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College of Agriculture and Life Sciences

ORBITING INNOVATIONS: PIONEERING SATELLITE TECHNOLOGIES RESHAPING THE FUTURE OF VINEYARD MANAGEMENT

A Project Paper

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Field of Viticulture

By

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ABSTRACT

In recent years, advances in satellite technology have significantly impacted vineyard management. Satellite systems like Landsat, Sentinel-2, PlanetScope, and SkySat provide valuable data for monitoring vineyard health, optimizing irrigation, and predicting yields. Landsat and Sentinel-2, with their specific resolutions and revisit intervals, are widely used for vine growth monitoring. Notably, the near-infrared and red band data from Landsat 8 are particularly effective in calculating vegetation indices, such as NDVI, to assess vine growth and detect potential diseases. In contrast, PlanetScope's high-frequency coverage and SkySat's high-resolution imagery offer significant advantages for real-time monitoring and detailed analysis of grapevine health. PlanetScope's daily global coverage allows for frequent monitoring of dynamic environments, while SkySat's 50 cm resolution is ideal for precise disease detection. This makes SkySat particularly effective in the early detection of Grapevine Downy Mildew. The combined use of Skysat and PlanetScope greatly improves the comprehensiveness and accuracy of vineyard disease management. In the future, the accuracy and efficiency of vineyard management will be further improved by combining hyperspectral imaging, microsatellite and artificial intelligence technologies. These technologies will provide more detailed spectral data and higher-frequency monitoring of vineyards, helping to optimize resource allocation, improve grape quality and address the challenges of climate change.

BIOGRAPHICAL SKETCH

Wanjia Ni is an international student at Cornell University, currently pursuing a Master of Professional Studies in viticulture.

Born in 1998 in Taiyuan, Shanxi Province, China, he has resided in Shanghai since birth.

In 2020, He moved to the United States to study Plant Science at the State University of New York at Cobleskill, where he graduated with honors in 2022. His academic and professional interests are centered on wine production and viticulture, which led him to complete an internship at E & J Gallo Winery in Canandaigua, New York.

This experience provided him with practical insights and skills in the wine industry, further motivating his current studies at Cornell University.

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TABLE OF CONTENTS

Introduction

As global agricultural technology continues to advance, precision agriculture have gradually become important pathways to improving agricultural production efficiency. In the field of viticulture, the application of precision management techniques is particularly significant because grape growth is highly influenced by environmental factors, which in turn have a crucial impact on grape yield and quality. Traditional vineyard management methods rely on manual observation and ground measurements, which are time-consuming and prone to errors, making it difficult to manage large-scale vineyards and complex environmental changes effectively. With the development of remote sensing technology, satellite data has gradually become an essential tool in vineyard management, providing efficient and accurate solutions.

In recent years, the application of Landsat series, Sentinel-2, and Planet Labs satellites in vineyard management has made remarkable progress. These satellites provide high-resolution, multispectral imagery, enabling vineyard managers to monitor and manage vineyards with greater precision. As satellite technology continues to advance, with improvements in resolution and shortened revisit cycles, the precision and intelligence of vineyard management will further enhance, offering stronger support for the global viticulture industry.

This paper reviews the current applications of satellite data in vineyard management, including yield prediction, disease monitoring, and irrigation management, and explores the future development directions of satellite technology and its potential impacts. By summarizing existing research findings, this paper aims to provide a reference for vineyard managers and researchers, thereby supporting the development and promotion of precision viticulture.

Satellites

Landsat

The Landsat series of Earth observation satellites, jointly developed and managed by NASA and the United States Geological Survey (USGS), has been a cornerstone of global environmental monitoring and resource management since its first launch in 1972. Over the decades, these satellites have undergone several generations of updates, each bringing advancements that have significantly contributed to fields such as scientific research, agriculture, urban planning, and environmental protection.

The latest generation in this series, Landsat 9, was launched on September 27, 2021, continuing the technological strengths of its predecessors while further enhancing data acquisition capabilities. Similar to Landsat 8, Landsat 9 carries two primary sensors: the Operational Land Imager (OLI-2) and the Thermal Infrared Sensor (TIRS-2). These sensors provide data across 11 spectral bands, including visible, near-infrared, shortwave infrared, and thermal infrared. The OLI-2 sensor offers a spatial resolution of 30 meters for most bands, with the thermal infrared band being captured at 100 meters but scaled to 30 meters. Additionally, Landsat 9 is equipped with a 15-meter resolution panchromatic band, enabling the generation of high-resolution black and white images.

Landsat 9, like Landsat 8, has a revisit time of 16 days, meaning it can image the same location on Earth every 16 days. The combined operation of Landsat 8 and Landsat 9 effectively reduces this revisit time to approximately eight days for any given location, significantly improving the timeliness and spatial coverage of the data. This consistency in key parameters such as resolution, spectral bands, and revisit time ensures that Landsat 9 will continue to provide high-quality data to support global environmental monitoring and resource management for years to come.

Despite being an older satellite, Landsat 7 remains in operation, although it has experienced significant data loss since its scan line corrector (SLC) failed in 2003, resulting in approximately 22 percent of the data in each image being missing. However, these gaps can be compensated by fusing Landsat 7 data with data from other satellites, such as Landsat 8 and Landsat 9. Landsat 7 data continue to be valuable, particularly for historical time-series analyses, as they provide a continuous record for long-term monitoring of changes on Earth's surface.

In vineyard management, Landsat data have been instrumental in improving practices such as yield prediction and grape ripening monitoring (Meyers et al., 2020). Surface reflectance products from Landsat 7 and 8 have been used to map vegetation indices like the Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) in vineyards. By analyzing these indices, vineyard managers have been able to assess spatial variability in vine growth and predict grape yields with greater accuracy. This allows for more informed decisions on resource allocation, such as optimizing irrigation and nutrient application to enhance yield and quality across different vineyard sections.

Furthermore, a new sampling protocol for grape ripening monitoring (Meyers et al., 2020) based on NDVI imagery, has been developed to maximize the representativeness of sampling while reducing the number of sampling points needed.

This method processes NDVI images to identify pixels representing different growth quartiles within a vineyard block, providing a more targeted and efficient approach compared to traditional random sampling methods. Field tests have demonstrated that this method can estimate fruit ripeness more accurately and consistently over multiple growing seasons, proving its practical value in vineyard management (Meyers et al., 2020).

Landsat data have also played a critical role in optimizing irrigation practices. Thermal infrared data from Landsat, combined with other data sources, have been used to generate high-resolution evapotranspiration (ET) maps (Knipper et al., 2018). These maps enable vineyard managers to monitor water use across different vineyard areas and detect signs of water stress. By identifying areas with higher water demand, managers can adjust irrigation practices to ensure water is applied where it is needed most, improving water use efficiency and maintaining vine health. Additionally, comparing ET data with grape yield maps allows vineyard managers to further refine irrigation strategies, ultimately enhancing both yield and quality (Knipper et al., 2018).

Through the integration of Landsat data across multiple aspects of vineyard management, vineyard managers have been able to make more informed and precise decisions, contributing to the overall efficiency and sustainability of viticulture practices.

Sentinel 2

Sentinel-2 satellites are a core component of the European Space Agency’s (ESA) Copernicus program, specifically designed for Earth observation and environmental monitoring. The program includes two satellites, Sentinel-2A and Sentinel-2B, launched in 2015 and 2017, respectively. These satellites work together to provide high-resolution multispectral imagery, which is widely used in agriculture, forestry, land cover monitoring, and disaster management. Their contributions are especially significant in the field of precision viticulture.

Sentinel-2 satellites are equipped with multispectral imagers (MSI) capable of capturing data in 13 different spectral bands, covering visible light, near-infrared, and shortwave infrared ranges. The spatial resolution of these bands varies between 10 meters, 20 meters, and 60 meters, with the 10-meter resolution bands being particularly crucial for monitoring grapevine health and land cover changes. The dual operation of these satellites allows for the same location on Earth to be imaged every 5 days, enabling timely detection of dynamic changes on the interested blocks.

