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Long range forecasts of the numbers of *Helicoverpa punctigera* and *H. armigera* (Lepidoptera: Noctuidae) in Australia using the Southern Oscillation Index and the Sea Surface Temperature

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Abstract

The use of long-term forecasts of pest pressure is central to better pest management. We relate the Southern Oscillation Index (SOI) and the Sea Surface Temperature (SST) to long-term light-trap catches of the two key moth pests of Australian agriculture, *Helicoverpa punctigera* (Wallengren) and *H. armigera* (Hübner), at Narrabri, New South Wales over 11 years, and for *H. punctigera* only at Turretfield, South Australia over 22 years. At Narrabri, the size of the first spring generation of both species was significantly correlated with the SOI in certain months, sometimes up to 15 months before the date of trapping. Differences in the SOI and SST between significant months were used to build composite variables in multiple regressions which gave fitted values of the trap catches to less than 25% of the observed values. The regressions suggested that useful forecasts of both species could be made 6–15 months ahead. The influence of the two weather variables on trap catches of *H. punctigera* at Turretfield were not as strong as at Narrabri, probably because the SOI was not as strongly related to rainfall in southern Australia as it is in eastern Australia. The best fits were again given by multiple regressions with SOI plus SST variables, to within 40% of the observed values. The reliability of both variables as predictors of moth numbers may be limited by the lack of stability in the SOI-rainfall correlation over the historical record. As no other data set is available to test the regressions, they can only be tested by future use. The use of long-term forecasts in pest management is discussed, and preliminary analyses of other long sets of insect numbers suggest that the Southern Oscillation Index may be a useful predictor of insect numbers in other parts of the world.

Introduction

Forecasting pest abundance or 'pressure' and its timing is considered central to aspects of integrated pest management (Dent, 1991). Phenological models, based on insect physiological time scales have been relatively successful at forecasting the timing of population peaks (e.g. Rhodes *et al.*, 1989; Bommarco & Ekbom, 1995) and are useful for timing control measures and sampling. Forecasting pest pressure is more problematic because many factors influence abundance. Such forecasts would be useful for control measures in the next season, such as determining insecticide budgets, or making strategic decisions on which crops to plant. Long term forecasts of abundance would be

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particularly useful for major pest species such as *Helicoverpa* spp. (Lepidoptera: Noctuidae). Abundance can vary greatly among years. Outbreak years can be particularly problematic if chemical companies are caught short of insecticide supplies (Waldren, 1991). High abundance of the increasingly insecticide resistant *Helicoverpa armigera* (Hübner) (Lepidoptera: Noctuidae) can make pest management particularly difficult (Forrester *et al.*, 1993).

As with many insects, year to year variation of *Helicoverpa* abundance can be related to weather variables. Regression analyses of long series of light-trap catches of *Helicoverpa punctigera* (Wallengren) (Lepidoptera: Noctuidae) (Maelzer *et al.*, 1996) and *H. armigera* (Maelzer & Zalucki, 1999) in Australia allow good predictions of the numbers of moths caught in any week between early November and the end of March, using winter and spring rainfall and trap-catches in previous weeks. The regressions can be used to predict light-trap catches 6–8 weeks ahead, starting in mid-November, but not earlier because the predictions are based on the cumulative number of moths caught up to mid-November, denoted here as CW_{20}, i.e. catch to week 20 from 1 July.

Neither Maelzer *et al*. (1996) nor Maelzer & Zalucki (1999) attempted to predict cumulative number of moths caught up to mid-November, but Oertel *et al*. (1998) suggest that CW_{20} for both *Helicoverpa* species could be predicted from rain falling in May to June or July in the winter breeding areas in the interior of Australia (fig. 1), thus allowing medium-term predictions (4–6 months in advance) of CW_{20}. Even longer-term predictions (*c*. 9–12 months) of CW_{20} may be possible with the Southern Oscillation Index (SOI) and/or Sea Surface Temperature (SST). Both these indices have been used to predict the probability of rain three months or more ahead in Australia (Clewett *et al.*, 1994; Partridge, 1994; Allan *et al.*, 1996; Stone *et al.*, 1996a) and, indeed, in other parts of the world (Stone *et al.*, 1996a).

Insect numbers have not yet been directly related to the Southern Oscillation Index or the Sea Surface Temperature although the numbers of many insect species are related to rainfall, e.g. the pasture cockchafer *Aphodius tasmaniae* Hope (Coleoptera: Scarabaeidae) in South Australia (Maelzer, 1964), the armyworm *Spodoptera exempta* (Walker) (Lepidoptera: Noctuidae) in Africa (Harvey & Mallya, 1995; Haggis, 1996) and *Mythimna convecta* (Walker) (Lepidoptera: Noctuidae) in Australia (McDonald *et al.*, 1995), the Queensland fruitfly, *Bactrocera tryoni* (Froggatt) (Diptera: Tephritidae) (May, 1961; Fletcher, 1987), and the Australian plague locust, *Chortoicetes terminifera* (Walker) (Orthoptera: Acrididae) in eastern Australia (Hunter, 1996).

Drake & Farrow (1988) suggested that global-scale disturbances of the El Niño-Southern Oscillation (ENSO) may influence insect migration when these disturbances result in exceptional rainfall in semi-arid regions and lead to large populations of migratory insects. Nicholls (1986a, 1991) reviews the relationships between ENSO and climate-related human health problems, which are dependent on expanded insect-vector populations in wetter, La Niña, years, causing diseases such as Ross River fever and Murray Valley encephalitis to become more prevalent. More recently, the Southern Oscillation Index has been correlated with dengue fever epidemics in the South Pacific (Hales *et al.*, 1996) and with periodic fluctuations in epidemics of malaria in Sri Lanka and on the Indian sub-continent (Bouma & Vanderkaay, 1996). Predictions of El Niño events may be used to forecast high and low risk years for future malaria epidemics (Bouma & Vanderkaay, 1996).

The Southern Oscillation Index and Sea Surface Temperature are properties of the air-mass to the north of Australia which are highly correlated with patterns of rainfall in eastern and northern Australia, as well as countries around the Pacific and Indian Oceans (McBride & Nicholls, 1983; Partridge, 1994; Allan *et al.*, 1996). The

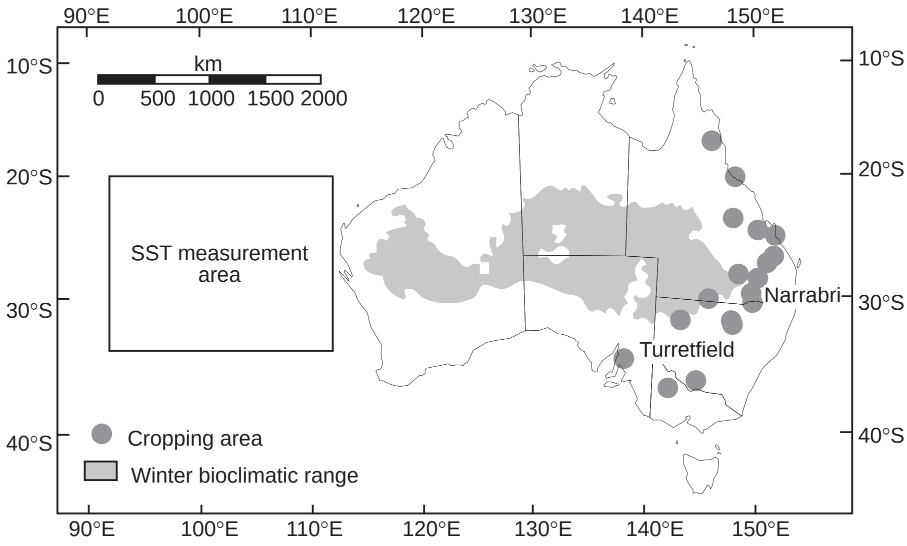

Fig. 1. The location of the two light trap sites in Australia, the main cropping areas, and the predicted distribution of *Helicoverpa punctigera* using a bioclimatic model which broadly indicates the extent of winter breeding. Also shown is the area of sea to the west of Australia from which the Sea Surface Temperature (SST) variable is derived.

