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Enhanced risk management and decision-making capability across the sugarcane industry value chain based on seasonal climate forecasts

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Abstract

Sugarcane industries worldwide are exposed to uncertainty associated with variable climate. This variability produces impacts across an integrated value chain comprising of the following industry sectors: cane growing, harvesting and transport, milling, and marketing. The purpose of this paper is to advocate a comprehensive systems approach for using seasonal climate forecast systems to improve risk management and decision-making capability across all sugarcane industry sectors. The application of this approach is outlined for decisions relating to yield forecasting, harvest management, and the use of irrigation. Key lessons learnt from this approach include the need for a participative R&D approach with stakeholders and the need to consider the whole industry value chain. Additionally, there is the need for climate forecast systems to target the varying needs of sugarcane industries.

Keywords: Sugarcane; Value chain; Climatic risk; Systems approach; Participative processes

1. Introduction

Sugarcane industries worldwide are located in regions of uncertain and variable climate. Dealing with this climatic variability is important to profitable and sustainable sugarcane production because stability of income from year to year affects the risk of farming and milling operations. Potential exists for seasonal climate forecasting to improve risk management and decision-making leading to enhanced

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industry competitiveness. Seasonal climate forecasting tools are increasingly used in risk management for annual cropping systems such as peanuts (Meinke and Hammer, 1997), maize (Singels and Potgieter, 1997), wheat (Hammer et al., 1996) and cotton (Dudley and Hearn, 1993). It is only more recently that the potential applicability of climate forecasting for perennial crops and sugarcane in particular, has been investigated (e.g. Everingham et al., 2001a,b; Hansen et al., 1998; Pulwarty and Eischied, 2001; Singels and Bezuidenhout, 1999).

Sugarcane is a tropical plant that is grown under diverse climates throughout the world, from sea level to 1500 m at latitudes between 36.7°N and 31.0°S. Humbert (1968) describes the ideal climate as a long, warm growing season and a fairly dry, sunny, cool, but frost-free ripening and harvest season, free from hurricanes and typhoons. Sugarcane industries are comprised of an integrated value chain comprising of growing, harvesting and transport, milling, and marketing sectors, and climate impacts across each of these sectors. Accordingly, the most appropriate climate forecasting system for tactical and strategic management across the industry value chain (farming, harvesting, milling, marketing sectors) is very much dependent on what decision point and what industry sector is being targeted.

By considering a system for the whole of industry, i.e. taking a comprehensive systems, or whole value chain approach (Muchow et al., 2001), the integration of seasonal climate forecasting with management strategies has the potential to benefit sugar industries in many areas, and in particular by:

1. Improved on-farm profitability by better use of scarce water resources, increased water use efficiency and higher sugar production, with minimal movement of nutrients and pesticides off-farm reducing the potential harmful environmental consequences of sugarcane production.
2. Improved planning for wet weather harvest disruption and early season sugar supply and better scheduling of milling operations leading to more effective use of resources, e.g. milling capacity, haulage equipment, shipping, together with enhanced on-farm profitability.
3. Enhanced industry competitiveness through more effective forward selling of sugar based on enhanced knowledge of amount of sugar supply and improved efficiency of sugar shipments.

This paper describes a research approach for realizing these benefits through the application of seasonal climate forecasting across the sugar industry value chain. The research approach is demonstrated as part of three case studies focusing on irrigation planning (Section 3), harvest management (Section 4) and yield forecasting (Section 5).

2. Research approach

The development of information alone, in the form of climate forecast systems, will not necessarily realise benefits to sugarcane industries. We advocate adoption of both a comprehensive systems approach and a participatory research process to best deliver enhanced risk management and decision-making capability based on seasonal climate forecasts. The advantage of the participative approach is that it tends to moderate against the frequent mismatch between knowledge systems of researchers and the knowledge systems of industry end-users, and facilitates the integration and adoption of scientific outputs to deliver industry benefits.

Taking a comprehensive systems research approach, we propose the following framework: (1) Identify, in partnership with industry, the key decisions influencing profitability that climate impacts. (2) Develop appropriate databases of climate and industry sector performance. (3) Identify and establish the role of appropriate climate forecast systems for different geographical regions and industry decisions. (4) Assess the capability of the climate forecast system to improve tactical decision-making based on climate forecasting across different components of the industry value chain. Finally, (5) implement the climate forecast system for enhanced risk management and decision-making and identify how outputs from such a system can be delivered or conveyed back to industry on a continuing basis.

2.1. Key industry decisions

An important prerequisite is to identify the key industry decisions influenced by seasonal climate forecasts and how these decisions impact across the industry value chain. Fig. 1 gives examples of decisions that the different industry sectors make, seasonal climate forecasts can influence. Whilst decisions are made for the specific components of the value chain, it is important to recognise that the chain represents an integrated system. The decisions made for a single sector can affect each of the sectors in the value chain.

