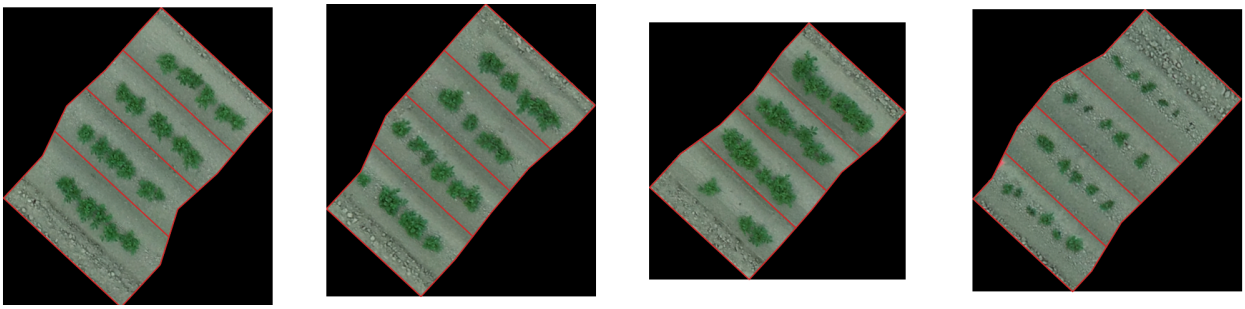

Figure 3: The four plots of the same batch detected in the field on a given date. Also shown are the three inter-ridge boundaries within the plots.

2.2 Time alignment and distortion correction

The raw RGB data consisting of stitched orthophotographic images of the trial fields obtained at several dates during the growth season are not spatially aligned between the dates and sometimes contain significant spatial distortions.

In the first post-processing step, we searched for the transformations between the reference frames of all images of the same trial field collected during the growth season. More specifically, we were interested in the transformation between the reference frame of one particular orthophoto and all other orthophoto's that preceeded and followed in time. The need for such transformations stems from the fact that the polygonal plot boundaries described in the previous section can be successfully detected only at certain dates during the growth season, when the plants have just the right size. Suppose, the polygonal boundaries of the plots have been identified on some reference date. To avoid having to detect the plots on another date, which is also often impossible, we would like to simply superimpose the previously detected boundary polygons on the second orthophoto. To do that we need to find a transformation of the reference orthophoto to the pixel coordinate system of the second orthophoto. We call this procedure the *time alignment* of the two orthophoto's. While in general this transformation can be rather complicated, in the present case, an affine transformation turns out to be completely sufficient, as was confirmed by the visual inspection of the transformed superimposed polygonal plot boundaries.

Time alignment relies on the presence of time-invariant features with the same physical position in the images. In the 2019 trials we had to rely on natural time-invariant features, such as the irrigation pipes. In the 2020 and 2021 trials we had artificial, square, 10 cm $\times$ 10 cm, red-colored markers installed in the fields that we could subsequently find in the images and use as reference points.

The detection of these red markers was aided by the pre-processing of the images, in which bright red pixels are filtered and grouped so that their position can be highlighted on an interactive image plot. The user is shown the image in question with dots in contrasting color plotted at the positions of the algorithmically detected markers. The user has to zoom in on the relevant portions of the field and manually select the middle of the markers.

To understand the simple mathematics behind the recovery of the affine transformation, let there be N markers with their (pixel) coordinates (x_i, y_i), $i = 1, \ldots, N$, on the reference date stored in the vector $\mathbf{p} \in \mathbb{R}^{2N}$ as $\mathbf{p}^T = [x_1, y_1, \ldots, x_N, y_N]$. Suppose that the same N markers have the coordinates $(\tilde{x}_i, \tilde{y}_i)$, $i = 1, \ldots, N$ in another orthophoto taken on another date.

Since a two-dimensional affine transformation is defined by just four numbers, two or more markers with known (same) physical positions in both orthophoto's are sufficient. Although the more markers one has, the more robust is the recovery of the transformation against the noise. With N markers the four transformation elements stored in the vector $\mathbf{t} \in \mathbb{R}^4$ can be recovered by solving the following linear algebraic problem:

$$\begin{bmatrix} 1 & 0 & x_1 & -y_1 \\ 0 & 1 & y_1 & x_1 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & x_N & -y_N \\ 0 & 1 & y_N & x_N \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \end{bmatrix} = \begin{bmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \vdots \\ \tilde{x}_N \\ \tilde{y}_N \end{bmatrix}. \tag{1}$$

Given a sufficient number of markers, there exists the unique least-squares solution $\hat{\mathbf{t}}^T = [\hat{t}_1, \hat{t}_2, \hat{t}_3, \hat{t}_4]$ to this problem, which can be used to determine the location of each vertex of the polygonal plot boundary in the second orthophoto. Let the (pixel) vertex coordinates on the reference date be (x, y), then the pixel coordinates

