From Oceans to Farms – the Agricultural Potential of Ocean-Based Forecasts

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Abstract

A prototype seasonal forecasting system designed for use by the agricultural community is described. A lagged statistical relationship is established between ocean temperatures and variables such as plant growth. Present day ocean temperatures, measured by satellite, are then used to predict future plant growth. The value of this system is assessed for the northern Queensland extensive grazing industry using one hundred years of historical data. This experiment indicates that production increases of 16% are possible, at the same time as a 12% reduction in soil loss. These benefits exceed those obtained using a forecast based on the Southern Oscillation Index (SOI). Somewhat surprisingly, the ocean-based forecasts also perform slightly better than a perfect knowledge of seasonal rainfall totals. This is because rainfall distribution is important, and predicting an index of plant growth takes this into account.

Keywords

Ocean, temperature, forecast, statistical, growth, grazing.

Introduction

Accurate climate predictions one or more seasons into the future are likely to be of considerable value to the agricultural industry in general. Not only would farmers benefit by being able to plan and manage more efficiently, but related industries such as farm suppliers, financiers, transport and storage stand to benefit also.

The key to climate prediction is ocean temperature. Ocean temperature affects the atmosphere on a large-scale, and for many months into the future. By measuring changes in ocean temperature now, it is possible to estimate atmospheric changes 3-6 months later. The ocean affects not only atmospheric moisture, and hence water available for rain, but also air temperature, cloudiness and wind patterns. Hence it might be expected that ocean temperatures could be related to growing conditions over land. The precise details of this relationship, and the ways in which this information might be used are the subject of this paper.

Methods

Partial least squares

The basis of the statistical prediction system is to develop a relationship between ocean SST (sea-surface temperature) and agricultural data using historical data. This relationship takes the form of a spatial map of the SST pattern most highly related to the agricultural data. The extent to which the SST at any particular time resembles this pattern gives an index that is a surrogate for the agricultural data if there is skill in the method. If the SST/data relationship is a lagged relationship, with SST lagging the agricultural data, then present values of SST can be used to predict future data. The technique is called partial least squares (PLS) (3).

The method is tested by trying to predict historical data, that is, performing a “hindcast”. The skill is assessed by correlating the original data and the SST index. We find that this explanatory skill can be quite high, but it can contain artificial skill; the skill often decreases when a true forecast is made. In order to reduce or eliminate artificial skill, we also perform hindcasts using cross-validation. This technique leaves out data from the year for which a hindcast is being made, and gives a fairer indication of true forecast skill.

Different agricultural variables

The most obvious agricultural variable to try and predict is yearly-average rainfall. However, the distribution of rainfall throughout the year can vary considerably, so those years with the same rainfall total can produce quite different pasture growth. What is really needed is a variable which acts to integrate (add up) rainfall. We find that a variable called growth index days (GID) is more useful. GID is a measure of the number of days during the year when conditions are suitable for plant growth. It is affected by the distribution of rainfall, as well as other factors like air temperature, soil moisture and cloudiness. There are plausible physical mechanisms relating all these variables to SST.

