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HERRAMIENTAS DE INFORMACIÓN DIGITAL: CLAVE PARA MEJORAR LA CARACTERIZACIÓN Y EL PROCESO DE POSICIONAMIENTO DE LOS HÍBRIDOS DE MAÍZ

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DIGITAL INFORMATION TOOLS: THE KEY TO IMPROVE THE HYBRID CHARACTERIZATION AND POSITIONING PROCESS

ABSTRACT

Digital Information Tools: The key to improve the hybrid characterization and positioning process.

The evaluation of experimental and commercial cultivars in comparative performance tests (CPTs) in different environments (multi-environment trials) allows the determination of genotype response patterns across different environments (E), genotype X environment interaction (GXE), and provide good selection guidelines to identify the best genotypes to advance in the pipeline. Nowadays, the use of the digital information technologies (DIT) of massive spatial data collections such as yield monitor and soil data can begin to be used in the CPTs to accurate measuring and recording of grain yield, generating large amounts of spatial information. This research was carried out at 41 commercial fields located in Argentina. The harvest of the strips was monitored with combines equipped with DGPS and the grain yield of each strip was weighed with weighing machines wagon. To compare hybrids within each E and GXE interaction, the MLM of ANAVA with spatial correlation was adjusted for each location (CPT- yield monitor). The inclusion of yield monitor data and the fitting of spatial models showed more power to find significant differences ($p<0.05$) in the parameters of GxE interaction. It could enable data-driven decision making to support advancement processes from precommercial to Commercial.

Palabras Clave
Caracterización de ambientes, monitor de rendimiento, Agricultura digital.

Keywords
Environmental Characterization, Yield Monitor, Digital agriculture.

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. With the cost of corn seed, it is imperative that yield be maximized (Bullock *et al.*, 1998).

Evaluating corn performance has long been important, 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, generating large amounts of geospatial information. 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 (ANOVA) 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.

To data, the models used to analysis yield monitor data of corn hybrid strip trial were mainly simple analysis of variance (ANOVA) or traditional regression techniques [Hatfield, 2012]. These models did not take spatial autocorrelation structure into account, which, in turn, affects the grain yield site-specific function 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 to increase the amount of data and information of each locality (CPTs of corn). The objective of this study is to compare the genotype response patterns across different E and GXE between the new approach using DIT (yield monitor data) vs traditional approach (without yield monitor). The selection and adoption of the best hybrid for each productive environment not only leads to increase the grain yield for the farmers, also leading to increased national grain production and net economic value.

MATERIALS AND METHODS

The study was performed, at 41 commercial production fields located in different provinces of Argentina (Figure 1).

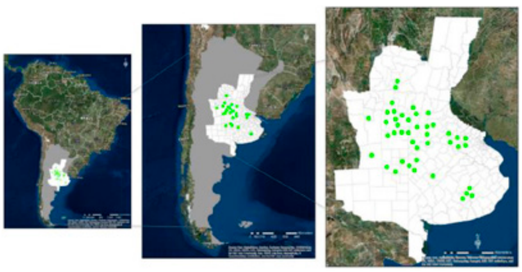

Figure 1. Yield monitors data for different CPTs strip trials.

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, 26 different hybrids (26 strips) were planted. The dimensions of each experiment depended on the size and spatial variability within the field. In average, the trial was 108 m wide and 350 m long (3.78 ha) and each hybrid was sown in 8 rows of 52.5 cm wide. Corn grain yield was measured on one second intervals and recorded using calibrated commercial yield monitors mounted on combines equipped with DGPS. Grain yield data were corrected to 14% grain moisture, spatially located and analyzed with ArcGis and R statistic platform. The data points located approximately 0.5 m from the borders of the sites were deleted before the analysis because the combine was unlikely to be full (Peralta et al., 2015).

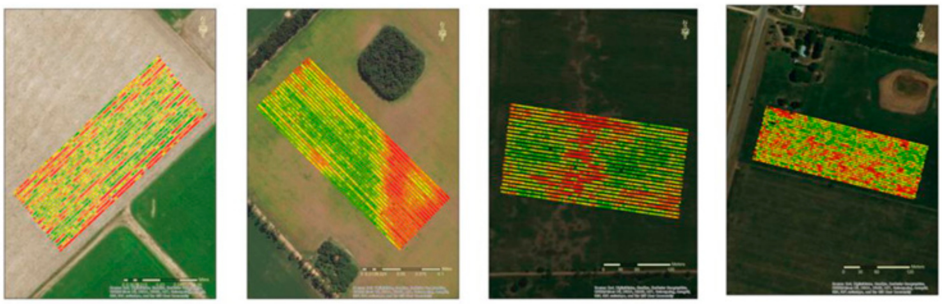

Figure 2. Yield monitors data for different CPTs strip trials.

Outliers, or atypical values, 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 using the freely available R software (R Core Team, 2015) and provide online access to source code to perform the analysis in R.