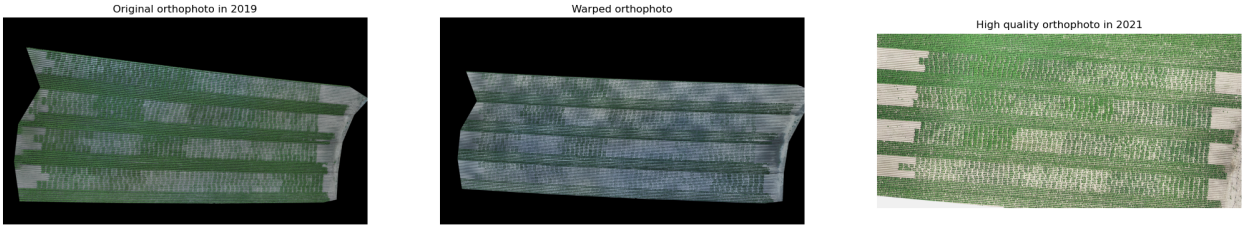

Figure 4: Original distorted 'orthophoto' of the Montfrin field taken in 2019 (left). The same image with distortion corrected by warping to achieve approximately the same inter-ridge distance across the field (middle). High-quality orthophoto of the Montfrin field taken in 2021 (right) confirms that the distortion in 2019 was an artifact of image stitching.

$(\tilde{x}, \tilde{y})$ of this vertex in the orthophoto from another date can be obtained as:

$$\begin{bmatrix} \tilde{x} \\ \tilde{y} \end{bmatrix} = \begin{bmatrix} \hat{t}_1 \\ \hat{t}_2 \end{bmatrix} + \begin{bmatrix} \hat{t}_2 & -\hat{t}_3 \\ \hat{t}_3 & \hat{t}_2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}. \tag{2}$$

The stitched orthophoto images of the Montfrin test field in 2019 contained an additional strong distortion, see Figure 4, making the inter-ridge distance measured on one side of the field strongly differ from the inter-ridge distance measured on the other side. The fact that it was a distortion of the image rather than the natural shape of the field is obvious from the high-quality orthophoto of the same field taken in 2021 (Figure 4, right). Since this distortion has consequences for both the estimation of the green area and the spatial correction, the original orthophoto was re-processed. The field image was warped so that the inter-ridge distance in the "left" part of the image, as measured with the help of selected polygonal vertices, became closer to the inter-ridge distance measured on the "right". The same transformation was used to warp the polygonal plot boundaries. No such distortions were observed or had to be corrected in other fields and years.

2.3 Leaf canopy segmentation and estimation

To measure the canopy area within the polygonal plot boundary, the image pixels are segmented into two disjoint sets: pixels of the canopy and pixels of the surrounding soil. Then, the canopy pixels are counted and the result converted to the cm^2 units.

While a human operator is usually very successful in segmenting an image, a fully automated segmentation procedure that would work in all circumstances is not available. The present dataset featured a variety of illumination and moisture conditions, both of which affect the color of pixels. Also, leaf canopy colors have systematic differences between genotypes, ranging from light green to almost purple. Therefore, every orthophoto had to be processed individually, resulting in different segmentation filters with date- and field-specific parameters. In all cases, the quality of segmentation has been confirmed by visual inspection of randomly selected plots of each genotype.

The green segmentation procedure consists of the following steps:

1. Convert the image to HSV format
2. Find date-specific range of the Hue channel for the canopy. This was done by analyzing the Hue channel histogram, which showed two peaks, canopy and soil, with the canopy peak growing in time. The Otsu method finds a good first guess of the lower Hue boundary. This guess can be refined by inspection of sample plots. Set all the pixels outside the Hue range to 'black'
3. Equalize Saturation and Value channels
4. Filter the Value channel by allowing only the pixels with the value below a threshold and setting all other pixels to 'black'
5. Obtain a grayscale image by applying a weighted combination (weights were manually adjusted to achieve the best segmentation) of some standard agricultural 'green' filters. The Hue Index (HI) [5], Excess Green

(EXG) [3], and Brightness Index (BI) [4]:

$$\text{BI} = \sqrt{\frac{r^2 + g^2}{2}} \tag{3}$$

$$\text{EXG} = 2g - (r + b) \tag{4}$$

$$\text{HI} = \frac{2r - g - b}{g - b} \tag{5}$$

6. Normalize the image, set all pixels below the threshold in column "thresh." in Table 3 to 'black', and binarize the image
7. Remove 'salt and pepper' noise by applying median blur with 3×3 kernel
8. White pixels – canopy, black pixels – soil

The parameters of the above segmentation procedures are provided in Table 3 for each field and date.

2.4 Conversion from pixels to cm^2

After segmentation, the mean canopy area S_{px} (in pixels) over each plot was determined by summing all white pixels within the geometrical boundaries of the plot and dividing by 24 – the number of plants in each plot. To convert a canopy area in pixels to its area in cm^2, we use the fact that the distance d_{cm} between the ridges in the field is determined by the planting device and is $d_{\text{cm}} = 75$ cm in the Veenklooster (V) and Kollumerwaard-SPNA (S) fields, and $d_{\text{cm}} = 74$ cm in the Montfrin (M) field.

