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Fiscal Optimization in Vineyards Using Computational Periodic Multispectral Visualization

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Abstract
Utilizing multispectral imaging, thermal entropy and interval imaging in viticulture offers a transformative approach for grapevine health assessment, asset protection, cost reduction and quality management. This technology allows for the extraction of key indices providing nuanced insights into plant vitality, soil conditions and waste reduction. This study delineates the process of computational interval imaging for early detection of diseases and pest infestations, and optimization of irrigation and nutrient strategies. The technology facilitates timely interventions, targeted resource allocation, and sustainable land management, aiming for economic gains, improved product quality and regulatory compliance.

1. Precision Agriculture

The utilization of multispectral imaging in assessing grapevine health signifies a transformative approach within the domain of viticulture. This technology is predicated on capturing images at various wavelengths beyond the visible spectrum, thereby enabling a more nuanced understanding of plant health than what can be detected by the human eye alone.

This concept is not new, with studies in California vineyards going back into the 1980s [1]. However, advances in low cost drones, sensors, and the rapid progression of image computing and AI have made it possible to access these benefits outside of the laboratory. Recent works have highlighted exciting potential in this area and this paper attempts to apply some of the more financially important concepts into practical use [2].

In essence, multispectral imaging allows for the extraction of specific indices, such as the Normalized Difference Vegetation Index (NDVI) or the Leaf Area Index (LAI), which are indicative of plant vitality. For instance, higher NDVI values generally correlate with healthier vegetation, revealing crucial insights into chlorophyll content, canopy density, and water stress levels.

One of the foremost applications of this technology is in the early detection of diseases and pest infestations. By identifying subtle changes in spectral reflectance, multispectral imaging can flag atypical plant behavior long before visible symptoms manifest. This early warning system permits timely intervention, thereby reducing the impact on yield and quality.

2. Significance

Ultimately, the motivation is to gain better control over economic and quality benefits. Vineyard management consists of numerous activities and there exists a large number of operations image computing can do for viticulture, including such topics as analysis of pruning, binding, shoot thinning, weeding, leaf thinning, topping, etc. Although these activities are of value, this paper will deal with larger issues specifically related to cost reduction and asset protection.

1. **Irrigation:** Targeted watering to avoid over-irrigation and water waste through analysis of organic matter content and moisture levels in the soil.
2. **Plant Stress:** Early detection of plant stress leading to informed decisions concerning fertilizer application for sustainable land management.
3. **Pesticides:** Targeted allocation of pesticides through identification and tracking of disease, insect and bird damage.
4. **Sun Exposure:** Optimization of leaf sun exposure through pruning, shoot and leaf thinning, binding and topping through the use of occlusion ratio calculations.
5. **Varietal Optimization:** Identification of grape varieties

within mixed blocks to aid in targeted care and differentiated harvest strategies based on grape variety.
6. **Efficacy Analysis:** Evaluation of the efficacy of agricultural practices implemented during a growing season using interval imaging.
7. **Harvest Review:** Post harvest analysis of picking efficiency, vineyard damage, and optimization opportunities to increase yield per acre.
8. **Long Term Planning:** Provides data for strategic planning for future growing cycles.

3. Irrigation

Multispectral imaging can also assist in optimizing irrigation strategies. By assessing the moisture content in the soil and leaves, vineyard managers can tailor their irrigation schedules to the specific needs of different sections within the vineyard. This leads to more efficient water usage, a critical consideration given the increasing scarcity and cost of this resource.

4. Soil Moisture

Thermal entropy is used to monitor soil moisture. We collect a baseline as a thermal imaging cleanplate with pixels (x_i, y_i) for new imagery rectified using homography with a measured soil moisture M. From this, we consider ambient temperature T, solar radiation R to evaluate the delta as:

$$\Delta M = (M - M_b) - \alpha (T - T_b) - \beta (R - R_b)$$

and when processed over the entire rectified image as:

$$\Delta M_{ij} = (M_{ij} - M_{b,ij}) - \alpha (T_{ij} - T_{b,ij}) - \beta (R_{ij} - R_{b,ij})$$

These deltas can then either be used in combination with a more formal Boltzmann equation from thermodynamics as $S = k \ln \Omega$, or statistically compared to field sampling (while still considering the logarithmic nature of thermodynamics) or turned over to a CNN using a loss function L as:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(F\left(T_{ij}, R_{ij}, L_{ij}, MC_{ij}; \theta\right) - M_{ij}\right)^2$$

For our work, the use of statistical data forms the short term baseline, the CNN the long term optimization and the Boltzmann equation as a heuristic constraint.

5. Leaf Moisture

Thermal entropy is not effective for leaf moisture and instead, multispectral imaging is employed. Although SWIR is capable, the high cost of these sensors motivates the use of 760 to 900 nm near-infrared (NIR) instead. Moist leaves absorb more NIR than dry ones. Since we need to compare our imagery to something, we normalize against 520 to 600 nm green and all values are reflectance R. This may be expressed as:

$$\text{NDWI}_{x_i,y_i} = \frac{(R_{\text{Green},x_i,y_i} - R_{\text{NIR},x_i,y_i})}{(R_{\text{Green},x_i,y_i} + R_{\text{NIR},x_i,y_i})}$$

Again, as with thermal soil entropy, we can use statistics or machine learning. However, it is not quite that simple.

6. Illumination Compensation

Challenges exist, such as the visibility of the internal shadow canopy which distorts key indicators. To resolve this, a scale-invariant feature transformation is used to normalize the aerial images [3]. The calculation of this involved a few steps and appears painful upon first glance. Let's dive into it, and you will see each step is manageable. Additionally, note that we use SIFT (Scale-Invariant Feature Transform) both here, as well as for feature matching in depth estimation below. Although not discussed here, this provides opportunities for reducing computational overhead.

6.1. Scale-Space Extrema Detection

This is the initial stage where SIFT looks for points over different scales and image locations. It uses a Gaussian blur $G(x, y, \sigma)$ and the Difference of Gaussians (DoG) to find potential interest points. The DoG is calculated as:

$$L(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x'^2 + y'^2}{2\sigma^2}} \cdot I\left(x - x', y - y'\right) dx' dy'$$

on image I and kernel G for pixels (x, y). The implementation for this involves solving the equation by repeating the equation for multiple values of σ.

6.2. Keypoint Localization

Once candidate keypoints are identified, SIFT performs a detailed fit to the nearby data for location, scale, and ratio of principal curvatures. This helps in eliminating edge responses.

The first-order derivatives are computed as:

$$\frac{\partial D}{\partial x} = \frac{D(x+1, y, \sigma) - D(x-1, y, \sigma)}{2}$$
$$\frac{\partial D}{\partial y} = \frac{D(x, y+1, \sigma) - D(x, y-1, \sigma)}{2}$$
$$\frac{\partial D}{\partial \sigma} = \frac{D(x, y, \sigma+1) - D(x, y, \sigma-1)}{2}$$

The second order partial derivatives are calculated as:

$$\frac{\partial^2 D}{\partial x^2} = D(x+1, y, \sigma) - 2D(x, y, \sigma) + D(x-1, y, \sigma)$$
$$\frac{\partial^2 D}{\partial y^2} = D(x, y+1, \sigma) - 2D(x, y, \sigma) + D(x, y-1, \sigma)$$
$$\frac{\partial^2 D}{\partial \sigma^2} = D(x, y, \sigma+1) - 2D(x, y, \sigma) + D(x, y, \sigma-1)$$

The cross partial

$$\frac{\partial^2 D}{\partial x \partial y} = \frac{D(x+1,y+1,\sigma) - D(x+1,y-1,\sigma) - D(x-1,y+1,\sigma) + D(x-1}{4}$$
$$\frac{\partial^2 D}{\partial x \partial \sigma} = \frac{D(x+1,y,\sigma+1) - D(x+1,y,\sigma-1) - D(x-1,y,\sigma+1) + D(x-1}{4}$$
$$\frac{\partial^2 D}{\partial y \partial \sigma} = \frac{D(x,y+1,\sigma+1) - D(x,y+1,\sigma-1) - D(x,y-1,\sigma+1) + D(x,y-}{4}$$

The Hessian Matrix, H can be written as:

$$H = \begin{bmatrix} \frac{\partial^2 D}{\partial x^2} & \frac{\partial^2 D}{\partial x \partial y} & \frac{\partial^2 D}{\partial x \partial \sigma} \\ \frac{\partial^2 D}{\partial x \partial y} & \frac{\partial^2 D}{\partial y^2} & \frac{\partial^2 D}{\partial y \partial \sigma} \\ \frac{\partial^2 D}{\partial x \partial \sigma} & \frac{\partial^2 D}{\partial y \partial \sigma} & \frac{\partial^2 D}{\partial \sigma^2} \end{bmatrix}$$

To eliminate the keypoints at the edges, the eigenvalues $\lambda_1, \lambda_2, \lambda_3$ of H are computed. A point is discarded if:

$$\min(|\lambda_1|, |\lambda_2|, |\lambda_3|) \times r < \max(|\lambda_1|, |\lambda_2|, |\lambda_3|)$$

where r is a constant, used to decide the ratio between the smallest and largest eigenvalues.

