# TOWARDS IMPROVED WHEAT YIELD FORECASTING FOR WESTERN AUSTRALIA

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## ABSTRACT

In this work, the current wheat yield forecasting system is improved for Western Australia (WA). Currently, the yield forecasting system is based on relationships between wheat yields and a stress index (SI) calculated for each local government area. In this paper, the SI was combined with the temporal NDVI patterns and cumulative rainfall (CR) data for the period 1991-2005. Partial least squares models were calibrated and validated using a leave-year-out approach. It was found that the model combining SI and NDVI was better than the model only using the SI and more robust across years. In-season forecasts were accurate from week 34 onwards. Using NDVI derived from MODIS did not decrease the accuracy of the model compared to using AVHRR data. It was concluded that the combined model significantly improved the current wheat yield forecasting system for WA, providing the means for accurate in-season wheat yield forecasts from week 34 onwards.

## INTRODUCTION

The Western Australian (WA) wheat-belt has a typical Mediterranean climate with semi-arid growing conditions. Accordingly, the amount and distribution of rainfall is the most important factor determining the length of the growing season and in-season crop growth (Stephens and Lyons, 1998). The typically sandy soil types have a limited water storage capacity which enhances dependence on regular in-season rainfall to achieve maximum yields. Based on soil characteristics, rainfall, temperature and humidity data, the stress index model (STIN) calculates a weighted cumulative stress index (SI) to account for the effect of water availability and drought on wheat growth (Stephens, 1998; Stephens et al., 1989). STIN is currently used to assess the impacts of drought on crop production and forms the basis for assessing exceptional circumstances and drought relief assistance. The relationship between the SI and wheat yield is used in the system of yield forecasting system in Western Australia. There are a number of factors affecting wheat yields that are unaccounted for in the current system, such as the effects of crop management, frosts, no seeding rains, and the effects of pests and diseases. The objective of this study is to improve yield forecasting in WA by combining the SI and the normalized vegetation index (NDVI) calculated from NOAA-AVHRR and MODIS data following a similar approach described by (Boken and Shaykewich, 2002).

## MATERIALS AND METHODS

### Ground-truth data

For the period 1991-2001, ground-truth data was available on a shire (local government area) basis from the Australian Bureau of Statistics (ABS) census and survey data. For the period 2002-2005 no ABS estimates at a shire level were available and therefore yields were estimated using delivery data and farmers estimates of wheat acreage by the Cooperative Bulk Handlers (CBH). The CBH data on acreage are prior-to-harvest estimates, and it is expected that this estimate is biased. The area actually delivered will vary (depending on e.g. rainfall), resulting in underestimated or overestimated yields respectively. To correct for these errors, yield estimates were compared with yields from control varieties that were used for at least 10 years in cultivar selection trials (457-2181 trials per year) across the WA wheat-belt. Mean relative deviations from trend-lines were determined and compared with ABS and CBH data. This indicated that the yield for 2002 (drought) and 2003 (post-drought) were strongly biased and so yields for these years were multiplied with a correction factor of 1.13 and 0.82 respectively. Only shires with more than 5000 ha of wheat and a strong relationship between ABS and CBH yields and consistent NDVI patterns were used for this study. This resulted in a dataset that included 50 shires and 745 unique shire-year combinations.

### Stress index and satellite imagery

In this study, STIN was used to calculate the stress index on a weekly basis using rainfall data from weather observation stations from the Australian Bureau of Meteorology and standard soil types (Stephens, 1998; Stephens et al., 1989). The remotely sensed data used in this study were provided by Landgate (Midland, Western Australia) and derived from AVHRR sensors on board NOAA satellites and MODIS sensors on board Terra and Aqua satellites. The 1991-2005 time-series included combinations of AVHRR/2 data measured by the sensor onboard the NOAA 9, 11 and 14 satellites and the AVHRR/3 data measured by the sensor onboard the NOAA 16 and 17 satellites. The AVHRR/3 values were calibrated to AVHRR/2 equivalents using a linear transformation based on cross calibrations on desert areas with low variation in NDVI (S. Cridland, personal communication). Standard cloud-masks were used and fortnightly maximum value composites were calculated. All areas with non-agricultural land (natural vegetation, salt pans etc) were masked out (for details see (Donald et al., Submitted)). Afterwards, mean NDVI values per shire were calculated, including all pixels from crop and pasture areas. Fortnightly composites were re-sampled to weekly values by linear interpolation. The mean temporal weekly NDVI values per shire were strongly smoothed using a digital filter. Lon time-series of MODIS data were not available. Therefore, MODIS NDVI values were converted to match AVHRR NDVI for the years 2003-2005 using two Richards-functions relating NDVI values from MODIS to AVHRR calibrated on data from January to September and October to December in 2004. The modified MODIS NDVI is referred to hereafter as “converted MODIS”.

