RECONSTRUCTING YIELD MAPS FROM INCOMPLETE YIELD MONITOR DATA

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Yield maps constitute one of the major information in order to understand grain yield spatial variability and its causes. Many times the farmer has more than one harvester operating but having more than one yield monitor is seldom the case. This work has objective of investigating the possibility of reconstructing yield maps using incomplete data sets. Mayze yield data from a farmers's field of 35 hectares located in Campos Novos Paulista, SP, Brazil was used for this study. The complete data set corresponding to one yield data reading for every 4 seconds on a 4.5 meters wide harvester generated a data set of 23346 data points. Using this data set, it was simulated to have an increasing number of missing passages of the harvester, namely, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 15 and the maps were reconstructed using geostatistical techniques to evaluate the semivariograms and to interpolate values for the locations of the missing points using the kriging method. The total harvest load obtained with the interpolated values plus the measured was not affected by the number of missing passages meaning that the reconstruction technique does not over neither under estimate yield values. The unbiasedness condition imposed on the kriging interpolation supports this result. The semivariograms for each data set with missing harvester passages are slightly different owing to lack of data in regions of higher variability than others. The yield maps produced with missing harvester passages are visually different from the complete data set map due to variability of yield data in short distances which the missing passages failed to properly evaluate.

Key words: Geostatistics, Spatial variability, Mayze,

INTRODUCTION

One of the major difficulties for the grain producing farmers in Brazil to adopt precision agriculture practices is the cost involved with yield monitors. In general farmers have three or more harvesting machines operating but may have only one of them equipped with yield monitor.

The objective of this paper is to investigate the possibility of reconstructing yield maps using incomplete data sets.

MATERIAL AND METHODS

Mayze yield data from a farmers's field of 35 hectares located in Campos Novos Paulista, SP, Brazil, from autumn cultivation was used for this study. The complete data set corresponding to one yield data reading for every 4 seconds on a 4.5 meters wide harvester generated a data set of 23346 data points. Using this data set, it was simulated to have an increasing number of missing passages of the harvester, namely, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 15 and the maps were reconstructed using geostatistical techniques to evaluate the semivariograms and to interpolate values for the locations of the missing points using the kriging method. General descriptive statistical parameters were calculated for each data set. Semivariogram models were fitted and the parameters analyzed. Scaled semivariogram was used compare the variability pattern for each data set. Assuming that a farmer has four harvesting machines from which one of them is equipped with yield monitor the map obtained by kriging interpolation was compared with the map for the complete data set. The geostatistical procedures were done following the recommendations contained in VIEIRA (2000).

RESULTS AND DISCUSSION

General descriptive statistical parameters were not significantly affected by the increasing number of missing monitors as shown in Table 1. Except for the number of points almost equal for YLD71 as compared to YLD81, these result seem to guarantee that the simulation technique used was appropriated.

Table 1. Descriptive statistical parameters.

Variable	**Mean**	**Median**	**Mode**	**SD**	**Kurt**	**Skew**	**Min**	**Max**	**n**
Yield									
Total	2720.16	2642.24	2484.54	609.99	1.74	1.03	1000.83	5497.30	23346
YLD11	2702.16	2635.62	2484.54	605.20	1.95	1.04	1053.57	5476.36	11021
YLD21	2702.77	2629.34	2087.91	606.53	2.09	1.08	1000.83	5476.36	7272
YLD31	2720.66	2660.47	2180.79	591.38	1.84	1.00	1053.57	5378.26	5853
YLD41	2744.23	2668.54	2726.46	604.73	1.63	1.01	1103.36	5378.26	4718
YLD51	2670.28	2609.45	2087.91	619.08	2.33	1.10	1058.55	5476.36	3795
YDT61	2660.91	2603.61	2454.91	577.13	1.60	0.87	1058.55	5452.38	3023
YLD71	2719.37	2654.09	1969.81	557.59	2.43	1.14	1355.98	5221.25	2580
YLD81	2668.39	2629.02	1873.09	580.79	1.66	0.81	1092.83	5405.10	2587
YDT91	2705.88	2634.89	2726.46	647.98	1.99	1.07	1103.36	5962.64	2471
YD101	2770.50	2706.19	2410.28	628.38	1.07	0.67	1092.83	5452.38	1631
YL151	2671.86	2631.95	2146.64	536.89	2.78	1.09	1411.99	5220.38	1436

Because the parameters of the semivariogram models fitted represent the spatial variability of the yield data, it can be seen in Table 2 that the spatial variability of the yield data was adequately preserved wit the increasing elimination of harvesting machine passages. Ten out of twelve semivariograms were fitted to the spherical model. The range of correlation was very similar for all semivariograms.