To find the pixel-to-cm conversion factor, we compute the average pixel distance d_{px} between the adjacent ridges in the field for a specific date (see Figure 2). Then, the area S_1 of a single pixel in cm^2 is given by:

$$S_1 = \left(\frac{d_{\text{cm}}}{d_{\text{px}}}\right)^2. \tag{6}$$

Thus, the canopy area S in cm^2 is obtained from the canopy area S_{px} in pixels as:

$$S = S_1 S_{\text{px}}. \tag{7}$$

3 Spatial effect removal

The mean plot canopies obtained after the transformation, plot localization, and segmentation procedures described above constitute the raw data and cannot be used to estimate the mean batch canopy, since the test fields are usually spatially nonuniform, which may systematically increase or decrease the canopy size in certain areas of the field. The spatial effect is well-illustrated in Figure 3, showing the four plots of the same batch, with the plot depicted in the right-most image having significantly smaller canopies than the other three plots. Obviously this plot has been affected by some unfavourable growth conditions and would pull down the estimate of the mean canopy if included in the calculations as it is.

```
library(statgenSTA)
library(SpATS)

CanopyMeasurement <- read.csv("/Path_to_Canopy_measurement.csv", header = TRUE, sep = ",")

TableToFit <- createTD(data = CanopyMeasurement, genotype = "Batch",
                       repId = "Block", subBlock = "Block",
                       rowCoord = "Row", colCoord = "Col")

FittedModel <- fitTD(TD = TableToFit, trials='trialname',traits = "Canopy",
                     design = "rcbd")

BLUEsTable <- extractSTA(STA = FittedModel, what = "BLUEs", keep = "Variety")
```

Listing 1: Code to produce the array of spatially corrected canopies from the raw measured array in R

We use the state of the art spatial effect removal method [6], implemented in the R-package SpaTS [1], that removes both random and fixed spatial effects and provides the Best Linear Unbiased Estimate (BLUE) of the mean batch canopy size. The typical output of the SpaTS package is illustrated in Figure 5. We apply the spatial effect removal to the raw canopy data obtained from all available orthophoto's.

field/date	H range	S range	S,V equalize	V filter	weights (BI,HI,EXG)	thresh.	blur
M-2019-04-10	[30, 80]	[0, 255]	yes	[0, 100]	0.8, 0.8, 1.0	0.5	yes
M-2019-04-19	[25, 100]	[0, 255]	no	[0, 110]	0.1, 0.3, 0.6	0.25	yes
M-2019-04-26	[25, 80]	[0, 255]	no	no	0.0, 0.0, 1.0	0.35	no
V-2019-05-24	[34, 180]	[52, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
V-2019-05-29	[34, 180]	[52, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
V-2019-06-07	[54, 180]	[52, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
S-2019-06-07	[36, 180]	[18, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
S-2019-06-19	[40, 180]	[41, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
M-2020-04-13	[31, 180]	[30, 255]	–	–	0.2, 0.2, 0.6	0.45	no
M-2020-04-16	[32, 180]	[30, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2020-04-18	[34, 180]	[52, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2020-04-22	[38, 180]	[52, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2020-04-25	[36, 180]	[47, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2020-05-27	[36, 180]	[33, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
V-2020-05-30	[27, 80]	[60, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
V-2020-06-07	[44, 180]	[41, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
V-2020-06-10	[50, 180]	[50, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
V-2020-06-12	[50, 180]	[55, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
S-2020-06-03	[44, 120]	[80, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
S-2020-06-10	[35, 120]	[70, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
S-2020-06-12	[35, 120]	[75, 255]	–	–	0.0, 0.0, 1.0	0.25	yes
S-2020-06-15	[35, 120]	[75, 255]	–	–	0.0, 0.0, 1.0	0.15	yes
S-2020-06-19	[40, 120]	[52, 255]	–	–	0.0, 0.0, 1.0	0.2	yes
M-2021-04-02	[35, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-04-07	[26, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-04-08	[28, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-04-16	[35, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-04-19	[35, 100]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-04-22	[35, 90]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-04-26	[30, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-05-02	[36, 90]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-05-04	[38, 100]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-05-08	[36, 90]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-05-11	[38, 80]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-05-14	[38, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
M-2021-05-19	[40, 80]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-05-20	[26, 50]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-05-24	[34, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-05-28	[26, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-05-31	[26, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-06-04	[34, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-06-07	[26, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-06-11	[26, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-06-18	[34, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
V-2021-06-23	[34, 60]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-06-18	[31, 50]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-06-23	[30, 50]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-06-28	[24, 40]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-07-03	[28, 62]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-07-05	[34, 60]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-07-08	[31, 62]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-07-14	[36, 75]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes
S-2021-07-16	[34, 62]	[0, 255]	–	–	0.2, 0.2, 0.6	0.45	yes

Table 3: Field- and date-specific parameters for canopy segmentation in orthophoto's.