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Southern Oscillation Index is the difference in atmospheric pressure anomalies between Tahiti and Darwin. It has been measured since 1852 and is usually expressed in Australia as a mean monthly value ranging from −40 to +40. When the monthly mean is strongly positive, much of eastern Australia is likely to receive above average rainfall; when strongly negative, rainfall in the same regions is usually well below average and a drought might ensue. This type of pattern is often associated with an El Niño event (McBride & Nicholls, 1983; Partridge, 1994).

The Southern Oscillation Index is being used for seasonal climate forecasting worldwide (Allan *et al.*, 1996; Stone *et al.*, 1996a) and increasingly in Australia to forecast weather events which influence agricultural processes, especially rain, the date of the last frost and the number of frosts in a season (Stone *et al.*, 1996b), and mean temperatures (Partridge, 1994; Nicholls *et al.*, 1996). In Australia, the Southern Oscillation Index has proven useful as an indicator of crop yields (Hammer *et al.*, 1991). Predictions of yields of wheat can be made with the Southern Oscillation Index several months ahead of harvest (Rimmington & Nicholls, 1993), the best predictor being the trend in the SOI, namely the SOI value near planting minus the mean value over the same months in the previous year. Similarly, the Southern Oscillation Index has been used to predict the average yield of sorghum well in advance of harvest (Nicholls, 1986b; Hammer & Muchow, 1991) and of pasture growth (Willcocks *et al.*, 1991). These relations between the SOI and agricultural processes have led to seasonal forecasts being quantified as climatic risk in models for better production management for a number of crops (Clewett *et al.*, 1991; Hammer *et al.*, 1991; Meinke *et al.*, 1996).

The Sea Surface Temperature is a more recently measured variable (since 1950). It is the deviation from the long-term average of the sea surface temperature, in °C, for each month in the area of the Indian Ocean bounded by latitude 20–34°S and longitudes 92–112°E (fig. 1). The Sea Surface Temperature varies between about −1.5 and +2.0°C (the deviation from the long-term mean) and has been less used than the Southern Oscillation Index for forecasts (Partridge, 1994).

Here we examine the use of Southern Oscillation Index and Sea Surface Temperature values for making earlier predictions than are presently possible of the numbers of *H. punctigera* and *H. armigera* at Narrabri (New South Wales) and at Turretfield (South Australia) (fig. 1).

Methods

Trap-catches of Helicoverpa *sp.*

Based on analyses of light-trap catches of *Helicoverpa* species (Maelzer *et al.*, 1996; Maelzer & Zalucki, 1999) the *Helicoverpa* 'year' is designated as the period 1 July to 30 June. The numbers caught in the trap each year are expressed as cumulative numbers from 1 July up to the end of the 20th week and hereafter are denoted as CW_{20} (Catch to $Week_{20}$). This catch is taken as the size of generation one in each year (Maelzer *et al.*, 1996; Maelzer & Zalucki, 1999).

The data comprised the values of CW_{20} for: (i) *H. punctigera* at Narrabri (New South Wales) for 11 years (1973–74 to 1977–78 and 1981–82 to 1986–87); (ii) *H. armigera* at Narrabri for 10 years (1973–74 to 1976–77 and 1981–82 to 1986–87); and (iii) *H. punctigera* at Turretfield (South Australia) for 22 years (1962–63 to 1983–84) (Maelzer *et al.*, 1996; Maelzer & Zalucki, 1999). We wished to predict the size of generation one in each year.

Climate and related variables

For the expression of monthly rain and monthly values of the Southern Oscillation Index and the Sea Surface Temperature (see below) the months of the calendar year were abbreviated as: Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec. Various measures of monthly rain are denoted by a suffix, e.g. $Rain_{Jun–Aug}$ (rain from June to August). For Narrabri, monthly rain from Myall Vale for the period 1973–1987 was used, as in Maelzer *et al.* (1996) and Maelzer & Zalucki (1999). To relate rainfall to the Southern Oscillation Index at Narrabri, we used the longer record for the near-by Wee-Waa Post Office, from 1885 *et seq*.

The SOI and SST were mean monthly values from 1883 *et seq*. and 1950 *et seq*. respectively and were taken from Clewett *et al.* (1994). They were lagged for up to two years, with the values of the lags being denoted as suffixes, e.g. Jan-2 (January two years ago), Jan-1 (January last year) and Jan-0 (January this year).

The mean monthly phase values of the SOI (Stone & Auliciems, 1992) for year-0 were also used to test the consistency of winter rainfall at Wee Waa.

Analyses

All analyses were by regression, mainly simple linear and multiple linear. Since correlations between variables can give biased regression statistics (Mosteller & Tukey, 1977; Jobson, 1991) correlation matrices were calculated for the monthly SOI, SST, and SOI versus SST values. Correlated variables were not chosen as separate variables in the same equation. Since the successive monthly values of both the SOI and the SST form autocorrelation series, autocorrelation was tested in each regression by the Durbin-Watson statistic (Wesolowsky, 1976).

To reduce the number of variables in the equations, we used 'composite' variables as recommended by Tabachnick & Fidell (1989). These were mainly differences between uncorrelated monthly SOI or SST values and are denoted, for example, as Jan-2 minus Jan-1. Such differences between months have proved to be useful for predicting the yield of wheat (Rimmington & Nicholls, 1993) and will be referred to as couplet differences.

To obtain useful couplet differences, we initially calculated the correlations between the chosen Y variable (usually some function of the trap catches) and monthly SOI (or SST) values. We chose the 4 to 5 months which gave the highest positive correlations with the Y variable and the 4 to 5 months which gave the highest negative correlations; and we calculated the difference between the positive and negative Southern Oscillation Index values for each pair of months, provided the values for the two months were not correlated, e.g. Nov-2 minus Sep-1. We also used the 4 to 5 months selected to examine means of two successive monthly values or means of two non-successive monthly values which are denoted with a plus sign, as in Jan-2 + Feb-1.

Finally, multiple regression was sometimes used to add a SST variable as a multiple regressor to an SOI couplet difference.

The scattergram of each regression indicated that each of the Y variables needed to be transformed to natural logs for homoscedasticity. The scattergram was also used to visually check for suspected outliers, especially in the mid-range of the Southern Oscillation Index variable. The omission of such outliers could be useful because much of the deviation from regression sometimes occurred within the SOI range −5 to +5. In many applications of the Southern Oscillation Index to agricultural processes, SOI values within the range −5 to +5 similarly show the least correlation with the predicted variable. For example, the influence of the SOI on the average yield of sorghum crops and of spring pasture growth is useful only when the SOI in spring is less than −5.0 or more than +5.0 (fig 4.3 in Partridge, 1994). Suspected outliers were tested by the significance of the departure of such points from the expected regression, as described by Bliss (1967).