6.3. Orientation Assignment

An orientation is assigned to each keypoint to achieve invariance to image rotation. The local image gradient directions are sampled around each keypoint, and a histogram is formed from the gradient orientations.

Given a keypoint located at (x, y) in image I, and we let $L(x, y, \boldsymbol{\sigma})$ with an orientation of $\theta(x, y)$ be the scalespace representation (i.e., the image convolved with a Gaussian kernel of standard deviation $\boldsymbol{\sigma}$) of I.

The gradient magnitude M (x, y) and the orientation $\theta(x, y)$ at each image point in a neighboring region around the keypoint can be calculated as follows:

$$M(x,y) = \sqrt{\left(\frac{\partial L}{\partial x}\right)^2 + \left(\frac{\partial L}{\partial y}\right)^2}$$
$$\theta(x,y) = \tan^{-1}\left(\frac{\frac{\partial L}{\partial y}}{\frac{\partial L}{\partial x}}\right)$$

A histogram is then formed of the gradient orientations. Each sample in the neighborhood contributes to the histogram with a weight equal to its gradient magnitude. The histogram could be formed over 36 bins covering the 360-degree range of orientations. The highest peak in the histogram is detected, and any other local peak that is within 80% of the highest peak is also considered to compute an orientation. This leads to the assignment of one or more orientations θ_{keypoint} to each keypoint.

6.4. Keypoint Descriptor

Finally, local image gradients are measured at the selected scale in the region around each keypoint. These are then transformed into a descriptor that allows for significant levels of local shape distortion and change in illumination.

While the descriptor is mainly computed through algorithmic steps, the underlying mathematics involves capturing local image gradients in a region around each keypoint. These gradients are then transformed into a more stable form that serves as the descriptor. Here is an outline of the mathematical foundations of this step:

As above, let $L(x, y, \sigma)$ be the scale-space representation of the image at the keypoint's scale, and consider a $d \times d$ region around the keypoint. Typically $d = 16$. this region around a keypoint serves as the local area where gradient magnitudes and orientations are computed for feature descriptor creation. The choice of d determines the extent of the local neighborhood and is critical for capturing sufficient detail while also allowing for generalization. In standard implementations of SIFT, $d = 16$, which means a 16 x 16 square region is examined around each keypoint.

The d x d region is further divided into smaller regions, often *4 x 4*, and for each of these sub-regions, an orientation histogram is generated. The orientation histogram is typically constructed with 8 bins, capturing the frequency of occurrence of gradient orientations in the *4×4* sub-region. Each pixel's gradient within these sub-regions contributes to these histograms.

To elaborate, let's assume we are dealing with a 16×16 region for a particular keypoint. This region would then be broken down into sixteen 4×4 sub-regions. For each of these *4×4* sub-regions, gradient magnitudes and orientations are calculated at every pixel using the image's scale-space representation at that keypoint's scale, denoted as $L(x, y, \sigma)$.

As a reminder, the gradient magnitude $M(x, y)$ and orientation $\theta(x, y)$ are computed as follows (and should look familiar):

$$M(x,y) = \sqrt{\left(\frac{\partial L}{\partial x}\right)^2 + \left(\frac{\partial L}{\partial y}\right)^2}$$
$$\theta(x,y) = \tan^{-1}\left(\frac{\frac{\partial L}{\partial y}}{\frac{\partial L}{\partial x}}\right)$$

Each gradient's magnitude is then weighted by a Gaussian function centered on the keypoint, and this weighted magnitude is added to one of the 8 orientation bins in the histogram corresponding to its orientation. This process is repeated for each of the *4×4* sub-regions, resulting in a 128-dimensional feature vector (16 sub-regions × 8 orientation bins = 128 dimensions).

Thus, the $d \times d$ region plays a pivotal role in constructing a rich, yet compact, descriptor for each keypoint, providing a balance between local detail and broader contextual information.

For each of these subregions, an orientation histogram is created. The histogram has 8 bins, and each sample point (x, y) in the sub-region contributes to the histogram. The contribution is weighted by the gradient magnitude $M(x, y)$ and also by a Gaussianweighted circular window with a standard deviation of:

$$\frac{d}{2}, \text{ i.e., } e^{-\left(x^2+y^2\right)/2\sigma^2}.$$

The orientation histograms from all *4×4* sub-regions are concatenated to produce a *4×4×8=128*-element feature vector for each keypoint.

Mathematically, the descriptor D can be represented as a vector: $D = [H_1, H_2, \ldots, H_{16}]$, where each H_i is an 8-bin histogram from a *4×4* sub-region.

Normalization is performed on D to enhance invariance to changes in illumination: $D = \frac{D}{\|D\|}$

After normalization, any element in D greater than 0.2 is clamped to 0.2, and then D is normalized again to account for non-linear illumination effects.

Finally, we have normalized pixels we can work with, removing illumination effects. There is a nuance however, that should be considered. When processing occurs on aerial photography, we typically compose a single image from the image array. This image, a form of composited panorama, is a blend of many overlapping images. For any given pixel, we may not know sources contributing to any given pixel. Worse, typical image compositing programs determine source blend weights not on the value of the pixel, but on the quality of geometric fit. Many pixels will be unfit due to specular highlights, or dynamic range issues such as underexposure. Further, not all images will contain the same levels of noise, due to the angle of incidence with both the leaf and the sun, which can result in flare (contrast reduction), perspective warp or time of day. This blending function then:

$$I_{\text{final}}(x,y,z) = \text{blend}\left(I_1'(x,y,z), I_2'(x,y,z), \ldots\right)$$

should consider these factors for each pixel for every image I, to ensure the best results. I will not be covering this issue here, but will cover in a future article illustrating the experimental results. For now, let us dwell on the next issue at hand.

7. Occlusion

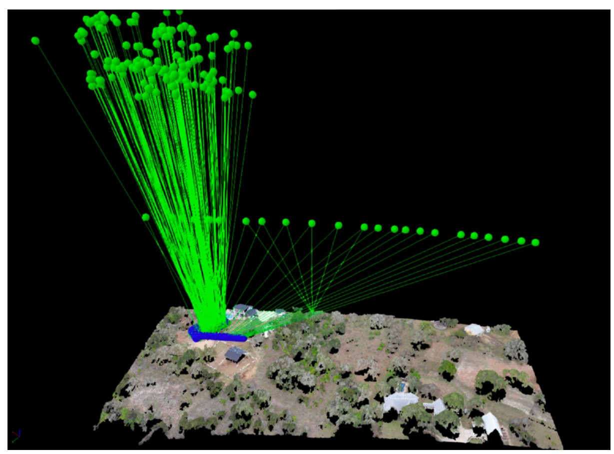
We need camera visibility to the soil, lower leaves, and other occluded objects. It is also important to understand leaf occlusion ratios to optimize pruning, shoot and leaf thinning, binding and topping.