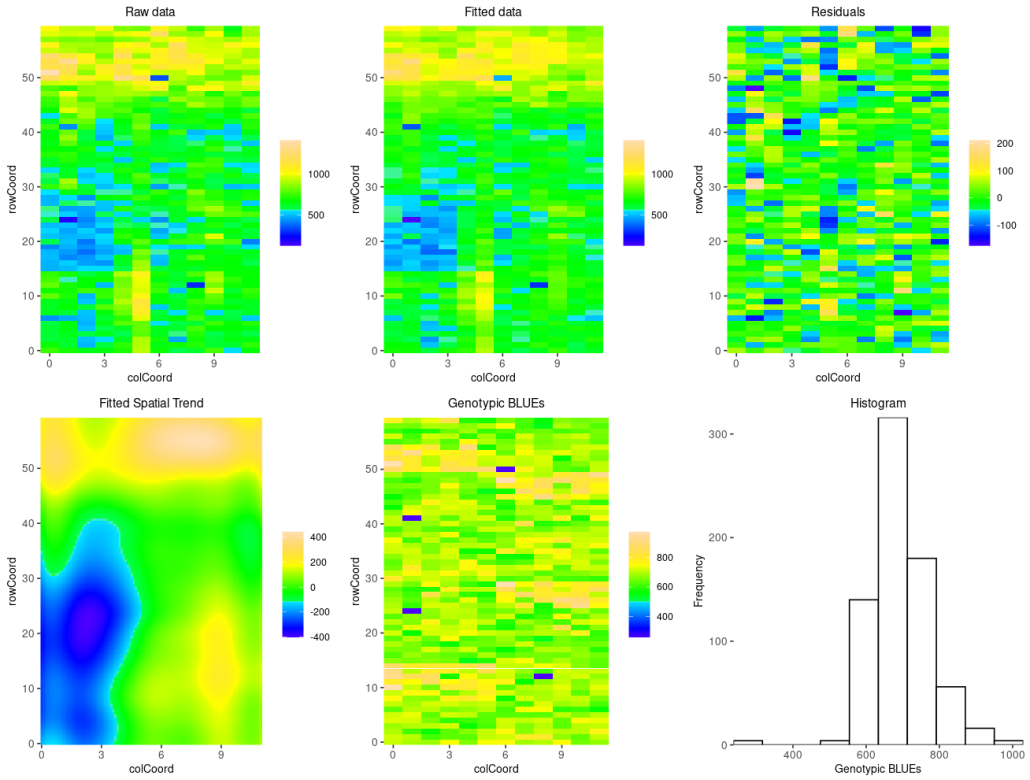

Figure 5: Spatial plot produced by the package SpaTS as an illustration of spatial effect removal.

4 Choice of the vitality measure

There is no universally accepted measure of the plant vitality. In fact, although it may be a matter of semantics, one could argue that the term 'vigor' is more applicable in the present situation. In any case, the size of the leaf canopy at the time of tuber bulking to a large extent determines the yield of potato plants, which is the ultimate goal of potato farmers. Therefore, the sooner a plant can develop a large canopy the more vigorous or vital is this plant. From this point of view, it appears that considering the time evolution of the canopy could eventually lead to a measure of vitality. Unfortunately, systematic analysis of the canopy time evolution could not be achieved in this project due to sparsity and inconsistency of the imaging dates. Nevertheless, a well-chosen single-time measurement of the canopy size may be indicative of the plant vitality as well. One should be aware though that a large canopy at a certain point in time could be either due to an early-emergent but relatively slow-growing plant or due to a late-emergent and fast-growing plant. Nevertheless, a relatively large canopy somewhere in the middle of the growth season, after the early 'transients' related to the emergence time and the initial rate of growth have passed, is surely indicative of the plant vitality. Indeed, as long as a plant acquires a large canopy at a useful point in time, i.e., not too late in the season, it can be considered a vital/vigorous plant, and it does not really matter whether it is due to an early emergence time or a fast initial growth rate.

Figure 7, Figure 8, and Figure 9 show the summary of the BLUE canopy data for each of the six genotypes at the available time points for each year and field. As one can see, the growth pattern and the attained canopy size are different between the fields and years. This can be attributed to the varying weather conditions and soil types, caused mainly by the difference in geographic location and the different times of the year the seed tubers were planted in each field (see Table 1, Table 2). Hence, a single *a priori* chosen day after planting cannot be used as a time point to take the vitality measurement. Therefore, our choice of the canopy measurement date is year- and field-specific and is guided by the data and the following basic principles:

- It should be possible to compare different batches within each genotype
- The plant-plant and batch-batch interactions should be avoided
- The growth has reached a stable phase in which batch ordering does fluctuate less

From this point of view, there is just one or two dates per year and field among the available data that can be used as the vitality measure. Indeed, in the early measurements not all plants have emerged yet, which does not

