ASSESSING THE NDVI-YIELD RELATIONSHIP ACROSS ENVIRONMENTS FOR WINTER WHEAT

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WSU WINTER WHEAT BREEDING EST. 1894

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INTRODUCTION AND OBJECTIVE

Vegetation indices derived from multispectral imagery are used by plant breeders to gain an accurate and cost-effective understanding of plant productivity. The predictive power of the normalized difference vegetation index (NDVI) has been seen to vary across environments, providing accurate yield estimates for some sites while offering minimal predictive value for others. Gaining insight about this phenomenon is essential for plant breeders who use vegetation indices for selection, including WSU Winter Wheat Breeding. **This study aims to better understand the changes in the predictive power of NDVI on winter wheat grain yield (bushels per acre) across environments.**

Figure 1. The drone is ready for an image-capture flight

DATA PIPELINE

- 54 trials across 15 site-year locations were included (6 sites across 2022, 2023, and 2024, with 3 missing).
- Flights were performed with a Sentera 6X multispectral sensor mounted on a DJI Inspire 2 roto copter (**Figure 1**), as close to the site-specific heading date as possible to best estimate late-season plant health. Vegetation indices were calculated from the spectral data for each plot. NDVI was computed as (NIR – RED) / (NIR + RED).
- Grain yield was recorded using a plot combine.
- Weather data from September 2014 through July 2024 were taken from six WSU AgWeatherNet stations most representative of the six locations of interest: Harrington, Kahlotus, Prescott, Kincaid, Ritzville, and Walla Walla.
- Statistical analysis and visualization was performed in R using the tidyverse, tidybayes, and brms.

METHODS

A Bayesian hierarchical model to estimate yield as a function of NDVI (**Figure 2**) was implemented with the brms R package. This model was chosen to stabilize trial-specific estimates while accounting for variation across trials nested within locations, as well as to accommodate outliers and heteroscedasticity. Bayesian R^2 values from the posterior sampling distribution were compared to bootstrapped R^2 values for each trial; the approaches delivered similar results, though the Bayesian model shrunk most estimates and produced narrower uncertainty intervals. The environmental component of the analysis was incorporated via weather data. For all six sites for the years 2015 to 2024, the total precipitation from September of the previous year to July of the year in question was calculated. A similar process was done for May to July total precipitation and average temperature. The 2022-24 values for the 15 site-year locations were compared to this historical data to get Z-scores, which were then combined into an overall stress score (**Figure 3**). Finally, the relationship between the overall stress score and median Bayesian R^2 was evaluated using a linear model.

Bayesian Hierarchical Model Specification

Likelihood

$$BUAC_{ijk} \sim \text{Student-t}(\nu, \mu_{ijk}, \sigma)$$

Linear Predictor

$$\mu_{ijk} = \alpha + \beta \cdot \text{NDVI}_{ijk} + u_{0j} + u_{0jk} + u_{1jk} \cdot \text{NDVI}_{ijk}$$

- $BUAC_{ijk}$: Observed yield for observation i in trial k within location j
- NDVI_{ijk}: Scaled NDVI for observation i
- μ_{ijk}: Expected yield
- α: Global intercept
- β: Global slope for NDVI_scaled
- u_{0j}: Random intercept for location j
- u_{0jk}: Random intercept for trial k within location j
- u_{1jk}: Random slope for NDVI_scaled for trial k within location j
- τ_{Location}: Standard deviation of location-level intercepts
- $\tau_{\text{Trial,int}}$: Standard deviation of trial-level intercepts
- $\tau_{\text{Trial,slope}}$: Standard deviation of trial-level slopes
- σ: Residual standard deviation
- ν: Degrees of freedom for the Student-t distribution

Figure 2. Bayesian hierarchical model used to estimate yield from NDVI and derive trial-specific R^2 values. The structure allows for both partial pooling of information across the site-year locations as well as deviations for specific trials

