

Seeing is believing I: The use of thermal sensing from satellite imagery to predict crop yield

Potgieter A B^{1,3}, Rodriguez D¹, Power B², Mclean J² and Davis P²

¹Queensland Alliance for Agriculture and Food Innovation (QAAFI), University of Queensland, Toowoomba QLD 4350, Australia

²Department of Agriculture, Food and Fisheries Queensland, Toowoomba QLD 4350, Australia

Abstract. Volatility in crop production has been part of the Australian environment since cropping began with the arrival of the first European settlers. Climate variability is the main factor affecting crop production at national, state and local scales. At field level spatial patterns on yield production are also determined by spatially changing soil properties in interaction with seasonal climate conditions and weather patterns at critical stages in the crop development. Here we used a combination of field level weather records, canopy characteristics, and satellite information to determine the spatial performance of a large field of wheat. The main objective of this research is to determine the ability of remote sensing technologies to capture yield losses due to water stress at the canopy level. The yield, canopy characteristics (i.e. canopy temperature and ground cover) and seasonal conditions of a field of wheat (~1400ha) (-29.402° South and 149.508°, New South Wales, Australia) were continuously monitored during the winter of 2011. Weather and crop variables were continuously monitored by installing three automatic weather stations in a transect covering different positions and soils in the landscape. Weather variables included rainfall, minimum and maximum temperatures and relative humidity, and crop characteristics included ground cover and canopy temperature. Satellite imagery Landsat TM 5 and 7 was collected at five different stages in the crop cycle. Weather variables and crop characteristics were used to calculate a crop stress index (CSI) at point and field scale (39 fields). Field data was used to validate a spatial satellite image derived index. Spatial yield data was downloaded from the harvester at the different locations in the field. We used the thermal band (land surface temperature, LST) and enhanced vegetation index (EVI) bands from the MODIS (250m for visible bands and 1km for thermal band) and a derived EVI from Landsat TM 7 (25m for visible and 90m for thermal) satellite platforms. Results showed that spatial variations in crop yield were related to a satellite derived canopy stress index (CSIsat) and a moisture stress index (MSIsat). A weather station level canopy stress index (CSIws) calculated at midday was correlated to the CSIsat at late morning. In addition, a strong linear relationship was observed between EVI and LST at point scale throughout the crop growth period. Differences were smallest at anthesis when the canopy closure was highest. This suggests that LST imagery data around flowering could be used to calculate crop stress over large areas of the crop. The harvested yield was related ($R^2 = 0.67$) to CSIsat using a fix date across all fields. This relationship improved ($R^2 = 0.92$) using

³ To whom any correspondence should be addressed.



both indices from all five dates across all fields during the crop growth period. Here we successfully showed that satellite derived crop attributes (CSIsat and MSIsat) can account for most of the variability in final crop yield and that they can be used to predict crop yield at field scales. Applications of these results could enhance the ability of producers to hedge their financial on-farm crop production losses due to in-season water stress by taking crop insurance. This is likely to further improve their adaptive capacity and thus strengthening the long-term viability of the industry domestically and elsewhere.

1 Background

Since the early settlers, the risk of crop failures has been part of the Australian agricultural production milieu. Climate is the main contributing factor causing volatility in crop production at a national, state and local scale. To date the risk of yield loss has been managed by farmers (at local level) through a variety of means (enterprise diversification, change in investment strategy or hedging of risk against price futures), which all equate to risk retention.

One approach to mitigate production risk is through crop insurance. That is why the insurance industry in Australia developed a crop insurance product (i.e. YieldShield™) as mechanism for transferring on farm downside risk. Producers can utilise this to enhance their ability to better deal with financial losses due to water stress and thus improve their adaptive capability and strengthen their economic long-term viability. This is currently done through accessing the predictive and integrative biophysical crop modelling technologies (Potgieter et al., 2003, Potgieter et al., 2005, Potgieter et al., 2006) within the Queensland Alliance for Food Innovation (QAAFI). Such an approach enables producers to offset their on-farm risk due to crop losses caused by water stress at regional or district (shire) level. However, this approach has very limited spatial specificity to a producer's own location since it captures the basis risk at an aggregated shire level. Here we set out to enhance the spatial granularity and specificity of downside risk by utilising remote sensing metrics that can assess crop yield losses due to water stress.

