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A Study of Different Platforms and Sensory Systems for Wheat Field Trials

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Mechanics and Process Technology

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Eivind Aleksander Bleken
Ås, May 15th, 2017

Abstract

In the field of agriculture several technical advances have been implemented to meet the growing demand with regards to food supply. As an indicator for grain yield in wheat different indices have been tested and evaluated such as the Normalized Difference Vegetation Index (NDVI), MERIS Terrestrial Chlorophyll Index (MTCI) and the Leaf Area Index (LAI). The first two is constructed to estimate differences in chlorophyll content while the last one is used to indicate plant coverage. They all utilize the difference in reflectance in the near infrared spectral band between healthy plants and either stressed plants or non-plants.

This thesis had 96 wheat plots consisting of 24 cultivars given two different levels of Nitrogen as fertilizer, 7.5 and 15 kg/daa. A multi-spectral camera, an agricultural robot and a drone was applied to collect data throughout the season of growth. At the end of said season traits such as grain yield and plant height was measured. The plant height was digitally estimated by using digital surface models and a regression model. The indices NDVI, MTCI and LAI were calculated based on scripts using Python. The values for the last index was determined by using NDVI threshold values and the ratio between predominantly green pixels to total pixels.

The correlation between NDVI and grain yield was not strong with the correlation between grain yield and MTCI being in the same realm of strength. LAI showed no statistical significance on any set of data and carried no merit with regards to correlations. It did however highlight the impact the inclusion of the near infrared spectral band offers when estimating plant coverage.

The correlation between manual and digital plant height values was strong and can quite possibly get stronger by enhancing the principals embedded in the method applied.

Contents

Abbreviations

NDVI	**N**ormalized **D**ifference **V**egetation **I**ndex
MTCI	**M**ERIS **T**errestrial **C**hlorophyll **I**ndex
DSM	**D**igital **S**urface**M**odel
LAI	**L**eaf **A**rea **I**ndex
GIS	**G**eographic **I**nformation **S**ystem
NIR	**N**ear **I**nfra**R**ed
REG	**R**ed-**E**d**G**e
RGB	**R**ed, **G**reen, **B**lue
GUI	**G**raphical **U**ser **I**nterface
UAV	**U**nmanned **A**erial **V**ehicle
MSL	**M**ean **S**ea **L**evel
GY	**G**rain **Y**ield
TKW	**T**housand-**K**ernel **W**eight
HLW	**H**ecto**L**iter **W**eight
DH	**D**ays to **H**eading
DM	**D**ays to **M**aturity
PH	**P**lant **H**eight
CRP	**C**alibrated **R**eflectance **P**anel

ABBREVIATIONS ABBREVIATIONS

Chapter 1

Introduction

In coherence with the increasing global population, with the estimated global population to reach 9.1 billion in 2050[9], a demand for food follows suit. In one of the fields of nutritional supply, more precisely in agriculture, several technological advances have been implemented to meet such a demand. From mechanical approaches such as High-Flex Tires to reduce soil compaction which in turn decrease grain yields[3] to Mini-chromosome technology that permits faster and more precise methods to enhance wanted traits[31]. In the realm of autonomy and the use of sensors the additions of driverless tractors completing predetermined routes have been added with incorporated software to evade obstacles. Further, sensors are utilized to monitor crops with regards to plant health, watering needs, nitrogen levels and more. The study of this thesis will revolve around sensory applications with segments of autonomy included.

The ability to predict grain yield prior to harvest is highly beneficial for optimal cultivar selection while the implementation of digital assessment of plant height would have the potential to eradicate the need for manual time consuming measuring methods. Both aspirations have been entertained with the use of indices and digital models, respectively. Addressing the former, indices such as NDVI (Normalized Difference Vegetation Index) and MTCI (MERIS Terrestrial Chlorophyll Index) have served as estimators for biomass and chlorophyll amount while LAI (Leaf Area Index) has served its purpose to gauge plant coverage per unit area.

The aforementioned indices are dimensionless ratios of wavelengths of reflectance of electromagnetic energy. The relationship between grain yield and NDVI has in other studies been affirmed as correlative[20] in addition to the correlation between the index and plant biomass[13]. Regarding the MTCI it has exhibited a direct linkage to actual chlorophyll content[7] and exhibited a strong linear relationship with plant coverage[28]. A high correlation between biomass and the LAI have been shown as well[27]. This index is based on the NDVI in many studies where a threshold value has been applied to differentiate between plants and non-plants for the calculation of the index. This has led to some amount of hindrance as the NDVI suffers from sensory saturation[15]. In this thesis the same procedure to produce the index will be revisited accompanied by a pixel sorting based approach.

In the field of digital mapping the geographic information system (GIS) has different ways to visualize and collect data of the terrain being obtained by sensors. Different models are frequently utilized to present elevation. Three commonly used models are DSM (Digital Surface Model), DEM (Digital Elevation Model) and DTM (Digital Terrain Model). The first one is based on light pulses emitted and captured on their return by the sensor for acquiring the variable distance. The second shows only ground elevation with both man-made and natural objects eviscerated, such as roads and trees. The third variation is created by contour lines as a result of stereo photogrammetry which is initially in 2D before interpolated into a DEM.

Questions for this thesis to answer are:

- **Will the NDVI and MTCI correlate with wheat grain yield?**
- **Will either or both of the approaches for the LAI correlate with grain yield?**
- **Will the data from a collected DSM reflect the manually measured plant heights?**

Chapter 2

Theory

For this thesis correlations between different indices for biomass, chlorophyll and plant coverage and the actual grain yield (GY) were calculated as well as the correlation between digitally estimated plant heights versus manual measurements. Prior to further dwelling on how to obtain mentioned data we will ponder the theory regarding wheat growth and the components for the monitoring of this.

2.1 Wheat growth

In the process of photosynthesis wheat, as most other plants, absorb solar radiation in the spectral waveband range known as Photosynthetically Active Radiation. This is approximately in the same range as visible light[19]. Wheat, using its chlorophyll, captures energy emitted from the sun in order to grow. The growth phases of wheat (*Triticum aestivum* L.) has been compartmentalized by the Zadoks System[23] with its stages organized and described in table 2.1. The stage numbers are the primary Zadoks code with secondary stages omitted. The germination starts as soon as the kernel is sown in stage 0 with some leaf development to complete stage 1. Stages 2-4 include a vertical elongation and the head development followed by the emergence of said head in stage 5. Flowering, the pollination, in stage 6 lasts for approximately 4 days where the kernels grow to a size that is unaltered in the next phases. In the next three stages, despite the absence of change in size, the kernel weight increases as the consistency evolve from "milky" to "doughy" until hardened in the ripening stage.

Table 2.1: *Wheat growth stages numerated by primary Zadoks code.*

Stage	**Description**
0	Germination
1	Seeding development
2	Tillering
3	Stem elongation
4	Boot
5	Head emergence
6	Flowering
7	Milk development in kernel
8	Dough development in kernel
9	Ripening

The highest levels of chlorophyll have been observed in the flowering phase and throughout the "milky" phase, namely stages 6 and 7[24], parallel with the aforementioned growth of the kernels.

2.2 Reflectance

Whenever a particle with an electric charge, being either positive or negative, is being accelerated an electromagnetic wave is created[18]. These waves contain energy which may be transmitted to receiving matter resulting in absorption or reflection. The electromagnetic energy spectrum is divided into wavelengths with gamma rays in the lower scope and long radio waves in the larger as shown in fig. 2.1. A continuous segment of wavelengths is often referred to as a spectral band. One such aforementioned band is the light visible to the human eye, ranging from approximately 390 to 700 nm providing us with sensory experiences based on energy reflected from different matter absorbed in our eyes known as "seeing".

It is possible to apply specific spectral bands to evaluate plant health and magnitude of chlorophyll production as healthy plants have a higher reflectance of near infrared (NIR) than unhealthy ones.[26]. This is because, absorption of energy at those relatively high wavelengths would not suffice in the making of chlorophyll to the extent that the plant

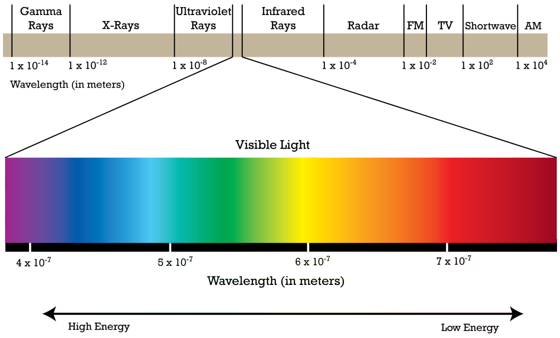


FIG. 2.1: *Electromagnetic spectrum. (Source:www.pion.cz)*

would overheat in the attempt[12]. Between the realms of visible light highly profitable for chlorophyll construction and the less favored energy provided by longer wavelength a spectral band exists named Red-Edge (REG) where the transition from low to high reflectance is most radical. These bands are visualized in fig.2.2 with the reflectance percentile for both a healthy and stressed plant along with the surrounding soil.

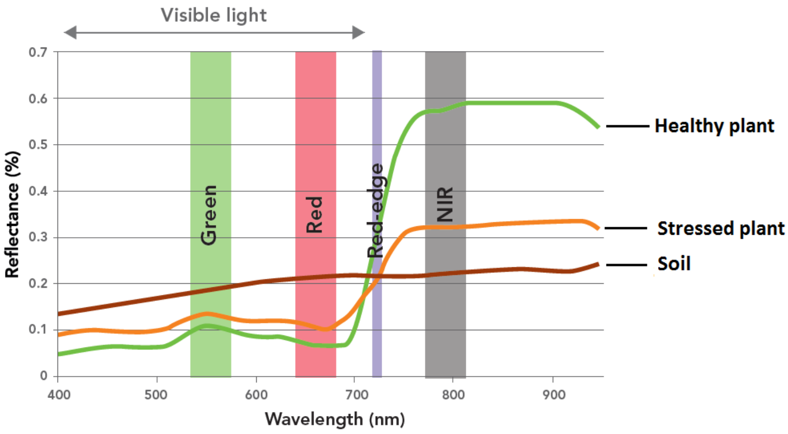


FIG. 2.2: *Reflectance of healthy and stressed plants as well as soil in different spectral bands. (Source:www.micasense.com)*

We will now consider three indices where different bands and segments of the electromagnetic spectrum will be utilized.

2.2.1 Normalized Difference Vegetation Index (NDVI)

As healthy plants will have a higher reflectance of NIR than unhealthy ones and other non-plant objects will appear lighter in that spectral band, as shown in fig.2.2. Thus the difference between the reflectance of NIR and the color red would be higher than the difference for an unhealthy specimen or for instance the ground. Further this difference is divided by the sum of both terms yielding the index

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2.1}$$

where NIR is the near infrared reflectance and RED is the red reflectance[1, 2, 17, 21, 25].

2.2.2 MERIS Terrestrial Chlorophyll Index (MTCI)

Observations have shown that with increased chlorophyll content there were both a decrease in the difference between the reflectance of REG and RED and an increase in the difference between the reflectance of NIR and REG[7]. Thus we obtain a new index to describe chlorophyll content which is

$$MTCI = \frac{NIR - REG}{REG - RED} \tag{2.2}$$

where NIR is the near infrared reflectance, REG is the red-edge reflectance and RED being the red reflectance.

2.2.3 Leaf Area Index (LAI)

When evaluating plant coverage the measuring of leaf area index is widely applied both with leaves who are and aren't flat[6, 29]. The common approach has its basis in finding the ratio between area consisting of leaves (vegetation) to the total area being evaluated. It is dimensionless and given as

$$LAI = \frac{\text{Leaf area}}{\text{Total area}} \tag{2.3}$$

This thesis will estimate this index using two different approaches, both of which will be further described in the chapter 3.

Chapter 3

Materials and Methods

This chapter will encompass the methods applied in the making of this thesis ranging from wheat growing facilitations, equipment implemented, different software and algorithms for analysis.

3.1 Field Trial Setup

24 cultivars of wheat were planted on May 12th, 2016 at Vollebekk Research Farm located in Ås, Akershus in Norway. The 24 cultivars represent the last 40 years of wheat grown in Norway[30], also represented by two different levels of fertilizing, 7.5 kg/daa and 15 kg/daa of Nitrogen, chronologically applied in the same historical time range. These two levels of fertilization will from this point on in this thesis be named 8 kg/daa and 15 kg/daa. The layout is presented in fig. 3.1 with each plot labelled with the cultivar name in a total of 96 plots, 4 of each cultivar. This setup is known as an alpha lattice split plot design, where each plot is labelled with the template `Name_Nitrogen level_Rep.number`. The rep. number represents which fertilizing block each block is located, starting from the left in fig. 3.1. For instance, `Zebra_15_1` is the label for the cultivar Zebra with 15 kg/daa of Nitrogen applied in the first of two instances of that fertilizing level. Furthermore, each plot is given a number of four digits, with the second being the row number and the last two the column numbers (the first digit is always 1), with 1101 being in the top left corner and 1812 in the bottom right corner in the

very same figure. Border plots on each side was also sown to buffer from environmental stress factors.

Demonstrant	Krabat	SW01074	Zebra	GN13618	PS-1	Krabat	SW11011
Polkka	SW01074	Reno	GN10637	Krabat	Seniorita	Zebra	SW11230
GN10521	Seniorita	SW21074	GN11542	Polkka	Arabella	GN11644	PS-1
Mirakel	GN10637	PS-1	SW11011	SW11011	SW21074	Tjalve	Reno
Zebra	Tjalve	Mirakel	Seniorita	Reno	Demonstrant	GN13618	Seniorita
Reno	Avle	Bjarne	Bastian	SW01074	Rabagast	SW21074	Avle
GN11644	Bjarne	Tjalve	Demonstrant	SW11230	Zebra	Runar	Arabella
SW11011	GN11542	Avle	Polkka	GN11644	GN10637	SW01074	GN10637
PS-1	SW11230	GN10521	Runar	Mirakel	Avle	Bastian	GN11542
Runar	SW21074	Arabella	Krabat	GN11542	GN10521	Rabagast	Polkka
Arabella	Rabagast	Rabagast	SW11230	Bastian	Runar	GN10521	Bjarne
Bastian	GN13618	GN13618	GN11644	Tjalve	Bjarne	Demonstrant	Mirakel

	8 kg Nitrogen
	15 kg Nitrogen
	15 kg Nitrogen
	8 kg Nitrogen

Fig. 3.1: *The field schematically visualized with the cultivar names and levels of Nitrogen referenced in the legend box. Border plots are not shown.*

The seeding rate was 23 g/m^2 and treatment of herbicides and fungicides were applied. Heading dates were manually recorded, along with maturity dates and plant height (PH). The number of days to heading (DH) and maturity (DM) were also noted. Heading and maturity are referenced in table 2.1. Successive to maturing, the trial was harvested and 1000-kernel weight (TKW), hectoliter weight (HLW) and protein content were assessed.

3.2 Equipment

The experimental process revolved around three main apparatus, namely a multi-spectral camera, an agricultural robot and an unmanned aerial vehicle (UAV). This section will highlight these.

3.2.1 Multi-Spectral Camera

As mentioned in section 2.2 and in accordance to the purpose of obtaining sensory data of the spectral bands from fig. 2.2 a multi-spectral camera from MicaSense named Parrot

Sequoia was employed. It had five separate sensors, one for each spectral segment, being near infrared, red-edge, green, red and commonly used RGB as shown in fig. 3.2.

Fig. 3.2: *Parrot Sequoia camera with the five different sensors presented as well as dimensions and miscellaneous features. (Source:www.micasense.com)*

To adjust for weather conditions, gauge relative distance for DSM and picture storage, a sunshine sensor served as an addition to the camera, shown in fig. 3.3. It had eight photo diodes with four filters, one for each of the four wavebands seen in fig. 2.2. Its low weight made for mounting of minimal hindrance.

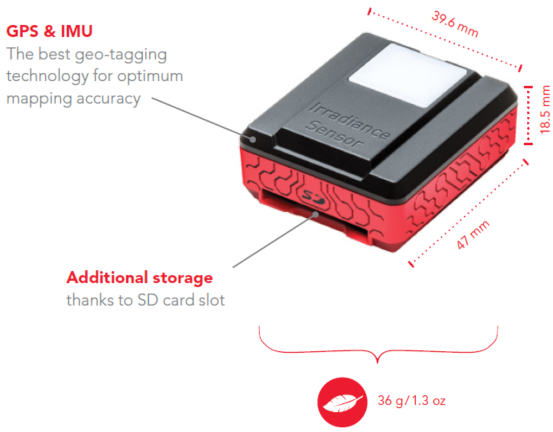
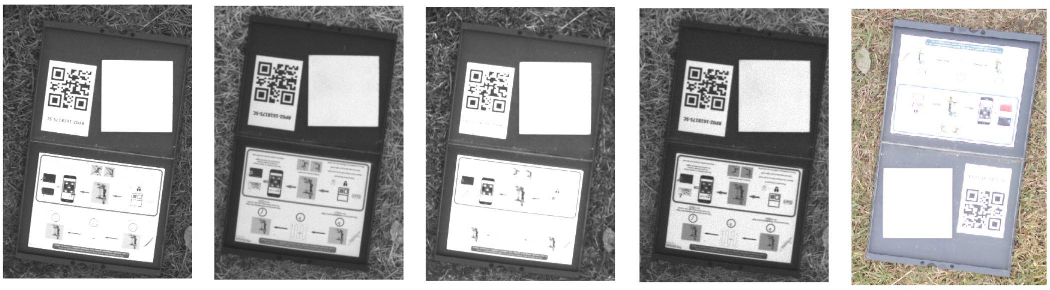


Fig. 3.3: *Sunshine sensor with features identified. (Source:www.micasense.com)*

The camera could either be set to take pictures automatically at set intervals or manually, either by pressing the button directly on the camera or by its Wi-Fi-connection.

Before either an automatic session of pictures were taken while attached to the UAV or by the user manually while operating the agricultural robot a picture was taken of the calibrated reflectance panel (CRP). Each session also included a picture of the very same plate which has known values of reflectance for both the visible and near infrared wavebands, shown in fig. 3.4.



(a) (b) (c) (d) (e)

FIG. 3.4: *Here we see the CRP in the top right corner in the plastic box next to the QR code in the spectral bands (a) Green, (b)Near infrared, (c) Red, (d) Red-Edge and (e) in the bottom left corner in the RGB picture. Note that the RGB picture is rotated 180 degrees as a standard.*

3.2.2 Agricultural Robot

As the title for this section implies a robot for agricultural needs was utilized, named Thorvald, a prototype for future editions. It weighed approximately 150 kg and had a low center of gravity. It utilized four 600 W motors with toothed belts for each wheel which could be controlled independently allowing for easy manoeuvring and rotation around its own center axis[4, 14]. Its built-in water proof PC computer used the software ROS (Robotic Operating System) while its weather proof screen was displayed with high brightness for outdoor use. Thorvald, both outdoors and as a digital visualization, is shown in fig. 3.5.

A rig for the attachment of the camera was mounted at the front. This, as well as the robot in action, can be seen in fig. 3.6. The camera and the sunshine sensor were mounted using Velcro on both the bottom and top surface on the tip of the rig, respectively.

The route travelled by Thorvald was one column at a time, travelling the length of the field in opposite direction on each column in relation to the previous one, taking two pictures for each plot. The camera was activated using a smart phone through Wi-Fi.

(a) (b)

Fig. 3.5: *Thorvald both (a) outside and (b) digitally visualized. Here we see the computer screen in the bottom part of the picture, next to the emergency stop button and the power switch.*

(a) (b)

Fig. 3.6: *Thorvald with (a) the rig for camera attachment shown (before attaching sensor and camera and(b) in the midst of both the wheat and the process of photographing.*

3.2.3 Unmanned Aerial Vehicle

A predetermined route was set up using a software application called Litchi for the DJI Phantom 3 drone. Before lift-off the camera was set to take a picture every 1.5 seconds until stopped by the user after landing. The UAV travelled at an altitude of 10 meters the first days and 15 meters half way out in the growing season to cover a larger area due to limitations in battery life. It flew in a very similar zigzag formation as Thorvald for optimal coverage of the wheat field. Both the route formation and UAV are shown in fig. 3.7 and 3.8, respectively.

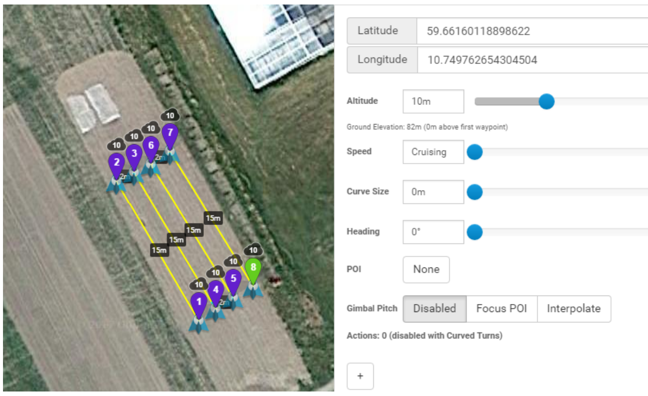


FIG. 3.7: *The route travelled with the options for the software shown.*

FIG. 3.8: *The drone (without the camera) and yours truly.*

A reoccurring obstacle was the loss of GPS signals which were imperative to a successful completion of the route set for the UAV. For this reason it was resorted to manual steering when necessary. This was accompanied by factors of hindrance being winds not longer being automatically stabilized against by the gimbal and visual estimation having to be made by the user. The latter revolved the user having to gauge when the UAV had to switch direction after completing a column of wheat plots.

3.3 NDVI and MTCI

The pictures taken as the drone completed its route were uploaded to Atlas, which is a cloud-based data platform by MicaSense. An example of all 5 cameras in action is shown in fig. 3.9.

Atlas compiled the pictures and returned a composed visual data file of the field with GPS coordinates and the earlier mentioned spectral bands incorporated, known as a GeoTIFF (fig. 3.10).

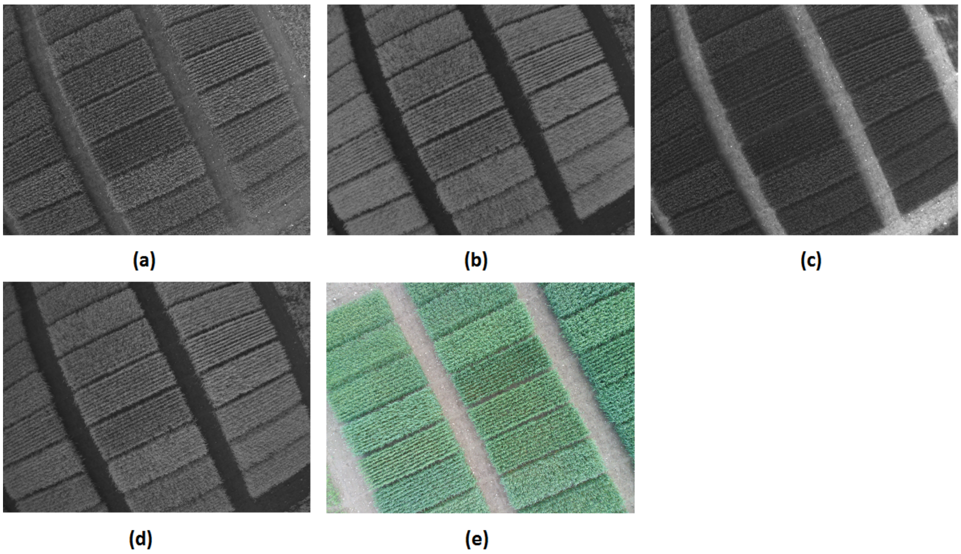


Fig. 3.9: *A picture for each of the 5 cameras. The spectral bands presented are (a) Green, (b)Near infrared, (c) Red, (d) Red-Edge and (e) RGB picture. Note that the RGB picture is rotated 180 degrees as a standard.*

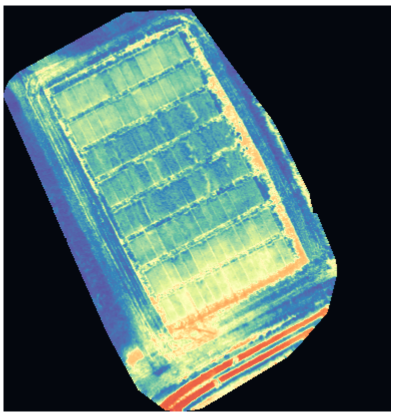


Fig. 3.10: *GeoTIFF as a product of compiling several pictures by Atlas software. The purpose for this visualization is to show the whole field as one picture.*

One of the contributors on this project, Gunnar Lange, developed a GUI, shown in fig. 3.11, using Python software for extracting data from the GeoTIFF files by making separate arrays for each spectral band data. By marking rectangles manually where the field plots were, both the NDVI and MTCI values for each rectangle were calculated by implementing formulas 2.1 and 2.2 in the source code before exporting the values to separate data files. For later referencing the rectangle selection a picture file showing where each enumerated rectangle was placed was also saved by his script. An example of such a reference picture is shown in fig.3.11 (c). Note however that this visualization is for giving the reader a sense of what it looks like and is not for visual inspection due to the size of the figure. The complete set of reference pictures are included in the appendix.

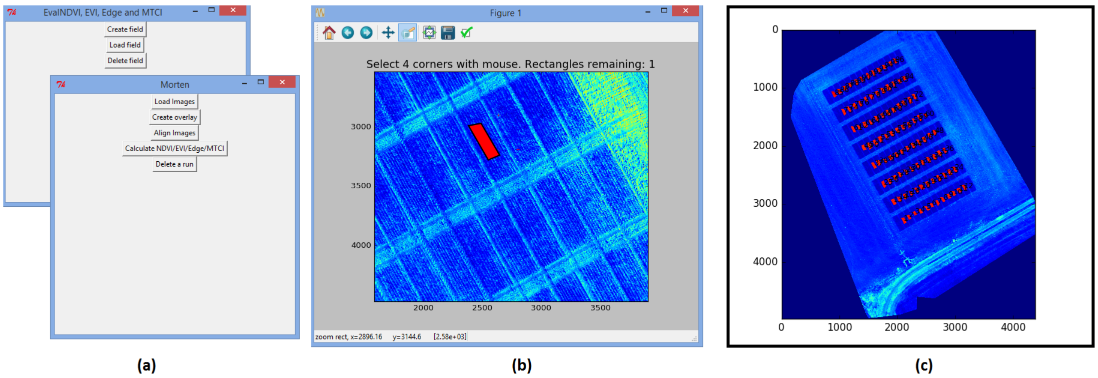


FIG. 3.11: *The GUI for NDVI and MTCI extraction from GeoTIFFs. Part (a) Shows the main menu with all buttons semi-covered by the menu emerging after loading the user custom named field. In this instance the field is named "Morten". Part (b) presents a glimpse of marking rectangles in the midst of the process. Part (c) shows the reference picture that is exported after a complete run.*

The use of the GUI step by step is presented in the flowchart in fig.3.12.