Site	Prec 1	Prec 2	Temp	Comb.	Rank
WAW 2022	1.05	3.11	1.42	1.86	1
KIN 2022	0.07	3.56	1.68	1.77	2
PCT 2022	0.43	2.61	1.8	1.62	3
HAR 2022	-0.46	1.51	1.55	0.87	4
RIT 2022	-0.9	1.83	1.39	0.77	5
KAH 2024	0.49	-0.21	0.72	0.33	6
WAW 2024	-0.22	0.48	0.7	0.32	7
HAR 2024	0.43	-0.16	0.36	0.21	8
RIT 2024	-0.22	-0.91	0.27	-0.29	9
HAR 2023	-0.79	0.22	-1.08	-0.55	10
WAW 2023	0.16	-1.11	-0.74	-0.56	11
RIT 2023	-0.75	-0.31	-0.91	-0.66	12
KAH 2023	-0.23	-1.05	-1.14	-0.81	13
KIN 2023	-0.48	-1.27	-1.27	-1.01	14
PCT 2023	-0.67	-1.28	-1.47	-1.14	15

Figure 3. Z-scores compared to 2015-2024 data for total precipitation from Sep-Apr (Prec 1), May-July (Prec 2), and average temperature from May-July (Temp), as well as a combined environmental stress score and site-year location rankings (1 is least stressed)

RESULTS AND DISCUSSION

There was variation in the predictive power of NDVI on grain yield across environments and trials. NDVI had no predictive power for several trials, while the highest Bayesian R^2 estimate was the 2023 AHR2 trial at Walla Walla, at 0.77 (**Figure 4**).

There is significant evidence that NDVI's predictive power is higher with more environmental stress, though the effect is not meaningful enough to be useful (p=0.008, Pearson r=0.36) (**Figure 5**).

Furthermore, many site-year locations exhibited a large degree of within-site variation (vertical lines of dots in Figure 5)**.** To attempt to account for this, the trials were split into four groups: Advanced, Preliminary, Herbicide, and Single Plot (SP); the rationale was there may be additive trial-type effects, or an interaction between trial type and environment. However, the relationship with predictive power does not seem to change at this level. As seen in **Figure 6**, the Advanced and Preliminary groups display similar patterns across environments and have similar predictive power overall.

Thus, at present it remains largely unclear why some site-year locations exhibited better predictions of yield using NDVI than others across most or all trials, and why predictive power often varied widely between trials planted next to each other.

