Emerging Methods for Early Disease Detection and Risk Prediction:

Scalable asymptomatic Grapevine Leafroll Virus Complex-3 detection through integrated airborne imaging spectroscopy, autonomous robotics, and cloud computing

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Context & Purpose:

The past three decades of terrestrial remote sensing research have delivered unprecedented insights into our fundamental ability to detect, quantify, and differentiate plant disease (Gold 2021). However, much of our fundamental knowledge in this domain has come from studies in non-agricultural systems and until recently, most agricultural studies, when extant, have focused on tree crops where canopy closure and large plot and plant size facilitate stress detection at low spatial resolution. Recent engineering innovations and advancements in constellation architecture design have refined the accuracy and scalability of airborne and spaceborne sensing platforms, enabling us to monitor diverse specialty crops, including grapevine, planted in smaller, spatially varied fields. Most prior work on grapevine remote sensing has aimed to detect water stress, with few studies addressing other abiotic parameters such as nitrogen content, yield, and fruit composition. Reports on proximal and remote sensing of grape disease have been focused on visible disease detection and predominantly limited to near surface deployments (Naidu et al. 2009; Oerke et al. 2016; Hou et al. 2016; MacDonald et al. 2016; Knauer et al. 2017; Bierman et al. 2019; Bendel et al. 2020; Gao et al. 2020; Lacotte et al. 2022; Sawyer et al. 2023). Plant disease alters how solar radiation interacts with leaves, canopy, and plant energy balance resulting in changes that are readily capturable in visible to shortwave infrared (VSWIR, 400-2400nm) hyperspectral imagery prior to symptom appearance (Gold et al. 2020). Exciting recent work has established that airborne imaging spectroscopy is capable of pre-symptomatic disease detection in multiple culturally important pathosystems, including olive quick decline syndrome (Zarco-Tejada et al. 2018, 2021) and infections of oak by *Phytophthora spp.* (Hornero et al. 2021) and *Bretziella fagacearum* (Sapes et al. 2022). This novel capacity combined with the anticipated spectral, spatial, and temporal coverage of forthcoming hyperspectral satellite systems, such as NASA's Surface Biology and Geology (SBG, Schneider et al. 2019) and ESA's Copernicus Hyperspectral Imaging Mission for the Environment (CHIME, Nieke and Rast 2018), will revolutionize imaging spectroscopy data availability for agricultural decision making, enabling disease monitoring at hereto unachievable resolutions while providing a robust foundation for multiscale risk estimation and surveillance networks.

While these studies in aggregate have proved imaging spectroscopy to be powerful tool for understanding, detecting, and mapping plant-fungal, oomycete, and bacterial interactions at scale, viral-plant interactions have yet to be explored at suborbital and beyond scales. Viral diseases, including that caused by Grapevine Leafroll Virus Complex 3 (GLRaV-3), cause $3 billion in losses to the US wine and grape industry annually (Naidu et al. 2014). GLRaV-3 infection significantly reduces vine longevity and causes the grapevine to misappropriate resources, resulting in uneven cluster ripening, changes to grape berry chemistry, reduced wine quality, and visible foliar reddening post-veraison in red grape varieties. Further challenging management is GLRaV-3's long (~12-month) latent phase, during which the host is infectious, but foliar symptoms are not yet apparent (Naidu et al. 2014; Blaisdell et al. 2016). Existing strategies to detect GLRaV-3 in the field are predominantly based on visual scouting by trained experts, a labor and time intensive process. This means that both latently infected red grape varieties and white grape varieties (which do not manifest visible foliar symptoms) serve as inoculum sources for nearby vineyards without grower recourse other than expensive ($40-50 per vine) molecular testing. Previous work has demonstrated the utility of remote sensing data for large-scale detection of symptomatic GLRaV-3 in red grape varieties (Hou et al. 2016; MacDonald et al. 2016) however these proof of concept studies have not yet transitioned from research to application, nor have they explored asymptomatic detection. Effective asymptomatic detection is critical for management, especially when the practicalities of deploying scouts across the hundreds of thousands of acres of grapevine grown in the United States is considered. Even under the most aggressive scouting plans, it takes at minimum 12 months, and more frequently, 18-24+ months, from date of first infection to date of removal.

