Using precision agriculture tools and improved data analysis for evaluating effects of integrated nutrient management programs

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Abstract. *Integrated nutrient management (INM) practices are becoming common under intensive agricultural systems in Chile. Practices include, the use of organic matter, in different sources, soil microbial inoculants, and the application of biostimulants, of different origin. Compared to the application of macronutrients, for example, the effects of these products on crops are rather modest and require lower experimental errors to be proven; besides, trials made at the field level, many times do not have true replications, and assignment of treatments is not random. Because of these reasons, most commonly, treatments effects cannot be proven, even though, visually, differences could be observed. To deal with this reality, precision agriculture tools and proper statistical techniques, usually those used in econometrics, that simulate ceteris paribus have been used. To compare different treatments, we have used regression with binary variables, controlling for ancillary variables such plant biomass and geographic position, and time, when this is relevant for the experiment. Besides we have corrected for spatial (and temporal) autocorrelation, using spatial lag or spatial autoregressive models. In all our experiments, field data was collected using systematic grid designs, with n>20 and an average intensity > 6 samples/ha. Plant vigor was estimated by NDVI using the active sensor OptRx (AgLeader Technologies) passed several times during the season. In the present work, results of several experiments in table grapes are presented. In all trials, plant biostimulants were applied and crop yield and quality were the response variable. Results have shown that the proposed methodology is useful to make better evaluations of field trials for INM practices and can be an excellent tool for companies wanting to evaluate their products at farmer´s fields.*

Keywords. *Integrated nutrient management, field experiments, econometrics, ancillary variables, NDVI, active sensors.*

Introduccion

Integrated nutrient management (INM) practices are becoming common under intensive agricultural systems in Chile (Ortega, 2015). Common practices include, the use of organic matter, from different sources, soil microbial inoculants, and the application of bio stimulants, of different origin. Compared to the application of macronutrients, for example, the effects of these products on horticultural crops are rather modest and require lower experimental errors to be proven; besides, trials made at the field level, many times do not have true replications, and assignment of treatments is not random. Because of these reasons, most commonly, treatments effects cannot be proven, even though, visually, differences could be observed. To deal with this reality, precision agriculture tools, and proper statistical techniques, usually those used in econometrics, that simulate ceteris paribus can be used.

The objectives of this work were to evaluate the use of precision agriculture tools, ancillary variables, and econometrics techniques to evaluate the effects of treatments in field experiments.

Materials and methods

Data presented here are from a field study conducted during the 2014/2015 season at one table grape producer located in the V region of Valparaiso in Chile.

Five fields were evaluated: three with a foliar bio stimulant (BS) treatment and two fields as control, with producer treatment. Prior to the application of the BS treatment, two fields had received the application of Cyanamide (a plant growth regulator), giving rise to three treatments: BS-Cyanamide, Control-Cyanamide, Control.

The BE treatment was evaluated in three fields with a total area of approximately 8.4 ha, whereas the control was evaluated in two fields with a total area of approximately 6.4 ha.

After the application of the treatments, the canopy of both groups of treatments was evaluated through the OptRx sensor that was operated approximately one meter from the canopy, from a ATV, below the parrón (Figure 1). The OptRx is an active three-band sensor, Green, Red and Near Infrared, from which the NDVI vegetation index, which estimates plant biomass, was calculated.

The evaluations were carried out on October 9, October 30, November 10, and December 5, 2014 and January 12 and January 28, 2015.

Figure 1. Active sensors OptRx mounted on ATV.

Within each field, a systematic grid of 20 sampling points / field was defined, which, on the average, corresponded to an intensity of 6.8 samples/ha. At each sampling point, the number of clusters / plant, and bunch weight were determined in four evaluation dates. Since the sampling was destructive, a buffer zone was determined around the original sampling point in order for the sample, at the following date, to be collected in an undisturbed position (Figure 2). At harvest, the bunches collected at each point were evaluated for: number of berries / bunch, weight of berries, pH and Brix.

Figure 2. Sampling points used with their corresponding buffer areas. The location of the points varied among dates within

the defined buffer zones.

Using tools from the Geographic Information Systems (GIS), MapInfo Professional and SMS, a set of data was constructed to determine the effects of evaluated treatments.

Data were analyzed using regression analysis based on the following basic models using the software STATA and its spatial library developed by Pisatti (Herrera, 2015).

The evaluated regression models were:

Static model:

$$y = X\beta + u \qquad (1)$$
$$u \sim N(0, \sigma^2 I_n)$$

Spatial autoregressive model:

$$y = X\beta + u \qquad (2)$$

$$u = \rho W u + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$

Spatial lag model:

$$y = \lambda W y + X\beta + u \qquad (3)$$
$$u \sim N(0, \sigma^2 I_n)$$

A combination of models (2) and (3) was also evaluated.

The basic regression model was (Wooldridge, 2013):

$$y = \beta_0 + \delta_0 BS + \delta_1 Cyanamide + \beta_1 NDVI + \beta_1 t + \mu \qquad (4)$$

Where:

y =bunch weight, berry weight, number of berries/bunch, Brix, pH.

To this basic model, other variables such a number of bunches were included. For the model at harvest, time effect was not considered.

It is worth

Results

The model that considered the four evaluation times determined that, corrected for initial biomass of the orchard, estimated by NDVI, the grape bunches coming from BS treated fields had an average weight 37 g lower (P <0.1) than the control. On the other hand, Cyanamide treatment increased bunch weight by 53 g (Table 1).

Table 1. Regression model to estimate bunch weight, considering the 4 evaluation times.

Variable	*Coefficient*	*p-value*
Intercept	509	0.01
BS	-37	0.08
Cyanamide	53	0.03
t	9	0.00
NDVI 9-10-14	-795	0.08

t=time, BS=binary variable (1=BS; 0=Control); NDVI=measure of plant biomass.

When only the data evaluated at harvest were considered, the effect of BS treatment, corrected for initial biomass, was -140 g (P <0.01).

In terms of grape quality measured at harvest, corrected by NDVI (at different measurement dates), some trends were observed: BS treatment showed a lower number of berries / bunch, higher berry weight, and lower sugar content (Table 2). No differences were observed in terms of pH.

Table 2. Treatment comparison at harvest using a regression model.

Variable	Treatment	n	Average	Std. Dev.	P-value*
N° berries/bunch	Control	40	70	20.0	
	BS	39	63	17.5	0.10
Berry weight (g)	Control	40	12.7	1.62	
	BS	39	13.5	1.45	0.16
pH	Control	40	3.8	0.1	
	BS	39	3.7	0.1	0.41
°Brix	Control	40	17.2	1.1	
	BS	39	16.5	1.4	0.05

*corrected by NDVI

None of the models, presented spatial autocorrelation, however, when considering it (equations 2 and 3), the adjusted R^2 of the models improved (Table 3). However, conclusions about treatment effects did not change.

Table 3. Spatial models for explaining bunch weight.

Criterios	Models*		
	SP.AUTO	SP.LAG	SP. AUTO+LAG
R^2 corregido	0.664887	0.66489	0.6653
AIC	-773890	-7740128	-7720632
BIC	-757304	-7574267	-7531076
Log(like)	393945	394006	394032

*SP.AUTO: spatial autoregressive model; SP.LAG: spatial lag model.

Conclusions

The use of precision agriculture tools, to sample, and to provide ancillary variables, together with proper regression techniques for data analysis, are fundamental to properly evaluate the effect of treatments under INM programs in Chilean horticulture crops. Each data set has its own peculiarity; however, the basic techniques are: spatial regression models with binary and ancillary variables.

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