A Remote Sensing-based Biophysical Modelling Approach for Estimation of Crop Yield in Irrigated Agriculture for Australian Conditions

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A thesis submitted for the degree of
Doctor of Philosophy in Environmental Sciences

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Australia
December 2014
CERTIFICATE OF AUTHORSHIP

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Name: Indira Wittamperuma Arachchige

Signature

Date
ACKNOWLEDGEMENTS

I would like to express my thanks to all the people and organisations that have helped me to complete my thesis successfully. I would like to thank Charles Sturt University for offering me a scholarship to carry out my PhD studies to complete the study. Also I would like to extend my deep gratitude to my employer in Sri Lanka, the Institute of Technology and the University of Moratuwa (ITUM) for granting me study leave. I express my heartiest gratitude and thanks to my principal supervisor Associate Professor Mohsin Hafeez for his help, guidance and encouragement. Throughout my study period his new ideas, inspiration and continuous support were very valuable. Especially, I am thankful for the constant technical and moral support he has given me during my studies. My sincere thanks also should go to my co-supervisor Associate Professor John Louis for his supervision and new ideas. His constructive criticism led me to add new ideas to the research.

I wish to express many thanks to my friend Kaleem Ullah for his technical and moral support. I am very much thankful for his tireless help in reading my thesis and giving his valuable comments. Moreover I would like to thank to my colleagues Mojtaba Pakpavar, Umair Rabbani, Partha Saha and Mahmood Kahn for their technical and moral support. I wish to express my gratitude to Jan Saunders for her help on reading my thesis for final editing.

I am also thankful to Coleambally Irrigation Cooperative Limited (CICL) management for facilitation in data collection as well to many farmers who allowed me to carry out data collections at their farms.

Finally, I am especially thankful to my mother, my husband Kalyana and my little son Thevindu for their patience, support and love. Without their support, I would not have come this far to complete my PhD.
ABSTRACT

With rising world population, irrigated agriculture faces the problem of accommodating increases in demand for food while maintaining the sustainable use of limited water resources. By 2030, demand for cereal for human and animal consumption is expected to increase by 50% from its level in 2000. Such high demand must be met despite less water being available for irrigated agriculture. Irrigated agriculture accounts for 40% of the world’s food production and uses over 70% of consumptive water. However with climate change and the pressure of population, there is no possibility that this level of water usage can be sustained into the future and thus there is an urgent need to improve water use efficiency and water productivity in the irrigated agriculture sector. In order to achieve improved efficiency and productivity, accurate crop yield estimation is crucial. This will also contribute to improved water resource management, food security at national and international levels, and food trade planning.

Many biophysical models have been developed for the estimation of crop yields in Australia and globally. For example, the Maizeman model was developed in Australia for estimating the yield of maize crops at farm scale while the ORYZA2000 model has been widely used for the estimation of rice crop yields. However, these models are only able to provide crop yield information at the farm scale and are not able to provide total crop yield production data at the irrigation system or catchment/basin scale. A number of research projects have been undertaken to develop catchment-scale yield models for forecasting the crop yields of different crop types using state-of-the-art remote sensing techniques in many countries. However, there have been very limited applications of remote sensing of broad acre irrigated crops grown in Australian conditions. This study has tried to estimate the spatial variability of crop yield using a remote sensing modelling technique in order to fill this gap in the research and to provide a practical and accurate model over the Coleambally Irrigation Area located in the Riverina region of NSW.
This study focused on yield estimation for maize/corn, rice and wheat, three crops commonly grown in the Coleambally Irrigation Area (CIA) which is located in the Murray Darling Basin. This study developed CIA-specific relationships between the Leaf Area Index (LAI) and the Normalised Difference Vegetation Index (NDVI) using satellite and on-ground measurements for the three crops grown in various soil types. The novel biophysical models developed are able to use the estimation of ground-based LAI in the CIA. In addition the biophysical models, incorporated with the object-oriented modelling technique, have been used for classifying the three irrigated crops in the area. In the classification phase, high and medium level spatial resolution optical satellite imagery was used in order to obtain highly accurate classification maps. The overall accuracy of the classification map obtained in this research was 78% for winter 2010 and 85% for summer 2010/11. The average producer and user accuracies for winter were 79% and 78% respectively and for summer 85% and 86% respectively.

The biophysical models and classification maps developed were integrated to extract biomass growth over the cropping season in the CIA. By integrating biomass production with the crop specific harvest index, the crop yield for each crop for the two seasons, winter and summer, was estimated a few weeks before the harvest. The estimation of crop yield for corn, rice and wheat were in 93, 91% and 86% in agreement with the published data.