Remote sensing has long been known for its aptitude and ability to increase spatial granularity across large areas (Potgieter et al., 2007, Richards and Jia, 1999, Doraiswamy et al., 2004, Doraiswamy et al., 2005, Potgieter et al., 2011) or within small paddocks (Rodriguez et al., 2005). In addition, previous studies have successfully developed and applied remote sensing metrics (i.e. thermal and vegetation) that can capture the relationship between yield and abiotic stresses and water stress at the canopy level at full cover as well as when cover is in-complete (Clarke, 1997, Idso et al., 1981, Moran et al., 1994, Sandholt et al., 2002). Most of these research efforts have never been applied in an operational sense across large regions that could be beneficial to industry and government agencies, mainly because of the very high cost involve in producing data outputs from them. Furthermore, there has never been enough imputes to apply such technologies to hedge downside risk at a farm scale till now. Since the advent of MODIS satellite platform and the more readily availability of Landsat imagery, acquisition costs of remote sensing have become more affordable, which will enhance the transferring of such technologies in for application in the insurance industry. Although much has been done on the canopy-thermal space metrics as mentioned earlier, currently no operational framework exist in Australia or internationally, which incorporates remote sensing technology within the Insurance industry for dry land cropping.

The main objective of this research is to determine the ability of remote sensing technologies to capture yield losses due to water stress at the canopy level. More specifically, calculating and applying crop water stress indices (canopy stress and moisture stress) within the crop canopy - thermal domain through utilising remote sensing at an aggregated field level. This approach could be extrapolated and applied to a national level to assist producers to hedge against downside on farm risk within a cropping season.

Outcomes from this study are likely to enhance the ability of producers to hedge their financial on-farm crop production losses due to water stress. This is likely to further augment the adaptive capability of rural cropping industries and thus strengthening its long-term viability domestically and internationally.

2 Methodology

Here we set out to determining the ability of crop water stress indices to capture yield, within the crop canopy – thermal space. To achieve this we selected a study area (~1400 ha wheat field) located in the Moree district of northern New South Wales (NSW) (Figure 1). Three automated climate stations were installed to measure temperature, rainfall and relative humidity at aggregated hourly and daily intervals from emergence to harvest (July to October). Although soils were very similar in texture some variability existed in starting soil water content mainly due to the slight differences in soil textures between station 2 (lighter soil) and stations 1 and 3 (darker heavier soil closer to creek) (Gillingham, personal communication, 2011).

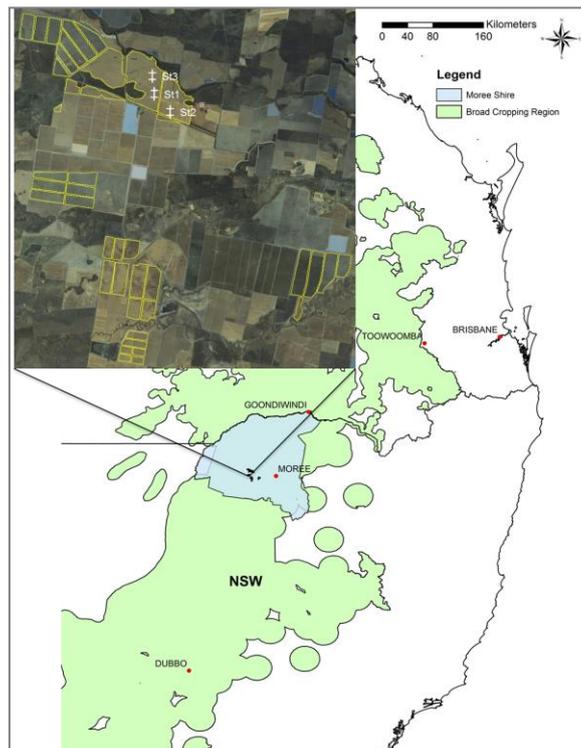


Figure 1: Showing the location the three weather stations and the outlines of the 39 wheat fields for the study area in northern New South Wales, Australia.

Climate and satellite data were acquired for five dates (9th July, 2nd August, 3 September, 11th September and 19th September) through the cropping season for wheat during 2011. The enhanced vegetation index (EVI) was calculated for Landsat TM 5 and 7 if available and acquired from MODIS13Q1. The EVI has is known to be an excellent surrogate for determining canopy vigour (Huete et al., 2002, Huete et al., 1994). Land surface temperature (LST) was calculated for Landsat from radiance and downloaded directly for MODIS11A1 band 1 (day time land surface temperature). The resolution of LST for MODIS is 1km x 1km grid cell size, while LST from Landsat has a resolution of 90m x 90m. In addition, emissivity was obtained from MODIS11A1 band 9 (31 emissivity), which was used to transform brightness temperature of the Landsat to LST. Rainfall, air temperature (T_a), humidity were obtained from each climate station while vapour pressure deficit (VPD) was calculated from temperature and humidity and used to deriving crop stress index (CSI) at a station level and crop canopy stress status (CCSS) within the vegetation – thermal domain (VTD).