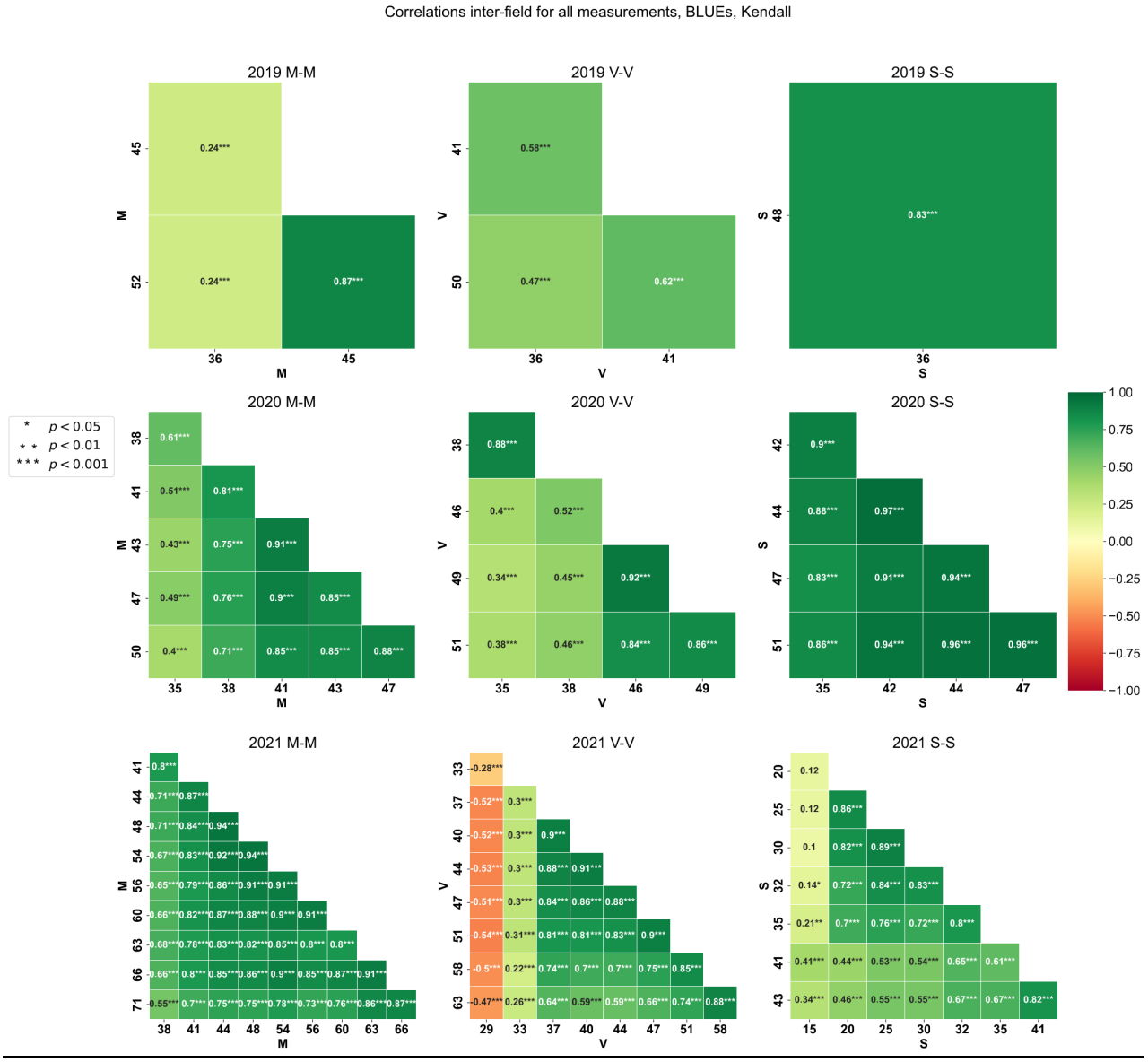

Figure 6: The Kendall τ coefficient is computed for each pair of measurements in one field. As we see the general trend is for the ordering to stabilize towards the end of the growth (bottom right of each correlation subplot). In this plot we show the stability measure with respect to a quantization of the vigor into three classes.

allow for a fair comparison of the batches. In the late measurements, the canopies of rapidly growing genotypes start "merging" not only inside the plots, but also with those of the neighboring plots, thus introducing plant-plant and batch-batch interactions.

As a measure of stability, we have chosen to compute the Kendall τ on the vector of quantized vigor, Figure 6. This means we have labelled the vigor measurements as high performers, 1, average performers, 2, and low performers, 3, in each day and computed the Kendall τ for all measurements of a field, pair-wise. The Kendall τ ranges from minus one to one and quantifies the instability of the three classes, i.e. if in two dates the labels of the batches have not changed the Kendall τ will be equal to one and close to -1 if all labels are perfectly reversed.

From 47 to 50 DAP's all plants have emerged, the canopies are not yet overlapping, and the batch ranking as measured by the Kendall τ has stabilized making this a good time range to consider and reducing the choice to one or two dates per field in each year. From Figure 7, Figure 8, and Figure 9 it is clear that this corresponds to the end of the exponential growth period and precedes the period of 'saturation' in the expected sigmoid growth curves. The remaining choice between the few acceptable dates was made by taking into account the quality of the orthophoto's, i.e., the precision of the canopy area measurements. It should be mentioned that these final choices do not alter the conclusions of the subsequent association/regression studies in any significant

way, since the data at these time points are very highly correlated, Table 4.

	M 52
M 45	96%

	S 48
S 36	90 %

	V 41
V 36	64%

	M 47	M 50
M 43	96%	96 %
M 47	-	98%

	S 47	S 51
S 44	99%	97 %
S 47	-	99 %

	V 49	V 51
V 46	99%	97%
V 49	-	97%

	M 54	M 56
M 48	98%	98 %
M 54	-	99%

	S 25	S 32
S 30	98%	97 %
S 25	-	97 %

	V 63	V 51
V 58	97%	96%
V 63	-	92%

Table 4: Correlations (Pearson) of canopy size at neighboring DAPs in 2019 (left), in 2020 (center), and in 2021 (right).

Our final choices of the dates for the vitality measurement are highlighted in green along the x-axis of In Figure 7, Figure 8, and Figure 9 and in Table 1, and Table 2.

