CROP MATURITY MAPPING USING A LOW-COST LOW-ALTITUDE REMOTE SENSING SYSTEM

Dr Troy Jensen¹, Assoc Prof Armando Apan², Mr Les Zeller³

¹ National Centre for Engineering in Agriculture & Faculty of Engineering and Surveying, University of Southern Queensland, Toowoomba, Qld, Australia.
² Faculty of Engineering and Surveying & Australian Centre for Sustainable Catchments, University of Southern Queensland, Toowoomba, Qld, Australia
³ Primary Industries and Fisheries, Department of Employment, Economic Development and Innovation, 203 Tor St, Toowoomba, Qld, Australia
troy.jensen@usq.edu.au

ABSTRACT

The aim of this investigation was to assess the ability of a low-cost low-altitude (LCLA) remote sensing system to map the maturity of a barley crop. The area imaged was a variety trial plot that was screening varieties for adaptation to potentially tough seasons, generally caused by lack of rain and heat during the early part of the growing season. An indication of the crop maturity available during the growing season would provide an additional layer to be assessed as part of the breeding program.

The LCLA remote sensing system consisted of two digital still cameras (Kodak CX7525): one camera to capture the colour portion of the spectrum and the other to capture the near-infrared. The cameras, along with controlling electronics were positioned in a purpose built unmanned aerial vehicle (UAV). The range of growth stages present varied from Zadok 43 to 59, including 14 different classes signifying the range of crop maturities.

Sample areas were randomly selected from the 176 variety plots displayed in this image. The statistical package SPSS was utilised to perform the discriminant function analysis. The classification results (when trying to predict the original 14 classes) indicated that the predictive power is weak, as only 23 % of the original grouped classes were correctly classified. As the classes represents individual growth stages of the crop, a difference of one in the Zadok scale can mean as little as an extra leaf unfolded or an extra tiller on the plant.

The accuracy was further improved by progressing into 6 secondary growth stages, 3 principal growth stages, and finally refining the classification to two classes – the primary growth stages: booting (Z40–49) and emergence (Z50–59). This resulted in an accuracy of classification of 83.5 %, which was considered acceptable, especially allowing for the fact that the image was taken over a month after the growth stages were recorded. This investigation demonstrated that the LCLA remote sensing system had the capacity to rapidly access maturity in multiple plots in the trial, providing an additional parameter in the variety evaluation matrix.

INTRODUCTION

There are numerous satellites that can provide remotely sensed imagery (e.g. Landsat, SPOT, IKONOS and ASTER), however the spatial and temporal resolution prevents their use in variety trials as was attempted in this investigation. Aerial imagery acquisitions resolve some of these issues (i.e. has finer spatial resolution and ability to be captured on demand), however, this system also creates other problems. The cost of imagery is very high when a dedicated mobilisation of the aircraft is required and there is the issue of availability of the plane and sensor, particularly when sourced from interstate where long transit distances are involved.

Several studies have shown that low-altitude platforms (e.g. kites, balloons, blimp and remotely controlled aircraft) have the capacity to be used as an alternative platform for observing various agricultural phenomena. Low-cost low-altitude remote sensing systems have been used on a number of recent investigations to: a) determine yield and protein relationships with imagery (Jensen et al. 2007); b) map spatial variability between and within agricultural (rice and soybean) fields (Inoue et al. 2000) and assess crop N status (Jia et al. 2004); c) monitor rangeland condition (Hardin & Jackson 2005); and d) detect weeds (Lamb & Brown 2001; Richardson et al. 1985).

Measuring crop parameters during the growing season is a useful tool in cereal breeding programs (Ferrio et al. 2005). Canopy reflectance provides a non-destructive way, that before harvest, can provide estimates that are very useful for selection, particularly in the early generations of a breeding program. Crop maturity assessment, regularly conducted as part of a breeding program, is traditionally achieved by crop dissection and/or visual inspection (Zadoks et al. 1974). These approaches are both labour intensive and subjective, limiting the number of observations made by a single observer, and the repeatability of the measurement (Scotford & Miller 2004).

The aim of this study was to evaluate the potential of assessing crop maturity using digital imagery acquired from a low-altitude platform.

METHODOLOGY

Study Area

The study area was located at ‘Lundavra’, a wheat and barley variety trial site in the Goondiwindi district of southern Queensland (150.087°, -28.056°), Australia. The site was established to screen both wheat and barley varieties for adaptation to potentially tough seasons, generally caused by lack of rain and heat during the early part of the growing season. In 2005, the trial was high yielding due to favourable seasonal conditions.