Statistics were encoded and generated using the R-statistical package. Yield data was obtained from data captured from the yield harvester maps as supplied by contractors. All of these data sets were manipulated within the Yield Editor[®], ArcMap, R-statistical and ENVI remote sensing packages. Furthermore, traditional least square regressions were used to determine the relationship of measured canopy temperature and land surface temperature from Landsat. Finally, crop canopy stress status was

contrasted against aggregated harvested yield data at 30m x 30m pixel and aggregated field levels within the coinciding vegetation – thermal space across the crop growth period.

2.1 *Vegetation and land surface temperature from MODIS*

The MODIS Enhanced Vegetation Index (EVI) was selected for its relative insensitivity to atmospheric and canopy soil background noise compared to other vegetation indices. In addition, it optimises the vegetation signal with improved sensitivity at higher biomass levels, which is a significant improvement on the traditional NDVI measure (Huete et al., 2002). The EVI provides a measure of biomass or vegetative canopy vigour over large areas (Campbell, 2002). The MODIS13Q1 product was downloaded for the five dates and band 2 (EVI) was utilised as a measure of canopy health. Land surface temperature (LST) was obtained from MODIS11A1 band 1 (day time land surface temperature). In addition, emissivity was obtained from MODIS11A1 band 9 (31 emissivity) that was used to transform brightness temperature of Landsat to LST. All MODIS data were downloaded from the NASA Earth Observing System (EOS) web site for the given dates for 2011 (www.edcimswww.cr.usgs.gov/pub/ims/welcome/). The MODIS products are geometrically and atmospherically corrected with reduced effects of viewing angle and bi-directional reflection, validated, and quality assured through the EOS program (Justice et al., 2002). The MODIS reprojecting tool (www.edcdaac.usgs.gov/datatools.asp) was used to sub-sample the “granule” to an area covering the study area. Images were stacked for the 2011 season using a GDA 1994 datum in ENVI software (ITT, 2008),

2.2 *Determining of Land Surface Temperature from Landsat TM*

The Landsat's Digital Number (DN) was converted into Radiance. This was done in the standard ENVI functionality. Radiance was then transformed into temperature measured as degrees Celsius. This was done by applying the inverse of the Planck function (Smith, 2005, Chander et al., 2009)

$$T = K2 / \ln[(K1 * \epsilon / CVR1) + 1] \quad [1]$$

where, T is in degrees Celsius, ϵ = Emissivity (taken from MODIS MOD11A1 daily values), CVR1 = cell radiance, K1 = 607.7 and K2 = 1260.5.

2.3 *Crop stress metrics*

Crop stress status was calculated for each climate station applying the crop stress index (CSI) as derived and applied by previous research (Idso et al., 1981, Jackson, 1983, Rodriguez et al., 2005) and is given as:

$$CSI = [\text{Canopy Temp} - \text{Air Temp}] / VPD \quad [2]$$

As crops transpire water is lost, which causes a reduction in leaf temperature due to evaporative cooling. Thus, for well-watered (poorly) situations crop transpiration increases (decreases) resulting in more (less) cooling and a reduced (increased) ensuing leave temperature or *vice-versa* (Allen et al., 1998). Therefore, positive (negative) CSI values represent a poorly-watered (well) crop as a result of leave surface temperature been much higher (lower) than that of surrounding environment due to different rates in transpiration at the leave level.

The calculation of crop canopy stress status (CCSS) was done within the concurring vegetation – thermal domain. This was done for each of the selected dates outlined before. Here we utilised the trapezoid shape formed when vegetation index is plotted versus land surface temperature (Moran et al., 1994, Clarke, 1997). This resulted in two directly calculated indices in the vertical and the horizontal axis of the VTD using the thermal and vegetation index bands from the MODIS as well as derived Landsat TM 5 and 7 satellite platforms. Figure 2 depicts the formation of the two indices where in this study canopy stress index (CSIsat=A/B) is derived in the vertical axis and moisture stress index (MSIsat=C/D) is derived in the horizontal axis.

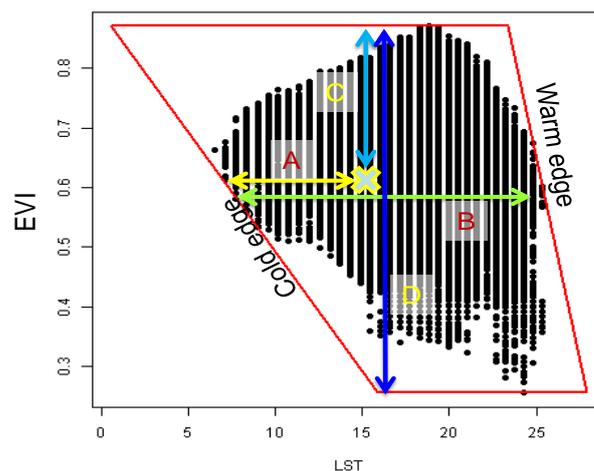


Figure 2. Showing the vegetation thermal domain (VTD) with canopy stress index and moisture stress index measured in the vertical and horizontal axis, respectively.