The use of couplet differences should not have affected the reliability of the regression statistics, because the variance of the difference between two random variables is the sum of the variances of the two variables (Mosteller *et al.*, 1973). Similarly, the means of monthly values of the SOI or SST should not have biased the regression statistics because the variance of each such mean should be equal to the mean of the attendant variances (Mosteller *et al.*, 1973).

The r^2 values of all regressions were corrected for sample size and for the number of coefficients in the regression (Draper & Smith, 1981), and each of the functions in the regressions was regressed on the rainfall which was known to be correlated with the appropriate Y variable (Maelzer *et al.*, 1996; Oertel *et al.*, 1998; Maelzer & Zalucki, 1999).

Results

Correlations between Southern Oscillation Index and Surface Sea Temperature variables

The successive monthly values of the Southern Oscillation Index from 1971 to 1994 form a series with strong autocorrelation (appendix 1) with many significant ($P < 0.05$) and highly significant ($P < 0.01$) correlations between monthly values of the SOI over a three year period. The correlations over the successive months of April to December each year illustrate the tendency of the Southern Oscillation Index to have the same sign (+ or −) for many months; the so-called 'phase-locking' described by Stone & Auliciems (1992). Since we wished to avoid using SOI variables which were correlated, rather than to remove the autocorrelation as outlined by Jobson (1991), we used the table in appendix 1 as a guide and avoided using couplet differences between months within the periods Apr-2 to Jan-1 and Apr-1 to Jan-0.

The monthly Sea Surface Temperature values over the same period showed fewer significant correlations than did the SOI (appendix 2). We used this table to avoid using correlated SST variables.

Correlations between SOI and SST monthly values were weaker and variable. The Sea Surface Temperature in January to March each year was weakly correlated ($P < 0.05$) with the Southern Oscillation Index from April to December of the previous year and of the following year. The correlation matrix was again used to avoid related variables.

With the choice of variables thus restricted, no correlation or autocorrelation was evident in the data set. The number of variables chosen for examination as independent

Table 1. For *Helicoverpa punctigera* and *H. armigera* at Narrabri. Statistics for log cumulative number of moths caught up to mid-November ($ln(CW_{20})$) in simple linear regressions with Southern Oscillation Index (SOI) variables, with the same SOI variables but with the omission of one outlier of the SOI variable in the range −2.5 to +2.5, and multiple regression with a Southern Oscillation Index (SOI) variable as X_1 and a Sea Surface Temperature (SST) variable as X_2. The regressions are numbered for convenience. Couplet differences of the SOI and the SST variables are denoted by 'minus' as in reg. no.1: Nov-2 minus Sep-1.

Reg.			Statistics for each regression				
no.	SOI variable as X_1	SST variable as X_2	r^2	*P*	intercept	X1	X2
	For *Helicoverpa punctigera*						
1	Nov-2 minus Sep-1		0.686	0.0010	6.836	0.039	
2	Nov-2 minus Sep-1; with the omission of one outlier		0.911	<0.0001	6.698	0.039	
3	Feb-1 minus Dec-1		0.545	0.0057	6.761	0.051	
4	Feb-1 minus Dec-1; with the omission of one outlier		0.723	0.0011	6.624	0.035	
5	Feb-1 minus Dec-1 as X_1; SST: Aug-2 minus Oct-1 as X_2		0.815	0.0005	6.777	0.021	0.987
	For *Helicoverpa armigera*						
6	Jan-1 minus May-1		0.709	0.0014	4.073	0.059	
7	Jan-1 minus May-1, with the omission of one outlier		0.844	0.0003	4.215	0.060	
8	Nov-2 minus May-1		0.761	0.0006	4.023	0.058	
9	Nov-2 minus Sep-1		0.726	0.0011	4.143	0.051	
10	Nov-2 minus Sep-1; with the omission of one outlier		0.834	0.0004	4.271	0.051	

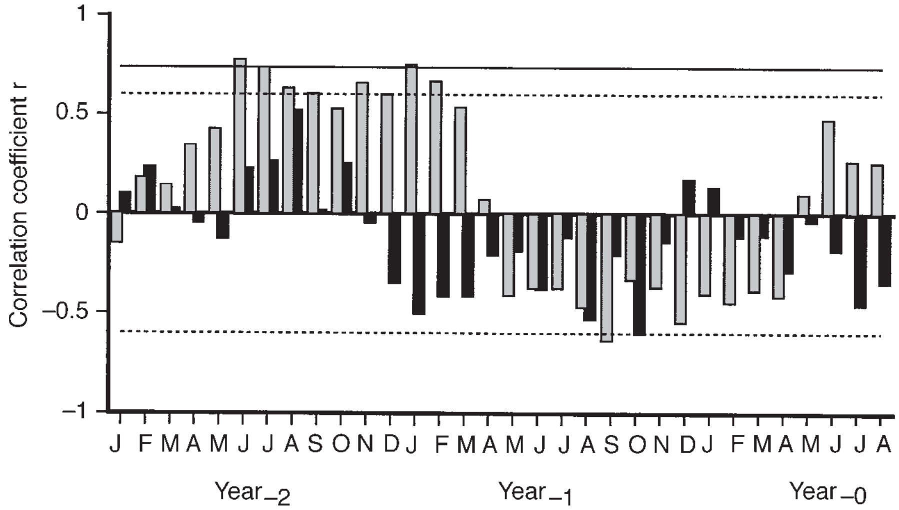

Fig. 2. Correlation (r) values between the $\log_e$ cumulative number of moths caught up to mid-November ($ln(CW_{20})$) trap catches of *Helicoverpa punctigera* at Narrabri each year with the mean monthly Southern Oscillation Index (stippled bars) and the mean monthly Sea Surface Temperature (solid bars) from Jan-2 (two years ago) to May-0 (this year). The lines denote significant values of r: (----) for $P = 0.05$, (——) for $P = 0.01$.

composite variables and the signs and probabilities of their correlations with each of the dependent variables are given in appendix 3.

Helicoverpa punctigera *at Narrabri*

The Southern Oscillation Index and ln(CW_{20})

Correlations between the $\log_e$ cumulative number of moths caught up to mid-November ($ln(CW_{20})$) and monthly SOI values (fig. 2) were significant ($P < 0.05$) for many single months. The pattern of correlations (fig. 2) was similar to that between the SOI and wheat yields (Rimmington & Nicholls, 1993), with many months of large positive correlations followed by many months of large negative correlations; and then further months of positive correlations, with the change in sign usually occurring from March to May each year. The change in sign is caused by the change in 'phase' of the SOI, and the long periods of correlations of one sign are dependent on the so-called 'phase-locking' of the SOI (Stone & Auliciems, 1992).

In general, the Southern Oscillation Index couplet differences which gave the most significant regressions with $ln(CW_{20})$ (table 1) involved the SOI values for those months which gave the largest positive correlations minus the values for those months which gave the largest negative correlations, e.g. Nov-2 minus Sep-1 (fig. 2; appendix 3). Means of SOI values for any two months with only positive or only negative correlations (appendix 3) rarely gave significant regressions, and mean SOI values over two non-consecutive months were also not often useful.

Five significant regressions for $ln(CW_{20})$ of *H. punctigera* are given in table 1 (nos. 1–5). The X variables were mostly different combinations of the same months (appendix 3).

The descriptions of the months within each couplet-difference are ordered in table 1 (and later tables) so that the most recent month is given last. This allows a check of the last month for which data are needed before a forecast can be made.