We can consider three aspects of the impact of climate on the sugarcane production system at farm level. Firstly, climate directly determines the processes of yield accumulation and the amount of sugar produced. Secondly, climatic conditions

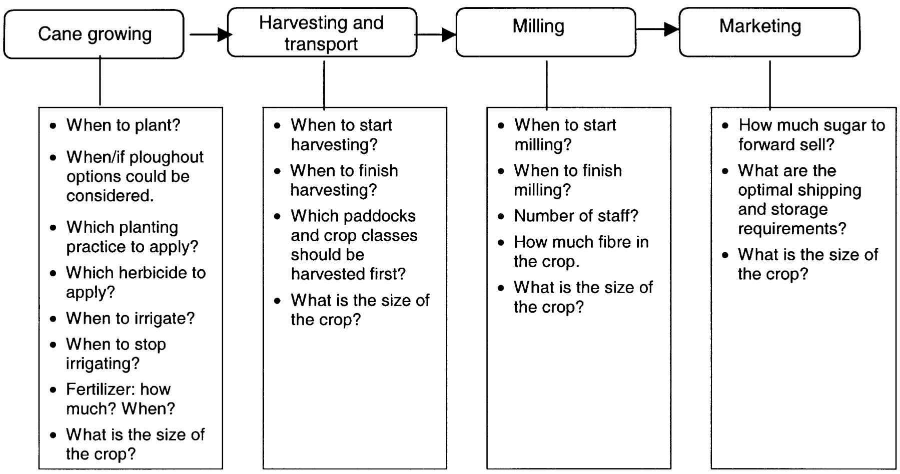

Fig. 1. The industry value chain and key decisions influenced by seasonal climate forecasts.

influence the development and spread of fungal diseases, insects, pests and weeds, which can restrict crop growth. Thirdly, climate, and rainfall in particular, sets the potential for runoff and deep drainage with possible environmental impact associated with the movement of nutrients and pesticides. If seasonal climate forecasts can be applied and integrated into the farm management system, forecasting offers the potential to improve farm management systems by improving yields, planting opportunities, application of fertilizers, herbicides (Cifuentes, 1997), pesticides and irrigation, all of which influence the ecological sustainability of sugarcane production.

Different farm decisions require climate forecasts for varying responses, lead-times and forecast periods. Table 1 presents three examples of how climate forecasts could be integrated with on-farm planning. These decision summaries were generated as part of the participatory research approach with a group of cane farmers from the Ingham (18.59°S, 146.25°E) sugar-growing region in Queensland, Australia. Whilst lead-times and forecast periods are likely to vary for sugarcane growing regions world wide, Table 1 does briefly illustrate some of the logic behind farmer planning and how climate forecasts can be integrated with the decision making process.

The issue of when to plant (decision 1) is a key decision bearing major importance to growers. In Ingham, farmers from predominantly wetter districts are concerned of the plant crop failing due to extremely wet conditions following the plant. Such farmers tend to plant in the months of July or August, but knowledge of future climate conditions can help farmers decide what planting strategies to employ. If at the end of June, there was a high chance of being wet in July, farmers could consider delaying the plant until August. This decision would then require knowledge by the end of July, of the chance of high rainfall in September–November. Farmers noted that if there was a high chance of high rainfall in September–November, they might consider not planting at all, or modifying planting strategies to encourage rapid germination.

Farmers from Ingham have also considered using climate forecasts to help decide if and when to plough out the existing crop (decision 2). This decision was primarily

Table 1
A list of key decisions influenced by climate forecasts that was developed by local industry decision makers in Ingham, Queensland, Australia

Decision	Timing of forecast	What is the chance of	This information will help
1	End of June	A high number of rain events in July?	Farmers decide when to plant and to identify appropriate planting strategies
	End of July	A high number of rain events in September–November?	
2	End of July	A high number of rain events in September?	Farmers from dry areas decide on appropriate ploughout strategies
3	At time of planting	Rain for the month following planting will exceed 15 mm?	Farmers decide whether a pre-emergent or knockdown should be applied

considered by farmers from dry areas in Ingham with no irrigation. These farmers would consider ploughing out and replanting in August if at the end of July there was a reasonable indication of rain events following the replant.

Once the cane is planted, there are two modes of herbicide action (decision 3) for controlling weeds: a pre-emergent or a post-emergent (sometimes referred to as a 'knockdown') herbicide. If conditions following planting were more likely to be dry, then farmers from Ingham would consider it more economical to apply a post-emergent herbicide. Conversely, if conditions following planting are more likely to be wet, thereby potentially restricting trafficability, then it would be more preferable to apply a pre-emergent herbicide at the time of planting.

There is a need however, to consider seasonal climate forecasts beyond the farm level, as sugarcane industries comprise an integrated value chain where climate impacts on the harvesting and transport, milling, and marketing and shipping sectors (Muchow et al., 1997). Knowledge of likely disruptions due to wet weather can allow harvest managers to enhance and better plan harvesting strategies for the coming season. Knowledge of the chance of high rainfall towards the end of the harvest season, may call for farmers and harvest operators to rethink typical harvesting strategies (see Section 4 for examples).

Rainfall forecasting would also be important for mill scheduling, which is subjected to considerable disruption because mechanical harvesting requires dry conditions. If there is likely to be rain interruptions during the harvest season then marketers can also factor this into planning so as not to over commit sugar supplies to customers.