Vineyards are difficult to monitor via remote sensing because of limited equipment viewing angle that challenges side and lower canopy symptom detection. The grapevine canopy is small relative to the image footprint of most air- or spaceborne sensors, and vines are bordered by inter rows of bare soil and/or non-vine vegetation, and shadows cast by the crop itself impart noise to the reflectance signal. Effective remote sensing requires large amounts of calibration and validation data, which can be challenging to obtain through traditional human field scouting. This has led to widespread interest in automated ground-based detection methods for early detection, and various techniques for data processing ranging from traditional statistical methods to deep learning models developed (Naidu et al. 2009; Bendel et al. 2020; Gao et al. 2020; Sawyer et al. 2023). Thus far, use of these methods has been limited to situations where leaves or branches are sampled and placed against a controlled background. The logical next step to bridge the research to application gap is deployment on uncrewed ground vehicles (UGV) capable of traversing in between rows without human intervention to collect validation data for aerial imagery at scale. However, vineyards in different geological locations have varying environmental challenges and management requirements. Designing robotic systems suitable for different environments, terrains, slopes, and tasks is critical for simplified, effective deployment and cost control.

Effective use of the afore described technologies is facilitated by machine and deep learning, which help to make sense of the underlying relationships within and amongst hundreds of highly correlated spectral bands. These approaches have been widely used in airborne plant-microbe interaction sensing as well as in the broader, adjacent domains of foliar functional ecology (Townsend et al. 2003; Sousa et al. 2021; Wang et al. 2020). Together these can support agricultural decision-making at unprecedented scales, but training and deploying these models is limited by the considerable compute and storage resources they require, severely limiting non-expert use. Cloud computing offers on-demand and nearly unlimited access to storage and computing resources—where connectivity allows. In agricultural areas with restricted internet connectivity, edge computing complements cloud computing by placing storage and computing nearer to data sources, enabling accurate models to be built and timely response. This distributed computing model enables models to be trained in the cloud and deployed at the edge (e.g. on users' devices), optimizing utility for agricultural decision-making (Rubambiza et al. 2022). These methods have been increasingly applied in agricultural remote sensing, including yield prediction, soil mapping, and land management (Rubambiza et. al 2023). Thus, edge and cloud computing are crucial for scaling current techniques and investigating the implications of future spaceborne missions for effective disease surveillance.

NASA's Airborne Visible/Infrared Imaging Spectrometer Next Generation (AVIRIS-NG) is an airborne instrument operated from the Jet Propulsion Laboratory in Pasadena, CA with extensive historic acquisitions in California, including over ~364,000 hectares (ha) of vineyards. The AVIRIS mission family, which includes Classic (C), Next Generation (NG), and the forthcoming AVIRIS-3, will continue to collect wide-swath, high spectral resolution (<10 nm), and highly uniform spectroscopic imagery (400 to 2400 nm) over diverse California biomes, including viticultural production areas. Additionally, NASA's forthcoming hyperspectral satellite Surface Biology and Geology will be based on the AVIRIS family architecture. AVIRIS-NG therefore represent perfect opportunity to generalize, optimize, and continuously validate models for early GLRaV-3 detection in vineyards. Thus, the goals of the work presented here are threefold:

1) Determine to what level of accuracy airborne imaging spectroscopy can detect asymptomatic GLRaV-3 infection across scales.
2) Deploy these models in a distributed, cloud computing system designed with stakeholder values and needs in mind.
3) Deploy an autonomous ground robotic training system to collect ground truth validation at scale in real time to improve model development.

