National Aeronautics and Space Administration

Building the foundations of a global plant disease surveillance system: Detecting plant-microbe interactions through integrated proximal and remote imaging spectroscopy

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Program: FY21 SURP **Strategic Focus Area: Water and carbon cycles**

Objectives

The objective is to use airborne hyperspectral imagery (HIS) collected in September 2020 by NASA's Airborne Visible/Infrared Imaging Spectrometer Next Generation (AVIRIS-NG) for the early detection of Grapevine Leafroll Virus (GLRV) infection in grapevine in California vineyards. Our overarching goal is to develop a scalable, remote sensing framework for detecting plant-pathogen interactions in grapevine, an economically important specialty crop. Our objectives and paired-underlying hypothesis are as follows: First, we compare and contrast supervised and unsupervised machine learning methods for symptomatic disease detection. We hypothesize that the optimal machine learning approach will be a combination of supervised methods given their history of success in other terrestrial imaging spectroscopy applications. Next, we compare statistical and physiological dimensionality reduction for improving disease detection precision. We hypothesize that dimensionality reduction will improve our detection accuracy and yield a set of wavelengths with known association with plant defense chemicals and core functional traits to link to known disease biology. Lastly, we work towards identifying the minimum threshold for detection with spaceborne imaging spectroscopy. We hypothesize that 15% disease incidence, half the recommended vineyard removal threshold, is sufficient to detect disease at the 30m spatial of the upcoming NASA Surface Biology and Geology (SBG) mission.

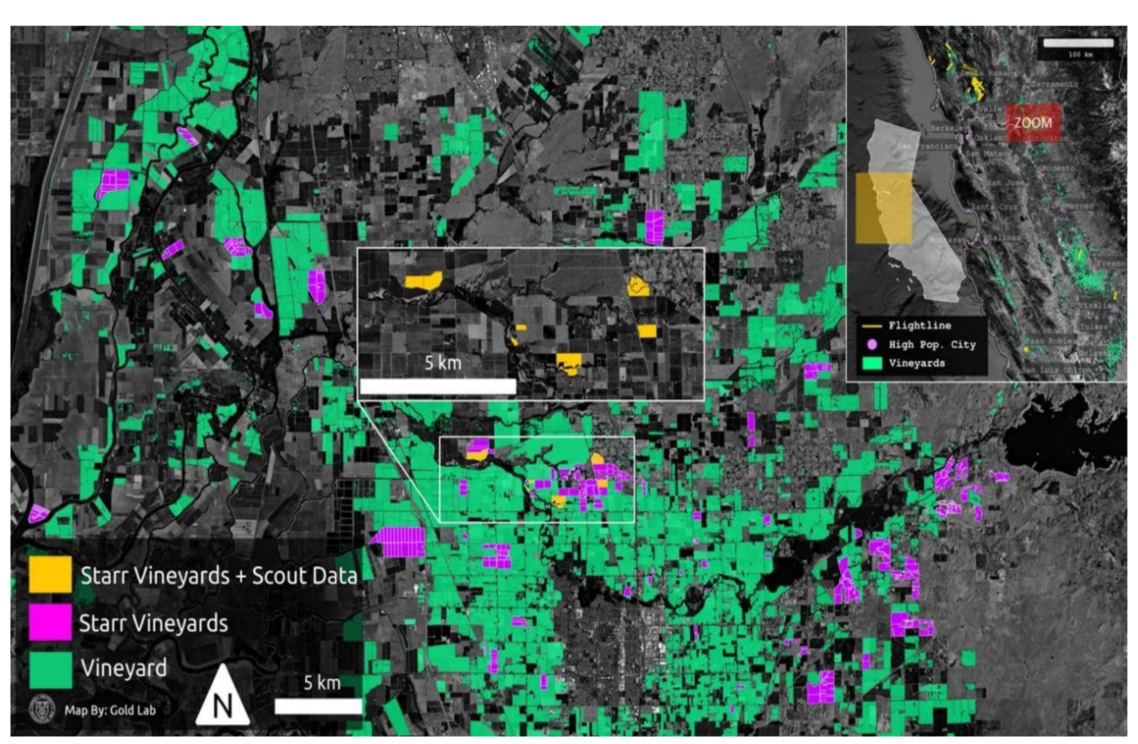
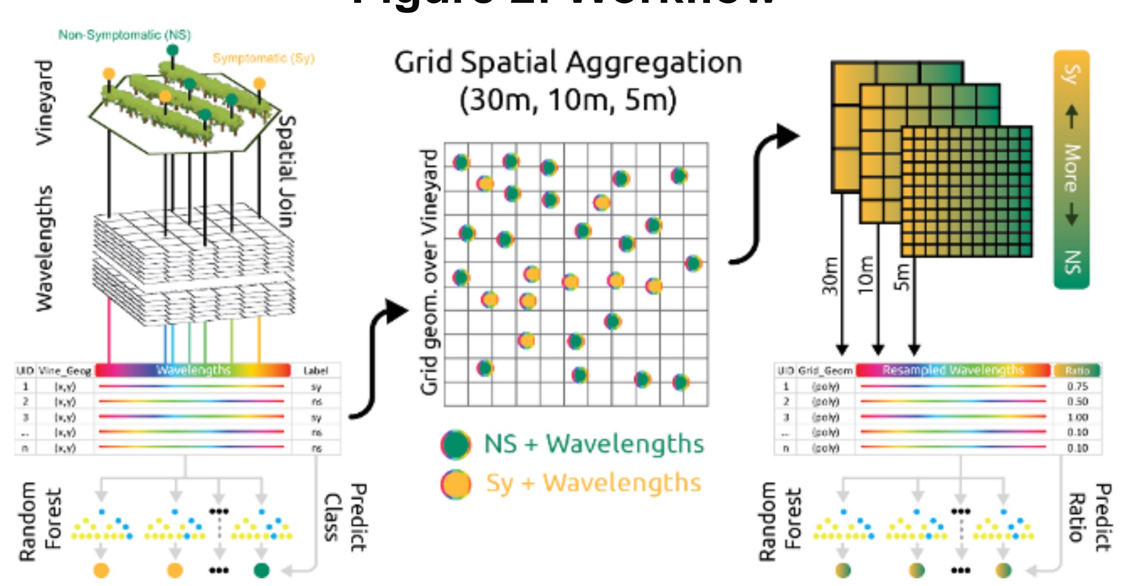