A major issue for all sectors of the sugar industry value chain is predicting the size of the crop. Since climate is a key driver of crop size, the ability to better estimate yields by incorporating climate forecasts could for example, assist farmers with planning fertilizer and irrigation regimes. Harvest operators and millers could better plan for the likely start and finish of the season. If forecast systems could predict in advance that there was going to be a large crop then the start of the harvest season might be brought forward. This would be especially the case if the forecast system would also indicate a high chance of wet weather at the end of the 'normal' harvesting period. Advance knowledge of crop size would also enhance forward selling strategies for marketing plans. It is evident, that seasonal climate forecasts offer the potential to improve many decisions that are made across the entire sugar industry value chain.

2.2. Data acquisition and database development

There are three main categories of data needed to effectively integrate climate forecasting with industry decision making: (1) climate-drivers such as the Southern Oscillation Index (SOI) and sea-surface temperatures (SST); (2) crop-drivers such as daily solar radiation, temperature, evaporation and rainfall; and (3) productivity information such as total sugarcane production. Issues associated with each of these forms of data include record length, missing values, spatial coverage and quality. Once appropriate and accurate databases have been developed, it is then necessary to maintain and update the databases as more data become available. Following this, climate forecast systems could then be considered.

2.3. Climate forecast systems

Climate forecast systems that are able to provide analogue seasons or years and thus some forecast distribution have become increasingly utilized in agricultural systems (Everingham et al., 2001a,b; Meinke and Hammer, 1997; Singels and Bezuidenhout, 1999; Hansen et al., 2001). Analogue systems are increasingly used since once the required analogue information is provided as output by the forecast system, daily data can be extracted for radiation, evaporation, rainfall, and temperature corresponding to that particular year or season. Thus, crop models can be run using that set of seasons corresponding to certain analogues rather than relying on the entire climate history for that season, location and application. An example of two forecast systems commonly used to produce analogue years are the 3-phase sea surface temperature (SST) system and the 5-phase Southern Oscillation Index (SOI) system (Stone and Auliciems, 1992; Stone, et al., 1996). The 3-phase SST approach (see for example Hansen et al., 1998, 2001) derives analogue years by partitioning years that correspond to El Niño, La Niña and neutral conditions. The 5-phase SOI phase climate forecast system utilises pre-determined clusters of the SOI representing patterns of variability in month-to-month values of the SOI. Five clusters or phases of the SOI were identified as: 'consistently negative' (neg), 'consistently positive' (pos), 'rapidly falling' (fal), 'rapidly rising' (ris) and 'consistently near zero' (nz). The 5-phase SOI system typically derives analogue years by partitioning years with the same SOI phase for those key months preceding the period of interest and then comparing how the distribution of the response (e.g. rainfall) changes among each of the phases.

For some locations, forecast accuracy can be increased by combining other oceanic and atmospheric parameters with ENSO (El Niño-Southern Oscillation) parameters in the forecasting method. Jury (1998) used southwestern Indian Ocean air pressure, north Indian Ocean surface meridional wind and Southern Ocean air pressure in conjunction with the SOI during September to November to forecast December to March rainfall for parts of South Africa. The South African Weather Service (SAWS) also uses a combination of statistical (Landman and Mason, 1999) and dynamic methods (Landman et al., 2001; Goddard et al., 2001) to forecast the probability of 3-monthly rainfall totals falling into three categories namely below normal, near normal and above normal.

2.4. Assessment

It is difficult to justify using a climate forecast system to enhance decision-making capability if the climate forecast is unable to add value to current decision making approaches. Assessing the capability of the climate forecast system to improve tactical decision-making could be performed in many ways. This often involves economic evaluations where the benefits and costs of tactical decision-making are computed. Since economic evaluations are very much dependent on specific decisions for specific locations we do not provide details of economic evaluations in this paper, but refer the interested reader to Antony et al., 2002 and Jones et al. (2000) as examples. For traditional climate forecast assessment methods we refer the interested reader to Murphy (1993), Barnston (1992), and Mason and Graham (1999). Sections 3–5 also consider alternative assessment methods of relevance to the particular application.

2.5. Implementation and delivery systems

There is a need to investigate appropriate delivery mechanisms of climate forecasts so that industry can access information and implement tactical planning based on this information. Climate forecast delivery systems vary with end user groups, decisions, and geographical regions. The authors advocate that forming working partnerships with the end user would greatly facilitate the development and implementation of suitable delivery. Whilst we propose that climate forecast delivery systems are important for providing the necessary forecast information to the end user, we consider that it is beyond the scope of this paper to discuss these in detail.

3. Irrigation case study

For many sugar-growing regions, the availability of irrigation water is not sufficient to meet crop demand. An important issue for farmers to address is how to best use a limited water supply and maximise the effectiveness of rainfall. Russell (1990) and Wegener (1990) have found that irrigating at strategically calculated times can increase sugarcane yields by up to 10 Mg ha^{-1} for locations in selected sugarcane growing regions in Australia. Inman-Bamber et al. (1999) reported a cane yield response of 41 Mg ha^{-1} to well timed irrigation amounting to only 179 mm. Thus, the value of integrating seasonal climate forecasting with irrigation scheduling is under investigation.

