Poster #18

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Background

Problem: An under-quantified hazard

Metal contamination in the environment is a widespread problem that results from mining, industrial processes, agricultural inputs, sewage sludge releases, and munitions activities. High metal contamination can inhibit crop growth, risk food safety, and jeopardize human health (1). Metals can also impede many aspects of ecosystem functioning, including biomass production, plant recolonization, and community assembly (2,3). However, identifying locations with high metal contamination is labor-intensive and costly, which prohibits large scale monitoring efforts.

Our inability to quantify metal contamination at scales that are relevant for land management decisions limits our ability to **predict how contamination alters ecosystem functions**; and subsequently undercuts our capacity to **assess and mitigate risks to communities, the environment, and food supplies.**

Figure 1. Multi-stressor pot experiment installed at OJ Noer Turfgrass Facility near Madison, WI.

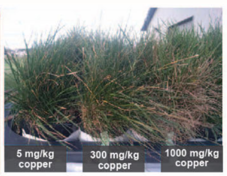

Figure 2. Higher contamination levels induced more biomass loss and visible stress.

Solution: Hyperspectral bioindicators

Hyperspectral remote sensing (imaging spectroscopy) collects hundreds of very narrow (~3-20 nm), contiguous bands. This increased spectral resolution allows for greater diagnostic capabilities than is possible with multispectral sensors (4).

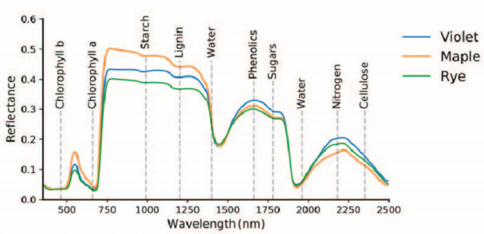

Figure 3. Example of vegetation spectra. Contiguous data over narrow bands yields more information. Figure by Adam Chlus.

When plants are exposed to environmental stressors, they can respond with detectable physiological or chemical changes. Spectroscopy is already in widespread use to measure agricultural productivity and plant functional traits (5, 6). The increasing availability of spaceborne hyperspectral imaging platforms offers unprecedented potential to collect remote, high-frequency, non-destructive measurements over large scales. These

Developing these features could **leverage local vegetation as passive, low-cost bioindicators of pollution.** Operationalizing this requires: (i) quantifying the physiological and chemical changes that contaminants induce in vegetation; (ii) differentiating between stress responses induced by contaminants versus other environmental stressors; (iii) assessing the interactive effects between multiple environmental stressors; and (iv) characterizing species-specific interactions with contaminants.

Methods

Metals of interest

This work focuses on chromium(VI) and copper contamination. Chromium(VI) is widely used to prevent corrosion in nuclear power reactors and other large-scale industrial facilities. It is also extremely hazardous to human health and drinking water sources. Identifying hyperspectral bioindicators for chromium(VI) would enable airborne sensors to monitor local vegetation for pre-visual stress responses as indications of accidental releases or slow leaks that might otherwise go unnoticed until such problems become obvious and cause more extensive damage.

Copper is essential for plant health, but can become toxic at high concentrations. **Given the relative differences in their toxicity, plant translocation pathways and stress responses to these metals may be sufficiently different (7,8,9) that vegetation exposed to different contaminants could be spectrally distinct.** The relatively lower risk of handling copper also made it feasible to incorporate a drought treatment to **explore whether metal-induced stress could be differentiated from other environmental stressors.**

Multi-stressor pot experiment

In the summer of 2021, we conducted a field experiment in which 147 pots of tall fescue were exposed to different types and concentrations of metal contamination (chromium(VI), copper, and copper + drought) ranging between 0 - 1000 mg/kg. We collected hyperspectral images over nearly 2 months in addition to leaf-level reflectance, and fluorescence measurements.

Data Collection

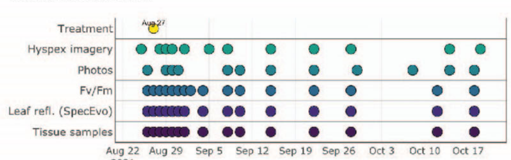

Figure 4. Daily (Aug 26 to Sep 5) and weekly (Sep 6 to Oct 18) data

Results

Minimum noise fraction shows potential

Though full analyses are not yet available, Figure 5 shows 3-band renderings of 5 hyperspectral images collected before contamination treatments were applied (Baseline), and at 4 time periods after exposure (1, 3, 9 and 19 days after treatment).

Images were processed using a minimumn noise fraction (MNF) transform (10). MNF is a standard approach to reduce noise in hyperspectral imagery (11,12).

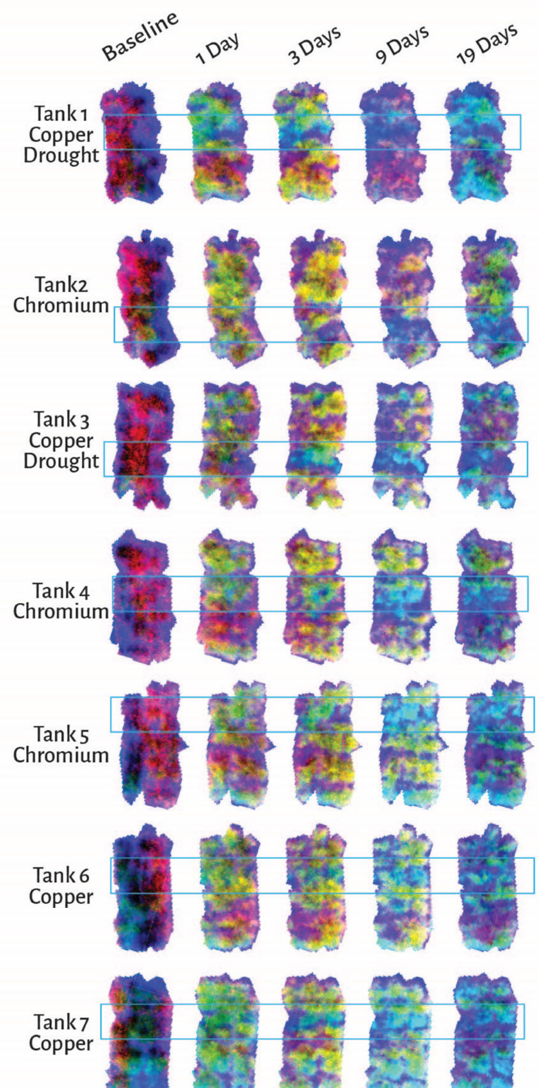

Figure 5. Minimum noise fraction (MNF) transform applied to subset of

It can be conceptualized as a linear transform that (i) rescales and decorrelates noise using the covariance matrix (noise whitening) and (ii) applying a principle component analysis (PCA) on the output. MNF components prioritize the best signal-to-noise ratio, rather than information content. Though components are not ecologically interpretable, they are ordered from best to worst image quality, making it easier to reliably differentiate between useful information and noise (13).

	Chromium treatments mg/kg	Copper treatments mg/kg	Color
High dose	500	1000	Blues
Moderately high dose	50 to 200	50 to 300	Reds
Low dose	0 to 25	0 to 25	Greens

Figure 6. Qualitative summary of how colors appear to overlay treatment concentrations in Figure 5.

The color distributions across all tanks broadly align with with high, moderate, and low treatment levels, as summarized above (Fig. 6). Though analyses are ongoing to fully quantify these changes, this visual rendering is an important milestone that suggests metal toxicity can induce detectable spectroscopic changes.

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