In vineyard management, Sentinel-2 data are extensively used to monitor the growth cycle and water status of grapevines. By analyzing NDVI (Normalized Difference Vegetation Index) time-series data, vineyard managers can identify various growth stages of the vines and adjust fertilization and pruning strategies accordingly. This data also helps in identifying growth variations within the vineyard, guiding targeted management practices such as customized interventions for different growth areas. Moreover, Sentinel-2 data make it possible to monitor the water needs of vineyards, allowing managers to optimize irrigation schedules based on the actual water status of the vines, ensuring their healthy growth even under drought conditions.

PlanetLabs

Planet Labs' PlanetScope and SkySat satellites play a crucial role in precision viticulture, offering unprecedented monitoring capabilities through frequent imaging coverage and high-resolution imagery.

The PlanetScope constellation, composed of hundreds of microsatellites, is one of the largest commercial satellite constellations in the world. These satellites cover every corner of the Earth daily, providing imagery with a resolution of 3 meters. This high-frequency coverage allows vineyard managers to monitor the health of grapevines daily, enabling the timely detection and response to any potential issues. In viticulture, PlanetScope data is particularly useful for tracking changes in vegetation indices, allowing for precise identification of vine growth conditions and physiological health. This capability is crucial for detecting early signs of nutrient deficiencies and disease.

SkySat satellites, on the other hand, provide even more detailed imagery with a resolution of 50 centimeters, capturing fine details of individual grapevines. This high resolution is particularly useful for detecting diseases in vineyards, such as grapevine downy mildew (GDM), which can spread rapidly. SkySat imagery can clearly show disease spots and color changes on vine leaves, information that is essential for accurately diagnosing diseases and assessing their severity.

By combining PlanetScope's broad coverage with SkySat's detailed analysis, vineyard managers can comprehensively monitor the health of their vineyards, from broad assessments to fine-grained analysis. For example, vineyard managers can use high-resolution imagery to identify high-risk areas in the vineyard and implement targeted management practices, such as enhancing disease control, adjusting irrigation strategies, or optimizing fertilization plans. This precise management not only can improves grape yield but also reduces resource waste, promoting more sustainable vineyard management.

Using satellite data

Phenology

A group of researchers studied the potential of Sentinel-2 to monitor the entire grapevine growth cycle over a seven-month period in a paper published in 2019 (Devaux et al., 2019). The researchers acquired satellite imagery between March 3, 2017, and October 10, 2017, for these four blocks. Time series were produced of NDVI, as shown in Figure 1.

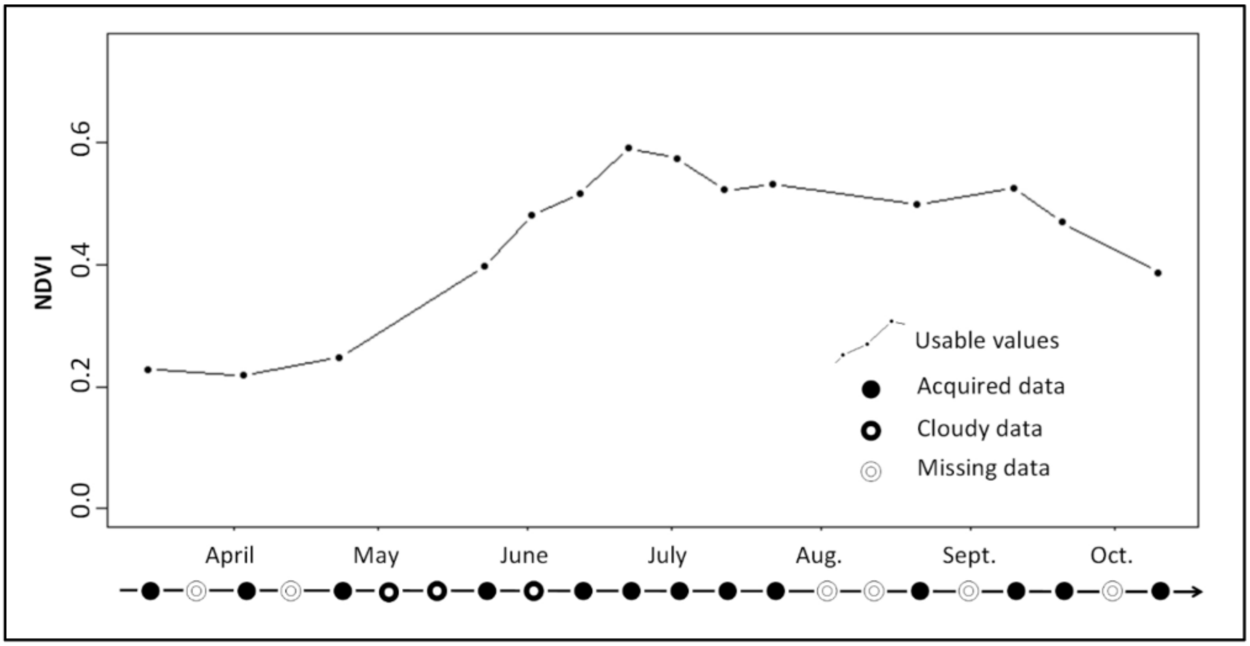


Figure 1: NDVI time series of B1 block. (Devaux et al., 2019)

The researchers found that this NDVI time series can be used to identify the different stages of grapevine development. For example, from April to mid-June, NDVI increased from about 0.2 to about 0.5, which corresponds to the stage when the vines are breaking bud and growing rapidly, and decreased after mid-June, due to summer pruning, and then decreased significantly after September, when harvesting took place (Devaux et al., 2019). During the veraison stage (August), NDVI values were close to 0.5, which more or less corresponded to values observed at this stage in other vineyards trained in the VSP system under similar growing conditions (Johnson, 2003; Johnson et al., 2001).

The researchers also produced a visualized NDVI mapping based on the satellite data, shown by Figure 2.