To accomplish this, we use multiple camera positions to form a sparse, casual, and irregular imaging array. It is certainly possible to use a plenoptic sensor, but we typically use drones in vineyards [4]. As such, I prefer to program in flight paths to create the sort of array needed, rather than add the weight of plenoptics. The flight path, while preprogrammed, is still irregular due to the imprecision of GPS, wind-induced roll, and noise in the altitude estimations. The drone then, becomes a camera with an array of points, which we can call P which equals $\{(x_1,y_1,z_1),(x_2,y_2,z_2),\ldots,(x_n,y_n,z_n)\}$. The overall flight path we can represent as F, where:

$$F(t) = \begin{cases} f_1(t) & a_1 \le t < b_1 \\ f_2(t) & a_2 \le t < b_2 \\ \vdots & \\ f_n(t) & a_n \le t < b_n \end{cases}$$

and each $f_i(t)$ defines the path between $(x_{i-1}, y_{i-1}, z_{i-1})$ and (x_i, y_i, z_i) where (a_1, b_i) is the interval of time for the edge (or segment, depending on your perspective). Although the path $(x_{i-1}, y_{i-1}, z_{i-1}) \rightarrow (x_i, y_i, z_i)$ is not a straight line, but effectively a spline, we ignore this since we are only using photos taken at each (x_i, y_i, z_i). This gives us $\Delta x_i, \Delta y_i, \Delta z_i \sim \mathcal{N}(0, \sigma^2)$ where Δ is the randomness about the requested position and σ^2 is just how bad it is (the scale of randomness).

We could regularize the positions via some clever adjustments and homography, but in my experience, this creates poor results. Recent impressive research in Fourier ptychography looks promising, but I have opted for a more brute force approach using feature matching and mask generation aided by infill [5].



Scatter of Camera Positions

This synthetic setup requires us to perform four critical steps; feature matching, derivation of stereopsis for depth calculations, infill and mask generation.

7.1. Feature Matching

Feature detection involves identifying interesting points in an image where the local image gradient is high. In the case of SIFT, a Difference of Gaussian (DoG) scale-space is computed to identify potential keypoint locations.

The DoG is defined as:

$$D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y)$$

where $G(x, y, \sigma)$ is the Gaussian blur operator, k is the scale factor between images, $*$ is the convolution operator, and $I(x, y)$ is the image.

7.2. Feature Descriptor

After detecting the keypoints, each keypoint is assigned an orientation and descriptor based on the local gradient. For a given keypoint

p with coordinates (x, y) and a scale of σ, the gradient magnitude m and orientation θ can be computed as:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$
$$\theta(x,y) = \arctan 2(L(x,y+1) - L(x,y-1), L(x+1,y) - L(x-1,y))$$

The SIFT descriptor may be defined, like a convolution kernal, and is often large, as in 128 dimensional vector composed of 16x16 subpixles around the keypoint.

7.3. Feature Matching

Now that we have the descriptors D_A and D_B in two of the images A and B, we need to find the matching pairs. A simple way is to use Euclidean distance:

$$\text{Distance}\left(D_{A_i}, D_{B_j}\right) = \sqrt{\sum_{k=1}^{128}\left(D_{A_i}[k] - D_{B_j}[k]\right)^2}$$

A match is often considered good if the distance is below a certain threshold, or if it is the smallest distance among all possible matches and satisfies the ratio test:

$$\frac{\text{Distance}\left(D_{A_i}, D_{B_j}\right)}{\text{Distance}\left(D_{A_i}, D_{B_{j'}}\right)} < r$$

where r is the ratio of the second closest distance $D_{B_{j'}}$ to the closest distance. In our testing, I prefer to use the absolute smallest distance even though the computation time can be substantially longer.

7.4. Derivation of Stereopsis

Once we have our set of correlated points, we can calcuate the distance based on disparity. Without going into all the details of speciic lens calibration, we can simplify the concept by considering the focal length f, (X, Y, Z) the coordinates of the point P in world coordinates, and an inter-camera baseline distance of T. If we take $x_A = f\frac{X}{Z}$ and $y_A = f\frac{Y}{Z}$ for camera A and $x_B = f\frac{X-T}{Z}$ and $y_B = f\frac{Y}{Z}$ for camera B, we can then compute the disparity x_A - x_B as: $d = x_A - x_B = f\frac{T}{Z}$ or when rearranged in the more direct form $Z = f\frac{T}{d}$. It is more complex than this in practice due to sensor and lens issues, but this is gist of the concept.

In any case, we now have Z for each of our associated match points.

7.5. Infill

We now have a sparse matrix of points. This infill uses a nearest neighbor estimation, a bit like Shepard's algorithm, except more constrained to ensure multiple directions of the sample points [6]. Since the geometric selection process is easily imagined and experimentally derived, I will not work it out now. However, the overall process can be represented as:

$$\hat{M}(x,y) = \frac{1}{k} \sum_{(x_i,y_i) \in \arg\min} \sum_{\substack{(x_1,y_1),\ldots,(x_k,y_k) \\ \text{distinct points in Known Points}}} \sum_{i=1}^{k} \sqrt{(x-x_i)^2 + (y-y_i)^2}\, M(x_i, y_i)$$

where M is our mask at each pixel (x, y), averaged with a weight of k selected sample points weighted by Euclidean distance.

7.6. Mask Generation

The final step is to generate a mask to eliminate pixels which are out of the depth range of interest. This effectively removes occluding pixels. Earlier we discussed the process of multi-image blending and the importance of keeping pixels of value. Likewise, in this step we refer back to our overlapping image array. By backprojecting the final panorama to the source pixels, we can now include multiple pixels from multiple images to reveal differing angles of the subject of the pixel.

This process completes the exposure of the portions of plant or soil of interest. Now we have pixels of value, which have be illumination normalized, thermal normalized (if thermal pixels) and are ready for classification.

8. Plant Stress

Efficient identification and management of plant stress is essential for both economic and environmental sustainability. Stress can indicate a variety of facets, some of which are:

- **Abiotic Stress:** Non-living factors such as drought, extreme temperatures, soil salinity, and nutrient deficiencies.
- **Biotic Stress:** Living factors like pests, diseases (bacterial, fungal, viral), and competition from other plants for nutrients and light.
- **Mechanical Stress:** Physical damage, perhaps from machinery, wind, or pruning.
- **Chemical Stress:** Exposure to pollutants or toxic chemicals like herbicides, pesticides, or heavy metals.

9. Physiological Indicators

Physiological indicators are specific changes or responses exhibited by an organism due to various external or internal factors. Here are some examples of physiological indicators in plants that can manifest as stunted growth, reduced photosynthetic rate, altered nutrient uptake, and water stress symptoms:

9.1. Stunted Growth

Plants subjected to unfavorable growing conditions, such as nutrient deficiencies, extreme temperatures, or inadequate light, may exhibit stunted growth. This can be observed as reduced overall size, shorter internodes, and smaller leaves.

9.2. Reduced Photosynthetic Rate

Reduced photosynthetic rate can result from several factors, such as insufficient light, nutrient imbalances, or water stress. Plants experiencing reduced photosynthesis may show yellowing or browning of leaves, as chlorophyll production declines. Additionally, decreased photosynthetic rate may lead to reduced production of carbohydrates and subsequent impaired growth.

9.3. Altered Nutrient Uptake

Nutrient deficiencies or imbalances can disrupt the metabolic processes of plants. Common indicators of nutrient-related physiological abnormalities include yellowing or discoloration of leaves (chlorosis), necrosis (tissue death), or interveinal chlorosis (yellowing in between leaf veins) associated with specific nutrient deficiencies.

9.4. Water Stress Symptoms

Insufficient water availability or excessive water loss can lead to various symptoms of water stress in plants. These include wilting, where the plant becomes flaccid and droopy due to the loss of turgor pressure. Another symptom is leaf curling, where leaves may fold or roll to reduce water loss through transpiration. Additionally, severe water stress can result in leaf senescence (premature aging), leaf abscission (shedding), or even plant death.

10. Biochemical Indicators

Biochemical indicators are specific molecules or compounds that can be measured to assess the physiological responses of an organism to stress or environmental changes. Here are some examples of biochemical indicators in plants:

10.1. Stress Hormones

Increased production of stress hormones like abscisic acid (ABA): ABA is a plant hormone that regulates various physiological processes, including stress responses. In response to water stress or other abiotic stresses, plants often increase the production of ABA. The measurement of ABA levels in plants can indicate the degree of water stress or other stressors they are experiencing.

