Analyzing crop health in vineyards through a multispectral imaging and drone system

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This paper describes a system for collecting and analyzing multispectral imagery to evaluate crop health and streamline vineyard management in small to medium-sized vineyards. The system consists of three main components: a sensor assembly with a multispectral camera, quadcopter with flight automation, and a web-based decision support information system for analyzing multispectral imagery. Multispectral imagery can provide a holistic view of crop health through the use of different indices. A widely used index is the Normalized Difference Vegetative Index, which uses red and near-infrared reflectance as a proxy measurement for plant health. The authors tested the system at a small vineyard located in Albemarle County, Virginia, to better inform vineyard management of existing problems and trends in primary crop and undergrowth. Preliminary findings indicate the value of using this indicator-based approach for analyzing crop health in vineyards.

Keywords—Multispectral, remote, sensing, viticulture, quadcopter

I. Introduction

Vineyards in Virginia are in a unique context. The scale of the grape-growing operations, land suitability, microclimates, and startup costs can be hurdles for grape farming in Virginia. Vineyards can struggle with crop diseases, like downy mildew, due to the dark, humid conditions that promote this disease.

This project began as an emergent collaboration between a vineyard manager of a mid-sized vineyard and winery in Albemarle County, Virginia, and the undergraduate authors. The aim of this collaboration was to explore ways to use multispectral imaging to support viticulture decisions [1].

One way to support these decisions is through the use of vegetation indicators, which are calculated from multispectral images and can provide a holistic evaluation of plant health. These indicators can help provide insights in comprehensive measurements of health such as *vigor*, which refers to how well a vine or vine area grows. An indicator approach differs from other approaches that use multispectral images which use empirical methods to evaluating correlations with multispectral data by comparing them to crop yield, pH levels, and berry weight [1].

The decreasing costs of sensors and drones means that multispectral imagery is potentially more accessible then traditionally collected satellite imagery. As crop health changes spatially and temporally, there is value for this application in higher frequency of data collection over smaller spatial extents.

II. Methods

The system designed by the authors consists of three main components: a sensor assembly with a multispectral camera, quadcopter drone with flight automation, and a web-based decision support information system for analyzing multispectral imagery. There were two primary functional requirements: (1) the ability to evaluate the health of the entire vineyard at a glance; and (2) the ability to digitally mark and save the location of vines which have been visually identified as diseased or dying while working in the vineyard. The first of these requirements was addressed through the implementation of an aerial multispectral system while the second was addressed through the creation of software application.

A. Aerial Data Collection

While several UAV platforms were tested in order to determine their suitability, the authors chose a DJI Phantom 4 drone (Figure 1). The platform was primarily chosen for its flexibility and ease of modification. The system also includes a web-based interface that enables users to place notifications over different index mappings.

Fig. 1. UAV platform with sensor assembly.

B. Multispectral Imaging

Multispectral imaging is based on the principle that objects reflect different wavelengths of ambient light differently, depending on their chemical composition [1]. Additionally, objects emit infrared radiation dependent on their temperatures. These properties make it possible to identify certain objects and chemical compounds from a distance, as well as their temperatures.

The multispectral camera used in this project, a Micasense Altum, includes five individual cameras that measure reflectance in distinct wavelength bands[1]. This multispectral camera includes a sixth camera which measures the thermal infrared, which spans the 3000-20000 nm range. The green camera is generally used to map the abundance of chlorophyll. The red camera is often used to identify factors, such as; humidity, crop type, soil quality, and plant stress. Additionally, this band shows sharp contrast between plants and soil, making it useful for establishing a baseline for other measurements. The reflectance of the red edge wavelengths is very sensitive to the concentrations of chlorophyll and can be used in tandem with the red band to determine crop health. The near-infrared is used mainly to measure moisture in the soil and analyze erosion risk [2]. In addition to this camera a DLS 2 sensor made by Micasense was used to improve radiometric light readings by reading light reflectance and angle while the drone is in flight. This additional sensor helps to reduce post-processing time.

Collectively, the data from these cameras can be used to compute vegetation indices, such as; the Normalized Difference Vegetation Index (NVDI), Normalized Difference Red Edge Index (NDRE), and Visible Atmospherically Resistant Index (VARI) [3]. These indices are used to monitor the health of plants.

C. Photogrammetry

In addition to multispectral imagery, the data collected by the camera in an aerial drone flight can be used to assemble a digital surface model using photogrammetry. Photogrammetry relies on having multiple pictures of the same area taken from different angles to determine depth, which, in this use case, results in an elevation map of the land surveyed. The commercial software Metashape, by Agisoft, was used for this analysis because of its Python API. Photogrammetry is commonly used in 3D modelling applications and surveying. Photogrammetry is incredibly versatile as it can be used to generate a depth map from any dataset which has location, elevation, extent, and angle for each image.