After completing the steps in the GUI by applying the flowchart a text file with for each index is created with mean values for each rectangle included.

3.4 Estimation of Plant Height

3.4.1 DSM Data Extraction

Atlas also returned a compiled visual data file of the field with every pixel containing the geographical altitude relative to the mean sea level (MSL)[10] in meters, known as a DSM. The file was compiled of pictures taken on day 67 (July 18th) which was close to the date of manual measuring. By applying the Fiji (ImageJ) software one could easily highlight rectangles and get the average data value for that area as demonstrated in fig. 3.13. Such a rectangle was made for each of the plots with the values being stored for further analysis.

3.4.2 Regression Model

Considering the difference in height from fig. 3.13 late in the growing season, after head emergence, such a low value of 14.9 cm did not reflect reality. Such a logical

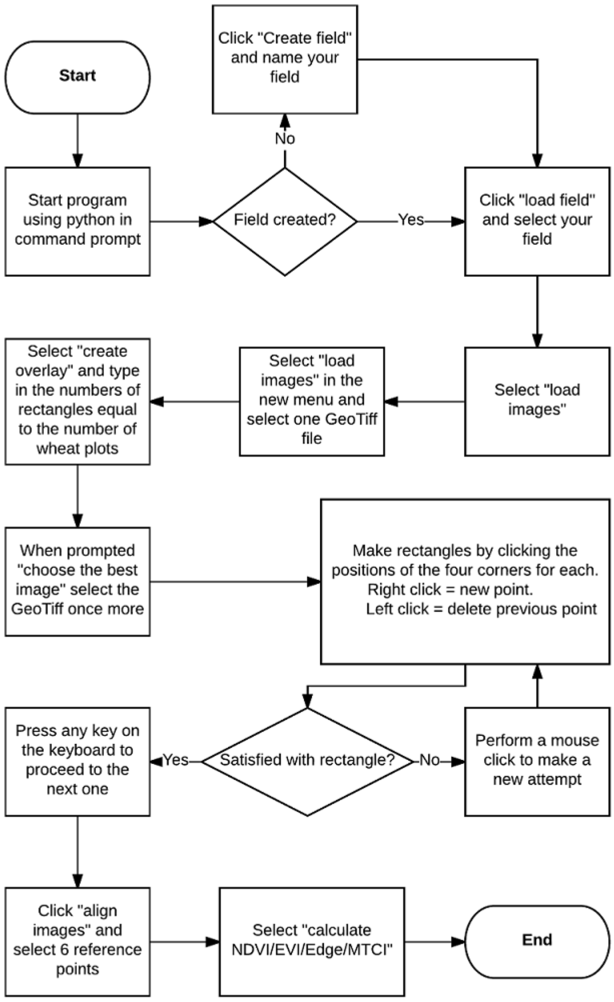


FIG. 3.12: *Step by step usage of the GUI for NDVI and MTCI.*

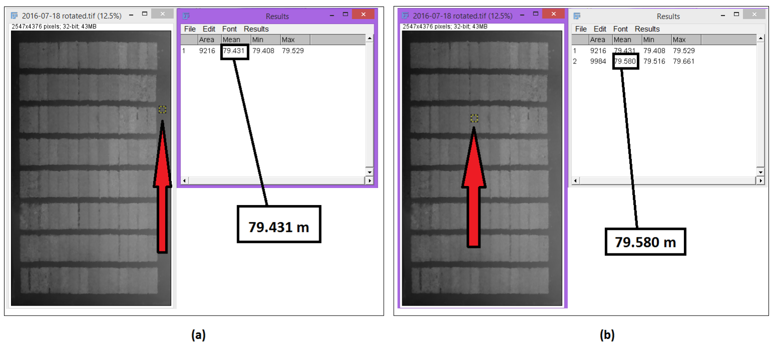


FIG. 3.13: *DSM of the field compiled from pictures taken July 18th 2016 processed in the Fiji software to measure (a) The ground level height at 79.431 m and (b) the wheat plot height at 79.580 m.*

dissonance was with high probability a product of uneven terrain in respect to the field as a whole compared to sea level and also within its own framework. To accommodate for said unbalanced surface an approach using linear regression was initiated. Both in the direction parallel to the rows and columns 9 measurements of ground height were extracted 3 times, two outer lines and one center, to base the regression calculation on. The next step consisted of averaging every group of three parallel points so that both the row and column direction had 9 points for further calculation (see fig. 3.14).

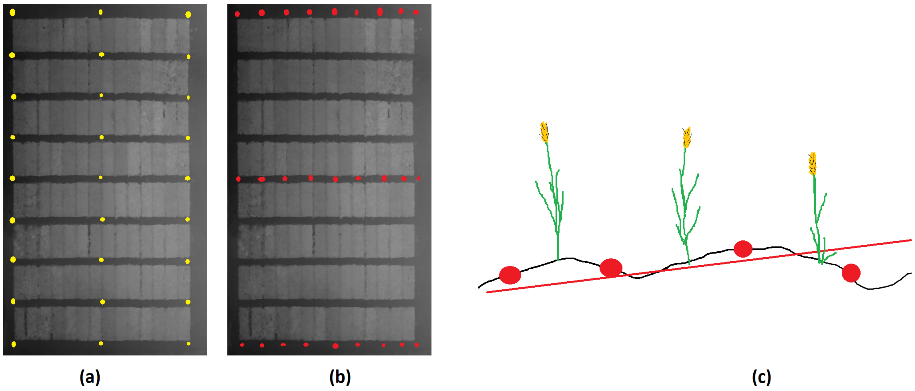


FIG. 3.14: *Points selected at ground level in the direction across (a) the rows and (b) the columns. The strategy to characterize the soil surface as a line based on measured heights in the field is illustrated in (c).*

In order to attain a line to characterize the ground both across the direction of the rows as well as the columns linear regression was applied to the nine points in said directions. Origo was chosen as the top left corner in both fig. 3.14 a and b which served as a zero point with its measurement to be subtracted from the other point values. Two linear equations for each direction were generated which where

$$y = -0.005x - 0.197 \tag{3.1}$$

for adjustment in the direction across the rows and

$$y = 0.081x + 0.004 \tag{3.2}$$

for adjustment across the column direction.

3.4.3 Python Source Code

To implement the adjustments from the lines in the previous section two functions, one for each equation, was written in Python:

```
def coladjust(colvalue):
    return ((colvalue*0.081*8)+0.004)*(-1)
```

```
def rowadjust(rowvalue):
    return (rowvalue*0.005*16)+0.197
```

The returned value for adjusting was either positive or negative depending on whether the line was decreasing or increasing, respectively. This was to adjust for either a drop or a rise in the terrain. The number 8 and 16 from the functions "coladjust" and "rowadjust" served as maximum values for x in the correlating formula as the values imported into these functions were fractions of the total path. Since the length of the plots were roughly double the width, 8 points down the path across the rows were equal to 16 points across the columns in reference to number of plots. Each wheat plot went through the process of having its value from the Fiji software imported into the Python script. Next the origo value would be subtracted before the adjustments in regards to its placement on the field in terms of row and column number were implemented as shown later in the same piece of source code:

```
sqnr = str(data_drone_dsm[i][0])
digitlist = [int(d) for d in str(sqnr)]
digitforcol = (digitlist[2]*10)+digitlist[3]
digitforrow = digitlist[1]
valueforcol = (digitforcol+1)/14.0
valueforrow = (9-digitforrow)/8.0
valuefromdata = data_drone_dsm[i][1]
valuezero = float(valuefromdata) - geozero
valueadjust = valuezero + coladjust(valueforcol) + rowadjust(valueforrow)
```

Note that this piece of source code has several parts omitted leaving the most descriptive part present. First it imported the variable "sqnr" which was the square number, or plot number, which was composed of four digits as mentioned in section 3.1. Next a list of these four digits individually was made ("digitlist") before the third and fourth digit were joined together to form one number ("digitforcol"). To determine its placement relative to the full length in the direction across the columns the number 1 was added because of the buffer column and divided by 14 for the same reason ("valueforcol"). For row adjustment, the digit had to be subtracted from 9 as origo was chosen in the opposite corner from where the counting of rows originally occured and then divided by 8 ("valueforrow"). The final step involved the zero point, or origo value, being subtracted from the value for the field plot ("valuezero"). Lastly, we obtain the value for the plot with adjustments being made respective to row and column number using the earlier mentioned functions.

For a quick example of the process, let's evaluate when wheat plot number 1511 and its value 79.968 was imported. Its digit for column adjustment would be 11 while the number for row adjustment would be 5, serving as x-values in the formulas 3.2 and 3.1 accordingly. The value would have the geozero value (79.643) subtracted and the values from said formulas, by implementing their functions, serving as adjustments, giving us $79.968 - 78.643 + (0.081 * (\frac{11+1}{14}) * 8 + 0.004)(-1) + 0.005(\frac{9-5}{8}) * 16 + 0.197 = 1.003$ (m).

These steps were repeated for day 57 (July 8th) where the DSM retrieved for that date was complete in regards to no missing field areas when compiling took place. Formulas similar to 3.2 and 3.1 were produced and defined as functions as can be seen in the appendix. This was for the calculation of indices from formulas 3.3 and 3.4 presented in section 3.6.

3.4.4 Plant Height Visualization

To visualize the values obtained in the previous segment for day 67 (July 18th) 96 rectangles were plotted in the same layout as the field using a separate Python script. Each rectangle then received a color intensity with an equal magnitude for all three components red, green and blue. That value was set equal to the wheat plot height obtained from the previous script multiplied by 100 for the value in cm. With the highest possible value being 255 for each component, which would be a white rectangle, and 0 for a black one, the interval was highly applicable considering the values of height being roughly around the 100 cm mark. This process is shown in the piece of source code as follows:

```
xaxis = range(13)
yaxis = range(9)

axes = plt.gca()
axes.set_xlim([xaxis[0],xaxis[12]])
axes.set_ylim([yaxis[0],yaxis[8]])

for i in range(len(values)):
    sqnr = str(data_drone_dsm[i][0])
    digitlist = [int(d) for d in str(sqnr)]
    digitforx = (digitlist[2]*10)+digitlist[3]
```

```
    digitfory = digitlist[1]

    axes.add_patch(patches.Rectangle((digitforx-1,digitfory-1),1,1,\
    facecolor="#%s%s%s" % (greenhexes[i],greenhexes[i],greenhexes[i])))
```

This condensed version of the source code shows the first two segments building the outer rims of the field with the use of axes. Looking at the following for loop with the range equal to the length of the "values" list (96) we see that "sqnr", short for "square number" is set to the imported values from the last code presented in section 3.4.3. That number is then split into digits in a list ("digitlist") before the last two digits will serve as column number while the third digit is the row number. These two numbers will also be x- and y-values in the field plot made by the aforementioned axes. Lastly, a rectangle will be plotted with the x- and y-values with their starting points being that value minus 1 so that, for instance, the rectangle with row and column number equal to 1 fills out the rectangle of one increment in both x- and y-axis from the origo. The final step is to let the rectangle be plotted with a color equal to the height value in cm. This is done by letting the three components of RGB be equal to both each other and the height value, set as arguments for "facecolor" where the hex equivalent for the height values are imported (omitted here).

The previous steps and source code was implemented for the later application of the Fiji Software to let these values of color intensity be visualized in a 3D surface plot.

3.5 LAI

In the previous sections data was extracted from compiled GeoTIFFs and DSM files received from the Atlas Software. For the LAI the pictures taken as the agricultural robot, Thorvald, was utilized. To calculate the LAI two approaches were exercised which are expanded upon in the following sections.

3.5.1 LAI by NDVI Thresholds

Gunnar Lange, mentioned in section 3.3, had written a script for extracting the NDVI values from each wheat plot by importing both the near infrared and the red reflectance pictures (fig. 3.15). A cropping of each picture followed to both focus on the center of the field while simultaneously remove interference by the robot itself. A GUI was made for the script but it consisted of simply selecting the folder with all the subfolders containing the picture, resulting in the non-existing need of a flowchart for the use of it as seen in section 3.3.

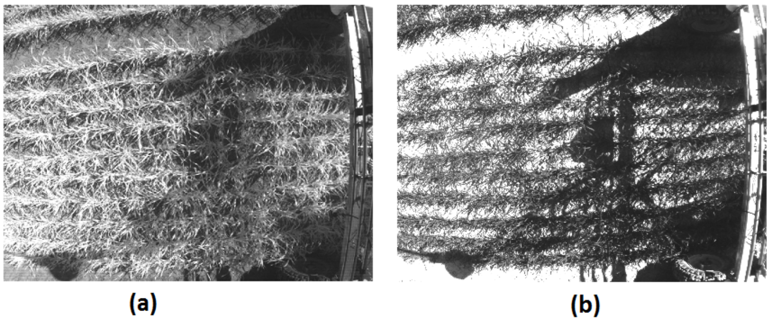


FIG. 3.15: *Pictures imported for the source code. The near infra red is demonstrated in (a) while (b) is the red reflectance. Both pictures are taken concurrently June 13.*

Looking at formula 2.3 we have the index defined as $LAI = \frac{Leafarea}{Totalarea}$. By setting a lower threshold value for NDVI values we can consider the values above said threshold value to identify plants while anything below identify either dead plants or non-plants. Letting the amount of pixels above the threshold value to be divided by the total number of pixels will result in the ratio between area of vegetation and area in total. Two thresholds were chosen, 0.2 and 0.4. The former was derived from previous studies concluding the threshold to vary between 0.08 and 0.4[8], hence an approximate mean from that interval was chosen as well as the maximum value. This is demonstrated in fig. 3.16.

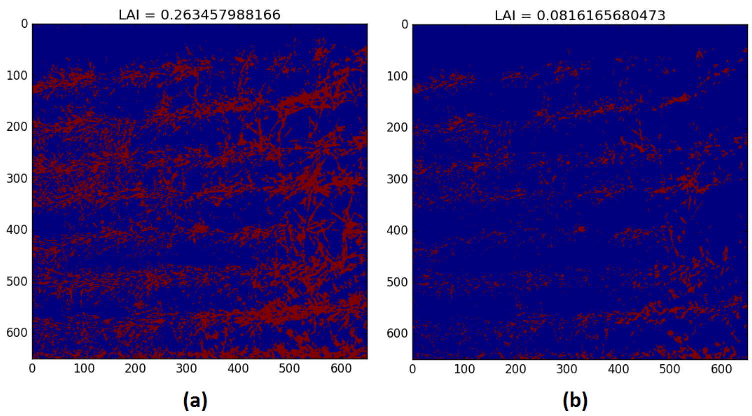


FIG. 3.16: *The LAI composed of pictures from fig. 3.15 by using formula 2.1 and 2.3 with the red color showing the NDVI pixels above the threshold and the blue below. We see the LAI above each figur when threshold values (a) 0.2 and (b) 0.4 were applied. Here we see the higher threshold naturally produces a lower LAI as more pixels will not be in the numerator for the index formula as they are less than the threshold.*

3.5.2 LAI by Green Pixel Ratio

Another approach to finding the ratio between the area of plants and area in total consisted of obtaining the number of pixels that were mainly green and divide that by the total number of pixels. This approach will be named the RGB approach from here on out. A pixel is considered to be mainly green if the intensity of green is bigger than both intensity of the red and blue components. By using the aforementioned source code that extracts a mean value of both pictures taken for each plot we can adjust the calculation part of the algorithm which is presented here:

```
RGB = img.open('filename.JPG')
RGB=np.array(RGB)
RGB = RGB[100:1500,100:1500]

Greens = RGB[:,:,1]
Reds = RGB[:,:,0]
Blues =RGB[:,:,2]

TotalPix = np.shape(Greens)[0]*np.shape(Greens)[1]
SuperGreens = 0

for i in range(np.shape(Greens)[0]):
    for j in range(np.shape(Greens)[1]):
        if Greens[i,j] > Reds[i,j] and Greens[i,j] > Blues[i,j]:
            SuperGreens += 1
        else:
            SuperGreens += 0

LAI = float(float(SuperGreens)/float(TotalPix))
```

The RGB picture is being imported, made into an array and then cropped. An array for all values of green, red and blue pixels are made and the number of total pixels are calculated based on the array size. This is followed by two for loops going through each pixel which will increase the variable ”SuperGreens” by one for each pixel value with a green value larger than both the red and blue ones. Finally the LAI is calculated by dividing the number the loops made by the total number of pixels.

3.6 Statistical Data Processing

In accordance with the field trial layout as described in section 3.1 the SAS software was utilized for the analysis of variance using PROC MIXED (SAS code included in appendix). It produced the least square means for three groups; one with the value for each of the 24 different cultivars and two with the value for the cultivar within each level of fertilizing, 8 and 15 kg/daa. The least square means for the same groups were not only calculated for indices and plant height, but also for grain yield (GY), manually measured PH, TKW, HLW, DM and DH. This software also presents the p-value needed for potentially rejecting the null hypothesis claiming there is no differences between the cultivars both dependently or independently with regards to the fertilizing differences. The p-value is the probability of the occurrence of the measured parameter if the null hypothesis is true. Thus, a low p-value will indicate that the null hypothesis may be rejected and that the findings are significant.

Earlier studies have found negative correlations between between PH and GY[5] as well as PH and chlorophyll content[11]. simultaneously, the NDVI and MTCI having been created to indicate chlorophyll content and in turn hypothetically correlate positively with GY. For that reason this thesis attempted to utilize the antagonistic relationship between those two indices and PH. After the MTCI, NDVI and height estimation values were extracted as previously described, two new parameters were introduced where each of the indices were divided by the estimated plant height for the same field plot. These ratio parameters were

$$MTCI \times PH^{-1} = \frac{MTCI}{PH} \tag{3.3}$$

where MTCI $\times$ PH^{-1} is the MTCI-PH-ratio [cm^{-1}], MTCI is the MERIS Terrestrial Chlorophyll Index and PH is the plant height [cm] and

$$NDVI \times PH^{-1} = \frac{NDVI}{PH} \tag{3.4}$$

where NDVI $\times$ PH^{-1} is the NDVI-PH-ratio [cm^{-1}], NDVI is the Normalized Differential Vegetation Index and PH is the plant height [cm]. These ratios were made to embolden the correlation to GY as they would hypothetically increase with an increase in the numerators and a decrease in the denominators.

Chapter 4

Results and Discussion

After all data have been extracted, calculated and organized the next steps involve analytical thinking as well as a critical assessment of the prior steps. This chapter will encompass these topics.

4.1 Conducted Measurements

4.1.1 NDVI and MTCI

The MTCI extracted from pictures taken by the UAV had its peak values on day 15 and 22 which may be a result of high reflectance from the ground itself (fig. 4.1). Pixel values were evaluated on soil areas on pictures taken by Thorvald which in turn were of the highest value compared to the vegetation. This would empower the hypothesis of high values because of soil reflectance. However, since the pictures taken while operating Thorvald were not calibrated (see section 4.2.6) one cannot be too certain if this is the case. The pictures used for MTCI and NDVI were a product of a GeoTIFF which in turn was a result of several pictures taken by the UAV with calibration included.

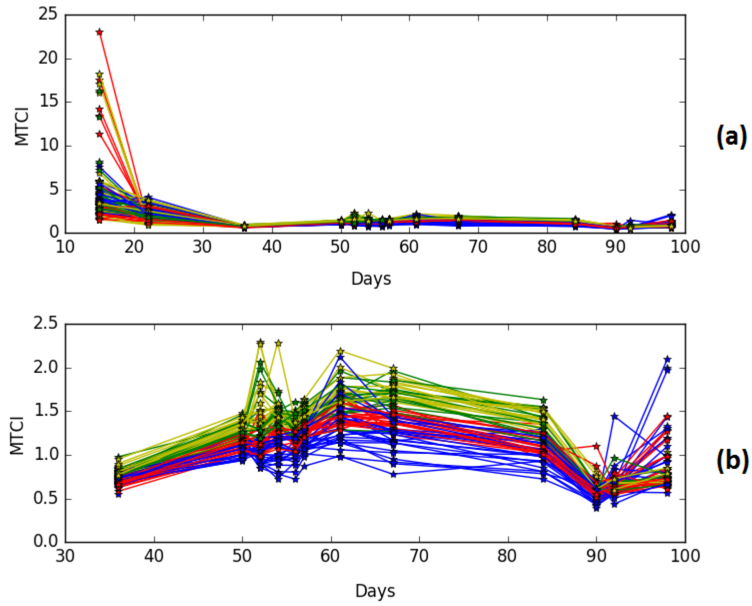


Fig. 4.1: *The MTCI for all 96 wheat field plots. Part (a) shows for all days of picture taking, while (b) has day 15 and 22 omitted. These values are retrieved from pictures taken by the UAV.*

Assuming day 15 and 22 produced misreadings one can see, as shown in fig. 4.1 (b) that the peak values are around days 50-70, which is the same interval from where heading occurred (stage 5 as referenced in section 2.1) to stages 6,7 and 8 prior to the final stage of ripening. This is also true for the NDVI as shown in fig. 4.2.

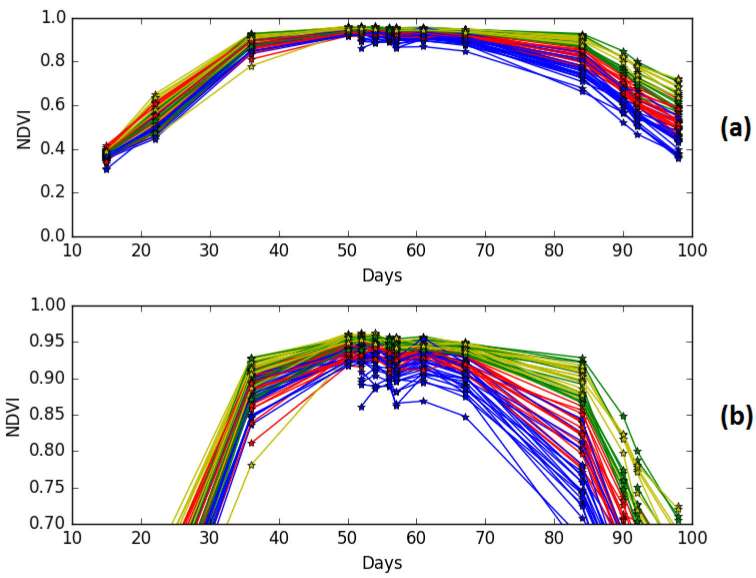


Fig. 4.2: *The NDVI for all 96 wheat field plots. Part (a) shows for all days of picture taking with (b) having a more narrow interval for the axis of NDVI values to highlight its peak period.*

The decline after day 84 seen both in fig. 4.1 and 4.2 is the ripening phase of the wheat growth where chlorophyll breakdown happens to fully develop the grain with the enzyme Chlorophyllase as a catalyst in the process[16].

The differences in fertilizing levels are shown in fig. 4.3 which show slightly lifted curves at least in the interval of approximately days 50-70 with regards to MTCI. This interval does not show particularly greater NDVI values but a smaller number of wheat plots being below the maximum value.

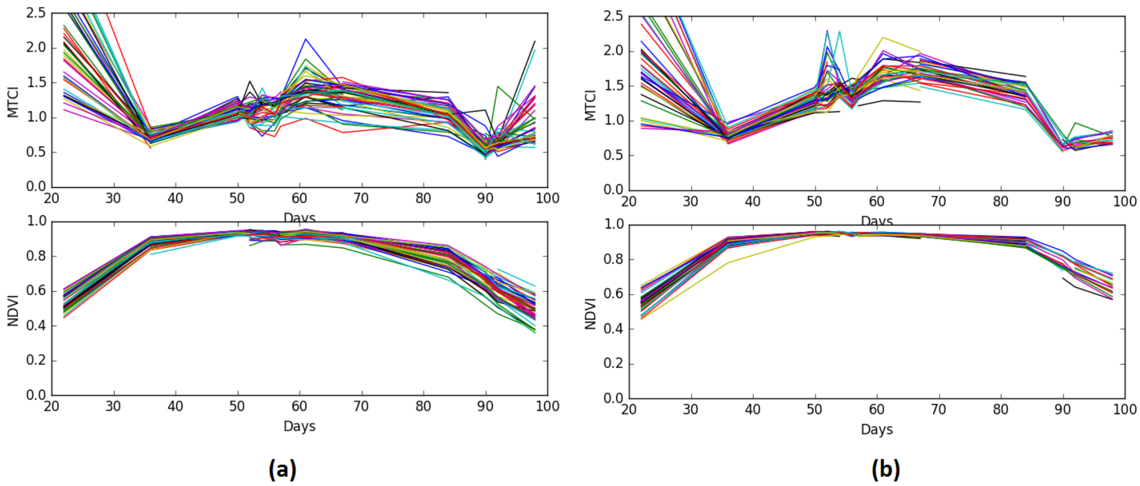


FIG. 4.3: *The MTCI and NDVI values for wheat plots given (a) 8k kg/daa and (b) 15 kg/daa of Nitrogen. Day 15 is omitted due to reason explained earlier yet day 22 was kept in order to show the incline in the NDVI curves between day 22 and 36.*

4.1.2 Estimation of Plant Height

As mentioned in section 3.4.4 a visualization of the wheat field was plotted with every rectangle within having a color intensity equally to the estimated heights in cm. This plot is presented in fig. 4.4.

Now that each rectangle with all the enclosed pixels, representing the wheat field, had a value between 0 and 255 the Fiji software could be utilized to visualize these data properties. Since all three components of RGB is equal these color intensities result in different levels of gray. A 3D surface plot was made where the z-axis marks the color intensity based on the RGB components, which in turn directly translates to the estimated values of height in cm as shown in fig. 4.5.

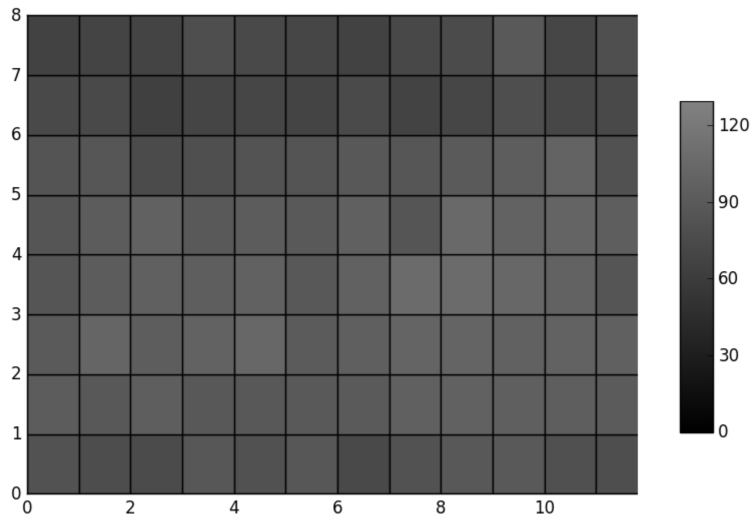


Fig. 4.4: *The field plotted with all 96 rectangles with a color intensity between 0 and 255 equal to the height in cm. The colorbar on the side is a scaled version needed to exert the needed interval for the values.*

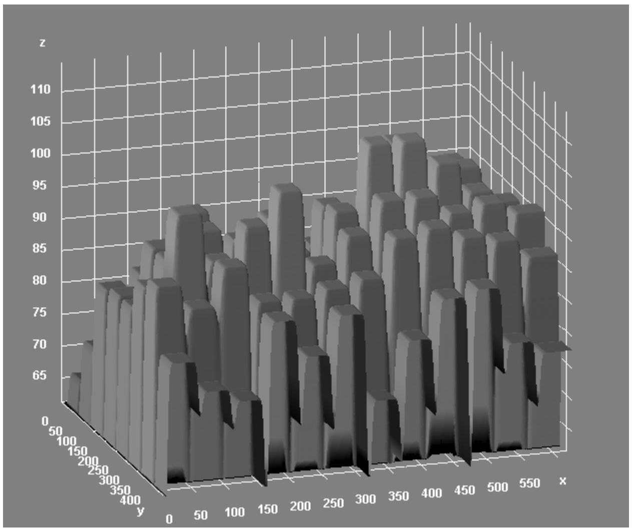


Fig. 4.5: *Each wheat plot represented as a 3D surface plot with the z-axis to indicate the height in cm.*

The blocks shown here may influence the reader to evaluate the visualization as incorrect due to the different height values does not reflect the even surface one thinks of when mentally picturing a wheat field. It is however important to remember that several cultivars with different levels of Nitrogen are included in this field trial and that the differences in height were easily observed while photographing occurred.