10.2. Altered Levels of Antioxidants

Environmental stresses, such as high light intensity, temperature extremes, or pollution, can induce the production of reactive oxygen species (ROS) in plants. To mitigate the damage caused by ROS, plants produce antioxidants such as ascorbic acid (vitamin C), glutathione, and enzymes like superoxide dismutase (SOD) and catalase. Measurement of antioxidant levels and activities can provide insights into the oxidative stress and overall plant health.

10.3. Osmolytes or Stress Proteins

Osmolytes are small organic compounds that help plants cope with osmotic stress, such as drought or salinity. Examples of osmolytes include proline, glycine betaine, and sugars. Their accumulation can serve as indicators of stress tolerance and adaptation. Additionally, stress proteins, like heat shock proteins (HSPs), are produced in response to various stresses and help protect the plant's cellular structures and proteins. Increased levels of osmolytes or stress proteins can be measured to assess the plant's response to stress.

11. Morphological Indicators

Morphological indicators are physical characteristics or changes in the structure of an organism that can indicate stress or abnormal development. Here are some examples of morphological indicators in plants:

11.1. Leaf Discoloration (Chlorosis)

Chlorosis refers to the yellowing or whitening of plant tissues, usually due to a lack of chlorophyll. Chlorosis can be caused by various factors, including nutrient deficiencies (e.g., iron or magnesium), pH imbalances in the soil, or diseases. Observing leaf discoloration can provide valuable information about the plant's nutrient status and overall health.

11.2. Necrosis (Localized Cell Death)

Necrosis manifests as dead or brown tissue in plant organs, such as leaves, stems, or roots. It can be caused by various stresses, including extreme temperatures, pathogen attacks, or physical injuries. Necrotic areas can provide clues about the specific stressors affecting the plant and help in identifying potential management strategies.

11.3. Abnormal Root Development

Roots play a vital role in plant anchorage, water uptake, and nutrient absorption. Stressful conditions, such as waterlogging, drought, or nutrient imbalances, can lead to abnormal root development. This may include stunted root growth, lateral root proliferation, or the presence of adventitious roots (roots forming on non-root tissues). Studying root morphology can provide insights into the plant's ability to cope with environmental conditions.

12. Spectral Indicators

Change in reflectance patterns detected through imaging technologies like multispectral or hyperspectral imaging, useful in precision agriculture.

Spectral indicators are derived from analyzing the electromagnetic radiation reflected or emitted by an object across different wavelengths. In the context of plants, spectral indicators can provide insights into their physiological and biochemical status. Here are some examples of spectral indicators in plants:

12.1. Reflectance Patterns

Reflectance patterns, obtained through techniques like multispectral or hyperspectral imaging, can reveal variations in light reflectance at different wavelengths. These variations are influenced by the properties of plant tissues, such as chlorophyll content, leaf structure, and water content. By analyzing reflectance patterns, researchers can identify spectral indices (e.g., normalized difference vegetation index, chlorophyll index) to assess plant health, stress levels, or nutrient status.

12.2. Absorption Features
Plants have characteristic absorption features in their reflectance spectra due to specific pigments, biochemicals, or water content. For instance, chlorophyll absorbs light strongly in the blue and red regions, resulting in lower reflectance in those wavelengths. Spectral analysis can help detect abnormal absorption patterns, indicating potential stressors like nutrient deficiencies or disease.

12.3. Fluorescence Emissions
Plants emit fluorescence, mostly in the red and farred regions, when they absorb light during photosynthesis. The intensity and pattern of fluorescence emissions can be indicators of stress, such as excessive light exposure or nutrient imbalances. Fluorescence spectroscopy can be used to measure fluorescence signals and derive parameters like the photochemical reflectance index (PRI) or the steady-state chlorophyll fluorescence yield (Fs).

13. Calculation
In leaf moisture, we use ratios of NIR and green. For plant stress, the most common method is the Normalized Difference Vegetation Index (NDVI) which looks at NIR versus 630 to 680 nm red. Higher NDVI values typically indicate healthier vegetation, as they reflect higher chlorophyll content and, thus, photosynthetic activity. Chlorophyll, the pigment responsible for photosynthesis, absorbs light most efficiently in the red band, whereas cell structure in leaves tends to scatter light in the near-infrared band. Therefore, a healthy, vigorously photosynthesizing plant will absorb more red light and reflect more near-infrared light, resulting in a higher NDVI value. The equation is simple and is:

$$\text{NDVI} = \frac{(NIR - Red)}{(NIR + Red)}$$

Field calibration is necessary due to soil background interference (and atmospheric interference in high altitude imaging). Although research has produced modified indices like the Soil-Adjusted Vegetation Index (SAVI) and the Enhanced Vegetation Index (EVI) that attempt to correct for these, field calibration appears more defensible, especially when combined with AI.

14. Nutrient Allocation
Resource allocation is another dimension where multispectral imaging can reduce cost and increase plant health [7]. By ascertaining the health and needs of individual grapevines, viticulturists can allocate resources more efficiently. For example, areas that exhibit signs of nutrient deficiency can be specifically targeted for fertilization, obviating the need for blanket applications that could be both wasteful and environmentally detrimental.

15. Pesticides
Computational imaging identifies pest management needs based on atypical reflectance patterns in plants, which can signify early stages of disease or pest infestation. The early detection allows for timely intervention, thus minimizing the impact on yield and quality.

Pest infestations also leave unique signatures on plant physiology. Similar to diseases, the stress induced by pests leads to alterations in the plant's typical reflectance in certain spectral bands. This altered state is readily captured through multispectral imaging. In many instances, the pest-induced damage is localized, affecting specific regions of the plant. Identification of these regions becomes easier with high-resolution imaging, thus allowing for more targeted interventions like localized pesticide application.

16. Principal Component Analysis (PCA)
PCA is a statistical method that reduces the dimensionality of the data by transforming it into a smaller set of uncorrelated variables called principal components. In the context of reflectance patterns, PCA can be used to identify the combination of wavelengths that contribute the most to the variation in the reflectance spectrum. By analyzing the loading values of the principal components, we can determine which wavelengths are responsible for the observed patterns.

PCA can be particularly useful for analyzing atypical reflectance patterns because it allows for the identification of underlying factors causing the variation. In this way, PCA can be used to catalog unique reflectance signatures. Beyond just snapshot assessments, multispectral imaging offers the advantage of high-resolution spatial and temporal mapping. This involves capturing data at various time intervals to monitor changes in plant health over time. Such time-series analysis can track the progression of a disease or the efficacy of a treatment strategy [8].

Fourier Space Conversion

To accomplish this, a Fourier transform is created from the input image $I(x, y)$ to its frequency form $F(u, v)$ as:

$$F(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I(x,y)e^{-i2\pi(ux+vy)}dxdy$$

16.1. Data Matrix Vectorization
This image, $F(u, v)$ is then vectorized into a 1D vector $\vec{f}$ as $\vec{f} = \text{vec}(F(u,v))$. We then take our time domain image sequence and organize it into a matrix as:

$$\mathbf{X} = \begin{pmatrix} -\vec{f}_1- \\ -\vec{f}_2- \\ \vdots \\ -\vec{f}_n- \end{pmatrix}$$

where now each column represents a feature in frequency space.

16.2. Mean Centering in Fourier Space
We will mean center X to ensure that the principal components are truly orthogonal and capture directions of maximum variance, rather than being influenced by the mean. Mean centering also reduces the effect of highly correlated variables. Multicollinearity can create complications, making it difficult to ascertain the individual

effect of each predictor on the response variable. Specifically, multicollinearity can result in unstable estimates of regression coefficients, where slight changes in the data can lead to significant shifts in the model parameters. Consequently, the interpretability of individual predictors becomes problematic. Mean centering, which involves subtracting the mean of each variable from each of its data points, shifts the data distribution such that its mean becomes zero. While mean centering facilitates interpretability and reduces numerical instability in some statistical calculations, it does not alter the inherent relationships between variables; the correlations between them remain unchanged. Although there are other methods to reduce multicollinearity, such as variable inflation factors or ridge regression, we have chosen to simplify the current work using mean centering until other techniques may be required [9,10].