In conclusion it can be stated that the general reliability and accuracy of this robust method is promising and the method has proved to be an effective tool in regional yield estimation in Australian conditions. The method proved to be stable and accurate for operational use for crop yield estimation at the irrigation system level across Australia.
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<th>Abbreviation</th>
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<tbody>
<tr>
<td>ABS</td>
<td>Australian Bureau of Statistics</td>
</tr>
<tr>
<td>ABARE</td>
<td>Australian Bureau of Agriculture and Resource Economics and Sciences</td>
</tr>
<tr>
<td>ALEXI</td>
<td>Atmospheric Land Exchange Inverse</td>
</tr>
<tr>
<td>ALI</td>
<td>Advanced Land Imager</td>
</tr>
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<td>ANRA</td>
<td>Australian Natural Resource Atlas</td>
</tr>
<tr>
<td>APAR</td>
<td>Absorbed Photosynthetically Active Radiation</td>
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<tr>
<td>APSIM</td>
<td>Agricultural Production Systems sIMulator</td>
</tr>
<tr>
<td>APSRU</td>
<td>Agricultural Production System Research Unit</td>
</tr>
<tr>
<td>ARVI</td>
<td>Atmospherically Resistant Vegetation Index</td>
</tr>
<tr>
<td>ASTER</td>
<td>Advanced spaceborne thermal emission and reflection radiometer</td>
</tr>
<tr>
<td>ASD</td>
<td>Analytical Spectral Device</td>
</tr>
<tr>
<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
</tr>
<tr>
<td>AWS</td>
<td>Automatic Weather Station</td>
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<tr>
<td>B</td>
<td>Biomass</td>
</tr>
<tr>
<td>BARC</td>
<td>Beltsville Agriculture Research Centre</td>
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<tr>
<td>BoM</td>
<td>Bureau of Meteorology</td>
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<tr>
<td>CASA</td>
<td>Carnegie-Ames-Stanford-Approach</td>
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<tr>
<td>CIA</td>
<td>Coleambally Irrigation Area</td>
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<td>CICL</td>
<td>Coleambally Irrigation Cooperative Limited</td>
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<td>CMA</td>
<td>Murrumbidgee catchment Management Authority</td>
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<tr>
<td>(C_p)</td>
<td>Air specific heat</td>
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<tr>
<td>CSIRO</td>
<td>Common Wealth Scientific and Industrial Research Organization</td>
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<td>CSU</td>
<td>Charles Sturt University</td>
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<tr>
<td>CWWSA</td>
<td>Coleambally Water Smart Australia</td>
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<td>d</td>
<td>Sun-earth distance</td>
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<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>DLCD</td>
<td>Dynamic Land Cover Dataset</td>
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<td>DLWC</td>
<td>Department of Land and Water Conservation</td>
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<tr>
<td>DVI</td>
<td>Difference Vegetation Index</td>
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<tr>
<td>DN</td>
<td>Digital numbers</td>
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<td>DPI</td>
<td>Department of Primary Industries</td>
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<tr>
<td>EO-1</td>
<td>Earth Observing 1</td>
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<tr>
<td>EPIC</td>
<td>Environmental Policy Integrated Climate</td>
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<tr>
<td>ET</td>
<td>Evapotranspiration</td>
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<tr>
<td>ETa</td>
<td>Actual Evapotranspiration</td>
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<tr>
<td>ETM</td>
<td>Enhanced Thematic Mapper</td>
</tr>
<tr>
<td>EVI</td>
<td>Enhanced Vegetation Index</td>
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<tr>
<td>FAO</td>
<td>Food and Agriculture Organization</td>
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<tr>
<td>f</td>
<td>Fraction of Photosynthetically Active Radiation</td>
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<tr>
<td>$F_s$</td>
<td>Post anthesis phase</td>
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<tr>
<td>FLAASH</td>
<td>Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes</td>
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<tr>
<td>G</td>
<td>Soil Heat Flux</td>
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<tr>
<td>GEPIC</td>
<td>GIS based Environmental Policy Integrated Climate</td>
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<tr>
<td>GESAVI</td>
<td>Generalised Soil Adjusted Vegetation Index</td>
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<tr>
<td>GIS</td>
<td>Geographic Information System</td>
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<tr>
<td>GLO-PEM</td>
<td>Global Production Efficiency Model</td>
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<tr>
<td>GPS</td>
<td>Global Positioning System</td>
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<td>H</td>
<td>Sensible Heat Flux</td>
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<tr>
<td>HI</td>
<td>Harvest Index</td>
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<tr>
<td>HI$_{\text{eff}}$</td>
<td>Effective Harvest Index</td>
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<tr>
<td>IREC</td>
<td>Research and Extension Committee</td>
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<tr>
<td>IRRI</td>
<td>International Rice Research Institute</td>
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<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
<td>ISODATA</td>
<td>Iterative Self Organising Data Analysis Technique</td>
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<tr>
<td>IWMI</td>
<td>International Water Management Institute</td>
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<tr>
<td>J</td>
<td>Julian day</td>
</tr>
<tr>
<td>Kc</td>
<td>Crop Coefficient</td>
</tr>
<tr>
<td>K_{24}</td>
<td>Average solar radiation for 24 hours</td>
</tr>
<tr>
<td>KC</td>
<td>Kappa Coefficient</td>
</tr>
<tr>
<td>K_{EXO}</td>
<td>Diurnal average sun exo-atmospheric radiation</td>