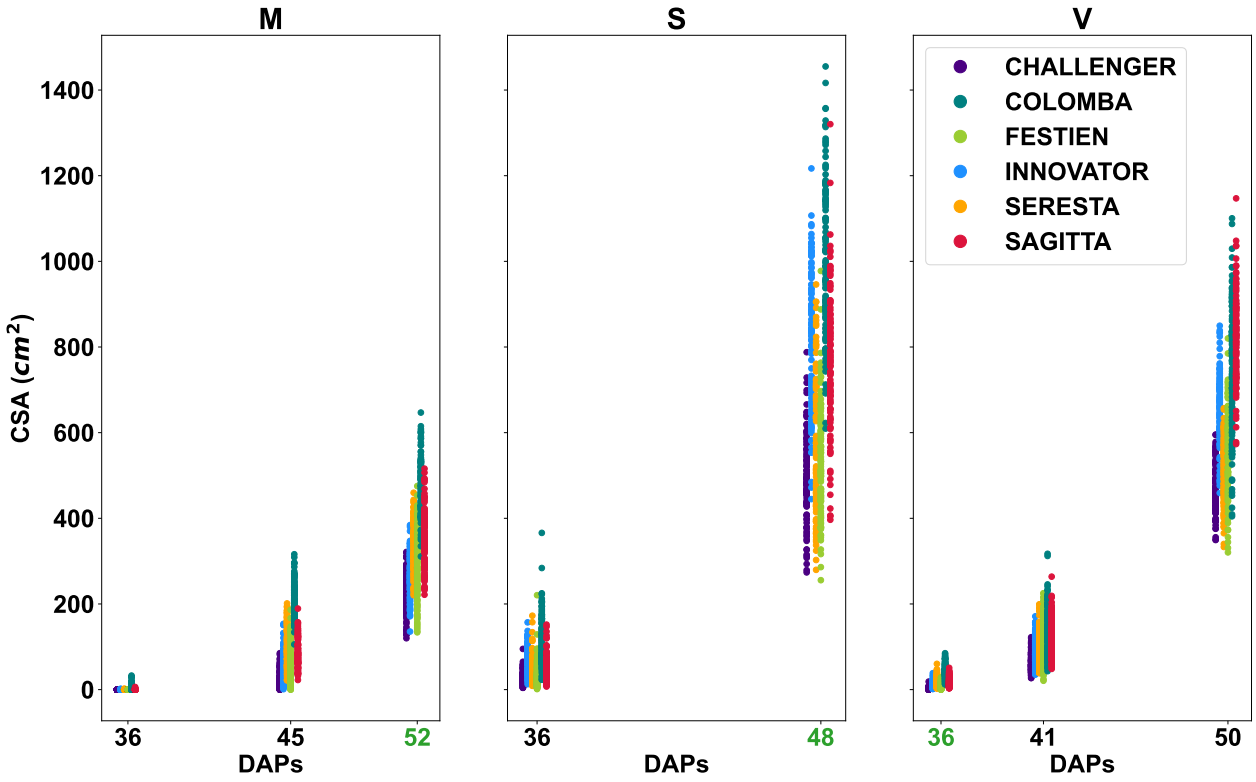

Figure 7: Summary of all available measurements in 2019 per genotype as scatterplots. The choice of the date for the vitality measurement is highlighted in green color on the x-axis.

5 Correlations in vitality across fields

After all the necessary steps for the vitality data extraction and removal of known effects, an exploratory analysis of the vitality data has been performed to ascertain the plausibility of the main project hypothesis that the vitality of a plant is determined, at least to a certain extent, by the seed tuber from which the plant has grown. The presence of such dependence could be inferred if the vitality of the plants produced by the seed tubers of a given batch, relative to other batches, was consistent for repetitions inside the field and, especially, across different fields.

