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Forecasting regional crop production using SOI phases: an example for the Australian peanut industry

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Abstract. Using peanuts as an example, a generic methodology is presented to forward-estimate regional crop production and associated climatic risks based on phases of the Southern Oscillation Index (SOI). Yield fluctuations caused by a highly variable rainfall environment are of concern to peanut processing and marketing bodies. The industry could profitably use forecasts of likely production to adjust their operations strategically. Significant, physically based lag-relationships exist between an index of ocean/atmosphere El Niño/Southern Oscillation phenomenon and future rainfall in Australia and elsewhere. Combining knowledge of SOI phases in November and December with output from a dynamic simulation model allows the derivation of yield probability distributions based on historic rainfall data. This information is available shortly after planting a crop and at least 3–5 months prior to harvest. The study shows that in years when the November–December SOI phase is positive there is an 80% chance of exceeding average district yields. Conversely, in years when the November–December SOI phase is either negative or rapidly falling there is only a 5% chance of exceeding average district yields, but a 95% chance of below average yields. This information allows the industry to adjust strategically for the expected volume of production. The study shows that simulation models can enhance SOI signals contained in rainfall distributions by discriminating between useful and damaging rainfall events. The methodology can be applied to other industries and regions.

Additional keywords: crop model, simulation, climate forecast.

Introduction

High rainfall variability is the major source of dryland yield fluctuations in north-eastern Australia (Hammer *et al.* 1987). In peanuts, yield depressions occur either due to a lack of rain (i.e. drought) or due to excessive rain at harvest (Meinke *et al.* 1996). These year-to-year yield fluctuations result in great income uncertainty and are of major concern to producers. To remain economically viable they must devise management options that can produce long-term, sustainable profits in such a variable environment. This requires some knowledge of likely climatic conditions for the season ahead. Significant, physically based lag-relationships exist between phases of the ocean/atmosphere El Niño/Southern Oscillation phenomenon and future rainfall in eastern Australia and, in fact, many other areas across the globe (Stone *et al.* 1996). Use of phases of the Southern Oscillation Index (SOI; Stone and Auliciems, 1992) in conjunction with a dynamic peanut simulation model (Hammer *et al.* 1995) allows better quantification of climatic risk prior to sowing a crop. Based on an analysis of historic weather records, Meinke *et al.* (1996) showed that probability distributions for potential yield and for harvest losses caused by rain differed strongly among SOI phases. This gives individual producers some scope to assess the production potential of the forthcoming season and associated climatic risks to production prior to sowing a peanut crop.

Climatically induced production uncertainties also cause concern post-farm gate. In particular, processing and marketing bodies require information that enables them to plan strategically for the season ahead. Such estimates cannot be derived using the method described

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by Meinke *et al.* (1996). Whereas producers require information targeted to their specific field conditions, processing and marketing bodies generally require estimates of likely district yield data for their operational planning. Compared with individual field data or output from a point-source model, the variability of district data is dampened by averaging across factors such as planting dates, soil types, management practices, cultivars, and regional climatic variability. Meinke and Hammer (1995*a*) have demonstrated how output from a point-source model can be used to estimate such district data. However, they did not include long-range rainfall forecasting in their approach.

Hence, in this paper we show for the Kingaroy region in north-eastern Australia how a point-source model can be used to forward-estimate production likelihood of district peanut yields based on the SOI phase in November–December. Although this type of information is generally not available prior to sowing, it is known shortly after the crop is planted and approximately 3–5 months before harvest. This should aid the industry in their strategic planning. Although this case study is industry and location specific (i.e. peanuts at Kingaroy), the methodology described is generic and has considerable potential to aid other industries at other locations (Stone *et al.* 1996).

Methods

The basic methodology used has been described in detail by Hammer *et al.* (1995), Meinke and Hammer (1995*a*, 1995*b*), Meinke *et al.* (1996), and Stone *et al.* (1996). Thus, we limit this section to a brief outline.