16.3. Covariance Matrix

The covariance matrix C of the mean centered data X_{centered} is then calculated as:

$$\mathbf{C} = \frac{1}{n} X_{\text{centered}}^{T} X_{\text{centered}}$$

16.4. Eigenvalue Decomposition

Next, the eigenvalue decomposition of the covariance matrix is performed to identify the principal components of the data. This step involves finding the eigenvalues λ and the corresponding eigenvectors of the covariance matrix C which contains our features as $\mathbf{Cv} = \lambda \mathbf{v}$.

Our eigenvectors determine the directions of maximum variance in a dataset, while eigenvalues express the magnitude or amount of variance along those directions. The larger the eigenvalue, the greater the amount of variance explained by its corresponding eigenvector. By analyzing the eigenvectors and eigenvalues, we can gain insights into the most significant patterns and trends in the data.

These signatures then, allow for early detection. Early detection equips growers with the information necessary for timely interventions, thereby helping to mitigate adverse impacts on yield and crop quality. Moreover, by identifying only those areas requiring treatment, multispectral imaging facilitates a more efficient and targeted allocation of resources like pesticides. This, in turn, aligns well with the goals of sustainable agriculture by minimizing waste and reducing the environmental impact.

16.5. Regulatory Impact

Targeted allocation of pesticides can help in meeting regulatory requirements. By utilizing precise and strategic application of pesticides, it becomes possible to minimize their overall usage while still effectively managing pests and complying with regulations.

Targeted allocation involves identifying and applying pesticides only in areas where they are needed, such as areas with high pest populations or specific problem areas. This approach ensures that the pesticides are used efficiently and minimizes cost, as well as their impact on non-target organisms and the environment. By reducing overall pesticide usage, targeted allocation can help meet regulatory requirements that aim to protect human health, safeguard ecosystems, and minimize the residues of pesticides in food and water sources.

16.6. Pesticide Resistance

The judicious allocation of pesticides is integral to sustainable pest management, mitigating the onset of pesticide resistance among targeted pests. Indiscriminate or excessive application of pesticides fosters rapid adaptive responses in pest populations, compromising the efficacy of existing chemical solutions. Such practices necessitate the deployment of increasingly potent, and potentially more hazardous chemicals, with deleterious consequences for product quality, environmental integrity, and human health.

By employing targeted allocation, the exposure of pests to chemical agents is minimized, thereby attenuating the selective pressure that drives resistance [11]. This judicious approach enhances the longevity of current pesticide formulations, delaying the need for stronger alternatives. Moreover, the incorporation of computational imaging techniques affords agricultural practitioners the ability to assess the effectiveness of alternative pest control methodologies. These include biological controls, crop rotation strategies, and integrated pest management systems. Such evaluations enable a reduction in overall pesticide reliance, thereby contributing to the sustainable management of pest populations.

Thwarting the development of pesticide resistance is of paramount importance for the longevity of effective pest management strategies. The integration of targeted pesticide allocation and computational imaging technologies aids sustainable agricultural practices, with consequent benefits for both ecosystem health and agricultural yield.

17. Sun Exposure Ratios (SER)

Sun exposure ratios (SER) are quantified by evaluating the proportion of exposed to occluded leaves, employing the stereopsis method delineated above. Monitoring the SER throughout the growing season serves as an instrumental tool within the realm of precision agriculture.Sunlight exposure is an essential variable in grapevine cultivation that directly impacts grape quality, yield, and overall vine health. The Sun Exposure Ratio (SER) in grapevines is a critical metric used to quantify the amount of sunlight received by the grape clusters and leaves. This ratio is pivotal in understanding the microclimate around the vine and is instrumental in shaping viticultural practices.

Sunlight plays a critical role in photosynthesis, the process by which plants convert light energy to chemical energy in the form of glucose, while concurrently generating oxygen. Adequate sun exposure is vital for optimal photosynthetic rates, which in turn affects the accumulation of sugars, acids, and other metabolites in grape berries. These biochemical constituents are integral to the taste, aroma, and mouthfeel of the resulting wine or grape products.

Furthermore, sunlight exposure can significantly influence the temperature and relative humidity around the grape clusters, thereby affecting transpiration rates and moisture content. This has implications for vine stress levels and susceptibility to various diseases and pests. For example, inadequate sunlight can create a humid environment that is conducive to the proliferation of fungal diseases, such as powdery mildew or botrytis. Conversely, excessive sunlight can result in sunburned grape clusters, leading to diminished quality and economic losses.

Sun Exposure Ratios can be systematically adjusted through various viticultural techniques like canopy management, which includes leaf thinning, shoot positioning, and pruning. By manipulating the vine canopy, viticulturists can optimize the microclimate to maximize grape quality. Additionally, SER data can guide the targeted application of inputs such as water and fertilizers, aiding in sustainable land management practices.

18. Varietal Optimization

In vineyards characterized by varietal heterogeneity, the application of a uniform management strategy is intrinsically suboptimal. Utilizing computational imaging and machine learning algorithms offers a quantifiable and objective method for identifying the unique needs of each grape variety, thereby facilitating the customization of management practices. Different grape varieties often exhibit distinct phenological characteristics, including but not limited to, bud break, flowering, fruit set, and ripening. These require tailored approaches for optimizing growth conditions such as irrigation schedules, nutrient applications, and pest management strategies. Advanced soil sensors and aerial imaging can aid in mapping these varietal differences within the vineyard, allowing for targeted treatments.

Varietal mixes can complicate the overall canopy management strategy. Practices like pruning, shoot thinning, and leaf removal might need to be adjusted on a varietal basis to achieve desired levels of sun exposure, which in turn affects fruit composition and ultimately wine quality. Utilizing computational imaging and data analytics, it becomes possible to quantify the canopy structure and optimize these practices for each varietal.

Each grape variety may have specific susceptibilities to diseases and pests, necessitating a more nuanced approach to pesticide and fungicide application. Here, early detection technologies such as multispectral imaging can identify atypical reflectance patterns, signaling the early stages of disease or pest infestation. This allows for the targeted allocation of pesticides and fungicides, reducing waste and environmental impact while preserving the efficacy of these treatments over time.

Finally, harvest time can vary between different grape varieties, and thus it becomes imperative to employ data analytics to schedule the optimal harvest time for each varietal based on factors like sugar levels, acidity, and tannin content. This enables a differentiated harvest strategy that maximizes both yield and quality.

The optimization of growth management in vineyards with varietal mixes necessitates a data-driven, highly individualized approach which can benefit from imaging, sensing, and data analysis. By doing so, growers can achieve an estate specific management strategy that enhances both the economic viability and environmental sustainability of their operations.

19. Efficacy Analysis

In viticulture, the application of interval imaging offers a temporal based method for evaluating various aspects of grapevine health, growth, and management practices. This technique captures images of the vineyard at regular intervals, thereby allowing for longitudinal assessments that can provide valuable insights into the efficacy of management strategies and environmental influences over time.

Interval imaging builds on top of multispectral or hyperspectral imaging. While the latter are adept at capturing spectral information at a single point in time, interval sequences can offer a dynamic view of phenological changes and responses to interventions, such as irrigation, fertilization, and pesticide application.

For example, following a specific irrigation or fertilization event, interval imaging can track the grapevines' phenological response, such as leaf expansion or fruit development, over an extended period. This can help viticulturists determine the efficacy of these interventions, and whether adjustments need to be made in the scheduling or quantity of future applications.

Additionally, interval imaging can assist in the early detection of biotic or abiotic stress factors, such as disease or nutrient deficiencies, before they manifest into more severe conditions that may require costly and potentially environmentally detrimental interventions. In terms of pest management, an interval series can provide evidence of pest activity or its effects, such as leaf damage, that may be too subtle to detect through less frequent observations. Such data can contribute to more timely and targeted pesticide applications, thereby enhancing both economic and environmental sustainability.