Materials and Methods:

Airborne Imagery Acquisition. Two airborne campaigns were conducted over the course of this research. In September 2020, spectroscopic imagery over vineyards in Lodi was acquired with NASA-JPL's AVIRIS-NG instrument on board a King Air B-200 aircraft from an altitude of ~1,000 m above ground level. The AVIRIS-NG platform samples the electromagnetic spectrum at 5 nm intervals within the 380 nm to 2510 nm spectral range resulting in 425 spectral channels. In total, this campaign, the "AVIRIS Wine Tour," collected imagery over 15,095 ha of California vineyards spanning Napa Valley, Sonoma Valley, Lodi, and Paso Robles, at peak grapevine foliage. In May 2022 and September 2022, the SBG High Frequency Time Series (SHIFT) campaign collected terrestrial and coastal marine AVIRIS-NG flight lines in the Southern California bight between Santa Barbara and the Channel Islands, as well as overlapping terrestrial flight lines in a 21 km x 68 km (1428 km2) rectangle stretching from Point Conception to Figueroa Mountain in the southern Coast Ranges. All AVIRIS-NG imaging used in this study are reflectance data and are publicly available and can be downloaded from the AVIRIS-NG data portal https://aviris.jpl.nasa.gov/dataportal/. All imagery was pre-processed according to domain best practices prior to analysis. For more details, please see Romero Galvan et al. (2023).

Ground Validation. During the AVIRIS-NG Wine Tour campaign, industry collaborators coordinated a team of trained field technicians to visually inspect ("scout") 109 ha of red grape varieties visible, foliar symptoms of GLRaV-3 according to industry best practices (Bolton, 2020). Scouting and geotagging of visibly diseased vines was conducted in September of 2020 and 2021 pre-harvest when symptoms were most apparent. In total, 1427 and 2398 GLRaV-3-infected vines were identified by the ground-scouting teams in 2020 and 2021 respectively. All grape clusters, green foliage, and canes were removed from the grapevines during mechanical harvest approximately one week after final airborne data acquisition in 2020. Cane tissue samples from 100 vines in 2020 and 10 vines in 2021, variably identified as diseased/non-diseased, were sent for commercial diagnostic testing to validate scouting accuracy. All samples sent for testing that had been identified as GLRaV-3-infected by the scouts returned positive for infection. No samples identified as non-infected by the scouts tested positive. Grapevine Red Blotch Virus was not detected in any samples tested. After mechanical harvest in 2020 and prior to 2021 bud break, industry collaborators removed diseased vines from the vineyards to prevent them from serving as an inoculum reservoir. Vines were given one of three labels: non-infected (NI), symptomatic (Sy), and asymptomatic (aSy). Vines that were not identified as visibly diseased by scouting teams in 2020 or 2021 were labeled as non-infected (NI). Vines identified as visibly diseased in 2020 (data acquisition year) were labeled as symptomatic (Sy). Vines identified as visibly diseased in 2021 were labeled asymptomatic (aSy). These vines were NOT visibly diseased in 2020, implying they were latently infected during the

2020 AVIRIS-NG flights. This assumption is well supported by the current understanding of GLRaV-3 disease biology (Naidu et al., 2014; Blaisdell et al., 2016) and the fact that all green foliage was removed from the vineyard during mechanical harvest shortly after data acquisition. Molecular testing to conclusively diagnose whether vines labeled aSy were truly asymptomatic during the 2020 flights was not possible given the study's scope and the expense of sample testing. Sy and aSy vines were geotagged with an RTK-GPS.

During the fall flights of the AVIRIS-NG SHIFT campaign (September 8-15, 2022) a scouting team of grape pathology researchers collected GLRaV-3 incidence data at a collaborating vineyard in Los Olivos, CA. A sub-sample of the scouted vines had canes selected using random stratified selection to send for commercial testing to verify identified symptoms were indeed due to GLRaV-3. Stratification was both spatial and according to grapevine variety and found the team to be ~90% accurate in identifying GLRaV-3 infected grapevines. Grapevine Red Blotch Virus was not detected in any samples tested. During human scouting, each infected vine of the field was identified by visually inspecting its canopy, and the location of its trunk was recorded by a handhold RTK-GPS device.