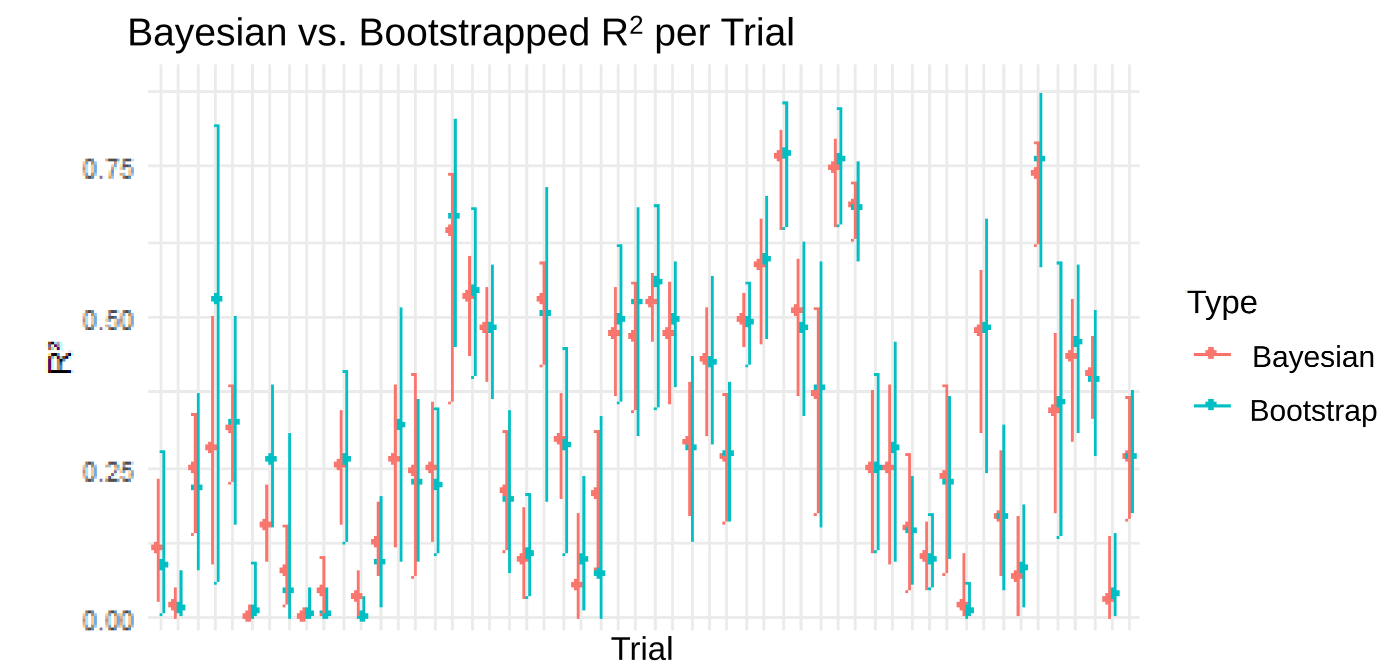

Figure 4. A comparison of Bayesian and bootstrapped R^2 for 54 trials, with medians as well as 95% credible intervals (Bayesian) and confidence intervals (bootstrapped)

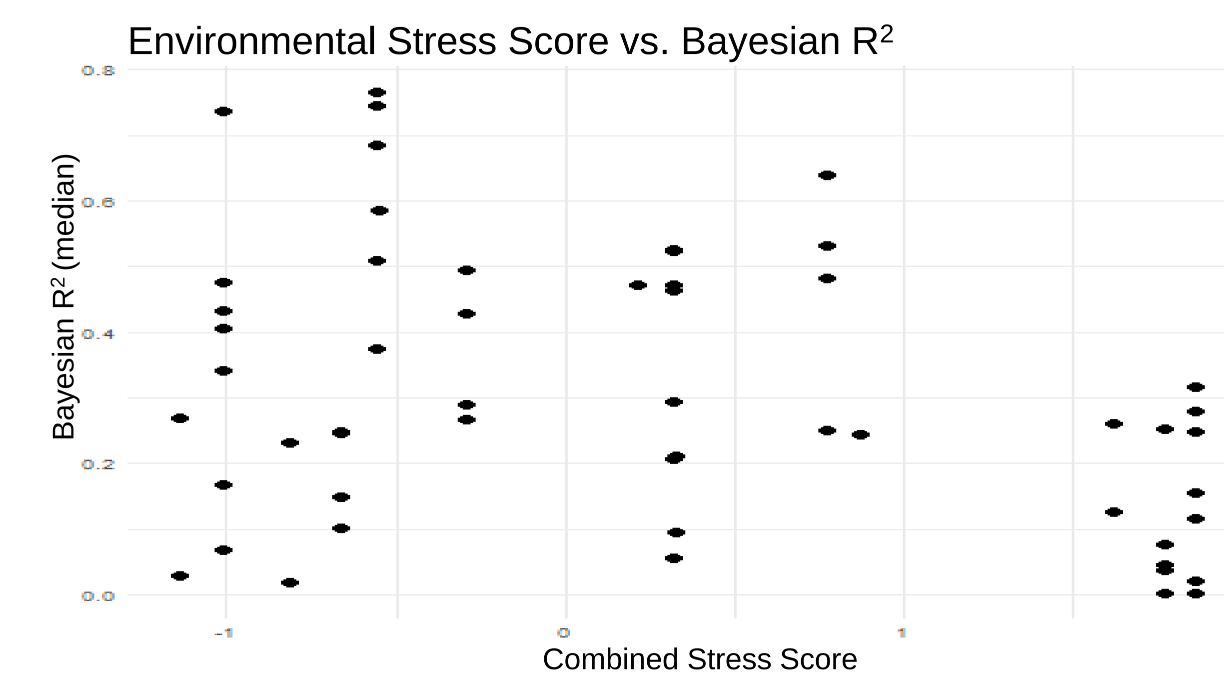

Figure 5. Environmental stress score (stress decreases going right) vs. Bayesian R^2 for the 54 trials

