Potential for Enviromic Information to Capture Genotype by Environment Interactions in Spring Wheat Variety Trials

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Modeling GxE

Multi-location cultivar evaluation is vital for plant breeding programs to identify cultivars with broad adaptation. The analysis of phenotypic plasticity through multiple trials has been performed through analytical methods such as Finlay-Wilkinson regression, in which the phenotypic mean within trials is used as a covariate to construct an environmental index (2). A limitation of this approach is the inability to make an inference for future trials as new trial means are not known. Modeling the reaction norms of cultivars through an environmental index constructed of environmental data instead of trial average phenotype gives the flexibility to make predictions (4). However, it is unknown what sort and magnitude of environmental data is sufficient to represent phenotypic plasticity.

Approach

Grain yield phenotypic plasticity of spring wheat cultivars was modeled through several prediction models while also testing several predictive environmental datasets. Six years of data were studied with twelve trials per year representing locations with average yield potential ranging from 1350 to 6700 kilograms per hectare. Individual trials were planted in an alpha-lattice design with the BLUE for each cultivar within a trial used for model training or testing. Five predictive environmental datasets and seven prediction models were tested.
Environmental datasets per trial include:
-Thirteen climatic variables such as temperature and relative humidity over the first hundred days after planting. These 1300 datapoints are called the daily environmental dataset in figures. (1)
-Daily weather data of the thirteen different climatic variables averaged over five wheat growth stages. These 65 datapoints are referred to as the growth environmental dataset in figures.
- Soil characteristics such as percent silt or sand composition. These eight datapoints are referred to as the soil environmental dataset in the figures. (3)
-A measurements of soil moisture and measurement of soil pH taken at planting. These 2 datapoints are referred to as the start environmental dataset in figures.
-A joint dataset composed of the four previous environmental datasets for a total of 75 datapoints referred to as joint environmental dataset in figures.

Multi-task prediction methods were implemented to model the reaction norm of studied cultivars at once; tested methods were linear regression, a single layer neural network (nnet), random forest, partial least squares, LASSO, and ridge regression with linear kernelized predictive data (rrblup_linear) and arc-cosine transformed predictive data (rrblup_ac1) (5).

Evaluation

Each dataset and model was evaluated in two validation schemes. The first scenario was leave one trial out within years or paired years in which one trial at a time had performance of wheat cultivars predicted based on models trained from the remaining trials. The second scenario was cross year prediction in which all of one year's trials were predicted based on the other paired year. Accuracy was evaluated with Pearson's correlation coefficient to measure relative accuracy of predicted performance within trials. Correlation coefficients were calculated in a pairwise manner between all trials for the within year scenario as a baseline comparison.