4.1.3 LAI

All 96 wheat plot values for the three approaches for estimating the LAI is presented in fig. 4.6. These values are based on the pictures taken while utilizing Thorvald.

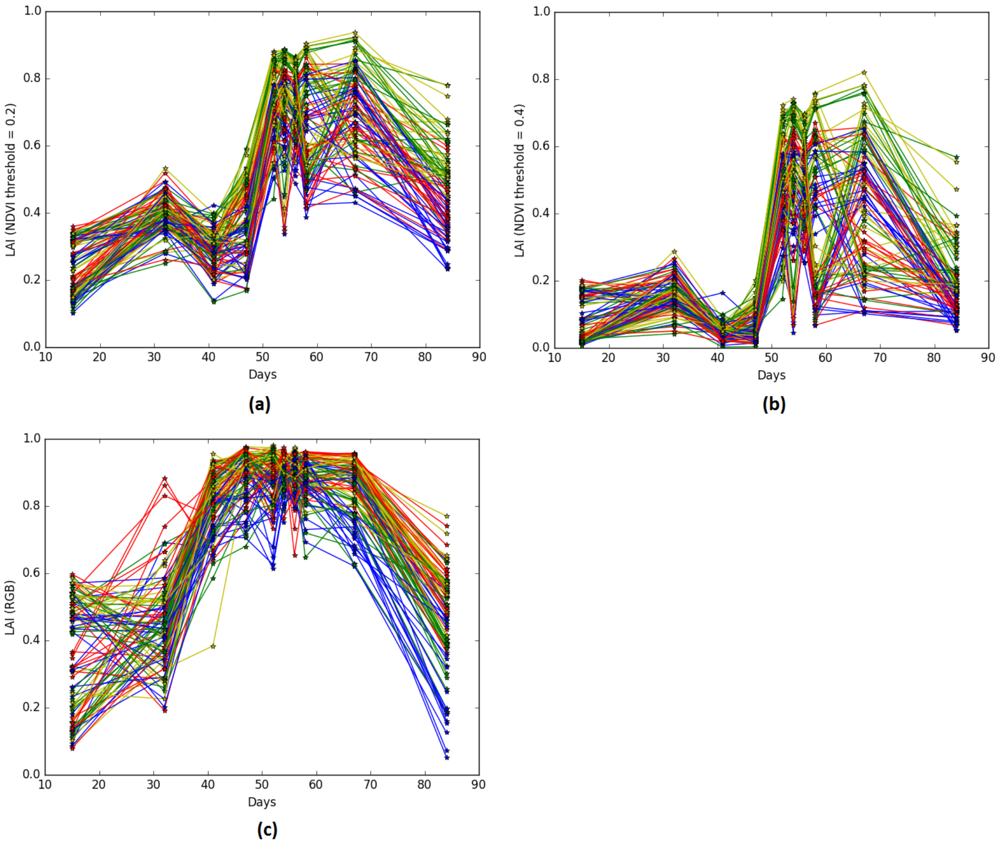


Fig. 4.6: *LAI estimated by the NDVI threshold approach with thresholds equal to 0.2 (a) and 0.4 (b) and by dividing predominantly green pixels to total pixels (c). All values are calculated using pictures taken by Thorvald.*

As we see with regards to the NDVI threshold approaches they share the same curvature but with lower values the higher the threshold is. The dump seen between days 30-50 is an anomaly as it should follow suit of the rise in the same interval for the NDVI (as seen in section 4.1.1). When comparing the NDVI threshold approach to the RGB pixel approach within the same interval we do not see this dump but a steady rise. This difference may be in a lack of calibration for the spectral pictures used for the NDVI threshold approach resulting in saturated pixels which in turn return false values. This does not happen for the RGB approach as it simply utilizes a regular RGB camera.

Pictures taken that way are precise enough to present the increase in green pixels from day to day in the initial growth phase as the plants widen their coverage.

Still evaluating fig. 4.6 one can see that both approaches have a rather steep decline after day 67. Being that the NDVI threshold approach produces an LAI comprised of sorting out NDVI values classified as vegetation it is natural to see the same decline as presented in fig. 4.2 from the very same period. The decline with regards to the RGB approach is simply because the wheat is in its final stages after heading, kernel development and ripening making for yellower heads. This of course has a major impact on the algorithm which calculates the ratio of predominantly green pixels to all pixels.

This difference in wheat texture and color is shown with an example of cropped pictures taken by Thorvald at two different days for the same wheat plot in fig. 4.7.

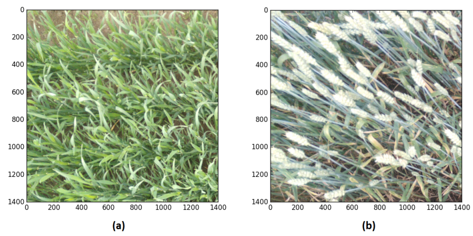


FIG. 4.7: *Picture taken and cropped for counting predominantly green pixels at (a) day 41 with an LAI equal to 0.903 and (b) day 84 with an LAI equal to 0.661.*

4.2 Statistical Analysis

4.2.1 P-values and Least Square Means for Traits

The probability (p-values) are presented in table 4.1 given that the null hypothesis stating there is no difference within the groups measured is true. The three groups are the cultivars, the fertilizing levels and the cultivars and fertilizing levels being affected by each other (Cultivar × Nitrogen level).

TABLE 4.1: *Probabilities for the groups, cultivar, Nitrogen level and Cultivar × Nitrogen level for the traits GY, TKW, HLW, DH, DM and PH (manually measured).*

Group	GY	TKW	HLW	DH	DM	PH
Cultivars	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Nitrogen level	0.1702	0.5373	0.3494	0.4777	0.1687	0.7349
Cultivar × N-level	0.1257	0.5136	0.6855	0.6803	0.1904	0.0151

What clearly stands out (with the exception of Cultivar $\times$ Nitrogen level p-value for plant height) is the significant findings in differences in the first group, Cultivars, for all traits being that all values here are < 0.05 which serves as a cut-off value.

The least square means for traits (GY, TKW, HLW, DH, DM and PH) are presented in table 4.2, 4.3 and 4.4 sorted by cultivars as only factor,cultivars treated with 8 kg/daa of Nitrogen and with 15 kg/daa, respectively. PH in these tables refer to the manually measured PH at the end of the growing season.

TABLE 4.2: *The least square means for traits for all cultivars*

Cultivar	**GY [kg/ha]**	**TKW [g]**	**HLW [g]**	**DH**	**DM**	**PH [cm]**
Bjarne	598.700	34.226	78.689	54.047	104.460	66.808
Zebra	613.690	38.493	79.544	51.841	105.450	81.021
Demonstrant	655.400	37.107	80.951	55.062	107.840	72.823
Krabat	593.740	34.944	79.125	56.109	104.640	69.440
Mirakel	588.840	35.625	78.936	53.427	103.680	84.306
Rabagast	572.430	32.396	79.015	56.224	105.960	65.469
Seniorita	611.990	35.919	81.117	56.279	106.980	78.820
GN11644	616.260	36.083	81.799	51.981	102.050	67.933
GN11542	619.530	32.443	79.567	52.536	106.080	74.519
GN13618	663.950	37.532	79.300	52.732	108.620	71.829
Arabella	670.120	37.343	78.420	50.620	106.700	74.591
GN10521	606.920	32.757	77.949	53.762	107.690	73.439
SW01074	606.670	36.484	79.907	53.589	105.330	66.978
GN10637	591.490	35.566	82.694	57.278	108.330	76.885
SW11230	701.840	39.380	78.629	52.584	105.020	77.111
PS-1	608.700	35.207	79.383	55.593	104.330	76.565
SW11011	651.190	42.276	80.795	50.831	107.530	73.734
SW21074	624.590	36.428	81.511	53.438	106.910	74.223
Tjalve	562.220	36.016	78.891	55.809	103.930	74.798
Avle	556.500	32.778	77.962	54.739	103.560	71.411
Bastian	590.750	30.327	78.930	50.577	106.300	68.349
Runar	529.170	36.924	79.722	51.253	103.470	82.010
Reno	557.270	37.680	78.992	50.812	103.150	83.808
Polkka	524.710	34.867	80.247	53.377	101.480	84.630

Table 4.3: *The least square means for traits for all cultivars given 8 kg/daa of Nitrogen.*

Cultivar	**GY [kg/ha]**	**TKW [g]**	**HLW [g]**	**DH**	**DM**	**PH [cm]**
Bjarne	522.270	34.732	78.155	54.263	102.290	67.494
Zebra	528.250	39.258	79.268	51.653	102.150	80.350
Demonstrant	546.820	38.516	80.572	54.478	104.600	70.283
Krabat	524.070	35.459	78.745	56.249	102.450	67.898
Mirakel	493.510	35.755	78.439	52.527	100.110	83.398
Rabagast	510.390	32.993	78.738	55.427	103.280	64.483
Seniorita	560.410	31.809	80.497	55.958	106.830	79.158
GN11644	542.670	37.693	80.976	51.955	99.779	67.587
GN11542	544.130	33.382	78.755	52.233	101.790	74.267
GN13618	590.510	38.586	78.983	53.506	106.330	70.672
Arabella	576.270	36.989	77.698	50.181	104.240	76.935
GN10521	534.510	33.716	77.772	53.463	106.100	72.219
SW01074	549.540	36.666	79.500	52.830	101.890	67.250
GN10637	532.990	36.655	82.067	57.080	106.910	75.182
SW11230	587.590	40.236	77.734	52.326	101.720	78.726
PS-1	527.170	35.543	79.028	55.451	101.660	78.490
SW11011	576.460	42.593	80.228	51.806	104.660	75.860
SW21074	526.800	36.636	80.783	53.135	103.830	74.299
Tjalve	485.800	36.309	78.995	56.156	100.950	75.578
Avle	478.320	32.509	77.347	54.570	101.830	68.562
Bastian	532.740	31.100	78.181	50.352	103.220	69.219
Runar	467.420	37.000	78.881	50.883	99.725	84.648
Reno	516.250	37.859	78.819	50.791	101.040	83.089
Polkka	436.770	34.404	79.689	52.228	97.613	88.352

Table 4.4: *The least square means for traits for all cultivars given 15 kg/daa Nitrogen.*

Cultivar	**GY** [kg/ha]	**TKW** [g]	**HLW** [g]	**DH**	**DM**	**PH** [cm]
Bjarne	675.120	33.720	79.223	53.832	106.630	66.123
Zebra	699.120	37.727	79.821	52.030	108.760	81.693
Demonstrant	763.980	35.698	81.329	55.645	111.080	75.364
Krabat	663.400	34.429	79.505	55.970	106.840	70.981
Mirakel	684.170	35.496	79.432	54.327	107.250	85.213
Rabagast	634.460	31.798	79.292	57.021	108.650	66.454
Seniorita	663.580	40.028	81.737	56.600	107.120	78.481
GN11644	689.850	34.474	82.623	52.008	104.330	68.279
GN11542	694.930	31.504	80.380	52.838	110.370	74.772
GN13618	737.390	36.479	79.618	51.957	110.920	72.986
Arabella	763.970	37.698	79.142	51.058	109.150	72.247
GN10521	679.340	31.797	78.126	54.061	109.290	74.659
SW01074	663.810	36.301	80.314	54.347	108.760	66.706
GN10637	649.990	34.477	83.321	57.476	109.760	78.589
SW11230	816.090	38.524	79.523	52.841	108.330	75.496
PS-1	690.240	34.870	79.739	55.736	107.000	74.640
SW11011	725.920	41.959	81.362	49.856	110.390	71.608
SW21074	722.380	36.220	82.239	53.741	110.000	74.147
Tjalve	638.650	35.724	78.786	55.463	106.900	74.018
Avle	634.680	33.047	78.576	54.909	105.290	74.260
Bastian	648.760	29.554	79.680	50.802	109.370	67.479
Runar	590.910	36.847	80.563	51.622	107.210	79.371
Reno	598.280	37.501	79.165	50.834	105.260	84.527
Polkka	612.640	35.329	80.805	54.525	105.340	80.907

Before further calculations it is evident that the doubling of fertilizer raised the average GY the most with a slight increase in DM, DH and HLW. The tables 4.3 and 4.4 show a slight decrease in TKW and PH but given the high values of p seen in table 4.1 for these both TKW and PH there is more likely that the levels of Nitrogen did not produce significant differences.

4.2.2 Correlations between Traits

Prior to evaluating the indices correlation between the traits themselves are presented in table 4.5. Note that the PH in this table and analysis is the manually measured plant height at the end of the season of growth.

TABLE 4.5: *Correlations between traits. These correlations are, as noted in section 4.2.1, a result of the least square means for the 24 cultivars only.*

Trait	**GY**	**TKW**	**HLW**	**DH**	**DM**
TKW	0.451				
HLW	0.073	0.291			
DH	-0.181	-0.299	0.199		
DM	0.593	0.106	0.200	0.131	
PH	-0.249	0.344	0.070	-0.184	-0.271

The strongest correlation is between GY and DM which is expected as cultivars getting ripe at an earlier stage will stop the kernel development at an earlier stage.

4.2.3 P-values and Least Square Means for NDVI, MTCI, PH, NDVI $\times$ PH^{-1} and MTCI $\times$ PH^{-1}

The p-value for the indices NDVI, MTCI and LAI were not always <0.05 for any group from day to day which may be because of several GeoTIFFs containing holes resulting in missing data. For NDVI and MTCI the groups for Nitrogen level and Cultivar $\times$ Nitrogen level never exhibited statistical significance as their p-values were >0.05 for each date. The final group, Cultivar, had a value of <0.05 for MTCI and NDVI six and eight times throughout the season, respectively. This is illustrated in fig. 4.8 and fig. 4.9.

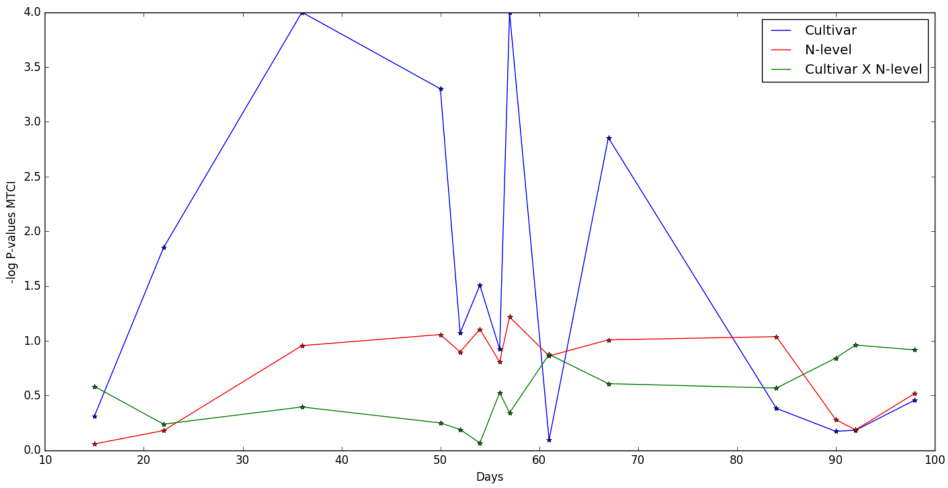


Fig. 4.8: *The -log of p-values for each group tested for the MTCI.*

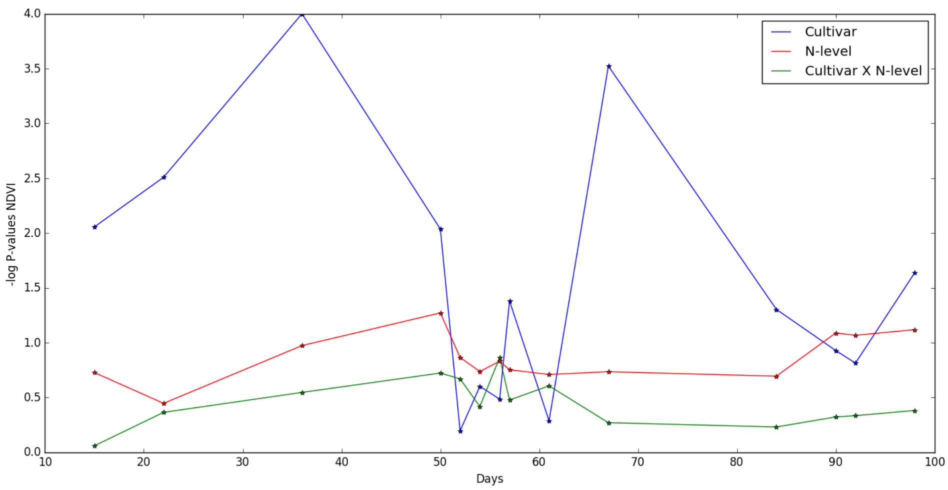


Fig. 4.9: *The -log of p-values for each group tested for the NDVI.*

Both figures are plotted using the -log value of the p-values. This is done to reflect the higher levels of significance of lower p-values. It is evident that the Cultivar group had the highest levels of significance throughout the days of taking pictures. Another observation to be made from both figures is the drop in -log values within that very same group in the interval of 50-60 days. A plausible explanation for this could be a high level of saturated pixels which in turn level out differences between cultivars.

Since the Cultivar group mostly exhibited significance the following figure will favor the 24 members of said group. The least square means for all 24 cultivars for both the NDVI and MTCI are shown in fig. 4.10.

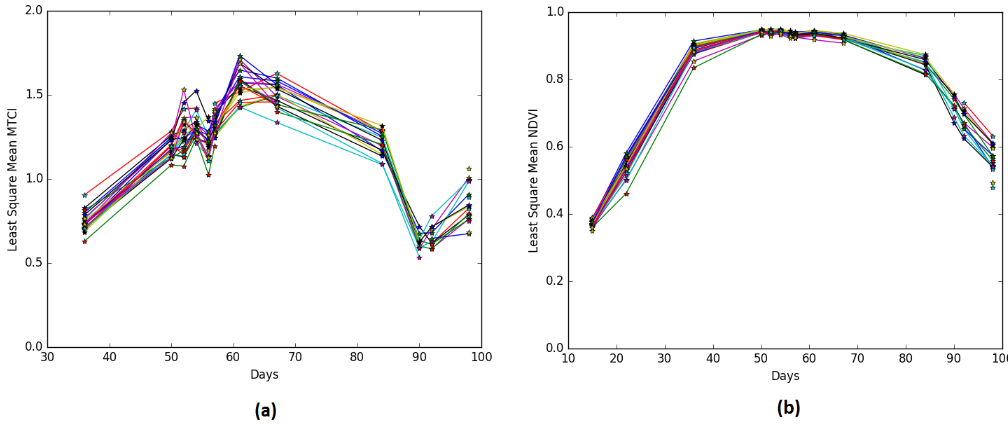


Fig. 4.10: *The least square means for (a) the MTCI (with first two days omitted) and (b) the NDVI. Both graphs are for the 24 cultivars.*

One can see the resemblance between the graphs in figures 4.1 and 4.2 and those in fig. 4.10 with regards to curvature.

Due to several days having high p-values implying no significant difference amongst the parameters tested for (between cultivars or nitrogen levels) as well as holes in the dataset the correlation was recalculated by using the only two days (57 and 67) with complete data and p-values low enough to indicate significant findings. These days were in the interval between day 52 and 67 where heading occurs which, as seen in section 4.1.1, have been the segment of time where the index values were the highest. A mean for the two dates were utilized for further calculation. The same procedure was followed with regards to PH, NDVI $\times$ PH^{-1} and MTCI $\times$ PH^{-1} as well. The least square means for said five indices are presented in table 4.6, 4.7 and 4.8 sorted by cultivars as only factor, cultivars treated with 8 kg/da of Nitrogen and with 15 kg/daa, respectively. PH in these tables refer to the estimated PH.

TABLE 4.6: *The least square means for indices for all cultivars.*

Cultivar	**NDVI**	**MTCI**	**PH** [cm]	**NDVI** $\times$ **PH**$^{-1}$ [cm^{-1}]	**MTCI** $\times$ **PH**$^{-1}$ [cm^{-1}]
Bjarne	0.932	1.412	57.827	0.037	0.052
Zebra	0.927	1.539	65.549	0.027	0.043
Demonstrant	0.930	1.409	64.998	0.028	0.040
Krabat	0.926	1.429	66.680	0.029	0.042
Mirakel	0.935	1.380	68.823	0.027	0.037
Rabagast	0.930	1.435	60.243	0.041	0.061
Seniorita	0.937	1.375	65.980	0.032	0.043
GN11644	0.937	1.496	54.333	0.036	0.055
GN11542	0.929	1.377	63.796	0.032	0.045
GN13618	0.924	1.490	61.707	0.033	0.050
Arabella	0.924	1.339	56.463	0.041	0.055
GN10521	0.929	1.299	61.424	0.031	0.041
SW01074	0.927	1.303	59.599	0.033	0.046
GN10637	0.935	1.426	60.019	0.034	0.048
SW11230	0.934	1.477	63.641	0.031	0.046
PS-1	0.930	1.414	63.737	0.031	0.044
SW11011	0.921	1.431	62.678	0.029	0.044
SW21074	0.927	1.439	59.376	0.036	0.052
Tjalve	0.921	1.354	60.690	0.034	0.046
Avle	0.926	1.351	60.152	0.038	0.052
Bastian	0.932	1.424	59.186	0.035	0.050
Runar	0.931	1.441	68.080	0.026	0.038
Reno	0.925	1.370	69.518	0.026	0.037
Polkka	0.917	1.355	69.478	0.024	0.034

TABLE 4.7: *The least square means for indices for all cultivars given 8 kg/daa of Nitrogen.*

Cultivar	**NDVI**	**MTCI**	**PH** [cm]	**NDVI** $\times$ **PH**$^{-1}$ [cm^{-1}]	**MTCI** $\times$ **PH**$^{-1}$ [cm^{-1}]
Bjarne	0.916	1.188	51.759	0.024	0.031
Zebra	0.907	1.342	59.932	0.018	0.027
Demonstrant	0.914	1.239	59.124	0.018	0.024
Krabat	0.914	1.288	57.988	0.021	0.029
Mirakel	0.919	1.164	61.843	0.018	0.022
Rabagast	0.914	1.279	51.736	0.029	0.042
Seniorita	0.925	1.214	56.801	0.023	0.030
GN11644	0.926	1.315	47.939	0.024	0.033
GN11542	0.913	1.218	56.076	0.022	0.030
GN13618	0.909	1.356	54.070	0.024	0.034
Arabella	0.909	1.192	46.932	0.031	0.040
GN10521	0.913	1.067	54.225	0.020	0.023
SW01074	0.915	1.173	51.312	0.023	0.030
GN10637	0.922	1.259	51.052	0.025	0.033
SW11230	0.921	1.326	56.434	0.021	0.029
PS-1	0.915	1.233	54.167	0.022	0.029
SW11011	0.906	1.256	53.776	0.020	0.028
SW21074	0.912	1.285	52.081	0.025	0.034
Tjalve	0.904	1.186	52.835	0.024	0.030
Avle	0.909	1.208	50.779	0.027	0.037
Bastian	0.916	1.285	52.501	0.022	0.030
Runar	0.916	1.221	59.767	0.016	0.022
Reno	0.915	1.232	64.199	0.017	0.023
Polkka	0.894	1.165	62.398	0.015	0.019

Table 4.8: *The least square means for indices for all cultivars given 15 kg/daa of Nitrogen.*

Cultivar	**NDVI**	**MTCI**	**PH [cm]**	**NDVI × PH^{-1} [cm^{-1}]**	**MTCI × PH^{-1} [cm^{-1}]**
Bjarne	0.949	1.636	63.894	0.018	0.030
Zebra	0.946	1.737	71.167	0.014	0.026
Demonstrant	0.946	1.578	70.871	0.015	0.025
Krabat	0.938	1.570	75.372	0.013	0.022
Mirakel	0.951	1.595	75.800	0.014	0.023
Rabagast	0.945	1.592	68.749	0.017	0.028
Seniorita	0.949	1.536	75.159	0.014	0.022
GN11644	0.947	1.678	60.727	0.019	0.032
GN11542	0.944	1.536	71.516	0.015	0.024
GN13618	0.939	1.624	69.343	0.015	0.026
Arabella	0.940	1.486	65.994	0.016	0.024
GN10521	0.946	1.530	68.623	0.016	0.026
SW01074	0.940	1.433	67.885	0.016	0.024
GN10637	0.948	1.593	68.986	0.015	0.025
SW11230	0.947	1.629	70.848	0.016	0.026
PS-1	0.946	1.595	73.307	0.014	0.024
SW11011	0.935	1.606	71.579	0.015	0.025
SW21074	0.942	1.594	66.670	0.016	0.027
Tjalve	0.939	1.522	68.544	0.016	0.025
Avle	0.942	1.493	69.526	0.016	0.024
Bastian	0.948	1.563	65.871	0.018	0.029
Runar	0.946	1.660	76.394	0.014	0.025
Reno	0.934	1.508	74.838	0.014	0.022
Polkka	0.940	1.545	76.561	0.014	0.023

Both NDVI and MTCI had a higher average least square mean in the 15 kg/daa group compared to 8 kg/daa. This is parallel to GY in section 4.2.1. The average PH was in fact higher for the 15 kg/daa group which is contrary to what was observed in section 4.2.1. This interesting finding has an effect of transference with regards to indices $NDVI \times PH^{-1}$ and $MTCI \times PH^{-1}$ as they have PH in their denominators.

4.2.4 Correlation between Grain Yield and NDVI, MTCI, PH, NDVI $\times$ PH^{-1} and MTCI $\times$ PH^{-1}

The correlation between the five indices in section 4.2.3 and GY is presented in table 4.9.

