Automated Assessment and Mapping of Grape Quality through Image-based Color Analysis

Zania Pothen * **Stephen Nuske.** *

* *Carnegie Mellon University, Pittsurgh, PA 15213 USA*
(zpothen, snuske)@andrew.cmu.edu

Abstract: The harvest operation for table-grapes and fresh market horticultural fruits is a large and expensive logistical challenge with the choice of harvest dates and locations playing a crucial role in determining the quality of the yield and in determining the efficiency and productivity gain of the entire operation. The choice of harvest dates and locations, particularly in red varieties, is planned based upon the development of the color of the grape clusters. The traditional process to evaluate the amount of ripe, fully-colored fruit is visual assessment, which is subjective and prone to errors. The number of locations where a grower will evaluate the fruit development is statistically insufficient given the size of commercial vineyards and the variability in the color development. Therefore, an automated approach for evaluating color development is desirable. In this paper, we use a vision-based system to collect images of the fruit zone in a vineyard. We then use color image analysis to grade and predict the color development of grape clusters in the vineyard. Using our approach we are able to generate spatial maps of the vineyard showing the current and predicted distribution of color development. Our imaging measurement system achieves R^2 correlation values of $0.42-0.56$ against human measurements. We our able to predict the color development to within 5% average absolute error of the imaging measurements. The prediction of spatial maps is important from the perspective of selective harvesting as it allows the precise targeting of productive zones during the harvest operation. To the best of our knowledge generation of these spatial maps that represent the current and predicted state of the color development of an entire vineyard block, before harvest and in high resolution, is a first of its kind.

Keywords: Computer Vision, Automation, Color Analysis, Precision Viticulture, Precision Harvest.

1. INTRODUCTION

Grape harvest operation is a large and expensive logistical challenge and hence requires cost effective solutions. The choice of harvest dates determines the quality of the yield. Grapes once harvested do not ripen and therefore must not be harvested when immature. While, on the other hand leaving the fruit on the vines for too long results in either the berries shattering, being damaged by wildlife and insects, or breaking down due to rot. Another important factor is the choice of harvest locations. In commercial vineyards, different regions mature at different rates. Identifying and targeting these zones enhances the efficiency and productivity gain of the harvest operation.

The traditional process to evaluate the amount of ripe, fully-colored, fruit is for a grower to visually assess color development at a set of locations in their vineyard. For large commercial vineyards, its economically intractable to exhaustively evaluate the entire field owing to the labour intensive nature of the work. The number of locations where a grower will evaluate the fruit development is statistically insufficient. Moreover, the evaluation process is subjective according to the person performing the visual evaluation. Therefore, an automated approach for evaluation of color development is desirable. Over the past few years, our research group has focused on developing a vision-based system (Fig. 1a) for automatic fruit-detection and high resolution yield-estimation. The images captured by our system are processed for assessing color development and grading of fruits (Fig. 1b).

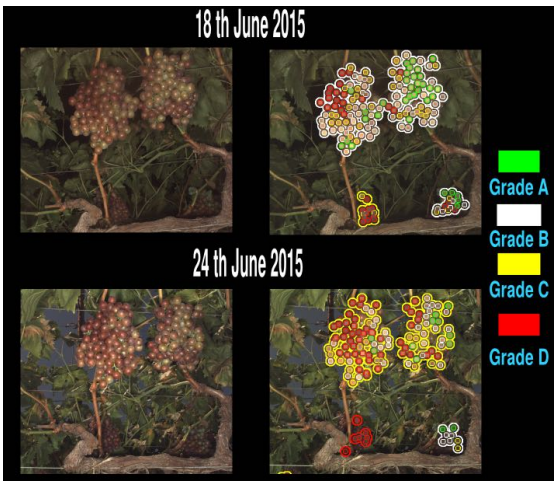
The main contributions of this paper are

(1) Use of color analysis for categorizing clusters of grapes into different stages of color development.
(2) Generating spatial maps of the vineyard showing distribution of color development
(3) Computing the rate of color development and using this to make future predictions of the spatial map

The approach presented in this paper has a clear application in the area of Precision Viticulture. The spatial maps can be used for differential management of vineyards to improve the color development in areas of low productivity. The maps also enable selective harvesting to optimize quality and increase harvest efficiency.

