


Fenômica: A Computer Vision System for High-Throughput Phenotyping

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ABSTRACT

Computer vision and image processing procedures could obtain crop data frequently and precisely, such as vegetation indexes, and correlating them with other variables, like biomass and crop yield. This work presents the development of a computer vision system for high-throughput phenotyping, considering three solutions: an image capture software linked to a low-cost appliance; an image-processing program for feature extraction; and a web application for results' presentation. As a case study, we used normalized difference vegetation index (NDVI) data from a wheat crop experiment of the Brazilian Agricultural Research Corporation. Regression analysis showed that NDVI explains 98.9, 92.8, and 88.2% of the variability found in the biomass values for crop plots with 82, 150, and 200 kg of N ha⁻¹ fertilizer applications, respectively. As a result, NDVI generated by our system presented a strong correlation with the biomass, showing a way to specify a new yield prediction model from the beginning of the crop.

KEYWORDS

Appliance, Biomass, Computer Vision, High-Throughput Phenotyping, Image Processing, NDVI

1. INTRODUCTION

The basic requirement of precision agriculture is to rapidly acquire trustworthy and reliable crop-growth information conveniently at low cost; this is also crucial to realizing accurate crop control and management (Ni et al., 2018). Information Technology is increasingly making contributions targeted to agricultural solutions. The periodic monitoring of aboveground biomass is a widely used agronomic parameter for characterizing crop growth status and predicting grain yield. For a long time, crop-growth information was acquired through destructive sampling in the field and indoor biochemical and biophysical measurements (Gnyp et al., 2014; Boschetti et al., 2007). Remote sensing as a non-

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destructive technique has been proved to have great potential in aboveground biomass estimation for crops, such as wheat (Cabrera-Bosquet et al., 2011; Fernández et al., 2019).

Up-to-date, non-destructive monitoring technologies based on characteristic description through reflectance spectra have shown various benefits, including non-destructibility, ready access to information, and excellent real-time performance. Hence, they have been widely used in the investigation into the monitoring of crop-growth indices and evaluation of agricultural devices. Although existing ground-based object spectrometers confer various advantages they also exhibit a few disadvantages, including high price, complex structure, tedious operation, and inconvenient field application (Ni et al., 2018). Development of imagery monitoring for crop growth promotes the development and implementation of some apparatus for crop-growth monitoring. The rapid and accurate estimation of aboveground biomass in a non-destructive way is useful for creating informed decisions on precision crop management. The current estimate of aboveground biomass is based on destructive measurements.

The monitoring of nitrogen is an essential tool for investigating many metabolic and structural processes in maturing wheat plants, such as yield formation and health status. Because nitrogen is not immobilized in soils and a plentiful reserve of plant-available nitrogen is not present, it is essential for optimal crop production to supply nitrogen by applying fertilizer during plant growth (Schirrmann et al., 2016).

To become more efficient, indirect methods using sensors for estimating those parameters have been proposed and implemented. At the plot scale, sensor principles are available that enable on-spot measurements without destructing the canopy, mostly with direct contact to wheat plants (Zhao et al., 2013). Devices measuring sunlight interception in the wheat canopy using radiative transfer models can model the leaf area index (Breda, 2003). Most of these principles involve time-demanding judgments or sophisticated determination protocols that can only be achieved manually in a stop-and-go style. Their use of high-throughput measurements was reviewed (Schirrmann et al., 2015).

Kipp et al. (2014) highlighted that the Normalized Difference Vegetation Index (NDVI) is a potential measure for detecting phenotypic differences in early plant vigor. Cabrera-Bosquet et al. (2011) reported that NDVI was useful to assess green biomass in addition to nutrient, pest, and water stress. NDVI was also used to calculate vegetation coverage from segmented transformed images to study canopies in field experiments using a mobile system (Svensgaard et al., 2014).

The objective of our work was to study the likelihoods of a low-cost imagery acquisition system for monitoring aboveground biomass of wheat under varying nitrogen fertilization. Therefore, this work presents the development of a computer vision system for high-throughput phenotyping, convening three modules. Firstly, an image capture software using RGB and IR cameras, linked to a low-cost and mobile appliance that provides a controlled environment at the field. Secondly, image-processing software for plant distinguishing measurement (morphometric and NDVI data). Lastly, a web application for the visualization of the relationship between NDVI and aboveground biomass.

This document is organized as follows. Section 2 presents the whole computer vision system developed and section 3 shows the results and discussion of a preliminary study considering the use of our system to compare NDVI and wheat biomass. Section 4 highlights our conclusions and future work about this study.

2. MATERIALS AND METHODS

This project based on the development of a computer vision system for high-throughput phenotyping, convening three modules, named “Fenômica”. This system captures and registers images from an appliance, processes them in order to get NDVI information, and presents results for comparison with crop biomass data. Next sections expose materials and methods used in each of these system modules.

2.1. Appliance

Our appliance is a structure (Figure 1) that provides support for cameras and sensors to collect images at the crop field, reducing the interference of climate variables (solar radiation, precipitation, wind, etc.). Based on Svensgaard, Roitsch, and Christensen (2014), we built a low-cost, mobile and simple imaging-box appliance to validate our system directly in the field.

The prototype used PVC pipes, considering the maximum height measures that a wheat crop can reach (~1.4 m), and a base of the structure of 1 m² to coverage a crop sample. The structure is easily and manually mountable, and does not require any hoisting or shifting machinery to manipulate it.

Ghanem, Marrou, & Sinclair (2015) highlight luminosity as one of the external variables that can influence the crop phenotype, since brightness and contrast are preponderant in obtaining data such as coloring and vegetation indexes. For this reason, we decided to use a light-tight blackout enclosure (Figure 2), blocking the ambient light on the plants during the image capture. This format also avoids the influence of other climate variables.

Luminosity also influences how our must capture digital images. It can directly induce the image obtained or even the response that the plant gives, since plants get energy from light through a process called photosynthesis, affecting their growth (Moore et al., 1995). Jones and Vaughan (2010) show the relevance of reflectance and fluorescence during image processing to obtain phenotypic data

Figure 1. “Fenômica” appliance schema

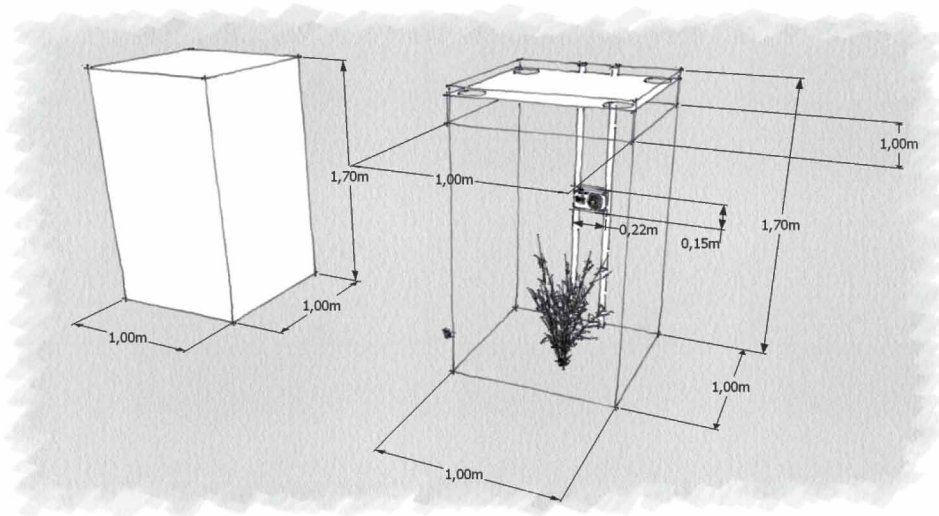


Figure 2. Blackout enclosure over the appliance at the field



from the plant. Goto (2003) also highlights that for good artificial lighting can combine yellow light (incandescent lamp) and white light (fluorescent lamp).