</tr>
<tr>
<td>KS</td>
<td>Sun’s external atmosphere radiation</td>
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<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
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<tr>
<td>LAT_y</td>
<td>Latitude</td>
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<tr>
<td>LULC</td>
<td>Land Use and Land Cover</td>
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<tr>
<td>LWMP</td>
<td>Land and Water Management Plan</td>
</tr>
<tr>
<td>MASAVI2</td>
<td>Modified Second Soil Adjusted Vegetation Index</td>
</tr>
<tr>
<td>MDB</td>
<td>Murray Darling Basin</td>
</tr>
<tr>
<td>MDBC</td>
<td>Murray Darling Basin Commission</td>
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<tr>
<td>METRIC</td>
<td>Mapping Evapotranspiration at high Resolution and with Internalized Calibration MODIS Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>m_{dry}</td>
<td>Weight of dried sample</td>
</tr>
<tr>
<td>MIA</td>
<td>Murrumbidgee Irrigation Area</td>
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<td>MLC</td>
<td>Maximum Likelihood Classifier</td>
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<tr>
<td>MO</td>
<td>Moisture Content</td>
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<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
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<tr>
<td>m_{wet}</td>
<td>Weight before drying the sample</td>
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<tr>
<td>MSE</td>
<td>Mean Square Error</td>
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<tr>
<td>MSI</td>
<td>Moisture Stress Index</td>
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<td>MSR</td>
<td>Multi Spectral Radiometer</td>
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<td>Abbreviation</td>
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</tr>
<tr>
<td>MTVI2</td>
<td>Modified Second Triangular Vegetation Index</td>
</tr>
<tr>
<td>MVC</td>
<td>Maximum Value Composite</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td>NWC</td>
<td>National Water Commission</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NDVI_G</td>
<td>Ground based Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NDII</td>
<td>Normalized Difference Infra-red Index</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infra Red</td>
</tr>
<tr>
<td>PAR</td>
<td>Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>PAR_{\text{incoming}}</td>
<td>Total amount of incoming Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>PAR_{\text{trans}}</td>
<td>Total amount of transmitted Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>PAR_{\text{ref}}</td>
<td>Total amount of reflected Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>PBL</td>
<td>Planetary Boundary Layer</td>
</tr>
<tr>
<td>PRI</td>
<td>Photochemical Reflectance Index</td>
</tr>
<tr>
<td>PVI</td>
<td>Perpendicular Vegetation Index</td>
</tr>
<tr>
<td>R</td>
<td>Solar Angle Range for diurnal sun exposition</td>
</tr>
<tr>
<td>Rah</td>
<td>Aerodynamic Resistance</td>
</tr>
<tr>
<td>RL_↓</td>
<td>Incoming Long Wave Radiation</td>
</tr>
<tr>
<td>RL_↑</td>
<td>Outgoing Long Wave Radiation</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>Rn</td>
<td>Net Radiation</td>
</tr>
<tr>
<td>Rs</td>
<td>Incoming Short Wave Radiation</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>RVI</td>
<td>Ratio Vegetation Index</td>
</tr>
<tr>
<td>SAVI</td>
<td>Soil Adjusted Vegetation Index</td>
</tr>
<tr>
<td>SAM-ET</td>
<td>Spatial Algorithm for Mapping Evapotranspiration</td>
</tr>
<tr>
<td>SARP</td>
<td>System Analysis for Rice Production</td>
</tr>
<tr>
<td>SEBAL</td>
<td>Surface Energy Balance Algorithm for Land</td>
</tr>
<tr>
<td>SEBS</td>
<td>Surface Energy Balance System</td>
</tr>
<tr>
<td>SLA</td>
<td>Specific Leaf Area</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite for observation of Earth</td>
</tr>
<tr>
<td>SR</td>
<td>Simple Ratio</td>
</tr>
<tr>
<td>SURF</td>
<td>Surface Reflectance</td>
</tr>
<tr>
<td>SVI</td>
<td>Spectral Vegetation Index</td>
</tr>
<tr>
<td>TOAR</td>
<td>Top Of Atmospheric Reflectance</td>
</tr>
<tr>
<td>T&lt;sub&gt;OPT&lt;/sub&gt;</td>
<td>Optimum temperature</td>
</tr>
<tr>
<td>T&lt;sub&gt;mean&lt;/sub&gt;</td>
<td>Mean temperature</td>
</tr>
<tr>
<td>T&lt;sub&gt;mean&lt;/sub&gt;</td>
<td>Mean temperature</td>
</tr>
<tr>
<td>T&lt;sub&gt;a&lt;/sub&gt;</td>
<td>Atmospheric temperature</td>
</tr>
<tr>
<td>T&lt;sub&gt;S&lt;/sub&gt;</td>
<td>Surface temperature</td>
</tr>
<tr>
<td>T&lt;sub&gt;g&lt;/sub&gt;</td>
<td>Soil temperature</td>
</tr>
<tr>
<td>Ts</td>
<td>Radiometric Surface Temperature</td>
</tr>
<tr>
<td>TCC</td>
<td>Total Channel Control</td>
</tr>
<tr>
<td>TM</td>
<td>Thematic Mapper</td>
</tr>
<tr>
<td>USGS</td>
<td>United States Geological Survey</td>
</tr>
<tr>
<td>W</td>
<td>Soil moisture</td>
</tr>
<tr>
<td>WRI</td>
<td>Weighted Rainfall Index</td>
</tr>
<tr>
<td>W&lt;sub&gt;S&lt;/sub&gt;</td>
<td>Solar angle hour</td>
</tr>
<tr>
<td>Y</td>
<td>Crop Yield</td>
</tr>
<tr>
<td>Symbol</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>------------------------------</td>
</tr>
<tr>
<td>$\alpha_S$</td>
<td>Surface albedo</td>
</tr>
<tr>
<td>$\rho_{air}$</td>
<td>Air density</td>
</tr>
<tr>
<td>$\rho_{ah}$</td>
<td>Aerodynamic resistance</td>
</tr>
<tr>
<td>$\rho R$</td>
<td>Red Reflectance</td>
</tr>
<tr>
<td>$\rho NiR$</td>
<td>Near infra Red Reflectance</td>
</tr>
<tr>
<td>$C_p$</td>
<td>Specific Heat of Air</td>
</tr>
<tr>
<td>$\Delta T$</td>
<td>Temperature Difference Between two surfaces</td>
</tr>
<tr>
<td>$\lambda_e$</td>
<td>Thermal conductivity</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Light use efficiency</td>
</tr>
<tr>
<td>$\varepsilon_r$</td>
<td>Maximum Light use efficiency</td>
</tr>
<tr>
<td>$\varepsilon_S$</td>
<td>Surface emissivity</td>
</tr>
<tr>
<td>$\varepsilon_a$</td>
<td>Atmospheric emissivity</td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>Evaporative fraction</td>
</tr>
<tr>
<td>$\lambda E$</td>
<td>Latent heat flux</td>
</tr>
<tr>
<td>$\tau_S$</td>
<td>Atmospheric single way transmissivity</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Solar declination</td>
</tr>
<tr>
<td>$Z_S$</td>
<td>Soil depth</td>
</tr>
</tbody>
</table>
1 INTRODUCTION