Figure 1: Study Area

Figure 2: Workflow



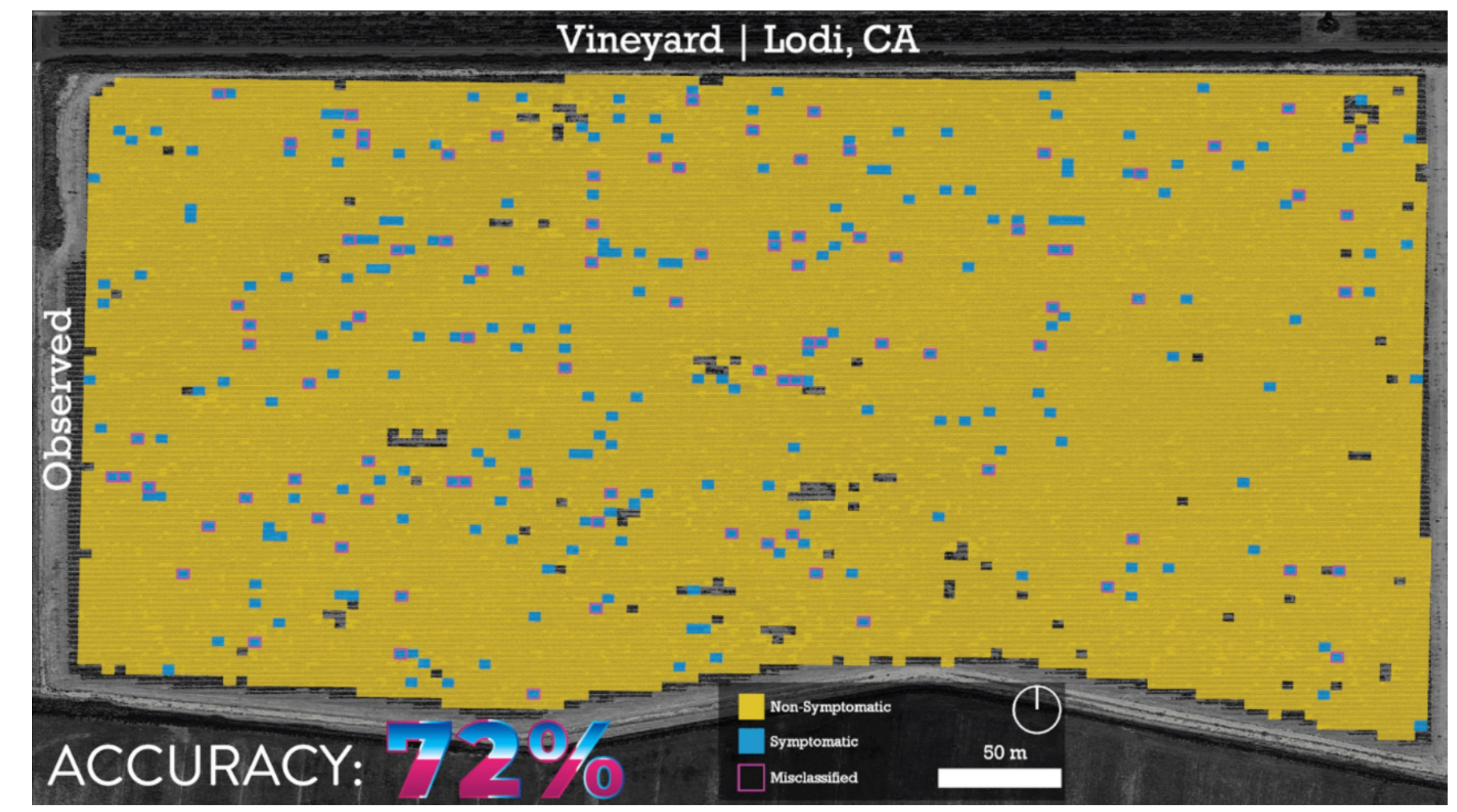
Background

Plant-pathogen interactions can impact a variety of plant traits that can be non-destructively sensed, from tissue color changes to foliar chemistry and various other traits[1]. Broadband and multispectral methods relying primarily on visible and near-infrared reflectance indices have been historically used to sense late stage plant disease[2,3]. Changes in continuous, short wave infrared (SWIR) has proved valuable for plant-pathogen interaction sensing due to SWIR sensitivity to a range of foliar properties[4]; including nutrient content[5,6,7,8], water[9], photosynthetic capacity[10], physiology[11], phenolics, and secondary metabolites[12,13,14]. Plant pathogens damage, impair, and/or alter foliar function, thus changing the chemical composition of foliage, such as through production of systemic effectors or secondary metabolites, or by presence of pathogen structures[15]. These changes can be sensed using both foliar and imaging-spectroscopy[16,17]. Recently, Zarco-Tejada et al. established that airborne hyperspectral imagery can be used for pre-symptomatic plant disease detection[18]. Here, grapevine and GLRV is proposed as a model pathosystem. Grape is the highest value fruit crop in the US grown on over one million acres, with 90% of this acreage located in California and is ideal for plant-pathogen interaction sensing due to its perennial nature, high value, and large number of economically important diseases.

Approach and Results

In collaboration with industry and academic colleagues, 280 acres of Aglianico, Cabernet Sauvignon, and Petite Sirah grapes were scouted for disease symptoms at peak time of year and a subset collected for confirmation testing (Figure 1). AVIRIS imagery was free of clouds, aerosols, and smoke. A bidirectional reflectance distribution function was applied to each acquisition to correct for view and illumination angle effects. Additionally, water absorption bands between (0-400nm, 1310-1470nm,1750-2000nm, 2400-2600nm) were removed for each acquisition. Some of the ground team data resulting from the scout effort were provided in a shapefile that stored point-geometry. The shapefiles provided a latitude and longitude as well as the corresponding disease-label for each location a scout identified GLRV. Data from the ground-teams that were not processed/stored in a geographic information system (GIS) were georeferenced using in-house GIS application and location details provided in the scout-documentation, the resulting points were then visually validated for spatial-accuracy. Once the