Furthermore, interval imaging can be a useful tool in hypothetical simulations for the financial investigation of grapevine physiology and behavior under different management conditions. These datasets can serve as empirical foundations upon which more predictive and prescriptive models can be developed, thereby contributing to the broader objectives of precision agriculture in viticulture.

Overall, the incorporation of interval imaging into viticultural practices can offer substantive insight in terms of monitoring, analysis, and optimization of various aspects of vineyard management. The longterm visual data generated can serve as an invaluable resource for practical management and marketing, facilitating a more nuanced understanding of grapevine dynamics and their response to managerial actions.

20. Long Term Planning

Moreover, interval imaging can serve as a robust framework for training artificial intelligence systems. Through the use of machine learning algorithms or other statistical methods, one can simulate the longterm outcomes of different management strategies based on the historical data collected. This enables vineyard managers to make more informed decisions about future budgets, yield predictions, resource allocation, cultivation practices, and even varietal selection for future planting, thereby optimizing for yield, quality and profitability in the long term.

For example, if interval imaging data show that a particular section of the vineyard consistently suffers from water stress, long-term planning may involve redesigning the irrigation system specifically for that area or altering the grape varieties planted to those that are more drought-tolerant. Alternatively, if the data indicate periodic outbreaks of a particular pest, preemptive and targeted pest control measures can be planned for future growing cycles.

21. Additional Sensors

In viticulture, optimizing grape quality and yield while maintaining sustainable practices often requires a nuanced understanding of multiple environmental variables. The incorporation of sensors to measure soil moisture, carbon dioxide levels, and volatile organic compounds (VOCs) represents a significant advancement in precision agriculture, enabling vineyard managers to make data-driven decisions that can positively impact both the crop and the environment.

22. Overview

Monitoring soil moisture levels is critical for efficient irrigation management. Overwatering can lead to root diseases and diluted fruit flavors, whereas underwatering may stress the vines, reducing yield and affecting grape quality. Soil moisture sensors provide real-time data, allowing for dynamic irrigation scheduling that can conserve water while optimizing vine health.

Carbon dioxide is a key component in the process of photosynthesis. Elevated CO_2 levels can indicate issues with soil respiration or may signify that certain management practices, like cover cropping or tillage, need to be adjusted. Monitoring CO_2 can provide insights into vineyard soil health, vine stress levels, and overall canopy vigor, which are vital parameters for grape quality. Volatile organic compounds play complex roles in plant health and pest management. They can attract or repel insects, serve as early indicators of disease, and may even influence the grape's flavor profile. Sensors that monitor VOC levels can provide a nuanced understanding of the vineyard's phytosanitary status and help implement timely interventions.

23. Carbon Dioxide & Soil Moisture

Monitoring carbon dioxide levels serves as an essential practice in viticulture for several reasons, contributing to both the optimization of vineyard management and the enhancement of grape quality. Elevated levels of carbon dioxide can directly influence plant physiology, affecting processes such as photosynthesis, transpiration, and stomatal conductance. These physiological changes can, in turn, impact the growth rate, yield, and overall health of grapevines.

Furthermore, elevated carbon dioxide levels can serve as an early warning indicator for certain detrimental conditions. For instance, high levels of carbon dioxide might suggest poor soil respiration, possibly due to waterlogged conditions, which could subsequently lead to root health issues. In large vineyards, localized monitoring of carbon dioxide can aid in the spatial allocation of resources, allowing viticulturists to pinpoint specific areas that may require attention, thereby enabling more targeted and efficient management practices. Perhaps most importantly however, carbon dioxide levels are cross checked against multispectral and thermal data to validate and fine tune results.

24. VOC Sensors Detail

During grape production, volatile organic compounds (VOCs) serve various essential functions, from plant signaling to interacting with biotic and abiotic stressors in the vineyard. VOCs emitted by grapevines are not merely byproducts but often act as key communicative signals in plant-plant and plant-insect interactions. For example, they can attract beneficial insects that prey on vineyard pests or deter herbivorous insects from feeding on grape leaves or fruit. Furthermore, specific VOCs may serve as markers for the onset of diseases or environmental stress conditions, allowing for more targeted and timely interventions.

The grapevine's VOC profile can also be indicative of its overall health and nutritional status. Stressors such as drought, extreme temperatures, or nutrient deficiencies can alter the VOC profile, serving as early indicators that may prompt preemptive management actions. For instance, an increase in certain stress-related VOCs could trigger more frequent irrigation or the application of specific nutrients to address a detected deficiency.

Moreover, soil microorganisms produce their own set of VOCs, which can impact grapevine health either positively or negatively. Some soil-borne VOCs promote plant growth and resilience, whereas others may inhibit growth or attract subterranean pests. Understanding the interactions between root systems and soil VOCs can offer insights into optimizing vineyard soil health and, by extension, grape quality.

From a viticultural perspective, grape varieties possess distinct VOC profiles, which can influence both their resistance to particular diseases and pests and their ultimate flavor profiles in wines. Therefore, the selection of grape varieties in a vineyard might be based, in part, on VOC analysis to match ecological conditions and desired wine characteristics.

25. Machine Learning

Through the use of machine learning, long term data collection continues to increase the precision of prediction. Machine learning algorithms are designed to analyze large amounts of data and identify patterns that can be used to make accurate predictions. As long-term data collection becomes more extensive, machine learning models have access to more data and can refine their predictions over time.

One of the main advantages of machine learning is the ability to continuously learn and improve from new data. With each new data point collected, machine learning algorithms can adjust their models and update their predictions. As a result, the precision of predictions increases over time as more data becomes available.

Additionally, machine learning models can also take advantage of historical data to make predictions. By analyzing past trends, patterns, and behaviors, these models can uncover insights that can help in making accurate predictions for the future. The more historical data that is collected and fed into the machine learning algorithms, the better they become at predicting outcomes.

Furthermore, machine learning can also identify complex relationships and interactions within the data that might not be apparent to humans. By automatically analyzing vast amounts of data, machine learning algorithms can uncover hidden patterns and correlations that can significantly enhance prediction accuracy.

26. Vineyard Management System

Finally, the data derived from multispectral imaging can be integrated into a comprehensive vineyard management system. Through the application of machine learning algorithms and data analytics, the imaging results can be used to predict yields and optimize harvest timings, ultimately maximizing both the quantity and quality of grape production.

When using computational imaging, the core of vineyard management can become monitors showing real-time situation displays highlighting estate condition. Visualizations are typically in the form of color overlays on aerial photography. The photography itself may be overlaid with fence lines, roads, boundaries and instructive interactive icons. In our work, click the icons can bring up important information specific to the location.

27. Visualization

Color overlays on vineyards can be a useful tool for providing a quick and realtime assessment of the estate's status. By layering color overlays onto aerial images of the vineyard, it becomes easier to identify and analyze various conditions and factors influencing the vineyard's health and productivity.

For instance, using color overlays can help identify areas of stress or disease in the vineyard. Different colors can be assigned to indicate different levels of stress or disease severity. This allows vineyard managers to quickly identify and prioritize areas that require attention, such as irrigation or pest control.

Color overlays can also be used to assess the uniformity of vine health and growth across the estate. For example, areas with lush green color may indicate healthy and vigorous growth, while areas showing yellow or brown hues may suggest nutrient deficiencies or water stress.

Additionally, color overlays can help monitor vineyard management practices and interventions. By comparing color overlays over time, it becomes possible to analyze the impact of specific actions, such as pruning or fertilization, on the vineyard's overall health and productivity.

Furthermore, color overlays can aid in identifying specific grape varieties or vineyard blocks. By associating different colors or patterns with different grape varieties, vineyard managers can quickly and easily locate specific vines or areas.

28. Temporal Context

The visualization of baselines, although useful, is not the ultimate goal. It is the display of changes in plant and soil health that bring the primary benefits. The ability to scroll through time, to see the dynamic nature of the precision agriculture, as well as long term trends can bring awareness not possible without the benefit of time lapse sensor data viewing.

The value of time-lapse for agriculture is not new, but it is surprisingly uncommon, especially when fused with multispectral and thermal sensing. In the 1960's, time-lapse was use to understand insect damage to corn crops [12]. However, the most common uses are macroscopic in nature , not monitoring the entire crop [13]. Ironically, some of the most advanced uses of time-lapse related to plants are by geologists, who want to understand how plants impact geophysical surveys in the search for oil, which is of little benefit to growers [14].