The potential usefulness of each regression (table 1, reg. nos. 1–5) can initially be determined by comparing the values of r^2 and p. In general:

1. The omission of an outlier in the mid-range of an SOI variable (from −2.5 to +2.5) (fig. 3) increased the r^2 value of some regressions with couplet differences by up to 33% (table 1; reg. no. 2 versus reg. no. 1; and reg. no. 4 versus reg. no. 3).

2. The addition of a Sea Surface Temperature variable in multiple regression increased the r^2 value by up to 50% (table 1, reg. no. 5 versus reg. no. 3).

3. The r^2 value of each regression with a Southern Oscillation Index couplet difference was no more than 10% larger than the r^2 value for a multiple regression with the two constituent SOI variables, suggesting that the couplet differences did not cause much bias to the statistics of the regressions.

Farmers and chemical companies are likely to be more interested in the arithmetic values of CW_{20} which may be forecast by the regressions rather than the r^2 and P values. This potential predictability can be measured roughly by the probability value of the regressions. Those regressions with a probability of 0.0005 or less gave mean deviations from the observed values of about 20%; those with a probability greater than 0.001 gave mean deviations of about 40%. Hence, forecasts with regressions 2 and 5 (table 1) would be especially suitable for forecasting high numbers of CW_{20}.

Regressions 1 and 2 (table 1) would allow forecasts in October of the previous year, 13 months ahead of CW_{20}; and regressions 3 to 5 would allow forecasts in early January of the current year, still 10 months ahead of the event.

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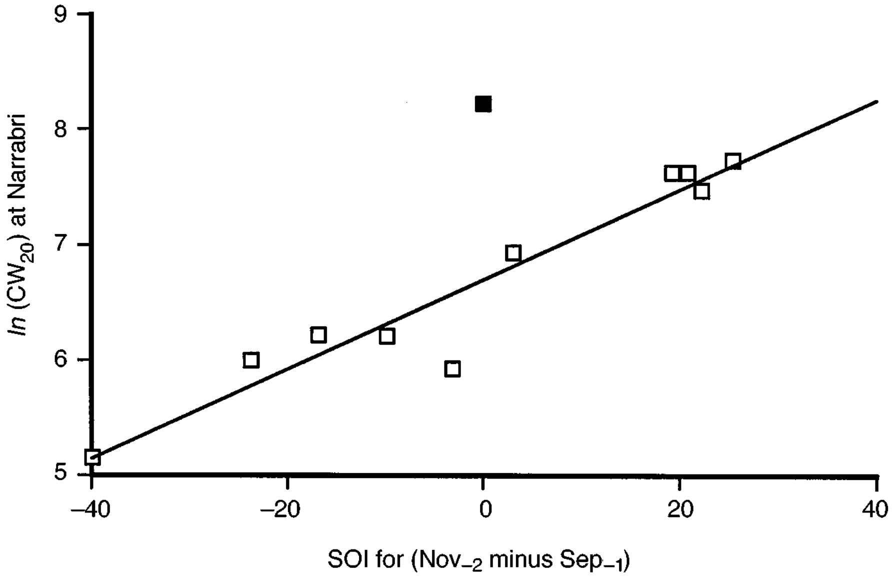

Fig. 3. The relationship between the $\log_e$ cumulative number of moths caught up to mid-November ($ln(CW_{20})$) each year and the Southern Oscillation Index for Nov-2 minus Sep-1. All points are included for reg. no. 1 in table 1, the black square is omitted for reg. no. 2.

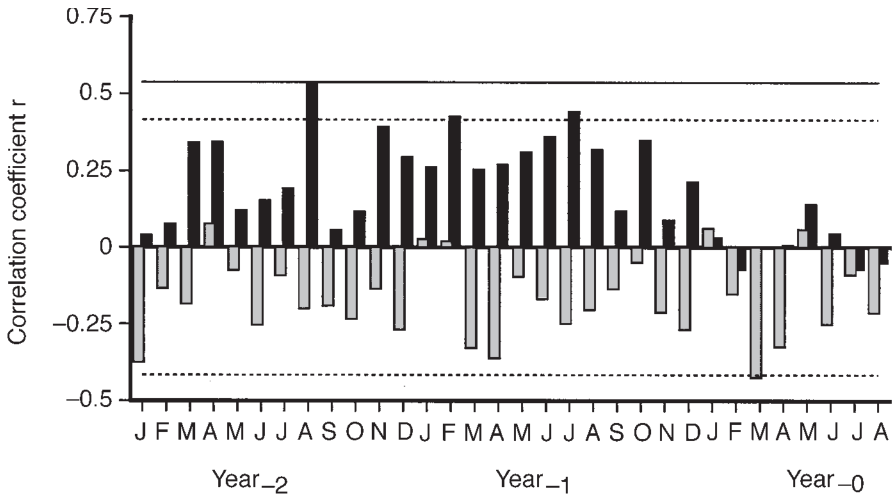

Fig. 4. Correlation (r) values between the $\log_e$ cumulative number of moths caught up to mid-November ($ln(CW_{20})$) trap catches of *Helicoverpa punctigera* at Turretfield each year with the mean monthly Southern Oscillation Index (stippled bars) and the mean monthly Sea Surface Temperature (solid bars) from Jan-2 (two years ago) to May-0 (this year). The lines denote significant values of r: (----) for $P = 0.05$, (——) for $P = 0.01$.

The Sea Surface Temperature and ln(*CW_{20}*)

Only one month (Oct-1) gave significant correlations between $\ln(CW_{20})$ and the Sea Surface Temperature (fig. 2; appendix 3) and the pattern of correlations was not strongly alternating. The only significant couplet difference was Aug-2 minus Oct-1 ($r^2 = 0.668$; $P = 0.0013$) but it could not be improved to give a more significant regression than those in table 1.

Helicoverpa armigera *at Narrabri*

The Southern Oscillation Index and ln(*CW_{20}*)

The correlations between the $\log_e$ cumulative number of moths caught up to mid-November and monthly values of the Southern Oscillation Index had the same promising pattern of strongly alternating signs as did the pattern for $ln(CW_{20})$ of *H. punctigera*. Many significant monthly

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Table 2. For *Helicoverpa punctigera* at Turretfield. Statistics for multiple regressions of $\log_e$ cumulative number of moths caught up to mid-November ($ln(CW_{20})$) on Southern Oscillation Index (SOI) and Sea Surface Temperature (SST) variables over the years 1962 to 1983. The regressions (reg. no.) are numbered for convenience. Mean values of the SOI or the SST over two non-consecutive months are denoted with a + sign, as in reg. no. 1: Dec-2 + Mar-0.

Reg. no.	SOI variable as X_1	SST variable as X_2	Statistics for each regression					Probabilities of regressions applied to	
			r^2	*P*	intercept	X_1	X_2	1962–1972	1973–1983
1	Dec-2 + Mar-0	Jul-1	0.535	0.0003	7.059	−0.050	1.222	0.133	0.0002
2	Mar-1 + Mar-0	nil	0.209	0.0190	7.083	−0.075			
3	Mar-1 + Mar-0	Aug-2	0.389	0.0036	7.047	−0.061	0.960	0.198	0.0220
4	Mar-1 + Mar-0	Aug-2 + Feb-1	0.506	0.0005	7.138	−0.063	1.400	0.078	0.0071
5	Mar-1	Aug-2 + Feb-1	0.495	0.0006	7.145	−0.045	1.506	0.054	0.0240

correlations (appendix 3) gave many couplet differences which were highly significant ($P < 0.01$), but not many could be built on. Regressions could be improved considerably by the omission of an outlier (table 1, reg. no. 7 versus reg. no. 6; and reg. no. 10 versus reg. no. 9). Only regressions 7 and 10 (table 1) were as significant as those for *H. punctigera* but all the regressions should allow forecasts for *H. armigera* which could distinguish between high and low populations.