### Partial least squares

A partial least squares (PLS) regression model was used to relate yield to a combination of x variates (Matlab, 2000; Wise et al., 2005). With PLS analysis, the x variates are recombined into latent vectors in such a way that it best describes the variation in both the x and y blocks (Geladi and Kowalski, 1986). Model 1 in Table 1 represents the current forecasting system and can, therefore, be considered as the control. Model 2 also included monthly NDVI from week 6 onwards, weekly cumulative rainfall (CR) values from week 31 onwards and interactions between SI and NDVI and SI and CR.

Table 1 Characteristics of the control and improved model

| Model | X blocks | x variables included | latent vectors |
|---|---|---|---|
| 1 | Yr + SI | 2 | 2 |
| 2 | Yr + SI + NDVI + CR + interactions | 91 | 10 |

In-season forecasts can only be based on data available at the moment of forecasting. Therefore, the smoothed NDVI values were re-calculated accordingly. Models including data from weeks 6 to 44 (end-of season), decreasing by a fortnight to a period of week 6 to 32 (mid August) were compared to evaluate in-season forecasting ability. All x and y variates were normalised per shire and combined into one large matrix.

## Cross-validation on independent data

A leave-year-out approach was used to test the predictability of yield in an unknown year. This means that models were calibrated on all years with one year left out. Then, yield for each shire of the year left out was predicted using the calibrated model. This was repeated for all years. To obtain insight in the prediction capability of the model, we used the percentage of variation accounted for by the cross validated model (using the leave-*year*-out predictions) with regard to the total variation in the dataset:

$$Q^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}, \qquad (1)$$

where y, $\bar{y}$ and $\hat{y}$ are the measured, mean and estimated yield value. The $Q^2$ has strong resemblance with $R^2$ but can become negative if the prediction of the model is inadequate (e.g. in case of over-fitting). The $Q^2$ is (as $R^2$) strongly sensitive to the variation within the data set, and so should be considered with caution.

## RESULTS

Low rainfall area’s have a quicker decline in NDVI after the peak of season than the high and medium rainfall area’s (Figure 1). The peak of season (maximum NDVI) typically occurred between weeks 30 and 40. Also, some clear false breaks are visible in 1992, 1993, 1997 and 1998 with increasing NDVI values outside the growing season.

The leave-year-out validation results are presented in Table 2. For yield, $Q^2$ values were 0.57 and 0.75 and the mean of relative errors per shire were 13% and 10% for model 1 and 2 respectively. The predictions for 2000 and 2002 (both drought years) were biased with larger errors than the other years. In 2005, predicted yields were more strongly scattered than in other years. In general the years based on ABS census data (1991-2001) were more accurate than the years based on converted CBH data (2002-2005).

Table 2 $Q^2$ and means of relative error per shire (RE, means of root mean squared error of predictions / mean calculated for each shire) for leave-year-out validation based on predictions including AVHRR data until week 44.

| Model | X variates included | $Q^2$ | RE |
|---|---|---|---|
| 1 | Yr + SI | 0.57 | 0.13 |
| 2 | Yr + SI + NDVI + CR | 0.75 | 0.10 |