D. Web Application

These solutions were brought together and oriented toward the user through the development of a full stack web application (Figure 2). This application allows the user to geographically overlay and interact with multispectral data through an array of indices. It also allows the user to track pinned locations of interest from the offline field application.

The full stack web application including a front-end graphical interface[2] and back-end server system[3] for storing aerial imaging and agricultural information. The frontend was tested with a test suite which includes the standard built-in React test and a separately developed test on key frontend components. In addition, the backend functionalities[4] were tested using a third-party application called postman. The functionality was successful if the data being served matched the data being requested.

Fig. 2. Front-end of Web Interface.

In addition, to ensure quality under a production-like environment before application deployment, the workflow used a Blue-Green Deployment model where two identical production environments work in parallel as a fail-safe. These environments are clones and use the same database backend and app configuration. This robust method allows the developers to test for functionality and performance before deploying the respective environment as the live version for production. Furthermore, with the use of Datadog, a monitoring

[1] Blue (465-485 nm), green (550-570 nm), red (663-673 nm), red edge (712-722nm), and near-infrared (820-860 nm)

[2] The frontend was developed using the JavaScript framework React JS

[3] the backend was developed using the Python library Django with data stored in an SQLite database

[4] The functionalities tested include get, post, update and delete request.

service for cloud-scale applications, the developers can analyze their applications performance metrics down to the kernel level for specific processes. This allows developers to efficiently optimize their resources to the most demanding processes based on infrastructure metrics like CPU and Memory utilization.

Another significant component to optimizing the workflow and deployment of the web app was using Docker, a containerization tool. Containers are a standardized unit of software that allows developers to isolate their app from its environment. They are extremely lightweight and only require a kernel to operate the web application.

The web application was deployed using a cloud provider, Amazon Web Services (AWS). A major advantage to the use of containers was the ability to automate 100% of the software delivery to AWS. In our case, Travis CI, a continuous integration and continuous deployment (CI/CD) tool was used fully automate our system into a production grade workflow. The CI/CD pipeline allows developers to automate container builds, test environments through test suites, injecting monitoring services, reverse proxy ingress, and deployment.

When a developer commits code to our remote code repository, the CI/CD pipeline is configured to pull the new repo and build the web app consisting of multiple docker containers. For reference, our web application's containers are the frontend client (React), the backend server (Django), a reverse-proxy for network routing between containers (Nginx), and our infrastructure monitoring service (Datadog). Then Travis CI runs specific test suites to our frontend client and backend server containers to check for any problems. If either container fails their test suites, then the CI/CD pipeline build would fail, notify the developers of the failed build, and prevent that errored code from being deployed to its respective environment. In addition, the pipeline would prevent that failed build from ever being merged to the master branch (production version), stopping it from affecting the live versions of the web application.

If all test suites were completed and successful, then Travis CI will fully build all the containers for the web application. Then Travis CI will tag each container with its correct identification and push the newly built containers to Docker Hub, a container registry. Then the pipeline will build the respective environment on AWS and prepare it for deployment. Once ready, the pipeline would then pull the new containers from the Docker Hub registry and deploy them to the environment. Finally, an important file instructs Travis CI how to build each container in the AWS instance and how to start operating the web app within the instance.

E. Offline Field Application

Because of limited internet connectivity at field site, it was important to develop an offline application. As there is no way to directly transfer geographic coordinates regarding marked vines while in the field, a local copy of this data needed to be created. This offline application allows the user to mark and save specific locations with notes before uploading them to the web application when internet connection becomes available.

The prototype field application consists of a GPS module connected via USB to a computer, a Python script to read and parse the data over serial connection, and a user interface developed in the Python Graphical User Interface (GUI) package Tkinter. This application sends user notes along with GPS coordinates to a JSON (JavaScript Object Notation) file which can be easily passed to the web application.

F. Calculating Indicators of Crop Health

Normalized Difference Vegetation Index (NDVI) have been investigated as a proxy for crop health [4]. The NDVI is the ratio of red (R) and near infrared (NIR) spectral bands, and was calculated using Eq. 1.

$$NDVI = (NIR - R) / (NIR + R) \tag{1}$$

The Normalized Difference Water Index (NDWI) has two alternatives which provide different functionalities. Eq. 2 is used to monitor water content in leaves using green bands (G), and Eq. 3 is used to monitor water content in water bodies using short-wave near-infrared (SWIR) [4]. The later equation requires the use of Short-Wave Infrared readings which were not available using the Micasense Altum sensor.

$$NDWI = G\text{-}NIR / G+NIR \tag{2}$$

$$NDWI = (NIR - SWIR) / (NIR + SWIR) \tag{3}$$

The Normalized Difference Red Edge Index (NDRE) (4) is a ratio of edge of Red (RE) and red band (R) and is primarily used to further differentiate between healthy regions of crop growth and dense canopy.

$$NDRE = (RE - R) / (RE+R) \tag{4}$$

Because it is sensitive to soil background effects, it is important to compare directly to regions with NDVI and Soil-Adjusted Vegetation Index (SAVI) values [5]. SAVI is an index that attempts to adjust for different levels of vegetation density. The equation (5) uses a value L to normalize the reading with reference to the interstitial soil present in images of the crop canopy [6],[7].

$$SAVI = ((NIR - R) / (NIR + R + L)) + (1 + L) \tag{5}$$

The SAVI uses the constant L as a means to calibrate the algebraic algorithm to the degree of noise presented by interstitial vegetation [8]. While SAVI is a popular and well researched index, this project team focused more exclusively on NDVI as a proxy for vine vigor.