The rest of the paper is organized as follows. Section 2 describes the related work on color analysis used in agriculture. Section 3 describes our system for evaluating grape cluster color. Section 4 describes the sensor setup, the

(a)



(b)

Fig. 1. An overview of the Yield Mapping System (a) Imaging Unit in Vineyard – consisting of stereo cameras and a pair of flashes for capturing high resolution images. (b) Left: Raw images of clusters on the 18th and 24th June 2015. Right: Image automatically processed to detect clusters and evaluate color development. Berries that are well-colored are highlighted by a red square. Clusters classified as having sufficient level of well-colored berries are highlighted with red contour. Those berries and clusters that are deemed not well colored are highlighted yellow.

data-set and the experimental setup. Results are presented in Section 5 and conclusion in Section 6.

2. RELATED WORK

The use of image analysis of fruit images has been widely employed in automating the fruit packing industry [Zhang et al., 2014]. Rodríguez-Pulido et al. [2012] presents a method of estimating the ripeness of grape berries by performing histogram thresholding on CIELAB and HSI color space of grape images.The structured conditions present in these settings make it easy for computer systems to perform inspection and sorting with high accuracy. However, performing such operations in the unstructured agricultural fields present a plethora of issues such as distinguishing fruit from similar colored foliage, dealing with occlusions and large variations in lighting conditions.

[Pothen and Nuske, 2016] presents a method that uses fruit texture for detection of berries out in the field. [Font et al., 2015, Reis et al., 2012] describe methods of using color analysis for the detection of grapes. In [Portalés and Ribes-Gómez, 2015], the authors present a portable vision system that performs preliminary quality assessment of grapes in the field right after they have been harvested. Bramley et al. [2011] use a modified Multiplex sensor, which is a flurosence-based optical sensor, mounted over the discharge conveyor of a harvestor to determine the anthocyanin content of the grapes and use this information to generate spatial maps of grape maturity. However, the above methods do not address the problem of fruit quality analysis in the field before harvest.

[Santos et al., 2012] presents an approach that uses NIR-based imagery to measure and generate map grape quality across a vineyard. [Martinez-Casasnovas et al., 2012] analyse the use of NDVI maps to delineate areas based on wine grape properties in the vineyard for selective harvesting. However, these methods do not track the color development of the grape clusters, which is an important parameter for assessing quality of table grapes. Moreover, the grape clusters are not classified into appropriate quality grades.

In this paper, we present a method that uses color analysis of berry clusters to classify clusters into four different grades and generate high resolution spatial maps of vineyards.

3. APPROACH

Our method is based on using color image analysis to grade and predict the color development of grape clusters in the vineyard. Using a high-resolution color camera, paired with a high-power, fast, xenon flash we collect images of the fruit zone. The images are processed to identify and grade grape clusters based on their stage of color development. The grape clusters are combined to create a spatial map of the entire vineyard. Using images collected over different dates, we compute the rate of color development, which is then used to make future predictions.

3.1 Grape Detection

The first stage of image processing is to detect the locations of berries in each image. We have developed an image processing algorithm [Nuske et al., 2011, 2014b] that can detect berries using the three visual properties of a grape - the color, the shape and the surface shading. Neighboring berries are then grouped into clusters. In [Nuske et al., 2011, 2014a,b] we have shown that the berry counts collected from the images is an accurate measure of yield.

3.2 Color Extraction and Grading

Alg. 1 illustrates the steps for color extraction and grading of berry clusters. Once we have detected the berries, we extract a measurement of color at each berry location using a color transform from the input RGB image. We desire a color space with a uniform spread of the transformed colors to aid assessing grape clusters, and more importantly, we require a color space that is invariant to spectrally uniform illumination change. The HSV color space meets all of the above criteria.

Robustness and invariance to illumination change is attained by using the H-layer in the HSV colorspace, as the H-layer encodes only the color and not the intensity information in the image. We compute the average H

Fig. 2. Grape clusters categorized into 4 grades depending on their color development.

Algorithm 1: Cluster Grading

```
foreach grade do
    foreach cluster do
        berry_cnt ← 0;
        foreach berry ∈ cluster do
            h ← ExtractHue(berry) ;
            if HueThreshold(h, grade) then
                berry_cnt ← berry_cnt + 1;
        berry_perc ← 100 (berry_cnt / total_berry_cnt);
        if ClusterThreshold(berry_perc, grade) then
            cluster_grade ← grade;
```

value of an image patch around the center of each berry. Line. 1 performs the above operation with the function `ExtractHue`().