Cruz (1997) described ways in which irrigation practices in Gauca, Colombia, could be modified before a likely occurrence of an El Niño event. Modifications include regular monitoring of soil water balance, alternate surge irrigation, using rigid irrigation tubes, sprinkler irrigation and daily control of irrigation water quality. Inman-Bamber et al. (2001) describe how the timing of irrigations and associated stress indices differ between El Niño and non-El Niño years. The key result identified in this paper was that in El Niño years there was a tendency to apply irrigations earlier than in non-El Niño years at stress levels ranging between 0.5 and 0.7.

3.1. Methods

In this case study we demonstrate how the 5-phase SOI climate forecast system can be used to improve irrigation management for sugar growing regions in Bundaberg

(24.50°S, 152.21°E), Queensland, Australia. In order to provide an integrating mechanism to link climate forecasting to irrigation scheduling, the APSIM-Sugarcane crop growth simulation model (Keating et al., 1999) has been utilised to provide crop yield simulation output that is then used to provide optimal timing scheduling for irrigation application. This approach is being tested in replicated field experiments in Bundaberg. Robertson et al. (1997) calculated 751 mm as the full irrigation requirement for this region, but allocations are often as low as 100 mm and seldom more than 400 mm. These allocations allow growers to irrigate two to eight times during the season. Field trials have been established to determine if these irrigations can be timed to coincide with periods of most severe water stress during the season and whether or not irrigation applied during these periods is better than a grower's skill in using limited water. Here skill is measured by comparing the size of the crop in Mg ha^{-1} produced by the grower with the size of the crop produced in the field trial. It is assumed that soil and climate conditions on the farmer's fields are the same as that for the field experiment. The progress of crops in the experiment were simulated each week and probable dates for the next irrigation were simulated by appending daily climate records of radiation, temperature and rainfall, for the past 110 years to the end of the climate record current at the time of simulation (11 January 2001). The most successful of a number of timing strategies was selected for each year. Analogue years were grouped by SOI phases and the median date of the appropriate SOI group was selected for the next irrigation.

3.2. Results

Fig. 2 demonstrates how the timing of the next irrigation (some time after the 11 January) varies with SOI phase. The most notable feature in Fig. 2 is that the median timing date for 'consistently positive' November/December SOI phases Julian day 54 (23 February) is later than the median timing date for the remaining phases. The November/December SOI phase for 2000 was positive so this simulation would suggest delaying the next irrigation. This result is likely to be due to the increased chance of experiencing above median rainfall for January when the SOI phase for November/December is 'consistently positive'.

3.3. Key lessons

Results to date show no benefit from the irrigation forecasting technique. This is not surprising because there was only one moderate stress period during the 6-month experiment, which both the cooperating grower and the forecasting method identified correctly. Growers participating in this research agree that forecasts of optimum timing for limited irrigation may not benefit the better growers but will assist many who do not use their allocations at the right time for fear of running out of water too early. Consequently, optimised water use patterns have been discussed at many grower meetings to show when limited irrigation is likely to be most useful as the season progresses. Delivery systems for conveying optimum irrigation times to cane farmers from Bundaberg are currently being tested.

4. Harvest management case study

Climate variability greatly affects harvesting and transport operations in the sugar industry value-chain. Sugarcane is harvested over a long period (e.g. 5–9 months) and rainfall events during this period disrupt the capability of moving cane from field to factory. Management allows for average disruption to the harvest season, but extreme rainfall events during the harvest can cause complications and impact significantly across the whole value chain.

Muchow and Wood (1996) used historical rainfall records from selected sugarcane growing regions in Australia to compute a measure of rainfall risk for varying times during the harvest season. They concluded that the risk of disruptive rainfall occurring at the end of the harvest season is greater than the risk associated with disruptive rainfall at the beginning of the season. Everingham et al. (2001b) previously investigated the potential usefulness of 5-phase SOI system to forecast rain events at the beginning (May–June) and end (October–November) of the Australian harvest season, thereby determining those years when harvest disruption due to rain would be more likely. These key periods were identified by industry to be important since knowledge of high rainfall during these months could influence decisions relating to the start and finish times of the harvest schedule and the order in which paddocks could be harvested. For example, a decision to delay the start of the season requires knowledge of a high chance of a high number of wet days in May–June, with a lead-time of approximately 1–2 months. If a forecast system suggests a high probability of excessively wet conditions during October–November, then farmers

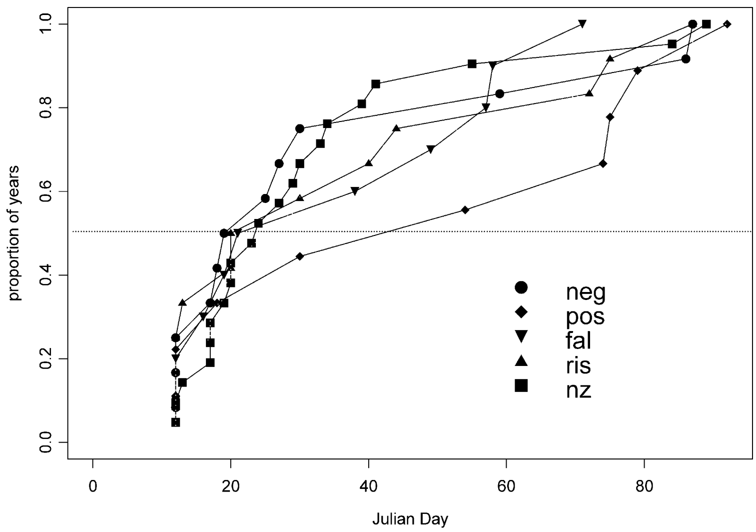

Fig. 2. Illustration of how the timing of the next irrigation varies with SOI phase. The horizontal axis shows the Julian day of year of the next irrigation and the vertical axis shows the proportion of the number of simulations that were applied on or before the corresponding Julian day. The horizontal line can be used to read the median Julian day of the next irrigation.