1.1 Background

In many parts of the world, the demand for water has exceeded supply as a result of a rapid increase in population, climate change and increasing demands from agriculture, industry and the urban sector.. Factors such as dietary changes, urbanisation, increasing demand for bio-fuel and hydropower are also placing more pressure on available water resources (Bos, 2004; IWMI, 2009; Teixeira, 2008). As a result, many countries are facing water scarcity.

With the rising world population, irrigated agriculture faces the problem of accommodating increased food demand while maintaining a sustainable use of limited water resources (Santos et al., 2008). The increasing demand for food can be met either by increasing agricultural land area or increasing the yield of existing agricultural areas with the same or even less utilisation of water resources. However the increased competition for water from different sectors limits the option of expanding the areas under agriculture (Ullah, 2011). Therefore, in the future it is most plausible to produce greater yield with less water use in irrigated agriculture. The major issue of availability of fresh water in irrigated agriculture is particularly crucial in arid and semi-arid areas where water scarcity is the major barrier to the production of food (Muthuwatta et al., 2010; Ullah, 2011).

Variations in water stress indicators around the globe are shown in Figure 1.1. The degree of water stress is defined by calculating the ratio of utilised water to total withdrawals (Smakhtin et al., 2004). According to the definition of the water stress indicator, if the index is greater than one the area is classified as a water scarce region. Higher indices indicate a high level of water resource exploitation and consequently a high risk of water scarcity is to be expected in these areas. The areas of highest water scarcity around the world are shown in red in the figure.
Figure 1.1: The global water stress indicator (Smakhtin et al., 2004)

The recent emergence of the world food crisis in 2008 led to a dramatic rise of 40% in the cost of food items within a short period - less than one year. One of the principal reasons for the food crisis was water scarcity resulting from the competing demands among different traditional water consumers for available water resources as well as the effect of climate change (IWMI, 2009). Water scarcity is fast becoming a critical issue in both developed and developing countries (IWMI, 2009). In many parts of the world, ongoing increases in population have also contributed significantly to the water scarcity demand (Smakhtin et al., 2004; Teixeira, 2008). Water scarcity can be either physical or economic in nature. Some parts of the world face physical water scarcity which is largely driven by agricultural water consumption, while other parts experience water scarcity resulting from economic or politically determined factors such as a lack of water resource development (IWMI, 2009).

Irrigation is the greatest consumer of fresh water accounting for approximately 70% of consumption. Global water produces 40% of world food production from only 17-18% of global arable croplands (Bastiaanssen et al., 2000; Seckler et al., 1998). Having water for irrigation to produce agricultural crops in arid and semi-arid areas has both positive and negative
outcomes. On the one hand it can produce higher yields; however it also leads to issues in the water table (Bos, 2004). The water table rise adversely affects the quality of water and therefore water users across all sectors must compete for the limited available supply of fresh water (Teixeira, 2008). Future water management authorities may have to consider a proper water accounting approach in order to achieve sustainable water resource development and to secure the available water (Molden, 1997; Teixeira, 2008).

Meeting the rapidly increasing demand for food with reduced water availability for irrigation may be possible if the water resources are managed more effectively. One tool that can assist in this is remote sensing. Remote sensing can be used to produce more reliable information on land use and land cover, the area irrigated, crop health and crop yield, evapotranspiration (ET) and crop water stress. This information can then be used for management of water resources (Bastiaanssen et al., 2000). Estimation of crop yield is becoming more important across the world because it is paramount in policy planning and decision making in agriculture. Growth in population necessitates increased production of food with less water available for agriculture (Serageldin, 1999a). This situation can only be addressed by managing water resources more efficiently. This in turn can be achieved by increasing productivity, in other words, by increasing the crop yield per unit of water consumed (Bastiaanssen & Ali, 2003). Moreover, crop yield is the ultimate key factor which describes the agricultural responses to water resource management (Molden & Sakthivadivel, 1999). Therefore the regional estimation of crop yield and the monitoring of crop growth are paramount in establishing the relationship between crop yield and hydrological processes in improving the productivity of water. The crop yield is also a key factor for rural development, food prices, cropland expansion and a measure for national food security (Bastiaanssen & Ali, 2003). In addition, it is beneficial for farmers in making their marketing plans in advance and in providing timely information for the optimum management of crops (Horie et al., 1992).
One of the most widely used crop growth models in establishing crop yield is the process-based crop growth simulation model which simulates physiological growth and the yield of a crop based on the interactions between environmental factors and plant physiological processes (Mo et al., 2005). Even though a process-based crop growth model can simulate crop yield in different environmental and management situations, it still faces great challenges in capturing the spatial and temporal variability in crop yield due to the uncertainty of spatial environmental-driven data such as weather, soil, management, irrigation and fertilisation (Shi & Xingguo, 2011). Retrieving this environmental information has necessitated the use of remote sensing in recent years because of its spatial and temporal density and repeatable measuring capability.

Australia is the driest inhabited continent in the world where extreme variability in rainfall and drought is very common. Rainfall is a limiting factor in agricultural productivity; however with irrigation, the productivity was increased significantly in the country (ANRA, 2012). The state and territory governments of Australia vest water rights for a variety of purposes including irrigation, industrial usage and to meet the demands of rural and urban communities. The major challenge the country faces is balancing water extraction by different users while maintaining the appropriate, healthy flow of rivers and the level of groundwater. This balance has been disturbed since last century due to the overexploitation of water resources for agriculture production (Chartres & Williams, 2006).

The agriculture industry plays a dominant role in the Australian economy. For agricultural activities the country utilises 52% of the country’s land and 52% of the country’s national water (ABS, 2012). Recent droughts in Australia and concerns about climate change have highlighted the need to manage agricultural water resources more sustainably. Within Australia, the Murray Darling Basin (MDB) is the largest catchment for irrigation activities and covers 1.06 million km\(^2\) or about 14% of the total area of Australia. The MDB is responsible for 37% of the country’s irrigating agricultural businesses, 53% of all irrigated agricultural land and 54% of irrigation water applied (Zuo et al., 2012).
The major irrigation areas within the basin include Goulburn-Murray, Murray, Murrumbidgee and Coleambally. In the MDB, 25% of diversions for irrigation are lost during conveyance in rivers, 15% are lost from canals and 24% are lost on farms, resulting in only 36% of the water initially diverted being available to crops (Chartres & Williams, 2006).

The Murrumbidgee and Coleambally Irrigation Areas are located in the Murrumbidgee catchment which utilises bulk water for food production, industry and urban water supplies. The Murrumbidgee catchment area is located in NSW and covers approximately 84,000 km² or about 8% of the Murray Darling Basin (ABS, 2010).

1.2 Problem Statement

Irrigated agriculture in Australia uses an average of 14,000GL annually of water which counts for 54% of all water used in Australia. However, the water allocated for irrigated agriculture is lost in many different ways. For example, from the water applied to crops, around 10-15% of water is lost through overwatering while inaccurate water use measurement on farms leads to loss of water due to its overuse (Ullah, 2011).