Figure 1 Leave-One-Trial Out Prediction Accuracy Within Years

Figure 2 Across Year Prediction Accuracy

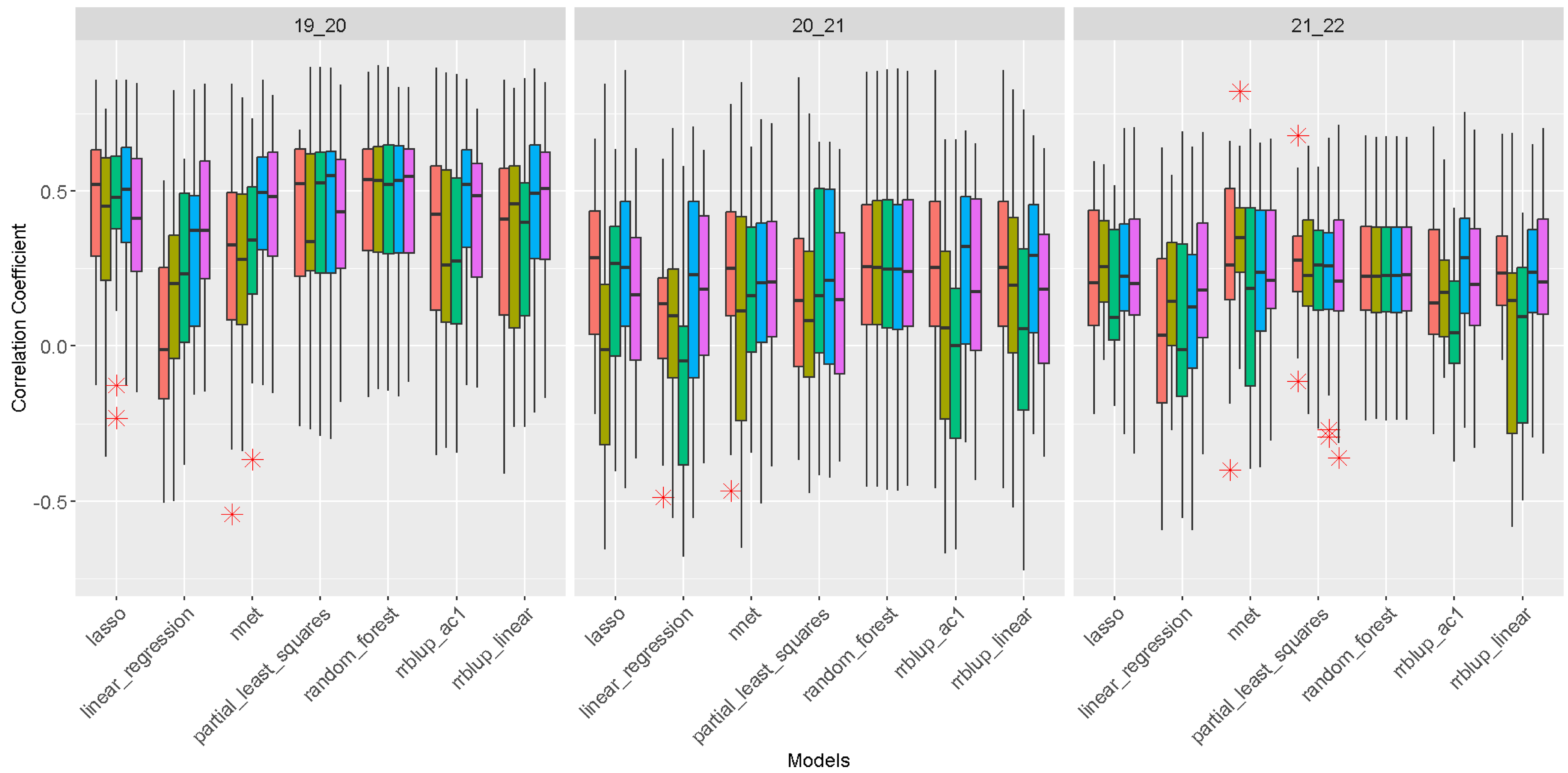

Figure 3 Random Forest Leave-One-Trial Out With Paired Years vs Across Year Accuracy