The original intention of this investigation was to compare traditional meter-resolution aerial imagery to that of the updated LCLA remote sensing system. Due to unforseen
delays by the commercial imagery provider, the acquired image was captured late in the growing season. In the conventional aerial image of the entire trial site (shown in Figure 1), little variability is evident due to the mature growth stage of the crop. Even though the site was imaged with the updated LCLA system, the planned comparison could not be undertaken due to the maturity of the crop. The potential of using the updated LCLA system to predict the stage of crop maturity was however evaluated, and will be reported in the following section.

A schematic representation of the barley trial layout is shown in Figure 2. Each plot consisted of four rows of plants, totalling 1.05 m wide and 5.0 m long. There are 192 plots per row and eight rows in total. The extent of the barley trial was 200 long x 50 m wide. The trial was planted on 24 May 2005 and harvested on 26 October 2005. The area analysed is indicated by the red box in both Figure 1 and 2.

The LCLA remote sensing system
The LCLA remote sensing system was based on the system developed and detailed in Jensen (2007). Rather than using 1.0 megapixel cameras as in the previously mentioned study, this investigation utilised 5.0 megapixel Kodak Easyshare CX7525 (specifications available from www.kodak.com) Digital Zoom Camera (Eastman Kodak Company, Rochester NY). As describe in the previous work, the 2-camera system (one camera to capture the colour and the other the near-infrared portion of the spectrum) was remotely triggered, and were sensitive to near-infrared light (once the NIR cut-out filter had been removed). The 2-camera sensor developed is shown in Figures 3 and 4.
Figure 1 Conventional aerial image taken of the wheat (top) and barley (bottom) variety trial site at ‘Lundavra’, October 2005. The area indicated in red box is the area analysed.

Figure 2 Schematic layout of the barley variety trial at ‘Lundavra’ showing the area analysed in the red box.
Figure 3 The 2-camera sensor utilising the CX7525 cameras.
The cameras were triggered by the use of hobbyist radio control equipment. The output of this equipment was a 50 Hz square wave (a pulse every 20 ms) with a pulse width of 0.9–2.1 ms, depending on the position of the radio control stick. The output was monitored by the use of a micro-controller (PICAXE-08, details at http://www.picaxe.co.uk). The logic in the programmable chip was used to monitor the pulse width on the designated channel of the radio equipment.

When image acquisition was initiated (by ‘flicking-up’ the elevator stick) the changed pulse width was detected and determined to be greater than a pre-programmed value (1.6 ms) resulting in a pulse being output from the PICAXE to trigger the cameras. In order to prevent the cameras going to sleep, a pulse of 2 s duration was sent every 25 s to the pre-shutter-release of the cameras to keep the cameras awake. The cameras and electronics were mounted in a balsa wood frame.

**Deployment**

The crop condition at the trial site is shown in Figure 5, and was approaching maturity, with noticeable variability evident in the image. The LCLA remote sensing system was deployed on 5 October 2005 by mounting the sensor inside the fuselage of a 2.5 m wingspan hobbyist unmanned aerial vehicle (see Figure 5) and manually flying the plane over the target area. The sky was nearly cloud free. As problems were initially encountered with the fuel filter, the first images were only acquired at 1300 hrs.

The flying height during this mission was 150 m (500 ft) with some images collected at 300 m (1000 ft). At the greater height, viewing the aircraft was difficult and control was nearly lost. The system was brought back to ground and the cameras checked. Each camera had logged 150 photos, however the radio control receiver aerial was across some of the images. This was rectified and a second mission undertaken, but staying at 300 m (500 ft). Images were only taken when heading in a northerly direction, and acquired over both the barley and wheat trial areas. One of the images captured over the wheat trial area is shown in Figure 6. Unfortunately, the aircraft crashed on landing and sustained repairable damage.

**Image analysis**

Although images were acquired from across both the wheat and barley trial areas, particular attention was given to the barley as it was the main focus of this investigation. The most appropriate colour and near-infrared images covering the focus area were selected and imported into ERDAS Imagine 9.1 (Leica 2007) for analysis. The near-infrared image covering the focus area was rectified to the corresponding colour image with a total control point error of 5.16 pixels. These two images were then layer stacked with a total control point error of 2.46 pixels. This stacked image was then rectified to the 1.0 m resolution conventional aerial image using a polynomial order two geometric model with 24 ground control points, producing a total control checkpoint error of 2.72 pixels and an output cell size equal to 0.0627 m.
One of the replicates in the barley trial area (see Figure 6) was the focus of this investigation, with 79 areas-of-interest (AOI) randomly selected from the 176 variety plots displayed in this image. As this was a variety evaluation trial, there were varying physiological characteristics that were selected, to enable the plant to cope with the contrasting environmental conditions present at this site. The contrasting physiological characteristics made this trial an ideal crop maturity study. Maturity assessments were conducted at anthesis (31 August 2005), about four weeks prior to the aerial image acquisition. The range of growth stages varied from Zadok 43 to 59, including 14 different classes signifying the range of crop maturities. Descriptions of these particular stages are given in Table 1 with Figure 7 displaying a histogram of the growth stages.