29. Data Driven Investigation

Time matters in vineyards and data driven investigation can optimize the use of limited personnel over large areas. Immediate investigation in vineyards is of critical importance for several reasons:

29.1. Disease and Pest Management

Vineyards can be prone to various diseases and pests that can spread rapidly if not identified and addressed promptly. Immediate investigation allows for early detection of any signs of disease or pest infestation, enabling vineyard managers to implement timely control measures, such as targeted spraying or removal of infected plants. This helps prevent the spread of diseases and minimizes potential crop loss.

29.2. Nutrient Imbalances
Identifying and addressing nutrient imbalances in vineyards is vital for maintaining optimal plant health and maximizing grape quality. Timely investigation allows for regular monitoring of nutrient levels in the soil and plant tissue. If deficiencies or excesses are identified, appropriate corrective measures, such as fertilizer application or soil amendments, can be implemented promptly to ensure the vines receive the necessary nutrients for healthy growth and fruit development.

29.3. Water Management
Efficient water management is crucial for vineyard sustainability and productivity. Immediate investigation helps monitor soil moisture levels, identify irrigation system issues, or detect water stress symptoms in the vines. By promptly investigating and addressing any water-related problems, vineyard managers can ensure proper hydration of the vines, prevent costly water waste, and optimize resource use.

29.4. Environmental Factors
Vineyards are exposed to various environmental factors such as extreme weather events, frost, hail, or heatwaves, which can have detrimental effects on grapevines. Immediate investigation allows vineyard managers to assess the impact of these factors on the vineyard and take swift action to minimize damage or implement protective measures. This can include deploying frost protection systems, providing shade, or implementing canopy management practices to mitigate the effects of extreme heat or sunburn.

29.5. Yield and Quality Optimization
Prompt investigation allows vineyard managers to identify and address any factors that may compromise yield and grape quality. This includes issues such as uneven ripening, uneven vine vigor, or fruit size variations. By identifying and addressing these issues immediately, vineyard managers can implement corrective measures, optimize vineyard management practices, and ultimately enhance yield quantity and quality.

30. Hardware Considerations Dynamic Image Capture
Live capture of vineyards is facilitated with a combination of aerial drones and fixed canopy cameras. The use of speciality cameras for multispectral and thermal imaging is employed. The multispectral camera hardware is designed as an array with varied narrow bandpass filters, while the thermal sensor operates at 7.5–14 µm. The resolution of the cameras is a tradeoff between imaging distance, optics and cost.

31. Dynamic Sensor Capture
To maximize machine learning, the use of soil moisture and gaseous sensors for carbon dioxide and VOC sensors is ideal. These sensors are instrumental for feature extraction in unsupervised machine learning algorithms. To facilitate communication, the sensors may be attached to an embedded SOC processor, operate off solar power and use LoRa for long distance communications.

32. Static Data Capture
Terrestrial LiDar is used to initially capture a clean plate of the vineyard. Multiple scans are registered and are used to build up point clouds with visibility captured from many positions.
This collected LiDAR data is then processed to create a detailed and accurate three-dimensional representation of the vineyard. This information can be used for a variety of purposes, such as vineyard management, crop yield estimation, and precision agriculture.

The terrestrial LiDAR system works by emitting laser beams and measuring the time it takes for the beams to return to the sensor after hitting objects in the environment. By capturing multiple scans from different positions, the system can gather data from various angles and perspectives, improving the overall visibility and accuracy of the point cloud representation.

Once all the scans are registered, meaning they are aligned and integrated into a single coordinate system, the point cloud is generated. This point cloud consists of millions of individual points, each representing a specific location in the vineyard. These points contain information about their spatial coordinates (x, y, z) and can also include additional attributes such as color or intensity.

The resulting point cloud can then be used for further analysis and visualization. For example, it can be used to identify and classify different objects in the vineyard, such as grapevines, rows, or structures like buildings or equipment. By analyzing these objects, vineyard managers can gain insights into the health and growth of the vines, identify potential issues or areas that require attention, and make informed decisions to optimize their operations.

33. Communications
For most sensor projects, our lab uses LoRa (Long Range) digital wireless data communication technology that enables long-range transmissions with low power consumption. Utilizing a proprietary spread spectrum modulation technique derived from chirp spread spectrum (CSS) technology, LoRa facilitates secure, bi-directional communication and is particularly useful in instances where both power efficiency and long-range capability are required. The purpose of the CSS implementation is to disperse the energy of a signal across a broader bandwidth than is strictly necessary for coherent communication. This diffusion is achieved by varying certain parameters of the signal, thereby rendering it more resistant to noise, interference, and unauthorized interception. The central premise of spread spectrum modulation is to utilize a bandwidth that exceeds the minimum required for transmitting the information.

LoRa operates at 915 MHz for North America under FCC Part 15, and its architecture comprises two main components: the LoRaWAN network protocol and the LoRa physical layer. The LoRaWAN protocol defines the communication protocol and system architecture for the network, whereas the LoRa physical layer specifically deals with the modulation aspect of the actual RF communication.

LoRa technology is already used in smart agriculture and is increasingly common for remote monitoring and control applications where existing network infrastructure is lacking, and the deployment of new connections would be economically unfeasible.

Given its capacity for long-range communication with relatively low power usage, LoRa is particularly advantageous for this application, which supports real-time monitoring and communication over large geographic areas.

34. Processing

This process is data and computation intense. As such the core code was written in GLSL to run on GPUs. The front end and data management is written in Java. Both languages were selected to assist in OS portability.

34.1. GLSL

The Graphics Library Shader Language (GLSL) offers a host of advantages that cater to the needs of contemporary computer graphics programming. One of the most crucial advantages lies in its capacity to give developers direct control over the graphical processing unit (GPU). This enables more sophisticated effects and computations to be executed directly on the GPU, resulting in a substantial speedup, as GPUs are highly optimized for parallel computation.

In addition to direct control, GLSL facilitates hardware acceleration for graphical computations. By allowing the hardware to perform what it is optimized for, GLSL enhances performance and speeds up rendering times, particularly in comparison to CPUbound operations.

While being close to the hardware, GLSL still maintains a high level of abstraction. The language abstracts many of the complexities associated with lowlevel hardware manipulation, making it accessible even for developers who are not experts in graphics hardware. Moreover, its compatibility with any hardware that supports OpenGL ensures portability across different systems and graphics hardware.

GLSL enables the programmability of the graphics pipeline. Developers can write custom vertex, geometry, and fragment shaders, thereby gaining granular control over how objects are rendered on the screen. This control is not confined to static instances; realtime modifications can be made. Graphical effects like lighting, shadowing, and texture mapping can be dynamically adjusted based on real-time input or computations.

On the subject of code structure, GLSL's modularity allows shaders to be compiled independently and linked together at runtime. This contributes to greater flexibility and reusability of code. Furthermore, its capacity for parallel execution is particularly suited for the parallel architecture of modern GPUs. Each shader operates independently on individual pieces of data, making the language inherently parallel.

GLSL is not merely functionally robust but also syntactically strong. It has a C-like syntax and features strong typing, which adds an additional layer of error prevention and enhances code reliability. This is especially important in complex graphics applications where computational precision is a priority. The language also incorporates a rich set of built-in mathematical functions that simplify the process of creating intricate graphical effects.

Finally, the development environment for GLSL is typically equipped with robust tools for debugging and profiling. This enables effective optimization and expedites the problem-resolution process, further contributing to the language's appeal for developers.

Thus, GLSL brings together an amalgamation of control, efficiency, and flexibility, thereby serving as an invaluable asset in the realm of computer graphics programming.

34.2. Java

Java is a high-level programming language that has been widely adopted for its distinct features and capabilities, which make it advantageous for a broad range of applications, from web-based to enterpriselevel systems.

One of the primary advantages of Java is its platform independence. The Java Virtual Machine (JVM) interprets compiled Java code, allowing the same program to run seamlessly on various operating systems without modification. This write-once, run-anywhere (WORA) philosophy significantly aids in software portability and reduces the costs and efforts associated with software deployment across heterogeneous systems.