Considering the luminosity influences and the use of near-infrared lenses (NIR) for imaging, we defined a luminosity configuration inside our appliance (Figure 3). Two 60W incandescent lamps and two 20W fluorescent lamps (connected to a battery) maintain the same incidence of light during the image capture, combined with the use of the enclosure.

2.2. Digital Cameras

We selected two high-resolution digital cameras to capture the images on top and side views. In both cases, it is possible to change the height of the cameras using rulers on the appliance structure.

LogiTech C270 HD camera registers side image views used to calculate the plant height. It offers a resolution of 1280×720 px, automatic light correction, autofocus, and no special lens filter applied.

GoPro Hero4 camera registers top image views used to get NDVI information. It offers a resolution of 4000×3000 px, and resources for NIR filters and communication using wireless network.

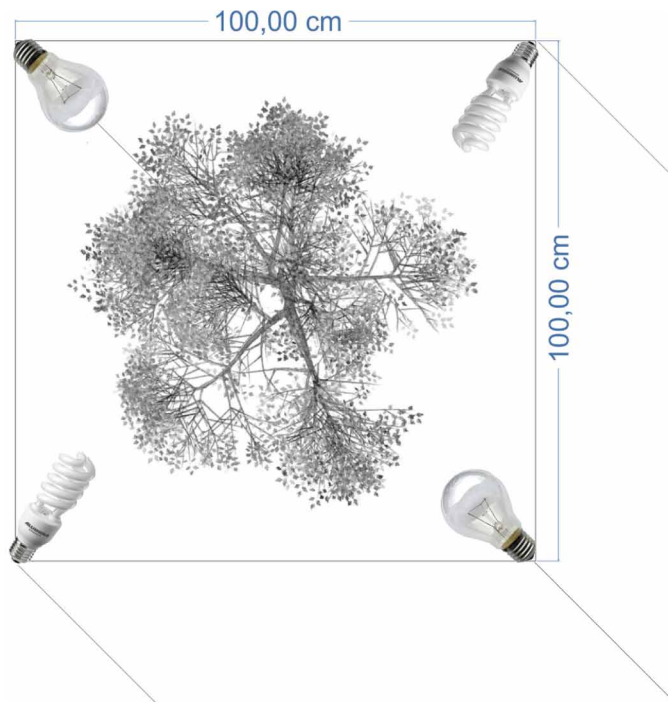
We also chosen an IRpro H-NDVI-RED 25-55 5.5mm Flat Lens for capture NDVI images. It generates flat images with the application of the Near InfraRed (NIR) filter. This sensor allows low light capture, autofocus adjustment, and same camera resolution.

2.3. Software Development Tools

We opted for the use of open source and multiplatform tools to implement “Fenômica,” offering portability and modularity of all the solution.

Java is the main programming language of our system, using Java Development Kit. SQLite and MySQL are the database versions, storing images (PNG format) and results, respectively. Apache

Figure 3. Luminosity configuration inside the appliance



Tomcat and Jersey framework manage and develop web services, and Bootstrap is the toolkit used for web resources (HTML, CSS and JS).

For image processing and analysis, we chosen the OpenCV (2019), a consolidated computer vision platform. In addition, our solution coupled the three modules using Apache Maven, allowing libraries and plugins interdependence.

2.4. Fenômica

Next sections present the three application modules of “Fenômica”, a computer vision system for high-throughput phenotyping.

2.4.1. FenômicaAPP Capture

This software aims to capture and store images obtained in the field. Users must provide general data about the capture, in order to offer a basic information for the image processing and analysis steps.

FenômicaAPP Capture has native communication with the digital cameras, using USB or Wi-Fi connections. It is composed of different modules: data persistence, image manipulation, database storage, transfer protocol and webservices. This modularity enables the portability of software, and its integration with the other “Fenômica” applications.

Next subsections present the application features.

2.4.1.1. Data Persistence

FenômicaAPP Capture begins accessing the application database using SQLite resources. We choiced this database because it does not have external dependencies, allowing a simple and fast execution, and running on computers with limited resources.

The creation of a blank new database occurs during the first program execution, automatically, and a new password for the administrator user is required. After, the user already has available the options menu to record crop images using data persistence resources.

The kernel of the application is the crop samples with the image records. Each register requests a crop description, the crop type, main supply, location, date, time, and images captured by top and side cameras accessed by our application, directly on field. Figure 4 (a) shows the application user interface where each sample is recorded.

2.4.1.2. Image Capture

We used the webcam-capture library (<http://webcam-capture.sarxos.pl/>) to get images from USB-connected camera. The installation requires only the camera hardware driver, if necessary. Our software administrates the rest of the functionalities. Figure 18 (b) shows a connection result to the LogiTech C270 HD USB camera.

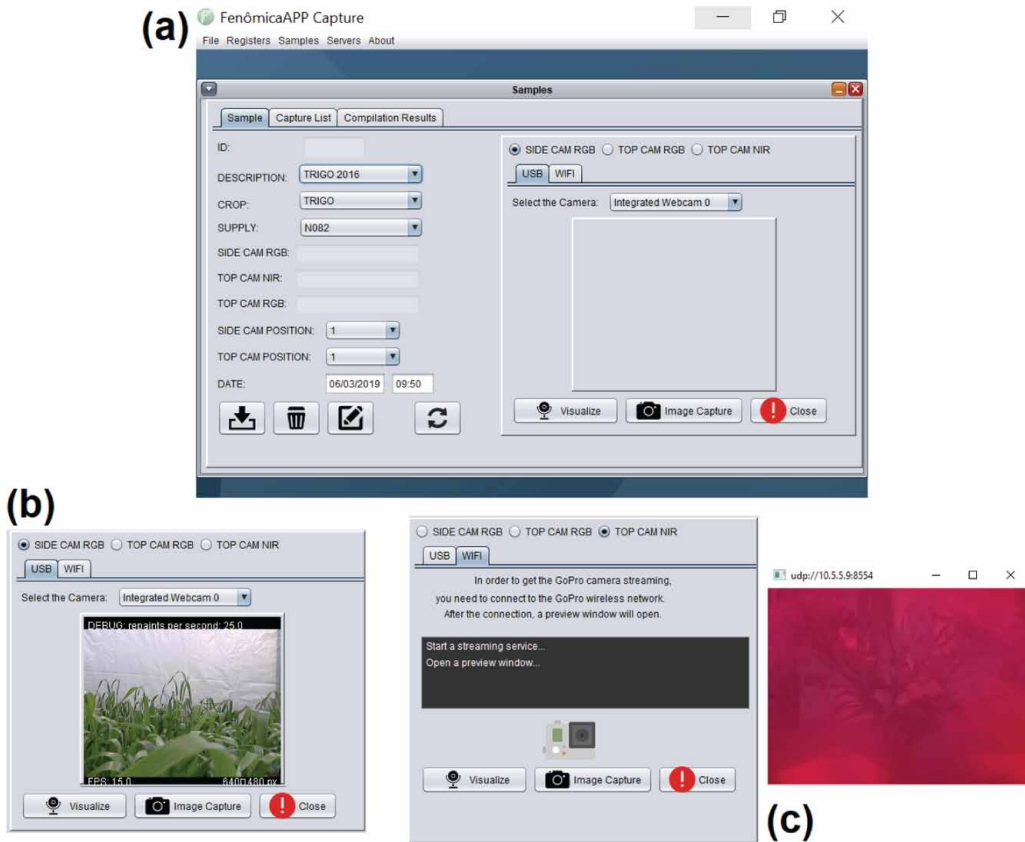
To get images from Wi-Fi camera, we created an http protocol communication using the org.apache.httpcomponents library. This protocol defines the sending of commands by GET method, in order to control and execute the video streaming. Default URL is: “<http://<ip>/camera/CM?t=<password>&p=%01>”, where *<ip>* is the IP camera address, *<password>* is the key to access the camera, and *p=%01* is the execution command. Figure 18 (c) shows a connection result to the GoPro Hero4 camera using NDVI-7 lens.