may prefer to harvest younger or better ratoons in the crop cycle earlier in the harvest season. Given that the potential for higher yields in the next season is greater for the younger ratoons, this harvest management strategy would reduce the risk of damage from wet weather harvesting and serious impact on the sugar yield for the next season. In addition, in years when there is a high risk of disruption due to rain events in October–November, harvest operators could ensure low lying areas are targeted as early as possible within the harvest season to reduce the risk of leaving cane unharvested. Results indicated that the usefulness of the climate forecast depended on lead-time, and location, with greater skill identified for the October–November period.

4.1. Methods

This case study presents some of the key findings in Everingham et al. (2001b) for Kalamia Mill (19.54°S, 147.41°E) in the Burdekin region of Queensland, Australia. The 5-phase SOI system was used to estimate the chance of having a high number of wet days over May–June and October–November at seven lead-times ranging from 0 to 6 months. Industry defined a 'high' number of wet days, to refer to a number greater than the upper quartile. Wet days are defined using a rule from the RAINRISK database (Muchow et al., 1996):

- If the daily total rainfall is greater than or equal to 10 mm but less than 20 mm, then that day is defined to be a wet day.
- If the daily total rainfall is greater than or equal to 20 mm but less than 40 mm, then that day and the next day, are defined to be wet days.
- If the daily total rainfall is greater than or equal to 40 mm, then that day and the next two consecutive days, are defined to be wet days.

Given climate forecast information, probabilities that differ significantly from 25% are of particular interest, since with no knowledge of climate forecasting the chance of experiencing a high number of wet days is 25%. Significance as calculated by S-Plus 2000 was determined at the 0.10 level by using an exact binomial test.

4.2. Results

Historical October–November records indicate (see Table 2) that when the SOI phase has been 'consistently negative' at the end of June, July, August or September the probability of experiencing a high number of wet days is statistically different to the climatological probability of 25%. This is also the case when the SOI phase has been 'consistently positive' at the end of July or August. When the SOI phase is 'consistently positive' at lead-times of 1–2 months, results indicate that the chances of experiencing a high number of wet days during October–November are somewhat increased. Conversely, a reduced chance of such events is suggested when the SOI phase is 'consistently negative' for the months preceding October–November.

The SOI phase system is less able to reduce uncertainty for experiencing a high number of wet days in May–June for the example of Kalamia shown in Table 2. However, 'rapidly rising' and 'consistently negative' SOI phases suggest that the risk of experiencing a high number of wet days during May–June is low and that operations could plan for a normal start to the harvest season with knowledge of those SOI phase patterns.

4.3. Key lessons

Some lessons learnt from this investigation are that seasonal climate forecasting can add value to decisions influenced by high rainfall events in October–November, but there is less skill associated with forecasting wet days for May–June. Growers participating in this research acknowledge that if these climate forecasts had been used in planning operations for the 1998 season, an early warning of the excessive rains experienced may have been heeded, since the SOI phase was 'consistently positive' from July 1998 through to March 1999. This would have had beneficial impacts from the farm through to the marketing sector of the Australian sugar industry for the 1998 season and subsequent seasons to follow.

Climate forecasts for key periods during the harvest season are now published in the Australian Canegrower, which is a magazine distributed to an industry audience comprising more than 7000 people. More participatory research is required however, for industry decision makers not part of the case study to better understand the strengths, limitations and concepts associated with climate forecast systems. The scientific team also recognises that the needs of the wider industry participants may

Table 2
Probability[a] of obtaining a high number (i.e. greater than the 75th percentile) of wet days in May–June and in October–November for each SOI phase at lead-times from 0 to 6 months at Kalamia

Lead (months)	Lead (months)	May–June					SOI phase for	October–November				
		neg	pos	fal	ris	nz		neg	pos	fal	ris	nz
0	March/ April	0.19	0.12	0.17	0.22	0.06	August/ September	**0.09**	0.36	0.10	0.33	0.16
1	February/ March	0.14	0.13	0.11	0.13	0.16	July/ August	**0.05**	**0.42**	0.36	0.11	0.22
2	January/ February	0.13	0.13	0.15	**0.05**	0.20	June/ July	**0.00**	**0.48**	0.22	0.35	**0.06**
3	December/ January	**0.05**	0.11	0.08	0.19	0.19	May/ June	**0.00**	0.36	0.25	0.28	0.16
4	November/ December	0.10	0.13	0.23	**0.00**	0.21	April/ May	0.11	0.35	0.13	0.19	0.28
5	October/ November	0.13	0.18	0.07	**0.06**	0.16	March/ April	0.13	0.31	0.22	0.39	**0.12**
6	September/ October	0.13	0.21	0.00	0.08	0.13	February/ March	0.07	0.39	0.21	0.17	0.22

[a] Probabilities that are significantly different from 0.25 at the 0.10 level are in bold.

differ slightly from the needs identified in regions where the participatory research has predominantly focused.

