Corn Yield Prediction with a Forced Crop Simulation Model

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Introduction

Crop simulation models can accurately predict yield with a priori knowledge of the soil properties and management practices. The models simulate plant development and growth, and soil processes to estimate yield. Knowing the demand for nutrients and water by the plants and the supply by the soil, deficiency factors can be calculated. These are used to limit plant growth and yield. Without knowing all the soil properties and inputs, site-specific yield prediction cannot be done accurately (Sadler et al., 2000).

Remote sensing allows continuous monitoring of the plant canopy in space and time. The plant canopy reflects the effects of most deficiencies and pests (Hatfield and Pinter, 1993). In this study, a crop simulation model was adapted to use canopy attributes derived from remote sensing. The objective was to assess how well corn yield can be predicted at the field level with a crop simulation model in conjunction with remotely sensed data.

Material and Methods

A prototype of the generic crop simulation model SALUS (Schulthess and Ritchie, 1997; Ritchie, 2000) was adapted so that it could be forced with remotely sensed information to predict corn (Zea mays L.) yield. Remotely sensed data were collected with a RESOURCE21 airborne multispectral system in 1997 and 1998. The forced crop simulation was calibrated with research plot level data from Lubbock, TX (1997) and Grand Island, NE (1998) and from seven farm fields from different locations in Nebraska (1998). In addition, yield data had been gathered from 22 fields (1998): twelve fields from the Holdrege, NE region and ten from the Geneseo, IL region. Whenever available, yield maps derived from a yield monitor were used to assess the spatial accuracy of the yield predictions. Elevator receipts were used to calculate the average yield of a field. Only results from the validation study (farms in NE and IL) are shown. Observed yield data were not known when the yield was predicted for the 22 fields reported in this poster.

Table 1 lists the hybrid characteristics and sowing dates. Only one genetic coefficient was modified during the validation: the number of leaves was adjusted to correct for differences in maturity type among hybrids. Maturity type is a parameter that can be derived from remotely sensed data.

Results

Prediction of average yield:

The average yield of the fields ranged from 8400 to 10900 kg/ha. The forced crop simulation model predicted the yield over the entire range of data (Fig. 1). On average, it under-predicted measured yield by 6.7%. This was due to an under-prediction of yields in the Holdrege, NE region. Better results were obtained for the Geneseo, IL region where the average error was only 0.5%.

Prediction of within field variability:

The simplest method to assess the spatial accuracy of the predicted yield is to visually compare the yield maps (Fig. 2). The forced crop simulation accurately predicted the areas with high and low yield, respectively.

Another method is to compare the frequency distributions of observed and predicted yield (Fig. 3). This method suggested that the model tended to over-predict the frequency of cells with a yield in the range between 3000 and 7000 kg/ha. However, it closely followed the frequency of cells with a yield above 7000 kg/ha.

Table 1. Characteristics of corn hybrids grown on 22 fields in 1998 in Holdrege, NE and Geneseo, IL. Yield data were adjusted to dry weight.

	Sowing Date	Hybrid/Type	Days to Maturity	Yield Monitor (kg / ha)	Yield (Elevator receipt) (kg / ha)	Predicted Yield (kg / ha)	Obs vs Predicted Error(%)
H	4/21/98	Mycogen 2677; Mycogen 2725	106-110/111-115	NA	9814	8568	-12.7
o	4/22/98	Mycogen 2725; Pioneer 34K77	111-115/108	NA	10307	9141	-11.3
l	4/22	Mycogen2725	111-115	NA	9798	8642	-11.8
d	4/23	Mycogen 7250; Pioneer 33R87	111-115/113	NA	10662	9475	-11.1
r	4/18	Pioneer 35N05 (Bt)	105	NA	8520	5392	-36.7
e	4/28	Mycogen 7250; Pioneer 3237	111-115/116+	NA	9644	10270	6.5
g	4/23	Mycogen7250; Pioneer 33R87	111-115/113	NA	10403	9671	-7.0
e	4/26	NC+ 4880	112	NA	10509	8929	-15.0
,	4/25	Pioneer 32I55	111-115	NA	10934	10275	-6.0
	4/22&4/24	Pioneer 33A14; 32I55 (Bt)	113/116	NA	10153	9734	-4.1
N	4/21	Pioneer 35N05; Pioneer 34K77; Mycogen2725	111-115	NA	10353	7789	-24.8
E	4/22	Pioneer 34G81; Pioneer34K77; GoldenHarvest2547	106-110/111-115	NA	10286	8870	-13.8
G	5/14	Field Corn	111	8791	9019	9666	7.2
e	5/5	High Oil	108	10506	10307	10127	-1.7
n	5/5	High Oil	108	10603	9506	9814	3.2
e	5/15	Field Corn	108	9426	9597	9909	3.3
s	5-14&24	Field Corn	105	9291	9358	9544	2.0
e	5/14	Bt	109	8791	10593	9332	-11.9
o	5/4	High Oil	114	9607	NA	9443	-1.7
,	5/13	Field Corn	108	NA	8860	8637	-2.5
	5/15	Field Corn	109	9314	9957	9438	-5.2
I	5/13	High Oil	110	8070	8467	8695	2.7
L	5/4	High Oil	113	11254	10848	10604	-2.2