TABLE 4.9: *Correlations for each index to GY within all groups. PH is here the estimated heights.*

	Index				
Group	**NDVI**	**MTCI**	**PH**	**NDVI $\times$ PH^{-1}**	**MTCI $\times$ PH^{-1}**
Cultivar	0.172	0.292	-0.333	0.221	0.315
8 kg/daa Nitrogen	0.373	0.392	-0.364	0.302	0.374
15 kg/daa Nitrogen	0.080	0.196	-0.284	0.067	0.178

Looking at table 4.9 we see that the correlation on any of the posts are not considerably high with no value being >0.5 either positively or negatively. Other studies have found correlations for NDVI of approximately the same magnitude (0.33)[22] and even lower[11]. The MTCI have shown to be a suitable estimator for chlorophyll content[7] which in turn has shown strong correlation to GY (0.63 and 0.69 for two different measuring parameters)[11]. The correlation seen here for this index did not follow suit. However, there are valuable considerations to be made. Firstly, there is a higher correlation to GY for the 8 kg/daa Nitrogen group in comparison to the group with 15 kg/daa, which is true for both the NDVI and MTCI. This may indicate that the cultivars who utilize the given fertilizer more efficiently than others create a bigger difference in GY which in turn result in a higher coefficient in correlation.

The PH (estimated) was in fact negative correlated with GY as seen in earlier studies mentioned in section 3.6. Inspecting the last two indices presented in the table (NDVI $\times$ PH^{-1} and MTCI $\times$ PH^{-1}) in comparison with the first two (NDVI and MTCI) a slight increase was produced. Even though this increase is small the approach should not be dismissed as the indices included to construct the parameters themselves did not result in high correlations to GY. There was in fact a decrease with this transformation for the other groups, still an increase with regards to the Cultivar group is favourable due to the low p-values for that category.

4.2.5 Correlation between Manual Measurements and Estimations in Plant Height

The groups first presented in section 4.2.1 had correlations between the plant heights, manually and algorithmically estimated, were 0.682, 0.586 and 0.605 for cultivars and 8 and 15 kg/daa of Nitrogen, respectively. This was based on digital estimations produced on day 67 which were further visualized in section 4.1.2. To have the highest coefficient of correlation in the Cultivar group also reflect the p-value of <0.0001 in regards to cultivars in contrast to values far greater for Nitrogen level and cultivar $\times$ Nitrogen level.

The correlation is relatively strong although a higher value was expected. This may very well be a result of only 54 points split into 3 rows and 3 columns to establish a model for the ground levels surrounding the wheat plots, whereas an increase in points could quite possibly produce a higher correlation. One implementation for enhancing the accuracy for the regression could be to have a line of points between every row and column. This way one could for every row and column make a regression line based on the mean value for points on each side. This is demonstrated in fig. 4.11.

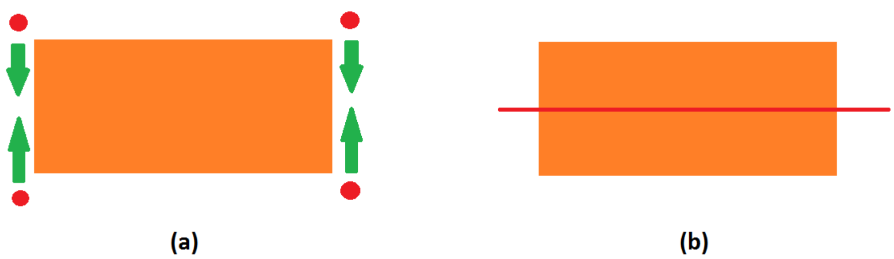


FIG. 4.11: *A possible implementation for regression to produce higher correlation. The wheat plot (orange rectangle) have soil points with height values measured on each corner. This figure shows the zooming in on one wheat plot and only a line made parallel to the columns. In (a) we see four points surrounding the wheat plot soon to partake in the creation of lines. Parallel points will merge with the mean used for regression (shown with the green arrows). In (b) we see a part of the line made for the column crossing through the wheat plot.*

In fig. 4.11 we see the procedure explained further. The line shown in (b) is a part of the line for the whole column where the position for this particular wheat plot on this column will serve as x in the line formula.

4.2.6 P-values and Least Square Means for LAI

The approach of implementing a NDVI threshold had p-values both $>$ and $<$ 0.05 with regards to cultivars for both thresholds with no pattern emerging when evaluating the data. The pictures taken for the calculation of this index were taken by Thorvald and not by the UAV hence missing data is not the cause for error but rather because the CRP was not utilized due to all pixels being saturated. For Nitrogen level and Cultivar $\times$ Nitrogen level the p-values were always > 0.05 for both thresholds. The strategy of calculating the ratio of predominantly green pixels to sum of pixels produced no p-value < 0.05 on any day for any group. What was common across the three approaches were the lowest p-values and hence most significant finding in difference amongst the cultivars themselves. For that reason the least square means for this group, as with the indices in section 4.2.3, were plotted in fig. 4.12.

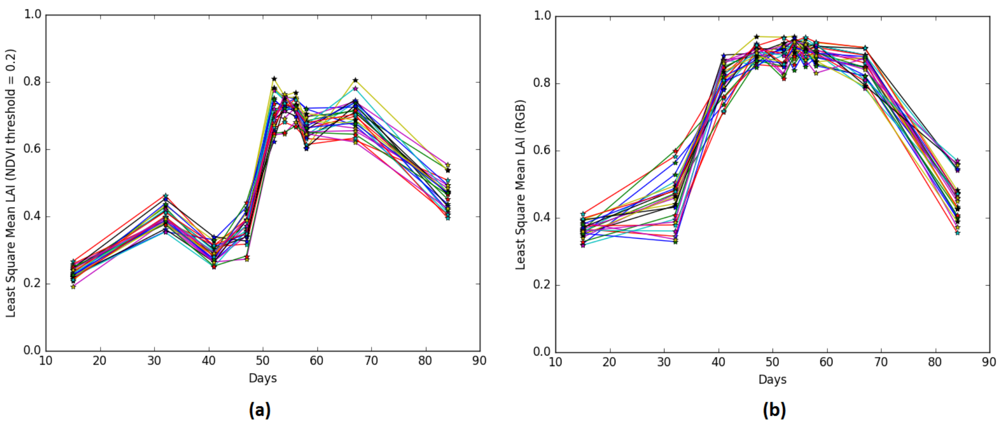


Fig. 4.12: *The least square means for (a) the LAI with the NDVI threshold of 0.2 and (b) the same index with the approach of calculating pixel ratio. The index with the 0.4 NDVI threshold is not included as its almost visually identical to (a), only lowered relative to the least square LAI axis.*

A resemblance can be seen between the least square means for the LAI plotted in fig. 4.12 and the previous plotted values in fig. 4.6.

The LAI is especially relevant prior to heading as a precursor to soil coverage and also the ability both to compete with weed and to withhold moisture. An early date where all three tactics (0.2 and 0.4 thresholds and RGB approach) had their lowest p-values were selected for further analysis, which was day 36 (June 17th). The p-values for both NDVI thresholds and RGB approach for this date is presented in table 4.10.

TABLE 4.10: *The p-values for all LAI approaches with regards to the groups for statistical testing.*

Group	**LAI (0.2 threshold)**	**LAI (0.4 threshold)**	**LAI (RGB)**
Cultivars	0.0037	0.0002	0.1078
Nitrogen level	0.3697	0.2891	0.5479
Cultivar × N-level	0.5335	0.3924	0.5110

We see the Cultivars group has the most entries with a p-value of statistical significance. For the RGB approach the value for the group is not below this cut-off but still the lowest value for this group in the days of wheat growth were LAI is particularly useful.

The least square means for day 36 is presented in table. 4.11

Table 4.11: *The least square means for LAI for both NDVI thresholds for cultivars and for cultivars given 8 and 15 kg/daa of Nitrogen.*

	Cultivars		**8 kg/daa N**		**15 kg/daa N**	
Cultivar	0.2	0.4	0.2	0.4	0.2	0.4
Bjarne	0.395	0.134	0.428	0.163	0.361	0.105
Zebra	0.463	0.228	0.464	0.225	0.462	0.232
Demonstrant	0.384	0.132	0.397	0.147	0.371	0.117
Krabat	0.415	0.175	0.431	0.199	0.399	0.151
Mirakel	0.427	0.172	0.420	0.172	0.435	0.172
Rabagast	0.420	0.175	0.401	0.167	0.440	0.184
Seniorita	0.433	0.183	0.454	0.208	0.413	0.158
GN11644	0.355	0.113	0.346	0.111	0.363	0.115
GN11542	0.388	0.141	0.360	0.115	0.415	0.166
GN13618	0.398	0.152	0.407	0.164	0.390	0.141
Arabella	0.363	0.123	0.371	0.131	0.354	0.116
GN10521	0.376	0.120	0.362	0.110	0.390	0.130
SW01074	0.354	0.121	0.350	0.119	0.357	0.122
GN10637	0.377	0.130	0.374	0.132	0.380	0.129
SW11230	0.438	0.204	0.469	0.225	0.407	0.183
PS-1	0.413	0.177	0.427	0.192	0.400	0.162
SW11011	0.376	0.148	0.399	0.172	0.353	0.124
SW21074	0.452	0.207	0.450	0.199	0.454	0.215
Tjalve	0.377	0.155	0.376	0.151	0.377	0.159
Avle	0.397	0.150	0.399	0.149	0.396	0.150
Bastian	0.383	0.129	0.380	0.123	0.387	0.134
Runar	0.388	0.145	0.409	0.169	0.366	0.121
Reno	0.400	0.157	0.421	0.178	0.379	0.137
Polkka	0.393	0.154	0.386	0.146	0.400	0.163

Not too unexpectedly we see in table 4.11 that the average LAI is higher for the 0.2 threshold than for 0.4. This is natural as more pixels will be recognized as plants algorithmically. This is however of more statistical significance for the group Cultivars in contrast to the other two being the p-value for both differences between Nitrogen levels and cultivars of different Nitrogen levels had high p-values as seen in table 4.10. This same group is also most relevant with regards to table 4.12.

TABLE 4.12: *The least square means for LAI using the RGB approach for cultivars (second column) and for cultivars given 8 and 15 kg/daa of Nitrogen.*

Cultivar	**Cultivar**	**8 kg/daa N**	**15 kg/daa N**
Bjarne	0.564	0.653	0.475
Zebra	0.345	0.323	0.367
Demonstrant	0.470	0.532	0.408
Krabat	0.436	0.425	0.447
Mirakel	0.472	0.517	0.427
Rabagast	0.507	0.517	0.497
Seniorita	0.442	0.525	0.359
GN11644	0.529	0.585	0.473
GN11542	0.583	0.656	0.510
GN13618	0.459	0.442	0.475
Arabella	0.431	0.441	0.422
GN10521	0.599	0.694	0.505
SW01074	0.396	0.445	0.347
GN10637	0.464	0.421	0.506
SW11230	0.329	0.345	0.313
PS-1	0.379	0.388	0.369
SW11011	0.336	0.332	0.340
SW21074	0.482	0.453	0.511
Tjalve	0.408	0.290	0.527
Avle	0.361	0.290	0.432
Bastian	0.495	0.584	0.406
Runar	0.487	0.382	0.592
Reno	0.480	0.506	0.453
Polkka	0.388	0.412	0.364

4.2.7 Correlation between Traits and LAI

Before evaluating different approaches for calculating LAI and their correlations with different traits we will look at the correlations between themselves. These will be within the Cultivar group as they had the lowest p-values and are presented in table 4.13.

TABLE 4.13: *The correlations between the three different LAI least square means values for the cultivars.*

Index	LAI (0.2 threshold)	LAI (0.4 threshold)
LAI (0.4 threshold)	0.952	
LAI (RGB)	-0.255	-0.461

Not surprisingly, the correlation between the two threshold methods was high as they followed the same procedures only with different cut-off-values. The RGB approach produced negative correlations between the other two which may be because the RGB camera does not go beyond the spectre of visible light in order to include the NIR spectral band. This tells us that visual inspection and indices based on spectral bands utilized to estimate chlorophyll content does not always go hand in hand.

The correlations between LAI and GY did not produce any strong relation, neither positive nor negative, so for this section other traits were included as presented in table 4.14.

TABLE 4.14: *The correlations between all LAI approaches and traits. This is for differences in cultivars only.*

	LAI (0.2 threshold)	**LAI (0.4 threshold)**	**LAI (RGB)**
GY	0.075	0.092	-0.147
TKW	0.105	0.278	-0.564
HLW	-0.060	0.033	-0.004
DH	0.163	0.131	0.005
DM	0.013	-0.049	0.130
PH	0.348	0.378	-0.264

As mentioned the correlations between LAI and GY is of no significance whatsoever as can be said among most findings in table 4.14. Of the few exceptions the positive correlation between LAI (0.4 threshold) and TKW is with some magnitude apparent while a higher value is showing between PH and both the NDVI threshold LAI indices.

This would indicate the plant growing both in terms of coverage and height. This would agree with PH and GY being antagonistic with regards to correlation, but this is not a safe conclusion to reach as it would have more merit if LAI were both positively correlated to PH and negatively to GY which it is not. The RGB approach in regards to plant height was a whole other story as it was negatively correlated. The RGB LAI was also the one producing the biggest correlation, although negaive, with TKW. Why a high visual coverage prior to heading would be negatively correlated to the final TKW is not easily explained, but being the highest correlation it is worth mentioning. A plausible reason, with regards to the p-values for the RGB LAI they were never below statistic significance in difference between the cultivars. This approach utilized a simple RGB (simple relative to multi-spectral cameras) to take pictures of very similar looking field plots in term of coverage. For that reason this high negative correlation may very well be dismissed altogether.

4.3 Reflections

To finish this chapter some reflections (of the cognitive kind) revolving the processes producing these results should be included.

The use of the UAV was as mentioned earlier troublesome at times with too many occurrences of having to steer manually. This was most likely the source of DSM and GeoTIFF files having holes after compilation. However the ability to receive these compiled data files was both time saving and convenient.

Thorvald on the other hand never had any obstacles while collecting data that halted the process from day to day. However, the reason for the UAV having 4 more days of taking pictures than Thorvald was because the wheat grew too high not to be damaged as it passed through. Not being able to calibrate using the CRP also brought limitations to the results.

To summarize, these two pieces of equipment brought much contrast when compared. The UAV had several elements malfunctioning with no warnings whereas Thorvald consistently responded to the input from the user in terms of manoeuvring. When the UAV and its software and the GPS all worked the whole picture taking session could last approximately 10 minutes while observing the UAV flying by. This was followed by easy uploading of pictures before receiving a compiled GeoTIFF/DSM file with calibration included. A session of taking pictures while operating Thorvald however was a slow process of approximately 45 minutes hoping rain to be absent due to the low ability to handle water for this prototype. Adding in the possibilities of getting false date due to no calibration selecting a superior between the two pieces of equipment is not an uncomplicated task.

Chapter 5

Conclusion

After studying different platforms and sensory systems for this wheat field trial it is of importance to evaluate questions asked in the initiation of this thesis.

The two indices NDVI and MTCI were measured by algorithms and software based on pictures taken by the UAV to hypothetically correlate with GY. The outcome was not of noteworthy magnitude although the numbers were in agreement with other studies revolving the subject at hand, mostly with regards to NDVI. There was a double edged sword involved in the procedure of selecting the data sets for these indices as the interval of days best suited for correlation analysis also had the lowest of significant p-values, possibly due to pixel saturation. Albeit correlations between the indices and GY were low one should not to dismiss these indices altogether. This is stated because of complications such as saturations and missing data in this study. Despite this rather ambivalent status upon the completion of this study this thesis did exhibit indications of the utilization of fertilizing. Those wheat plots treated with lower levels of fertilizing levels did show a higher correlation to GY due to difference in utilization of Nitrogen amongst the cultivars.

Another index evaluated for possible correlation to GY was the LAI, estimated using three approaches. Two of these implemented different NDVI thresholds serving as cut-off values to differentiate between plants and non-plants. The third one used regular RGB pictures for the calculation of a ratio between predominantly green pixels to total pixels. None of the three approaches provided statistical significance with any consistency from day to day with regards to data. For this reason a particular date prior to the interval applied for NDVI and MTCI correlations analysis was chosen. This date was in an important period of time where the wheat plants would be competing with weed while having to withhold moisture. From this data no noteworthy correlations were produced although some were apparent between PH and the NDVI threshold LAI indices. Albeit this, negative correlations should have been present between these indices and GY to be in accordance with findings in both this and other studies, which was not the case. Considering the two very similar approaches implementing NDVI thresholds and the RGB utilization there was a negative correlation exhibited between them. This might demonstrate the impact the NIR band has with regards to estimating plant coverage which the naked eye can not possibly include.

The most fruitful of correlations calculated, in the hopes of making the time consuming manual measuring of plant height obsolete, was the correlation between manual measurements and the digital estimations. Not only was it strong, it was also a product of a method that could be enhanced through longer and more specified source codes applying the same principals of which it was based on.

5.1 Further Research

This thesis is somewhat of a pilot study leading to a larger project at the Norwegian University of Life Sciences (NMBU). This project includes building a virtual field and the selection of genomes. This will facilitate for other theses and studies to be initiated. In July this year a paper involving the very same topic of study, setup and people as this thesis will be published as a part of a conference in France named IFAC 2017. It is referenced in this thesis.

Concurrently with the writing of this thesis new generations of the agricultural robot, Thorvald, are either near completion or in the works. Soon we will see versions with narrower wheels and a higher clearance as to not damage the monitored vegetation.

Bibliography

[1] Aase, J. and Siddoway, F. (1980). Determining winter wheat stand densities using spectral reflectance measurements. *Agronomy Journal*, 72(1):149–152.

[2] Asrar, G., Fuchs, M., Kanemasu, E., and Hatfield, J. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. *Agronomy journal*, 76(2):300–306.

[3] Baus, A. E. J. (2001). Industrial service agricultural tire. US Patent 6,263,933.

[4] Burud, I., Lange, G., Lillemo, M., Bleken, E., Grimstad, L., and From, P. J. (2017). Exploring robots and uavs as phenotyping tools in plant breeding. In *IFAC 2017 World Congress*.

[5] Canevara, M., Romani, M., Corbellini, M., Perenzin, M., and Borghi, B. (1994). Evolutionary trends in morphological, physiological, agronomical and qualitative traits of triticum aestivum l. cultivars bred in italy since 1900. *European Journal of Agronomy*, 3(3):175–185.

[6] Chen, J. M. and Black, T. (1992). Defining leaf area index for non-flat leaves. *Plant, Cell & Environment*, 15(4):421–429.

[7] Dash, J. and Curran, P. J. (2004). Evaluation of the meris terrestrial chlorophyll index. In *Geoscience and Remote Sensing Symposium, 2004. IGARSS'04. Proceedings. 2004 IEEE International*, volume 1. IEEE.

[8] De Beurs, K. M. (2008). Modeling of land surface phenology with satellite imagery. In *Madison Land Surface Phenology Workshop*.

[9] DESA, U. (2010). United nations department of economic and social affairs/population division (2009b): World population prospects: The 2008 revision. *Internet: http://esa. un. org/unpp (gelesen am 16*.

[10] Fraczek, W. (2003). Mean sea level, gps, and the geoid. *ArcUsers Online*.

[11] Gao, F., Ma, D., Yin, G., Rasheed, A., Dong, Y., Xiao, Y., Xia, X., Wu, X., and He, Z. (2017). Genetic progress in grain yield and physiological traits in chinese wheat cultivars of southern yellow and huai valley since 1950. *Crop Science*, 57(2):760–773.

[12] Gates, D. M. (2012). *Biophysical ecology*. Courier Corporation.

[13] Goswami, S., Gamon, J., Vargas, S., and Tweedie, C. (2015). Relationships of ndvi, biomass, and leaf area index (lai) for six key plant species in barrow, alaska. Technical report, PeerJ PrePrints.

[14] Grimstad, L., Phan, H. N., Pham, C. D., Bjugstad, N., and From, P. J. Initial field-testing of thorvald, a versatile robotic platform for agricultural applications.

[15] Haboudane, D., Miller, J., Tremblay, N., Pattey, E., and Vigneault, P. (2004). Estimation of leaf area index using ground spectral measurements over agriculture crops: Prediction capability assessment of optical indices. In *XXth ISPRS Congress:" Geo-Imagery Bridging Continents". Istanbul, Turkey*, pages 12–23.

[16] Hörtensteiner, S. (1999). Chlorophyll breakdown in higher plants and algae. *Cellular and Molecular Life Sciences CMLS*, 56(3-4):330–347.

[17] Lukina, E., Stone, M., and Raun, W. (1999). Estimating vegetation coverage in wheat using digital images. *Journal of Plant Nutrition*, 22(2):341–350.

[18] Maxwell, J. C. (1865). A dynamical theory of the electromagnetic field. *Philosophical transactions of the Royal Society of London*, 155:459–512.

[19] McCree, K. J. (1981). Photosynthetically active radiation. In *Physiological Plant Ecology I*, pages 41–55. Springer.

[20] Morgounov, A., Gummadov, N., BELEN, S., KAYA, Y., Keser, M., and Mursalova, J. (2014). Association of digital photo parameters and ndvi with winter wheat grain yield in variable environments. *Turkish Journal of Agriculture and Forestry*, 38(5):624–632.

[21] Rouse Jr, J., Haas, R., Schell, J., and Deering, D. (1974). Monitoring vegetation systems in the great plains with erts.

[22] Rutkoski, J., Poland, J., Mondal, S., Autrique, E., Pérez, L. G., Crossa, J., Reynolds, M., and Singh, R. (2016). Canopy temperature and vegetation indices from high-throughput phenotyping improve accuracy of pedigree and genomic selection for grain yield in wheat. *G3: Genes— Genomes— Genetics*, 6(9):2799–2808.

[23] Simmons, S., Oelke, E., and Anderson, P. (1985). Growth and development guide for spring wheat.

[24] Simova-Stoilova, L., Stoyanova, Z., and Demirevska-Kepova, K. (2001). Ontogenic changes in leaf pigments, total soluble protein and rubisco in two barley varieties in relation to yield. *Bulgerian Journal of Plant Physiology*, 27:15–24.

[25] Smith, R., Hick, P., Adams, J., and Stephens, D. (1995). Forecasting wheat yield in a mediterranean-type environment from the noaa satellite. *Australian Journal of Agricultural Research (Australia).*

[26] Starr, C. (2005). Biology: Concepts and applications. thomson brooks/cole. isbn 053446226x.

[27] Tavakoli, H., Mohtasebi, S., Alimardani, R., and Gebbers, R. (2014). Evaluation of different sensing approaches concerning to nondestructive estimation of leaf area index (lai) for winter wheat. *Int. J. Smart Sens. Intell. Syst*, 7(1):337–359.

[28] Viña, A., Gitelson, A. A., Nguy-Robertson, A. L., and Peng, Y. (2011). Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. *Remote Sensing of Environment*, 115(12):3468–3478.

[29] Watson, D. J. (1947). Comparative physiological studies on the growth of field crops: I. variation in net assimilation rate and leaf area between species and varieties, and within and between years. *Annals of Botany*, 11(41):41–76.

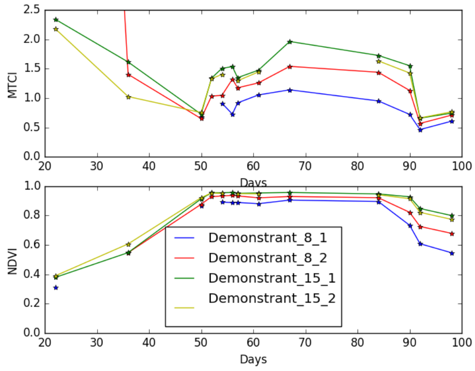
[30] William, A., Alain, B., and Maarten, V. G. (2011). *The world wheat book: a history of wheat breeding*, volume 2. Lavoisier.

