Corn Geospatial strategy: A more deeply understanding of hybrid competitiveness and performance by combining digital tools and data modeling.

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The comparative performance trials (CPT) of experimental and commercial cultivars in multi-environment trials, allow the determination of genotype (G) response to the different environment (E) and interaction (GxE). The final goal is to provide selection guidelines to identify the best genotypes to advance in the pipeline of the breeding program. Nowadays, the use of the digital information technologies to monitoring yield can be used in the CPTs to accurate measuring and recording of grain yield as well as the local environmental context. This research was carried out at 138 locations corresponding to commercial fields located in Argentina. The harvested was made with yield monitor and weighing machine wagon. To compare the grain yield of hybrids within each E and GXE interaction, the MLM of ANAVA with spatial correlation was adjusted for each location. Whereas, for CPT-without spatial data the ANAVA simple was applicate. The new analytic strategy showed greater power to: (a) find significant differences ($p<0.05$) in the GxE interaction, (b) increase 2.5 times the amount of information generated, i.e. than 1 CPT (1 location) analyzed with the new strategy. The new approach improves the data-driven decision making to support advancement processes from precommercial to commercial.

1. Introduction

Farmers must find ways to maximize yield on every acre. This is especially vital in the U.S., Brazil and Argentina where the largest amount of corn is produced (Kelly, 2006). Being able to place the correct corn hybrid in the best location is important and requires research.

Evaluating corn performance has long been a must for breeding programs, and methodologies used have changed over time. Tools exist today to improve the quality and quantity of data gathered at the farm level. In the current years, the use of the new digital technologies of massive data collections such as yield monitor can begin to be used in the CPTs to accurate measurement and recording of grain yield. Recent works used the yield monitor in corn strip trials, but the models used to analysis grain yield data were mainly simple analysis of variance or traditional regression techniques (Hatfield, 2012) since they only use the average yield of each hybrid (strip) to generate the analyzes of competitiveness between the different hybrids and environmental indices and to study the interaction GxE.These models did not take spatial autocorrelation structure into account, which, in turn, affects the grain yield site-specific estimation, leading to inflated variance and most likely wrong conclusions (Peralta et al., 2016).

The current research project provides novel points in use monitors harvest in corn hybrid strip trial and apply spatial models estimate yield as well as environmental index at sub-strip divisions. The objective of this study is to compare DIT (yield monitor data) vs traditional approach (without yield monitor) to study the genotype response patterns across different E and explore GXE. The selection and adoption of the best hybrid for each productive environment not only leads to increased grain yield for the farmers, but also increasing national grain production and net economic value.

2. Materials and Methods

The study was performed, at 138 locations, corresponding to commercial production fields located in different provinces of Argentina (Figure 1).

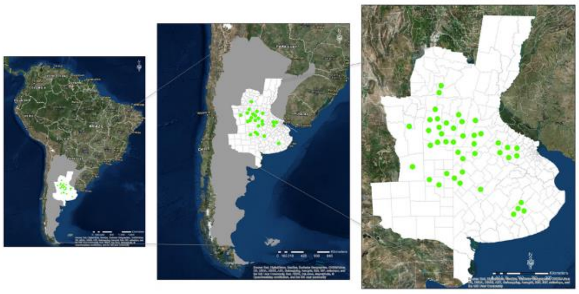

Fig. 1. Yield monitors data for different CPTs strip trials.

Crop management and tillage practices varied between fields and were chosen by the farmer. No-tillage (direct seeding) is widespread in the region and it was a feature common to all fields in this study.

In each location, 25 different hybrids (25 strips) were planted. The dimensions of each experiment depended on the size and spatial variability within the field. An average trial was 108 m wide and 400 m long (3.98 ha) and each hybrid was sown in 8 rows of 52.5 cm wide (Figure 2). Corn grain yield was measured every one second and recorded using calibrated commercial yield monitor mounted on a combine equipped with DGPS (Figure 2). Grain yield data were corrected to 14% grain moisture, spatially located and analyzed using nlme package of R language (R Core Team, 2015). The data points located approximately 5 m from the borders of the sites were deleted before the analysis because the combine was unlikely to be full ((Peralta et al., 2015).). The yield monitor data were filtered using the software yield editer (Sudduth and Drummond, 2007).