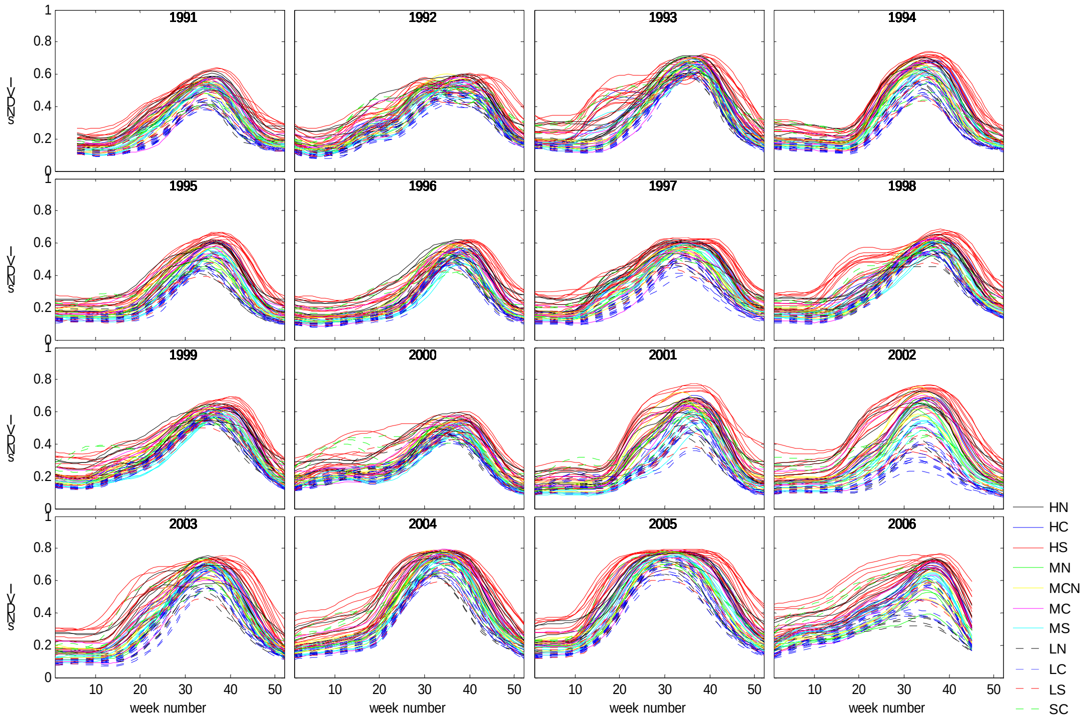

Figure 1. Temporal smoothed NDVI patterns for 1991-2006. Legend refers to composite names for high, medium and low rainfall (H, M, L) in northern, central north, central and southern (N, CN, C, S) shires. SC refers to Southern Coastal shires.

Prediction accuracy slightly decreased when including only data before the peak of season (Figure 2). Obviously, accuracy decreased when predictions were based on early season measurements only. Accuracy of the multivariate model strongly decreased when predicting before week 34 and approached the accuracy of model 1.

The combination dataset (AVHRR combined with converted MODIS) produced approximately similar in-season forecasts for the leave-year-out cross-validation as the AVHRR dataset. This indicates that AVHRR and MODIS data can be combined to estimate a long time-series of MODIS data.

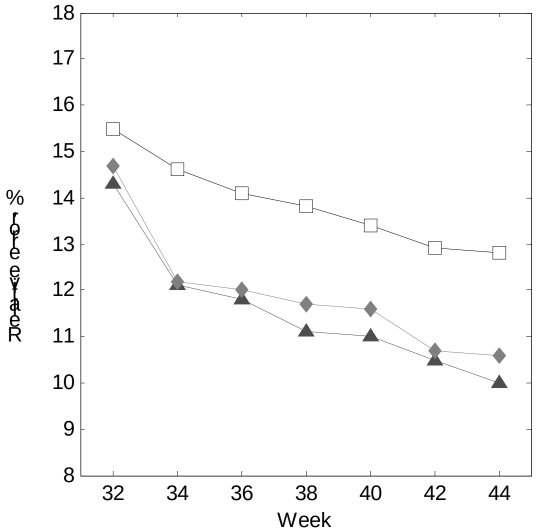

Figure 2. Relative errors of in-season forecasting for yield across years for (□) model 1, ▲AVHRR data, model 2 ♦ AVHRR and MODIS data, model 2. Relative errors are means of relative errors per shire, calculated as root mean squared error of predictions / mean.

## DISCUSSION AND CONCLUSION

In Western Australia, yields vary strongly between years in response to varying climatic conditions, but particularly rainfall. The methodology presented in this paper was capable of explaining most of the temporal variation in yield per shire without knowledge of sown acreages or location of wheat paddocks.

The wheat yield forecasting system of Western Australia is based on STIN and the calculation of moisture stress based on surplus or deficient moisture (Stephens, 1998; Stephens et al., 1989). The multivariate models including STIN-SI values and monthly values of smoothed NDVI and cumulative rainfall were more accurate and robust than the models based only on the SI. This indicates that this approach would be a considerable improvement on the current yield forecasting system, making it more accurate and more robust especially in dry years.

NDVI values can be used to estimate wheat yields directly (Labus et al., 2002; Patel et al., 2006; Quarmby et al., 1993; Salazar et al., 2007; Smith et al., 1995) or can be used in combination with a simulation model to estimate the intercepted radiation (Doraiswamy et al., 2005; Jongschaap, 2006; Moriono et al., 2007). Currently, there is no accurate method available in WA for differentiating annual crops without contrasting temporal growth patterns (Potgieter et al., 2007). Therefore, NDVI values were derived from all types of crops including pastures. Although NDVI values of crops and annual pastures in WA generally respond in a similar way to seasonal conditions, accuracy may be further improved if other crop types and pastures can be masked out. The independent leave-year-out validations showed that the models performed accurately in most years. In general, model errors for the years 1991-2000 were smaller than for the years 2002-2005. This may be linked to availability of the ABS census data or the transition from AVHRR/2 to AVHRR/3 sensor data. We expect that at least part of these larger errors were due to inaccuracies in the ground truth data.

NDVI values from AVHRR and MODIS are different but strongly correlated (Gallo et al., 2005). With the empirical conversions used to combine AVHRR and MODIS time-series only a minor decrease in prediction results were found. This allows MODIS data to be used for future predictions, potentially improving robustness as the higher spatial resolution allows a better vegetation mask to be used. Also, the sensor calibrations and stability of MODIS is expected to be superior to AVHRR.

The methodology presented here was able to accurately predicted yield with relative errors of 10-12% from week 34 onwards. It is concluded that the combination of the STIN model stress index and temporal patterns of remotely sensed NDVI was a considerable improvement over the current wheat yield forecasting system.

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