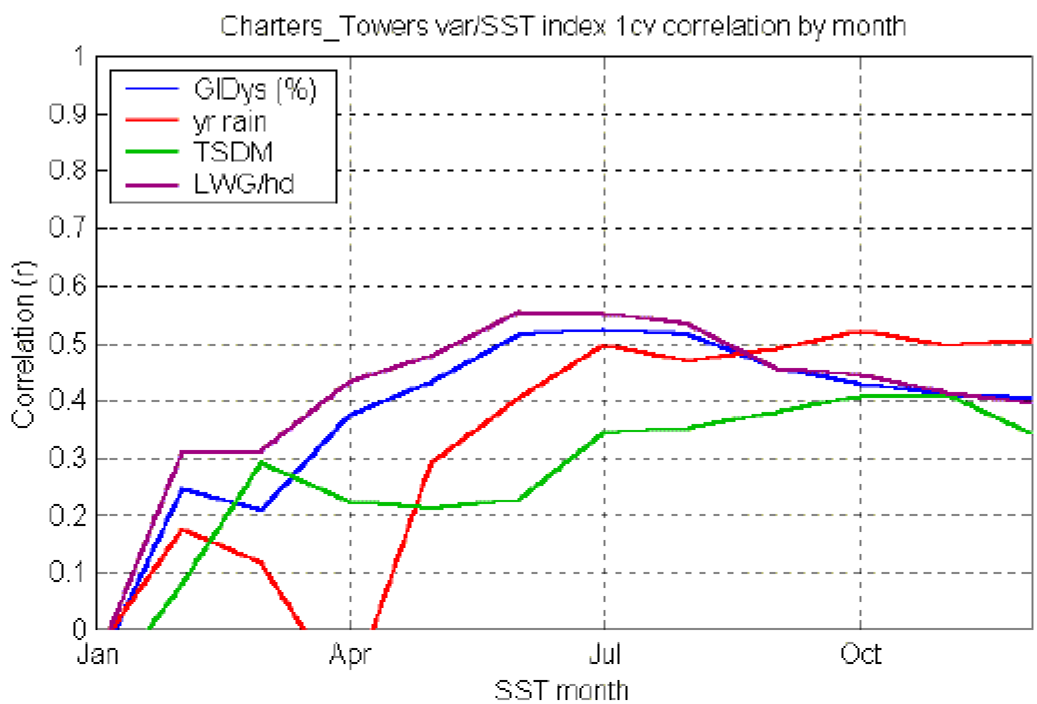

Figure 1. Skill in predicting various agricultural variables, averaged from July to June, at Charters Towers using monthly values of SST.

From Fig. 1 we see that the cross-validated skill of predicting GID exceeds the skill of predicting rainfall in June, which is the month in which predictions for the extensive grazing industry are required. The skill for live weight gain (LWG) is higher again, but this variable is not as useful for the farmer to know. Given a prediction of GID, the farmer can make stocking rate adjustments depending on the amount of feed that is forecast to grow in the following year.

Note that any skill above about 0.5 is considered useful.

This analysis must be done for each industry and each region. We have started to look at cropping regions in northern NSW/southern Queensland, and there is evidence here that GID is not as useful as a prediction of rainfall. We are still trying to understand the reasons for this.

We note also that the period over which the agricultural variable is averaged can be quite important. For example, there may be periods where GID is almost always zero, or almost always a maximum. It is important to encompass those portions of the year when the variable is truly variable, and therefore might be connected to SST variability.

Different regions

In Queensland and South Australia we can demonstrate useful skill in predicting GID. However, we have been unable to find any useful skill in regions in Western Australia (Kimberley and Gascoigne) and in central Australia. This is true whether we try and predict GID, rainfall or wheat yield.

There are two possible reasons for the difficulties in these regions:

1. The statistical connections may be more complicated than can be described by the PLS technique. Different areas of ocean may influence these regions at different times of year. It is known that the north-west cloud band requires several independent conditions to produce rain. Development of more flexible non-linear statistical techniques may help here.

2. The western side of the country is affected more by the Indian Ocean than the Pacific Ocean, and observations in the Indian Ocean are very sparse up until the satellite data became available in 1981.

Different data sets

Most of the work to date has used the GISST3 data set of ocean SST (2). A recent publication (4) has thrown doubt on the last twenty years of this data set, arguing it has less energy than it should. We find that hindcasts using the Reynolds (4) data set have improved skill using years since 1981. A new version of GISST has just become available which apparently fixes the problem.

Because of the availability of satellite data, SST data sets are more accurate since the end of 1981. We find that hindcasts made using data since 1981 are more accurate, although the time series are shorter. We will have to learn how to live with these shorter data sets, both in order to get useful skill in some regions, and to use output from numerical ocean/atmosphere models.

Results

The example we have studied most carefully is that of predicting GID averaged over 12 sites in the shire of Dalrymple. It is an area in northern Queensland where the main agricultural industry is extensive grazing, and where the major influence might be expected to be from the Pacific Ocean via El Nino/Southern Oscillation (ENSO). Fig. 2 shows the SST pattern associated with GID in Dalrymple using data from 1887 to 1995. There is a clear east Pacific Ocean ENSO signal here, but also a strong influence from the Tasman Sea/South Pacific and Coral Sea. The cross-validated skill using this pattern is 0.54. Using more recent SST data from Reynolds improves the skill to 0.81, although over a shorter period.