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, every cells 20 m long is an Environmental Index (EI). 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 including hybrids x EI interaction, a MLM of ANAVA was adjusted for each locality:

$$Y_{ijk} = \mu + H_i + a_j + Ha_{ij} + e_{ijk}$$

$$\mathrm{cov}(e_{ijk}, e_{i'j'k'}) = exp\left(-d_{(e_{ijk}, e_{i'j'k'})} / \rho\right)$$

Yijk Is the observed performance for the i-genotype, in the j-environment, k-observation (within the frame)
μ: Constant of the model
Hi: Hybrid i- effect
αj: Effect of the j- environment
Hαij: Interaction of the i-th hybrid with the j- environment
eijk: Error term

RESULTS AND DISCUSSION

The new strategy allows to increase the quantity and ranges of environments (from 15 to 180 qq/ha), increase the EI for same location (16:1) and capture greater variability in the data (Figure 3). Besides, in increases the amount of data points by range of EI.

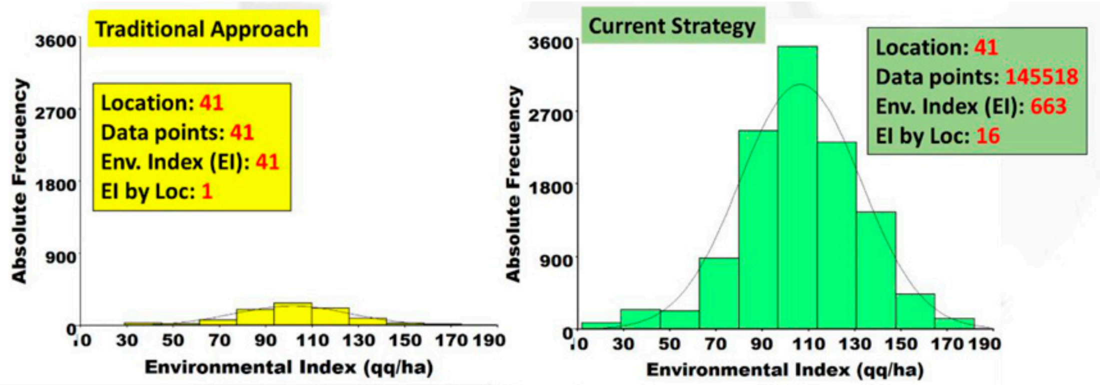

Figure 3. Data summary between analytical approaches.

By having a wider range or 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 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 estimation of regression models' parameters, improve the understanding of the stability of hybrids through different environments and generate more robust models (Figure 4).

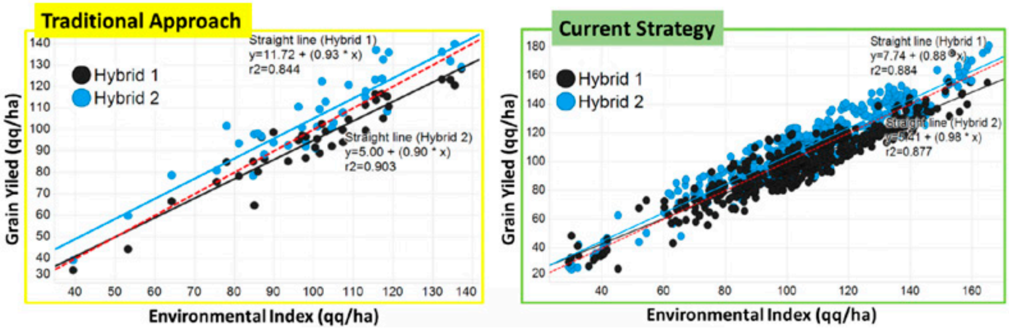

Figure 4. Stability plot between analytical approaches.

The new strategy allows to capture and better understand G*E interaction, achieve comparisons in environments greater than 150 qq/ha, decrease the standard error (mean estimation) 2.23 times and have high resolution hybrid performance characterization (Figure 5). This greater understanding of the performance by EI is key to make the best recommendation (hybrid choice) for each environment.

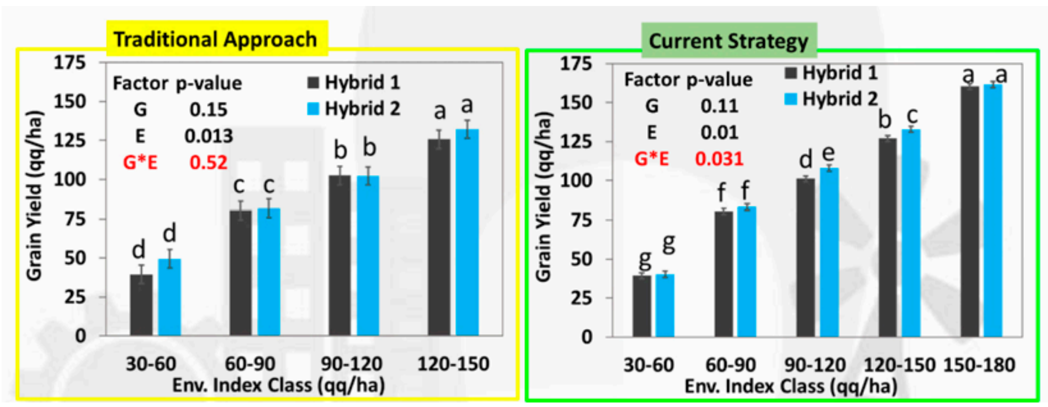

Figure 5. Hybrid response between analytical approaches.

CONCLUSION

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.

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