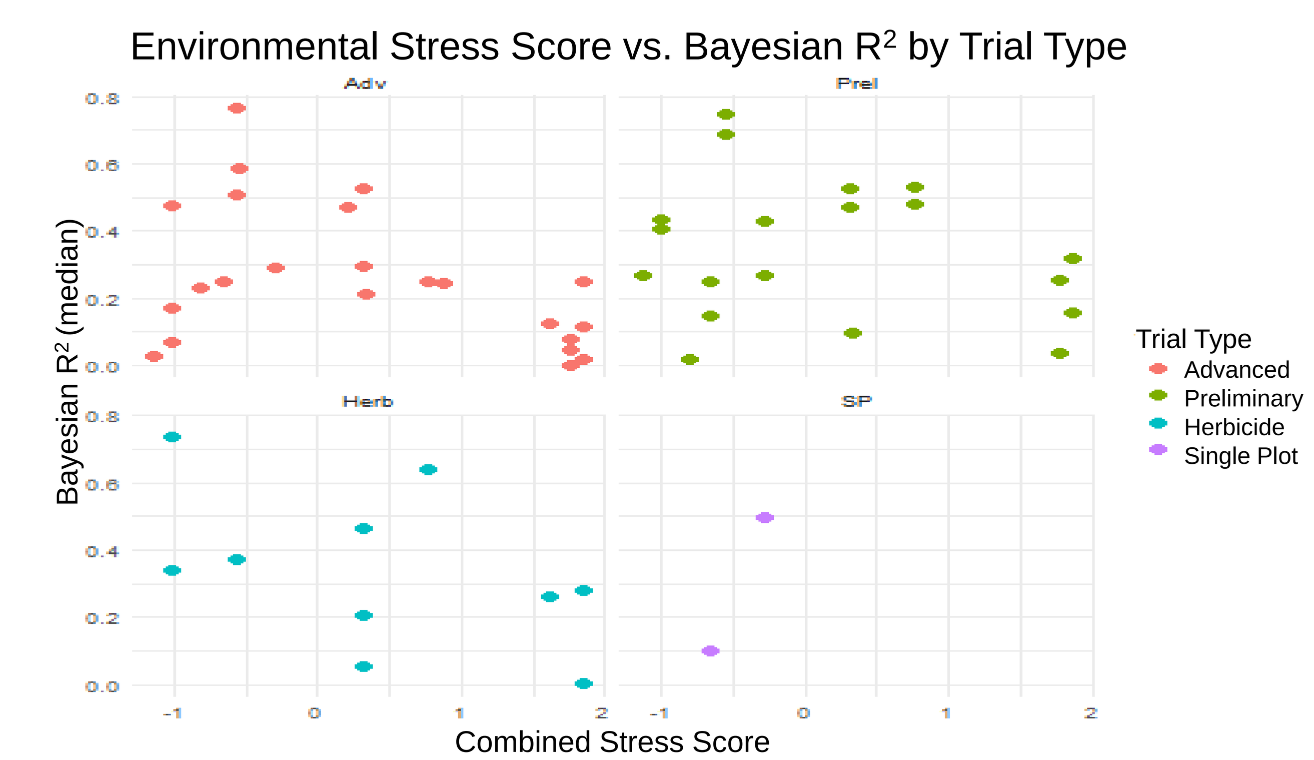

Figure 6. Environmental stress score vs. Bayesian R^2 for the 54 trials, broken up by trial type

FUTURE RESEARCH

- Explore specific weather events and varieties planted at each site-year location to understand why predictive power is stronger for certain sites or trials.
- Use other vegetation indices to see whether predictive power improves and whether it changes across environments.

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