Because of the water scarcity in the country, Australian irrigation companies have tended to improve the efficiency of water use by introducing modern irrigation infrastructure. The Coleambally Irrigation Cooperative Limited (CICL) has installed modern automated technologies such as Total Channel Control (TCC) systems to minimise water losses and thus to improve the efficiency of channel delivery systems in the Coleambally Irrigation Area (CIA). This system has achieved 90% delivery efficiency at the system level and enables farmers to get water within two hours of ordering, as compared to 24 hours under the previous system (Smith & Nayar, 2008; Ullah, 2011). To offer farmers a similar or better efficiency in their water use at farm level requires a rapid and accurate water accounting system which takes into account the actual crop water requirements.
Any management decision in farming associated with higher inputs can be risky since yields vary from season to season and within different rainfall regions. Field experiments are often limited to a few locations and seasons, and often do not represent the whole scale of possible outcomes. To sample the effects of climatic variability and associated management responses adequately may require many decades of experimentation, particularly in areas where such variability is high. Validated simulation models of yield forecast however allow studies of interactions of seasonal variability and specific management practices.

In Australia there is an inherent concern about forecasts of the yield being able to mimic the risks and to maximise the fit between farm activities and the market. For instance internet facilities are emerging in order to alert the farmers on the probability of expected yields in particular regions in order to allow them to prepare for market changes. Agricultural authorities are supporting these activities through sites such as [http://www.dpi.vic.gov.au/agriculture/grain-crops/crop-production/crop-yields-losses](http://www.dpi.vic.gov.au/agriculture/grain-crops/crop-production/crop-yields-losses). They have employed simple methods to forecast yields in response to the farmers’ growing needs for information. The award for the best application for smart phones in 2012 was given to a yield forecasting application. This implies that there truly is a great need in Australian agriculture for yield forecasting.

Many biophysical models have been developed to estimate crop yield in Australia. For example, the MaizeMan model has been developed in Australia for estimating the yield of maize/corn crops at farm scale. Similarly, the ORYZA2000 model has been widely used for the estimation of rice crop yields. However, these models are only able to provide crop yield information at the farm scale and are not able to provide total crop yield production information at the irrigation system or catchment/basin scale. A number of previous research attempts have been made to develop catchment scale yield models for forecasting crop yields of different crop types using state-of-the-art remote sensing techniques in many other countries but there has been very limited information for broad acre irrigated crops grown in Australian conditions. In addition, the literature
suggests that there was no crop yield estimation method using remote sensing data integrating Photosynthetically Active Radiation (PAR), light use efficiency and energy balance for irrigated crops grown in Australian conditions.

1.3 Research Hypothesis

The current study has been carried out based on the following research hypothesis:

- Remote sensing-based novel algorithms can be used to obtain the ground-based Leaf Area Index (LAI) and, further, they can be utilised to develop accurate crop classification maps using object-oriented classification techniques.
- A remote sensing-based method can be used to accurately forecast the production of maize, rice and wheat. This method will provide a scientific basis to better understand the relationship between crop water use and crop yield for various common soil types in the Coleambally Irrigation Area.

1.4 Thesis Objectives

The main objectives of the research are as follows:

- To develop a CIA specific relationship between the Leaf Area Index (LAI) and the Normalised Difference Vegetation Index (NDVI) using satellite-derived and on-ground measurements for three crops, namely maize/corn, rice and wheat.
- To determine land use and land cover classifications using hybrid classification techniques embedded within object-oriented classification techniques from high and medium spatial resolution optical satellite imagery and to compare it with spectral classification techniques and validation of the mapped area using ground truth data.
To test the applicability of a remote sensing-based biophysical yield estimation model for three irrigated crops (maize, rice and wheat) in the CIA and to use this model for forecasting yield prior to harvest, taking into account spatial variability of soil types.

This study will provide farmers and irrigation managers with a better understanding of water use efficiency and water productivity in the production of maize, rice and wheat in various soil types in the CIA and provide pathways for improving water use efficiency by enabling them to predict the crop yield of these three irrigated crops in advance. Furthermore it is beneficial for farmers to make their marketing plans in advance and this will enable them to obtain timely information for the optimum management of growing crops.

Scientific models based on remote sensing, which provide an enormous range of spatial and temporal signatures from farm fields, can contribute to the provision of reliable tools to serve as precise regional as well as local yield forecasters. The crop yield estimation before harvesting is also of benefit to the food trade industry for making policies, establishing pricing and managing transportation.

1.5 Structure of the Thesis

Chapter 1 details the current situation in regard to available water resources and outlines the future scenario with respect to the increasing population. The importance of irrigated agriculture on a global scale and in the context of Australian conditions is also discussed. Chapter 1 further describes the importance of crop yield estimation for water resource management in irrigated agriculture, the research questions and the objectives of the research related to irrigated agriculture water issues.

Chapter 2 provides a general overview of the study area and its prominent features with respect to irrigated agriculture. This chapter further presents the geographical location, climate, soils, geology, surface and groundwater resources and the cropping regime in the CIA.
Chapter 3 provides background information obtained through the literature review related to:

- the development of empirical models for the estimation of ground-based LAI in irrigated agriculture; the importance of biophysical parameters such as LAI and its different estimation methods; the commonly used vegetation indices for the estimation of LAI; and the different types of instruments involved in LAI measurements.
- the basic image classification methods including visual and digital image classification techniques in satellite remote sensing; the usefulness and details of land use and land cover classification; the different methods used in digital image classification to prepare land use and land cover maps such as pixel-based and object-based classification methods and the comparison of the advantages and disadvantages of the two methods; the merits, drawbacks and application of supervised, unsupervised and hybrid classification techniques; the assessment of the accuracy of land use and land cover classifications and the most widely used accuracy assessment methods such as error matrix and Kappa coefficient; and land use and land cover classification approaches in irrigated agriculture in Australia.
- all the remote sensing-based methodologies used for the estimation of crop yield in irrigated agriculture and their advantages and disadvantages; different crop growth parameters and their relationships with biomass growth and crop yield revealed through past studies; and a summary of crop yield statistics obtained from different studies around the globe for different environmental conditions.

Chapter 4, the methodology adopted to fulfil the various objectives of the current research is described in detail. The first part of the chapter describes the methodology used for the development of novel models for the estimation of LAI using different satellite images. The following section
explains the methodology of the hybrid object-oriented classification technique for the development of land use and land cover classification maps for irrigated crops in the CIA. In the same chapter, the steps implemented to create the error matrix, which was used for the accuracy assessment of the land use and land cover classification, are explained. The final section of the chapter explains the Carnegie-Ames-Stanford-Approach (CASA) estimation procedure which is used to estimate the final crop yields of the three crops. All the steps involved in the CASA model are discussed including estimation of Photosynthetically Active Radiation (PAR), Absorbed Photosynthetically Active Radiation (APAR), incoming solar radiation, biomass and the steps involved in the estimation of crop yield.

