Title
Imagers as Sensors: Correlating Plant CO2 Uptake with Digital Visible-Light Imagery

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Introduction: Use imagers to predict hard-to-measure natural phenomena

Some phenomena are difficult to measure

- **Existing sensors are hard to use in the field**
  Measuring some biological phenomena require ***bulky*** or ***invasive*** sensors which make deployments difficult to manage and increase experimental error.
- **More creative sensing techniques are required**
  These issues suggest the use of a ***model*** based on other sensing modalities which can provide sufficiently ***accurate prediction*** as a substitute for direct measurement.

Imagers are an untapped sensing modality

- **Domain knowledge can suggest meaningful ways to process images of a given biological phenomena**
  Biologists know which signals are important for understanding a particular phenomena. This ***domain specific*** knowledge can be codified into a set of ***image features*** which we can compute.
- **Models based on image features turn imagers into first-class biological sensors**
  These models can predict ground-truth that isn't readily apparent from the images, a technique we call ***applied vision***. Unlike general vision, the ground-truth is not easily recognizable by humans.

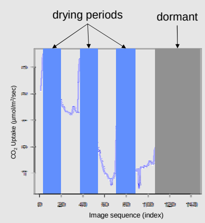
Problem Description: Estimating CO_2 uptake of a drought tolerant moss from images

Field measurement of CO_2 uptake is bulky and invasive

- **What is CO_2 uptake?**
  CO_2 uptake (μmol/m²/sec) is the amount of CO_2 ***absorbed*** or ***released*** by a plant during photosynthesis. Domain knowledge suggests that the ***greenness*** of the plant should be a good predictor of CO_2 uptake.
- **Why is CO_2 uptake important?**
  Dense measurement of plant CO_2 uptake can be extrapolated to entire forests. Such measurements can be used to refine the model of the ***global carbon cycle***.

Experimental Setup

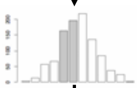
- **Water the moss and cycle light source on and off**
  Simulate a rain event and subsequent days and nights. The moss dries as water evaporates; during darkness, the water is redistributed. When dry throughout, the moss becomes dormant.
- **Measure CO_2 uptake using spectroscopy**
  Moss samples are kept in a controlled environment (left top), intake and exhaust air's CO_2 contents is measured (left bottom). Labeled graph of CO_2 uptake from one drying cycle shown to the right.



Proposed Solution: Build statistical models from ground truth data gathered in the lab

Building sensing imagers

Start with images taken of a biological event stored in a database

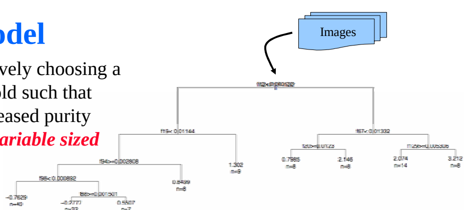


Compute domain relevant image feature set

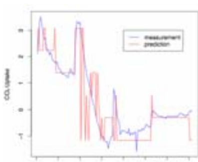
Find the most correlated image features and generate a model from this set to predict the biological event

Regression based model

Build a ***regression tree*** by recursively choosing a feature and corresponding threshold such that examples in child notes have increased purity (resulting tree on right). Creates ***variable sized*** pseudo-bands based on the data.



Prediction accuracy

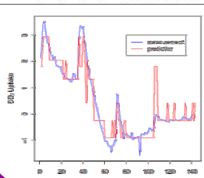


Classification based model

Lab sensor measurement error	0.10 μmol
Acceptable model error	0.50 μmol
Model's RMS error	0.74 μmol

Explanation of error

- too few classes to cover all drying states
- many classes had too little training data
- classes of fixed size, doesn't reflect reality



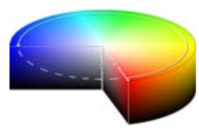
Regression based model

Lab sensor measurement error	0.10 μmol
Acceptable model error	0.50 μmol
Model's RMS error	0.49 μmol

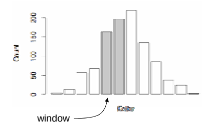
Better prediction

- nine (9) "bands" chosen intelligently
- "bands" are ***data adaptive*** rather than static

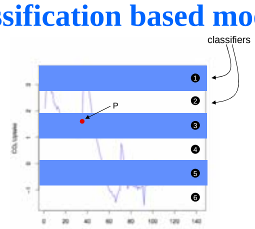
Extracted Features



- Domain knowledge suggests that color, specifically ***greenness***, is a good predictor
- Compute HSV (Hue, Saturation, Value) ***histogram***
  - more stable than RGB
  - inexpensive to compute
- Compute a set of variable sized ***windows***, grouping similar colors (right bottom)



Classification based model



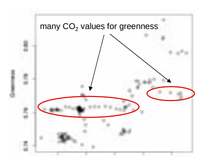
Classifier	1	2	3	4	5	6
Response	-2.19	1.54	3.08	2.33	-1.37	-3.21

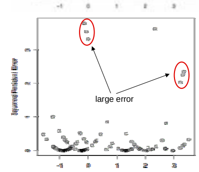
Response is the distance to the hyper-surface separating class K from all other points

- **Training**
  Divide range of values into six ***equal-sized*** bands and train six binary ***SVM*** based classifiers using all generated features.
- **Prediction**
  A point P is in class K if the Kth binary classifier responds most strongly (table to the left). A classified point P is assigned the ***median*** value of class K.

Error analysis

- Likely locations of high error revealed by rudimentary greenness measure (right top)
- Many different CO_2 measurements for a greenness value makes prediction more difficult
- The squared error is ***parabolic-shaped*** because one value is assigned to each "band" (right bottom).





Biological reason:

- Same approximate color for different stages of drying
- Moss drying stage dictates CO_2 uptake