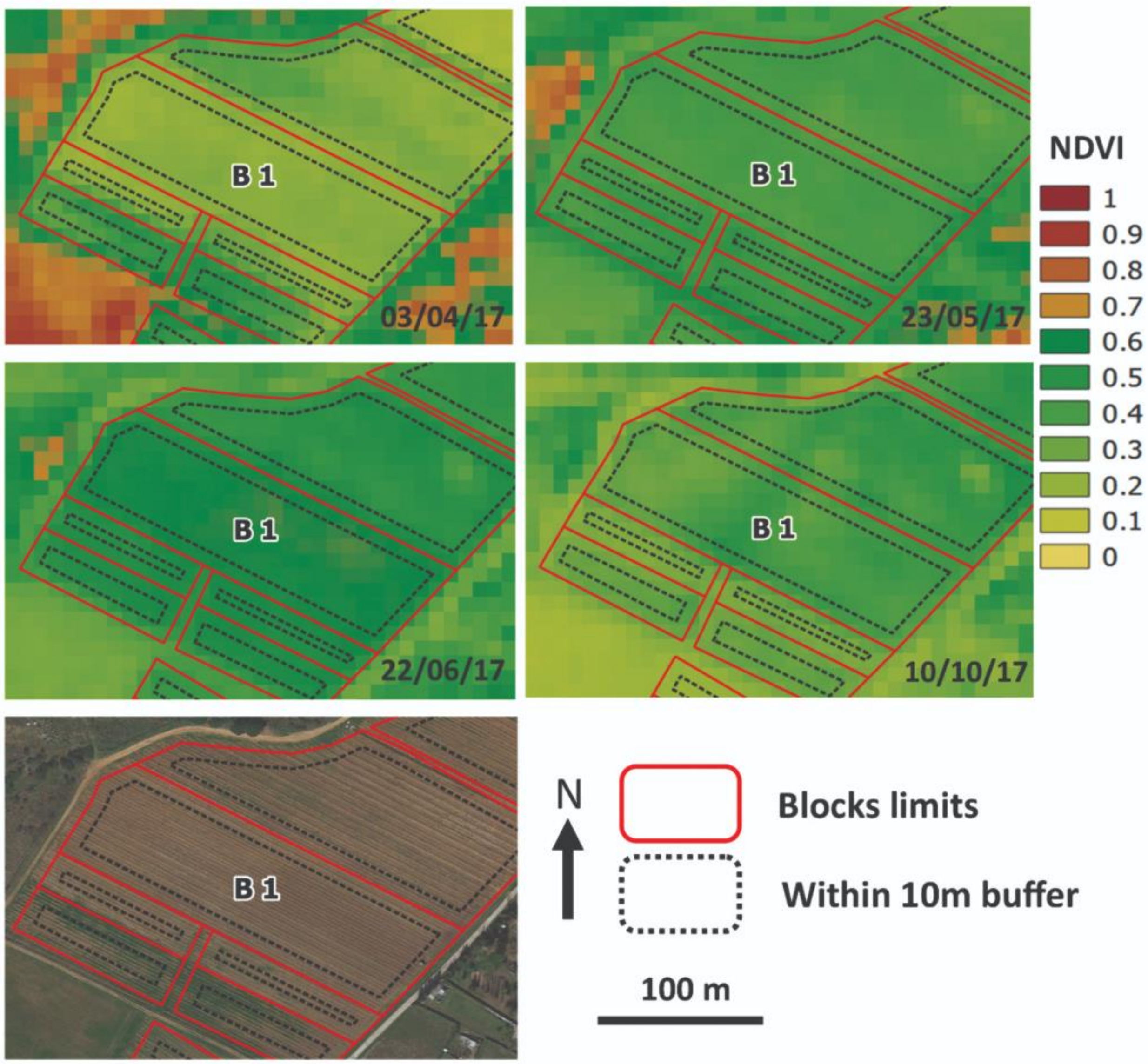


Figure 2: NDVI mapping of B1 block. (Devaux et al., 2019)

In Figure 2, we can use the visualization to observe more intuitively the significant changes in NDVI in different months. The image in the upper left corner was taken in April 2017, when the NDVI value was not high. It was not until June 2017 that the NDVI reached its highest, reflecting the vigor of the summer vine growth. The NDVI mapping for October 2017 reflects some degree of variation within the same block. We can see lower NDVI values reflected in the western part of block B1, which corresponds to the early senescence of the canopy.

The researchers produced time series of NDVI for four different blocks of interest. It is shown by Figure 3.

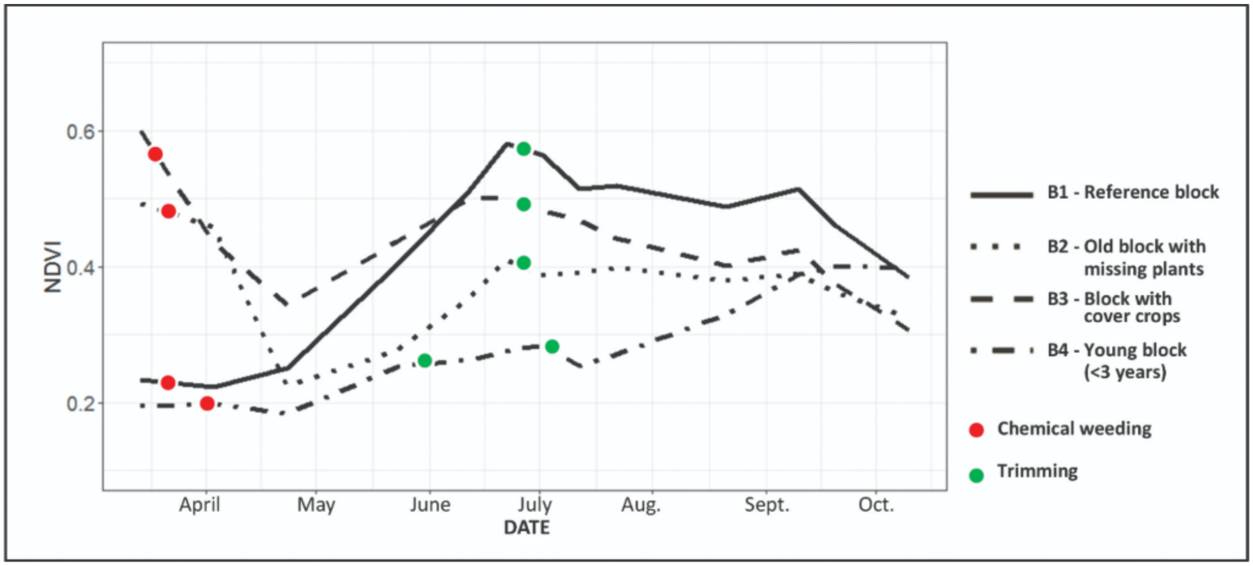


Figure 3: NDVI temporal dynamics for the four blocks of interest (B1, B2, B3, B4) (Devaux et al., 2019)

Figure 3 shows the effects of weed management and row management practices, with each block showing a significant decrease in NDVI after chemical weed control. NDVI also decreased slightly after summer mowing. Notably, NDVI was significantly higher in April in blocks B2 and B3 than in blocks B1 and B4, due to the higher photosynthetic activity of the inter-row cover crops in B2 and B3, and the lower albedo of the bare soil in B1 and B4, which resulted in lower NDVI.

In block B4, NDVI values were higher despite the fact that the vines were pruned in early June, which may be related to the higher number of young vines in the block, which quickly resumed growth without fruit burden. After harvest in September, vine growth resumed due to the fall rains in Mediterranean climatic conditions, which relieved the summer water stress, leading to another increase in NDVI. Afterwards, the vines in all blocks gradually showed signs of senescence and NDVI values gradually declined.

This study consistently demonstrated that NDVI time series from Sentinel-2 can effectively track vine phenology and growth from budbreak to dormancy. NDVI trends were consistent with key vineyard events such as summer pruning and harvesting.

The use of NDVI mapping to visualize spatial variability within vineyard blocks is another important contribution. These maps can help vineyard managers identify areas of low or high vigor to guide targeted interventions such as precision fertilization or selective pruning.

Irrigation

The use of the Sentinel-2 satellite in vineyard management goes beyond monitoring vine growth. In a study published in 2021, researchers Laroche-Pinel et al. (2021) explored the feasibility of using Sentinel-2 satellite imagery to monitor vineyard water status at a large scale and high temporal resolution. With climate change and decreasing water resources, especially in arid regions such as the Mediterranean, water management in vineyards is becoming increasingly important. This study aimed to provide a solution through remote sensing to help winegrowers optimize water use, reduce the impact of water stress on vines, and promote sustainable vineyard development.

This study was conducted in 36 vineyards in the south of France over a three-year span (2018-2020). The main focus was on Syrah grapes but also included vines of other varieties. The study covered different climatic conditions, ranging from high rainfall in 2018 to dry years in 2019 and 2020. The study area included plots of approximately 1 hectare each. In each vineyard, one to six 20 × 20 m subplots were selected for data collection. These subplots were selected based on the Sentinel-2 20-m pixel grid, soil and vegetation variability, and the time required to measure stem water potential (SWP) in the field. SWP values were measured for five to ten stems in each subplot, totaling over 3200 measurements. To assess the water status of the grape plots, researchers measured SWP and processed it following standard steps. These measurements ranged from 0 (indicating well-watered) to -2 MPa (indicating extreme water stress). Reflectance-based stem water potential (rSWP) was then estimated using Sentinel-2 imagery.

The researchers used a supervised regression machine learning algorithm to generate a model for predicting rSWP. Specifically, they extracted two types of features from Sentinel-2 satellite images: band reflectance values and vegetation index. These features were used to predict rSWP values for grapevines. The research team tested a variety of supervised regression algorithms to assess their performance in predicting rSWP. Ultimately, by comparing the performance of these algorithms, they found that linear regression and Bayesian ridge regression models performed best in most cases, especially in plots without grass cover.