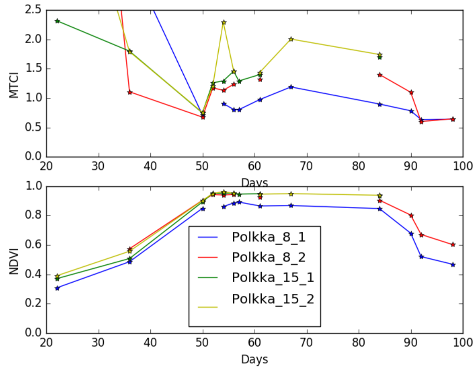
[31] Yu, W. and Birchler, J. A. (2007). Minichromosomes: The next generation technology for plant genetic engineering. *ISB News Report.*

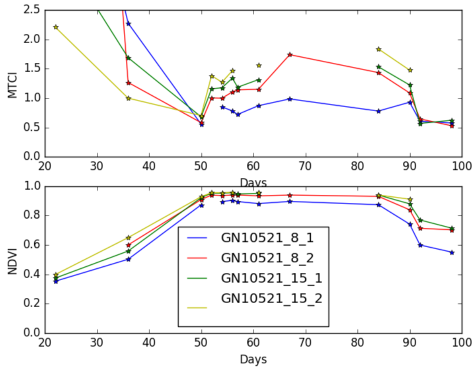
Appendix A

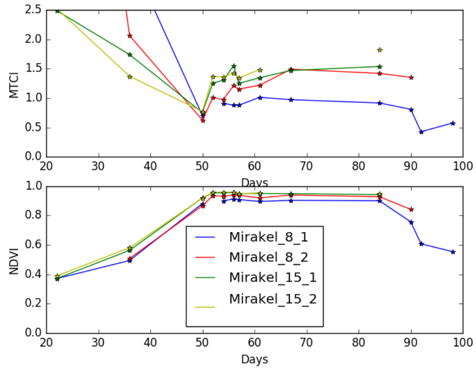
Index Plots

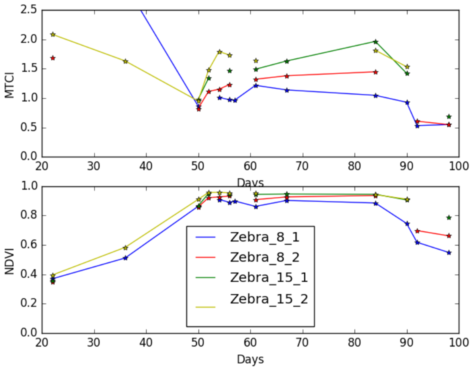
A.1 MTCI and NDVI







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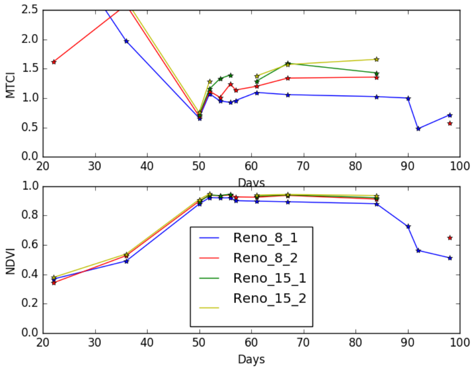
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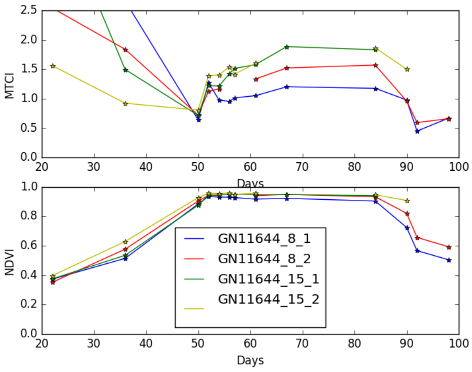
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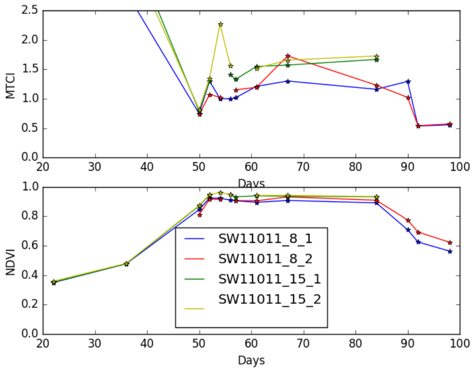
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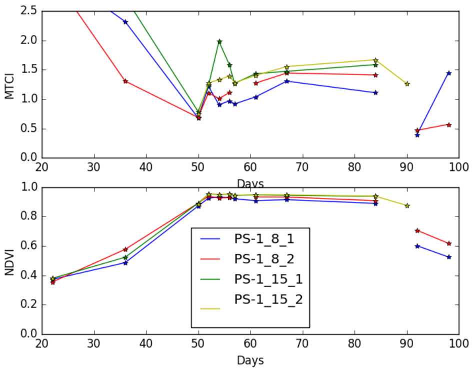
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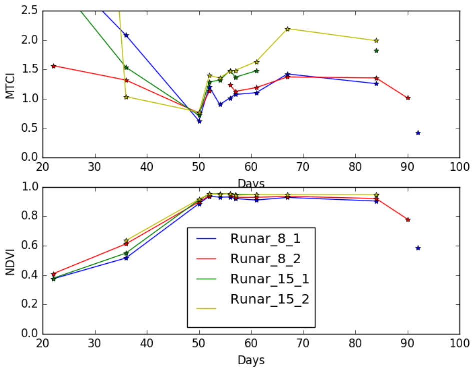
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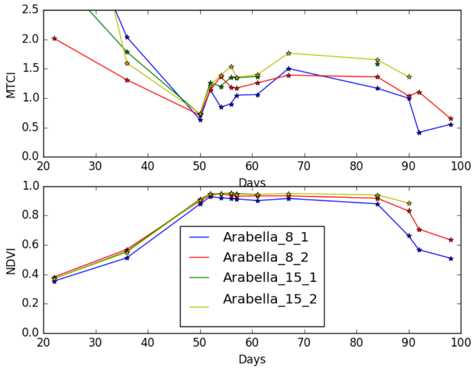
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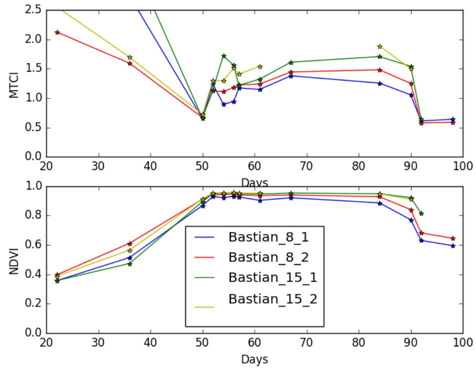
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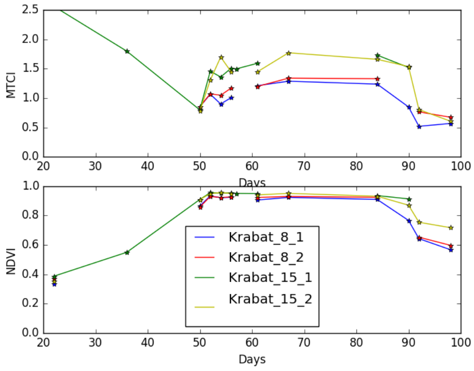
Days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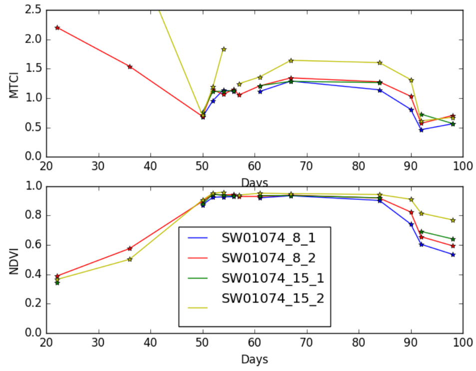
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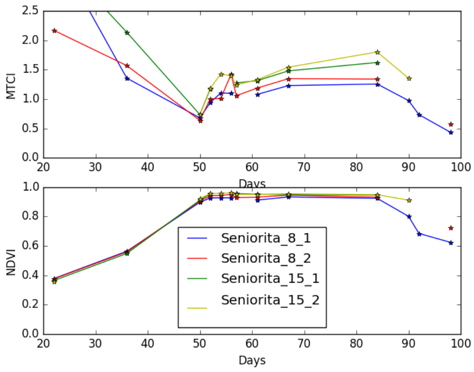
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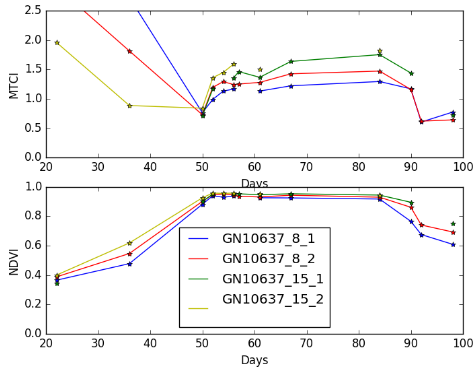
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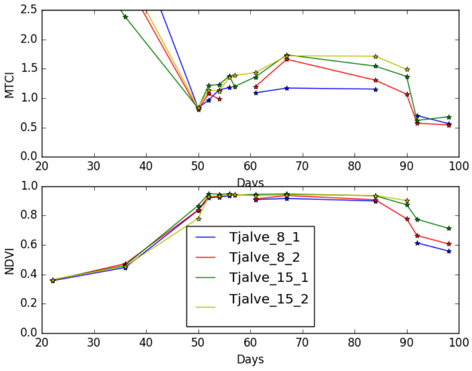
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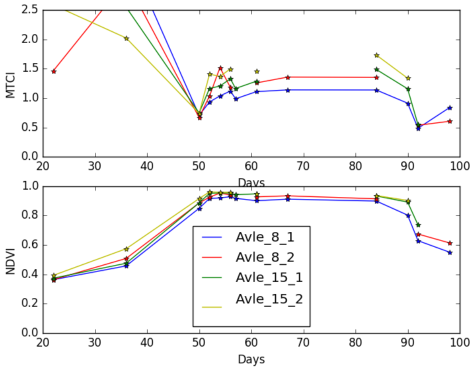
Days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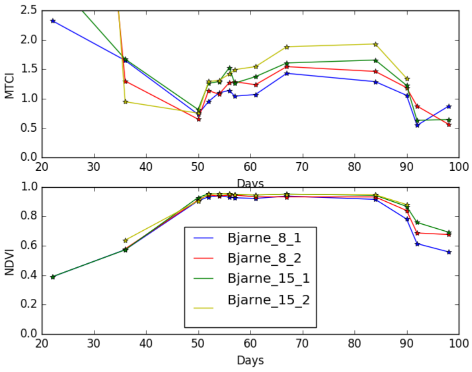
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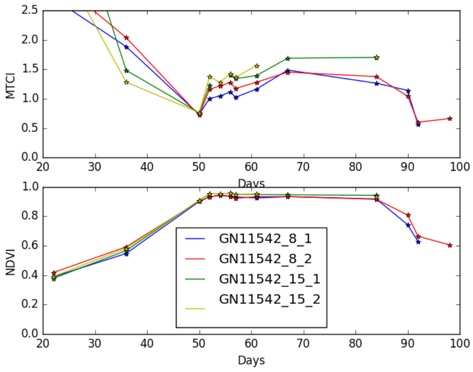
Days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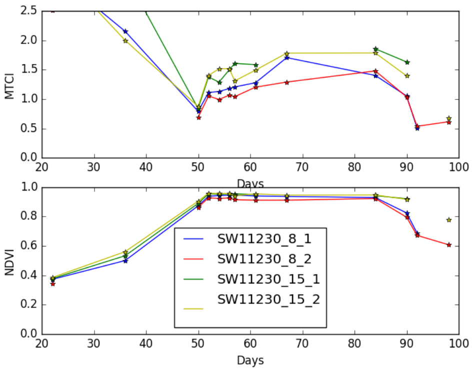
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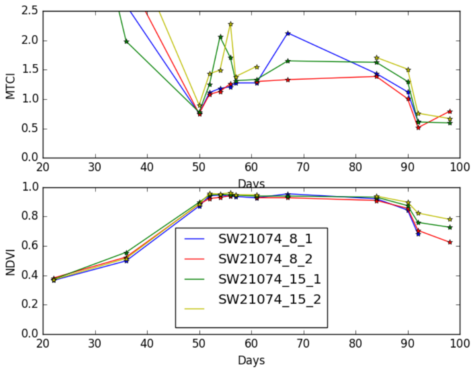
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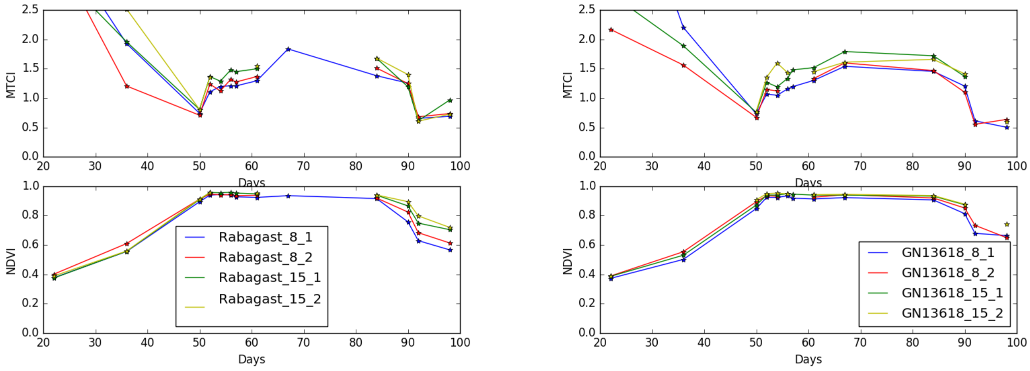
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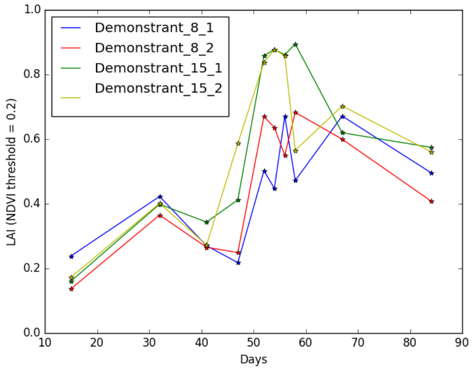
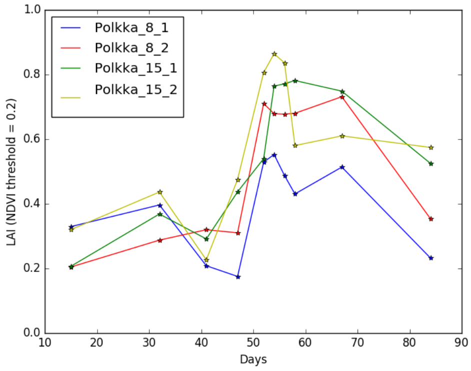
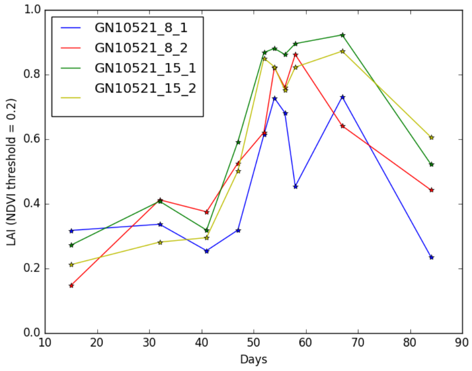
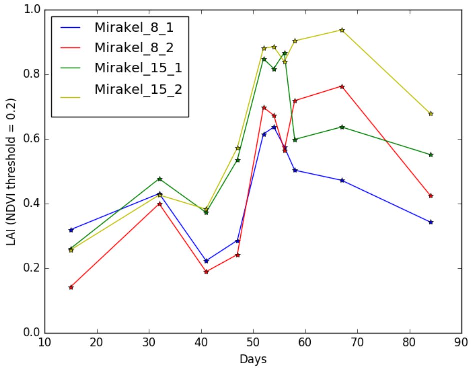
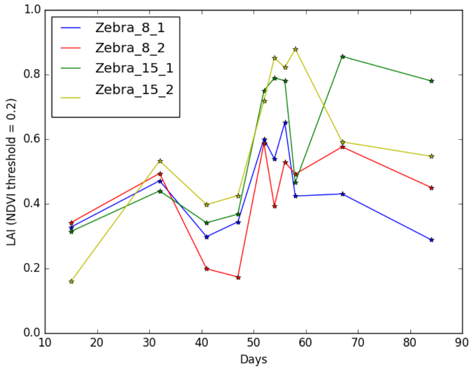
A.2 LAI with 0.2 NDVI Threshold

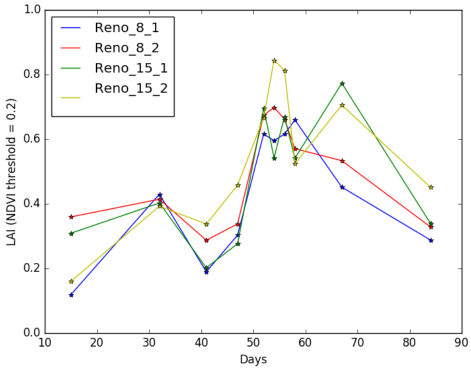


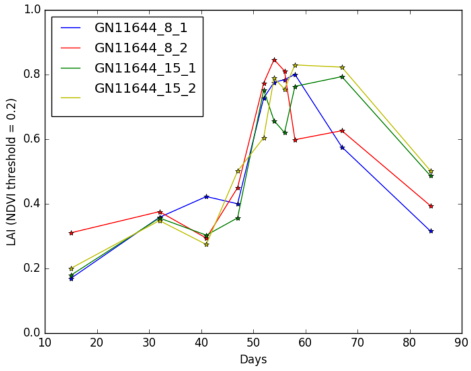








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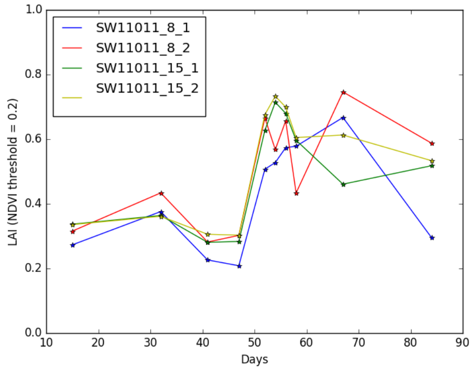
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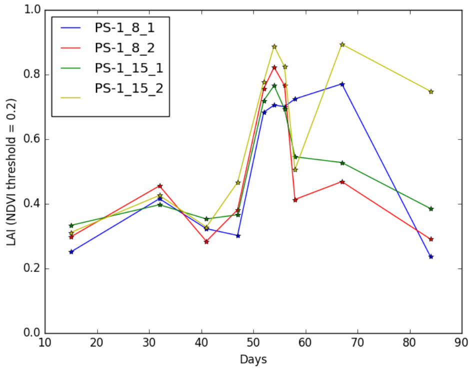
Days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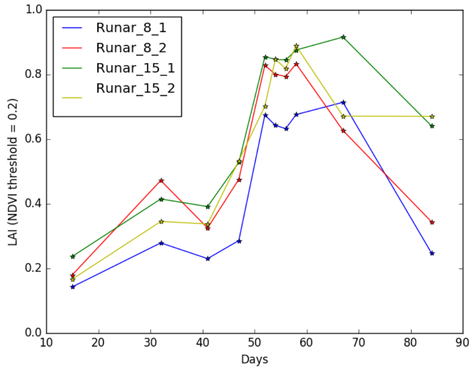
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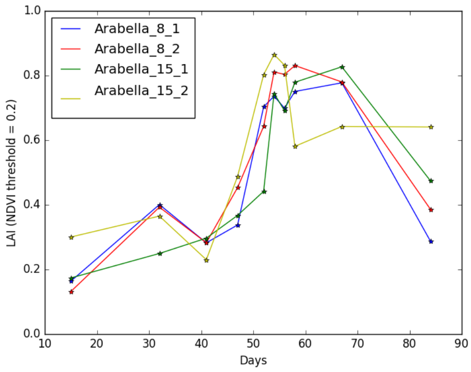
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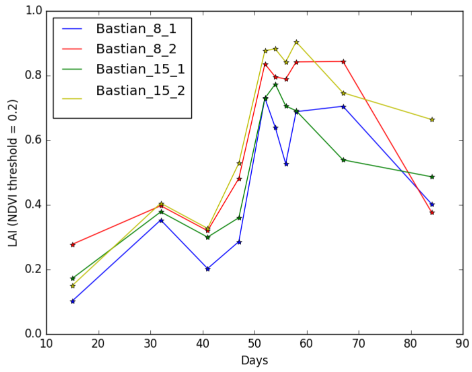
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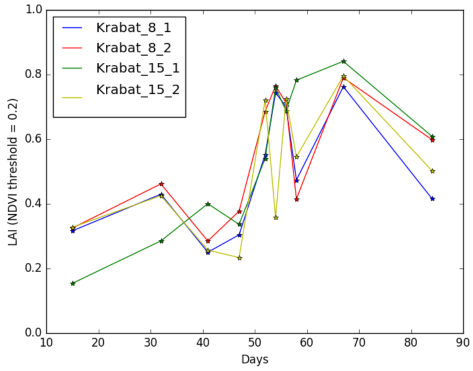
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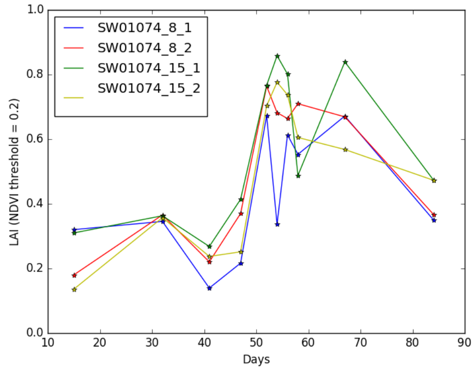
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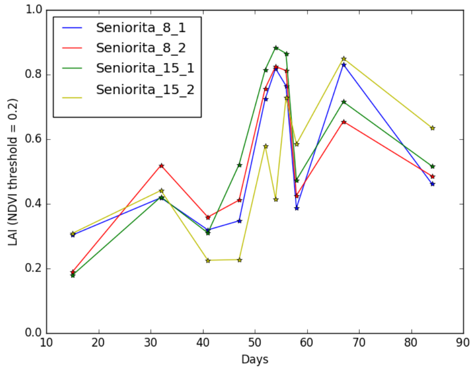
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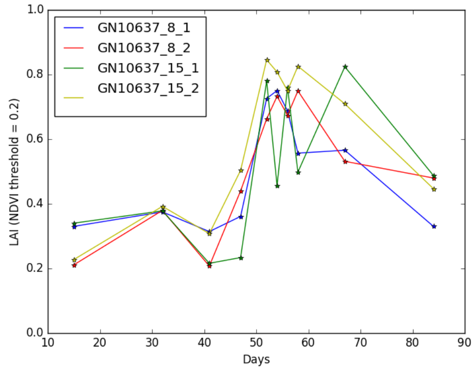
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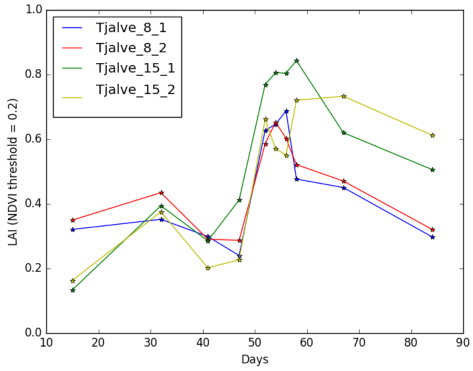
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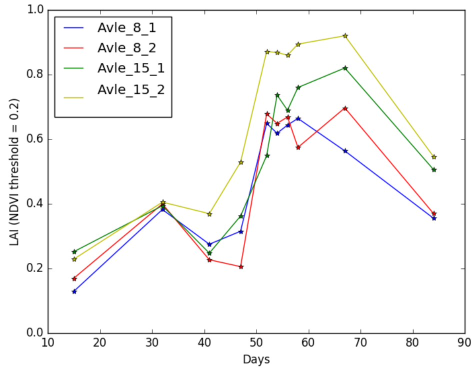
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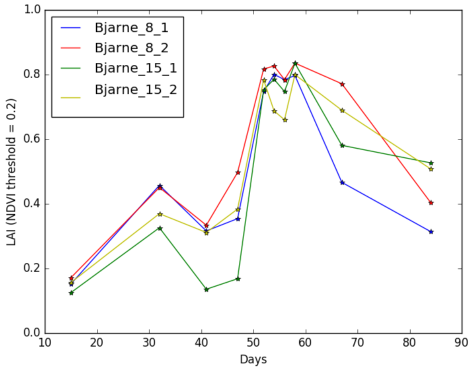
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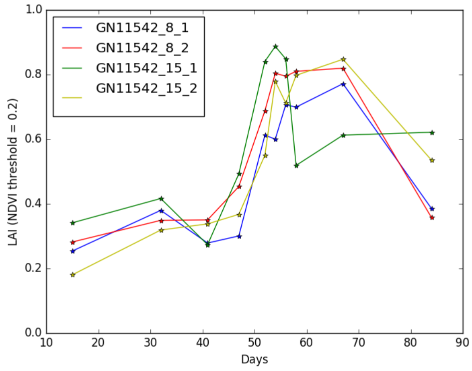
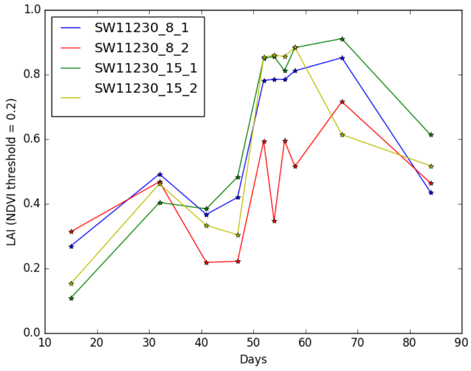
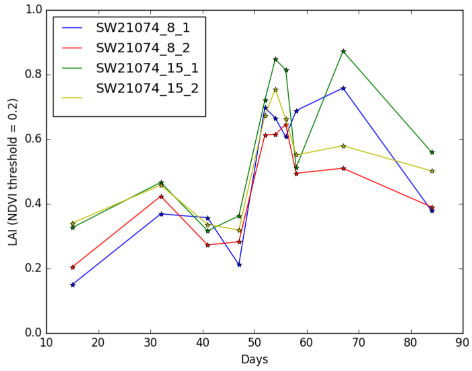
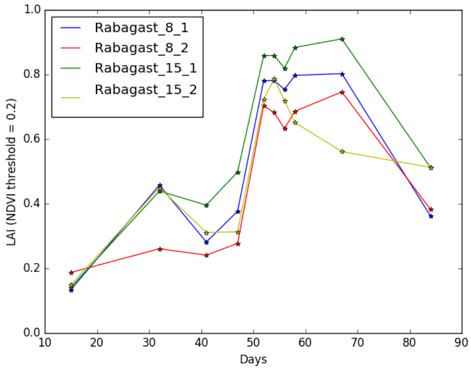
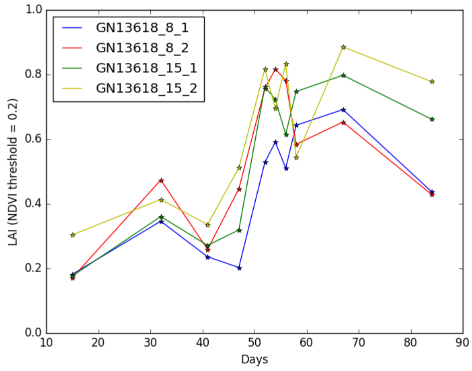
Days


GN11542_8_1
GN11542_8_2
GN11542_15_1
GN11542_15_2
LAI (NDVI threshold = 0.2)
Days

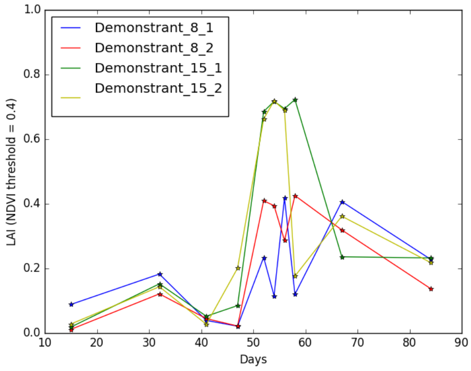

SW11230_8_1
SW11230_8_2
SW11230_15_1
SW11230_15_2
LAI (NDVI threshold = 0.2)
Days

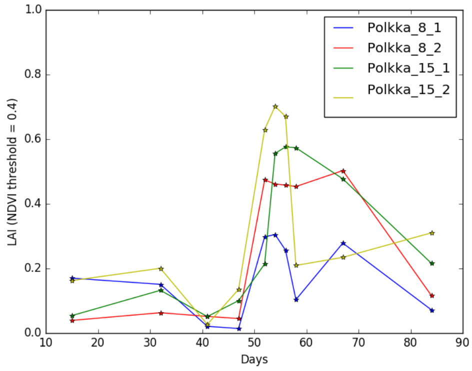

SW21074_8_1
SW21074_8_2
SW21074_15_1
SW21074_15_2
LAI (NDVI threshold = 0.2)
Days

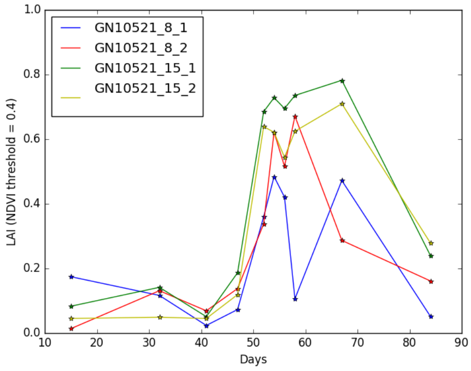

Rabagast_8_1
Rabagast_8_2
Rabagast_15_1
Rabagast_15_2
LAI (NDVI threshold = 0.2)
Days