The benefit of using a forecast of GID was simulated using historical data over 100 years using a very simple category system. In years when the forecast GID was in the top 20% of values, stocking rates were increased by 20%. When the forecast GID was in the bottom 20% of values, stocking rates were decreased by 20%. Otherwise no changes were made. Results for different forecast systems are shown in Table 1. The two main features to note are the improvement in annual live-weight gain (LWG) and reduction in soil loss obtained when using the SST-based forecast system. This compares very favourably to the benefit of using the SOI-based phase system (5), and even shows a slight improvement over a perfect knowledge of seasonal rainfall. The latter result seems somewhat surprising until it is realised that the time distribution of rainfall is very important, a factor which a prediction of GID is able to take into account.

Conclusion

Statistical seasonal climate forecasts based on ocean surface temperatures show considerable potential for increased efficiency in agricultural enterprises. The precise details of the forecast method are likely to change depending on region and industry, requiring a careful study of each case. It has been demonstrated that forecasting rainfall is not necessarily the best way to proceed.

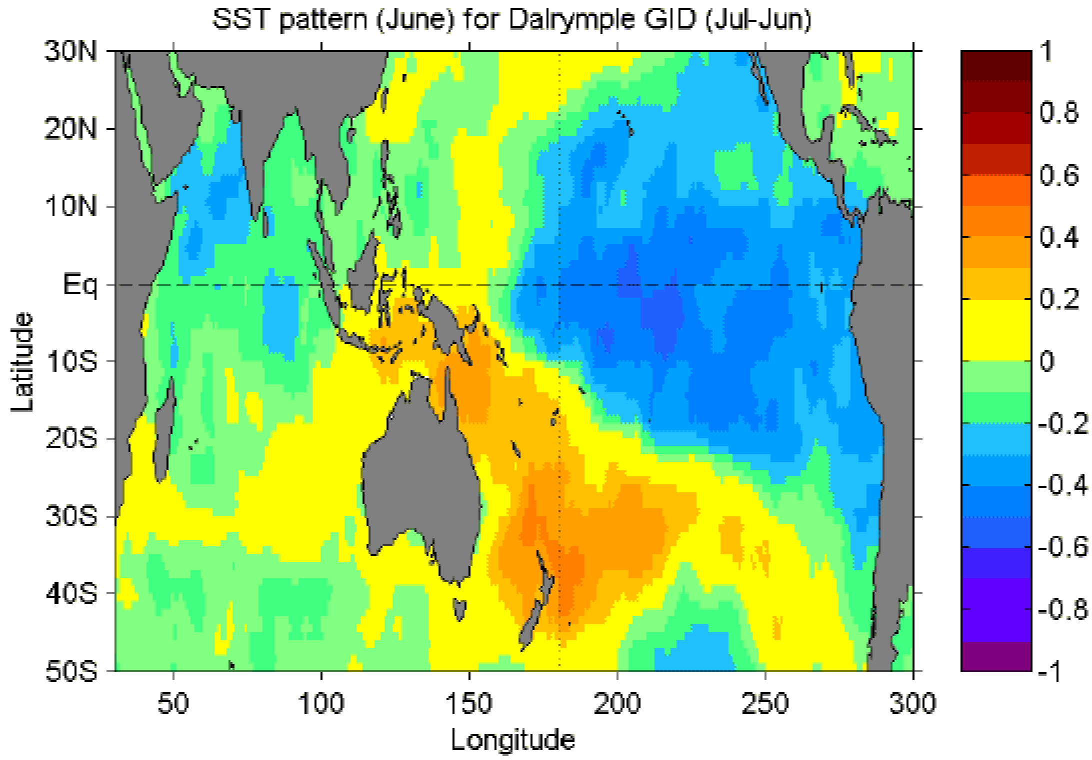

Figure 2. SST pattern (June) for Dalrymple GID averaged from July to June using GISST3.

Forecast	Annual LWG (kg/ha)	% change in LWG	Soil loss (kg/ha)	% Burns
None	21.1	0	1598	50
Phase	21.9	4	1465	37
SST	24.4	16	1413	39
Perfect rainfall	23.9	13	1480	33

Table 1. Comparison of forecasting systems on liveweight performance, soil loss and number of fire opportunities for open eucalypt woodlands in north-east Queensland.

Acknowledgments

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