Chapter 5 and 6 presents the results and analyses these results against the objectives of the research. In Chapter 5, the performance of the newly developed novel models for the estimation of LAI for irrigated crops is analysed with model performance parameters. The land use and land cover classification maps of the CIA, created for two seasons, are presented and investigated for accuracy using the error matrices. Chapter 6 presents, the spatial variations in the crop yield of maize, rice and wheat along with the final crop yield statistics for 2010/11 are presented and compared with the published data.

The final chapter is the conclusion and recommendation section of the thesis which presents the summary of the research. The chapter summarises all the research carried out and in addition it proposes new ideas arising from the current research for further investigation and the places where the current research can be improved by introducing new techniques and different methodologies.
2 COLEAMMBALLY IRRIGATION AREA

2.1 General Overview

The agriculture industry plays a dominant role in the Australian economy. Agricultural activities in Australia are extensive, ranging from broad acre pastoral and cropping actively to concentrated livestock and horticultural production. For these agricultural activities the country utilises 52% of its land and 52% of the nation’s water (ABS, 2012). The Murray Darling Basin (MDB) is Australia’s most important agricultural region, containing three quarters of all irrigated crops and pastures of the country (MDBC, 2009). In 2008-09 the MDB accounted for 38% of the country’s irrigating agricultural businesses, 53% of all irrigated agricultural land and 54% of irrigation water applied (ABS, 2010). The Murrumbidgee catchment area located in New South Wales (NSW) covers approximately 84,000 km² or about 8% of the MDB (Figure 2.1). The catchment produces irrigated crops ranging from seasonal crops including rice, cereals, vegetables, oilseeds to annual crop such as pasture, and perennial crops such as wine grapes, citrus and stone fruit (Hope & Wright, 2003). The agriculture industry in the Murrumbidgee catchment area provides more than $1.9 billion in annual income and comprises 25% of NSW’s fruit and vegetable production, 42% of NSW’s grape production and 50% of Australia’s rice production (Green et al., 2011; Murrumbidgee CMA, 2008).

The Murrumbidgee Irrigation Area (MIA) and the Coleambally Irrigation Area (CIA) are the largest irrigation areas in the Murrumbidgee catchment and produce the highest proportion of irrigated commodities out of the entire production from the catchment (Hope & Wright, 2003). The MIA and CIA were formed as government-owned irrigation areas in 1924 and between 1958 and 1970 respectively. While the MIA consists of a number of irrigation areas, the CIA is localised only to one area and has its own major supply canal network.

Water is supplied to the CIA from the Murrumbidgee River, one of the major tributaries of the Murray River, through the 41km long Coleambally Main Canal and 477km of supply channels. Burrinjuck and
Blowing Dams, the largest storages in the Murrumbidgee catchment, are operated by the State Water Corporation. Water supply is regulated from these two major dams (Ullah, 2011) which store water for irrigation, farm stock, domestic and town purposes during the winter and distribute the water to the irrigation farms during the summer. The Burrinjuck receives the bulk of its inflows from the upper catchment of the irrigation area while the Blowing Dam receives its inflow from the Snowy Mountains Hydro-Electric Scheme (Hope & Wright, 2003). The main diversion point for the CIA is located upstream of Darlington Point. The irrigation network in the CIA operates under gravitational force through open earthen channels and is controlled by solar energy in association with automated water ordering and accounting technologies.

For the current research, the CIA was selected as the study area. It is located in the lower Murrumbidgee catchment area on the southern side of the Murrumbidgee River and administratively belongs to the Riverina District of NSW (Figure 2.2). The area is predominantly rice based and supplements this with other agricultural products such as soybeans, winter cereals, sheep, wool and limited horticultural products (Hope & Wright, 2003). The major irrigation water sources in the area are surface water and groundwater. In 2010/11 the CIA supplied 265,570ML of surface water and 9,316ML of groundwater with 55 bore licences (CICL, 2011). The CIA has semi-arid climatic conditions characterised by winter-dominant rainfall. Geographically the area is positioned between 145° 40’ 30” E, 34° 40’ 30” S and 146° 6’ 57” E, 35° 3’ 11” S. Generally the area is characterised by a flat topography with a slope of 0° and mean elevation is 120m from the mean sea level (McVicar & Van Niel, 2010; Ullah, 2011).

The CIA was originally established in 1960 as a government irrigation scheme. Prior to the establishment of the scheme, it was a large pastoral area. The area was one of the locations selected to make use of diverted excess water from the Snowy Mountains Hydro Power Scheme. The irrigation water in the CIA was managed by the Department of Land and Water Conservation (DLWC) until 1991 and from then on it was administered as a part of the Murrumbidgee Irrigation Area and Districts. In
1997, it was transformed into a State-owned corporation. With the transfer of all ministerial shareholdings and rights to farmers in the CIA, the irrigation corporation was privatised and the Coleambally Irrigation Cooperative Limited (CICL) was established in 2000 and since then the area has been managed by the CICL. The CICL holds the CIA irrigation water license and now operates 79,000ha of intensive irrigation containing 495 farms owned by 362 business units (CICL, 2011).

![Map of the Murrumbidgee catchment area](image)

**Figure 2.1: The Murrumbidgee catchment area (Rabbani, 2008)**

Rice became the major crop in the irrigation area in the first decade of irrigation in the CIA. Although the water table was low prior to irrigation, it rose significantly over the decade from 1981 due to channel seepage, flood irrigation, unsuitable soil types and different irrigation practices. This resulted in low agricultural productivity due to salinity and water logging. In response to this, a 30 year Coleambally Land and Water Management Plan (LWMP) was developed by the local community to manage the shallow water table and salinity problems which occurred in the late 1980s and early 1990s. The objective of the plan was to maintain the practicality and sustainability of the CIA and thus to make the area productive. It was suggested that the water table would rise in an area of 50,000ha by 2013 and
60,000ha by 2023. In other words, at least 25% of the total area of the CIA would be salt affected by 2023 if action over water logging and the salinity problem was not taken. After the plan was implemented in mid 1999, there was a positive trend towards a decline in the shallow water table and the affected area was reduced to 1,500ha in September 2004 (IREC, 2005).