Regressions 6 to 8 (table 1) would allow forecasts in June of the previous year, 17 months ahead of CW_{20}, whilst regressions 9 and 10 could be used for forecasts in the first week of October of the previous year, still 13 months ahead of the event.

Helicoverpa punctigera *at Turretfield*

The pattern of correlations between the $\log_e$ cumulative number of moths caught up to mid-November at Turretfield and monthly values of the Southern Oscillation Index (fig. 4; appendix 3) was quite different to any of the patterns at Narrabri, and the pattern of building composite variables was different. For the first time, significant SOI variables were not couplet differences but were mean SOI values of non-consecutive months (table 2, reg. nos.1–4; appendix 3), but none of the simple regressions with SOI variables were highly significant (e.g. table 2, reg. no. 2). Regressions were improved considerably with the addition of Sea Surface Temperature variables in multiple regressions (table 2, reg. nos. 1, and 3–5). None of the regressions would allow forecasts before April of the current year, 7 months ahead of CW_{20}.

The correlations between the Sea Surface Temperature and $ln(CW_{20})$ had a different pattern (fig. 4) to that with the SOI (fig. 4), and to that between the SST and $ln(CW_{20})$ at Narrabri (fig. 2). Again, significant composite variables comprised mean values over non-consecutive months. However, the regressions with the SST means could only be made more significant by the inclusion of the same SOI variables as were previously used for multiple regressions (table 2; appendix 3).

The 22 years of trap records at Turretfield allowed a test of the consistency of the association between the trap catches and the Southern Oscillation Index and the Sea Surface Temperature. When the functions were applied to only the years 1962 to 1972 or only the years 1973 to 1983 (table 2, last two columns), none of the regressions were significant ($P < 0.05$) for 1962 to 1972 and all were significant for 1973 to 1983, suggesting some degree of inconsistency between the two subsets of 11 years. The results suggest that the associations between the $\log_e$ cumulative number of moths caught up to mid-November and either the Southern Oscillation Index and/or the Sea Surface Temperature were different for the two subsets of years, a point which is further discussed below.

The Southern Oscillation Index and winter rain at Narrabri

The highly significant regressions between the SOI and $ln(CW_{20})$ of each species at Narrabri (table 1) might be explained by there being similar relations between the SOI and winter rain over much of the winter breeding area of *H. punctigera*. The reliability of forecasts of CW_{20} would be considerably enhanced if the SOI could be related to winter rain for many more years than the 10 to 11 that are available for trap catches. So the association between the SOI and $Rain_{May–June}$ at Wee Waa was examined in detail, with the same lags as were employed for the trap data. The Sea Surface Temperature could not be used because of its short record.

For all 110 years of recorded rainfall, regressions of $Rain_{May–June}$ on the Southern Oscillation Index were significant ($P < 0.05$) for the monthly values of Feb-2, Aug-1, Sep-1 and Nov-1 and that for Oct-2 was nearly significant (appendix 3). Many couplet differences between the positive and negative months (appendix 3) gave significant regressions, and the two regressions with the highest r^2 values are given in table 3.

The reliability of each of the two functions was 'tested' by applying it to subsets of 55 years and of 22 years. The pattern was essentially the same for the two functions (table 3). The first 55 years (1885 to 1939) provided no evidence of significant regression (table 3, reg. nos. 1 and 6) but the second 55 years (1940 to 1994) showed high significance ($P < 0.01$) (table 3, reg. nos. 2 and 7). All the subsets of 22 years for the first function showed no evidence of significance (table 3, reg. nos. 1–5). The first three subsets of the second function also showed no significance (table 3, reg. nos. 6–8), but the last two subsets showed significance (table 3, reg. nos. 9 and 10). These results suggest that the association between rainfall and the Southern Oscillation Index was different in the two 55 year periods, with the association being stronger in recent years.

However, simple correlation analysis may mask otherwise important relationships that exist between the Southern Oscillation Index and rainfall (Stone *et al.*, 1996b), and the comparative frequencies of phase values of the SOI may provide a better test of the consistency of the

Table 3. The Southern Oscillation Index (SOI) and total rain in May to June at Wee Waa, New South Wales. Statistics for the simple regression of rain May to June on a composite SOI variable as in table 1 for each of: (i) all 110 years; (ii) subsets of 55 years; and (iii) subsets of 22 years. The regressions are numbered (reg. no.) for convenience.

Reg. no.	SOI variable	All 110 years		Subsets of 55 years		Subsets of 22 years	
		Years	*P*	Years	*P*	Years	*P*
1	Oct-2 minus Aug-1	1885–1994	0.0012	1885–1939	0.078	1885–1906	0.089
2				1940–1994	0.009	1907–1928	0.338
3						1929–1950	0.709
4						1951–1972	0.101
5						1973–1994	0.058
6	Oct-2 minus Nov-1	1885–1994	0.0038	1885–1939	0.510	1885–1906	0.958
7				1940–1994	0.009	1907–1928	0.428
8						1929–1950	0.656
9						1951–1972	0.026
10						1973 –1994	0.046

association between rainfall and the SOI. The phase values cannot be used simply in regression because their numeric values, from 1 to 5, are not related linearly to the monthly SOI. They are 'cluster' levels, each of which is characterized by particular mean values of the SOI in two consecutive months and by the difference between these two means (Stone & Auliciems, 1992). They have been related to the probability of rainfall exceeding the median or any percentile (ibid.), and in particular, the SOI phase for March to April has been variously linked to rain from May to July (Rain $_{\text{May–July}}$) over the whole world (Stone *et al.*, 1996a). For $\text{Rain}_{\text{May–July}}$ at Wee Waa, a Kolgomorov-Smirnov test suggested that the frequency of each of the phases 1 to 5 for the first 55 years was not significantly different from the frequency in the second 55 years.

Discussion

The role of the Southern Oscillation Index and Sea Surface Temperature in the ecology of Helicoverpa *sp.*

Do forecasts using the Southern Oscillation Index and the Sea Surface Temperature relate to the ecology of *Helicoverpa* sp.? Rainfall, at the appropriate time and place drives the abundance of host plants in inland areas and within cropping areas (Zalucki *et al.*, 1994). However, subsequent rainfall on the developing generation tends to reduce survival and subsequent abundance (Kyi *et al.*, 1991; Titmarsh, 1993; Maelzer *et al.*, 1996; Maelzer & Zalucki, 1999). The various combinations of Southern Oscillation Index variables which gave the most significant regressions with CW_{20} for *H. punctigera* were all correlated with $\text{Rain}_{\text{May–Jun}}$ at Narrabri. The Southern Oscillation Index couplet differences for *H. armigera* (table 1, reg. nos. 6–10) were similarly correlated with $\text{Rain}_{\text{May–June}}$ at Narrabri.

The Southern Oscillation Index usually predicts rain approximately three months ahead with good probability (Partridge, 1994), so the SOI value for Mar-0 or Apr-0 would predict Rain $_{\text{May–Jun}}$ which is correlated with CW_{20} (Oertel *et al.*, 1998). Detailed study of El Niño-Southern Oscillation components has suggested quasi-biennial cycles of around 18–35 months and lower frequency cycles of around 32–88 months (Allan *et al.*, 1996). It is these quasi-biennial cycles, characterized by 'the tendency for years of positive SOI (wet years) to follow years of negative SOI (dry years), and *vice versa*' (Rimmington & Nicholls, 1993), which allow correlations of the SOI with trap catches of *Helicoverpa* spp. and with $\text{Rain}_{\text{May–June}}$ 12 to 15 months earlier. For this reason, most SOI couplet differences were more strongly correlated with $ln(CW_{20})$ than were either of the individual SOI values.