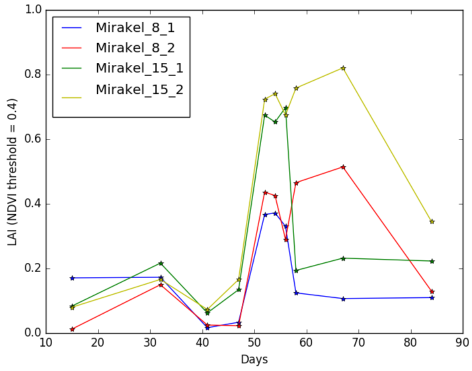

GN13618_8_1
GN13618_8_2
GN13618_15_1
GN13618_15_2
LAI (NDVI threshold = 0.2)
Days

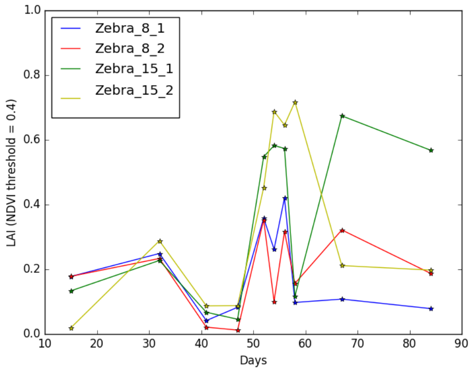
A.3 LAI with 0.4 NDVI Threshold

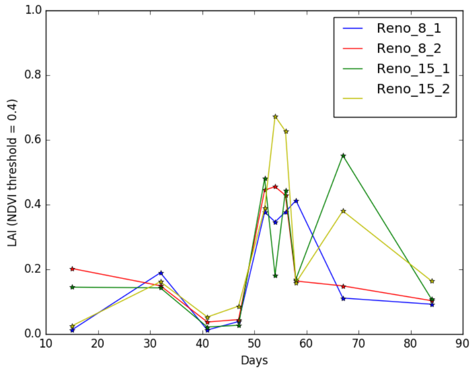


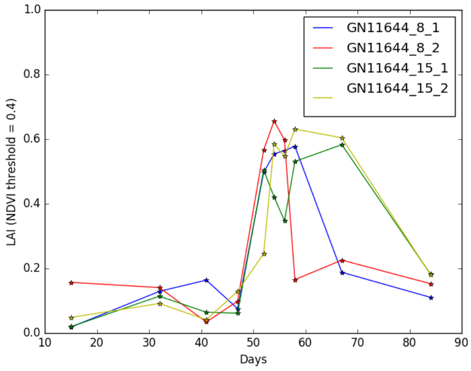


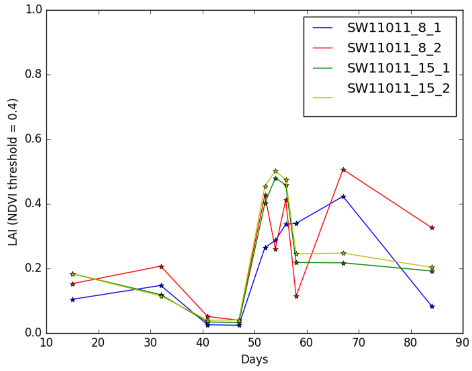


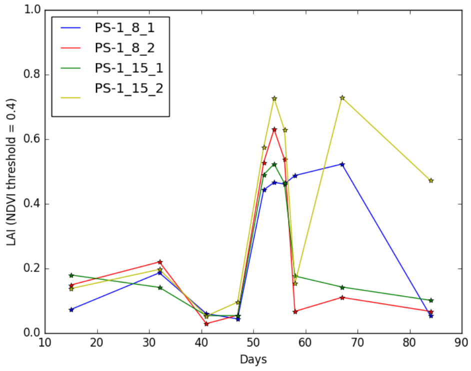


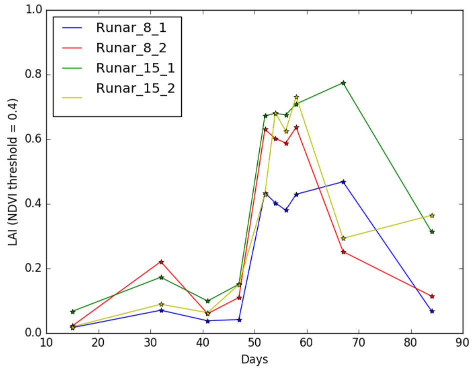


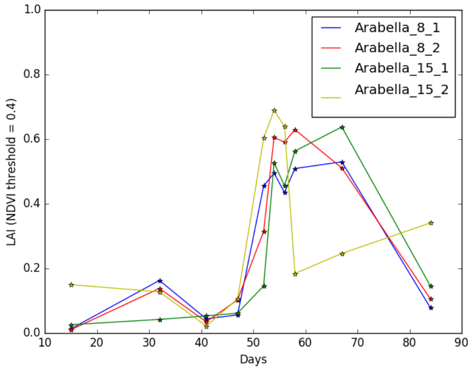


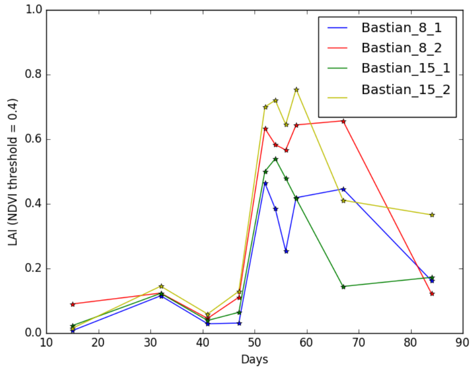

GN11644_8_1
GN11644_8_2
GN11644_15_1
GN11644_15_2
LAI (NDVI threshold = 0.4)
Days

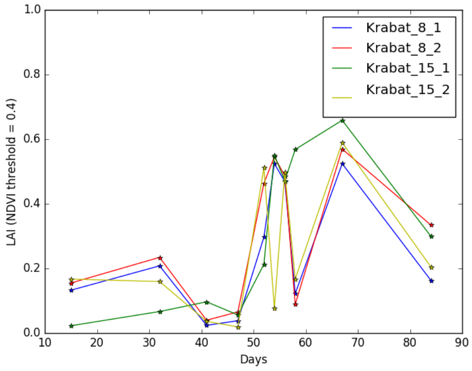

SW11011_8_1
SW11011_8_2
SW11011_15_1
SW11011_15_2
LAI (NDVI threshold = 0.4)
Days

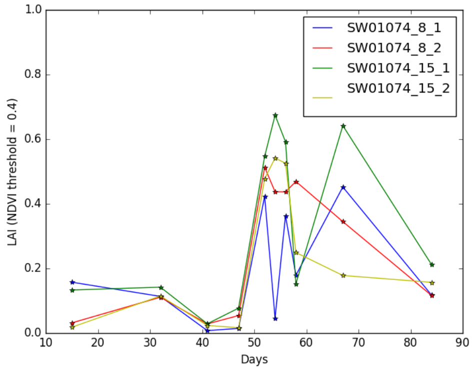

PS-1_8_1
PS-1_8_2
PS-1_15_1
PS-1_15_2
LAI (NDVI threshold = 0.4)
Days

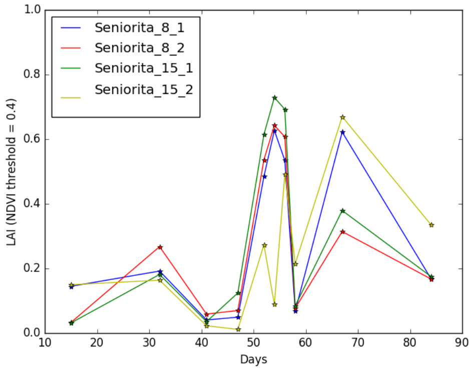

Runar_8_1
Runar_8_2
Runar_15_1
Runar_15_2
LAI (NDVI threshold = 0.4)
Days

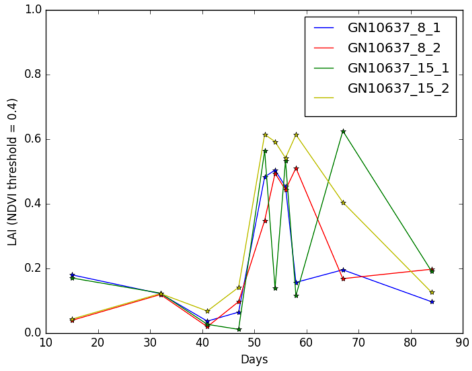

Arabella_8_1
Arabella_8_2
Arabella_15_1
Arabella_15_2
LAI (NDVI threshold = 0.4)
Days

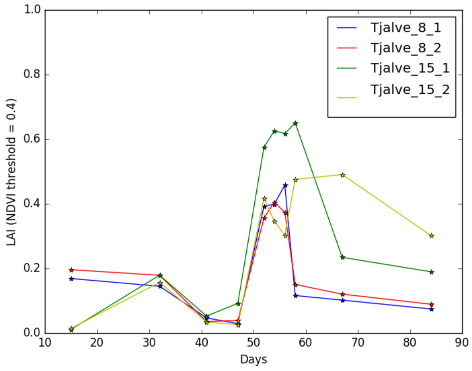

Bastian_8_1
Bastian_8_2
Bastian_15_1
Bastian_15_2
LAI (NDVI threshold = 0.4)
Days

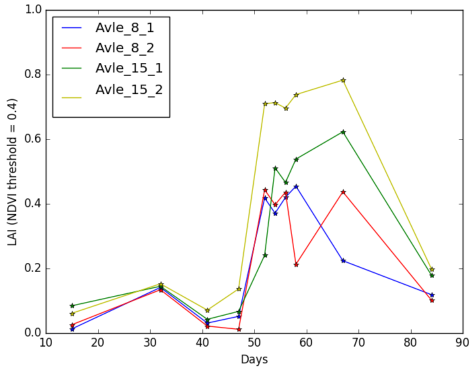

Krabat_8_1
Krabat_8_2
Krabat_15_1
Krabat_15_2
LAI (NDVI threshold = 0.4)
Days

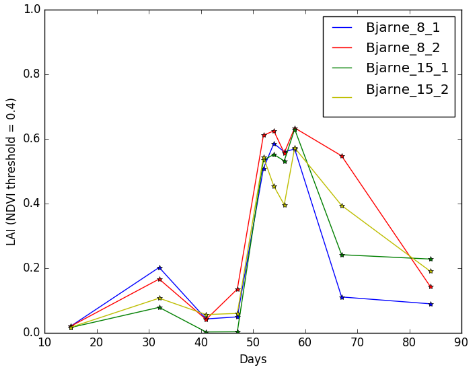

SW01074_8_1
SW01074_8_2
SW01074_15_1
SW01074_15_2
LAI (NDVI threshold = 0.4)
Days

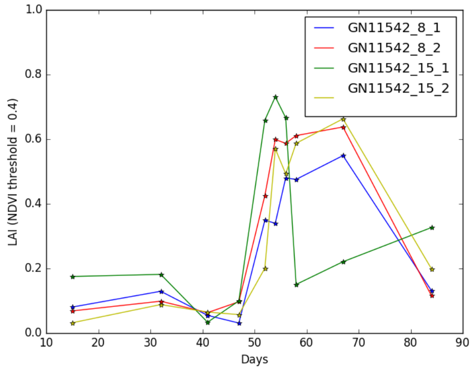

Seniorita_8_1
Seniorita_8_2
Seniorita_15_1
Seniorita_15_2
LAI (NDVI threshold = 0.4)
Days

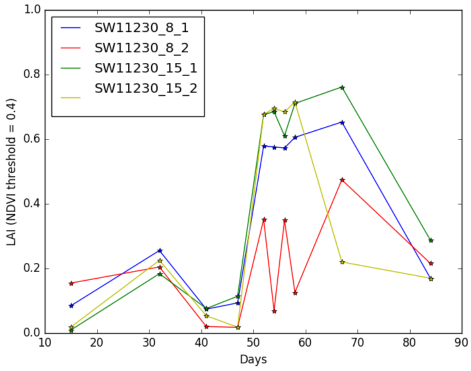

GN10637_8_1
GN10637_8_2
GN10637_15_1
GN10637_15_2
LAI (NDVI threshold = 0.4)
Days

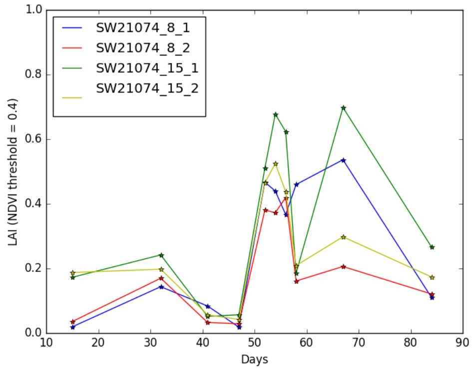

Tjalve_8_1
Tjalve_8_2
Tjalve_15_1
Tjalve_15_2
LAI (NDVI threshold = 0.4)
Days

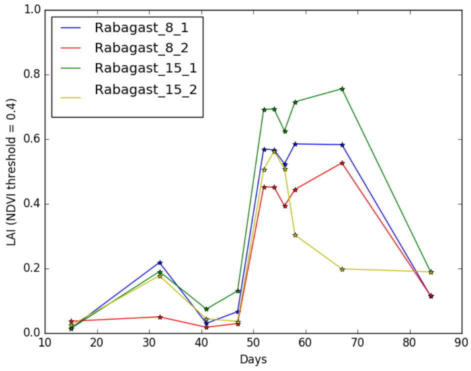

Avle_8_1
Avle_8_2
Avle_15_1
Avle_15_2
LAI (NDVI threshold = 0.4)
Days

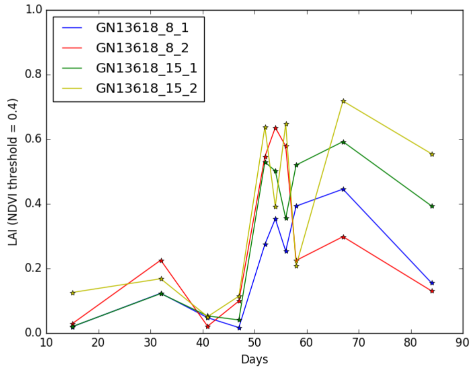

Bjarne_8_1
Bjarne_8_2
Bjarne_15_1
Bjarne_15_2
LAI (NDVI threshold = 0.4)
Days


GN11542_8_1
GN11542_8_2
GN11542_15_1
GN11542_15_2
LAI (NDVI threshold = 0.4)
Days

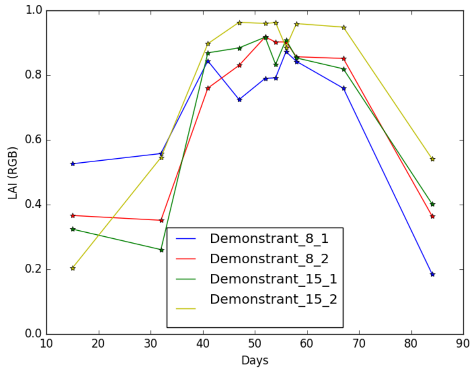

SW11230_8_1
SW11230_8_2
SW11230_15_1
SW11230_15_2
LAI (NDVI threshold = 0.4)
Days

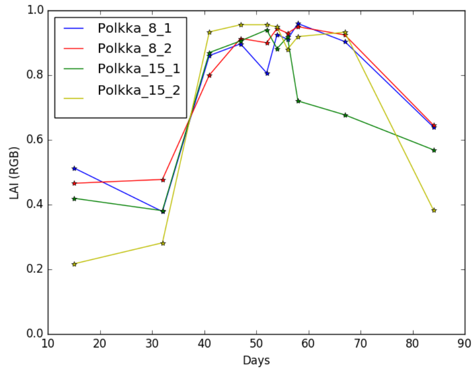

SW21074_8_1
SW21074_8_2
SW21074_15_1
SW21074_15_2
LAI (NDVI threshold = 0.4)
Days

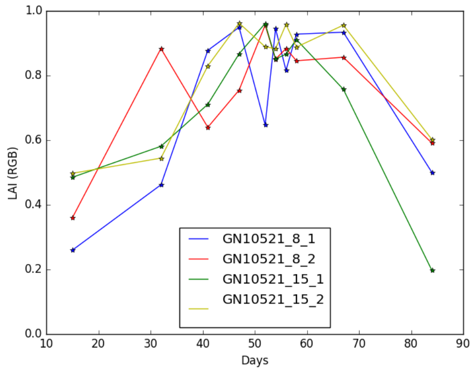

Rabagast_8_1
Rabagast_8_2
Rabagast_15_1
Rabagast_15_2
LAI (NDVI threshold = 0.4)
Days

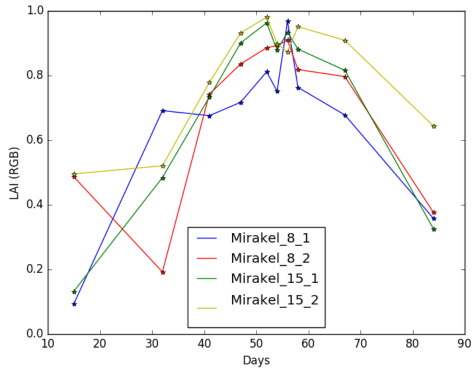

GN13618_8_1
GN13618_8_2
GN13618_15_1
GN13618_15_2
LAI (NDVI threshold = 0.4)
Days