Ground Robot Data Acquisition: The study's data was gathered from a vineyard situated in central California using the PhytoPatholoBot (Liu et al. 2022) in mid-September 2022 in coordination with the AVIRIS-NG SHIFT Campaign. The data consisted mostly of timestamped RGB images of canopy side views captured by a custom-designed camera with enhanced strobe lighting. The images were 4,096x3,000 pixels with a field of view of around 50x60 degrees. The camera was programed to collect images at 1 second per frame interval, and 12 strobe lights adjacent to the camera were synchronized with the camera shutter to provide uniform lighting conditions. The camera system was placed about 0.7m away from the canopy and mounted on to a Husky four-wheel differential drive robot base (Clearpath Robotics Inc.). The robot moved autonomously through the crop rows by following a pre-defined sequence of GPS control points at a speed of approximately 0.5 m/s. To navigate through the vineyard, a custom-designed PID line tracking program guided the robot, using localization and attitude data obtained from the SMART-7 navigation system (Novatel Inc.). The SMART-7 system provided RTK calibrated GPS information and INS attitude information at a frequency of 10Hz. The RTK signal was transmitted through a 900MHz radio from a mobile RTK base station situated at the edge of the field. During data collection, localization and attitude data was also timestamped and recorded along with the RGB images. After the data collection, 100 images were randomly selected from one end of the field and segregated into 4 tiles of 2,048x1,500 pixels for manual annotation of visible symptoms in the form of masks. Due to the time constraints only 77 tiles were completed in time. The annotated tiles were further divided into a training subset of 41 tiles, a validation subset of 10 tiles and a testing subset of 26 tiles randomly. Apart from the annotated dataset, 14 consecutive rows located in the middle of the field were selected separately to compare with the human scouting result in scale. The reserved dataset contained 10,588 images with their time stamp and geo-referencing information and was not annotated. We then used our previously developed near-real time semantic segmentation model for image disease detection (Liu et al., 2022). Unlike conventional classification and bounding box detection models used for fast image-level disease identification, this model provides pixel-level detailed masks to identify symptoms in images. This model was modified with multi-level feature cross-links and transposed convolution-based resolution restoration to improve segmentation accuracy while maintaining efficiency suitable for embedded robotic deployment. For more detail, please see Liu et al. (2023).

Cloud Computing. The cloud computing system architecture consists of three major components that provide an adaptable pipeline for disease detection: (1) NASA Cloud (2) the edge lab at Cornell university, and (3) the Microsoft Azure Cloud. AVIRIS-NG data was downloaded from the NASA cloud and pre-processed (e.g. BRDF correction, etc.) at the edge lab, and then aligned with stakeholder ground truth validation. The training data can be uploaded to the cloud or remain entirely on the edge device.

This system was intentionally designed not to retain training data uploaded into the cloud, only the model. The below steps were followed to deploy the models developed in Romero et. al 2023 in the Azure cloud.

1) Serialization: The models developed in Romero Galvan et. al 2023 were serialized using Python's pickle library. Serialization transforms the trained random forest models into bits that can be quickly sent over a network and recreated in the new location.
2) Model Upload: The upload process involved specifying the model's location on the local computer, the model's name, any relevant tags, and the Azure Machine Learning workspace where the model was stored. Each model must have a unique name within a workspace. Versions of the model are created automatically if a model name is registered more than once.
3) Azure ML Workspace: Azure ML is a platform-as-a-service (PaaS) offering for data processing in the Azure Cloud. A workspace is a logical partition of computing and storage servers for a single project. Models are indexed by names and versions within the workspace.
4) Model Download: Downloading the model can be done either programmatically (ideal for areas with limited cloud connectivity) or manually (useful for checking model parameters and size before deployment). The manual download is done through the Azure portal, a user-friendly interface for managing resources in the Azure Cloud.

This automated pipeline inputs pre-processed imagery and outputs a classified raster. We then compared the resulting latency and model accuracy in executing disease inference requests with models/data deployed in the public cloud and edge clouds across three experimental training/testing conditions: (1) cloud-based model and cloud-based SI data (control setup), (2) local model and local SI data, (3) local model and cloud-based SI data. For more detail, please see Rubambiza & Romero Galvan et al. (2023).