data was able to be used for a spatial join query, GIS and remote-sensing python libraries such as Rasterio, GDAL, and Geo-Pandas were used to spatially-sample the AVIRIS acquisitions where the ground-data and the imagery spatially overlapped (Figure 2). Once data was properly formatted into a pandas dataframe, the data was consequently split into training and testing a starting split of 70/30 respectively. Using Scikit-Learn's random forest classification, an initial model was trained over a set of points and AVIRIS imagery over one vineyard in the city of Lodi. Here, we observed clear spectral differences that allowed for differentiation between healthy and GLRV infected vines at one-meter resolution with an average 72% accuracy on the testing dataset (Figure 3). We hypothesize these spectral differences are linked to inherent disease physiology and will scale as has been seen with other physiology-linked processes.

Figure 3: Test dataset results



Significance/Benefits to JPL and NASA

The use of remote sensing to advance plant disease detection represents an innovative opportunity to further the use of Earth system science research to benefit society and inform decision making while advancing applications-focused research in precision agriculture, one of the priorities outlined for Surface Biology and Geology in the 2018 NASA Decadal Survey and strategic priorities. The ability to non-destructively sense plant disease would greatly benefit modern agriculture and food security. Early intervention is key to successful disease mitigation. Farmers can apply systemic fungicides to stop disease before it spirals out of control, but these are only effective when applied early during the infection process. Worldwide, plant disease research and early intervention efforts are often constrained by a lack of local expertise to devote to prevention, a lack of resources to devote to monitoring and/or remediation, and a lack of qualified personnel to allocate to both these tasks. The use of remote sensing to advance plant disease research represents an opportunity to avoid these challenges and make a difference in the lives of farmers worldwide while advancing applications focused research on precision agriculture, one of the goals outlined in the NASA Decadal Survey (ESAS, National Academies, 2018).

Publications

Romero, F., Pavlick, R., Baumgartner, K., Fujiyoshi, P., & Gold, K. (2020, December). Assessing the Utility of Historic NASA Imaging Spectroscopy Data to Detect Plant Disease in California Vineyards. In AGU Fall Meeting Abstracts (Vol. 2020, pp. B004-0001).

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