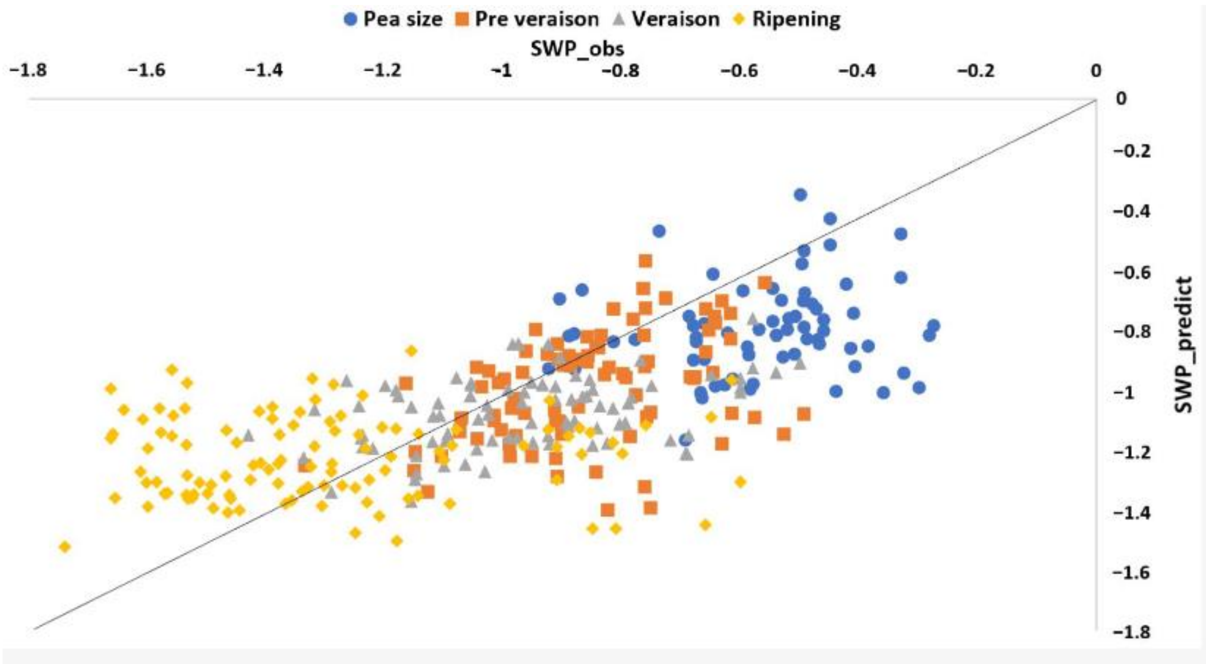


Figure 4: SWP Predicted vs. Observed according to development stage of grapes. (Laroche-Pinel et al., 2021)

As can be seen in Figure 4, water stress gradually increased as the season progressed from the pea-size stage to the maturity stage, which is in line with the prediction of the model. At the pre-transition and transition stages, the model's predictions were closer to the actual observations, with data points more concentrated on the diagonal, indicating that the model's predictions were more accurate at these stages.

However, at the maturity stage, the data points were more widely distributed, and the actual observed SWP values ranged from -0.6 to -1.8, suggesting that the model's predictions were less favorable at the maturity stage than at the other stages. This may be due to the fact that under high water stress, grapevines undergo changes in other physiological mechanisms, such as the accumulation of sugars in berries and changes in the leaf area to fruit ratio, which may affect the optical properties of leaves and thus reduce the prediction accuracy of the model.

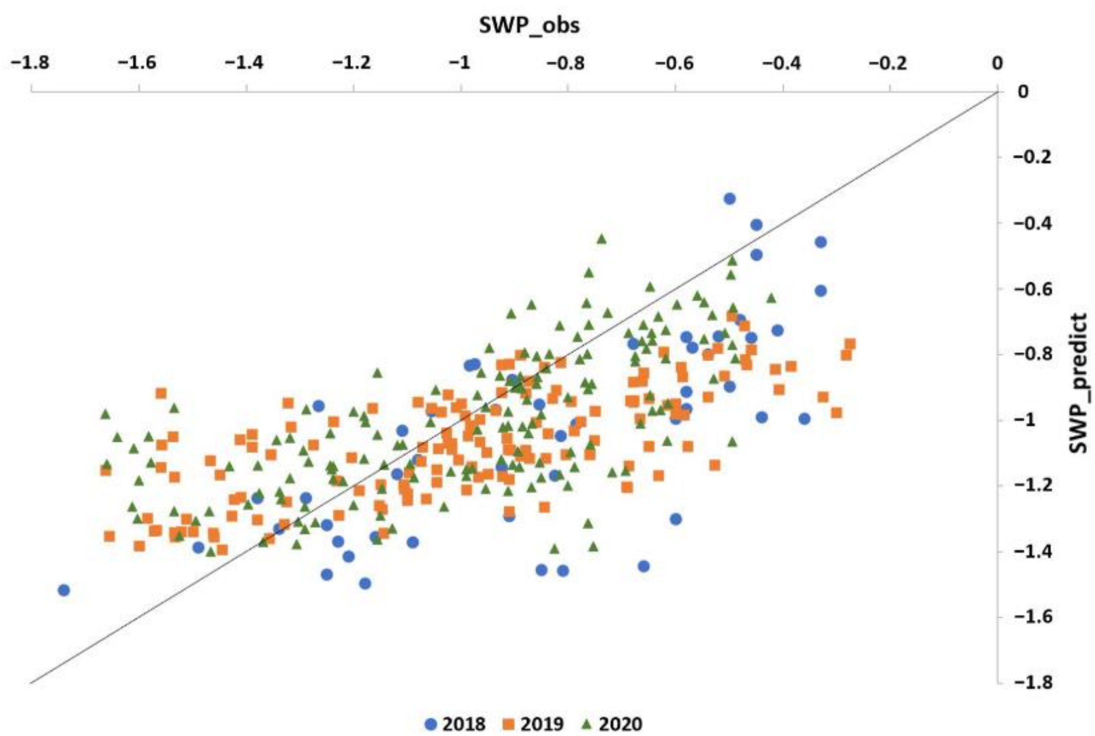


Figure 5: SWP Predicted vs. Observed according to study year. (Laroche-Pinel et al., 2021)

From the results, it can be seen that most of the data points were distributed around the diagonal line, indicating that the model generally showed high accuracy in predicting rSWP in different years. However, in the high water stress region (SWP_obs close to -1.8 MPa), the model's predictions were slightly off, which may reflect a decrease in the model's prediction accuracy under extreme water stress conditions. Overall, this figure illustrates the performance of the model in three different vintages, showing that it is effective in predicting rSWP in grapevines under a wide range of climatic conditions. Despite some errors in extreme water stress, the model's overall predictions remained highly accurate.

To conclude this study, by utilizing Sentinel-2 satellite imagery and multiple machine learning algorithms, Laroche-Pinel et al. (2021) successfully predicted rSWP in different years and under different climatic conditions. This not only demonstrates the great potential of remote sensing technology in precision agriculture but also provides a reliable tool for fine-grained monitoring of crop health. Although the climatic conditions varied from year to year, the model still showed good robustness and reliability.

The standard indicator of water stress in grapevines is leaf water potential (LWP), usually measured using a pressure chamber. In some cases, pressure chamber measurements are also used in irrigation schemes in commercial vineyards (Girona et al., 2006). However, this method requires individual measurements for each leaf, limiting its applicability across large heterogeneous areas. While researchers have developed LWP mapping techniques utilizing high-resolution thermal imaging to isolate changes in plant canopy temperatures (Bellvert et al., 2016), providing this type of information regularly over large areas is challenging and may require calibration for different climates and grape varieties. Another tool for monitoring vineyard water stress and utilization is the measurement of evapotranspiration (ET), which quantifies the amount of water lost to the atmosphere from the vines and the surface.

In their 2018 research paper, Knipper et al. (2018) used a variety of satellite remote sensing techniques to optimize irrigation management for vineyards in California's Central Valley by estimating ET.

They utilized data from multiple satellite platforms. Geostationary Operational Environmental Satellite (GOES) provided high temporal resolution surface temperature data, primarily used in the ALEXI model for estimating ET on a regional scale. Landsat data, offering 30-meter resolution, was used to generate ET maps, while MODIS provided data for time series analysis. The combination of data from these satellites allowed for detailed ET estimation at different scales, helping to fine-tune irrigation practices.