Table 1: Explanation of the growth stages describing the barley crop based on Zadok et al. (1974).

<table>
<thead>
<tr>
<th>Zadok Scale</th>
<th>Booting</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td></td>
</tr>
<tr>
<td>41</td>
<td>Flag leaf sheath extending</td>
</tr>
<tr>
<td>43</td>
<td>Boots just visibly swollen</td>
</tr>
<tr>
<td>45</td>
<td>Boots swollen</td>
</tr>
<tr>
<td>47</td>
<td>Flag leaf sheath opening</td>
</tr>
<tr>
<td>49</td>
<td>First awns visible</td>
</tr>
<tr>
<td>Inflorescence emergence</td>
<td>First spikelet of inflorescence just visible</td>
</tr>
<tr>
<td>50</td>
<td>¼ of inflorescence emerged</td>
</tr>
<tr>
<td>53</td>
<td>½ of inflorescence emerged</td>
</tr>
<tr>
<td>57</td>
<td>¾ of inflorescence emerged</td>
</tr>
<tr>
<td>59</td>
<td>Emergence of inflorescence completed</td>
</tr>
<tr>
<td>Anthesis</td>
<td></td>
</tr>
</tbody>
</table>

A table was generated containing the growth stage and band information (both colour and near-infrared) for the AOI selected. This data was then imported into the statistical
analysis package SPSS. The package was utilised to perform the discriminant function analysis (DA) which was conducted using a stepwise method of entering a variable based on the Wilks lambda using the observed group sizes to determine the probabilities of group membership. This procedure was undertaken to evaluate the ability of the LCLA remote sensing system to predict the growth stage of the crop.

Figure 6 Selecting the AOIs from the individual plots in the investigated area covered by the red box in Figures 2 and 3.
RESULTS AND DISCUSSION

The classification results, using the original 14 classes, indicated that the predictive power is weak, as only 23% of the original grouped classes were correctly classified and only 14% of the cross-validated cases correct. This lack of power was resultant from the large number of original classes. As the classes represent individual growth stages of the crop (Zadoks et al. 1974), a difference of one in the Zadok scale can mean as little as an extra leaf unfolded or an extra tiller on the plant.

Due to the large number of classes and the minor difference between each class, classifying into 14 classes was going to be problematic, resulting in the low accuracy of classification. The first iteration of refining the classification entailed reducing the classes to align with the plant secondary growth stages (detailed in Table 2), with the grouped secondary growth stages labelled as ‘Grouped Zadok’.

Using the same parameters as the previous case, this classification resulted in an accuracy of 38% of original grouped cases correctly classified, with 34% of cross-validated grouped cases correctly classified. This was an improvement on the previous classification, but the difference between the growth stages of these ‘secondary’ classes was still fine. To further refine the classification, slight variations of the principal plant growth stages (as described by Zadok (1974)), were used to potentially provide a more accurate classification. Details of the principal growth stages are shown in Table 3.

![Figure 7](image_url)  
Figure 7  The frequency and distribution for the 14 different growth stages.
T. Jensen, A. Apan & L. Zeller

Table 2 The Zadoks range for the grouped secondary growth stages.

<table>
<thead>
<tr>
<th>Grouped Zadoks</th>
<th>Zadok range</th>
<th>Crop growth stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40-45</td>
<td>Early booting</td>
</tr>
<tr>
<td>2</td>
<td>46-49</td>
<td>Late booting</td>
</tr>
<tr>
<td>3</td>
<td>50-52</td>
<td>First spikelets visible to &lt;1⁄4 of inflorescence emerged</td>
</tr>
<tr>
<td>4</td>
<td>53-54</td>
<td>1⁄4 to &lt;1⁄4 of inflorescence emerged</td>
</tr>
<tr>
<td>5</td>
<td>55-56</td>
<td>1⁄2 to &lt;1⁄4 of inflorescence emerged</td>
</tr>
<tr>
<td>6</td>
<td>57-59</td>
<td>3⁄4 of inflorescence emerged to emergence completed</td>
</tr>
</tbody>
</table>

Table 3 The Zadoks range of the 3 principal growth stage classes.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Zadok scale</th>
<th>Crop growth stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40-49</td>
<td>Booting</td>
</tr>
<tr>
<td>2</td>
<td>50-54</td>
<td>Early emergence</td>
</tr>
<tr>
<td>3</td>
<td>55-59</td>
<td>Late emergence</td>
</tr>
</tbody>
</table>

The classification results for the 3 principal growth stages are shown in Table 4. The results are more encouraging with 65% of the original cases classified correctly and 63% of the cross-validated classified correctly. In the booting class (Z40–49) approximately 50% were correctly classified with 50 being classified into both of the emergence classes. The early emergence class (Z40–54) had more than 90% correctly classified. In the late emergence class, over 90% of the cases were misclassified as early emergence. To further refine the classification, two classes were attempted based on the primary growth stages: booting (Z40–49) and emergence (Z50–59). The classification results for these classes are shown in Table 5.