Having computed color values for each berry in a cluster, we now define a grading scheme for categorizing clusters based on their color development. The color development is normally expressed as a percentage of berries within a cluster that have colored. We find optimal H value thresholds to separate clusters into one of 4 categories (Fig. 2):

- Grade A - represents clusters at the onset of verasion (color development) where less than 20% of the berries have changed color.
- Grade B - represents clusters where verasion has progressed with 40% of the berries having changed color.
- Grade C - represents clusters at a stage after verasion where 60% of the berries have develop a rich pink color.
- Grade D - represents clusters that are harvest ready with over 80% of the berries have reached full color development and have a deep red color.

Line. 1 invokes the function `HueThreshold`() to check if a hue belongs to a grade. Line. 1 invokes the function `ClusterThreshold`() to check if the percentage of berries matches the desired threshold for a grade. Finally, line. 1 assigns a grade to the cluster. The result of the process is presented in Fig. 1b.

We combine the percent of clusters of individual vines for a given grade across the vineyard to generate a spatial map as shown in Fig. 6a. The spatial patterns for the percent of clusters generally follow those for yield [Bramley and Hamilton, 2004, 2007].

3.3 Prediction of Cluster Color Development

The benefits of having color information is having the ability to predict the harvest dates and locations in vineyards. In order to be able to do this, we need to have an estimate of the color progression. For computing the progression, we collect images of the same location in the vineyard on different dates. We then estimate the rate of change of color by locating and comparing the color information of the same berries in the images collected on different dates. This rate of color change in tandem with the current spatial map can be used to predict a future map. The prediction of spatial maps is important from the perspective of selective harvesting as it allows the precise targeting of productive zones during the harvest operation.