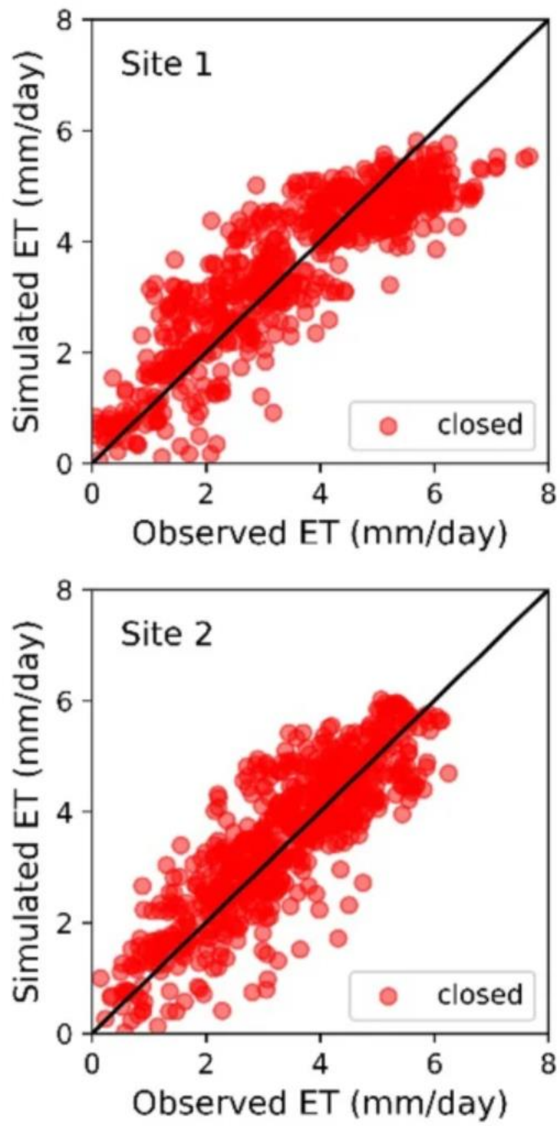


Figure 6: Scatter plots between Simulated ET and Observed ET at two sites (Site 1 and Site 2). (Knipper et al. 2018)

As observed in Figure 6, the scatter plots show a high degree of consistency between the simulated ET and the observed ET, with most data points distributed near the diagonal line, indicating that the simulated results closely match the actual observed values. Particularly at higher ET values, the correlation between simulated and observed data shows more deviation, possibly reflecting limitations in the model's predictive capabilities under certain conditions.

ET exhibits clear seasonal fluctuations, with the highest values occurring in the summer months and the lowest in winter. Additionally, peaks in precipitation typically coincide with increases in ET, indicating that rainfall directly affects soil moisture and ET in the following days.

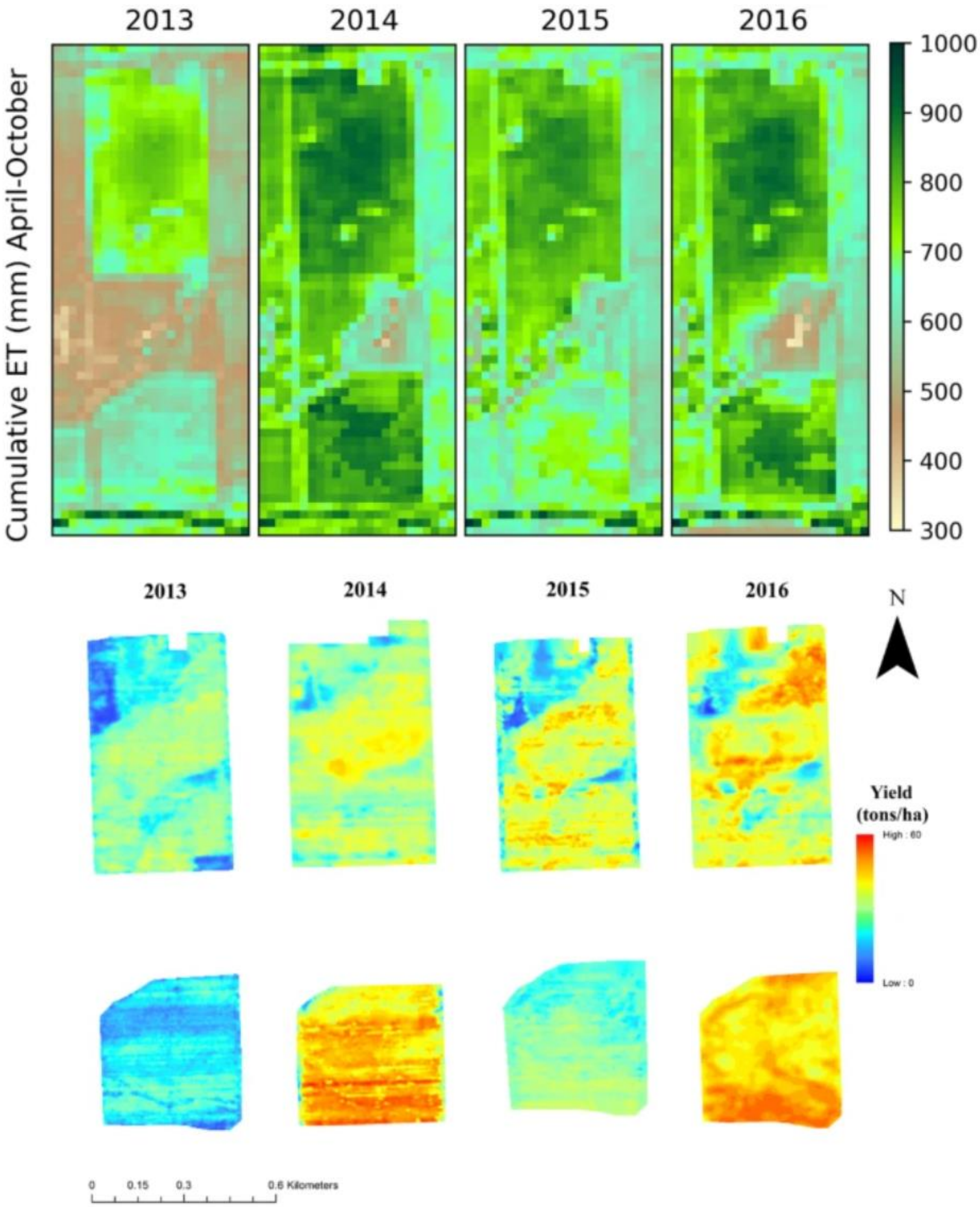


Figure 7: Demonstration of the spatial relationship between Cumulative ET and grape yield between 2013 and 2016. *(Knipper et al. 2018)*

In the upper part of Figure 7, some areas clearly show lower ET values, related to differences in soil conditions and vegetation cover in those areas. Overall cumulative ET was significantly lower in 2013 and 2015 compared to 2014 and 2016, which may be related to drought conditions during those years.

The lower part of the figure shows grape yields between 2013 and 2016. By comparing cumulative ET with grape yields, a spatial correlation between the two can be observed. For instance, the yield maps for 2014 and 2016 show higher yields in the southern part of the site, which overlaps with areas of higher ET.

ET maps can accurately monitor water use in different areas of the vineyard with an average absolute error of only 0.6 mm/day, allowing vineyard managers to identify areas of under- or over-use. Using this data, vineyard managers can implement variable rate irrigation systems to apply the right amount of water and nutrients to different areas of the vineyard, improving water use efficiency and ensuring uniformity of yield and quality of grapes.

Yield prediction

Yield prediction in vineyards had always been a very labor-intensive and time-consuming task, and traditional yield predictions also had high errors while consuming a large number of grape samples. Remote sensing data provided detailed spatial and temporal information about grape growth, which was very useful for grape yield prediction.

In a paper published in 2017, researchers Sun et al. (2017) from California used Landsat surface reflectance products from 2013 and 2014 to map the satellite-based Normalized Vegetation Index (NDVI) and Leaf Area Index (LAI) for two Pinot Noir vineyards in California. They used two satellites, Landsat 7 and 8, and the MODIS LAI product to train a MODIS resolution model using MODIS pixel resolution LAI and surface reflectance samples. The resulting regression tree was ultimately applied to Landsat surface reflectance (which had a native resolution of 30 meters) to generate Landsat-scale LAI maps. The feasibility and potential of utilizing satellite data for yield prediction were explored.

The study area included two vineyards, with one (Site 1) planted with 9–10-year-old Pinot Noir vines, and the other (Site 2) with 6–7-year-old vines. LAI data were collected using ground-based measurement tools, and the satellite data were processed to generate NDVI and LAI maps.