SOI phases

The forecast method used is based on knowledge of SOI phases in November and December. Generally, peanuts are planted in the district between mid October and the end of December. Thus, any information based on this knowledge is available at the end of the 'sowing window'. Using principal components analysis and cluster analysis to categorise monthly average SOI values resulted in 5 SOI phases or 'types' (Stone and Auliciems 1992; Stone *et al.* 1996). These are termed here (*i*) consistently negative (cons −ve), (*ii*) consistently positive (cons +ve), (*iii*) rapidly falling (rapid fall), (*iv*) rapidly rising (rapid rise), and (*v*) near zero. Historic SOI values combined with rainfall records going back to 1905 can then be grouped into the 5 categories based on the phase analysis.

Simulation procedures

The peanut simulation model estimates paddock yields (i.e. point source data) from given soil moisture characteristics, estimated planting dates, and climatic conditions (Hammer *et al.* 1995). It requires daily meteorological data (i.e. minimum and maximum temperature, solar radiation, and rainfall) as inputs. The model was run for successive years for a peanut monoculture followed by a winter fallow. A simulated peanut crop was 'sown' between 15 October and 31 December if a minimum of 30 mm of rain fell within 5 days and if a minimum of 35 mm of plant-available soil moisture was stored in the soil profile. All of these rules were derived in accordance with local practices and knowledge. Up to 4 successive planting opportunities were considered. Losses due to rain at harvest were estimated. Such losses occur due to fungal attacks of pods associated with wet conditions causing delays in harvest. No harvest losses were predicted if the total crop was harvested within 15 days after reaching maturity. Thereafter, harvest losses were incurred at a rate of 5% per day, resulting in a total crop loss after 35 days (Meinke and Hammer 1995*a*).

Comparison of district and simulated yields

District yields represent the average for a geographically diverse region but simulated yields represent the average for one particular location. Hence, district and simulated yields will always differ in their mean and standard deviation. To assess year-to-year yield variability, we removed this characteristic of the data by calculating normalised district and simulated yields:

$$y_{\mathrm{n}} = (y_{\mathrm{i}} - y)/\mathrm{s.d.}$$

where y_{n} is the normalised yield, y_{i} is the yield achieved for a season, y is the average yield for all seasons, and s.d. is the standard deviation. To obtain estimates of district rather than paddock yields, results were averaged across simulated planting dates and expressed as standard deviations from the mean rather than as absolute yields. Meinke and Hammer (1995*a*) demonstrated how this procedure results in fair estimates of district yield variation.

Model yields were converted to number of standard deviations from the mean. These estimates were stratified according to SOI category, and cumulative distribution functions (CDFs) of simulated peanut yield fluctuations were calculated and tested for significant differences applying the Kolmorogov–Smirnov test (Conover 1971). Simulation results for the years for which district yield data are available (post 1953; period of rapid industry expansion) are indicated separately (closed symbols, Fig. 1).

Results and discussion

Rainfall amount and temporal distribution over north-eastern Australia are strongly influenced by the El Niño/Southern Oscillation phenomenon (McBride and Nicholls 1983; Stone *et al.* 1996). This, in turn, influences crop growth and yield to varying degrees, depending on severity and timing of water limitation and/or crop damage caused by excess rain. This makes the usefulness of rainfall events difficult to assess in terms of their contribution to crop production. However, physiologically based simulation models can be used as 'filters' to assess the value of rainfall over a growing season. For individual peanut producers, Meinke *et al.* (1996) showed that higher harvestable peanut yields (i.e. yields adjusted for estimated harvest losses due to rain) are generally associated with a consistently positive SOI phase in August–September.

When we processed their point-source data according to methods outlined by Meinke and Hammer (1995*a*) to produce district yield estimates, we found no such relationship due to the 'averaging' effect of district-type data (data not presented). However, using November–December phases instead of August–September phases resulted in a highly significant segregation of harvestable yield CDFs by SOI phase (Fig. 1). These CDFs, expressed as standard deviations from the mean, were tested for significant difference among SOI phases. Phases that did not differ significantly were combined. This resulted in 3 distinct categories whereby phases 'cons −ve' and 'rapid fall' formed a group of low-yielding years, phase 'cons +ve' a group of high-yielding years, and phases 'near zero' and 'rapid rise' were representative of the 'all years' case. We found that under positive SOI conditions, above-average district yields can be expected in 80% of years, whereas under either negative or rapidly falling SOI conditions only 5% of years were above the mean, but 95% of years resulted in below-average yields (Fig. 1).