At the end of the crop image capture, the data are ready to send to the next steps (image processing and analysis, and presentation results).

2.4.2. FenômicaAPP Processing

Treatment and analysis of the samples occur after the image capture, in order to get crop data information. FenômicaAPP Processing is an abstract module, receiving image and parameters by FenômicaAPP Capture, and reports different image data through computer vision techniques. These

Figure 4. (a) User interface with options to register each crop sample; (b) Image acquisition resources for RGB images by USB camera; and (c) IR images by wi-fi camera



techniques aim to correlate plant phenotype images with biomass and crop yield, and offer as output values such as NDVI vegetation index, crop height, green color and resampling images.

Following subsections present the computer vision techniques applied in our software.

2.4.2.1. NIR-Image Processing

We used the GoPro Hero 4 camera with the NDVI-7 lens (fixed on the top of the appliance) to acquire NIR images. Figure 5 presents an example of NIR-image capture.

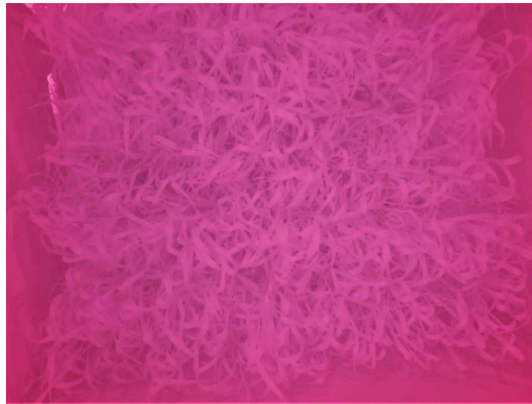
NDVI value is the main index to obtain the correlation with biomass and crop yield. In doing so, our software follows a sequence of analysis and processing from NIR images to get NDVI value, presented by the next subsections:

- NIR to Binary (Negative, Thresholding and Grayscale filters);
- Generating bounding boxes (Regions of interest);
- Calculating NDVI.

2.4.2.2. NIR to Binary

The first procedure is to convert the original image to a new binary image, in order to process optimization and contribute to software performance.

Figure 5. NIR-image obtained by GoPro Hero4 camera using NDVI-7 lens



Firstly, the software executes the grayscale operation and negative filter, respectively, inverting the colors of an image. Next, it applies the thresholding to segment the image, highlighting regions and objects of interest. Figure 6 shows the process considering as input the image of the Figure 5.

Our procedure differs visually from the standard outputs of commercial and free software. In ImageJ (2019), for example, it is possible to use plugins (like PhotoMonitoringPlugin) generating red tones to NDVI output. Figure 7 (a) shows the ImageJ NIR output, and Figure 7 (b) shows our NIR output after conversions, using the same original image. We can observe the similarity between ImageJ and our proposal.

Figure 6. (a) Applying Grayscale; (b) Negative; and (c) Thresholding filters

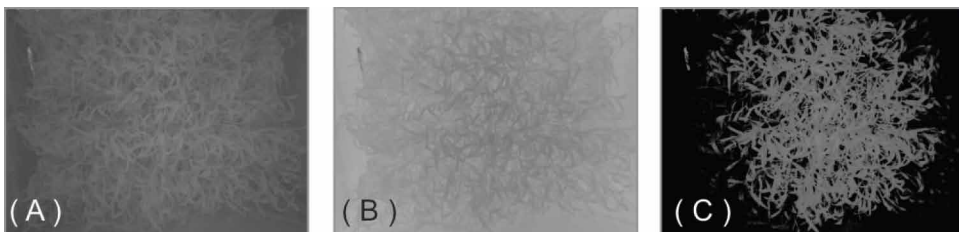
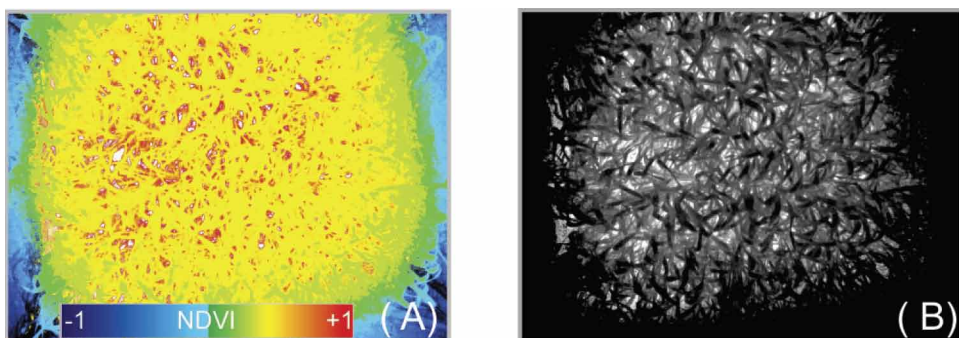


Figure 7. (a) NIR-image outputs from the same original image using ImageJ; and (b) FenômicaAPP processing



2.4.2.3. Generating Bounding Boxes

To define the NDVI reference value, it is necessary to analyse the relevant objects of interest on each image. In this context, we observed in field that the appliance design during the image capture allowed a small light entrance near the soil, since its base of support is straight. As the soil is not always uniform, we considered that small curved angles could favor alterations on the edges of the images.

With this in mind, we segmented images abstracting areas with probability of sunlight entry. To mitigate this problem, we chose to generate new resampling images considering bounding boxes defined by a cut-off percentage from the top, bottom and sides. Our software generates images with 25% (blue rectangle – outer), 30% (red rectangle – middle) and 35% (orange rectangle – inner) cut from the ends of each image as shown in Figure 8.

2.4.2.4. Calculating NDVI

This procedure has the purpose to obtain the NDVI value from the definition of an image region of interest. We used a 35% cut-off bounding box definition (Figure 8, orange rectangle – inner) uniformly segmenting all images used in our preliminary experiment.

NDVI minimum, maximum and mean consider values of each image pixel analyzed. As the previous steps based on gray scales and pixel abstraction, we used Equation 1 for the color tone value:

$$RGB = 256 * 256 * r + 256 * g + b \quad (1)$$

Values are saved and stored in FenômicaAPP Coleta. The conversion considers the NDVI index variation between -1 and +1, generally used in agricultural researches. According to Weir & Herring (2000), values equal to or less than 0 indicate no vegetation or exposed soil; and values close to +1 indicate large amount of photosynthetically active plants.

2.4.2.5. RGB-Image Processing

We used the LogiTech C270 HD USB camera (fixed on the side of the appliance) to acquire RGB images. Figure 9 presents the result of a capture.