The analysis focused on three specific days during the growing season—DOY 93, DOY 173, and DOY 253—representing early, mid, and late stages of vine growth. The results showed clear spatial patterns in the NDVI and LAI data, reflecting the dynamics of vine growth in the fields. For example, higher NDVI and LAI values in the center of Site 1 indicated more vigorous vine growth in that region, while lower values in other areas were associated with different soil textures, such as gravelly loam, which has poor water-holding capacity (Sun et al., 2017).

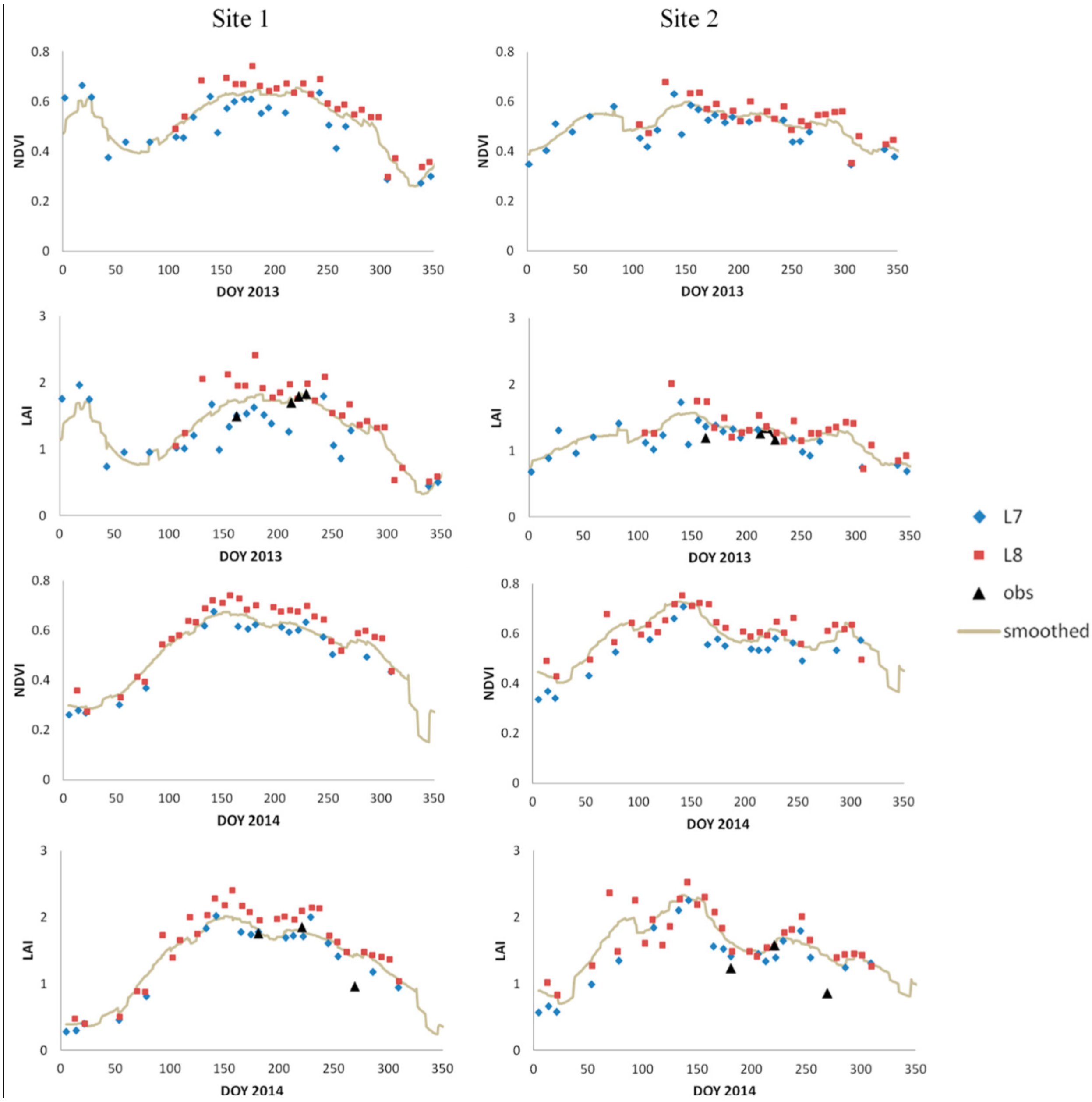


Figure 8: Time series of Landsat NDVI, LAI, and ground-measured LAI for two sites in 2013 and 2014. (Sun et al. 2017)

In comparing the data from Landsat 7 and Landsat 8, it was noted that the NDVI and LAI data from both satellites were generally in good agreement, although the values from Landsat 8 were consistently higher. This difference was attributed to the different spectral response functions of the two satellites (Roy et al., 2016; Sun et al., 2017).

The study found strong correlations between grape yields and the remotely sensed vegetation indices. The timing and amount of irrigation, as well as its frequency and distribution throughout the season, will have a significant impact on canopy and crop development. However, because vineyard soils vary in physical and chemical properties, any uniformly applied inputs will produce different patterns of spatial variability. Canopy management practices, such as leaf removal and hedging, will also affect canopy density. From the results of this study, the correlation between NDVI and yield ranged from 0.66 to 0.83, while the correlation between LAI and yield ranged from 0.53 to 0.82 (Sun et al., 2017).

Ultimately, the researchers concluded that NDVI and LAI data obtained during the period DOY 156 through DOY 221 had the best correlation with yields, with a prediction error of approximately 10% to 18%, which was lower than the industry average of 30%. However, this correlation may not be universally applicable to all vineyards, as the optimal date window for such predictions would vary depending on factors like climatic conditions and rainfall.

Sampling

Meyers et al. (2020) proposed a new sampling protocol for grape ripening monitoring based on Landsat 7 satellite NDVI (Normalized Vegetation Index) imagery. The central aim of the research was to maximize the representativeness of the samples by optimizing the sampling protocol while reducing the number of actual sampling points. An algorithm was designed to process NDVI images and locate pixels representing different quartiles (left tail, median, right tail) of a vineyard block. The method was field-tested in several vineyards in California's Central Valley, and results showed that the NDVI3 method was able to estimate fruit ripeness more accurately and was temporally stable compared to traditional random sampling methods (R20) and commercial sampling methods (CM8) (Meyers et al., 2020).