Solid symbols on the CDFs in Fig. 1 indicate the years for which district yield data are available and during which the industry expanded rapidly. It shows a strong bias towards higher yields regardless of SOI phase, but particularly under 'cons +ve' conditions. This is related to below-average harvest losses during that period (Meinke and Hammer 1995*a*). It demonstrates the value of using simulation models to extend the period of local experience by simulating production for the entire climate record. Meinke and Hammer (1995*a*) found that average simulated yields for the period 1962–82 were 44% higher than for the overall period. This was caused by more frequent and reliable summer rain and less rain during the harvest period in autumn.

The value of using models as 'filters' to discriminate between useful and damaging rainfall events is further demonstrated in Fig. 2. When accumulated rainfall from 1 January to 31 May was segregated into November–December SOI phases and the resulting CDFs were tested for significance, only the combined phases 'cons −ve' and 'rapid fall' differed significantly from the other CDFs. Even then, there was little difference in 70% of years and only the highest 30% of years of phases 'cons −ve' and 'rapid fall' had approximately 100 mm less rain than the other distributions. This type of rainfall analysis does not discriminate between positive and negative rain effects on crop growth, indicating the need to pursue the analysis through to effects on the production system.

We stress that the current peanut simulation model does not account for effects of waterlogging, pests, or diseases on production (Hammer *et al.* 1995). Including such factors in the model would likely improve our current forecasting capabilities but requires further research.

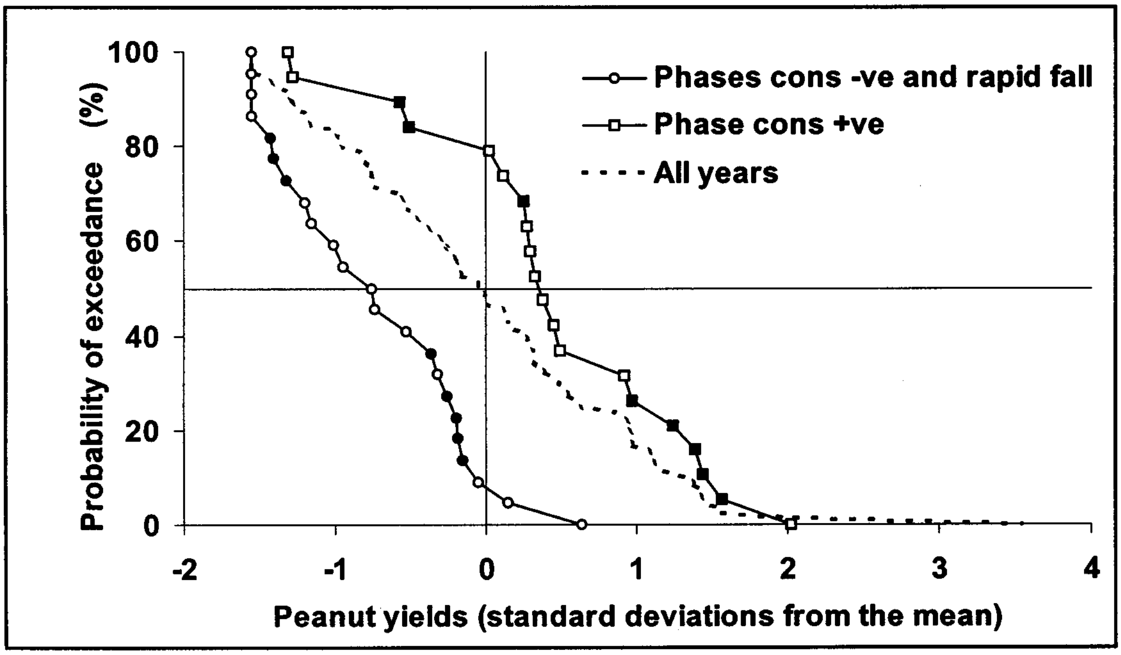

Fig. 1. Probability of exceeding simulated district peanut yields (expressed as number of standard deviations from the mean) by SOI phase. Solid symbols represent the years after 1953, i.e. the period of industry expansion. The all-years case contains all 5 phases and does not differ significantly from the combined near zero and rapid rise case.