This procedure allows getting data such as crop height and medium-hue green. Among the several variables of phenotyping, the plant color can present some relevance in scientific research,

Figure 8. Bouding boxes used to generate new resampling images

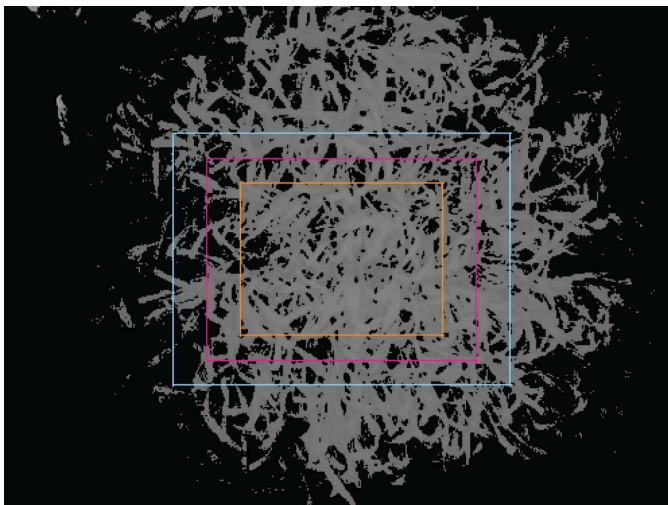


Figure 9. RGB image obtained by LogiTech C270 HD USB camera



since it can expose tone variations due to crop phenology and manifest variations according to fertilizer rates (Lin, 2015).

To obtain this data, we defined a sequence of steps using RGB images, detailed in the following subsections:

- Calculating medium-hue green;
- Calculating medium-crop height.

2.4.2.6. Calculating Medium-Hue Green

This procedure generates a new green mask image using negative filter and thresholding to highlight the leaf area. Based on Ganesan & Rajini (2014), we used HSV colorpace because hue property can typically be represented quantitatively by a single number (base pigment), useful to detect the perceived colors. Saturation (depth of the pigment) and value (darkness of the pigment) are confounded, indicating pixel intensity.

All pixels of the original image are analysed to define a new resampling image segmenting only leaf area (Figure 10). After, we used the green image mask to calculate the medium-hue green value. This value may be useful to monitor the evolution of the vegetative phase of the plant, because suggest chlorophyll, essential in photosynthesis, allowing plants to absorb energy from light.

Our approach defined a value range from 0 to 100, similar to NDVI, in order to facilitate data analysis.

2.4.2.7. Calculating Medium-Crop Height

As a basis for size detection, this procedure creates a new image only with the edges of the plants, applying linear spatial filters (Figure 11). Our method used the Canny algorithm (Canny, 1986) and the Hough transform (Duda & Hart, 1972).

To calculate the medium-crop height, we considered pixel connectivity, analyzing neighboring pixels and detecting connection points. This generates a list of clustered areas, where each area can represent an object of interest (in our case, crop leaves). Therefore, we can identify the crop heights (Y-axis) from side camera on the appliance, and draw on image horizontal lines to highlight them (Figure 12).

Figure 10. Green image mask generated after color detection process

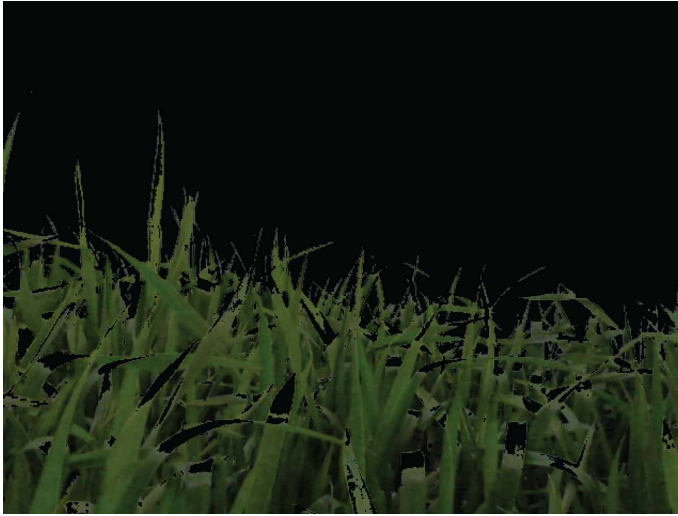
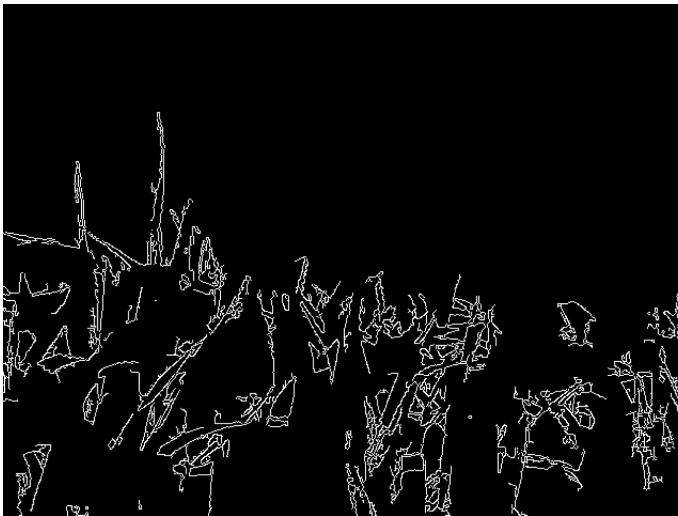


Figure 11. Image of the crop generated after edge detection process



Our method also defines a threshold (k) to calculate the medium-height ($k = 20$). As an example, if the number of leaves in the sample is equal to the k -value, the eight shortest and the eight highest values for plant height are discarded. Thus, the final medium-height is based on four observations. Samples with k -value different from twenty had a proportional discard. This process was necessary to account for the variability observed in plant height. Based on the samples processed in our work, this method was effective.

2.4.3. FenômicaAPP Web

FenômicaAPP Web is a responsive solution to mobile devices. It presents the results after entire process of capture and image processing, showing statistics and graphics per analysed crop sample. Communication between other “Fenômica” system modules occurs via webservice.

Figure 12. Plant heights highlighted on image, and used to the medium-height crop

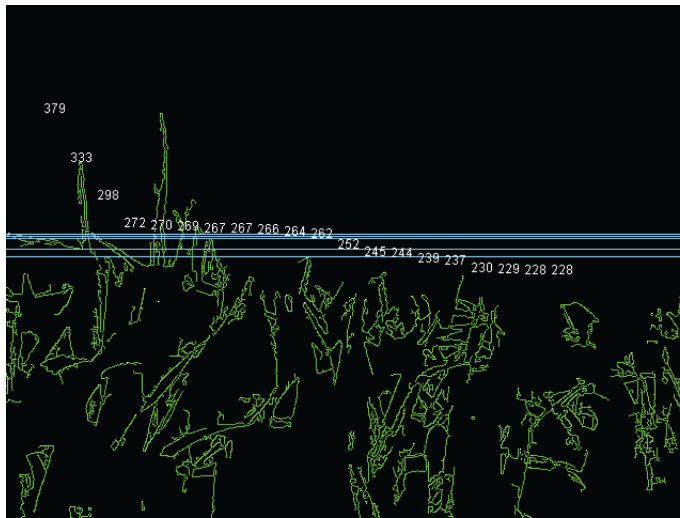


Figure 13 highlights the dashboard user interface, and following subsections present the steps to use this application.