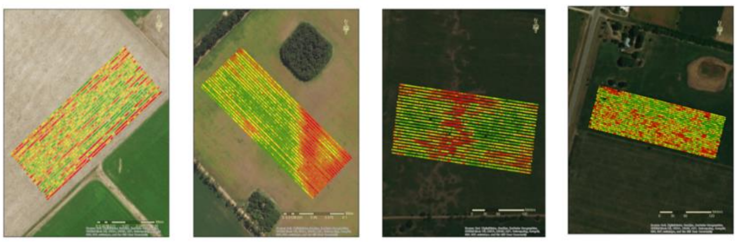

Fig. 2. Yield monitors data for different CPTs strip trials. Green and red color is higher and lower grain yield, respectively

Outliers are observations that fall outside the general pattern or distribution of the data set. The outliers were removed following a protocol of Córdoba et al., 2016. The whole protocol was developed in R language (R Core Team, 2015).

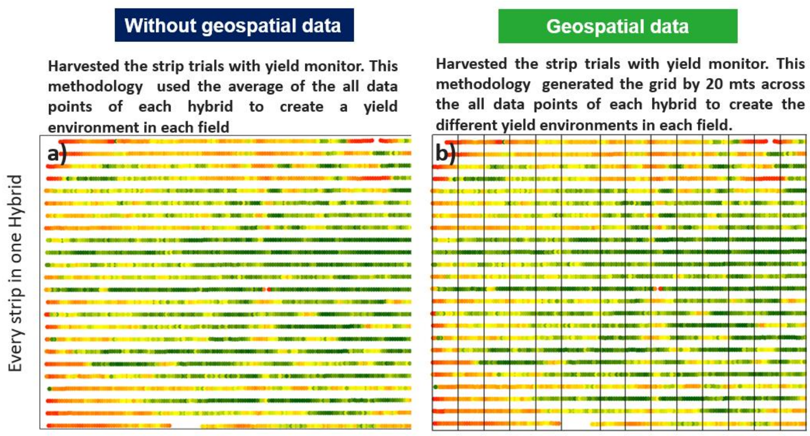

Fig. 3. Yield monitor data of strip trial. a) the strategy "without geodata only used the average on grain yield across the all data points" b) the strategy "with geodata used grid and the all data points to create the yield environment"

Yield data were divided into cells 20 m long (in the direction of the corn rows) and 12 m wide containing all hybrids. In this work, for every cells 20 m long an environmental index (EI) was calculated. The 20-m length was chosen as the minimum length that would provide a robust yield estimate, based on our previous unpublished data and the work of others (Scharf et al., 2005). In order to compare hybrids within each EI and hybrids x EI interaction, the following MLM was fitted for each location:

$$Y_{ijk} = \mu + H_i + a_j + Ha_{ij} + e_{ijk}$$
$$cov(e_{ijk}, e_{i'j'k'}) = exp\left(-d^{\rho}_{(e_{ijk}, e_{i'j'k'})}\right)$$

Y_{ijk} Is the observed performance for the i-genotype, in the j-environment, k-observation (within the frame); μ: Constant of the model; H_i: Hybrid i- effect; a_j: Effect of the j- environment; Ha_{ij}: Interaction of the i-th hybrid with the j-th environment; e_{ijk}: Error term

3. Results and Discussion

The new strategy allows to increase the number of EI (from 138 to 690 – 1:5) and the range of environments explored (from 20 to 140 at location level and from 15 to 160 qq/ha at row-within-location level) (Figure 4).