3 Results and Discussion

3.1 Canopy stress measured from satellites a good surrogate for determining crop water stress

EVI values peaked between 3 and 10th September. This was close to the flowering date of 7th September 2011. Station 2 showed lower EVI values during emergence and green-up and after flowering confirming the lower observed plant density and shallower sandier soil for that station. In addition EVI values were higher during the entire cropping period across all stations. This exemplifies its ability to have higher sensitivity to address atmospheric and soil background noise resulting in enhancement of the canopy greenness spectral signature. Average CSI for station 1, 2 and 3 were 0.49, 0.59 (slightly stressed) and -0.26 (less stressed) over the duration of the crop growth period, respectively. In addition, moderate correlations of calculated CSI (at 12 noon) for stations 1 and 2 and stations 2 and 3 equate to r-squares of 0.80 and 0.73, respectively. This further confirmed the variation in soil attributes (e.g. clay content) across field. Difference in surface temperature from the Landsat imagery and station infrared thermometer measurements were the smallest at and around flowering. This concurs with previous research that showed that the CSI is closely mimicking plant water stress when the plant canopy is at full closure (Idso et al., 1981). Therefore, application of the VTD approach (Moran et al., 1994) overcomes the limitation of measuring crop stress during early stages of crop growth when cover is in-complete as showed here.

3.2 Determining crop yield from the vegetation – thermal domain (VTD)

Very high wheat yields of 6.79 t/ha, 5.62 t/ha and 6.86 t/ha for station 1, 2 and 3, respectively, were observed. An aggregated harvested yield of 6.27 t/ha was recorded for the entire single study field. Huge variation however existed between fields with a low of 1.31 t/ha t/ha and a maximum of 6.84 tons/ha on average. Suggesting enough variability to be able to attain the ability of the VTD approach to predict actual wheat yields across multiple fields.

At a point (station) scale (aggregated yield and Landsat data), the regression coefficients (R^2) for maximum EVI, CSIsat (Day of year (DOY) 246; around flowering), cumulative CSIsat and cumulative MS and harvested field scale wheat yield were 0.95, 0.95, 0.96 and 0.91, respectively. Thus suggesting that the stress measured at canopy level across the entire crop growth period can explain most of the variation in final harvested field scale wheat yields. The period around flowering showed the highest correlation and concurs with previous findings at point scale (Rodriguez et al., 2005). However, when applying the fixed date approach (DOY 246) the CSIsat could only explain 67% of the variability in wheat yields across all fields. Final wheat yields across all 39 fields showed a significantly high r-square of 0.92 when contrasted against multiple CSS variables (i.e. coinciding CSIsat and MSIsat metrics for the five dates between DOY 190 to DOY 262). Thus, suggesting that

the prediction of final wheat yield is achievable at different times during the crop growth season when assessing impact of water stress on wheat yield across larger regions.

Accuracies, although varying, will increase as the season progresses and as flowering and maturity are approached (Potgieter et al., 2003). This analysis clearly exemplifies that a strong relationship exist between crop canopy status metrics, within the vegetation – thermal domain, and actual observed wheat yield. The ability of calculating yield losses due to water stress through the use of remote sensing metrics, at the canopy level, will not only establish spatial specificity, but are likely to lead to (i) increased uptake of crop insurance product, (ii) enhanced transfer of downside on farm risk (i.e. mitigation) and (iii) improved capability of hedging of the reduction of on farm income due to crop losses caused by water stress. Outputs from this study is likely to further the understanding of canopy-thermal space science and the development of new crop insurance products within the dry land grain cropping as well as pastures/livestock industries.

4 Conclusion

Here we have shown the use of remote sensing metrics that relate to the canopy-thermal environment. Such metrics have been derived and applied here to capture crop losses due to water stress at canopy level across a number of wheat fields for the 2011-cropping season. Validation of such technologies (derived from the thermal bands of MODIS and/or Landsat TM) has not been operationally done before within Australia and specifically, for application in the insurance industry. Outcomes from this project will further our understanding of the causalities and science operating at the crop canopy and thermal space domain within a sub-tropical environment. This is likely to lead to the extrapolability of such methodologies across larger regions and seasons. Furthermore, outputs will enhance the availability of crop insurance products at more localised spatial scale and will link to other applications that link thermal imagery and bio-physical point scale crop modelling (e.g. plant breeding or precision agriculture). It is envisaged that the application of these CSS metrics will lead to enhancing of the accuracy of the regional crop-forecasting framework currently operational in Australia (Potgieter et al., 2008, Potgieter et al., 2005, Potgieter et al., 2006).

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