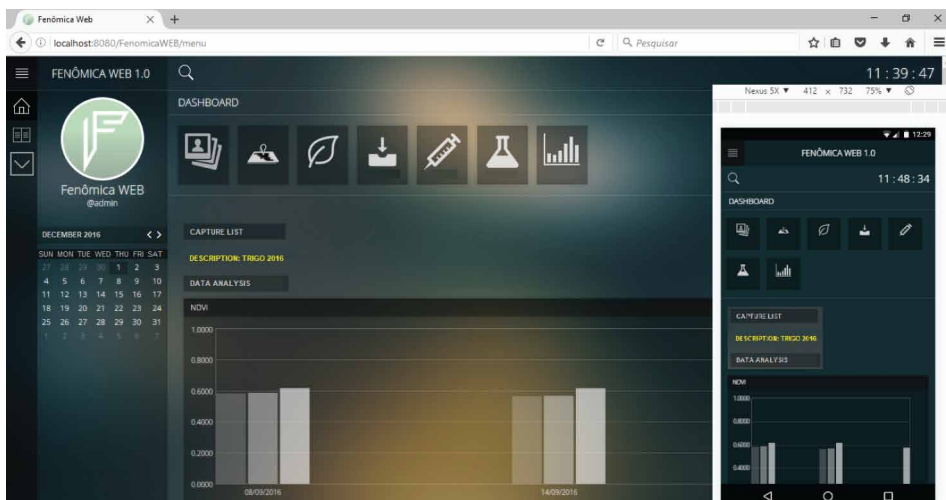
2.4.3.1. Data Persistence

To use this application, the user must enter using your credentials in a login interface. For the first access, FenômicaAPP web offers a link to sign up requiring a key provided by administrator.

After registration, user can request data already included and processed by other modules, filtering according your interest. Some resources are available to view and analyse results in this application, as rounding values on tables and adding missing values.

All the services offered are evoked by the HTTP protocol, transparente to the end user. Default URL is: “http://<ip>:<port>/<app>/rest “, where <ip> is the IP server address, <port>

Figure 13. Results in a dashboard user interface (desktop and mobile devices)



is the port communication, <app> is the application, and rest contains user requests encapsulated using POST method.

2.4.3.2. Viewing Results

FenômicaAPP web displays different views in home page. User can select from them that samples of interest must used to create charts, as well general and per sample indexes: NDVI, medium-hue green, medium-crop height, and biomass.

Figure 14 shows an example of view, showing the NDVI timeline evolution in the bar graph, considering three crop samples and their nitrogen (N) fertilizer rates. In the line chart, only one of the samples selected. This presentation model is similar to other available indexes.

3. RESULTS AND DISCUSSION

In addition to the system for high throughput phenotyping, our aim was also to apply this solution in a real case. Next sections present a preliminary study in order to investigate the relationship.

3.1. Study Areas

We executed image captures in two stages: calibration and study. Software and hardware calibrations considered experimental area (Lat 28°12'30.38"S, Lon 52°23'4.18"W) of the Biotrigo Geneticist Company (<http://biotrigo.com.br>), based on Passo Fundo, Brazil. Six plots sown in rows considered three wheat cultivars: TBIO Sinuelo, TBIO Toruk and Wheat Rice (Figure 15, replicas side-by-side).

Plots are close in order to obtain a similar rainfall index, and to apply the same N fertilizer dosage. Throughout the calibration time, our appliance captured images one plot per cultivar. Replications served as source for cutting plant material to biomass drying process.

Study stage considered the validation of our system using experimental area (Lat 28°22'94.72"S, Lon 52°90'88.82"W) of Embrapa Wheat, based on Carazinho, Brazil (Figure 16). We used only one wheat cultivar, BRS Parrudo (Embrapa, 2019), splitting the sample field into three plots with different N fertilizer rates.

According to Caierão et al. (2014), this cultivar is an innovative proposal in the aspect of vegetal ideotype, combining resistant stems, standing leaves, high vigor in the initial plant development and excellent resistance to the main wheat biotic stresses. Its medium-height is

Figure 14. NDVI chart generated to analyse temporal variation of the crop, considering N applications

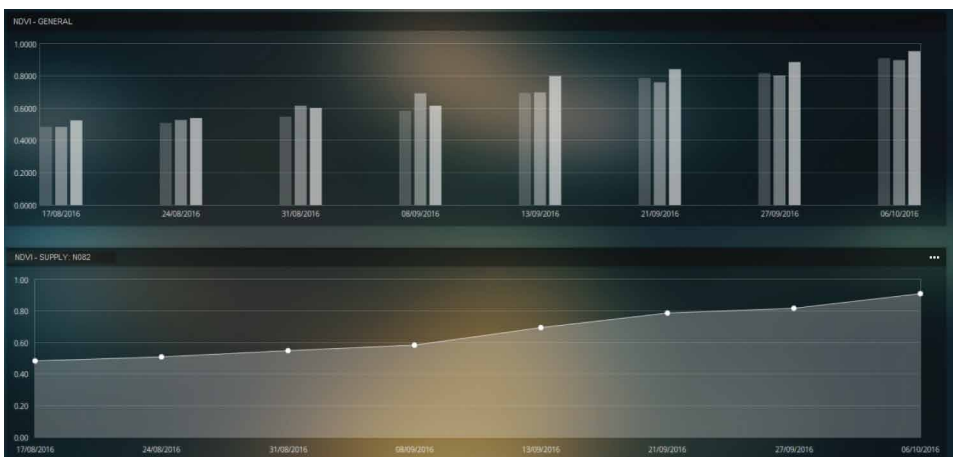
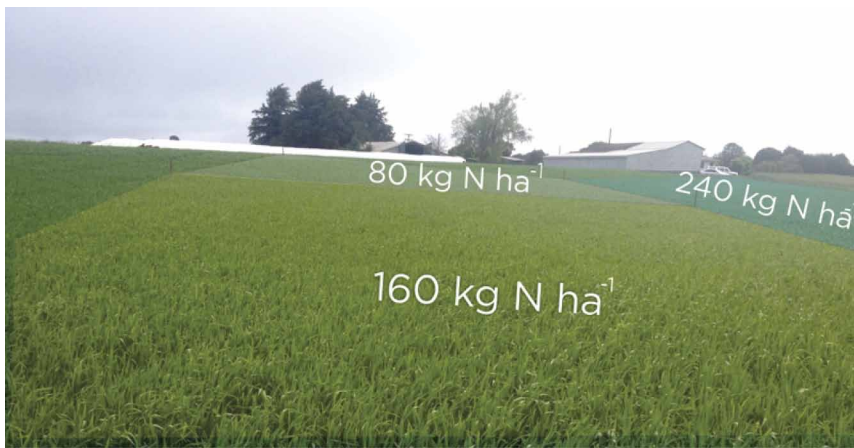


Figure 15. Biotrigo experimental plots



Figure 16. Embrapa wheat experimental plots



85cm and the average production is $7,700 \text{ kg ha}^{-1}$, with an early cycle of 85 days until coming into ear, and 135 days until ripening.

The sowing of the study stage experiment occurred on June 13, 2016, and the emergency on June 26, 2016. N fertilizer rates divided the sample field into three plots: 82 kg N ha^{-1} (N082), 150 kg N ha^{-1} (N150), and 200 kg N ha^{-1} (N200). These different N rates allowed verifying crop yield differences and the correlation between NDVI, biomass, medium-hue color and medium-crop height. According to Rodrigues et al. (2000), there is a significant interaction between biomass and N application periods. Table 1 and Table 2 show dates and N and urea application rates.

All crop management practices, such as sowing, fertilization, nutrition and biomass-drying and weighing process, was the responsibility of the Biotrigo and Embrapa Trigo. Weekly, we executed manual and appliance data collection.

3.2. Correlation Analysis Between Biomass and NDVI

This section presents comparisons between NDVI, generated from our solution, and wheat biomass for BRS Parrudo, reported by Embrapa Wheat. We considered eight straight weeks of observation (seven weeks after sowing), considering the capture of images and the cuts of plant material. Observation period occurred on mornings, once a week, between on August 16, 2016, and October 4, 2016.

Following subsections show results obtained on each plot, considering its N application. To compare the results, we used Spearman's correlation.