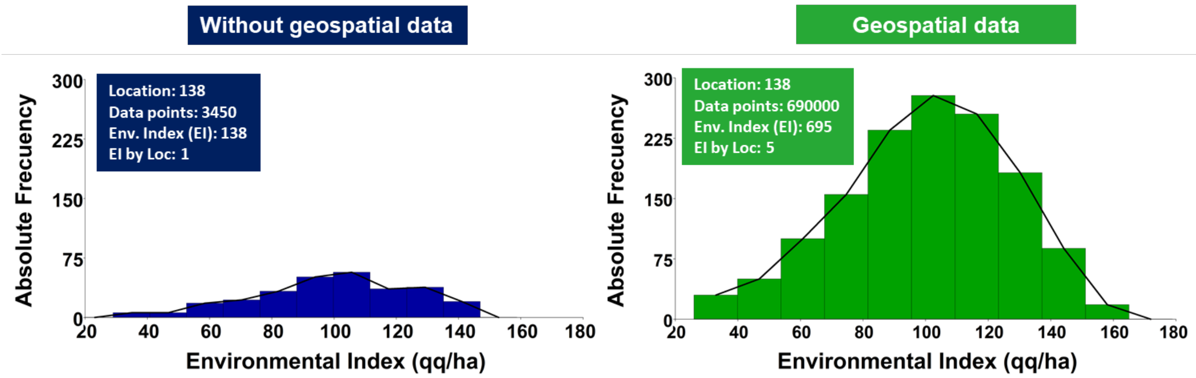

Fig. 4. Data summary between analytical approaches

By having a wider range of EI and a greater number of data points, two main goals are achieved with the new strategy:

Evaluate hybrid stability: Understanding the performance of hybrids in low and high yielding environments is key to assure the stability of hybrids. With the new strategy, it is possible to explore more extreme environments, even in years when the weather conditions are not restrictive.

Make better decisions: The new strategy allows to improve the understanding of the stability of hybrids through different environments, create more comparison across more EI and generate more robust models (Figure 5).

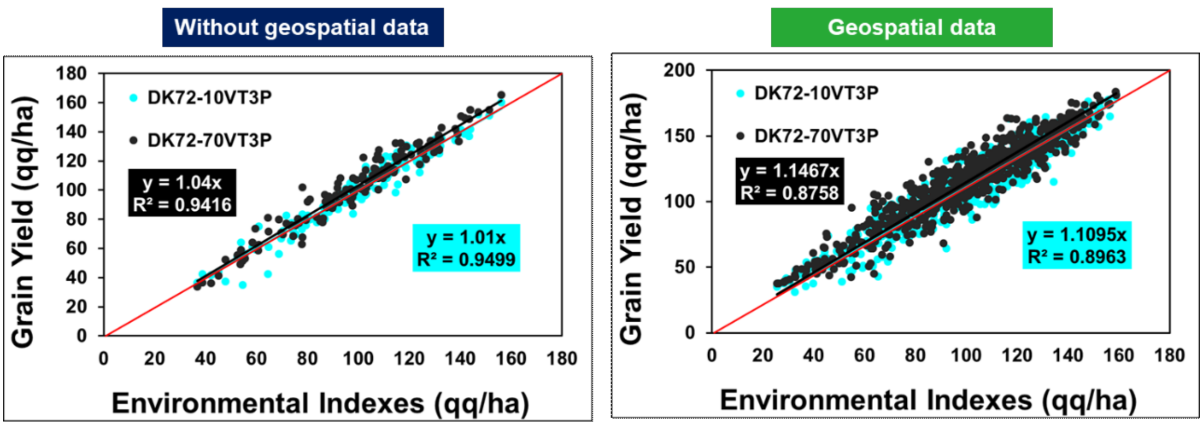

Fig. 5. Regression plot between analytical approaches

The new strategy allows to better understand G*E interaction, achieve comparisons in environments greater than 150 qq/ha, decrease the standard error (mean estimation) 2.5 times, and have high resolution hybrid performance characterization (Figure 6). This better understanding of the performance in a wider range of environmental is key to make the best recommendation about the positioning of the hybrids across the different environmental indexes