Since 2000, three LWMPs have been operating successfully in the CIA. These programmes are operated to ensure that the design of farms maximise water use efficiency and they are adapting to the LWMP long-term sustainability targets. These LWMPs have become the most successful projects in the field of natural resource management within the MDB. The Federal Government withdrew their support for the LWMP financial incentive program in 2009/10 but the NSW State Government continued its support of the program (CICL, 2011).

![Figure 2.2: Coleambally Irrigation Area in relation to Australia (Jackson, 2009; Watt, 2008)](image)

In 2002, the Coleambally Irrigation Cooperative Ltd (CICL) introduced Total Channel Control (TCC) automated technologies to use water more efficiently in response to the declining water availability in the CIA. The TCC replaced manually operated channel gates with automatic control gates and supplied water near on-demand to customers, minimising
water losses through zero outfall or escapes to the drainage system. Before
the implementation of automated technologies, the irrigation system was
based on the traditional channel supply gravity system and operated
manually by dropping logs and doors. In order to ensure that customers
were supplied with the water level, requested irrigation channels were run
slightly above the requested flows. As a result of the traditional manual
operation system and excess releases, large volumes of water were lost to
the channel system. Now the CICL operates the most modern irrigation
system, having open earth channels and controlling its entire delivery
channel system automatically. It is the first irrigation system in the world
with these characteristics (Smith & Nayar, 2008).

2.2 Climate

An automatic weather station (AWS) was installed in the northwest of
CIA in 2007. It is an FAO-56 commercial grade unit which measures and
records all normal weather parameters. The data collected from the AWS is
relayed on the radio-based AdCon Environmental Monitoring System. In
2008, the weather station was improved to be aligned with CICL’s existing
water operation communications network. Additional components such as
soil heat flux and a net radiometer were also installed in the upgraded AWS
in contribution with Charles Sturt University (CSU), allowing CSU
researchers to gather data to proceed with their studies. In the same year, a
second AWS, which is almost identical to the first one, was installed in the
southeast part of the CIA. These two AWSs provide weather data for the
two regions, the northwest and the southeast of the CIA (CICL., 2008).

The CIA is characterised by warm and dry climatic conditions, with
hot summers and mild winters. As the irrigated area is positioned in
Australia's winter rainfall climate zone, rainfall is normally very consistent
in the winter months (Jackson, 2009; Ullah, 2011; Watt, 2008). According
to Figure 2.3, since 1962 the long-term daily maximum and minimum
average temperatures have been 23.3°C and 9.3°C, respectively. The
warmest month of the year is January with a long-term average maximum
temperature of 31.8°C while the coldest month is July with a long term average minimum temperature of 2.9°C (CICL., 2008).

The reference evapotranspiration calculated by Penman-Monteith equation also shows considerable difference between summer and the winter months. The long-term monthly evapotranspiration ranges from 280.9mm in January to 44.2mm in June with average annual evapotranspiration of 1,723mm. In contrast to temperature and evapotranspiration, as can be seen in Figure 2.4, there is little significant variation in rainfall. The long-term annual average rainfall is 396.4mm (CICL., 2007). However in 2010/11 year the annual rainfall was 739mm which was the second highest since 1920 (CICL, 2011)
2.3 Soils of the CIA

The crop type grown on a farm may be affected by the type of the soils in the CIA. There are a variety of soil types with different properties found within the CIA. The different properties of these soils must be taken into account in the design and establishment of irrigation and farming practices and are also important for managing and sustaining the present systems (Hornbuckle et al., 2008). For example, areas with heavier grey soils are regarded as the most suitable for irrigated crops (Van & talsma, 1964). The spatial distribution of soil types may assist the CICL to determine the suitability of crop types for different paddocks. The dominant soil types found in the area are: sandhill formations, red brown earth, prior stream formations, non-self-mulching clay and self-mulching clay. The spatial distribution of soil types in the CIA is shown in Figure 2.5. According to Figure 2.5 the dominant soil type in the southern part is prior stream formation while in the northern part it is self-mulching clay with a few pockets of red brown earth (Watt, 2008). A description of these soil types is provided below.

Figure 2.4: Long term average evapotranspiration and rainfall (CICL., 2009)
types as provided by (Hughes, 1999; Taylor et al., 1979; Taylor & Hooper, 1938; Watt, 2008) are given below.

![Spatial distribution of soil types in the CIA (Watt, 2008)](image)

**Figure 2.5: Spatial distribution of soil types in the CIA (Watt, 2008)**

### 2.3.1 Sandhill formation

Sandhill formation can be found in the north and western part of the CIA and is not widespread compared to red brown earth, prior stream formations and self-mulching clays. The sandhill formation soil category was created from early channel sediments. Normally, this type of soil lies beneath a sandy, cemented soil layer of varying thickness up to 2m (Watt, 2008).
2.3.2 Red brown earth

The red brown earth soil category is quite dominant in the area and is widespread over the north-west and central parts of the CIA. The formation of this soil type is quite similar to the sandhill formation. It is generally characterised by sandy loams and loams. Red brown earth is ideal for the production of crops due to its high water-holding capability, although the soil needs to be fertilised for crop production.

2.3.3 Prior stream formations

This soil type is also fairly dominant in the area and widely spread over the southern part with a few pockets in the northern and western part of the CIA. It is characterised by a shallow surface horizon of underlying heavy clay subsoil. This soil type also needs to be fertilised in order to produce crops.

2.3.4 Self-mulching clays

The self-mulching clay is mainly found in the northern part of the CIA. The main compound of this soil type is clay which has regenerating properties. This type of soil is ideal for rice crops.

2.3.5 Non-self-mulching clay

Non-self-mulching clay is not widely spread over the area. A few patches of this type of soil can be found in limited amounts over the north and western parts of the irrigation area. This soil type, which is normally found to disperse on wetting, has a very thin surface crust. For example some soils can be found with a top soil of 5-20cm depth.