Table 1. N fertilizer rates applied in sample field

Date	N082	N150	N200
02/07/2016	54 kg ha ⁻¹	54 kg ha ⁻¹	54 kg ha ⁻¹
26/07/2016		34 kg ha ⁻¹	59 kg ha ⁻¹
04/08/2016	28 kg ha ⁻¹	28 kg ha ⁻¹	28 kg ha ⁻¹
09/08/2016		34 kg ha ⁻¹	59 kg ha ⁻¹
Total	82 kg ha ⁻¹	150 kg ha ⁻¹	200 kg ha ⁻¹

Table 2. Urea (CH₄N₂O) rates applied in sample field

Date	N082	N150	N200
02/07/2016	120 kg ha ⁻¹	120 kg ha ⁻¹	120 kg ha ⁻¹
26/07/2016		75,6 kg ha ⁻¹	131 kg ha ⁻¹
04/08/2016	62 kg ha ⁻¹	62 kg ha ⁻¹	62 kg ha ⁻¹
09/08/2016		75,6 kg ha ⁻¹	131 kg ha ⁻¹
Total	182 kg ha ⁻¹	333,2 kg ha ⁻¹	444 kg ha ⁻¹

3.2.1. Analysis of N082 Plot

Table 3 presents results for N082 plot. Figure 17 shows a very strong correlation between NDVI and wheat biomass (Rs-value = 0.9887). As a result, a linear equation could estimate the wheat biomass from the NDVI (Equation 2) considering N082 fertilizer rate:

$$y = 287.91x - 108.44 \quad (2)$$

3.2.2. Analysis of N150 Plot

Table 4 presents results for N150 plot. Figure 18 shows a very good correlation between NDVI and wheat biomass (Rs-value = 0.9284). As a result, a linear equation could estimate the wheat biomass from the NDVI (Equation 3) considering N150 fertilizer rate:

Table 3. Results for 82 kg N ha⁻¹ fertilizer rate

Date	Biomass (g)	NDVI (-1 to +1)	Green (0 to 100)	Height (mm)
16/08/2016	31.443	0.484	55.743	19.473
23/08/2016	38.720	0.509	41.930	30.110
30/08/2016	49.795	0.548	53.638	41.434
06/09/2016	63.048	0.584	60.703	68.051
13/09/2016	80.345	0.695	45.428	68.210
21/09/2016	119.560	0.787	22.164	64.453
27/09/2016	132.120	0.818	14.917	101.706
04/10/2016	153.288	0.910	15.374	117.052

Figure 17. Correlation between NDVI x Biomass in N082 plot

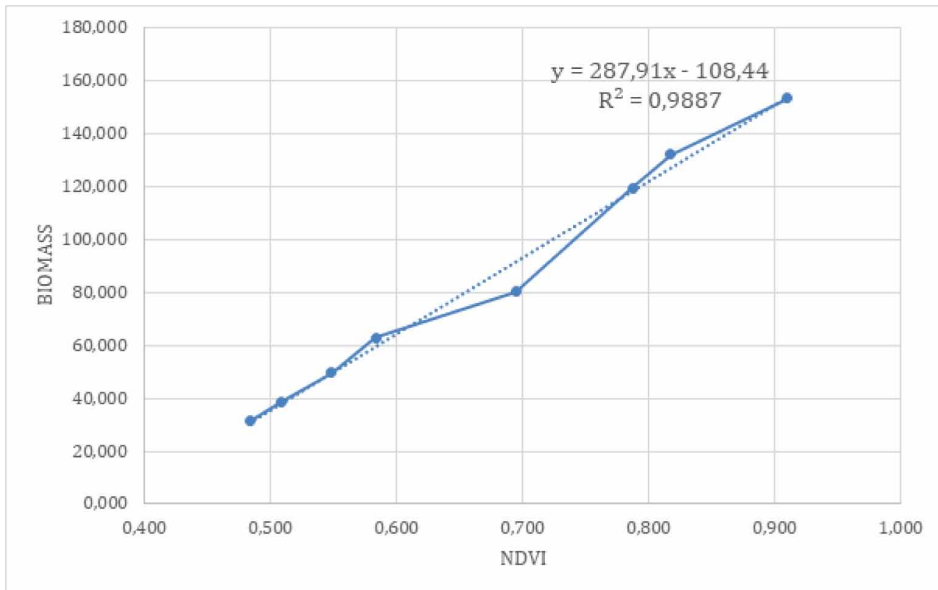


Table 4. Results for 150 kg N ha⁻¹ fertilizer rate

Date	Biomass (g)	NDVI (-1 to +1)	Green (0 to 100)	Height (mm)
16/08/2016	31.980	0.484	56.363	39.317
23/08/2016	37.335	0.527	56.117	35.401
30/08/2016	49.725	0.616	52.054	51.647
06/09/2016	63.048	0.693	45.428	68.210
13/09/2016	89.740	0.698	64.488	71.543
21/09/2016	114.430	0.761	9.990	70.855
27/09/2016	131.460	0.803	15.316	105.357
04/10/2016	170.096	0.899	30.952	109.114

$$y = 342.02x - 148.33 \quad (3)$$

3.2.3. Analysis of N200 Plot

Table 5 presents results for N200 plot. Figure 19 shows a good correlation between NDVI and wheat biomass (R_s -value = 0.882). As a result, a linear equation could estimate the wheat biomass from the NDVI (Equation 4) considering N200 fertilizer rate:

$$y = 273.61x - 111.17 \quad (4)$$

3.2.4. Discussion

According to Gowda et al. (2011), biomass has a strong correlation with crop yield of plants such as wheat, and Cabrera-Bosquet et al. (2011) show NDVI as a Potential Tool for Predicting Biomass.