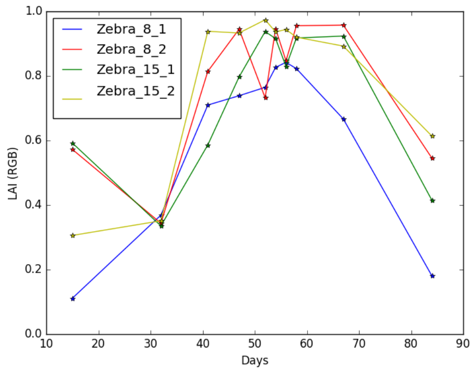
A.4 LAI using RGB

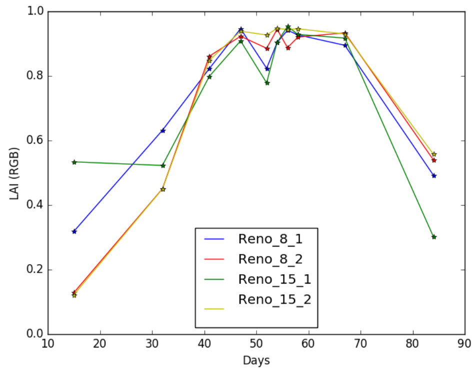


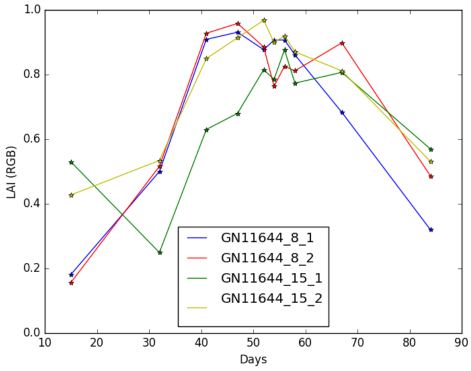


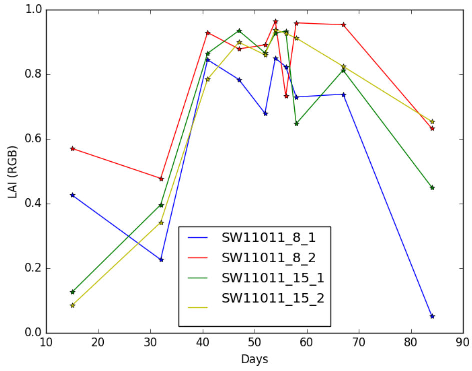


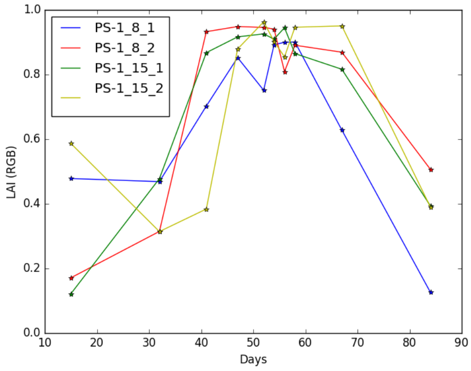


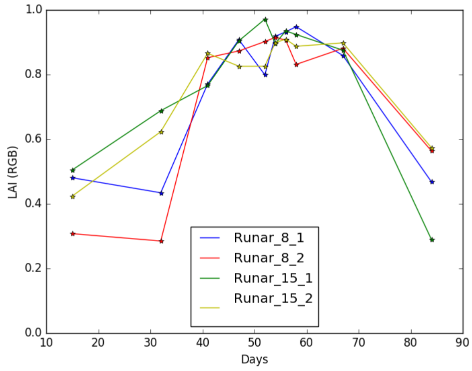


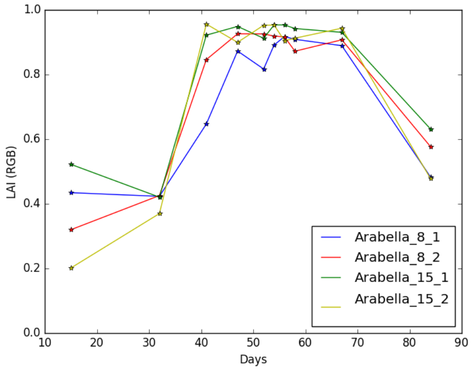


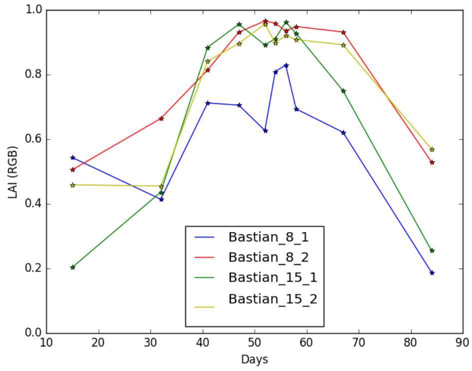

LAI (RGB)
Days
GN11644_8_1
GN11644_8_2
GN11644_15_1
GN11644_15_2

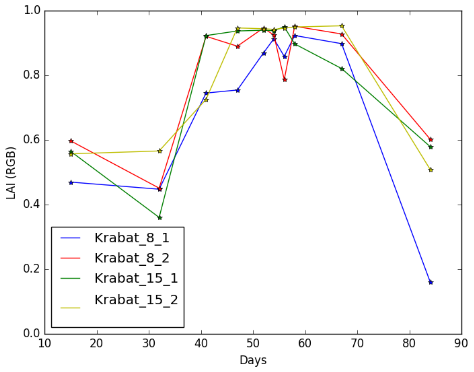

LAI (RGB)
Days
SW11011_8_1
SW11011_8_2
SW11011_15_1
SW11011_15_2

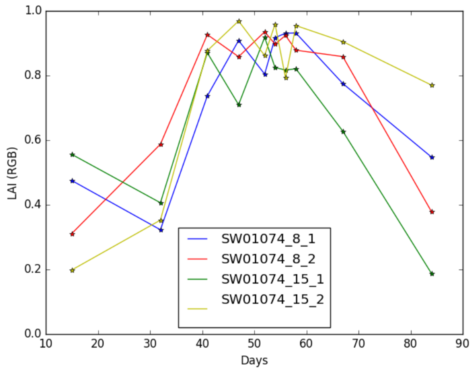

LAI (RGB)
Days
PS-1_8_1
PS-1_8_2
PS-1_15_1
PS-1_15_2

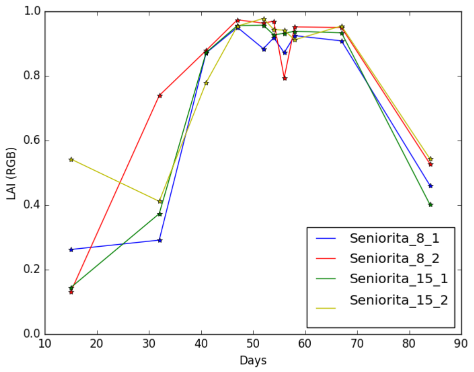

LAI (RGB)
Days
Runar_8_1
Runar_8_2
Runar_15_1
Runar_15_2

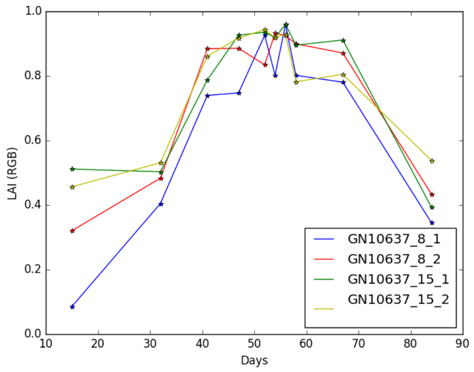

LAI (RGB)
Days
Arabella_8_1
Arabella_8_2
Arabella_15_1
Arabella_15_2

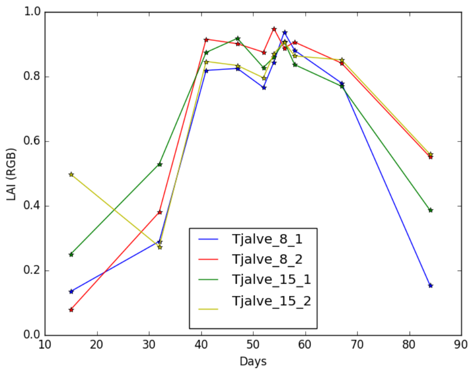

LAI (RGB)
Days
Bastian_8_1
Bastian_8_2
Bastian_15_1
Bastian_15_2

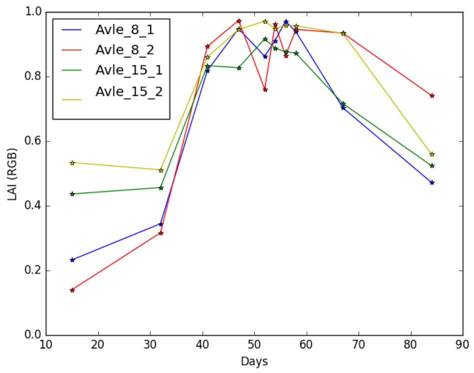

LAI (RGB)
Days
Krabat_8_1
Krabat_8_2
Krabat_15_1
Krabat_15_2

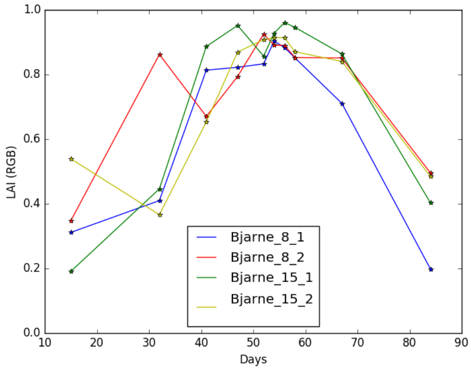

LAI (RGB)
Days
SW01074_8_1
SW01074_8_2
SW01074_15_1
SW01074_15_2

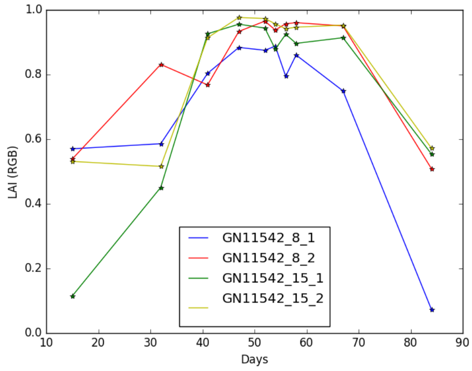

LAI (RGB)
Days
Seniorita_8_1
Seniorita_8_2
Seniorita_15_1
Seniorita_15_2

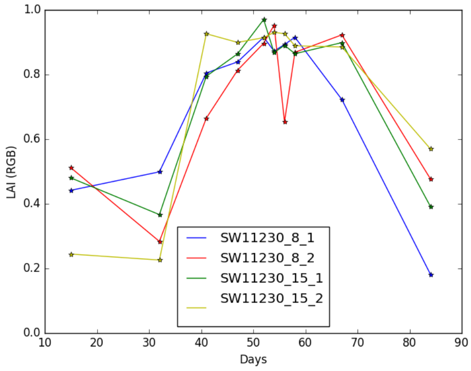

LAI (RGB)
Days
GN10637_8_1
GN10637_8_2
GN10637_15_1
GN10637_15_2

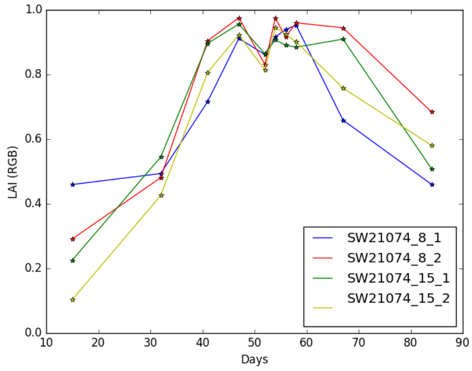

LAI (RGB)
Days
Tjalve_8_1
Tjalve_8_2
Tjalve_15_1
Tjalve_15_2

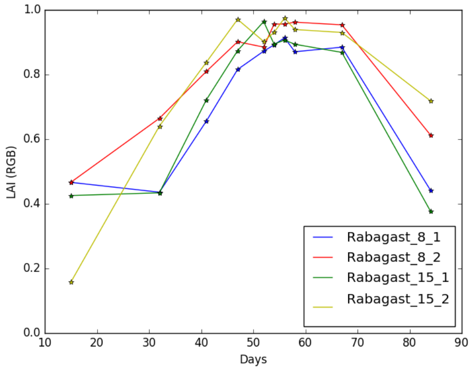

LAI (RGB)
Days
Avle_8_1
Avle_8_2
Avle_15_1
Avle_15_2

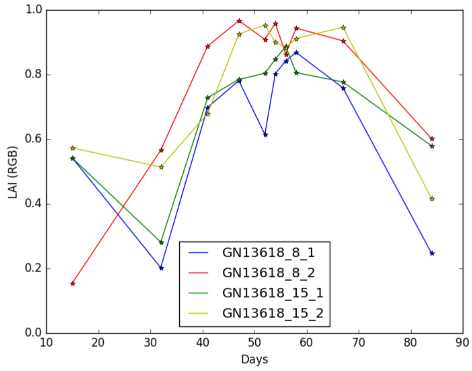

LAI (RGB)
Days
Bjarne_8_1
Bjarne_8_2
Bjarne_15_1
Bjarne_15_2


LAI (RGB)
Days
GN11542_8_1
GN11542_8_2
GN11542_15_1
GN11542_15_2


LAI (RGB)
Days
SW11230_8_1
SW11230_8_2
SW11230_15_1
SW11230_15_2


LAI (RGB)
Days
SW21074_8_1
SW21074_8_2
SW21074_15_1
SW21074_15_2


LAI (RGB)
Days
Rabagast_8_1
Rabagast_8_2
Rabagast_15_1
Rabagast_15_2


LAI (RGB)
Days
GN13618_8_1
GN13618_8_2
GN13618_15_1
GN13618_15_2

Appendix B

Python Source Codes and SAS code

B.1 Script for Importing Values from Gunnar Langes Script and Organizing for Further Analysis

```
infile = open('robotLAI 0,2.txt','r')
lines = infile.readlines()
infile.close()
infile = open('thorvaldnumbers.txt','r')
numbers = infile.readlines()
infile.close()
"""
The file 'robotLAI 0,2.txt' (as well asthose for 0.4 and RGB) all had
the template:
Date: 16.05.27
Sq.numb:1 LAI: value
Sq.numb:2 LAI: value
Sq.numb:3 LAI: value
...etc

The file 'thorvaldnumbers.txt' had 96 lines for the transformation
from the zigzag path Thorvald travelled to the square numbers assigned
in the field setup.
The first lines are:
96
81
80
65
```

```
64
49
...etc
"""
for i in range(96):
    values = []
    a = int(numbers[i])
    for j in range(a,979,98):
        values.append(lines[j])

    valuesfloats = []
    for k in range(len(values)):
        b = values[k].split()
        c = b[2]
        d = float(c)
        valuesfloats.append(d)

    print valuesfloats
```

B.2 Script for Plotting MTCI and NDVI

```
import matplotlib.pyplot as plt

def emptysquare(value):     #   Function for setting 'EmptySquare' to 0.0
    word = set('a')
    if word & set(value):
        return True

def zero_to_nan(values):    #   Function setting 0.0 to 'nan' for plotting
    return [float('nan') if x == 0.0 else x for x in values]

infile = open('Drone_MTCI.txt','r') #   MTCI values for all 96 wheat plots
drone_mtci = infile.readlines()
infile = open('Drone_NDVI.txt','r') #   NDVI values for all 96 wheat plots
drone_ndvi = infile.readlines()
infile = open('Fields_grouped.txt','r') #   Fields grouped by cultivars
breeds = infile.readlines()
"""
'Drone_MTCI.txt' and 'Drone_MTCI.txt' share this template for every line:
Sq.nr, 2016_05_27, 2016_06_03, 2016_06_17, ...
'Fields_grouped.txt' has this template for every line:
Sq.nr,Breed_Nkg_rep,Sq.nr,Breed_Nkg_rep,Sq.nr,Breed_Nkg_rep,Sq.nr,Breed_Nkg_rep

Another script was made with the same template as Fields_grouped only
it had only four rows, two for 8 kg of N and two for 15 kg.
"""

days_drone = [15,22,36,50,52,54,56,57,61,67,84,90,92,98]
days_drone_skip = [days_drone[i] for i in range(1,len(days_drone))]

rownumber = 10      #   number corresponding with cultivar number
breedlist = breeds[rownumber]
b_list = breedlist.split(',')
labellist = ['b-','r-','g-','y-']
dotlist = ['b*','r*','g*','y*']



for k in range(0,len(b_list)-1,2):
    a = b_list[k]
    b = str(a)
    c = []
    for i in b:
        c.append(i)


    number = ((int(c[1])-1)*12)+(int(c[2])*10)+(int(c[3]))
    data_drone_mtci = drone_mtci[number].split(', ')
```

```
    data_drone_ndvi = drone_ndvi[number].split(', ')

    for i in range(1,len(data_drone_mtci)):
        if emptysquare(data_drone_mtci[i]) == True:
            data_drone_mtci[i] = 0

    for i in range(1,len(data_drone_ndvi)):
        if emptysquare(data_drone_ndvi[i]) == True:
            data_drone_ndvi[i] = 0


    data_drone_mtci = [float(data_drone_mtci[j]) for j in range(1,len(days_drone)+1)]
    data_drone_ndvi = [float(data_drone_ndvi[j]) for j in range(1,len(days_drone)+1)]
    data_drone_mtci_skip = [data_drone_mtci[i] for i in range(1,len(data_drone_mtci))]
    data_drone_ndvi_skip = [data_drone_ndvi[i] for i in range(1,len(data_drone_ndvi))]

    data_drone_mtci_skip = zero_to_nan(data_drone_mtci_skip)
    data_drone_ndvi_skip = zero_to_nan(data_drone_ndvi_skip)

    plt.subplot(2,1,1)
    plt.plot(days_drone_skip,data_drone_mtci_skip,'%s' % labellist[k/2],label=b_list[k+1])
    plt.plot(days_drone_skip,data_drone_mtci_skip,'%s' % dotlist[k/2])
    plt.xlabel('Days')
    plt.ylabel('MTCI')

    plt.subplot(2,1,2)
    plt.plot(days_drone_skip,data_drone_ndvi_skip,'%s' % labellist[k/2],label=b_list[k+1])
    plt.plot(days_drone_skip,data_drone_ndvi_skip,'%s' % dotlist[k/2])
    plt.xlabel('Days')
    plt.ylabel('NDVI')
    plt.legend(loc='best')

plt.show()
```

B.3 Script for Making Regression Lines

```
"""
The following five functions are made from the formulas for regression:

y = slope * x + intercept
"""
def average(numbers):
    Sum = 0
    for i in numbers:
        Sum += i
    return float(Sum)/float(len(numbers))

def meanXY(xlist,ylist):
    Sum = 0
    for i in range(len(xlist)):
        Sum += float(xlist[i])*float(ylist[i])
    return Sum/len(xlist)

def XSquared(numbers):      #   Takes the x-values as argument
    Sum = 0
    for i in numbers:
        Sum += (float(i))**2
    return Sum/len(numbers)

def slope(xmean,ymean,meanxy,xsquared):
    return ((xmean*ymean)-meanxy)/((xmean**2)-xsquared)

def intercept(xmean,ymean,slope):
    return ymean - (slope*xmean)
"""
The next function takes a list as an argument, makes a new list starting at 0,
letting the next values be the differences instead of the original values.
This is to still keep the difference from list value to list value intact.
"""
def zerolist(values):
    listfromzero = [0]
    for i in range(len(values)-1):
        dif = (float(values[i+1])-float(values[i]))
        listfromzero.append(dif+listfromzero[i])
    return listfromzero

colxlist = range(9)
rowxlist = [i*2 for i in range(9)]

"""
The next six lists are the two groups of three lines of 9 points, one for rows
```

```
and one for columns.
"""

colcords_upper = [78.697,78.792,78.852,78.928,78.986,79.087,79.157,79.246,79.381]
colcords_lower = [78.741,78.778,78.836,78.903,78.965,79.067,79.148,79.237,79.321]
colcords_center = [78.768,78.914,79.037,79.105,79.209,79.277,79.386,79.403,79.484]

rowcords_left = [78.690,78.642,78.697,78.743,78.760,78.885,78.885,78.859,78.733]
rowcords_right = [79.379,79.311,79.376,79.469,79.471,79.505,79.510,79.421,79.287]
rowcords_center = [79.989,78.935,79.016,79.096,79.155,79.154,79.161,79.080,78.968]

colcordsavg = []
rowcordsavg = []

"""
This for loop takes the 27 points for each direction and calculates 9
mean values based on those who are parallel with the direction.
"""
for i in range(len(colcords_upper)):
    templist_col = [colcords_upper[i],colcords_lower[i],colcords_center[i]]
    templist_row = [rowcords_left[i],rowcords_right[i],rowcords_center[i]]
    colavg = average(templist_col)
    rowavg = average(templist_row)
    colcordsavg.append(colavg)
    rowcordsavg.append(rowavg)

colavgzero = zerolist(colcordsavg)
rowavgzero = zerolist(rowcordsavg)

colxmean = average(colxlist)
colymean = average(colavgzero)
colxymean = meanXY(colxlist,colavgzero)
colxsquared = XSquared(colxlist)
colslope = slope(colxmean,colymean,colxymean,colxsquared)
colinter = intercept(colxmean,colymean,colslope)

rowxmean = average(rowxlist)
rowymean = average(rowavgzero)
rowxymean = meanXY(rowxlist,rowavgzero)
rowxsquared = XSquared(rowxlist)
rowslope = slope(rowxmean,rowymean,rowxymean,rowxsquared)
rowinter = intercept(rowxmean,rowymean,rowslope)

print 'Regression line for cols are y = %.3fx + %.3f' % (colslope,colinter)
print 'Regression line for rows are y = %.3fx %.3f' % (rowslope,rowinter)
"""
The last two lines gave us:
Regression line for cols are y = 0.081x + 0.004
```

```
Regression line for rows are y = -0.005x -0.197

The other DSM used, with its own points, gave us:
Regression line for cols are y = 0.335x + (-0.010)
Regression line for rows are y = -0.098x + (0.093)
"""
```

B.4 Script for Producing Height Values Based on Regression Script

```
def coladjust(colvalue):    # colvalue is a fraction which is column number/14
    return ((colvalue*0.081*8)+0.004)*(-1)    # formula based on regression script


def rowadjust(rowvalue):    # rowvalue is a fraction which is row number/8
    return (rowvalue*0.005*16)+0.197          # formula based on regression script
"""
For the other DSM used the functions were:
def coladjust(colvalue):
    return ((colvalue*0.335*8)-0.010)*(-1)


def rowadjust(rowvalue):
    return (rowvalue*0.098*16)-0.093
"""
geozero = 78.643            # zero point for regression axes obtained by Fiji

infile = open('Drone_DSM_Fiji.txt','r')
drone_dsm = infile.readlines()
data_drone_dsm = [drone_dsm[i].split(', ') for i in range(1,len(drone_dsm))]
"""
The file 'Drone_DSM_Fiji.txt' were the values for each wheat
plot using Fiji. The file had this template for each line:
SquareNumber,value
"""
values = []
for i in range(len(data_drone_dsm)):
    sqnr = str(data_drone_dsm[i][0])
    digitlist = [int(d) for d in str(sqnr)]
    digitforcol = (digitlist[2]*10)+digitlist[3]
    digitforrow = digitlist[1]
    valueforcol = (digitforcol+1)/14.0
    valueforrow = (9-digitforrow)/8.0       # zero point for axes on opposite side of map
    valuefromdata = data_drone_dsm[i][1]
    valuezero = float(valuefromdata) - geozero
    valueadjust = valuezero + coladjust(valueforcol) + rowadjust(valueforrow)
    values.append(valueadjust)

for i in range(len(data_drone_dsm)):
    print 'Square Number: %s : %.3f m' % (data_drone_dsm[i][0],values[i])
```

B.5 Script for Plotting the Wheat Field

```
import matplotlib.pyplot as plt
import matplotlib.patches as patches


infile = open('Drone_DSM.txt','r')
drone_dsm = infile.readlines()
data_drone_dsm = [drone_dsm[i].split(', ') for i in range(1,len(drone_dsm))]
"""
'Drone_DSM.txt' is the result of the script adjusting heights based on
regression with this template for every line:
Sq.nr, Value.
The last line before this comment made a split where the comma is.
"""

values = []
for i in range(len(data_drone_dsm)):
    value = float(data_drone_dsm[i][1])
    values.append(value*100)            # from m to cm

xaxis = range(13)
yaxis = range(9)

hexes = [hex(int(i)) for i in values]
hexessplit = [i.split('x') for i in hexes]
greenhexes = [i[1] for i in hexessplit]
"""
From cm to integer to hex. This is because the color format in the bottom
of this script uses hex.
"""

axes = plt.gca()
axes.set_xlim([xaxis[0],xaxis[12]])
axes.set_ylim([yaxis[0],yaxis[8]])

for i in range(len(values)):
    sqnr = str(data_drone_dsm[i][0])
    digitlist = [int(d) for d in str(sqnr)]
    digitforx = (digitlist[2]*10)+digitlist[3]
    digitfory = digitlist[1]

    axes.add_patch(patches.Rectangle((digitforx-1,digitfory-1),1,1,\
    facecolor="#%s%s%s" % (greenhexes[i],greenhexes[i],greenhexes[i])))
```

B.6 Script for plotting P-values

```
import matplotlib.pyplot as plt
import math as m

Days = [15,22,36,50,52,54,56,57,61,67,84,90,92,98]
infile = open('ndvi p values groups.txt','r')
table = infile.readlines()
table = [table[i].split(',') for i in range(len(table))]
"""
'ndvi p values groups.txt' had the template:
date,date,date,date...etc
p-value cultivar, p-value cultivar...etc
p-value N-level, p-value N-level....etc
p-value cult X N-level, p-value cult X N-level...etc
"""
for i in range(1,4):
    for k in range(len(table[0])):
        table[i][k] = float(table[i][k])

Cults = [table[1][i] for i in range(14)]
Ferts = [table[2][i] for i in range(14)]
CultFert = [table[3][i] for i in range(14)]

Inst_cults = 0
Inst_ferts = 0
Inst_culfer = 0

for i in range(len(Cults)):
    if Cults[i] > 0.05:
        Inst_cults += 1
    if Ferts[i] > 0.05:
        Inst_ferts += 1
    if CultFert[i] > 0.05:
        Inst_culfer += 1

Cults = [-m.log10(i) for i in Cults]
Ferts = [-m.log10(i) for i in Ferts]
Cultfert = [-m.log10(i) for i in CultFert]

print 'p-value higher than 0.05:'
print '%d times for Cultivar' % Inst_cults
print '%d times for N-level' % Inst_ferts
print '%d times for cultivar X N-level' % Inst_culfer

plt.plot(Days,Cults,'b-',label='Cultivar')
plt.xlabel('Days')
```

```
plt.legend(loc='best')

plt.plot(Days,Ferts,'r-',label='N-level')
plt.xlabel('Days')
plt.ylabel('P-values')
plt.legend(loc='best')

plt.plot(Days,CultFert,'g-',label='Cultivar X N-level')
plt.xlabel('Days')
plt.ylabel('-log P-values NDVI')
plt.legend(loc='best')

plt.plot(Days,Cults,'b*')
plt.plot(Days,Ferts,'r*')
plt.plot(Days,CultFert,'g*')
"""
This print read:
p-value higher than 0.05:
6 times for Cultivar
14 times for N-level
14 times for cultivar X N-level
"""
```

B.7 Script for Calculating Correlations (General Version)

```
import matplotlib.pyplot as plt

"""
The following are functions needed to calculate
the coefficient of correlation; r
"""

def average(numbers):
    Sum = 0
    for i in numbers:
        Sum += i
    return float(Sum)/float(len(numbers))

def deviation(numbers,average):     # deviation formula for correlation
    Sum = 0
    for i in numbers:
        Sum += ((i-average)**2)
    return Sum

def deviatemulti(xlist,xmean,ylist,ymean):
    Sum = 0
    for i in range(len(xlist)):
        first = xlist[i] - xmean
        second = ylist[i] - ymean
        Sum += first * second
    return Sum

def correlation(sumdevmulti,sumdevx,sumdevy):
    nu = sumdevmulti
    de1 = (sumdevx)**0.5
    de2 = (sumdevy)**0.5
    de = de1 * de2
    return nu/de


infile = open('Drone_NDVI.csv','r')
table = infile.readlines()
table = [table[i].split(';') for i in range(len(table))]
"""
The file 'Drone_NDVI.csv' is a csv version of an Excel file.
The template for each line is:
Effect;Entry;N_level;Avling;NDVI_2016_05_27;NDVI_2016_06_03....etc
"""
infile = open('16BMLROBOT_lsmeans.csv','r')
tablemat = infile.readlines()
```

```
tablemat = [tablemat[i].split(';') for i in range(len(tablemat))]
"""
The file '16BMLROBOT_lsmeans.csv' is a csv version of an Excel file.
The template for each line is:
Effect;Entry;N_level;DH;DM;Avling;TKW;HLW;PH;
"""

Days = [15,22,36,50,52,54,56,57,61,67,84,90,92,98]
Rs = []
column = 5  # column number to check correlation for in '16BMLROBOT_lsmeans.csv'
print tablemat[0][column]
for k in range(4,18,1):
    YieldsCult = []
    YieldsN8 = []
    YieldsN15 = []

    MeansCult = []
    MeansN8 = []
    MeansN15 = []
    for i in range(1,25,1):     # These lines are the cultivars group
        YieldsCult.append(float(tablemat[i][column]))
        value = table[i][k]
        if len(value) < 2:
            value = 0
        else:
            value = float(value)
        MeansCult.append(value)

    for i in range(27,74,2):    # These lines are cults and cults X N-level
        YieldsN8.append(float(tablemat[i][column]))
        value8 = table[i][k]
        YieldsN15.append(float(tablemat[i+1][column]))
        value15 = table[i+1][k]
        if len(value8) < 2:
            value8 = 0
        else:
            value8 = float(value8)
        if len(value15) < 2:
            value15 = 0
        else:
            value15 = float(value15)
        MeansN8.append(value8)
        MeansN15.append(value15)

    Meanslist = [MeansCult,MeansN8,MeansN15]
    Yieldslist = [YieldsCult,YieldsN8,YieldsN15]
    relations = []
```

```
    for i in range(3):
        xmean = average(Meanslist[i])
        ymean = average(Yieldslist[i])
        devx = deviation(Meanslist[i],xmean)
        devy = deviation(Yieldslist[i],ymean)
        devmulti = deviatemulti(Meanslist[i],xmean,Yieldslist[i],ymean)
        r = correlation(devmulti,devx,devy)
        relations.append(r)
    Rs.append(relations)

    print
    print '%s' % table[0][k]
    print 'Correlation: cultivars is %.3f' % relations[0]
    print 'Correlation: 8 kg of Nitrogen is %.3f' % relations[1]
    print 'Correlation: 15 kg of Nitrogen is %.3f' % relations[2]

RsCult = [Rs[i][0] for i in range(len(Rs))]
RsN8 = [Rs[i][1] for i in range(len(Rs))]
RsN15 = [Rs[i][2] for i in range(len(Rs))]

plt.subplot(3,1,1)
plt.plot(Days,RsCult,'b-',label='Cultivar')
plt.plot(Days,RsCult,'b*')
plt.xlabel('Days')
plt.ylabel('Correlation NDVI to Yield')
plt.ylim(-0.6,0.6)
plt.legend()

plt.subplot(3,1,2)
plt.plot(Days,RsN8,'b-',label='8 kg N')
plt.plot(Days,RsN8,'b*')
plt.xlabel('Days')
plt.ylabel('Correlation NDVI to Yield')
plt.ylim(-0.6,0.6)
plt.legend()

plt.subplot(3,1,3)
plt.plot(Days,RsN15,'b-',label='15 kg N')
plt.plot(Days,RsN15,'b*')
plt.xlabel('Days')
plt.ylabel('Correlation NDVI to Yield')
plt.ylim(-0.6,0.6)
plt.legend()

"""
The correlations for each day is plotted for each group and
also printed out.
Example:
```

```
NDVI_2016_07_01
Correlation: cultivars is -0.083
Correlation: 8 kg of Nitrogen is -0.100
Correlation: 15 kg of Nitrogen is 0.012
"""
```

B.8 SAS code provided by Morten Lillemo

```
proc import datafile='c:\sas\2016\16bmlrobotsplit.csv'  out=feltdata replace;
delimiter=';';

proc print;

proc mixed covtest data=feltdata;
class Entry N_level Rep Block Col;
model Avling = entry N_level entry*N_level /outp=resids;
random rep N_level*rep block(N_level*rep) Col /s;
lsmeans  entry N_level entry*N_level ;
ods output LSMeans=lsm;

proc export data=resids outfile='c:\sas\2016\residuals.csv' replace;
delimiter=';';

proc export data=lsm outfile='c:\sas\2016\lsmeans.csv' replace;
delimiter=';';

run;
```

Appendix C

Collected Data

Table C.1: *Trait data part 1/4.*

Sq.Nr.	Entry	Name	N_level	Rep	Block	Col
1101	3	Demonstrant	8	1	1	1
1102	24	Polkka	8	1	1	2
1103	12	GN10521	8	1	1	3
1104	5	Mirakel	8	1	1	4
1105	2	Zebra	8	1	1	5
1106	23	Reno	8	1	1	6
1107	8	GN11644	8	1	2	7
1108	17	SW11011	8	1	2	8
1109	16	PS-1	8	1	2	9
1110	22	Runar	8	1	2	10
1111	11	Arabella	8	1	2	11
1112	21	Bastian	8	1	2	12
1201	4	Krabat	8	1	3	1
1202	13	SW01074	8	1	3	2
1203	7	Seniorita	8	1	3	3
1204	14	GN10637	8	1	3	4
1205	19	Tjalve	8	1	3	5
1206	20	Avle	8	1	3	6
1207	1	Bjarne	8	1	4	7
1208	9	GN11542	8	1	4	8
1209	15	SW11230	8	1	4	9
1210	18	SW21074	8	1	4	10
1211	6	Rabagast	8	1	4	11
1212	10	GN13618	8	1	4	12
1301	13	SW01074	15	1	1	1
1302	23	Reno	15	1	1	2
1303	18	SW21074	15	1	1	3
1304	16	PS-1	15	1	1	4
1305	5	Mirakel	15	1	1	5
1306	1	Bjarne	15	1	1	6
1307	19	Tjalve	15	1	2	7
1308	20	Avle	15	1	2	8
1309	12	GN10521	15	1	2	9
1310	11	Arabella	15	1	2	10
1311	6	Rabagast	15	1	2	11
1312	10	GN13618	15	1	2	12
1401	2	Zebra	15	1	3	1
1402	14	GN10637	15	1	3	2
1403	9	GN11542	15	1	3	3
1404	17	SW11011	15	1	3	4
1405	7	Seniorita	15	1	3	5
1406	21	Bastian	15	1	3	6
1407	3	Demonstrant	15	1	4	7
1408	24	Polkka	15	1	4	8
1409	22	Runar	15	1	4	9
1410	4	Krabat	15	1	4	10
1411	15	SW11230	15	1	4	11
1412	8	GN11644	15	1	4	12

Table C.2: *Trait data part 2/4. Table showing Heading date (HD, days after July 1st), PH [cm], DH,DM, Lodging, GY [kg/ha], TKW [g] and HLW [g]*