Similar quasi-biennial rhythms probably occur with the Sea Surface Temperature but they have not been studied yet. So the role of the SST variable in the regression functions for $ln(CW_{20})$ is obscure, and the regression functions can best be thought of as predictive rather than as explanatory.

The influence of the Southern Oscillation Index and the Sea Surface Temperature on trap catches of *H. punctigera* at Turretfield is more difficult to explain because the influence of the SOI on rainfall becomes more complex westwards across Australia, and the SST has more influence on the probability of winter rain in parts of southern and eastern Australia (Partridge, 1994; Holton, 1998). Winter rain in much of the winter breeding area of *H. punctigera* would be influenced by both the SOI and the SST, as suggested by their joint inclusion in composite variables for multiple regressions at Turretfield (table 2). The difference in the regressions for the two subsets of 11 years (table 2, last two columns) may be due to the trap catch at Turretfield being influenced in different years by different weather over different areas of the winter breeding area of *H. punctigera*.

The reliability of forecasts at Narrabri

The reliability of forecasts of the cumulative number of moths caught up to mid-November (CW_{20}) for both *Helicoverpa* species at Narrabri depend on: (i) the robustness of the regressions suggested and (ii) the reliability of the relationship between the SOI and $\text{Rain}_{\text{May–June}}$. Because of the large number of variables in the data set, there is a high *a priori* probability of finding significant regressions. We have tried to minimize this problem by avoiding autocorrelated variables, and by finding composite variables which are differences or means of monthly values and may therefore give regressions which are robust and more realistically significant.

The continuing reliability of the relation between the Southern Oscillation Index and rain at Narrabri is of special interest because Narrabri has been taken as representative of the breeding area of *H. armigera* in New South Wales and southern Queensland. It also has the same probability of rain in May to June in relation to phases of the SOI in March to April as does most of western New South Wales and southwestern Queensland (Stone *et al.*, 1996a). These areas comprise much of the eastern portion of the winter breeding area of *H. punctigera* (fig. 1) and probably contribute most of the moths in CW_{20} at Narrabri in most years.

Forecasts of $ln(CW_{20})$ of both species of *Helicoverpa* at Narrabri are likely to be reasonably accurate because: (i) the regression functions give significant regressions with $Rain_{May–June}$; and (ii) the relationship between phases of the SOI and rain at Wee Waa seems not to be different between the first and the second subsets of 55 years of records.

On the other hand, the regressions of $Rain_{May–June}$ on the SOI and SST (table 3) do suggest that the relationship between rain and the SOI and SST has changed in some way over the last 55 years (1940 to 1994). Such a change may not be unusual because the weather is well documented as being a chaotic system rather than a system with a single steady state (Gleick, 1988), and variability within the historical weather record has been documented frequently. Pittock (1975) documented the occurrence of a significantly greater mean precipitation over southeastern Australia between 1914–1945 and 1946–1978; and Hammer *et al*. (1991) found that the regions in which the Southern Oscillation Index strongly affects rainfall have changed over time. The latter concluded that the lack of stability in the SOI-rainfall correlation over the historical record could be a major limitation to the use of the Southern Oscillation Index by agricultural managers, and suggested that predictive relationships based on relatively short periods of recent data may produce better forecasts than those based on all available historical data. So perhaps the lack of a significant relationship between Rain $_{May–Jun}$ and the SOI in the earlier period of years (1885–1939) (table 3; reg. nos. 1 and 6) is not as important as the significant relationship in the last 55 years (1940–1994) (table 3, reg. nos. 2 and 7).

We cannot be sure, of course, that the relationship between Rain $_{May–Jun}$ and the SOI will not change again in the future. We therefore have no option other than to use our regressions to forecast the abundance of the two *Helicoverpa* species each year and to 'test' the suitability of the various regressions by the closeness of the predicted numbers to the observed ones.

The variability of rain in southern Australia

The apparent variability between the two subsets of 11 years of catches of *H. punctigera* at Turretfield (table 2) suggest that the prediction of trap catches and of rainfall in the southern and western portions of the winter breeding area of *H. punctigera* may be more difficult and less reliable than it is in eastern and northern Australia.

The Southern Oscillation Index has been found to be of limited use in southern Australia for rainfall forecasting in the critical April to October cereal crop growing season, which coincides with the period critical for winter breeding of *H. punctigera* in the southern and western interior of Australia. Instead, the Sea Surface Temperature and the presence and strength of the 'major seasonal longwave trough in the middle and upper levels of the atmosphere' have been incorporated into 'Holton forecasting computer models' which may provide forecasts of growing season rainfall, seasonal rainfall and wheat crop yields over much of southern Australia (Holton, 1998). Trap catches of *H. punctigera* at Turretfield might well be predicted more accurately with 'Holton models' but as yet no relationship has been found (I. Holton, personal communication). The question of the reliability of forecasts of trap catches at Turretfield and other southern trap sites must therefore be left unresolved.

Forecasts of insect numbers worldwide

The Southern Oscillation Index is correlated with changes in worldwide rainfall (Stone *et al*., 1996a). We expect the numbers of insects should be correlated with, and hence forecast by, the SOI, with a unique relationship reflecting the biology and ecology of each species. Initial analyses indicate this is true for *S. exempta* in east Africa, even though Harvey & Mallya (1995) could not find a simple correlation with ENSO events; for the moths *Panolis flammea* (Denis & Schiffermüller) (Lepidoptera: Noctuidae) and *Bupalis piniarus* (Linnaeus) (Lepidoptera: Geometridae) in Germany (data for 1880 to 1940 from Varley *et al*., 1973); and for outbreak years of the Australian plague locust, *C. terminifera* (data from 1910 to 1943; ibid.), (Maelzer & Zalucki, unpublished).

Forecasts in pest management

Forecasts of population size and phenological occurrence of pests have long been held to be a central feature of pest management (Dent, 1991). The rationale is that control tactics can be better targeted if the timing of peak pest abundance can be forecast. Generally, such timing has been achieved by sampling fields for insect pests. However, sampling for damaging stages gives little time to make decisions and is somewhat akin to dealing with the problem of the stable door after the horse has bolted. It is better, therefore, to sample some earlier non-damaging stage (viz. the egg or adult for Lepidoptera) and make some prediction of how many eggs the adults will lay and/or how well eggs would survive and so give rise to a damaging pest density. Most so-called integrated pest management programmes (IPM) would use this approach.

Given knowledge of a species age-distribution, the thermal requirements for development, and temperatures experienced by the species' stages in the field, forecasts of the peak of adult emergence in the next generation are relatively straightforward. The size of that peak is a little more problematic. Using such an approach, forecasts have been pushed back earlier in time and are more removed from the decision of when and if to apply a control measure. For both *H. punctigera* and *H. armigera*, it is quite feasible to use a record of the cumulative trap catch in a region and the weather experienced during the period of trapping to project population increase around one generation in advance. A knowledge of the weather affecting the relevant generation greatly improves the accuracy of predictions (Maelzer *et al.*, 1996; Maelzer & Zalucki, 1999).