4. EXPERIMENT

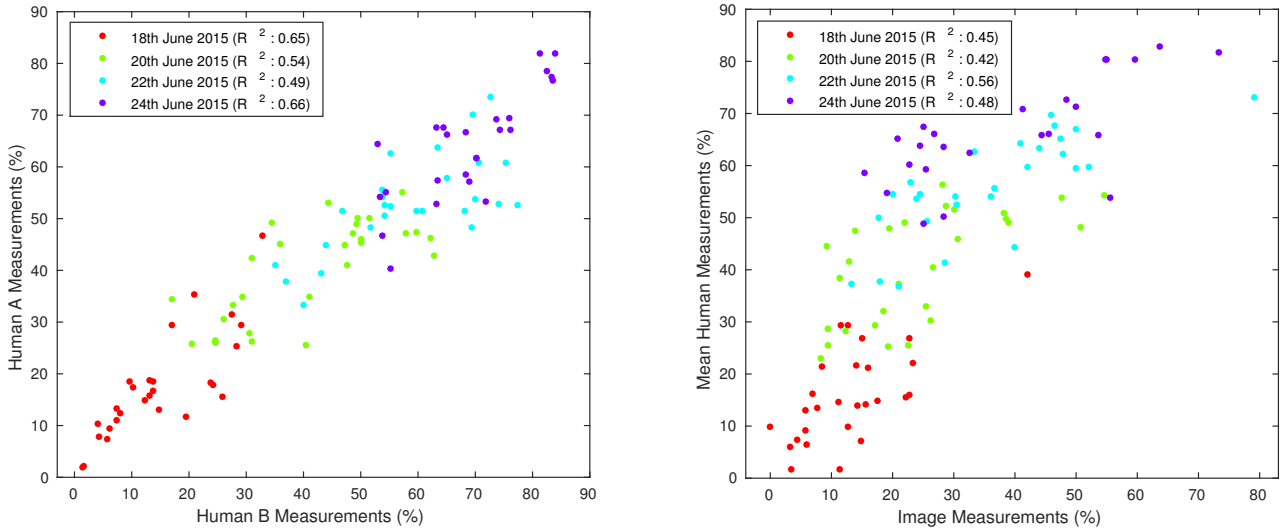
4.1 Sensor

Our imaging system is a custom built stereo rig consisting of a pair of identical RGB Pointgrey Grasshopper cameras (with 8.8mm lens and baseline of 90mm) and a pair of Xenon flashlamps (5 − 10J) (Fig. 1a). The system is setup such that it maintains a neutral whitebalance, it is optimized for low motion blur, captures images with increased depth-of-focus, and uses low illumination power for fast-recycle times permitting high-frame rates. This camera and illumination design maintains high image quality at high vehicle velocities and enables deployment on large scales. The images are captured at 4288×2848 resolution. The imaging system is mounted onto a farm vehicle and depending on the size of the fruit zone it is mounted at 0.9 to 1.5m from the fruit zone. The farm vehicle was driven at 5.4km/hr. through each row and the images were captured at 5Hz.

We use a Trimble Ag GPS 422 unit, which is logged and synchronized against the camera images, for generating the geospatial maps. The color grade measurements from each image is therefore associated with a GPS latitude longitude. The map is generated using a north aligned grid evenly spaced at 1 meter increments across the dimensions of the field. We then smooth the color measurements onto the grid by taking a weighted median of surrounding measurements.

4.2 Dataset

We focus our work on *Flame Seedless* red table-grape varietal. The clusters, at the onset of veraison, transition



(a) (b)

Fig. 3. Measurement Comparison : (a) Scatterplot present the variation between two human measurements. (b) Scatterplot present the variation between the mean human measurements and the image measurements. We note that the human and image measurements are not linear, as the humans estimate a more drastic change in the the color development than what was observed in the images taken of the vineyard on each of the four dates ($18^{th}, 20^{th}, 22^{th}$&$24^{th}$ June 2015). See example images in Fig. 4

.

Table 1. Flame Seedless Dataset

Details	**Values**
Collection Dates	18th, 20th, 22nd& 24^{th}June, 2015
Harvest Date	29^{th}June 2015
Location	Delano, California
Vineyard Type	Split-V gable
Total Acres	20

from opaque bright green, to a yellow, onto a rich pink and finally reach full color development as a deep red which is slightly translucent.

Table 1 specifies the details of the dataset. The vines are trained in a split system in which each vine is trained into two cordons and the shoots grow over a V-gable trellis such that the fruit hangs in two distinct sections at an angle on each side of the row.

The imaging data was collected for the entire the north or the south side of alternate rows. The same rows and sides were imaged on each of the four dates.

4.3 Calibration

We randomly select 116 vines in the vineyard as calibration plots. Each of these calibration plots is vissually assessed by an industry expert - viticulturists or growers - and a color development value is assigned for each plot for each of the four grades. The images of vines from the calibration plots are paired with the corresponding color development and grade assigned by the industry experts. Using manual samples collected at the time of imaging has the advantage that a calibration can be established immediately and that the calibration can be assured to be representative of the current vineyard variety and training system.

For each calibration plot we extract the hue for all the detected berries and then sort the hue values in descending order. We then find the optimal hue values that separate the sorted hue values according to the color development values assigned by the industry expert.

5. RESULTS

5.1 Comparison between human and imaging measurements

Fig. 4. Images of cluster for the 4 imaging dates. The color development over the four days is a slow gradual change.

Fig. 3a shows a scatterplot to visualize the correlation between measurements made by two humans independently for grade D over time. The dispersion of the scatter plot indicates low correlation between the humans which is also reflected in their R^2 correlation values.

Fig. 3b shows a scatterplot to visualize the correlation between mean human measurements and measurements from the imaging system (R^2 of 0.42 - 0.56). The plot shows a bias - the human measurements are higher compared to that of the image measurements. This reflects a tendency for the humans to overestimate cluster percentages as time progresses. When we examine the images (Fig. 4) for each of these days we do not see any evidence of the dramatic changes recorded in the human measurement, instead we see a gradual change which is clearly captured in the imaging results.