Results:

We identified distinct spectral signatures for asymptomatic GLRaV-3 vines that differentiate them from both non-infected and symptomatic grapevines and assessed scalability across 1,3, and 5m resolution. Using random forest, we were able to differentiate between non-infected (NI), asymptomatic (aSy), and symptomatic (Sy) GLRaV-3 infected vines based on spectral signatures alone. The two best-performing models were trained on 3m resampled spectroscopic imagery with Savitzky-Golay smoothing applied and dimensionality reduced to 10 principal components. These models achieved accuracies of 87% and 85%, respectively, when discriminating between NI vs. aSy and NI vs. (aSy+Sy) vines. Model performance was generally consistent across spatial scales from 1m to 5m but peaked at 3m resolution. Our models, while accurate, tended to over-classify areas as diseased, particularly near the vineyard boundaries, likely due to confounding co-occurring abiotic stress. When classifying between all three classes, most misclassifications are between Sy and aSy vines, indicating that these two groups share enough spectral similarity for the models to confuse them. The spectral similarity is likely GLRaV-3- infection, which is known to affect vine biology prior to symptom appearance (Gao et al., 2020; Naidu et al., 2009). SWIR wavelengths were crucial for accurate class differentiation, which suggests asymptomatic detection is driven by disease physiology, as these wavelengths are the most correlated with vegetative biochemistry and physiology. These results underscore the necessity of full-spectrum imagery for accurate asymptomatic disease detection, as well as the need to reduce confounding due to co-occurring abiotic stress. Future work will leverage time-series thermal sensing to reduce this source of error and improve model precision. Further discussion of this work can be found in Romero Galvan et al. (2023).

We successfully implemented a fully automated pipeline for GLRaV-2 detection in red grape varieties using real-time semantic segmentation networks and the autonomous PPB robot. This system navigates autonomously and provides disease incidence ratings comparable to human scouting, thus contributing valuable calibration data at scale for remote sensing systems. The PPB autonomously traversed through the vineyard using RTK-GPS system following the predefined waypoints and collected the data using a custom strobe light enhanced camera. A near real-time embedded network was successfully trained to segment infected regions and canopy areas to calculate incidence and symptom severity, and locations of the infected vines identified by robot and human scouting were compared. Experimental results showed a strong agreement between the two evaluation methods. The semantic segmentation system had a 5.94% misdetection rate (94.06% accuracy) and 11.3% false positive rate, which strongly correlated with the outcomes generated by human scouting (~90% accurate). However, it should be noted that the field had a relatively high GLRaV-3 infection rate, and this evaluation may be biased due to imbalanced sampling. Future work will iteratively refine and deploy this system to build improved GLRaV-3 detection models across the entire SHIFT campaign imagery acquisition zone. Further discussion of this work can be found in Liu et al. (2023).

We developed an adaptable cloud-based system for detecting GLRaV-3 in grapevine using airborne imaging spectroscopy data. Our system only requires spectroscopic imagery from an airborne or spaceborne source and a user-supplied shapefile specifying location coordinates and boundaries to run. The stakeholder can supply additional training data to improve model accuracy in their specific location, but this is not required. Local training on Edge with 4MB data achieved 84% accuracy in 27.1 seconds, while Edge and Azure ML cloud configurations both achieved 86% accuracy, with runtimes of 35.6 seconds and 86.5 seconds, respectively. Our cloud-based architecture addresses three key goals: social impact, research reproducibility, and user privacy. We achieve social impact by offering a user-friendly service, deploying refined models as web endpoints for on-demand data inference. To maintain user privacy, all sensitive data remains on the user's edge device. This design aspect is critical for widespread adoption, as stakeholders frequently have reservations about, or outright restrictions against, proprietary data sharing. The system also promotes reproducible research through Azure ML's features for systematic model registration, tracking, and tagging. Further discussion of this work can be found in Rubambiza & Romero Galvan et al. (2023).

Together, this integrated system enables data-driven decision-making for viticultural stakeholders by leveraging cutting-edge spectral imaging, robotics, machine learning, and cloud computing to facilitate scalable, asymptomatic disease detection. Our work improves management decision-making while serving as a guide for others in the remote sensing community to develop accessible, use-inspired, remote sensing applications for agricultural stakeholders. This integrated, transdisciplinary, systems-based approach can aid grape growers to deploy their limited ground resources (e.g. molecular diagnostics, human scouts) more strategically, thereby complementing existing farm ecosystems without replacing invaluable user expertise. As we advance towards the imminent global imaging spectroscopy era, critical next steps for this work include assessing scalability of our findings to spaceborne resolution (~20-30m), implement a fully closed loop data training system between the ground robot and airborne imagery, and merge this system into existing, open source, and user-friendly data management applications, such as the MyEV tool suite (Bates, 2023), to achieve our overarching goal to empower agricultural stakeholders to use spaceborne imaging spectroscopy data to inform disease management decision-making regardless of their programming, remote sensing, and GIS expertise.