Medium term predictions (*c.* 4–5 months in advance) of the likely spring population size of the two species can be made using the amounts of rain falling in putative source areas (Oertel *et al.*, 1998). Refinements of such predictions can be made that take into account not only rain but also vegetation response (i.e. change in vegetation) and soil type, to plot the size and distribution of the suitable winter breeding habitat (W.A. Rochester, personal communication; see http://pest.cpitt.uq.edu.au/forecast/intro.html).

Such short to medium term predictions may not be useful

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for pest management because the predictions, as for the *Helicoverpa* spp., are made at a regional level and cannot substitute for sampling for decision-making within specific fields. Nevertheless, such predictions may prove useful in the psychological sense of backing up sampling programmes, and forecasts of greatly above average populations could usefully stimulate the movement of chemical stocks for pest control.

Forecasts up to 13 months in advance are possible with the Southern Oscillation Index or Sea Surface Temperature as predictors of weather (above). Such information may be of use to pest managers. The most accurate distinctions which can be made with the regression models are between low trap catches and high. Such predictions are likely to be of use to crop protection companies needing to decide how much stock to have on hand for the coming season. Such decisions often need to be made well in advance. Furthermore, forecasts of high populations in outbreak years will usefully stress the need for more precise management because egg counts will be higher, insecticide applications will need better timing, and spray failure due to continuing pest pressure becomes a possibility. Forecasts of low populations, on the other hand, may allow the use of 'softer' control measures, such as inundative releases of parasites or use of biological insecticides such as nuclear polyhedrosis virus, which will slow the development of insecticide resistance. Depending on a cost benefit analysis relevant to the particular crop, long term forecasts may also influence planting decisions.

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References

Allan, R., Lindsay, J. & Parker, D. (1996) *El Niño-Southern Oscillation and Climatic Variability*. 405 pp. Collingwood, Victoria, Australia, CSIRO.

Bliss, C.I. (1967) *Statistics in biology, vol.1*. 558 pp. New York, McGraw-Hill, Inc.

Bommarco, R. & Ekbom, B. (1995) Phenology and prediction of pea aphid infestations on peas. *International Journal of Pest Management* **41**, 109–113.

Bouma, M.J. & Vanderkaay, H.J. (1996) The El Niño Southern Oscillation and the historic malaria epidemics on the Indian subcontinent and Sri Lanka: an early warning system for future epidemics. *Tropical Medicine and International Health* **1**, 86–98.

Clewett J.F., Howden, S.M., McKeon, G.M. & Rose, C.W. (1991) Use of systems analysis and the Southern Oscillation Index to optimise management of grain sorghum production from a farm dam irrigation system. pp. 307–328 *in* Muchow, R.C. & Bellamy, J.A. (*Eds*) *Climatic risk in crop production. Models and management for the semi-arid tropics and sub-tropics*. Wallingford, CAB International.

Clewett, J.F., Clarkson, N.M., Owens, D.T. & Abrecht, D.G. (1994) *Australian rainman: rainfall information for better management*. Brisbane, Department of Primary Industries.

Dent, D. (1991) *Insect pest management*. 604 pp. Wallingford, CAB International.

Drake, V.A. & Farrow, R.A. (1988) The influence of atmospheric structure and motions on insect migration. *Annual Review of Entomology* **33**, 183–210.

Draper, N.R. & Smith, H. (1981) *Applied regression analysis*. 2nd edn, 699 pp. New York, John Wiley.

Fletcher, B.S. (1987) The biology of dacine fruit flies. *Annual Review of Entomology* **32,** 115–144.

Forrester, N.W., Cahill, M., Bird, L.J. & Layland, J.K. (1993) Management of pyrethroid and endosulphan resistance in *Helicoverpa armigera* (Lepidoptera: Noctuidae) in Australia. *Bulletin of Entomological Research* Supplement Series. Supplement No. 1, 132 pp.

Gleick, J. (1988) *Chaos*. UK, William Heinemann Ltd.

Haggis, M.J. (1996) Forecasting the severity of seasonal outbreaks of African armyworm, *Spodoptera exempta* (Lepidoptera: Noctuidae) in Kenya from the previous year's rainfall. *Bulletin of Entomological Research* **86**, 129–136.

Hales, S., Weinstein, P. & Woodward, A. (1996) Dengue fever epidemics in the South Pacific: driven by El Niño Southern Oscillation? *Lancet* **348**, no. 9042

Hammer, G.L. & Muchow, R.C. (1991) Quantifying climatic risk to sorghum in Australia's semi-arid tropics and subtropics: model development and simulation. pp. 205–231 *in* Muchow, R.C. & Bellamy, J.A. (*Eds*) *Climatic risk in crop production. Models and management for the semi-arid tropics and sub-tropics*. Wallingford, CAB International.

Hammer, G.L., KcKeon, G.M., Clewett, J.F. & Woodruff, D.R. (1991) Usefulness of seasonal climate forecasts in crop and pasture management. pp. 15–23 in *Proceedings: Conference on Agricultural Meteorology*. Bureau of Meteorology, Box 1289K, Melbourne, Victoria, Australia, 3001.

Harvey, A.W. & Mallya, G.A. (1995) Predicting the severity of *Spodoptera exempta* (Lepidoptera: Noctuidae) outbreak seasons in Tanzania. *Bulletin of Entomological Research* **85**, 479–487.

Holton, I. (1998) Prediction of growing season rainfall and crop yields in southern Australia. *Australian Meteorological Magazine* **47**, 327–338.

Hunter, D.M. (1996) Rapport entre les pullulations du Criquet australien, *Chortoicetes terminifera* (Walker) (Orthoptera: Acrididae) et la pluviometrie dans l'interieur aride de l'Australien. *Secheresse* **7**, 87–90.

Jobson, J.D. (1991) *Applied multivariate data analysis. Vol. 1: regression and experimental design*. 621 pp. New York, Springer-Verlag.

Kyi, A., Zalucki, M.P. & Titmarsh, I.J. (1991) Factors affecting the survival of the early stages of *Heliothis armigera* (Hübner) (Lepidoptera; Noctuidae). *Bulletin of Entomological Research* **81**, 263–271.

Maelzer, D.A. (1964) Rainfall and changes in abundance of *Aphodius tasmaniae* Hope (Coleoptera: Scarabaeidae) in the lower S.E. of South Australia. *Australian Journal of Zoology* **12**, 263–278.

Maelzer, D.A. & Zalucki, M.P. (1999) Analysis and interpretation of long term light trap data for *Helicoverpa* spp. (Lepidoptera: Noctuidae) in Australia: the effect of climate and crop host plants. *Bulletin of Entomological Research* 89, 455–464.

Maelzer, D.A., Zalucki, M.P. & Laughlin, R. (1996) Analysis and interpretation of long term light trap data for *Helicoverpa punctigera* (Lepidoptera: Noctuidae) in Australia: population changes and forecasting pest pressure. *Bulletin of Entomological Research* **86**, 547–557.

May, A.W.S. (1961) *A taxonomic and ecological study of the Dacinae*

(Family: Trypetidae). PhD thesis, University of Queensland, Brisbane, Queensland, Australia.

McBride, J.L. & Nicholls, N. (1983) Seasonal relationship between Australian and the Southern Oscillation. *Monthly Weather Review* **111**, 1998–2004.

McDonald, G., New, T.R. & Farrow, R.A. (1995) Geographical and temporal distribution of the common armyworm, *Mythimna convecta* (Lepidoptera: Noctuidae) in eastern Australia: larval habitats and outbreaks. *Australian Journal of Zoology* **43**, 601–629.

Meinke, H., Stone, R.C., & Hammer, G.L. (1996) SOI phases and climatic risk to peanut production: a case study for northern Australia. *International Journal of Climatology* **16**, 783–789.