5.2 Spatial maps of cluster percentages

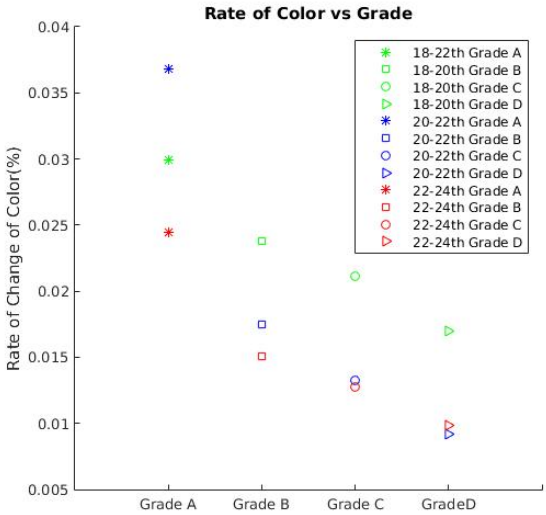


Fig. 5. Rate of color development for each grade over time.

Fig. 6b and Fig. 6c presents maps of the color development on two separate days for Grades B and D obtained using image measurements. These spatial maps are compared with the spatial yield map shown in Fig. 6a.

We note that the crop heavy regions located in the northern area have lesser counts of grade D clusters and more counts of grade B clusters. Similarly the low yield southern regions show the opposite trend. These reflect the findings made in [Bramley and Hamilton, 2004, 2007].

The steady rate of increase in Grade D clusters counts is almost matched by the steady rate of decrease in Grade B clusters counts thus maintaining a constant count in the intermediary Grade C clusters. This is reflected in the spatial maps where the overall intensity of the Grade B cluster maps drops with time, while the intensity of Grade D maps increases.

The result both indicates that variations in color development are large across a vineyard block and also the pattern remains somewhat stable through time.

5.3 Prediction

Fig. 5 shows the rate of color development for each grade over time. The rate is higher in green immature grape clusters (Grade A) versus the harvest ready deep red grape clusters (Grade D). This rate of color development declines as more berries in the cluster reach full color development.

From this graph, we use the mean rate of change for each grade to predict the color development from the initial date (18^{th}June) of data collection. Fig.7 shows a comparison of the Mean Cluster Percentage of image measurements versus predicted measurements for each grade over time. The predictions follow similar trend to the image measurements. We our able to predict the color development to within 5% average absolute error of the imaging measurements.

Fig. 6d shows the predicted spatial maps for the Grades B and D for 24th June. The predicted maps capture similar cluster patterns as compared to the image measurements in Fig. 6c.

6. CONCLUSION

Our method has demonstrated that it possible to collect measurements of color-development using automated image analysis. We have shown that it is possible to categorize grape clusters into different grades according to color development and compute the progression of color change across a commercial vineyard. We also demonstrate that our approach can be used to create dense, high-resolution spatial maps of the current as well as the predicted state of the crop. To our knowledge, these types of georegistered spatial maps that show the current and predicted state of color development in vineyards have not previously been collected at such high-resolution on an entire vineyard block during the growing season.

Results collected from the vineyard environment highlight the difficulty to have accurate human measurements of color development. Manual measurements are subjective and substantial discrepancy in assessments were found between a group of humans. While this creates an issue with definitively evaluating the accuracy of the image measurements, this conversely points towards the conclusion that the subjectivity of a human assessor is precisely the need for an objective automated measurement.

Moreover, the spatial maps generated indicate that there is a large variation in color-development across in vineyards, and that this requires an efficient and dense measurement approach which cannot be achieved by sparse manual measurements.

Automated image measurements of the state of the crop will enable growers to utilize site specific field managements techniques to improve the quality of their crop and conserve their resources. Predictions of the spatial map will provide growers with value able information to plan and schedule their harvest operations.

To our knowledge, these types of georegistered spatial maps that show the current and predicted state of color development in vineyards have not previously been collected non-destructively at such high-resolution on an entire vineyard block before harvest.

ACKNOWLEDGEMENTS

This work is supported in part by the US Department of Agriculture under grant number 20126702119958 and the National Grape and Wine Initiative. The authors would