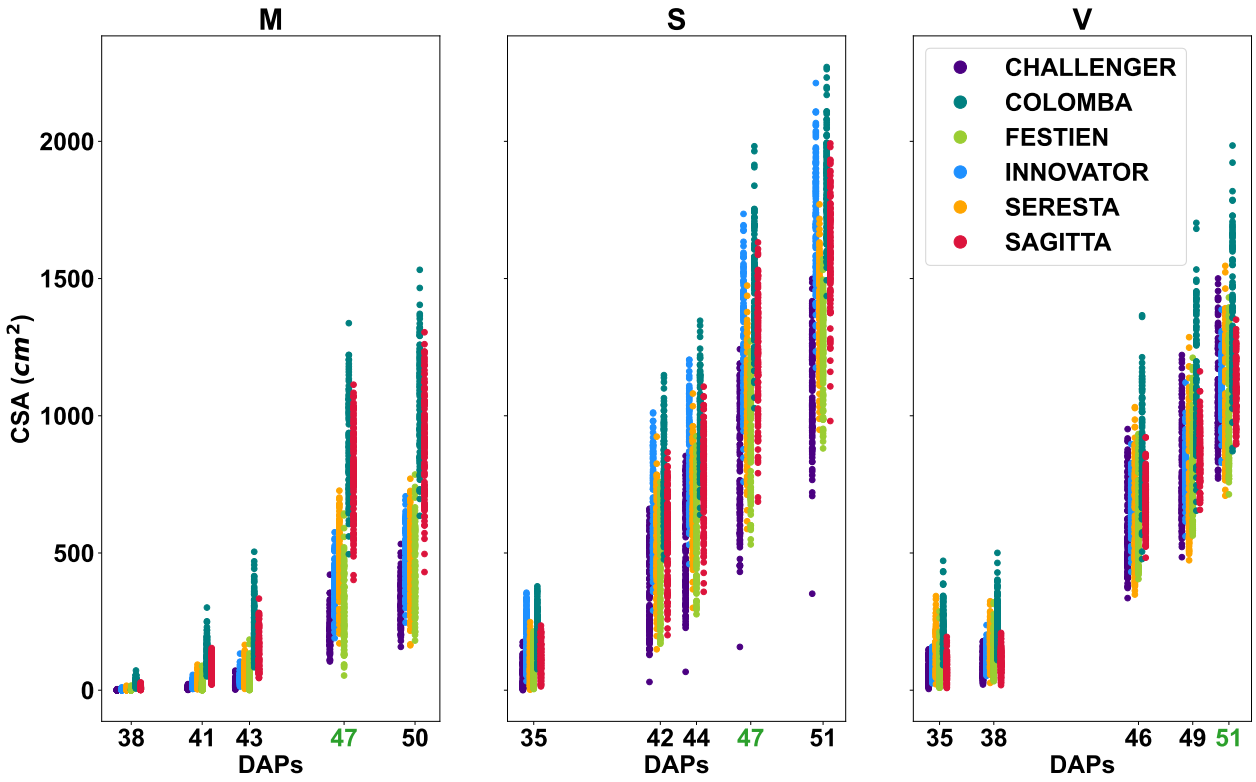

Figure 8: Summary of all available measurements in 2020 per genotype as scatterplots. The choice of the date for the vitality measurement is highlighted in green color on the x-axis.

Pearson correlation of the vitality data provides an adequate measure of consistency. Correlation analysis can only be applied within a given year, where tubers of the same batches were planted in three different fields. As was mentioned above, while the same genotypes were tested in both years, the seed-tuber batches had a different production origin in each year and cannot be directly compared for consistency.

Correlations between the raw and spatially corrected (BLUE) vitality data across fields in each year are shown in Figure 10 and Figure 11. The symbols along the horizontal and vertical axes denote the test fields. The range of statistical significance (p-value) of these correlation results is indicated with the star symbols next to the value: three stars, $p < 0.001$, two stars, $p < 0.01$, one star, $p < 0.05$, or no stars – not significant. One can see that both the raw and the BLUE data significantly correlate across the fields in all years, with the spatial effect removal leading to a slight increase in the correlation. It is also apparent that the field of Montfrin (M) in 2021 does not correlate with the other two experimental fields. We hypothesise that this lack of correlation is due to very early frost in the growth which strongly hindered the growth of varieties Challenger, Festien, and Seresta thus resulting in a lack of correlation for the full field measurements. The fact that the correlations are not perfect in the other cases can be explained by the influence of the weather and soil conditions, inconsistent application of the herbicide, and the aging of the seed tubers.

Figure 12 presents the correlations individually for each genotype and shows a much more varying picture. Here it is easy to see how adverse weather in M 2021 negatively affected Challenger, Festien, and Seresta.

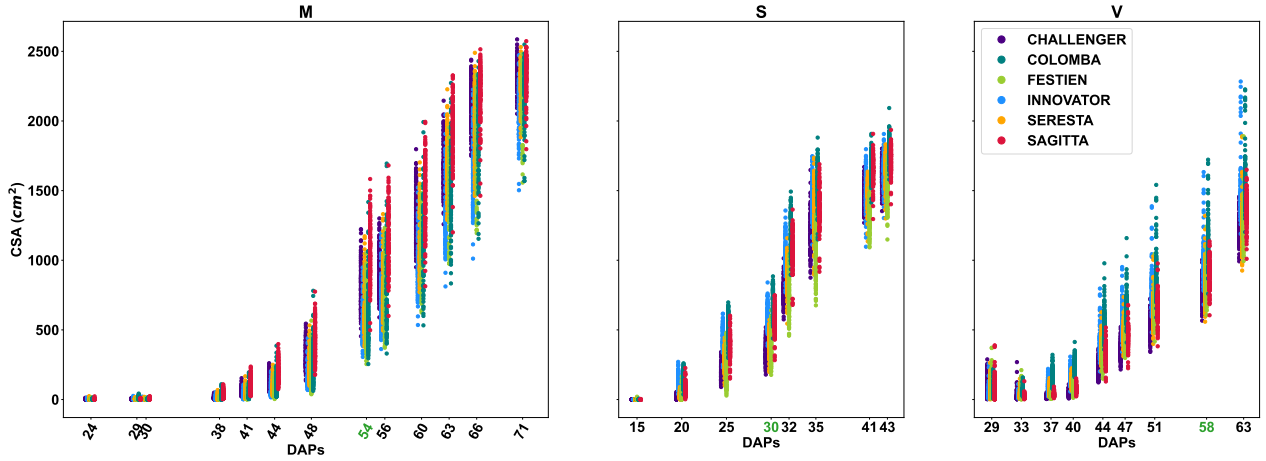

Figure 9: Summary of all available measurements in 2021 per genotype as scatterplots. The choice of the date for the vitality measurement is highlighted in green color on the x-axis.