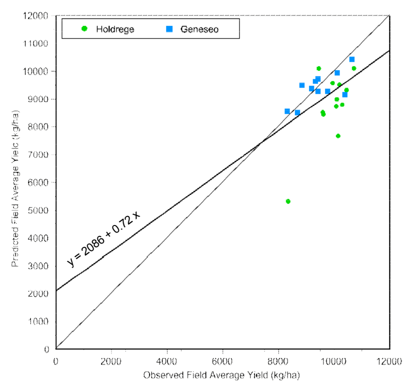

Fig. 1. Comparison of observed and predicted average yield of 22 corn fields in 1998. (Observed yield data were not known at time of prediction).

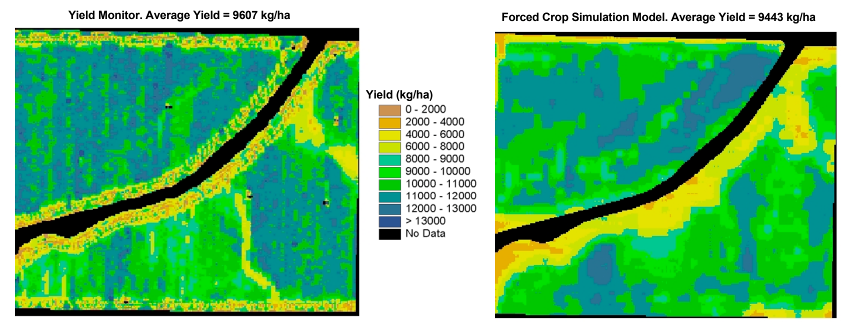

Fig. 2. Comparison of yield maps derived from a yield monitor and with a forced crop simulation model. The corn field is located in the Geneseo, IL region and its size is 16 ha.

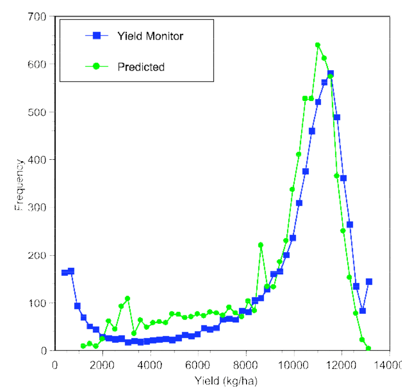

Fig. 3. Frequency distribution of observed (yield monitor data) and predicted yield data for a corn field in the Geneseo, IL region (1998)

Discussion

The fields in this study were planted with a wide range of hybrids, including Bt- and high oil corn. In the Geneseo region, the model accurately predicted yield for all of these hybrid types, without adjusting the genetic coefficients. Additional analysis showed that the under-prediction of the yield of some fields in the Holdrege region was probably due to different canopy architecture of some of the hybrids. Algorithms are in development that can detect and correct for such hybrid differences.

The forced crop simulation model accurately predicted the within-field variability of yield indicating that it is probably capable of predicting yield for fields that have higher or lower average yield than the validation data set.

The results from the validation showed that remote sensing and crop modeling complement each other. A great advantage of yield maps derived with this methodology is that they can be used for scouting, since the technique is non-destructive. The forced crop simulation model is currently being refined to generate in-season yield forecasts and yield maps. They can be used to optimize in-season crop management, scouting, and grain marketing.

References:

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