Relationship of Phenomics and Agronomics on Irrigated Spring Wheat

Lucy Goracke, Peter Schmuker, Sheri Rynearson, Chamaporn Paiboonvorachat, Milton Valencia Ortiz, Kesaven Veloo, Sindhuja Sankaran, Michael Pumphrey
gorackel@oregonstate.edu, www.linkedin.com/in/lucy-goracke-3aa6b32b4

United States Department of Agriculture
National Institute of Food and Agriculture
Research and Extension Experiences for Undergraduates (REEU)
Project: 1021788

Washington State University

INTRODUCTION

Wheat is a globally important food crop that experiences a constant push towards improvement. With the rise of high throughput phenotyping, interest regarding the relationship between phenomic and agronomic data has grown within agricultural research.

By increasing the understanding of the connection between phenomics and agronomics, breeders and growers will be able to more accurately predict the performance of specific genotypes, allowing for more precise selection towards high-yielding and stress-tolerant varieties. With this study, we attempted to find highly correlated relationships between phenomic and agronomic data from irrigated spring wheat that could then be used to inform the selection process.

DATA

Data was collected in 2022 and 2023 from an ongoing spring wheat trial located in Othello, WA. The trial contained three separate irrigation treatments: full, partial, and low. Within each treatment, six genotypes were grown, half of which were hard red varieties and the other half which were soft white.
Drone images were collected weekly using a MicaSense RedEdge-MX camera. Photosynthesis rate was measured twice with an LI-6800 Portable Photosynthesis System. Three agronomic end traits – yield (bushel/acre), protein content (%), and yield/protein deviation - were measured at harvest.

SIGNIFICANCE OF THE YIELD/PROTEIN DEVIATION

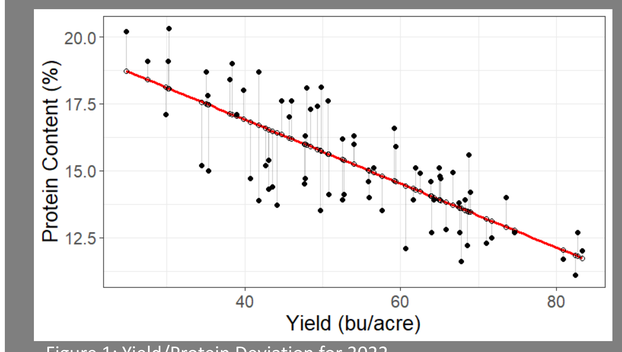

Figure 1: Yield/Protein Deviation for 2022

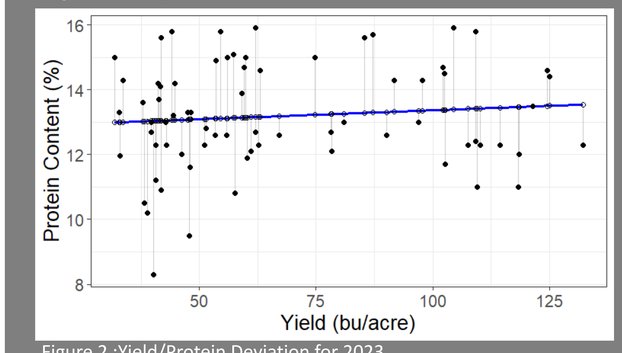

Figure 2 :Yield/Protein Deviation for 2023

- Protein is an important agronomic trait that determines what end-use a variety will have
- Typically, there is an inverse relationship between yield and protein content
- When assessing the predictive power of this relationship, it was found that it varies significantly between years

METHODS

- Qgis was used to align shapefiles to drone images.
- R was used to remove impact of soil and calculate NDVI using the aligned shapefiles and drone images.
- Correlation tests were run for each MicaSense RedEdge-MX flight and LI-6800 collection date to determine the most associated timepoint.
- Anova tests were performed to obtain fitted values for each variety and its respective performance in each irrigation treatment.
- The fitted values were then used to assess the correlation between variety performance by irrigation treatment and the previously determined best fit phenomic timepoint.