Table 2. Semivariogram parameters

Variable	**Model**	**C_0**	**C_1**	**a**	**r^2**	**RMSE**	**DD**
Yield							
Total	Spherical	73768.66	252148.16	318.07	0.9967	521.34	22.63
YLD11	Spherical	68241.61	247212.51	310.34	0.9955	570.77	21.63
YLD21	Spherical	61613.50	259193.23	306.67	0.9888	850.59	19.21
YLD31	Spherical	61613.39	249193.12	312.66	0.9942	589.71	19.82
YLD41	Spherical	61613.51	249193.22	283.84	0.9868	1208.04	19.82
YLD51	Spherical	77051.16	250845.43	312.89	0.9801	1039.51	23.50
YDT61	Spherical	57993.27	230371.99	275.53	0.9780	1268.83	20.11
YLD71	Spherical	57993.19	220371.95	324.15	0.9810	1777.58	20.83
YLD81	Exponential	34558.59	253194.18	233.42	0.9626	1667.54	12.01
YDT91	Exponential	29234.66	342327.24	317.36	0.9590	2821.24	7.87
YD101	Spherical	17573.97	322234.69	271.00	0.9619	2492.46	5.17
YL151	Spherical	32593.26	218743.21	300.00	0.8838	3558.65	12.97

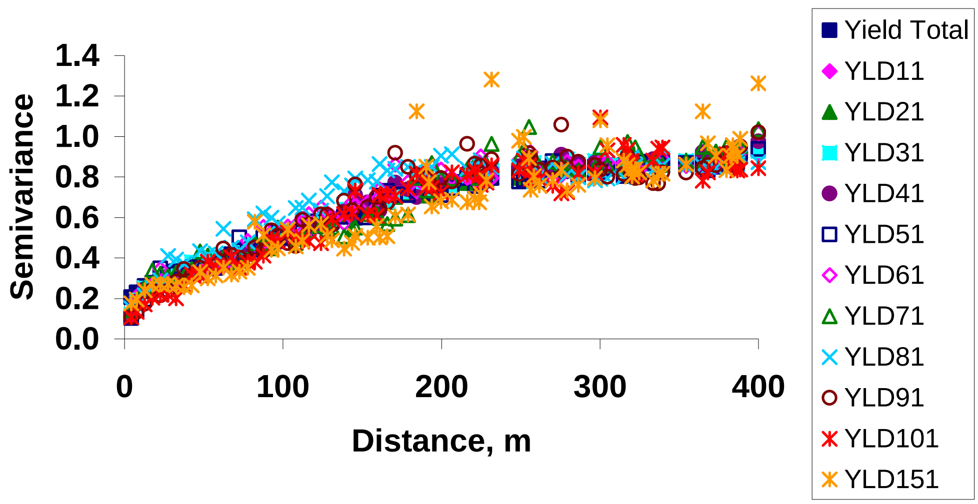

Figure 1. Scaled semivariograms for all the yield data sets.

The scaled semivariograma shown in figure 1 reveals that, except for YLD151 (the data set with the largest missing passages), all others coalesced to one single trend which is the expression of the spatial variability of the yield data.

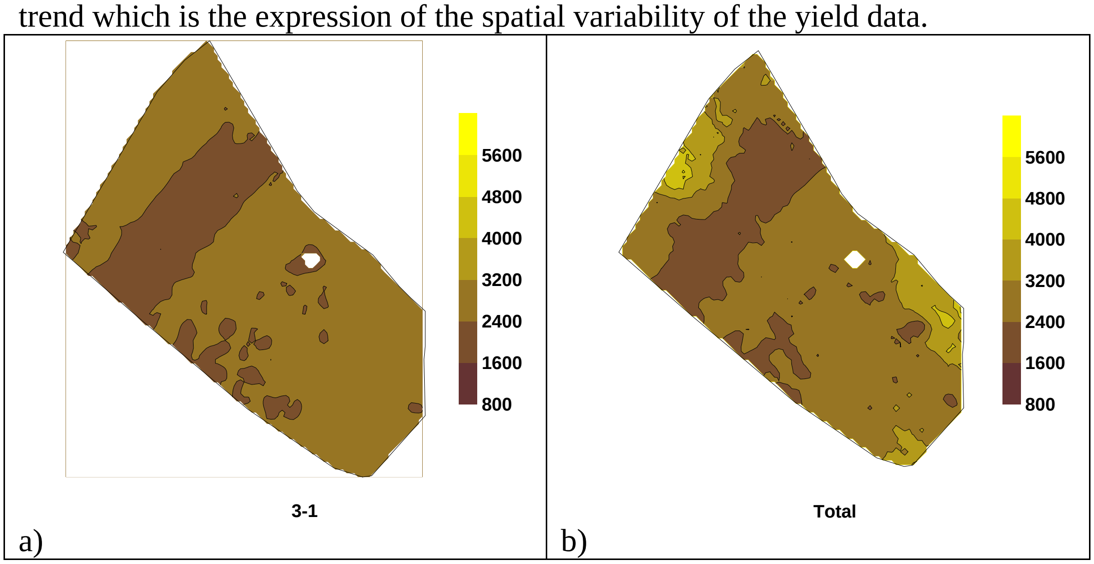

Figure 2. Yield maps obtained with kriging interpolation: a) Data set composed of a simulation of 4 harvesting machines from which only one has yield monitor; b) Complete data set.

The visual comparison of the yield maps for a data set with four harvesting and only one with yield monitor (YLD31) and the one with the complete data set (Yield Total) (Figure 2) shows that the reconstruction technique misses the specific regions of high yield but reproduced well all the other places.

CONCLUSIONS

The yield maps produced with missing harvester passages are visually different from the complete data set map due to variability of yield data in short distances which the missing passages failed to properly evaluate.

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