Figure 18. Correlation between NDVI x Biomass in N150 plot

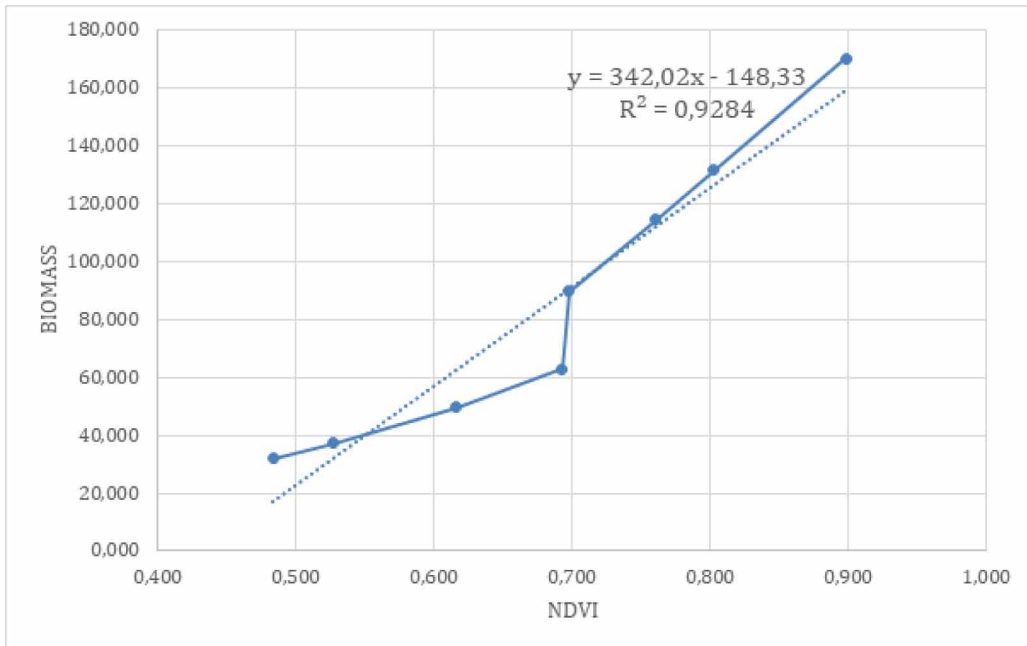


Table 5. Results for 200 kg N ha⁻¹ fertilizer rate

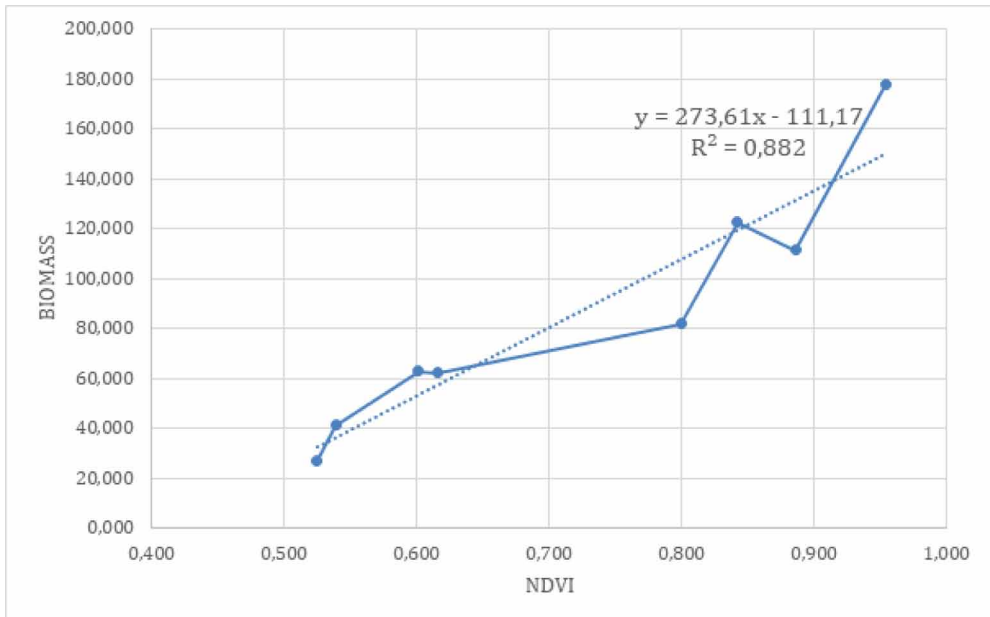
Date	Biomass (g)	NDVI (-1 to +1)	Green (0 to 100)	Height (mm)
16/08/2016	27.253	0.525	46.826	6.262
23/08/2016	41.455	0.539	56.544	35.507
30/08/2016	62.873	0.602	35.748	46.990
06/09/2016	62.403	0.616	64.488	71.543
13/09/2016	82.143	0.800	45.428	68.210
21/09/2016	122.665	0.842	27.782	87.313
27/09/2016	111.363	0.886	30.956	102.129
04/10/2016	177.523	0.954	14.886	116.364

Automating this process can allow researchers and geneticists a quick and easy way to estimate values for their experiments. Traditional process for biomass usually takes the entire period of the crop. On the other hand, image analysis can offer useful data in time, if necessary.

With this in mind, we observed the results and correlations considering our sample, and we noted that there are good trends as well as certain discrepancies in some data.

N200 plot indicates a high variability of biomass, including decrease values of wheat biomass in relation to the previous date. This situation only occurs when external disturbances affect plant growth. In our experiment, these variations occurred due to excessive rainfall in the field during the experiment. In some cases, we measured 101mm of rain in a single day during September 2016. According to Embrapa Wheat, lodged wheat was one of the visible problems. As N200 plot received a substantial quantity of nitrogen, its dimensions stretched in comparison to other plots, and probably

Figure 19. Correlation between NDVI x Biomass in N200 plot



this fact contributes to evidence of the problem. Figure 20 shows the variability between N200 plot and other analysed plots (N082 and N150).

Regarding the crop yield, Figure 21 shows the yield of grains in kg ha^{-1} , considering four samples of each plot of the study. N082 plot presented the best yield average, not coinciding with that expected for N applications. However, we observed that one hectare in N200 plot presented the highest yield. Considering crop yield and NDVI and biomass indices, we observed a similar variation for N200, repeated on a smaller scale for N082 and N150, retaining a variability pattern.

3.3. Medium-Crop Height and Medium-Hue Green Analysis

During the experiment, we perceived the plant growth process in the image processing, as expected. However, as wheat can lodge because of excessive rainfall, identifying crop height can be a difficult task. Considering NVDI values, it is possible to follow the evolution of the plant, without depending on the height, because the plant continues to absorb energy.

Figure 22 shows a comparison between medium-crop height and NDVI values, highlighting the plant growing in same weeks, and its stagnation in others. This information may be useful to detect patterns and trends in plant behavior after climatic situations.

Considering the medium-hue green values, we did not find an interesting relationship with NDVI values. Figure 23 shows a trend to decrease the medium-hue green values as the plant grows and matures, without a regular pattern. Wheat changes its coloration from shades of green to shades of yellow, a loss of color expected close to harvest time (Figure 24).

Although the medium-hue green values were not useful for this experiment, this measure may be useful to analyse other crops that do not have this natural color variation.

4. CONCLUSION

We concluded that our high-throughput phenotyping approach presented some potentials. Firstly, “Fenômica” appliance is low-cost, mobile, detachable and simple to use on the field (no tractor to

