Assessing Potential Hyperspectral Bioindicators for Metal-Induced Vegetative Stress

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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 costly and labor-intensive, which prohibits large scale monitoring efforts.

Our inability to quantify metal contamination at relevant scales 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.**

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).

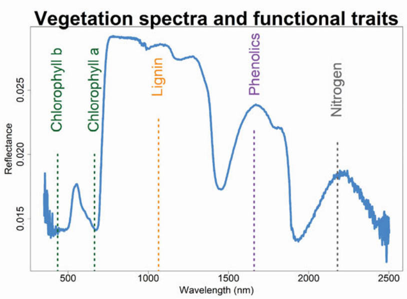

Figure 1. Example of vegetation spectra. Contiguous data over narrow bands yields more information.

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 could be used to identify diagnostic spectral features associated with vegetative stress responses to known chemical constituents.

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

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.

Figure 2. Multi-stressor pot experiment installed at OJ Noer Turfgrass Facillty near Madison, WI.

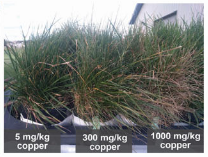

Figure 3. Higher contamination levels induced more biomass loss and visible stress.

Linear mixed-effects modeling

Reports of metal exposures altering reflectance at numerous wavelengths and vegetation indices use diverse methods and are often poorly replicated. It is not clear whether these findings are generalizeable, or whether they are specific to particular plant-metal species combinations. I used linear mixed-effects modeling to assess the explanatory power of the metal dose to predict the reported bioindicators. I used backwards model selection by ANOVA. This approach has the advantage of summarizing the utility of many reported bioindicators using a unified, comparable method.

Results

Assessing previously reported bioindicators

Figure 4 is a visual summary of how reported bioindicators performed on data collected from my experiment.

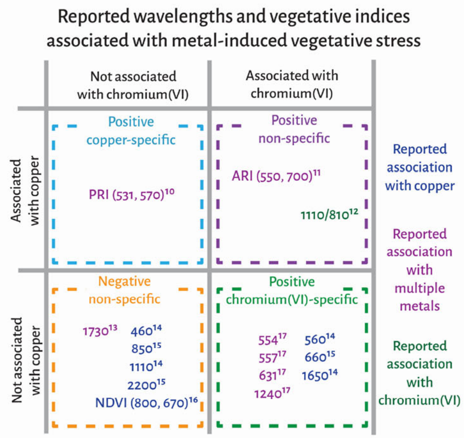

Figure 4. Vegetation indices and single wavelengths (nm) previously reported in association with copper, chromium(VI), or multiple metals.

The **lower left quadrant** shows bioindicators that were reported to have an association with exposure to copper, or metals in general, but for which my regressions found no significant relationship with eith copper or chromium(VI) dose. The **upper right quadrant** shows bioindicators reported in association with chromium(VI) or multiple metals. These indicators were significantly related to doses of both types of metal in my tests, making them ineffective in differentiating between metal exposures, but potentially helpful in monitoring for general metal contamination.

The **upper left quadrant** shows a bioindicator reported in association with several metals, but which my tests found was only significantly related to copper dose. The **lower right quadrant** shows bioindicators reported in association with copper or multiple metals, but which were only significantly related to chromium(VI) dose in my analyses.

There are many reasons why the reported bioindicators may not perform as one might have expected. To start, using reflectance at a single wavelength as a bioindicator is likely to be confounded with instrument noise or other sources of error. The purpose of using a normalized difference is to compare the change in a wavelength of interest relative to another that is generally stable. Single wavelengths are included in this analysis in the interest of synthesizing literature as it was reported.

Additionally, these bioindicators came from studies spanning a broad range of plant and metal species, growing conditions, development stages, exposure treatments, measurement protocols, and analytical methods. Limited replication means we have only a little insight into how these parameters may interact and produce ungeneralizable results. This underscores how imperative it is to further standardize experimental and analytical approaches to replicate realistic environmental exposures. There remains considerable opportunity to link metal-induced spectral changes to known physiological and chemical mechanisms.

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