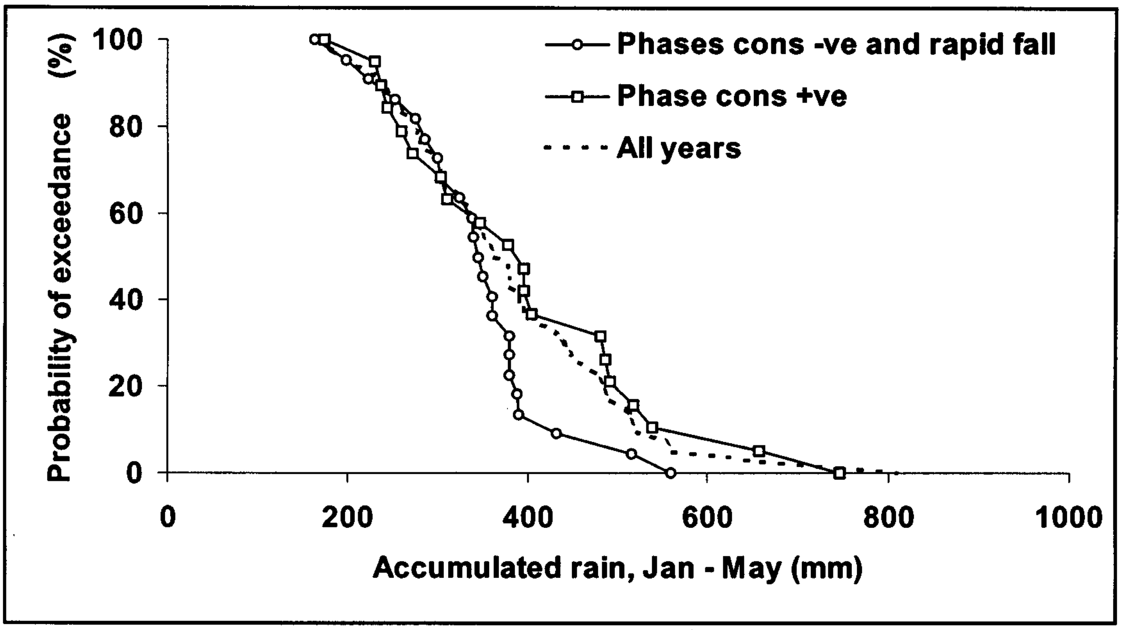

Fig. 2. Probability of exceeding accumulated rainfall (1 January to 31 May) by SOI phases.

The 'forecasting' method applied in this study is based on using historic climate patterns as analogues of future climate. It assumes that the variability of future climate will be similar to that of the historic record and that the existing historic climate records are an adequate representation of the true climatic variability. Although both assumptions are frequently challenged by climatologists (e.g. Meehl and Washington 1996; Nicholls 1996), potential errors are unlikely to be substantial considering the time-frame of the forecast (up to 5 months) and that of the historic record (starting in 1905).

Conclusions

The study showed that there is considerable scope to combine district yield estimates derived from point-source models with SOI phase information to gain a prior knowledge of regional production potential. Although this example only investigated one summer crop (peanuts) in one region of Australia (Kingaroy), similar types of analyses can be conducted for other crops and in other regions. The study shows that simulation models can act as filters to assess the true value of rainfall to production and so enhance SOI signals contained in rainfall distributions by discriminating between useful and damaging rainfall events. Specifically, we found that using November–December SOI phases to estimate likely regional peanut yields showed an 80% chance of exceeding the average district yield when the SOI phase was consistently positive, but only a 5% chance of exceeding the average district yield when the phase was either negative or rapidly falling. Combining this information with estimates of total area planted results in an estimate of the total production volume for a region. This information is available 3–5 months prior to harvest and thus gives the industry a reasonable lead-time to adjust their operations or marketing strategies. The methodology can be extended to include other crops and other regions.

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