Figure 20. General correlations between NDVI x Biomass

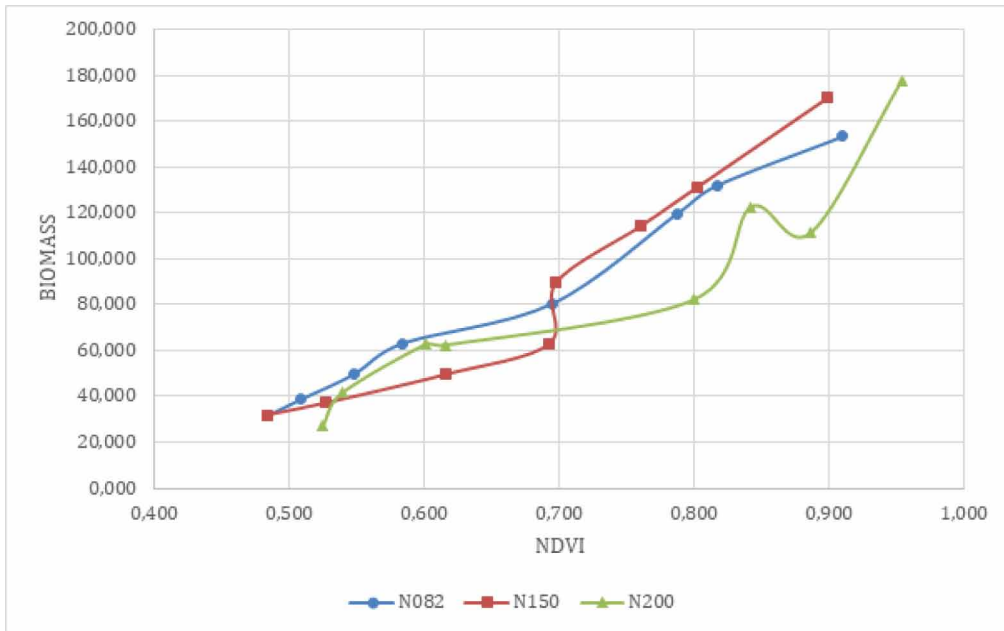


Figure 21. Comparison of crop yield considering four samples of each plot

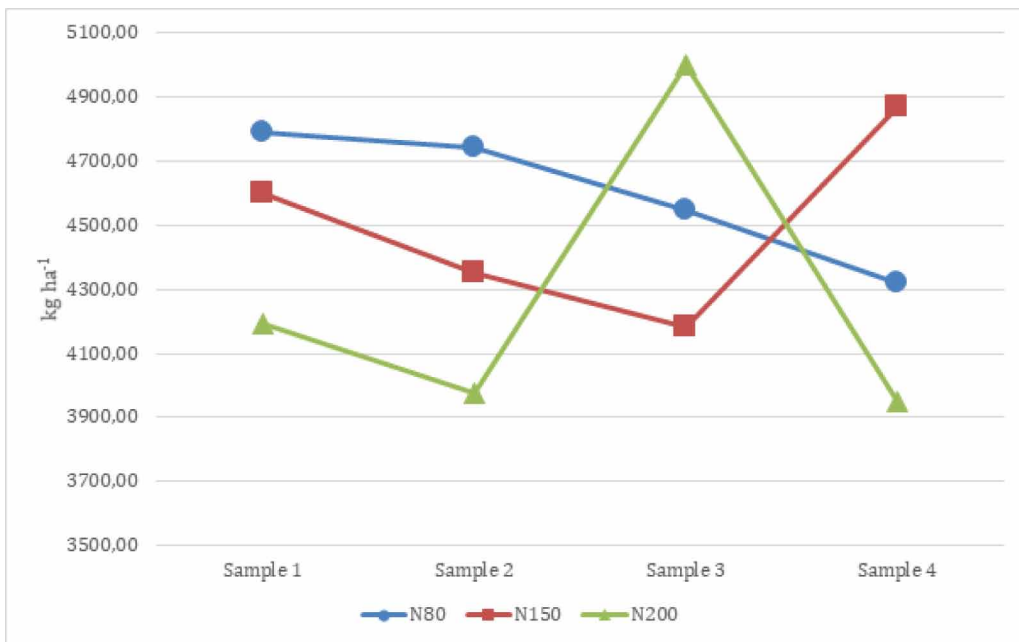


Figure 22. Evolution of plant growth per plot, considering NDVI and medium-crop height relationship

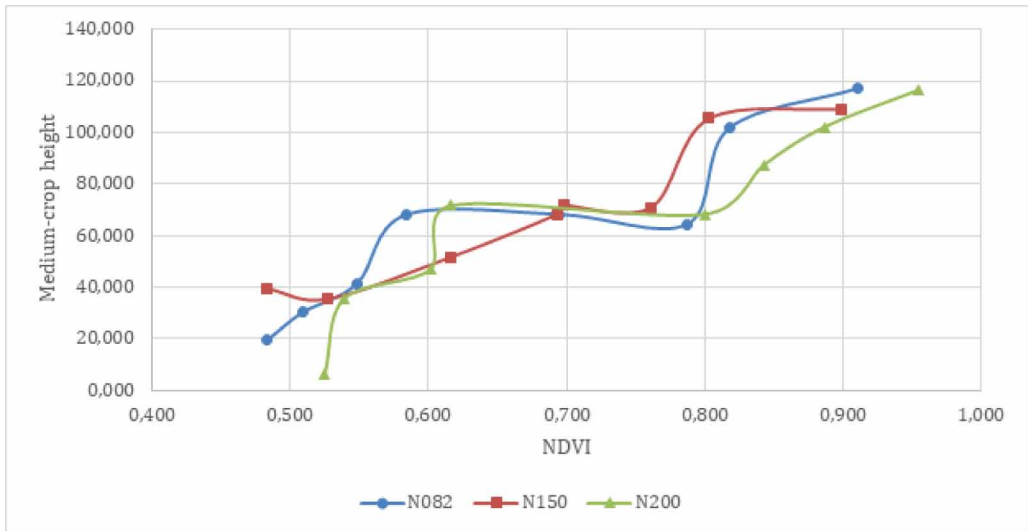
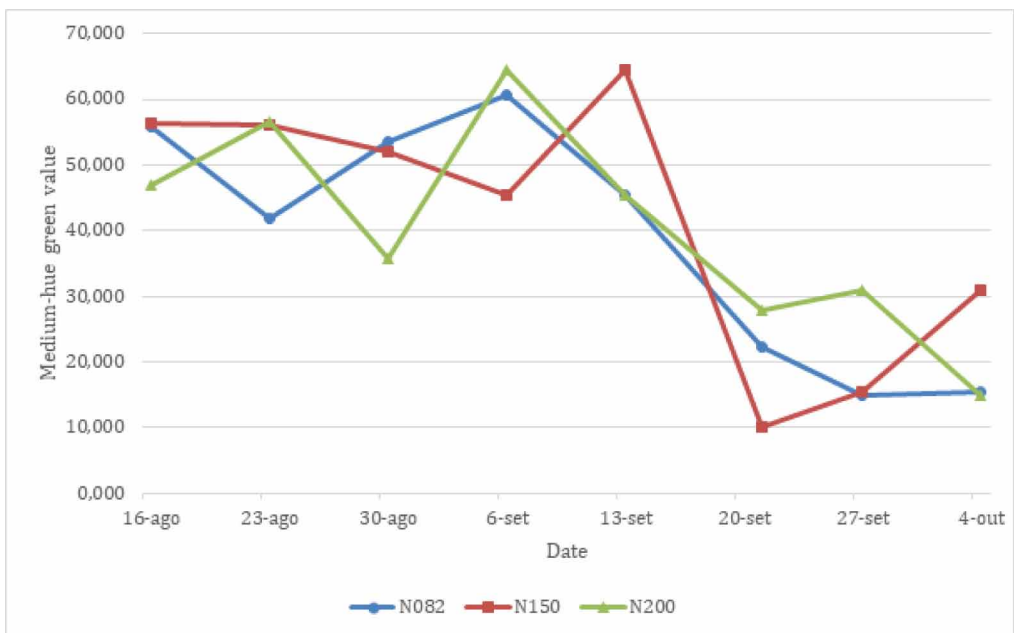


Figure 23. Evolution of the medium-hue green value per plot



lift is necessary). Fenômica computer vision system enables farmers and researches to store crop data in a unique software platform. Proposed solution also considers a complete process of acquisition, processing and presentation for crop analysis. Modularity of system may also allow a partial upgrade to include other phenotypic measures.

We also presented a preliminary study showing strong correlations between NDVI and biomass. NDVI calculated by our application presented a direct relation with the crop yield considering the

Figure 24. One of the appliance side images showing the wheat close to harvest time



plots of the study. It was also possible to define the creation of equations to estimate yield from the beginning of the crop only by images.

Medium-crop height and medium-hue green measures no presented relevant results. We only highlighted that NVDI can follow the evolution of the plant, without depending on the height. However, we suggested a new case study to get a better understanding of the relationship of these variables with biomass and NDVI.

This study reinforces that the use of computer vision systems can contribute to Agronomy professionals during crop management tasks. Computational analysis can provide instant information weekly (or even daily), correlate field and image data, and improve the crop quality and yield.

As future work, we intend to offer new features and validations, citing below:

- Exploring the use of our system with cereal grain crops;
- Investigating other phenotypic measures and obtain them from images (e.g. leaf shapes and plant stem);
- Using new camera filters to get more relevant data (thermal and multispectral images);
- Customizing parameters to crop regions defined by user;
- Applying deep learning techniques to analyze big sample data in order to discover new relationships between phenotypes;
- Developing a mobile application software to use on the field, without appliance, considering treatment of external environmental noise impact.

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