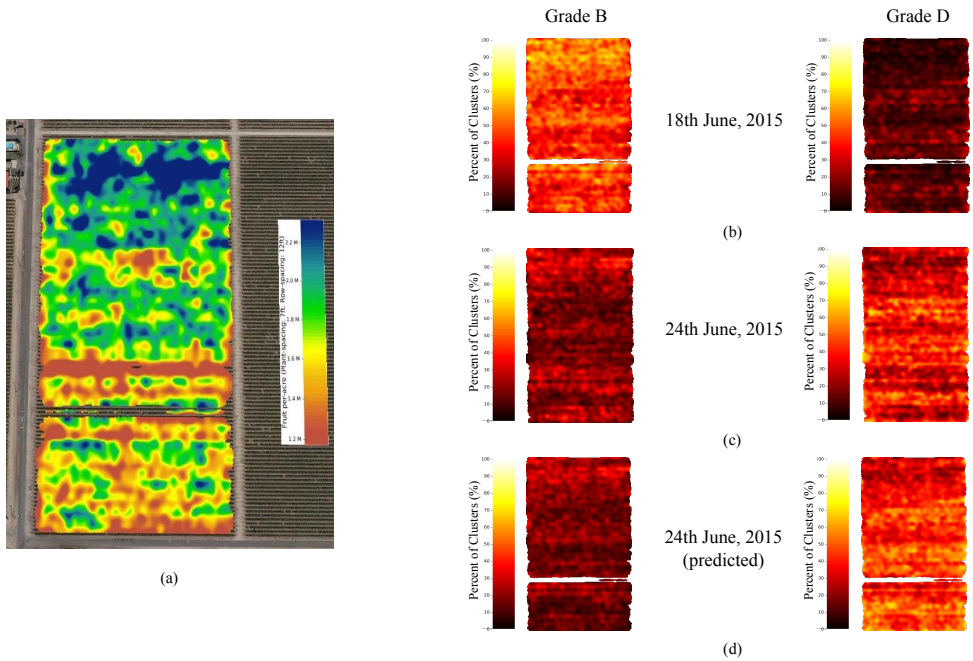


Fig. 6. Spatial Maps of the Flameseedles Vineyard: (a) Yield Map of the berry count across the field. Spatial Map of percentage of clusters for Grades B and D on the 18th June (b), 24th June (c), and the predicted map for the 24th June. To the authors knowledge such spatial maps, that measure and predict the color development in vineyards, have not previously been collected at such high-resolution on an entire vineyard during the growing season.