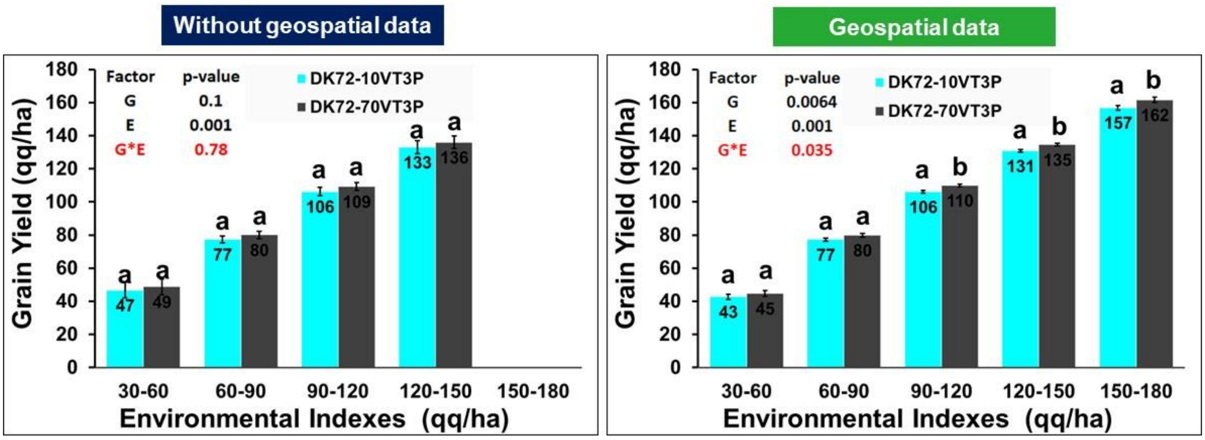

Fig. 6. Hybrid response between analytical approaches. Different letters indicate statistically significant differences ($p < 0.05$). Vertical bars indicate standard error of mean for each EI class (qq/ha).

4. Conclusions

The current research project provides a novel approach to use harvest monitors and spatial data in corn hybrid strip trials that allows to generate more data and information. It could enable data-driven decision making to support advancement processes from precommercial to Commercial and positioning the right hybrid product for a specific yield environment. The next step is to continue working on the integration of "Big Geodatabases" (weather, soil, yield, remote sensing, diseases) to develop new analytic approaches.

5. References

1. Córdoba M.; Bruno C.; Costa J.L; Peralta N.; M. Balzarini. 2016. Multivariate Methods in Management Zone Delineation for Precision Agriculture. Computers and Electronics in Agriculture. 143: 95-107.
2. Hatfield, J.L. 2012. Spatial Patterns of Water and Nitrogen Response Within Corn Production Fields. Agricultural Science. Pag 73:96.
3. Kelly, J. 2006. How will corn find the acres it needs? Corn and Soybean Digest. 66: 40.
4. Peralta, N.R.; Costa, J.L; Balzarini, M.; Castro Franco, M.; Córdoba, M; Bullock, D. 2015. Delineation of management zones to improve nitrogen management of wheat. Computers and Electronics in Agriculture. 110: 103-113.
5. Peralta, N.R; Assefa, Y.; Du, J.; Barden, C.; Ciampitti, I. 2016. Mid-Season High-Resolution Satellite Imagery for Forecasting Site-Specific Corn Yield". Remore Sensing. 8(10), 848.
6. R Core Team. (2015). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. URL http://www.R-project.org/.
7. Pinheiro J, Bates D, DebRoy S, Sarkar D, R Core Team (2020). _nlme: Linear and Nonlinear Mixed Effects Models_. R package version 3.1-144, <URL: https://CRAN.R-project.org/package=nlme>.
8. Scharf, P.C.; Kitchen N.R., Sudduth K.A., Davis J.G., Hubbard V.C., and Lory J.A. 2005. Field-scale variability in optimal N fertilizer rate for corn. Agron. J. 97:452–461.
9. Sudduth, K.A., and S.T. Drummond. 2007. Yield Editor: Software for removing errors from crop yield maps. Agron. J. 99:1471–1482. doi:10.2134/agronj2006.0326