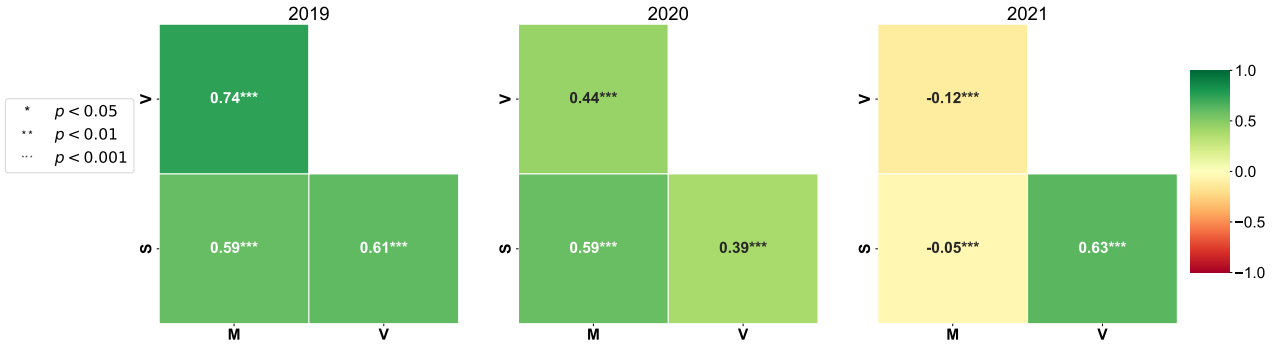

Figure 10: Correlations in raw vitality data between the fields in 2019 (left) and 2020 (middle), and 2021 (right).

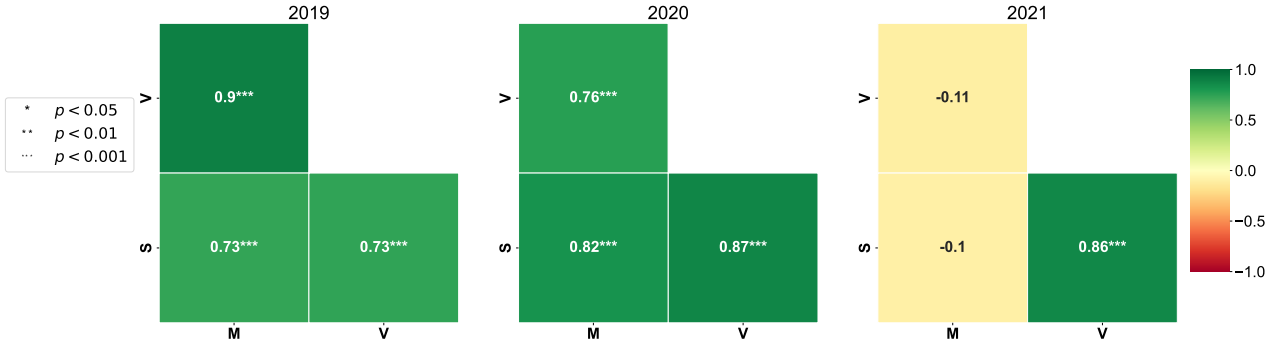

Figure 11: Correlations in spatially-corrected (BLUE) vitality data between the fields in 2019 (left), 2020 (middle), and 2021 (right).

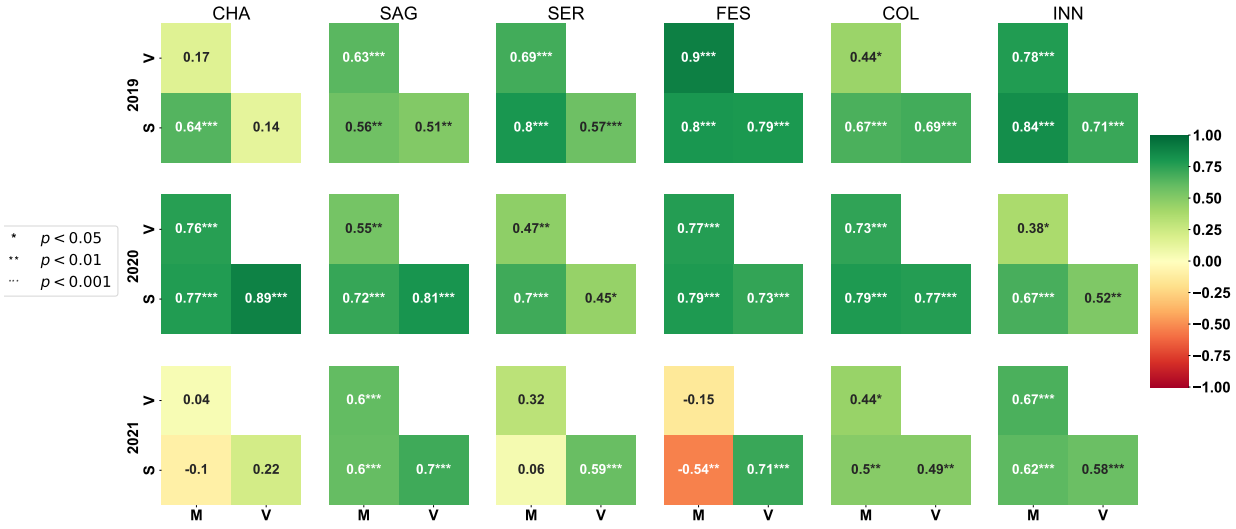

Figure 12: Correlations in spatially-corrected (BLUE) vitality data between the fields per genotype in 2019 (top row) and 2020 (middle row), and 2021 (bottom row).

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