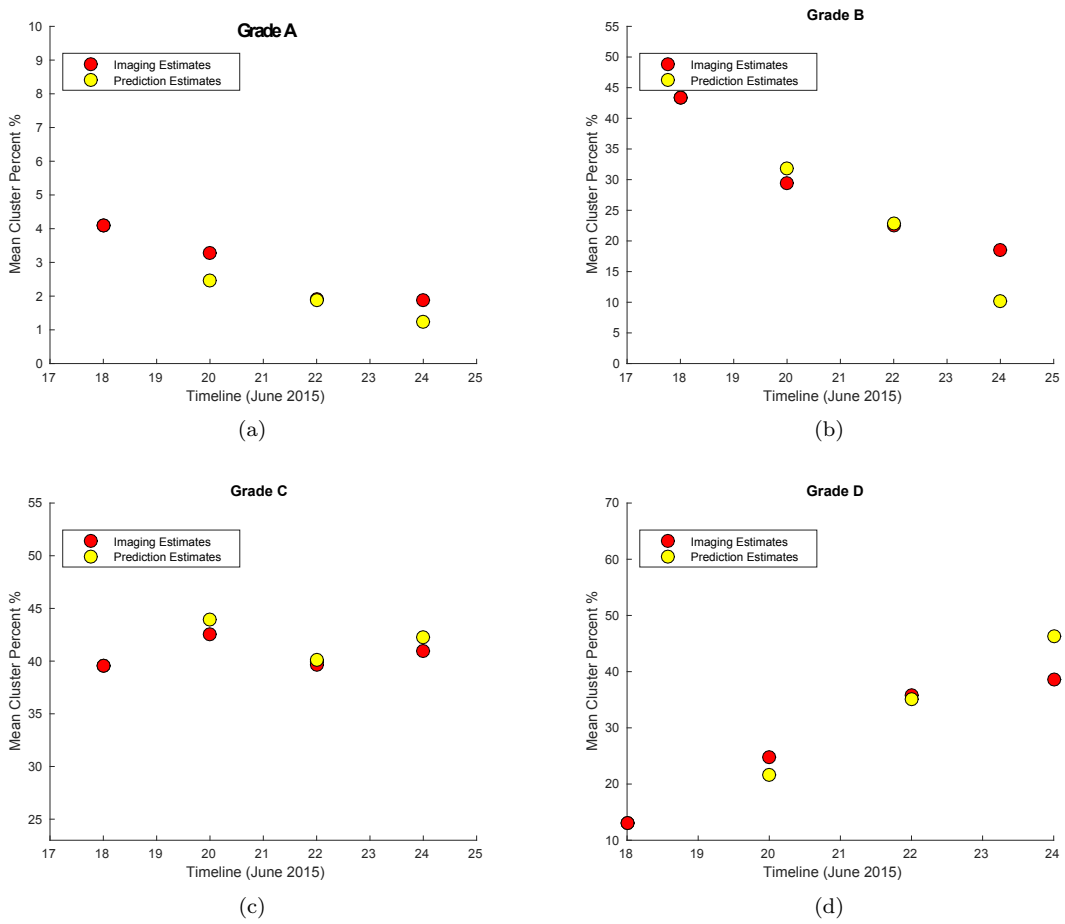


Fig. 7. Mean Cluster Percentage of image measurements versus predicted for the four grades over time.

like to thank the following people who assisted in collecting the data for this paper; Luke Yoder, Maha Afifi and Franka Gabler.

REFERENCES

Bramley, R. and Hamilton, R. (2004). Understanding variability in winegrape production systems. *Australian Journal of Grape and Wine Research*, 10(1), 32–45.

Bramley, R. and Hamilton, R. (2007). Terroir and precision viticulture: Are they compatible? *Journal International des Sciences de la Vigne et du Vin*, 41(1), 1.

Bramley, R., Le Moigne, M., Evain, S., Ouzman, J., Florin, L., Fadaili, E., Hinze, C., and Cerovic, Z. (2011). On-the-go sensing of grape berry anthocyanins during commercial harvest: development and prospects. *Australian Journal of Grape and Wine Research*, 17(3), 316–326.

Font, D., Tresanchez, M., Martínez, D., Moreno, J., Clotet, E., and Palacín, J. (2015). Vineyard yield estimation based on the analysis of high resolution images obtained with artificial illumination at night. *Sensors*, 15(4), 8284–8301.

Martinez-Casasnovas, J.A., Agelet-Fernandez, J., Arnó, J., and Ramos, M. (2012). Analysis of vineyard differential management zones and relation to vine development, grape maturity and quality. *Spanish Journal of Agricultural Research*, 10(2), 326–337.

Nuske, S., Achar, S., Bates, T., Narasimhan, S., and Singh, S. (2011). Yield estimation in vineyards by visual grape detection. In *Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Nuske, S., Gupta, K., Narasimhan, S., and Singh, S. (2014a). Modeling and calibrating visual yield estimates in vineyards. In *Field and Service Robotics*, 343–356. Springer.

Nuske, S., Wilshusen, K., Achar, S., Yoder, L., Narasimhan, S., and Singh, S. (2014b). Automated visual yield estimation in vineyards. *Journal of Field Robotics*, 31(5), 837–860.

Portalés, C. and Ribes-Gómez, E. (2015). An image-based system to preliminary assess the quality of grape harvest batches on arrival at the winery. *Computers in Industry*, 68, 105–115.

Pothen, Z. and Nuske, S. (2016). Texture-based fruit detection via images using the smooth patterns on the fruit. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation (to appear)*.

Reis, M.J., Morais, R., Peres, E., Pereira, C., Contente, O., Soares, S., Valente, A., Baptista, J., Ferreira, P.J.S., and Cruz, J.B. (2012). Automatic detection of bunches of grapes in natural environment from color images. *Journal of Applied Logic*, 10(4), 285 – 290.

Rodríguez-Pulido, F.J., Gómez-Robledo, L., Melgosa, M., Gordillo, B., González-Miret, M.L., and Heredia, F.J. (2012). Ripeness estimation of grape berries and seeds by image analysis. *Computers and electronics in agriculture*, 82, 128–133.

Santos, A.O., Wample, R.L., Sachidhanantham, S., and Kaye, O. (2012). Grape quality mapping for vineyard differential harvesting. *Brazilian Archives of Biology and Technology*, 55(2), 193–204.

Zhang, B., Huang, W., Li, J., Zhao, C., Fan, S., Wu, J., and Liu, C. (2014). Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. *Food Research International*, 62, 326–343.