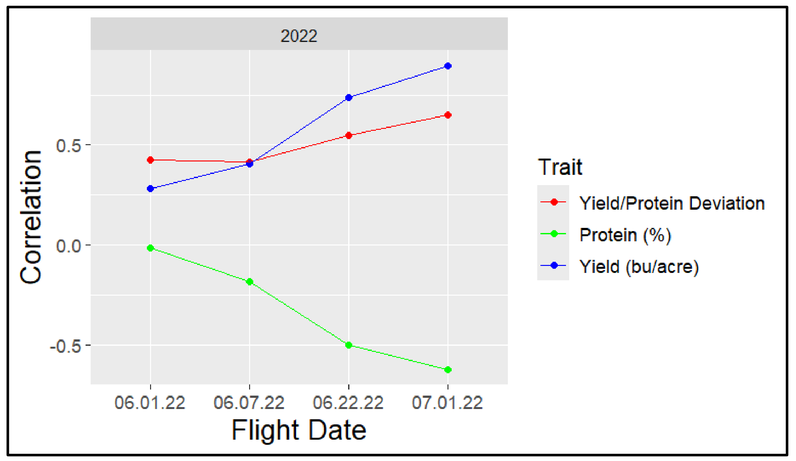

Figure 3: Correlation of drone flight dates and agronomic end traits for 2022

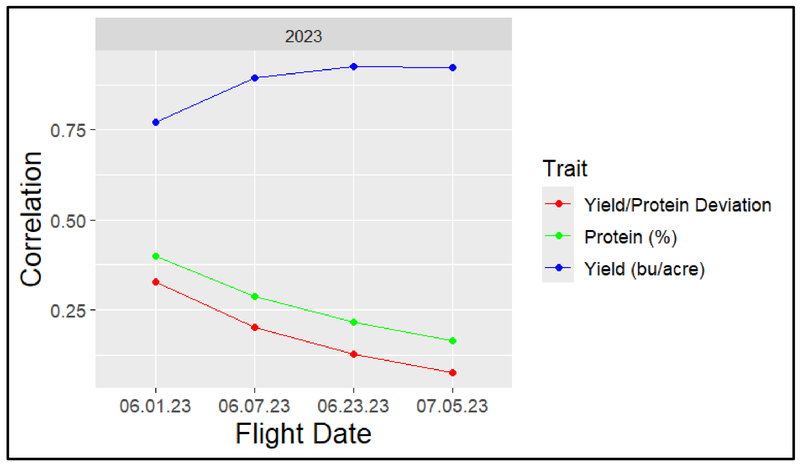

Figure 4: Correlation of drone flight dates and agronomic end traits for 2023

RESULTS

- Relationship between agronomic traits, yield and protein content, was found to be inconsistent
- High correlation was found with late season dates for all agronomic traits - 07/01 for NDVI and photosynthesis in 2022, 07/05 for NDVI and 06/23 for photosynthesis in 2023
- The initial correlation becomes insignificant when broken down into each irrigation treatment

CONCLUSIONS/NEXT STEPS

- More impact is coming from management practices than genotype performance
- Perhaps individual phenomic dates would be more predictive for each agronomic end trait - more research is needed to understand these complex relationships

IMPACT OF INDIVIDUAL IRRIGATION TREATMENTS ON NDVI/YIELD CORRELATION

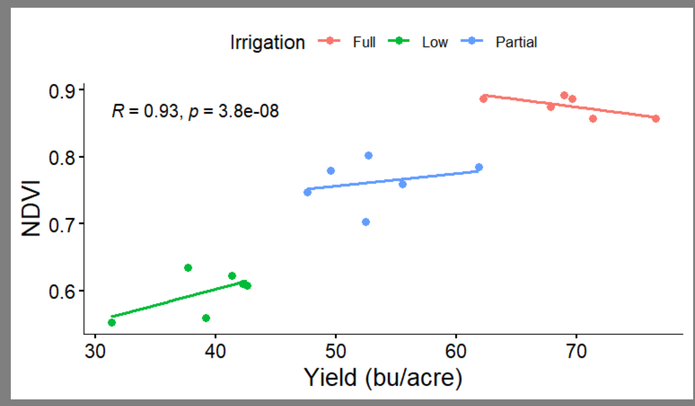

Figure 5: Correlation of most associated NDVI date and yield within each irrigation treatment for 2022

