THE PREDICTABILITY OF CANE PRODUCTION IN THE SOUTH AFRICAN SUGAR INDUSTRY USING SEASONAL CLIMATE OUTLOOKS AND THE CANESIM YIELD FORECASTING SYSTEM

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Abstract

Timely and accurate yield forecasts prior to and during the milling season present opportunities to improve various industry activities, such as milling operations, international trade and agronomic optimisation. The Canesim model-based yield forecasting system was used to quantify prediction skills at different times of the year, using historic climate data and a history of seasonal climate outlooks from the South African Weather Services. Yield prediction skill was low in September prior to the milling season (11%), but increased significantly towards March (36-43%). Some results showed that predictions in irrigated areas can still be improved significantly. Prediction skills were improved by 2% to 12% when seasonal climate outlooks issued at the beginning of the year (January to May) were used. Results also suggest that some mills may benefit more than others from climate outlooks.

Keywords: sugarcane, modelling, yield forecast, Canesim

Introduction

Timely and accurate yield forecasts before and during the milling season present opportunities to improve various industry activities, such as milling operations, international trade and agronomic optimisation. Bezuidenhout and Singels (2001) described an operational model-based yield forecasting system developed in the South African sugar industry. They also evaluated the accuracy of the system against production data at mill and industry scale for the period 1980 to 2002 (Bezuidenhout and Singels, 2003).

Previous assessments assumed complete records of climate data for the season. In contrast, when the system is used operationally, climate data are still incomplete and climate analogue years from the past, in conjunction with seasonal climate outlook information, are used to simulate future production (Everingham *et al*., 2002). The accuracy of the system at different stages before and during the milling season and the value of using seasonal climate outlook information have thus not previously been quantified.

This short communication discusses the accuracy of the Canesim model-based yield forecasting system at different times of the year, both at mill and industry level, and assesses the value of seasonal climate outlook information from the South African Weather Services (SAWS).

Methods

The simulation configuration developed by Bezuidenhout and Singels (2001) was used. This entailed nine crops per milling season (April to December) per Homogeneous Climate Zone (HCZ) from 1980 to 2002. Simulated results were compared with corrected actual historic mill production information, also derived by Bezuidenhout and Singels (2003). Climate data for HCZs were compiled from climate databases at the South African Sugar Association Experiment Station (SASEX) and the University of KwaZulu-Natal (Lynch, 2003; Schulze and Maharaj, 2003). Data were selected and evaluated using a method not described in this paper.

Climate data was assumed to terminate on a specific date (Table 1). This was repeated in each season (1980 to 2002), and the remainder of the season was simulated using data from more than one historic analogue year. Nine analogue years, representing a neutral climate outlook, were selected according to the method described by Everingham *et al.* (2002). These results were used to calculate the forecasting system's operational accuracy at different times of the year over the period 1980 to 2002. Accuracy was expressed in terms of skill, indicating the percentage of natural variability explained by the forecast (0% = no skill, 100% = variability fully explained). The number of times that yields were forecast in the right direction (i.e. higher or lower than the previous season) was also expressed as a percentage.

The seasons from 1998 to 2002 were re-simulated according to the abovementioned technique, but using actual seasonal SAWS climate outlooks, as opposed to neutral outlooks, to select analogue years. Results were compared with those obtained when using neutral outlooks, to quantify the enhancement in skill when using climate outlook information.

Results and conclusions

Table 1 summarises, for different times of the year, (i) the forecast skill, (ii) the frequency of forecasting in the right direction, *viz.* directional skill, and (iii) the enhancement in skill due to the use of climate outlook information.

As can be expected, forecast skills generally increase as the milling season progresses. At mill level, skills increased on average from 11.6% in September prior to the milling season to 33.3% in December. It should be noted, however, that skills at the Komati, Pongola, Umfolozi and Entumeni mills deteriorated significantly towards the end of the season. Possible explanations for these inaccuracies can be that, (i) the simulations may be over-simplifying crop conditions and are therefore exaggerating dry and wet seasons, and (ii) mill crush rates may decline towards the end of the season, causing late season harvested crops to have lower weights than those assumed in the simulations. It should also be noted that the skill of forecasts issued in September prior to the milling season was generally higher at mills with longer cropping cycles, due to the relatively smaller proportions of the crops that were still outstanding at that time.

Although forecast skills were often less than 30%, the system frequently correctly forecast the direction of future yields compared with the previous season. For example, the directional skill in September prior to the milling season was 73% (Table 1). This information may be valuable for marketing, cash flow and mill maintenance planning.