Sq.Nr.	HD	PH	DH	DM	Lodging	GY	TKW	HLW
1101	7	67	56	101	0	366.67	37.0	79.5
1102	7	85	56	94	0	300	34.0	79.0
1103	7	70	56	103	0	350	32.1	77.2
1104	5	85	54	98	0	366.67	34.9	77.0
1105	4	81	53	100	0	383.33	38.1	78.0
1106	4	87	53	98	0	383.33	36.4	77.7
1107	4	67	53	95	0	433.33	39.0	79.9
1108	3	76	52	101	0	500	42.3	79.1
1109	6	80	55	98	0	416.67	35.4	78.0
1110	1	86	50	95	0	416.67	36.4	77.5
1111	0	79	49	98	0	483.33	37.0	76.2
1112	1	69	50	100	0	450	30.5	77.0
1201	7	67	56	101	0	483.33	36.2	78.8
1202	3	67	52	101	0	550	37.0	79.2
1203	7	80	56	104	0	533.33	31.7	79.8
1204	8	75	57	106	0	516.67	37.4	81.7
1205	7	75	56	100	0	483.33	35.8	78.5
1206	6	70	55	101	0	466.67	33.1	77.3
1207	5	66	54	102	0	550	35.3	77.2
1208	3	75	52	101	0	583.33	32.9	78.7
1209	3	80	52	102	0	633.33	40.2	77.4
1210	4	76	53	102	0	600	35.2	79.6
1211	6	65	55	101	0	550	32.3	78.1
1212	3	70	52	105	0	616.67	38.0	78.6
1301	5	65	54	106	0	583.33	37.1	79.4
1302	3	87	52	104	5	550	38.4	78.7
1303	4	76	53	107	0	666.67	37.1	81.8
1304	7	76	56	104	5	666.67	35.5	79.7
1305	5	86	54	105	10	650	37.3	79.0
1306	6	69	55	104	5	650	33.8	78.8
1307	8	72	57	105	0	650	36.8	78.9
1308	7	75	56	104	5	616.67	33.1	78.2
1309	5	76	54	109	0	683.33	31.4	77.8
1310	3	75	52	108	0	766.67	36.8	79.1
1311	9	65	58	108	0	650	30.6	78.9
1312	3	72	52	113	5	750	37.2	79.8
1401	3	79	52	109	5	683.33	38.2	79.6
1402	9	75	58	109	5	650	35.6	83.2
1403	3	75	52	109	0	700	32.3	80.2
1404	1	71	50	110	5	733.33	42.2	80.0
1405	8	76	57	107	5	683.33	49.7	81.6
1406	3	67	52	109	0	633.33	29.7	80.0
1407	7	74	56	112	0	750	35.7	81.6
1408	5	82	54	104	0	616.67	35.2	81.6
1409	3	80	52	106	50	566.67	35.3	80.5
1410	7	71	56	106	0	666.67	34.7	79.8
1411	3	75	52	109	30	833.33	38.0	79.6
1412	2	67	51	104	0	666.67	34.5	82.6

TABLE C.3: *Trait data part 3/4.*

Sq.Nr.	**Entry**	**Name**	**N_level**	**Rep**	**Block**	**Col**
1501	10	GN13618	15	2	1	1
1502	4	Krabat	15	2	1	2
1503	24	Polkka	15	2	1	3
1504	17	SW11011	15	2	1	4
1505	23	Reno	15	2	1	5
1506	13	SW01074	15	2	1	6
1507	15	SW11230	15	2	2	7
1508	8	GN11644	15	2	2	8
1509	5	Mirakel	15	2	2	9
1510	9	GN11542	15	2	2	10
1511	21	Bastian	15	2	2	11
1512	19	Tjalve	15	2	2	12
1601	16	PS-1	15	2	3	1
1602	7	Seniorita	15	2	3	2
1603	11	Arabella	15	2	3	3
1604	18	SW21074	15	2	3	4
1605	3	Demonstrant	15	2	3	5
1606	6	Rabagast	15	2	3	6
1607	2	Zebra	15	2	4	7
1608	14	GN10637	15	2	4	8
1609	20	Avle	15	2	4	9
1610	12	GN10521	15	2	4	10
1611	22	Runar	15	2	4	11
1612	1	Bjarne	15	2	4	12
1701	4	Krabat	8	2	1	1
1702	2	Zebra	8	2	1	2
1703	8	GN11644	8	2	1	3
1704	19	Tjalve	8	2	1	4
1705	10	GN13618	8	2	1	5
1706	18	SW21074	8	2	1	6
1707	22	Runar	8	2	2	7
1708	13	SW01074	8	2	2	8
1709	21	Bastian	8	2	2	9
1710	6	Rabagast	8	2	2	10
1711	12	GN10521	8	2	2	11
1712	3	Demonstrant	8	2	2	12
1801	17	SW11011	8	2	3	1
1802	15	SW11230	8	2	3	2
1803	16	PS-1	8	2	3	3
1804	23	Reno	8	2	3	4
1805	7	Seniorita	8	2	3	5
1806	20	Avle	8	2	3	6
1807	11	Arabella	8	2	4	7
1808	14	GN10637	8	2	4	8
1809	9	GN11542	8	2	4	9
1810	24	Polkka	8	2	4	10
1811	1	Bjarne	8	2	4	11
1812	5	Mirakel	8	2	4	12

Table C.4: *Trait data part 4/4. Table showing Heading date (HD, days after July 1st), PH [cm], DH,DM, Lodging, GY [kg/ha], TKW [g] and HLW [g]*

Sq.Nr.	HD	PH	DH	DM	Lodging	GY	TKW	HLW
1501	3	72	52	107	0	683.33	35.5	79.6
1502	7	71	56	106	0	650	33.8	79.6
1503	6	80	55	105	5	583.33	35.1	80.4
1504	1	71	50	109	5	716.67	42.5	82.8
1505	1	81	50	103	10	600	36.8	79.6
1506	6	69	55	108	0	666.67	35.7	81.2
1507	5	76	54	109	5	783.33	38.7	79.5
1508	4	70	53	106	0	683.33	34.1	82.7
1509	6	85	55	109	50	666.67	33.9	79.5
1510	5	75	54	113	10	683.33	31.5	80.3
1511	1	70	50	111	20	666.67	30.2	79.1
1512	6	75	55	110	15	600	34.4	78.5
1601	6	72	55	109	30	666.67	33.5	79.5
1602	7	79	56	108	5	666.67	30.2	81.7
1603	1	70	50	111	5	783.33	37.4	79.1
1604	5	72	54	112	0	750	34.6	82.4
1605	6	75	55	111	0	783.33	34.4	81.2
1606	7	70	56	110	0	650	31.8	79.6
1607	3	82	52	110	5	750	38.6	80.1
1608	8	82	57	112	10	716.67	34.7	83.5
1609	5	75	54	108	5	716.67	33.3	79.1
1610	5	75	54	111	0	750	32.5	78.6
1611	1	80	50	110	50	683.33	38.6	81.0
1612	3	65	52	109	30	716.67	34.4	79.6
1701	7	66	56	105	0	550	35.0	79.0
1702	3	78	52	104	0	583.33	40.0	80.4
1703	2	67	51	103	0	600	36.5	81.8
1704	7	75	56	103	0	533.33	37.1	79.8
1705	5	70	54	109	0	650	39.1	79.5
1706	4	75	53	107	0	550	38.0	82.1
1707	3	84	52	104	5	516.67	38.1	80.0
1708	5	68	54	105	0	616.67	37.0	80.1
1709	1	70	50	106	0	600	32.2	79.1
1710	6	66	55	108	0	616.67	34.0	79.5
1711	3	75	52	110	0	666.67	35.3	78.2
1712	5	72	54	109	0	633.33	40.0	81.5
1801	2	75	51	105	0	550	43.0	81.0
1802	3	77	52	101	0	583.33	40.2	78.1
1803	6	77	55	102	0	550	35.8	79.7
1804	1	80	50	102	5	516.67	38.9	79.7
1805	6	77	55	109	0	583.33	32.2	81.4
1806	5	70	54	102	0	483.33	32.2	77.6
1807	2	75	51	109	0	666.67	36.8	79.0
1808	8	76	57	109	0	616.67	35.9	82.8
1809	3	75	52	104	0	616.67	33.5	79.0
1810	1	92	50	101	0	516.67	34.1	80.3
1811	5	69	54	104	0	616.67	33.8	79.3
1812	3	81	52	102	5	550	35.9	79.8

Table C.5: *Values extraced from DSM using Fiji and estimated values part 1/2. All in meters.*

SqNr	Fiji_Value 18.07	Est.value 18.07	Fiji_Value 08.07	Est.value 08.07
1101	79.283	0.820	76.061	0.341
1102	79.283	0.774	76.289	0.378
1103	79.307	0.752	76.409	0.306
1104	79.473	0.872	76.627	0.333
1105	79.460	0.812	76.786	0.300
1106	79.564	0.870	77.061	0.384
1107	79.470	0.730	77.126	0.258
1108	79.610	0.823	77.396	0.336
1109	79.716	0.883	77.514	0.263
1110	79.775	0.896	77.793	0.350
1111	79.729	0.804	77.825	0.191
1112	79.759	0.787	78.047	0.221
1201	79.397	0.924	76.428	0.512
1202	79.406	0.887	76.524	0.417
1203	79.514	0.949	76.759	0.460
1204	79.494	0.883	76.855	0.365
1205	79.543	0.885	77.064	0.382
1206	79.595	0.891	77.203	0.330
1207	79.651	0.901	77.412	0.348
1208	79.764	0.967	77.687	0.431
1209	79.815	0.972	77.817	0.370
1210	79.840	0.951	77.935	0.296
1211	79.878	0.943	78.103	0.273
1212	79.895	0.913	78.298	0.276
1301	79.384	0.901	76.661	0.549
1302	79.544	1.015	76.927	0.624
1303	79.513	0.938	77.011	0.516
1304	79.610	0.989	77.263	0.577
1305	79.704	1.036	77.416	0.538
1306	79.632	0.918	77.520	0.451
1307	79.718	0.958	77.748	0.488
1308	79.815	1.008	77.892	0.440
1309	79.856	1.003	78.081	0.438
1310	79.869	0.970	78.256	0.421
1311	79.934	0.989	78.432	0.406
1312	79.952	0.960	78.564	0.346
1401	79.350	0.857	76.929	0.621
1402	79.463	0.924	77.037	0.538
1403	79.547	0.962	77.290	0.599
1404	79.573	0.942	77.454	0.572
1405	79.656	0.978	77.618	0.544
1406	79.604	0.880	77.714	0.449
1407	79.746	0.976	77.932	0.476
1408	79.893	1.076	78.127	0.479
1409	79.941	1.078	78.341	0.502
1410	79.948	1.039	78.514	0.483
1411	79.938	0.983	78.636	0.414
1412	79.852	0.850	78.710	0.296

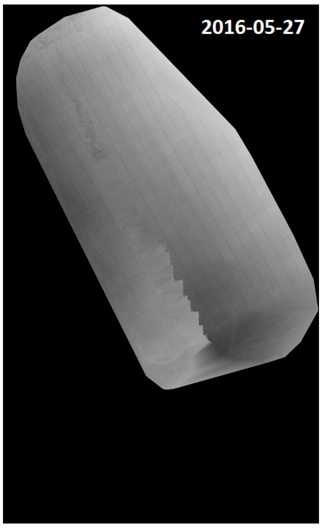
Table C.6: *Values extraced from DSM using Fiji and estimated values part 2/2. All in meters.*

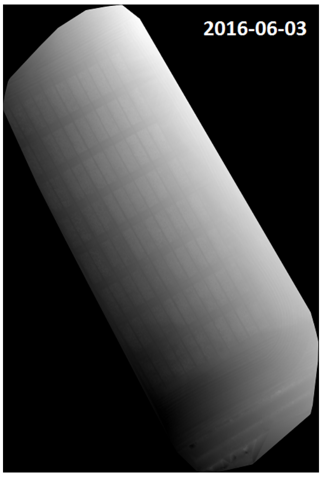
SqNr	Fiji_Value 18.07	Est.value 18.07	Fiji_Value 08.07	Est.value 08.07
1501	79.362	0.859	77.090	0.586
1502	79.478	0.929	77.293	0.598
1503	79.566	0.971	77.502	0.615
1504	79.532	0.891	77.583	0.505
1505	79.614	0.926	77.776	0.506
1506	79.625	0.891	77.945	0.484
1507	79.742	0.962	78.163	0.511
1508	79.686	0.859	78.235	0.391
1509	79.927	1.054	78.516	0.481
1510	79.903	0.984	78.648	0.421
1511	79.968	1.003	78.777	0.359
1512	79.954	0.942	78.953	0.343
1601	79.354	0.841	77.228	0.528
1602	79.421	0.862	77.451	0.560
1603	79.363	0.758	77.549	0.466
1604	79.441	0.790	77.719	0.445
1605	79.536	0.838	77.905	0.439
1606	79.589	0.845	78.093	0.436
1607	79.670	0.880	78.323	0.475
1608	79.702	0.865	78.466	0.426
1609	79.792	0.909	78.622	0.391
1610	79.859	0.930	78.737	0.314
1611	79.967	0.992	79.002	0.388
1612	79.835	0.813	79.076	0.270
1701	79.260	0.737	77.245	0.349
1702	79.306	0.737	77.505	0.418
1703	79.264	0.649	77.599	0.320
1704	79.353	0.692	77.747	0.277
1705	79.417	0.709	77.939	0.277
1706	79.443	0.689	78.129	0.276
1707	79.548	0.748	78.407	0.363
1708	79.525	0.678	78.484	0.248
1709	79.597	0.704	78.688	0.261
1710	79.725	0.786	78.775	0.156
1711	79.700	0.715	79.087	0.277
1712	79.764	0.732	79.261	0.259
1801	79.193	0.660	77.383	0.291
1802	79.264	0.685	77.610	0.327
1803	79.309	0.684	77.774	0.299
1804	79.459	0.788	78.003	0.337
1805	79.448	0.730	78.091	0.233
1806	79.467	0.703	78.249	0.200
1807	79.471	0.661	78.393	0.153
1808	79.581	0.724	78.627	0.195
1809	79.656	0.753	78.823	0.200
1810	79.844	0.895	79.109	0.294
1811	79.703	0.708	79.203	0.197
1812	79.835	0.793	79.410	0.212

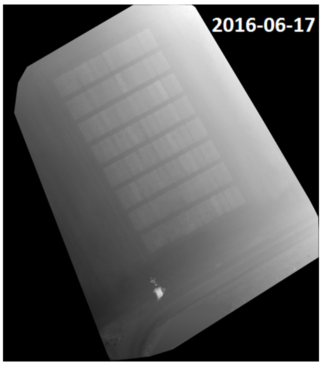
Appendix D

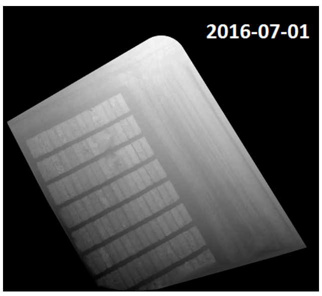
GeoTIFF/DSM files and Reference Pictures

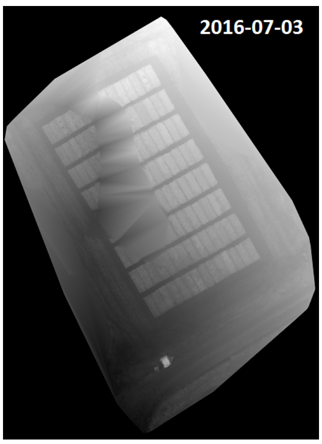
D.1 GeOTIFF/DSM files

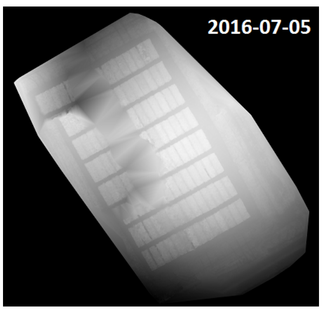


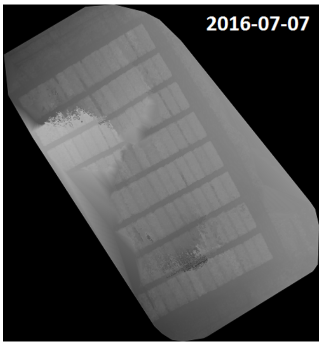








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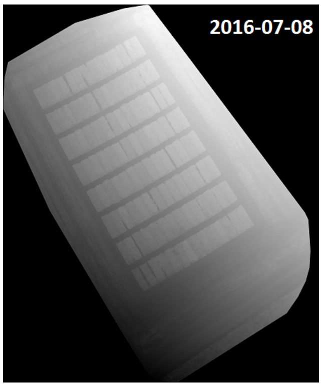
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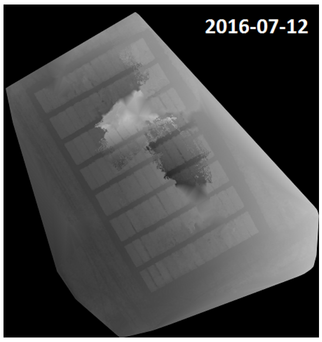
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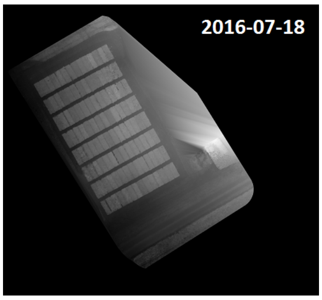
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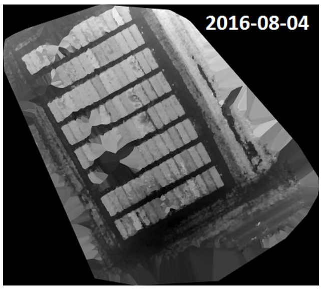
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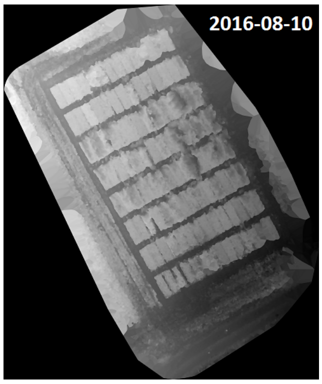
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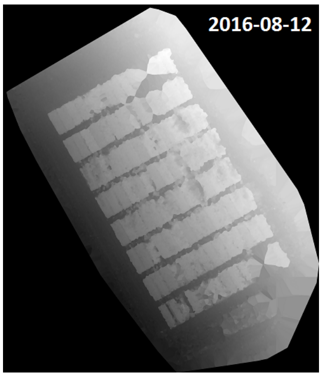
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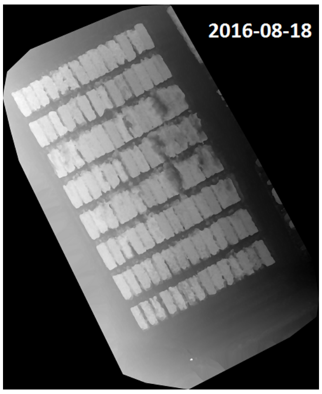
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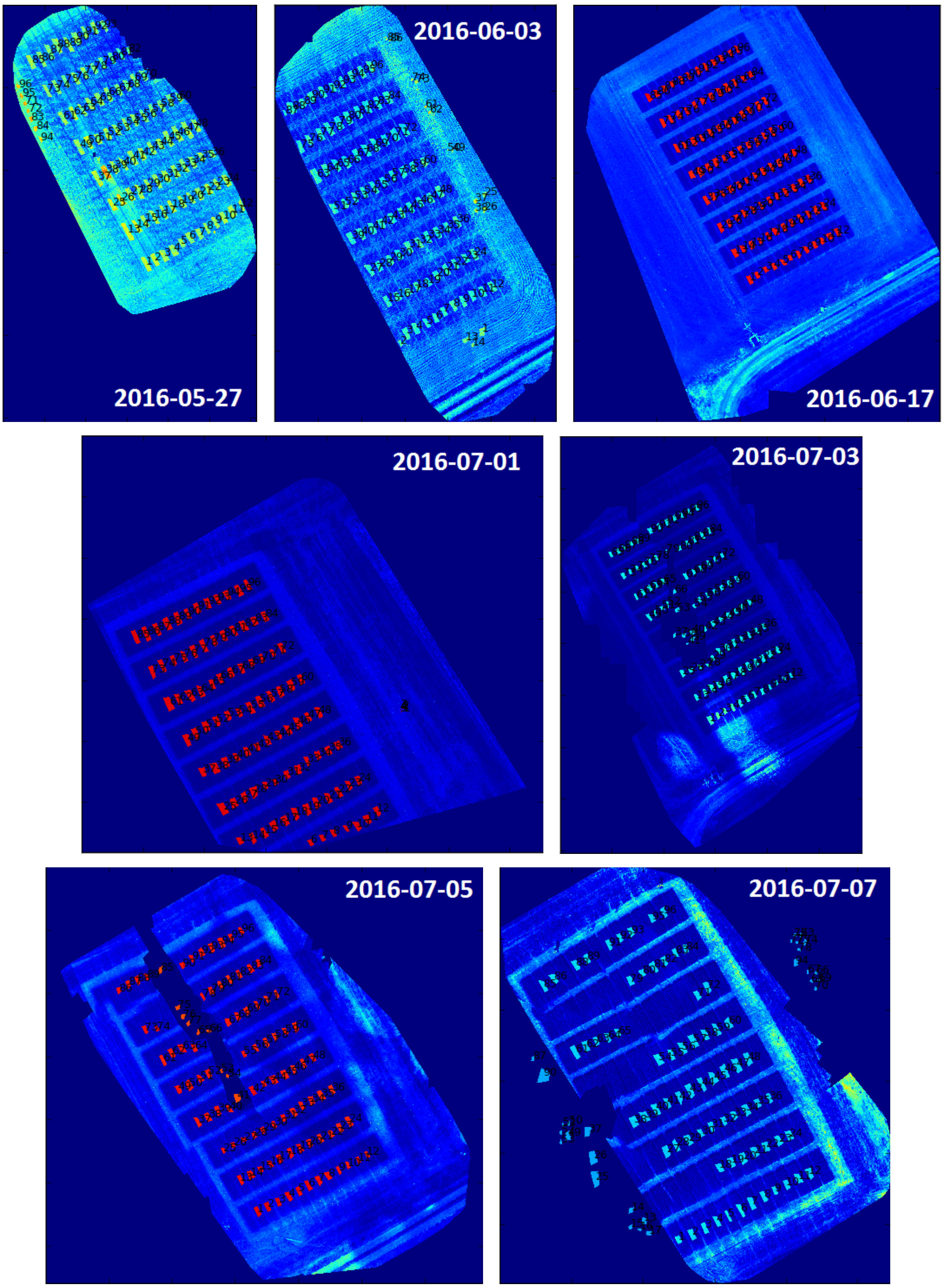
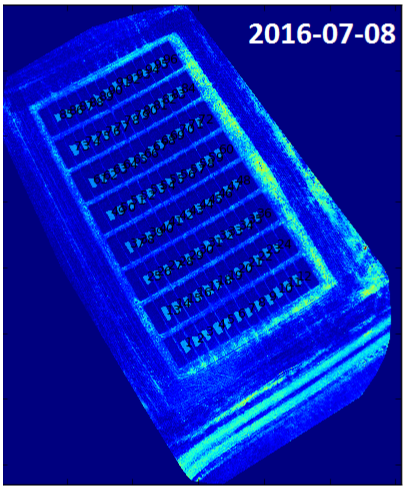
D.2 Reference Pictures

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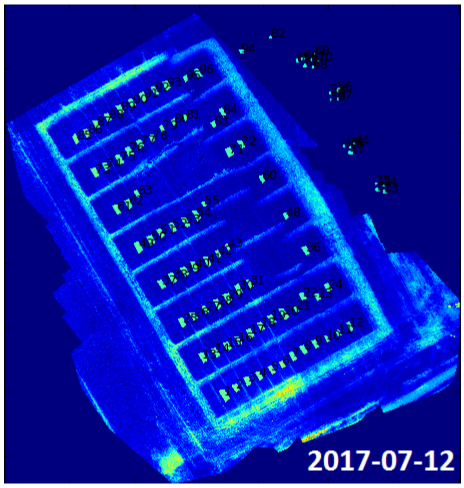
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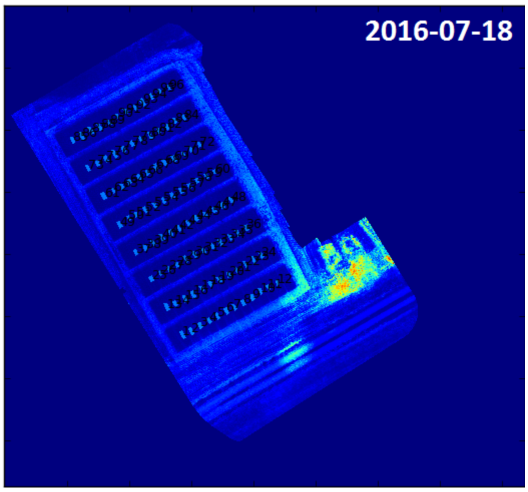
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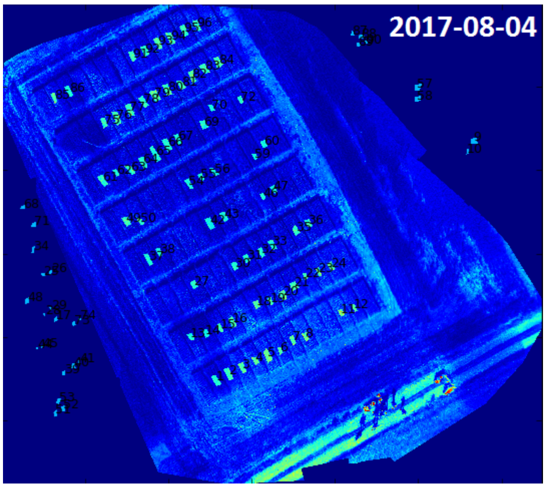
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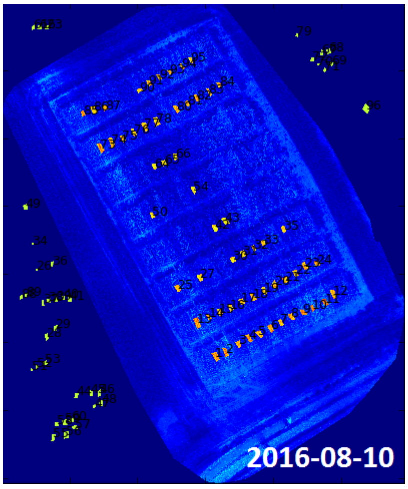
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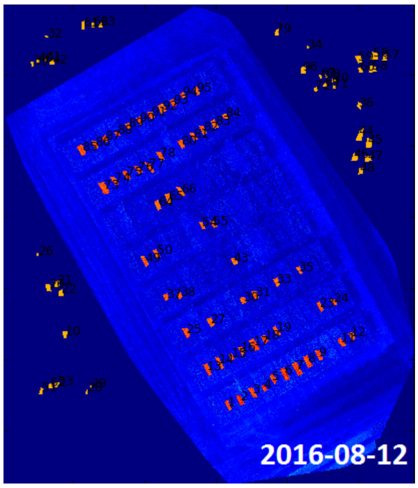
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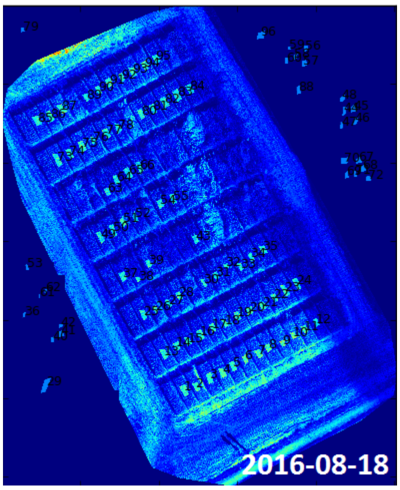
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