5. Crop forecasting case study

Climate is a key driver that affects sugarcane productivity levels (Muchow et al., 1997). Advanced knowledge of climate through seasonal climate forecasts could then be used to enhance risk management decisions associated with crop size across the whole of industry. At the farm level, growers could plan to fertilize less (more) if they expect a season to have low (high) crop demand for nutrients. As noted in the Section 2.1, crop size influences the start time of the harvest and milling season. At the marketing sector, improved yield forecasts can enhance forward selling and shipping strategies.

It is now well accepted that the ENSO phenomenon significantly affects global weather patterns. Understanding how the ENSO phenomenon affects specific crops such as sugarcane is less understood. This can be partly attributed to the many other factors affecting crop size such as farm management practices and pests and disease, as well as economic and environmental considerations.

Some progress has however been made on the relationship between ENSO and sugarcane productivity. Pulwarty and Eischeid (2001) found that for Trinidad and the South Caribbean, rainfall in April–July is inversely related to the size of the crop in the following harvest season. Further to this, they noted that the El Niño or warm ENSO events were associated with much higher than normal rainfall during this period in the year following the ENSO event peak. Conversely, La Niña or cold ENSO events are associated with lower than normal rainfall for the same period. As an example, the El Niño event of 1997–1998 was associated with very low yields in 1999. Hansen et al. (1998) found similar results for Florida sugarcane yields. Florida sugarcane yields tended to be higher in years that were preceded by La Niña conditions. The authors noted that the reduced rainfall and higher temperatures often associated with La Nina winters contributed to better growing conditions for the crop.

Kuhnel (1994) investigated the relationship between ENSO and sugarcane productivity levels for different regions in Australia. Kuhnel found that yields for northern and southern sugarcane districts in Queensland tend to be inversely related with the value of the SOI in the year before harvest, which usually commences around June.

Everingham et al. (2001a) examined the relationship between yields and SOI phases for Australian sugar yields. Everingham et al. made use of Monte Carlo procedures to determine which of the five SOI phases were most useful for indicating when Australian sugarcane yields are likely to be above (or below) the long-term median for eight mill locations of relevance to the Australian sugar industry. Everingham et al. (2001a) found that the 5-phase SOI system offers the potential to improve sugarcane estimates but success varies with geographical location and SOI phase.

Singels and Bezuidenhout (1999) have also used SOI phases to identify how yields for the South African sugar industry vary between SOI phases. Their research targeted the needs of the South African sugar industry, which is affected by limited water supply. Singels and Bezuidenhout found yields tended to be reduced when the SOI phase in November was consistently negative. Singels and Bezuidenhout suggested that the reduced crop size is associated with reduced likelihood of rainfall in February, which is an important period for cane growth.

Other yield forecasting methods used by the South African sugar industry include that by Jury (1998). Jury provides a categorical sugar production forecast (industry average yield expressed as a percentage anomaly) in November of the year preceding the milling year. It is based on statistical relationships between industry sugar yield and the following predictors—SOI, eastern Atlantic surface meridional wind, northern Indian Ocean surface meridional wind, and Southern Ocean air pressure.

Another approach is to use simulation models such as Canegro and ACRU-Thomson (Lumsden et al., 2000) and Canesim (Singels et al., 1999). Such simulation models require site-specific daily climate data and other inputs such as soil properties and management factors. Climate variables include daily rainfall, temperature, radiation, wind and humidity. The simulation approach could provide estimates from field level up to the whole of industry through appropriate means of aggregation of model inputs and/or outputs (Hansen and Jones, 2000).

The Canegro, ACRU-Thomson and Canesim models are used to forecast yield by extending simulations into the future. This is achieved by combining recently observed climate data to represent that part of the crop cycle that has been completed, with historic sequences to represent a likely future scenario. One or more sequences could be used to forecast the future, thereby introducing an element of uncertainty inherent to forecasts. Actual daily climate sequences are used rather than long term mean values in order to capture the effect of erratic rainfall distribution on crop growth.

The case study presented in this section will focus on the current yield forecasting method used in the South African sugar industry. The forecast has been conducted operationally since 2000. A report is distributed every second month from February through to November to representatives of the 15 mills and approximately 50,000 growers as well as to the South African Sugar Association (SASA) management (see Bezuidenhout and Singels, 2001). Millers use the information to augment field-based estimates from growers to plan the milling schedule for the coming season. The mill opening date for example is a crucial decision. SASA has also used long-lead forecasts to formulate the annual industry business plan and to support decisions regarding the forward selling of sugar on the export market. Although yields are forecasted at the industry, mill supply area and district level, this case study will focus on the latter.

