Leveraging Drone Imagery and Microclimate Models to Map Disease-Related Environmental Conditions in Coastal Shrublands

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About Me

- CSU Monterey Bay B.S. Earth Systems, Science & Policy
- San Jose State M.S. Organismal Biology, Conservation & Ecology
- UC Santa Cruz Ph.D. Environmental Studies
- CSU Monterey Bay
 - STEM Lecturer, Staff Researcher
 - SI Science Coordinator
 - Adjunct Research Faculty
- UC Santa Cruz
 - Senior Drone Pilot
 - GIS Technician
 - Drone Instructor
- Drone Camp Committee & Instructor





Neofusicoccum australe (Botryosphaeriaceae)

- Confirmed outbreaks in S. Cal. in cultivated and wildland landscapes
- Ubiquitous endophytic fungal pathogen
- Disease associated with prolonged leaf wetting and environmental stress.
- Causes blight and canker diseases in many woody plant species



Host Species

Wooly-Leaf Manzanita Arctostaphylos tomentosa



Sandmat Manzanita Arctostaphylos pumila





Is there a gradient of disease pressure with distance from the coast because of variation in leaf wetness duration?

Are the two manzanita species with differing coastal distributions affected differently by disease?

The Challenge

Working in often impenetrable shrubland:

- 1. Find the target plant species.
- 2. Measure disease severity in those plants.
- 3. Measure the gradient in leaf wetness.

Can we use drones and machine learning to provide useful and accurate data more easily or better than traditional approaches?

Why use drones to study plant health?

- 1. Increased canopy accessibility and reduced impact
- 2. Increased spatial extent at high resolution
- 3. Multispectral sensors
- 4. Topographic data
- 5. Cover Classification
- 6. Canopy Health Assessment





0 2.5 5 10 Meters

Drone Mapping

- 246-ha Fort Ord Natural Reserve
 - 40.7-ha study area
 - oak woodland, coastal sage scrub, maritime chaparral
- Flights: July 23-24, 2021
- Multispectral (2.5 cm/px)
- Topographic (5 cm/px)
- Canopy height
- Surface slopes

- Ground Survey Points
 - 11,622 total points
 - 10 shrub species
 - Bareground and deadwood
 - 6,973 in training site



Imagery Classification Workflow



Cover Classification Results



	ADFA	ARPU	ARTO	CERI	SD	BG	CSS	QUAG
Precision	0.84	0.89	0.77	0.17	0.90	0.96	0.73	0.98
Recall	0.68	0.87	0.92	0.80	0.93	0.92	0.70	0.83
F1	0.72	0.88	0.83	0.28	0.91	0.94	0.71	0.89

Overall Accuracy 0.85

Detka, J., Coyle, H., Gomez, M., & Gilbert, G. S. (2023)

Key Take-Aways

- Approach accurately identified tree and shrub species and vegetation gaps.
- Distinguishing between two manzanita shrub species
- Viable approach for accurate species identification and landscape mapping needs
- Some modeling uncertainty with:
 - Less common species (*C. rigidus*)
 - intermixed canopies (Coastal sage scrub)



Estimating Leaf Wetness Patterns



Methods – Meteorological Data Collection

- 2020-21 Water Year
 - 4 Onset Hobo Dataloggers
 - RH, Air Temp, Leaf wetness
 - 10-min logging interval.
- Summer 2022
 - 7 DIY Arduino Stations
 - RH, Air Temp
 - Solar-powered !!
- 2020-2022 UCNRS Met Station
 - RH, Air Temp
 - Solar Radiation
 - Windspeed



Leaf Wetness Modeling – Empirical Threshold Approaches

- *RH* > 87% (Wichink Kruit et al., 2004)
- *RH* > 90% (Gleason et al., 1994)
- *RH* > 92% (Gillespie et al., 2021)
- *Dewpoint depression $\leq 2^{\circ}C$

Dewpoint: temperature at which the air can no longer hold all of its water vapor.

Dewpoint depression: difference between current air temperature and dewpoint temperature.