References

1. Bendel, N., Kicherer, A., Backhaus, A., Köckerling, J., Maixner, M., Bleser, E., et al. 2020. Detection of Grapevine Leafroll-Associated Virus 1 and 3 in White and Red Grapevine Cultivars Using Hyperspectral Imaging. Remote Sensing. 12:1693.
2. Bierman, A., LaPlumm, T., Cadle-Davidson, L., Gadoury, D., Martinez, D., Sapkota, S., et al. 2019. A High-Throughput Phenotyping System Using Machine Vision to Quantify Severity of Grapevine Powdery Mildew. Plant Phenomics. 2019 https://spj.sciencemag.org/journals/plantphenomics/2019/9209727/
3. Blaisdell, G. K., Cooper, M. L., Kuhn, E. J., Taylor, K. A., Daane, K. M., and Almeida, R. P. P. 2016. Disease progression of vector-mediated Grapevine leafroll-associated virus 3 infection of mature plants under commercial vineyard conditions. Eur J Plant Pathol. 146:105–116.

4. Efficient Vineyard - T. Bates. Efficient Vineyard - T. Bates. Available at: https://www.efficientvineyard.com
5. Gao, Z., Khot, L. R., Naidu, R. A., and Zhang, Q. 2020. Early detection of grapevine leafroll disease in a red-berried wine grape cultivar using hyperspectral imaging. Computers and Electronics in Agriculture. 179:105807.
6. Gold, K. M. 2021. Plant Disease Sensing: Studying Plant-Pathogen Interactions at Scale. mSystems. 0:e01228-21.
7. Gold, K. M., Townsend, P. A., Chlus, A., Herrmann, I., Couture, J. J., Larson, E. R., et al. 2020. Hyperspectral Measurements Enable Pre-Symptomatic Detection and Differentiation of Contrasting Physiological Effects of Late Blight and Early Blight in Potato. Remote Sensing. 12:286.
8. Hornero, A., Zarco-Tejada, P. J., Quero, J. L., North, P. R. J., Ruiz-Gómez, F. J., Sánchez-Cuesta, R., et al. 2021. Modelling hyperspectral- and thermal-based plant traits for the early detection of Phytophthora-induced symptoms in oak decline. Remote Sensing of Environment. 263:112570.
9. Hou, J., Li, L., and He, J. 2016. Detection of grapevine leafroll disease based on 11-index imagery and ant colony clustering algorithm. Precision Agric. 17:488–505.
10. Knauer, U., Matros, A., Petrovic, T., Zanker, T., Scott, E. S., and Seiffert, U. 2017. Improved classification accuracy of powdery mildew infection levels of wine grapes by spatial-spectral analysis of hyperspectral images. Plant Methods. 13:47.
11. Lacotte, V., Peignier, S., Raynal, M., Demeaux, I., Delmotte, F., and da Silva, P. 2022. Spatial–Spectral Analysis of Hyperspectral Images Reveals Early Detection of Downy Mildew on Grapevine Leaves. International Journal of Molecular Sciences. 23:10012.
12. Liu, E., Gold, K. M., Combs, D., Cadle-Davidson, L., and Jiang, Y. 2022. Deep semantic segmentation for the quantification of grape foliar diseases in the vineyard. Frontiers in Plant Science. 13 Available at: https://www.frontiersin.org/articles/10.3389/fpls.2022.978761
13. Liu, E., Monica, J., Gold, K., Cadle-Davidson, L., Combs, D., and Jiang, Y. 2023. Vision-based Vineyard Navigation Solution with Automatic Annotation. arXiv.org. Available at: https://arxiv.org/abs/2303.14347v1
14. MacDonald, S. L., Staid, M., Staid, M., and Cooper, M. L. 2016. Remote hyperspectral imaging of grapevine leafroll-associated virus 3 in cabernet sauvignon vineyards. Computers and Electronics in Agriculture. 130:109–117.
15. Naidu, R. A., Perry, E. M., Pierce, F. J., and Mekuria, T. 2009. The potential of spectral reflectance technique for the detection of Grapevine leafroll-associated virus-3 in two red-berried wine grape cultivars. Computers and Electronics in Agriculture. 66:38–45.
16. Naidu, R., Rowhani, A., Fuchs, M., Golino, D., and Martelli, G. P. 2014. Grapevine Leafroll: A Complex Viral Disease Affecting a High-Value Fruit Crop. Plant Disease. 98:1172–1185.
17. Nieke, J., and Rast, M. 2018. Towards the Copernicus Hyperspectral Imaging Mission For The Environment (CHIME). In *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, , p. 157–159.
18. Oerke, E.-C., Herzog, K., and Toepfer, R. 2016. Hyperspectral phenotyping of the reaction of grapevine genotypes to Plasmopara viticola. J Exp Bot. 67:5529–5543.
19. Romero Galvan, F., Pavlick, R., Trolley, G. R., Aggarwal, S., Sousa, D., Starr, C., et al. 2023. Scalable early detection of grapevine virus infection with airborne imaging spectroscopy. Phytopathology®. Available at: https://apsjournals.apsnet.org/doi/10.1094/PHYTO-01-23-0030-R
20. Rubambiza, G., Galvan, F. R., Pavlick, R., Weatherspoon, H., and Gold, K. M. Towards Cloud-Native, Machine Learning Base Detection of Crop Disease with Imaging Spectroscopy. Journal of Geophysical Research: Biogeosciences. n/a:e2022JG007342.
21. Rubambiza, G., Sengers, P., and Weatherspoon, H. 2022. Seamless Visions, Seamful Realities: Anticipating Rural Infrastructural Fragility in Early Design of Digital Agriculture. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, CHI '22, New York, NY, USA:

Association for Computing Machinery, p. 1–15. Available at: https://doi.org/10.1145/3491102.3517579
22. Sapes, G., Lapadat, C., Schweiger, A. K., Juzwik, J., Montgomery, R., Gholizadeh, H., et al. 2022. Canopy spectral reflectance detects oak wilt at the landscape scale using phylogenetic discrimination. Remote Sensing of Environment. 273:112961.
23. Sawyer, E., Laroche-Pinel, E., Flasco, M., Cooper, M. L., Corrales, B., Fuchs, M., et al. 2023. Phenotyping grapevine red blotch virus and grapevine leafroll-associated viruses before and after symptom expression through machine-learning analysis of hyperspectral images. Frontiers in Plant Science. 14 Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10036814/
24. Schneider, F., Ferraz, A., and Schimel, D. 2019. Watching Earth's Interconnected Systems at Work. Eos. Available at: https://eos.org/science-updates/watching-earths-interconnected-systems-at-work.
25. Sousa, D., Fisher, J. B., Galvan, F. R., Pavlick, R. P., Cordell, S., Giambelluca, T. W., et al. 2021. Tree Canopies Reflect Mycorrhizal Composition. Geophysical Research Letters. 48:e2021GL092764.
26. Townsend, P. A., Foster, J. R., Chastain, R. A., and Currie, W. S. 2003. Application of imaging spectroscopy to mapping canopy nitrogen in the forests of the central Appalachian Mountains using Hyperion and AVIRIS. IEEE Transactions on Geoscience and Remote Sensing. 41:1347–1354.
27. Wang, Z., Chlus, A., Geygan, R., Ye, Z., Zheng, T., Singh, A., et al. 2020. Foliar functional traits from imaging spectroscopy across biomes in eastern North America. New Phytologist. 228:494–511.
28. Zarco-Tejada, P. J., Camino, C., Beck, P. S. A., Calderon, R., Hornero, A., Hernández-Clemente, R., et al. 2018. Previsual symptoms of Xylella fastidiosa infection revealed in spectral plant-trait alterations. Nature Plants. 4:432–439.
29. Zarco-Tejada, P. J., Poblete, T., Camino, C., Gonzalez-Dugo, V., Calderon, R., Hornero, A., et al. 2021. Divergent abiotic spectral pathways unravel pathogen stress signals across species. Nat Commun. 12:6088.