G. Calculating temporal changes in indices

Calculating the differences of the indices in a location helps to identify changing crop conditions. However, given images of the same plot of land taken at different times, there is no guarantee that pixels in the same location on each image corresponds to the same geographical location. This means that pixelwise calculations are sensitive to noise caused by the images being misaligned. To counter this, the calculation involves sets of pixels in a location of interest. Each index has a set of intervals that indicate the crop conditions. The process counts the number of pixels that fall into each interval and expresses it as a proportion of the total number of pixels. By aggregating the pixels in this way, the effects of noise are greatly reduced. The data can be tracked over time to detect changes in crop conditions as indicated by all the supported indices.

III. Results

The authors tested the system at a small vineyard located in Albemarle County, Virginia, to better inform vineyard management of existing problems and trends in primary crop and undergrowth. Preliminary findings indicate both the utility of the Normalized Difference Vegetation Index (NDVI), but also the value of indices regarding water saturation. A push for data-informed agriculture and viticulture has led to the development of a number of multispectral indices targeted specifically for crop informatics.

A short flight can provide very many detailed images to be assembled using photogrammetry. The pixel to pixel combinations of these images create images encoded with NDVI values, such as this image in Figure 3.

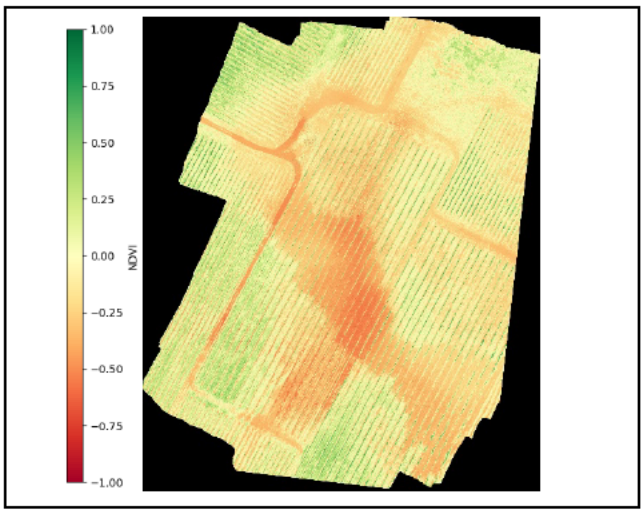

Fig. 3. NDVI Image of Client Vineyards from October 9th, 2019.

The redder regions in the image represent a negative NDVI value in that area. The greener areas, representing healthier, positive NDVI values. A challenge in analysis is posed by the inter-row areas that near the vines. This creates noise when trying to analyze the vines themselves.

Figure 3 indicates a large unhealthy section that begins at top left and stretches to the bottom right corner of the image. In meeting with the vineyard manager, the team verified that this is an area in the field suffering from erosion. Since more nutrient-right soil has been eroded, the vegetation in that area has suffered. This shows that this index has the ability to indicate areas of erosion as a secondary measure from plant health.

IV. Discussion and Conclusion

Using multispectral images collected by UAV's could provide significant support for farmers and vineyard managers. As these technologies continue to decrease in cost and availability to researchers and agricultural stakeholders alike, more diagnostic models can be developed for different applications, crops, and regions.

Access to this kind of data may help farmers plan for and manage their crops in different ways. Insights could be cross referenced with expert knowledge and physical testing. Additionally, there are a number of opportunities for adding sensor technology into vineyard fields in order to verify and augment multispectral data.

The project was successful in achieving its initial goals of creating a system that enabled the end user to evaluate the overall health of the vineyard and identify areas of concern. In a feedback session with an end user to review the web application and discuss features, the user indicated the usefulness of the web application both in visualizing the fields and in its potential to streamline crop management through its crop documentation features.

V. Future Work

One area of focus for future work for this project involves capturing and processing a complete data set for an entire growing season. Having that data could enable matching multispectral data with empirical health testing or expert health measurement. Exploring the temporal changes over a growing season could provide important insights for additional functionality to the web app.

Another area for future work is analysis of water saturation indices with known field conditions. After sufficient amount of field-report data is collected (i.e. with the field interface created in this project), further exploration could be done to analyze water saturation as determined through multispectral imaging. This information may be useful in predicting certain crop conditions based on multispectral imaging alone.

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