Statistical Models & Machine Learning Approaches

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- Linear
 - Logistic Regression
 - Linear Discriminant Analysis
- Non-linear
 - Gaussian Naïve Bayes
 - Decision Trees
 - K-nearest Neighbor

Machine Learning

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- Support Vector Machine
- Random Forest
- eXtreme Gradient Boosting
- Multilevel Perceptron







Results – Empirical Model Performance

- DPD and RH > 90% model predictions performed best.
- *RH* > 87% model tended to overestimate 'Wet' events
- *RH* > 92% model most conservative model for 'Wet' classification predictions

Models	Accuracy	Precision	Recall	$\mathbf{F1}$
$\mathrm{RH} > 87$	85.25 (84.95 - 85.55)	$0.81 \ (0.003)$	$0.95 \ (0.002)$	$0.87\ (0.002)$
$\mathrm{RH} > 90$	$88.13 \ (87.91 - 88.35)$	$0.90 \ (0.003)$	$0.87 \ (0.002)$	0.89(0.002)
$\rm RH > 92$	$86.37 \ (86.05 - 86.69)$	$0.93 \ (0.004)$	$0.81 \ (0.005)$	$0.87\ (0.003)$
DPD	$88.50 \ (88.26 - 88.74)$	$0.87 \ (0.003)$	$0.92\ (0.003)$	0.90(0.002)

Statistical and Machine Learning Model Performance

- Highest performing models used only RH and DPD
- All performed similarly to winning empirical models

MLP model was
computationally FASTER!

Models	Accuracy	Precision	Recall	$\mathbf{F1}$
LDA	88.68 (88.43 - 88.93)	$0.87 \ (0.005)$	$0.90 \ (0.005)$	0.89(0.002)
\mathbf{LR}	$88.64 \ (88.39 - 88.89)$	$0.86\ (0.005)$	$0.92\ (0.005)$	0.89(0.002)
GNB	$88.61 \ (88.34 - 88.88)$	$0.87 \ (0.006)$	$0.90 \ (0.006)$	$0.88 \ (0.002)$
CART	$88.79 \ (88.52 - 89.06)$	$0.88 \ (0.007)$	$0.89\ (0.007)$	$0.88 \ (0.002)$
KNN	88.85 (88.50 - 89.20)	0.88(0.004)	$0.89\ (0.007)$	$0.89\ (0.003)$
$_{\rm SVM}$	88.63 (88.38 - 88.88)	$0.86 \ (0.005)$	$0.92\ (0.005)$	$0.89 \ (0.002)$
\mathbf{RF}	88.24 (88.01 - 88.47)	$0.87\ (0.006)$	$0.89\ (0.006)$	$0.88 \ (0.002)$
XGB	$88.29 \ (87.99 - 88.59)$	$0.87 \ (0.006)$	0.89(0.006)	$0.88 \ (0.003)$
MLP	$88.65 \ (88.35 - 88.95)$	$0.87 \ (0.018)$	$0.90 \ (0.028)$	$0.88 \ (0.005)$



Relating manzanita canopy health to leaf wetness duration

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

A. pumila

A. tomentosa



Ground surveys - manzanita canopy health

- 30-m line intercept transects
- Four coastal distances
- For each manzanita species : status, symptoms, dominant leaf color



Results - Canopy dieback and coastal distance

- A. pumila
 No pattern in canopy dieback across coastal gradient
- A. tomentosa
 - Decreasing % canopy dieback with increased distance from the coast





Results - Leaf wetness duration and manzanita canopy dieback

- Analysis of krigged DPD model vs. drone imagery canopy dieback
- Increasing leaf wetness duration, increased canopy dieback in *A. tomentosa*
- Weaker pattern for A. pumila



Detka, J., Jafari, M., Gomez, M., & Gilbert, G. S. – *In Review* 10.2139/ssrn.4977771

Future Directions

- 1. Expand research to include diverse forest systems for pathogen impact studies.
- 2. Collaborate with forestry experts on drone-based pest detection and rapid response.
- 3. Enhance training for professionals in drone tech and geospatial analytics.

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A. pumila and N. australe dieback

- A. pumila dieback extent may be underestimated.
 - Rapid dieback creates canopy holes
 - Difficult to determine dieback causes in standing deadwood.



A. tomentosa and N. australe dieback

- Endemic to foggy coastal hillsides
- Fuzzy leaves may explain disease
- Localized infection, persistent disease, but low plant mortal