Mosteller, F. & Tukey, J.W. (1977) *Data analysis and regression; a second course in statistics*. 588 pp. New York, Addison-Wesley.

Mosteller, F., Rourke, R.E.K. & Thomas, G.B. (1973) *Probability with statistical applications*. 2nd. edn, 527 pp. New York, Addison-Wesley.

Nicholls, N. (1986a) A method for predicting Murray Valley encephalitis in southeast Australia using the Southern Oscillation. *Australian Journal of Biological and Medical Sciences* **64**, 587–594.

Nicholls, N. (1986b) Use of the `southern oscillation to predict Australian sorghum yield. *Agricultural and Forest Meteorology* **38**, 9–15.

Nicholls, N. (1991) Teleconnections and health. pp. 493–509 *in* Glantz, M., Katz, R. & Nicholls, N. (*Eds*) *ENSO teleconnections lining worldwide climatic anomalies: scientific basis and social impacts*. Cambridge, Cambridge University Press.

Nicholls, N., Lavery, B., Frederiksen, C., Drosdowsky, W. & Torok, S. (1996) Recent apparent changes in relationships between the El Niño-Southern Oscillation and Australian rainfall and temperature. *Geophysical Research Letters* **23**, 3357–3360.

Oertel, A., Zalucki, M.P., Maelzer, D.A., Fitt, G.P. & Sutherst, R. (1998) Variation in the size of the first spring generation of *Helicoverpa punctigera*: the effect of weather in winter breeding areas. *Australian Journal of Entomology* **38**, 99–103.

Partridge, I.J. (ed.) (1994) *Will it rain? The effects of the Southern Oscillation and El Niño on Australia*. 56 pp. Queensland Department of Primary Industries; Information Series Q194015.

Pittock. A.B. (1975) Climatic change and the pattern of variation in Australian rainfall. *Search* **6,** 498–504.

Rhodes, A.A., Morse, J.G. & Robertson, C.A. (1989) A simple multigeneration phenology model: application to *Scirtothrips citri* (Thysanoptera: Thripidae) prediction on California oranges. *Agriculture, Ecosystems and Environment* **25**, 299–313.

Rimmington, G.M. & Nicholls, N. (1993) Forecasting wheat yields in Australia with the Southern Oscillation Index. *Australian Journal of Agricultural Research* **44**, 625–632.

Stone, R. & Auliciems, A. (1992) SOI phase relationships with rainfall in eastern Australia. *International Journal of Climatology* **12**, 625–636.

Stone, R.C., Hammer, G.L. & Marcussen, T. (1996a) Prediction of global rainfall probabilities using phases of the Southern Oscillation Index. *Nature* **384**, 252–255.

Stone, R.C., Nicholls, N. & Hammer, G.L. (1996b) Frost in Northern Australia: trends and influence of phases of the Southern Oscillation. *Journal of Climate* **9**, 1896–1909.

Tabachnick, B.G. & Fidell, L.S. (1989) *Using multivariate statistics*. 2nd edn, 746 pp. New York, Harper and Row.

Titmarsh, I.J. (1993) *Mortality of immature Lepidoptera: a case study with* Heliothis *species (Lepidoptera; Noctuidae) in agricultural crops on the Darling Downs*. PhD thesis. The University of Queensland, Brisbane.

Varley, G.C., Gradwell, G.R. & Hassell, M.P. (1973) *Insect population ecology: an analytical approach*. 191 pp. Oxford, Blackwell.

Waldren, K.J. (1991) *Heliothis* in Western Australia: pest status and current research. pp. 73–76 *in* Twine, P.H. & Zalucki, M.P. (*Eds*) *A review of* Heliothis *research in Australia*. Queensland Department of Primary Industries Conference and Workshop Series, Brisbane.

Wesolowsky, G.O. (1976) *Multiple regression and analysis of variance*. 292 pp. John Wiley & Sons, Inc.

Willcocks, J.R., McKeon, G.M. & Day, K.A. (1991) Using the Southern Oscillation Index to predict the growth of *Heteropogon contortus* pasture in southeast Queensland. pp 36–39 in *Proceedings: Conference on Agricultural Meteorology*. Bureau of Meteorology, Melbourne, Victoria, Australia.

Zalucki, M.P., Gregg, P.C., Fitt, G.P., Murray, D.A.H., Twine, P. & Jones, C. (1994) Ecology of *Helicoverpa armigera* (Hübner) and *H. punctigera* (Wallengren) in the inland of Australia: larval sampling and host plant relationships during winter and spring. *Australian Journal of Zoology* **42**, 329–346.

Appendix 1

Significant correlations (X = $P < 0.01$; O = $P < 0.05$) between months of the mean monthly Southern Oscillation Index over a period of 30 months, from January two years before (Jan-2) to June in the current year (Jun-0) for 1971 to 1992.

Month	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J
F	M	A	M	J																					
Year	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-0
-0	-0	-0	-0	-0																					
Jan-2																									
Feb-2	X																								
Mar-2	X	X																							
Apr-2	X	X	X																						
May-2				X																					
Jun-2				O	X																				
Jul-2				X	X	X																			
Aug-2				O	X	X	X																		
Sep-2				X	X	X	X	X																	
Oct-2				X	X	X	X	X	X																
Nov-2						X	O	X	X	X															
Dec-2					O	X	X	X	X	X	X														
Jan-1					O	X	X	X	X	X	X	X													
Feb-1						O	X	X	X	X	X	X	X												
Mar-1							X	X	X	X	X	X	X	X											
Apr-1							X	X	X	X	X	O	X	X	X										
May-1																X									
Jun-1																X	X								
Jul-1																X	X	X							
Aug-1																X	X	X	X						
Sep-1																X	X	X	X	X					
Oct-1															X	X	X	X	X	X	X				
Nov-1					O													X	O	X	X	X			
Dec-1						O											O	X	X	X	X	X	X		
Jan-0																		X	X	X	X	X	X	X	
Feb-0																		X	X	X	X	X	X	X	X
Mar-0																		O		X	X	X	X	X	X
X																									

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Apr-0 X X O X X
X X
May-0
X
Jun-0
X X

Appendix 2

Significant correlations (X = $P < 0.01$; O = $P < 0.05$) between months of the mean monthly Sea Surface Temperature over a period of 30 months, from January two years before (Jan-2) to June in the current year (Jun-0) for 1971 to 1992.

Month	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J
Year	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-0	-0	-0	-0	-0	-0
Jan-2																														
Feb-2	O																													
Mar-2	O	X																												
Apr-2		X	X																											
May-2		O	X	X																										
Jun-2			X	X	X																									
Jul-2				X	X	X																								
Aug-2						X	X																							
Sep-2				O	O	X	X	X																						
Oct-2						O	O	X	X																					
Nov-2									O																					
Dec-2						O		O			X																			
Jan-1												X																		
Feb-1													X																	
Mar-1									O	X			O	X																
Apr-1									X	X	O			X	X															
May-1											X				X	X														
Jun-1									X					O	X	X	X													
Jul-1											X					X	X	X												
Aug-1											O							X	X											
Sep-1									O	O						O		X	X	X										
Oct-1											O	O	O	X				X	X	X	X									

Nov-1					O			O	X	O	X
Dec-1						O					
	X										
Jan-0											
		X									
Feb-0											
O	O	O	X								
Mar-0											
X			O	X							
Apr-0											X
O				X	X						
May-0											
					O	X					
Jun-0											X
				O	X	X	O				

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