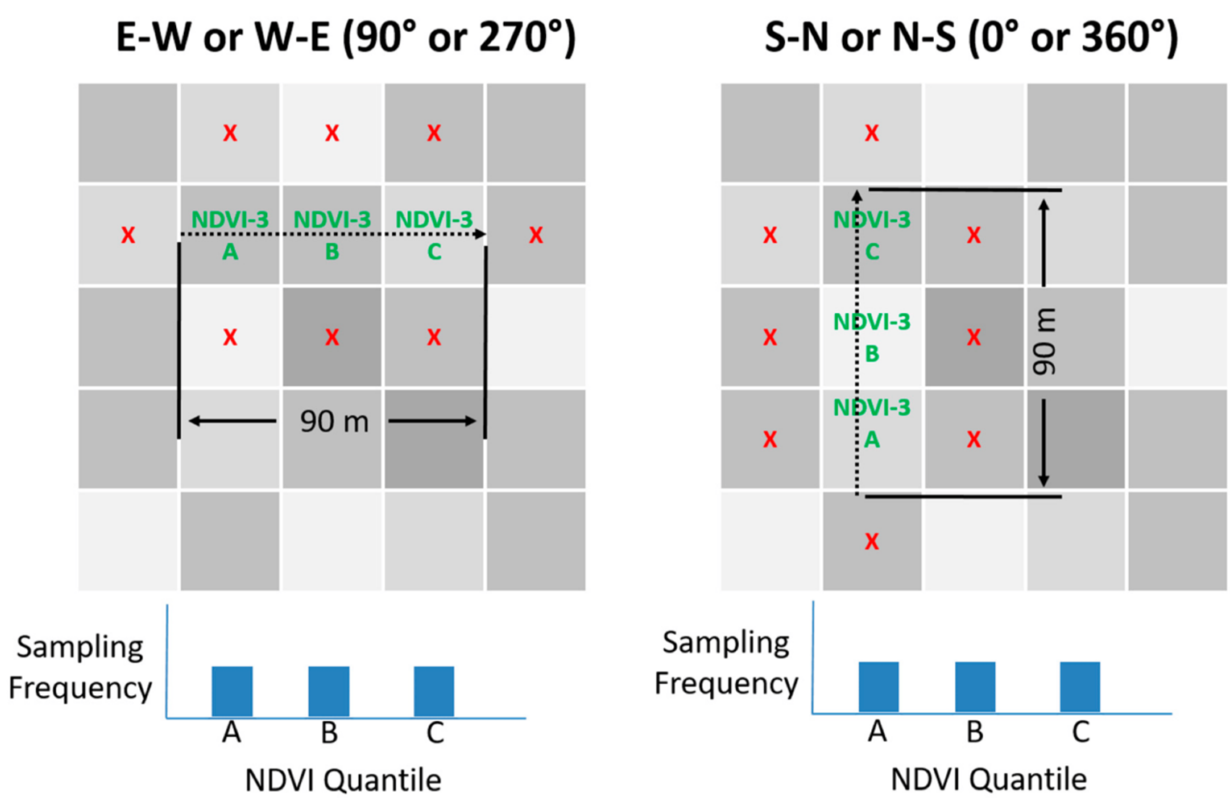


Figure 9: Illustration of three-pixel normalized difference vegetation index (NDVI) directed sampling method. Dashed arrow represents path of travel during sampling. 'X's denote that sampling does not include vines from nearby pixels. Note that the path of travel is always limited to a single vineyard row and pixel orientation will differ from row orientation for rows that are not planted ether North-South or East–West. (Meyers et al. 2020)

Specifically, Meyers et al. (2020) devised an algorithm to organize the NDVI values within the vineyard in ascending order and divided them into three quartiles representing different intervals of growth status within the vineyard. Rather than simply relying on random sampling, this approach pinpointed the pixel combinations that best represented the three quartiles by comparatively analyzing all possible combinations of three consecutive pixels. This strategy not only took into account the spatial heterogeneity within the vineyard but also revealed the micro-growth patterns hidden behind the vegetation indices through the NDVI data.

In practice, this innovative approach allowed researchers to obtain data that were highly consistent with the overall condition of the vineyard with a very small number of sampling points. This approach not only reduced the sampling effort but also significantly improved the representativeness of the sampled data. More importantly, the sampling protocol was stable over multiple growing seasons, demonstrating its validity across years and environmental conditions. The development of this protocol was a successful application of remote sensing technology to vineyard management (Meyers et al., 2020).

Disease Detection & Monitoring

Until the 2010s, satellite technology was limited by long revisit cycles and poor spatial resolution, which made it impractical to accurately monitor diseases like grapevine downy mildew (GDM), which can spread rapidly over a period of days. Although free data from space agencies such as Landsat and Sentinel-2 are available, their spatial resolution is too coarse to detect disease symptoms on individual vines. In addition, the specialized structure of vineyards and trellis cropping systems—plant rows separated by soil, cover crops, and other vegetation—adds to the difficulty of monitoring. The presence of this heterogeneity in the field makes it difficult to clearly attribute changes in reflectance in remotely sensed images to the health of the target crop.

Researchers Kalaney et al. (2023) from Cornell University explored the severity and incidence of GDM detection through spectral vegetation indices (VIs) in Cornell University vineyards in Geneva, NY, USA. The primary objective of this study was to evaluate the effectiveness of different VIs for detecting GDM under different canopy conditions and to determine which VIs are best suited for early disease detection.

GDM, caused by *Plasmopara viticola*, is very likely to spread rapidly in vineyards, especially in rainy areas such as New York State, and can cause massive vine mortality, which can seriously affect grape yield and quality. Traditional disease detection methods rely on visual observation, but this method is time-consuming and difficult to apply on a large scale. VIs, which analyze the reflectance of plants to light in different spectral bands, can be used to quickly detect plant health, and therefore have the potential to be an effective tool for early detection of GDM.

The study used SkySat and PlanetScope satellite imagery data in conjunction with ground disease ratings for data collection. The data were analyzed using a variety of VIs such as the NDVI, Enhanced Vegetation Index (EVI), and Atmospheric Resistance Vegetation Index (ARVI). These indices were used to assess the severity and incidence of GDM.

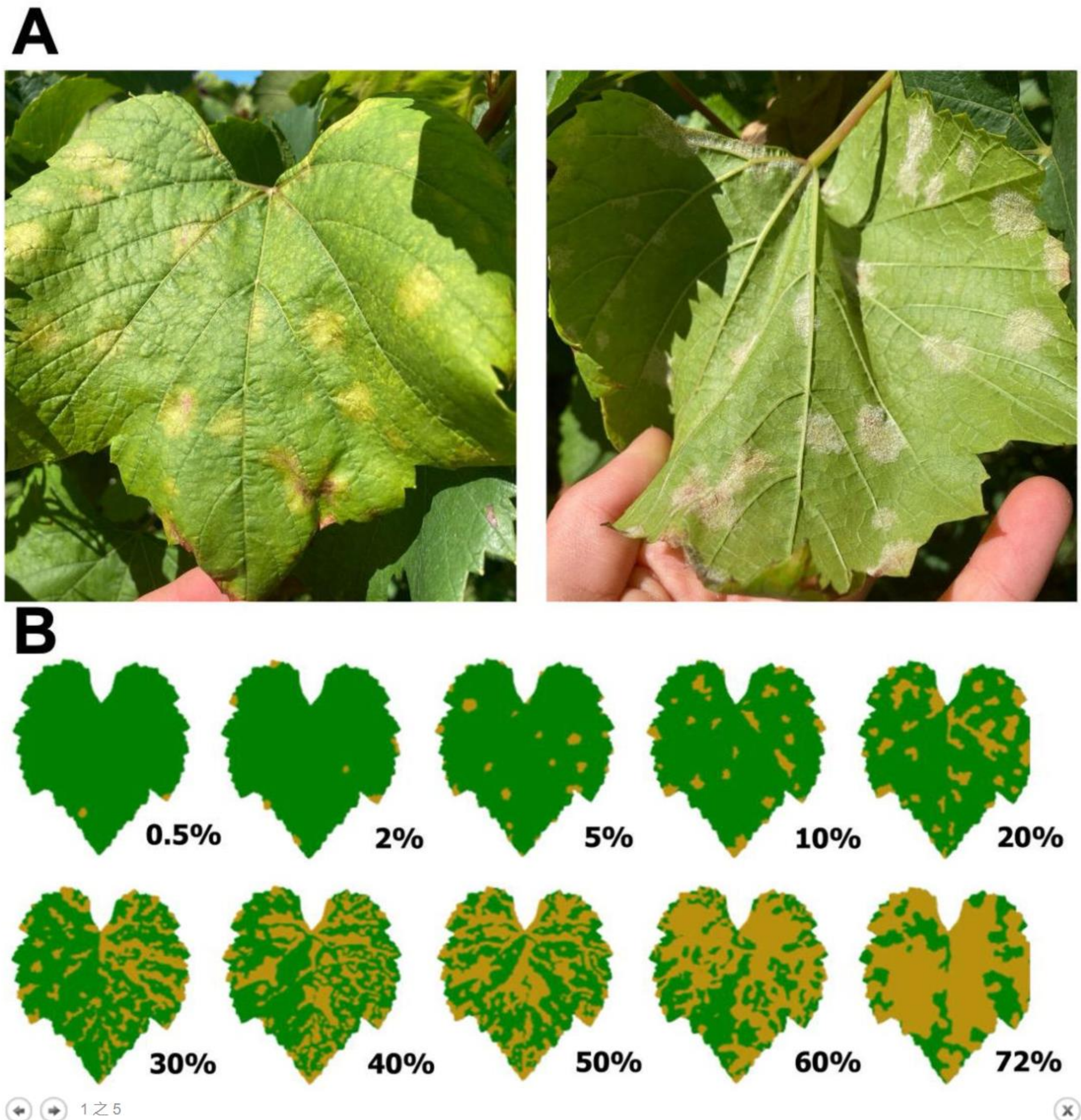
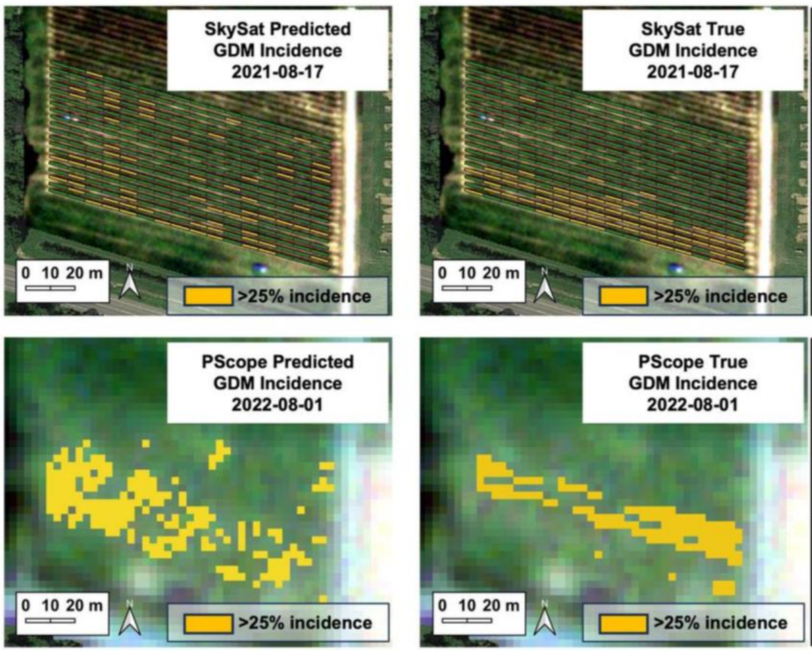