Seasonal climate outlook information was the most valuable in January, where industry level skills were improved by an average of 8% over the period 1998 to 2002. The value of climate outlook information deteriorated from January towards the winter. Also, climate outlook information issued in September often had a negative effect on forecast skills. Generally, the Amatikulu and Eston mills showed promising improvements in skill when using the climate outlook, whereas skills at the Noodsberg, Union Co-op and Umfolozi mills were lower.

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Table 1. Forecast skill, directional skill (compared with the previous season) and skill enhancement due to the use of climate outlook information for the canesim yield forecasting system, summarised for different mills and the industry at different times of the season.

	Forecast skill (%)						Directional skill (%)						Climate outlook enhancement in forecast skill (%)				
	Date when climate data terminates						Date when climate data terminates						Date when climate data terminates				
Mill	1-Sep$_{y-1}$	1-Jan	1-Mar	1-May	1-Sep	1-Dec	1-Sep$_{y-1}$	1-Jan	1-Mar	1-May	1-Sep	1-Dec	1-Sep$_{y-1}$	1-Jan	1-Mar	1-May	1-Sep
Komati	12.4	63.3	80.3	69.4	25.1	5.0	75.0	87.5	87.5	75.0	75.0	75.0	-3.5*	-7.9	6.6	-4.1	0.0
Malelane	5.5	23.0	28.0	28.6	27.4	26.0	63.6	63.6	59.1	59.1	50.0	40.9	-11.5*	6.5	0.8	-1.5	0.1
Pongola	14.2	22.1	38.2	25.5	-35.3	-10.9	63.6	54.5	59.1	54.5	59.1	54.5	-3.0	1.9	6.2	-1.2	-3.2*
Umfolozi	3.7	18.0	25.8	27.0	16.9	15.6	54.5	59.1	77.3	81.8	81.8	81.8	9.3	-1.3	-6.0	-1.7	-0.4
Entumeni	11.7	14.6	21.6	23.0	14.2	13.1	72.7	59.1	72.7	68.2	77.3	77.3	-20.6	7.7	-0.1	-2.4	0.1
Felixton	3.6	11.8	29.8	39.6	46.6	45.7	54.5	63.6	86.4	90.9	95.5	95.5	-2.1	8.4*	0.8	0.9	-0.2
Amatikulu	6.1	16.3	41.9	54.6	60.2	61.5	77.3	59.1	81.8	90.9	95.5	95.5	-11.8	27.7	15.0	9.4	-0.6
Darnall	8.6	17.2	37.0	54.6	52.2	52.8	68.2	77.3	86.4	86.4	86.4	90.9	-12.0	15.7	13.2*	6.5*	0.8
Gledhow	10.8	8.0	24.4	32.4	33.9	34.9	72.7	81.8	90.9	90.9	90.9	86.4	-3.2	17.8	12.8*	6.5	0.7
Noodsberg	21.7	34.2	44.8	45.7	51.0	47.1	68.2	81.8	86.4	81.8	77.3	72.7	0.9	-1.3	-2.3	-0.4	-1.1
UnionCoop	21.7	34.6	40.3	40.6	45.1	44.0	63.6	72.7	81.8	77.3	81.8	81.8	1.5	-1.0	-2.2	-0.4	-1.3
Maidstone	9.8	8.9	29.7	36.4	31.5	32.7	72.7	68.2	81.8	81.8	81.8	72.7	-5.1	4.2	5.7	2.6	-0.5
Eston	12.9	22.1	20.9	25.2	22.1	23.9	77.3	63.6	72.7	77.3	77.3	77.3	10.3	12.4	14.8	3.4	3.9
Sezela	10.0	24.8	40.1	49.1	52.4	52.1	63.6	77.3	86.4	81.8	86.4	90.9	-9.5	-0.6	0.9	6.4	0.6
Umzimkulu	21.3	32.9	46.1	55.5	54.7	55.4	63.6	68.2	72.7	72.7	77.3	72.7	0.5	2.1	0.3	2.1	0.3
Mean	**11.6**	**23.4**	**36.6**	**40.5**	**33.2**	**33.3**	**67.4**	**69.2**	**78.9**	**78.0**	**79.5**	**77.7**	**-4.0**	**6.1**	**4.4**	**1.7**	**-0.1**
Industry	**11.3**	**23.2**	**43.2**	**54.0**	**57.3**	**57.9**	**72.7**	**59.1**	**77.3**	**77.3**	**81.8**	**81.8**	**-0.9**	**11.6**	**10.1**	**8.2**	**-0.5**

* Statistically significant (P=0.1)