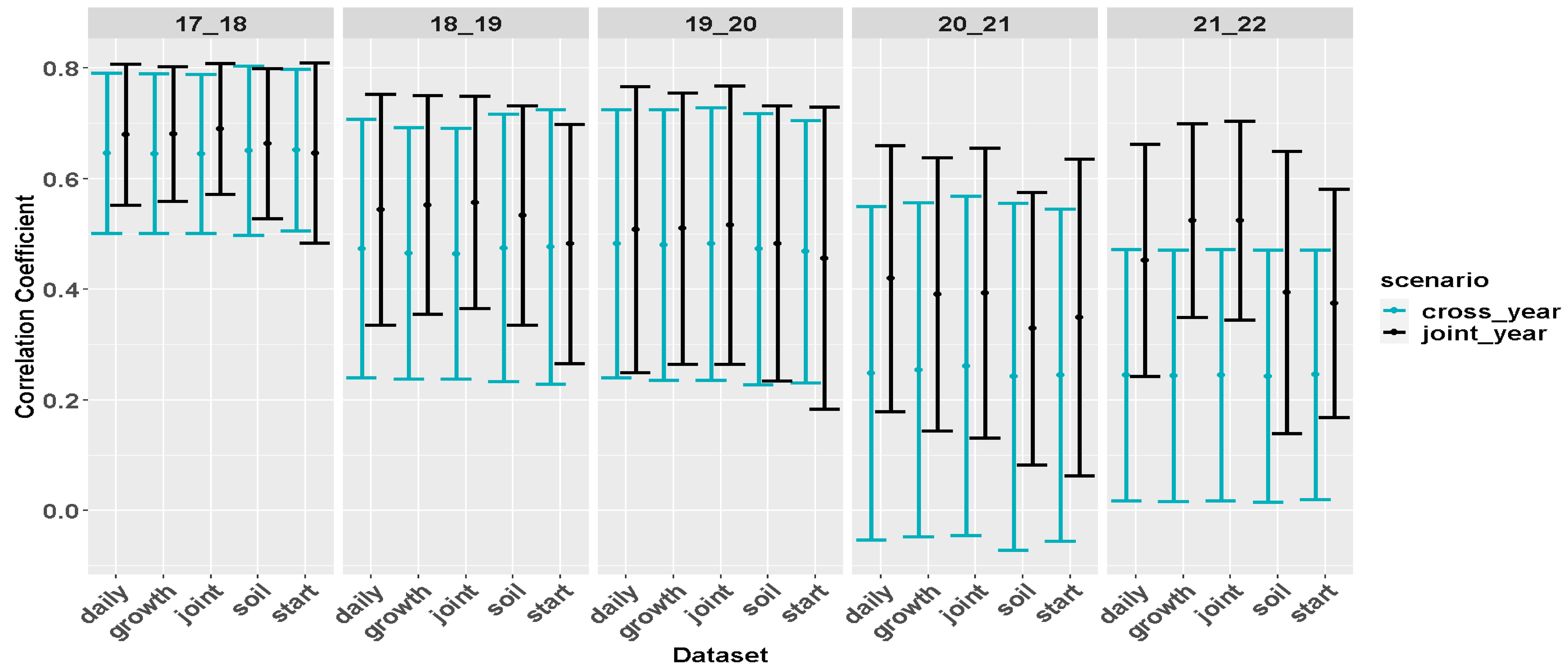

Figure 3 shows random forest results for predicting across years versus predicting one trial at a time with two paired years of data combined.
-Combining years together to predict one trial at a time gives substantial improvements in accuracy compared to cross year prediction with all datasets, especially with 20_21 and 21_22 paired years.
-The plasticity induced by a new growing season cannot always be captured by the previous or following growing season.

Predicting Trials Within Year

Figure 1 shows results for predicting one trial at a time within years.

-All models besides linear regression performed similarly with all environmental datasets.
-The pairwise correlation between locations was outperformed with all datasets and models besides linear regression, showing that environmental modeling can capture phenotypic plasticity better than trial averages.
-Linear regression with only the start dataset performed as well as more complex methods and datasets.
-When examining prediction accuracy at a location per year, no locations were predicted more accurately than others on average.
-Depending on the year, the same location may be easier or harder to predict.
-Combinations of datasets and models can have different prediction accuracy for the same trial, however they may predict several trials on average equally well.

Predicting Trials Across Year

Figure 2 shows results for predicting one year of trials based on another year's yield and environmental data. Results from only three sets of paired years are shown for sake of space but are representative of trends for all the data. Correlation results are recorded within trials per year, not across all trials at once.

-Accuracy results across years are lower than respective results within years for all years studied.
-Random forest performed the most consistently while rrblup_linear/ac1 was variable depending on the year pair.
-Linear regression with the start environmental dataset performed as well as more complex methods.

Conclusions

Capturing the reaction norm of wheat cultivars can be accomplished efficiently with small enviromic datasets. Prediction methods that are capable of variable selection or regularization perform practically equally. Making predictions between years is challenging as cultivars perform more unpredictably in each new growing season's environmental conditions as compared to a new location.

Sources

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