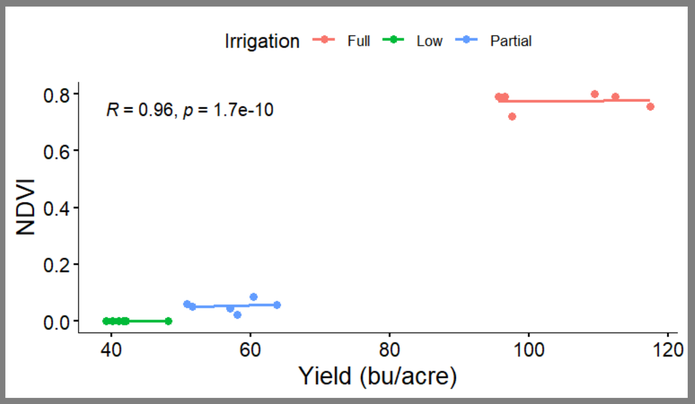

Figure 6: Correlation of most associated NDVI date and yield within each irrigation treatment for 2023

Fig. 7: Correlations by Treatment in 2022

Trait	All	Full	Partial	Low	Source
Yield	0.61	-0.41	-0.33	0.39	LI-6800
Deviation	0.35	-0.39	0.21	-0.86	LI-6800
Protein	-0.50	0.00	0.31	-0.73	LI-6800
Yield	0.90	-0.70	0.26	0.59	RedEdge-MX
Deviation	0.65	-0.71	-0.69	-0.53	RedEdge-MX
Protein	-0.62	-0.05	-0.55	-0.59	RedEdge-MX

Fig. 8: Correlations by Treatment in 2023

Trait	All	Full	Partial	Low	Source
Yield	0.89	0.45	-0.10	-0.89	LI-6800
Deviation	0.14	0.54	0.47	0.58	LI-6800
Protein	0.22	0.56	0.47	0.57	LI-6800
Yield	0.92	0.05	0.15	-0.10	RedEdge-MX
Deviation	0.07	-0.11	0.67	-0.38	RedEdge-MX
Protein	0.16	-0.11	0.68	-0.38	RedEdge-MX

Figures 7 and 8: Correlation values between each source of phenomic data and three agronomic end traits across all treatments and within each treatment by year. Correlations were calculated using fitted values obtained from an ANOVA predicting variety performance by irrigation treatment and the most associated phenomic timepoint. Using data from all treatments and both years, a moderately positive relationship for yield and a weakly positive relationship for deviation were found with a reversal in trend for protein between 2022 and 2023.

ACKNOWLEDGEMENTS

1. Funding provided by USDA Research and Extension Experiences for Undergraduates, Project 1021788
2. Thank you to WSU Phenomics Lab for collecting and providing all data

SOURCES

Bogard, M., Allard, V., Brancourt-Hulmel, M., Heumez, E., Machet, J.-M., Jeuffroy, M.-H., Gate, P., Martre, P., & Le Gouis, J. (2010). Deviation from the grain protein concentration–grain yield negative relationship is highly correlated to post-anthesis N uptake in winter wheat. *Journal of Experimental Botany*, *61*(15), 4303–4312. https://doi.org/10.1093/jxb/erq238

Broadband Greenness. (n.d.). Www.nv5geospatialsoftware.com. https://www.nv5geospatialsoftware.com/docs/broadbandgreenness.html

Honecker, A., Schumann, H., Becirevic, D., Klingbeil, L., Volland, K., Forberig, S., Jansen, M., Paulsen, H., Kuhlmann, H., & Léon, J. (2020). Plant, space and time - linked together in an integrative and scalable data management system for phenomic approaches in agronomic field trials. *Plant Methods*, *16*(1), 1–13. https://doi.org/10.1186/s13007-020-00596-3

Principles of Remote Sensing - Centre for Remote Imaging, Sensing and Processing, CRISP. (n.d.). Crisp.nus.edu.sg. https://crisp.nus.edu.sg/~research/tutorial/optical.htm

White, J. W., Andrade-Sanchez, P., Gore, M. A., Bronson, K. F., Coffelt, T. A., Conley, M. M., Feldmann, K. A., French, A. N., Heun, J. T., Hunsaker, D. J., Jenks, M. A., Kimball, B. A., Roth, R. L., Strand, R. J., Thorp, K. R., Wall, G. W., & Wang, G. (2012). Field-based phenomics for plant genetics research. *Field Crops Research*, *133*, 101–112. https://doi.org/10.1016/j.fcr.2012.04.003