Figure 10: A: Foliar status of GDM-infected grapes. B: For assessing downy mildew severity. (Kalaney et al., 2023)

The researchers used a series of steps to generate and analyze image data for the grapevine panels when processing SkySat and PlanetScope images. Firstly, for the SkySat images, they generated a mask to isolate the range of pixels covered by each of the three or four grapevines. They used a Duro RTK GNSS receiver with sub-centimeter accuracy to geo-align the vineyard trellis columns and generated a GEOJSON file containing the trellis panel polygons based on these precise geographic coordinates. The panels were then assigned to a "high" or "low" disease severity and incidence category based on reconnaissance ratings close to the date of capture.

Because of the lower spatial resolution of the PlanetScope images, the researchers used a different approach. They assigned each panel's disease severity and incidence class to a coordinate point at the center of mass of the panel polygon, and then inserted this data on a 3 x 3 meter grid to generate per-pixel severity and incidence classes that matched the spatial resolution of the PlanetScope image. Ultimately, these pixels were categorized as high or low severity and morbidity (Kalaney et al., 2023).

Through these steps, the researchers were able to generate and analyze the disease status of grapevines using the properties of different satellite images. Kalaney et al. (2023) utilized various VIs from TOA reflectance and PlanetScope imagery, such as NDVI, EVI, and NDRE, to assess vegetation health and its correlation with GDM severity. They employed Spearman rank correlations to identify VIs most negatively associated with the disease and used the Mann-Whitney U statistic to detect early-season impacts. Random forest classifiers were trained for automated detection of high GDM damage areas, with feature importance assessed using permutation importance (Kalaney et al., 2023). This study effectively integrated satellite imagery data for GDM monitoring and detection.



Precision	High Inc.	0.36
	Low Inc.	0.73
Recall	High Inc.	0.36
	Low Inc.	0.73
F1	High Inc.	0.36
	Low Inc.	0.73
Overall Accuracy		0.62

Precision	High Inc.	0.21
	Low Inc.	0.92
Recall	High Inc.	0.33
	Low Inc.	0.87
F1	High Inc.	0.26
	Low Inc.	0.90
Overall Accuracy		0.82

Figure 11: True GDM incidence (right) and model predictions (left) for SkySat and PlanetScope Random Forest classifiers trained for each image type on the full 2020-2022 spectral band dataset. (Kalaney et al., 2023)

From the final analysis results obtained, GDM incidence reached 100% in at least one panel over the three-year observation period, while severity ranged from 57% to 82%, with most panels maintaining low disease intensity due to regular biocide use. Whereas panels in the high incidence category were not observed until specific dates in 2020, 2021, and 2022, typically earlier than the point at which severity exceeded 10%, PlanetScope imagery in 2022 captured late-stage GDM better than did SkySat. SkySat data showed that panels with high incidence and severity had significantly lower VIs than the low incidence and low severity panels, and these differences were particularly pronounced in the 2020 and 2021 images. PlanetScope data performed better in identifying incidence categories, particularly in the 2020 and 2022 images, where NDVI was the best metric for distinguishing incidence categories (Kalaney et al., 2023).

The performance of the Random Forest model showed that SkySat had the best performance for the GDM severity classifier in 2021, but the 2022 model performed poorly. The PlanetScope model was the most accurate on the 2020 dataset, and although the model performance decreased slightly in 2022, it still outperformed the SkySat data overall.

How growers can access satellite data

If vineyard managers want to access these satellite data, there are generally two ways to do so.

The first option is to use public service platforms that provide free access to satellite data. For Sentinel-2 data, vineyard managers can start by signing up for a free account on the Copernicus Open Access Hub. After registration, they gain full access to Sentinel-2 imagery. On this platform, users can search for specific images by entering details such as geographic location, time frame, and satellite operation periods. Once the appropriate data is found, it can be downloaded at the desired resolution. The multispectral images include several bands, which managers can use to calculate NDVI using near-infrared (NIR) and red bands. These calculations can be performed through online tools or basic GIS software. This method is entirely free and allows users to tailor the data selection and processing to their needs, making it suitable for those with some technical background.

For Landsat satellite data, users can obtain it at no cost through the U.S. Geological Survey's (USGS) EarthExplorer platform. The process is similar: users first create a free account on EarthExplorer. With an account, they can access imagery from all Landsat satellites, including the latest from Landsat 8 and Landsat 9. One of the key benefits of Landsat data is its extensive historical archive, which is invaluable for long-term environmental monitoring and analysis of changes over time. Like the Sentinel-2 service, this free platform is well-suited for users who are comfortable with downloading and processing the data independently.

The second option for accessing satellite data to inform vineyard management is to use commercial services that offer not just NDVI imagery, but also more sophisticated data analysis features, such as crop health assessments and soil moisture monitoring. Leading providers in this space include Planet Labs, Skywatch, EOS Data Analytics, and others. These services require a subscription fee, but the major advantage is that they take care of data acquisition and analysis, regularly delivering comprehensive reports on various aspects of interest to the users. Subscription fees for these services typically range from several thousand to tens of thousands of dollars annually, depending on the level of service and data required.

Conclusion

Satellite data have revolutionized vineyard management, offering unprecedented precision and efficiency in monitoring and optimizing various aspects of viticulture. The integration of remote sensing technologies, as evidenced by studies using satellites like Landsat, Sentinel-2, and those developed by Planet Labs, has enabled vineyard managers to make more informed decisions, leading to improvements in yield prediction, disease detection, and resource management.

Looking to the future, ongoing advancements in satellite technology are likely to bring even greater benefits to vineyard management. The development of satellites with higher spatial resolution and more frequent revisit times could further enhance the ability to monitor vineyard conditions in near real-time. For example, higher resolution imagery could improve the detection of subtle changes in vine health or soil conditions that might be missed with current technologies. Similarly, increased revisit frequency would allow for more timely interventions, potentially preventing issues before they become critical.

Moreover, the integration of satellite data with other emerging technologies, such as robotics, machine learning and artificial intelligence, holds promise for even more sophisticated analysis and decision-making tools. These advancements could lead to the development of predictive models that anticipate vineyard needs based on historical data, current conditions, and weather forecasts, enabling a proactive rather than reactive approach to vineyard management.

In conclusion, the use of satellite data in vineyard management has already made a significant impact, providing vineyard managers with the tools to optimize yield, manage water resources, and combat diseases more effectively. As satellite technology continues to advance, the potential for even more precise and timely management practices will only grow, further enhancing the sustainability and profitability of viticulture.

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