Concurrency is another domain where Java excels. It has a robust, built-in model for multithreading, allowing for application development with improved responsiveness and performance. This makes Java particularly useful for server-side applications where multiple clients may be interacting with the application concurrently.

Security is a critical concern in modern software development, and Java addresses this by incorporating a comprehensive security model. It includes features like runtime security checks and an extensive set of APIs that provide cryptographic operations, secure communication, authentication, and access control. This robust security framework makes Java an attractive choice for developing secure applications.

Java also boasts an extensive standard library, which provides pre-compiled classes and methods for tasks ranging from network communication and database connectivity to user interface development. This significantly accelerates the development process, allowing developers to focus on implementing business logic rather than "reinventing the wheel."

Additionally, the object-oriented nature of Java fosters code reusability and maintainability. It encourages developers to follow best practices and design patterns, making it easier to build scalable and maintainable applications. The type-checking mechanism of the Java compiler also aids in identifying errors at an early stage, reducing the debugging time.

Software development in Java is further facilitated by a rich ecosystem of Integrated Development Environments (IDEs), frameworks, and libraries, which enhance developer productivity. Robust tools for profiling, debugging, and automated testing are available, allowing for effective and efficient development cycles. The combination of Java and GLSL produces high performance, highly portable applications.

35. Future Research

Multispectral imaging and thermal entropy has its limitations, especially in the realm of biochemical indicators. It cannot directly measure specific biochemical changes such as the production of stress hormones like abscisic acid, altered antioxidant levels, or the accumulation of osmolytes. Such biochemical parameters require more specialized assays for accurate evaluation. Furthermore, the technology's focus is primarily on above-ground plant parts, rendering it ineffective for assessing underground structures like root morphology.

That being said, these same biochemical indicators are also difficult to determine for inspectors and require detailed chemical analysis, including sample preparation, extraction, purification and quantification for analysis with high-performance liquid chromatography or mass spectrometry.

36. Full Automation

Integration of the sensor data described in this paper with an drip irrigation system with injectors for fertilizer and pesticides holds promised for fully automated optimizations. This type of irrigation system may be referred to as fertigation or chemigation. This type of drip irrigation system allows for the precise, but manual, application of water, fertilizers, and pesticides through a single drip irrigation network. It is designed to maximize efficiency in nutrient and chemical delivery directly to the root zone of plants. This consolidation of functions aims to optimize resource utilization, enhance crop yield, and minimize environmental impact. Our goal is to combine the metrics collected by our methods with automated flow control of chemicals and fertilizers during the drip irrigation process.

Using real-time sensor data from image computation and gas sensors attached to a fertigation or chemigation system, vineyard managers can create a feedback loop that enables automated decision-making and adjustments.

The imaging data can provide essential information about the spatial distribution of the vines, such as their size, shape, and density. This information can be used to create a precise map of the vineyard, which can then be correlated with the sensor data. As an example, the image data can identify areas that require more or less irrigation or fertilizer based on plant size or vegetation density, gently adjust flow and monitor results automatically. In many ways it has the same characteristics as an automated pool chlorination system, where sensors control chlorine injection to maintain the ideal balance. Operator guidance helps tune the decisions of the automation system, requiring less and less intervention over time.

This level of automation can lead to several benefits. Firstly, it can improve resource efficiency by precisely targeting irrigation and fertilization, reducing wastage and optimizing resource utilization. Secondly, it can enhance the health and yield of the vines by ensuring they receive the appropriate amount of water, nutrients, or chemicals at the right time and in the right areas. Lastly, it can reduce cost and save time and labor for vineyard managers, as the system can operate autonomously, making adjustments and decisions without requiring constant manual intervention.

37. Phenolic Compounds and Taste

However, there is promise of aerial measurement of antioxidant levels using remote UV-Vis spectroscopy. The areas of promise are in with 2,2-diphenyl-1picrylhydrazyl, Ferric Reducing Antioxidant Powers, or enzymatic assays for superoxide dismutase, catalase, and peroxidases. This is a ripe area for future research, especially since antioxidants are important not only for yield, but for the phenolic composition of grapes. Phenolic compounds contribute to the taste, color, and antioxidant properties of the end product [15].

38. Conclusion

Utilizing multispectral imaging, thermal entropy analysis, and interval imaging , viticulturists can enhance their awareness regarding vineyard changes. These tools facilitate rapid identification of regions requiring closer scrutiny and enable retrospective assessments to comprehend how past management decisions have influenced current yield. The overarching benefit of computational imaging is twofold: it offers robust mechanisms for safeguarding vineyard assets and also contribute to waste minimization. Consequently, these advantages collectively serve to elevate the overall profitability of vineyard operations.

Vineyard with Feature Points Highlighted at Right

References

1. Pagliai, M., Lamarca, M., & Lucamante, G. (1983). Micromorphometric and micromorphological investigations of a clay loam soil in viticulture under zero and conventional tillage. *Journal of Soil Science, 34*(2), 391-403.
2. Vrochidou, E., & Papakostas, G. A. (2023). Leveraging computer vision for precision viticulture. *Computer Vision and Machine Learning in Agriculture, Volume 3,* 177-213.
3. Poblete, T., Ortega-Farías, S., & Ryu, D. (2018). Automatic coregistration algorithm to remove canopy shaded pixels in UAV-borne thermal images to improve the estimation of crop water stress index of a drip-irrigated cabernet sauvignon vineyard. *Sensors, 18*(2), 397.
4. Pérez Nava, F., Pérez Nava, A., Rodríguez Valido, M., & Magdaleno Castellò, E. (2015). Plenoptic cameras. *Biologically Inspired Computer Vision: Fundamentals and Applications*, 175-200.
5. Cui, B., Zhang, S., Wang, Y., Hu, Y., & Hao, Q. (2022). Pose correction scheme for camera-scanning Fourier ptychography based on camera calibration and homography transform. *Optics Express, 30*(12), 20697-20711.
6. Shepard, D. (1968, January). A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM national conference* (pp. 517-524).
7. Jaberi-Aghdam, M., Momayezi, M. R., Bagheri, N., Azizi, P., & Nasri, M. (2024). Nitrogen assessment by remote sensing and multispectral imagery in maize (Zea mays L.). *Journal of Crop Science and Biotechnology, 27*(1), 31-41.
8. Chowdhury, M., & Anand, R. Automated Pest and Disease Identification in Agriculture using Image Processing.
9. Robinson, C., & Schumacker, R. E. (2009). Interaction effects: centering, variance inflation factor, and interpretation issues. *General Linear Model Journal, 35*(1), 6-11.
10. Enwere, K., Nduka, E., & Ogoke, U. (2023). Comparative analysis of ridge, bridge and lasso regression models in the presence of multicollinearity. *IPS Intelligentsia Multidisciplinary Journal, 3*(1), 1-8.
11. Mertz, R. W., Hesler, S., Pfannenstiel, L. J., Norris, R. H., Loeb, G., & Scott, J. G. (2022). Insecticide resistance in Drosophila melanogaster in vineyards and evaluation of alternative insecticides. *Pest management science, 78*(3), 1272-1278.
12. Sparks, A. N., & Facto, L. A. (1966). Mechanics of Infrared Cinematography in Studies with the European Corn Borer. *Journal of Economic Entomology, 59*(2), 420-422.
13. IIJIMA, M., ORIBE, Y., HORIBE, Y., & KONO, Y. (1998). Time lapse analysis of root elongation rates of rice and sorghum during the day and night. *Annals of Botany, 81*(5), 603-607.
14. Blanchy, G., Watts, C. W., Richards, J., Bussell, J., Huntenburg, K., Sparkes, D. L., ... & Binley, A. (2020). Time-lapse geophysical assessment of agricultural practices on soil moisture dynamics. *Vadose Zone Journal, 19*(1), e20080.
15. Pérez-Álvarez, E. P. (2017). Cover crops in viticulture: A strategy to modify grape and wine phenolic composition. In *Phenolic Compounds: Types, Effects and Research* (pp. 179-212).