5.1. Methods

Ten analogue daily weather sequences for the future are selected based on seasonal rainfall forecasts provided by the South African Weather Service (see Section

2.3). The number of sequences selected from each tercile depends on the forecasted probability that rainfall will fall within the given tercile. One sequence is selected for every rounded 10% of probability. Once the number of sequences to be selected from each tercile is determined, it is then necessary to choose the actual sequences. Sequences are selected which include the percentile of the rainfall total for the relevant period that corresponds to the closest cumulative frequency at the midpoint of each tercile (17, 50 and 83%) are selected. The total number of simulations is limited to ten owing to restrictions in computing resources. The Canesim model then combines the observed climate with the 10 analogue climate sequences to calculate final yield. The mean and standard deviation of these 10 yield values are reported. Estimates are expressed as percentages of the corresponding yield of the previous season.

The method will be demonstrated for 14-month-old crops harvested in August 2000 and August 2001 in the Tongaat district (29.34°S,31.08°E) in the North Coast region of KwaZulu Natal, South Africa. Fig. 3 illustrates the method of selection of analogue sequences for the Tongaat station based on the January 2001 rainfall forecast. The forecasted probability of February to April rainfall to fall within the above-normal, normal, and below-normal terciles were 20, 40 and 40%, respectively. The analogue sequences selected would be from the years 1985 and 1984 (from the above normal tercile), 1986, 1982, 1987 and 1972 (near normal tercile) and 1980, 1994, 1983 and 1968 (below normal tercile). Table 3 summarizes the information used for each forecast. The August 2000 and August 2001 crops were forecasted in the preceding months of September, November, January, March, May and July.

5.2. Results

Fig. 4(a), (b) illustrates the forecast yield probability distribution generated at each forecast date. The model estimated cane yield for the August 2000 crop to be

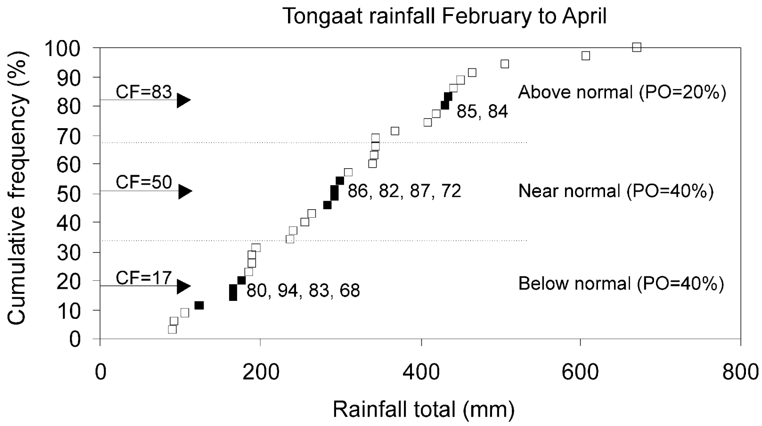

Fig. 3. An example of the selection of analogue climatic sequences based on rainfall forecasts. The graph depicts cumulative frequency (CF) of February to April rainfall totals for the Tongaat station as well as the years selected to represent likely future climate scenarios based on the forecasted probabilities (PO) of rainfall occurring in three terciles.

165% of the value obtained in 1999. Forecasts throughout the season indicated that yields would be higher than the 1999 season. These indications strengthened as the season progressed. The early under-estimation of yield can be partly attributed to the relatively 'normal' forecast chance of rainfall occurring in the top tercile over the summer months of the 1999/2000 season (see Table 3), given that rainfall actually fell in the above normal tercile.

Cane yield for the August 2001 crop was well below that of 2000 due to prolonged dry spells during the late summer and winter. These conditions generally correlated well with the rainfall forecast for these periods. The inferior 2001 crop was already forecasted in September 2000, 11 months in advance. In all cases except the May

Table 3
Climate information used for the yield forecasts of the August 2000 and August 2001 crops[a]

August 2000 crop						
Forecast date	September 1999	November 1999	January 2000	March 2000	May 2000	July 2000
Climate forecast period	OND	DJF	FMA	AMJ	JJA	ASO
Above normal	30%	30%	30%	20%	40%	20%
Near normal	50%	50%	50%	50%	50%	40%
Below normal	20%	20%	20%	30%	10%	40%
Analogue years						
Above normal	83, 97, 85	91, 96, 85	84, 89, 69	97, 87	81, 87, 88, 83	78, 79
Near normal	88, 98, 87, 76, 79	81, 82, 97, 86, 89	86, 82, 87, 98, 96	82, 99, 98, 86, 89	86, 95, 94, 78, 91	94, 97, 82, 93
Below normal	94, 84	83, 93	94, 83	77, 80, 83	92	89, 96, 92, 98
August 2001 crop						
Forecast date	September 2000	November 2000	January 2001	March 2001	May 2001	July 2001
Climate forecast period	OND	DJF	FMA	AMJ	JJA	ASO
Above normal	20%	20%	20%	30%	30%	20%
Near normal	40%	40%	40%	50%	50%	40%
Below normal	40%	40%	40%	20%	20%	40%
Analogue years						
Above normal	83, 97	91, 71	85, 84	97, 69, 87	81, 87, 88	78, 79
Near normal	88, 98, 67, 71	81, 82, 97, 68	86, 82, 87, 72	98, 82, 75, 99, 74	77, 86, 70, 95, 94, 69, 74	94, 70, 82, 77
Below normal	80, 94, 84, 91	80, 83, 93, 79	80, 94, 83, 68	68, 80		96, 92, 98, 89

[a] Forecasted probabilities of 3-monthly rainfall totals falling into a given tercile and the analogue years that were selected on that basis to complete simulations of two crops, are shown for each forecast date.

forecast, the final simulated yield fell within the 50% spread of the forecasted yield distribution [Fig. 4(b)].