Table 4 The classification results for the 3 principal growth stages.

<table>
<thead>
<tr>
<th>Classification Results&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Growth Stage</th>
<th>Predicted Group Membership</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Original</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Count</td>
<td>1240-49</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>2 250-54</td>
<td>2</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>3 255-59</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>47.6</td>
<td>47.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.8</td>
<td>92.9</td>
</tr>
<tr>
<td></td>
<td>Cross-validated&lt;sup&gt;a&lt;/sup&gt; Count</td>
<td>1240-49</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>2 250-54</td>
<td>2</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>3 255-59</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>47.6</td>
<td>47.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.8</td>
<td>92.9</td>
</tr>
</tbody>
</table>

<sup>a</sup> Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

<sup>b</sup> 64.6% of original grouped cases correctly classified.

<sup>c</sup> 63.3% of cross-validated grouped cases correctly classified.
The classification results for the classes based on the primary growth stages of the crop is quite acceptable (83.5% correctly classified), especially considering that the image was taken over a month after the growth stages were recorded. The varieties of the trial that were not as advanced when the growth stages were recorded have continued to remain behind the more advance varieties, with this being indicated by the cases correctly classified. Greater differentiation may have been possible had the duration between the growth stages assessment and the image acquisition been minimised.

The results presented in this paper detail the capacity to assess crop maturity quite late in the growing season. This system compares well with the more complicated sensing system detailed by Scotford and Miller (2004) that used a radiometer and ultrasonic device to achieve good maturity assessment up to crop growth stage 31.

Table 5 The classification results for the primary growth stages.

<table>
<thead>
<tr>
<th>Classification Results\textsuperscript{a,c}</th>
<th>Primary growth stage</th>
<th>Predicted Group Membership</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Count</td>
<td>1 Z40-49</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>2 Z50-59</td>
<td>2</td>
<td>56</td>
</tr>
<tr>
<td>%</td>
<td>1 Z40-49</td>
<td>47.6</td>
<td>52.4</td>
</tr>
<tr>
<td></td>
<td>2 Z50-59</td>
<td>3.4</td>
<td>96.6</td>
</tr>
<tr>
<td>Cross-validated\textsuperscript{a}</td>
<td>1 Z40-49</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>2 Z50-59</td>
<td>2</td>
<td>56</td>
</tr>
<tr>
<td>%</td>
<td>1 Z40-49</td>
<td>47.6</td>
<td>52.4</td>
</tr>
<tr>
<td></td>
<td>2 Z50-59</td>
<td>3.4</td>
<td>96.6</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

\textsuperscript{b} 83.5% of original grouped cases correctly classified.

\textsuperscript{c} 83.5% of cross-validated grouped cases correctly classified.

CONCLUSIONS

The capacity of the low-cost low-altitude remote sensing system to assess crop growth stage was investigated in this study. Considering the timing difference between the maturity assessment and the image acquisition, the system performed well. With a classification accuracy of 83.5%, the system was able to accurately determine the primary growth stages (booting (Z40–49) and emergence (Z50–59)) of the crop.

This ability to monitor crop maturity could prove useful to determine the harvesting strategy in both trial areas (such as the one being investigated) and in broader scale operations. This capacity is important when inclement weather conditions are pending and the whole area cannot be harvested in the time available. This system also provides another assessment tool that can be used to evaluate the varieties grown in this trial.

If detail finer than the primary growth stage is required, further work will be needed to determine the full capabilities of this system. Additionally, if the target area is not captured within a single image, additional effort will be required to collect sufficient ground control points to enable the images to be geometrically rectified and mosaiced, before any analysis can be conducted.

1241
REFERENCES


BRIEF BIOGRAPHY OF PRESENTER

Applying engineering technologies to agriculture is something that Troy has been doing since he commenced work with the Department of Primary Industries in 1987.

Since this time, he has worked as a research engineer and has gained extensive applied research experience in such diverse areas as: agricultural machinery precision agriculture, remote sensing, controlled traffic farming, and native grass seed harvesting and management.

Troy recently completed his PhD titled "Using a Remotely Controlled Platform to Acquire Imagery for Grain Crop Mapping" and is currently a Senior Research Fellow with the National Centre for Engineering in Agriculture at the University of Southern Queensland.