This case study was conducted during a poorly-predicted wet season (2000) and a well-predicted dry season (2001). The study illustrates the potential advantages in linking a simple crop model with climate forecasts by using the analogue substitute approach.

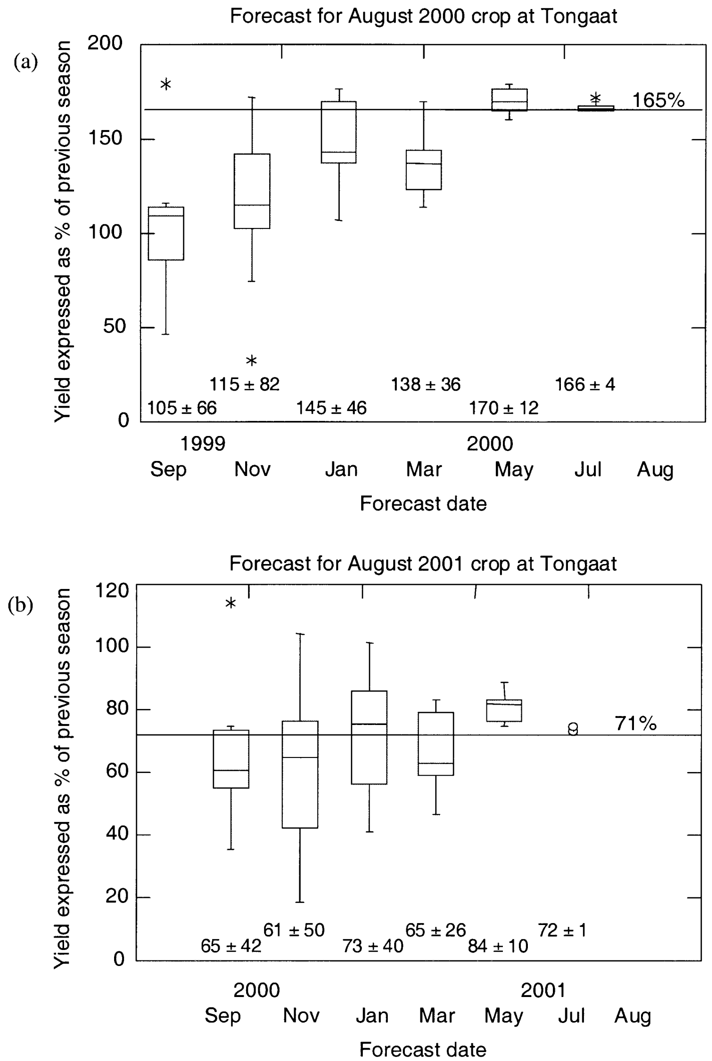

Fig. 4. Box plots of yield distributions forecasted at different dates for the August 2000 (a) and August 2001 (b) crop. The mean plus or minus two standard deviations are reported to the industry (shown at bottom of graph).

5.3. Key lessons

Four key lessons can be concluded from this study. First, the accuracy of climate forecasts plays a very important role in the accuracy of crop forecasts, especially at long lead-times. Inaccurate climate forecasts cause early forecast yield distributions to deviate substantially from the final yield. Second, the limited number of analogue seasons (10) used here could lead to volatile (changing substantially with successive forecasts as the season progresses) forecast yield distributions. Increased computing power could easily address this weakness. Third, another weakness is the long length of analogue weather sequences selected on the basis of SAWS forecasts for the next 3-month period. The remaining (future) part of the growing season for which an analogue sequence is needed could be as long as 15 months. Skilful climate forecasts with lead-times longer than 3 months could be useful in addressing this issue. Fourth, a key strength of this method is that forecasted climate sequences are replaced regularly with actual climate data as it becomes available. This leads to updated and realistic forecasts as the season progresses.

6. Conclusions

The most important lesson from our experience to date is that we have to go beyond the 'science' of climatology and link this with participative implementation processes to realise the benefits of emerging knowledge to industry. Initially industry acknowledged that climate forecasts would be useful, but the challenge was to understand how industry would actually use a climate forecast to enhance decision-making processes. After successive meetings, scientists better understood industry needs, and industry better understood concepts associated with climate forecasts, and, as a result, key decision points and the necessary climate forecast outputs were defined. Hence the key lesson was that the 'action learning' participatory research process greatly facilitated the integration of climate forecast systems into a decision framework.

The sugarcane industry is particularly challenging given the interdependencies of the different sectors of the value chain and the diversity of decision-makers. That said, the embryonic research to date, has highlighted significant potential benefits for sugar industries worldwide. The challenge remains, for these benefits to continue to be realised in practice and in some cases, for these benefits to be realised by the extended industry audiences, within and across different sugarcane growing countries.

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