2.4 Geology of the CIA

The CIA is located in the MDB which is largely formed with 600m thick non-indurate deposits (Prathapar et al., 1997). The basin consists of a number of sub-regions based on the geomorphology of the area. The Riverina Plain is a sub-region located in the south east of the basin. The CIA is located closer to the central eastern side of the plain in an alluvial fan (Prathapar et al., 1997; Ullah, 2011).
The Coleambally region consists of non-indurate sediments with varying thicknesses from 100 to 200m. Three basic geological units have been identified in the CIA. These units are the Renmark Group, the Calivil Formation and the Shepparton Formation (Brown & Stephenson, 1991; Watt, 2008). The Renmark group which covers the largest area in the basin bedrock is the oldest stratigraphic unit. The Calivil Formation mainly consists of pale grey quartz sand with kaolin and carbonaceous clay, the most widespread of the three. Groundwater users in the area extract water by tapping this formation as it the most transmissive aquifer in the CIA. The Shepparton Formation has a low hydraulic conductivity of 2-3m per day. It consists of silt and silty clay with lenses of fine to coarse sand and gravel (Prathapar et al., 1997).

2.5 Surface and Ground Water Resources in the CIA

The surface water distribution in the CIA is managed by the CICL. The water is supplied to the CIA from the Murrumbidgee River through a main canal and supply channels and at present, the area is entitled to 621GL of surface water. The water allocation to the area is decided based on the availability of surface water and yearly maximum water allocations for general security entitlement. Annual water allocation statistics data from 1982/83 to 2010/11 are shown in Figure 2.6. The MDBC cap was introduced in 1994/95 due to a severe drought in the previous 10 years. As a result of the implementation of the MDBC cap, the water allocation for the area declined and agriculture in the area was adversely affected.

Table 2.1 shows fluctuations in the water diversions to the area after the introduction and implementation of the MDBC cap in 1994.
Figure 2.6: Annual water allocation statistics data from 1982/83 to 2010/11 for general security entitlement (CICL, 2011)
Table 2.1: Annual Diversion of Surface Water to the CIA after Introduction of MDB Cap (CICL., 2010).

<table>
<thead>
<tr>
<th>Year</th>
<th>Volume (ML)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995/96</td>
<td>484,632</td>
</tr>
<tr>
<td>1996/97</td>
<td>621,777</td>
</tr>
<tr>
<td>1997/98</td>
<td>548,023</td>
</tr>
<tr>
<td>1998/99</td>
<td>483,823</td>
</tr>
<tr>
<td>1999/00</td>
<td>387,609</td>
</tr>
<tr>
<td>2000/01</td>
<td>499,275</td>
</tr>
<tr>
<td>2001/02</td>
<td>505,534</td>
</tr>
<tr>
<td>2002/03</td>
<td>407,063</td>
</tr>
<tr>
<td>2003/04</td>
<td>325,285</td>
</tr>
<tr>
<td>2004/05</td>
<td>340,161</td>
</tr>
<tr>
<td>2005/06</td>
<td>388,177</td>
</tr>
<tr>
<td>2006/07</td>
<td>179,460</td>
</tr>
<tr>
<td>2007/08</td>
<td>70,025</td>
</tr>
<tr>
<td>2008/09</td>
<td>88,185</td>
</tr>
<tr>
<td>2009/10</td>
<td>141,989</td>
</tr>
</tbody>
</table>

Through a network of piezometers located in the CIA, the quality of the groundwater is monitored twice yearly. Groundwater quality is variable throughout the area. The areas located in the north and south of the CIA have a better water quality while the areas in the central, west and southern parts of the CIA show high salinity levels. Generally summer cropping is very limited in the CIA and such cropping generally occurs with the help of groundwater. Groundwater extraction in the 10 years prior to 2010/11 within the CIA is given in Table 2.2. According to the data given in the table, it is evident that there was a significant reduction in groundwater use in 2010/11 compared to 2009/2010. The availability of more surface water and higher rainfall in the CIA resulted in the reduction in the extraction of water from groundwater bores in the area.
Table 2.2: Groundwater Extraction for the Past 10 Years in the CIA.

<table>
<thead>
<tr>
<th>Year</th>
<th>Groundwater extraction (ML)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/11</td>
<td>9,316</td>
</tr>
<tr>
<td>2009/10</td>
<td>53,992</td>
</tr>
<tr>
<td>2008/09</td>
<td>28,803</td>
</tr>
<tr>
<td>2007/08</td>
<td>25,731</td>
</tr>
<tr>
<td>2006/07</td>
<td>48,102</td>
</tr>
<tr>
<td>2005/06</td>
<td>26,748</td>
</tr>
<tr>
<td>2004/05</td>
<td>39,174</td>
</tr>
<tr>
<td>2003/04</td>
<td>33,122</td>
</tr>
<tr>
<td>2002/03</td>
<td>45,561</td>
</tr>
<tr>
<td>2001/02</td>
<td>35,416</td>
</tr>
</tbody>
</table>

2.6 Cropping Systems in the CIA

2.6.1 Crop types and cropping patterns

Irrigated agriculture is the driving force of the economy in the CIA and local communities are highly dependent on the irrigated agriculture. Typically crops are grown in the CIA in two seasons, summer and winter, mainly with irrigation water. The summer crops, grown from October to March, that include rice, soybeans, maize (corn), grapes, prunes, sunflowers and lucerne while the winter crops, are grown from April to September, that include wheat, oats, barley and canola. Pasture is grown in both seasons for grazing. Rice and corn are the main summer crops. Wheat is the major winter crop while barley and canola are the second and third most important crops during the winter season in the CIA.

Rice is the predominant summer crop in the CIA. It consumes 50-70% of the supplied water to the area as the crop is continuously flooded throughout the cropping season (Humphreys et al., 2006; Humphreys & Robinson, 2003; Ullah, 2011; Van Niel & McVicar, 2004b). There was a remarkable decrease in rice production area in the CIA since 2000/01 due to severe drought and low water allocation. The area under the rice reduced
from 30,440ha in 2000/01 to only 90ha in 2007/08 while the total irrigated area for major crops reduced from 67,492ha to 14,346ha during this period (CICL, 2011). However, cropped area started to increase again since 2009/10. The irrigated areas of six main crops and their proportion of water delivery from 1997/98 to 2010/11 are shown in Table 2.3. The drastic change in rice cropping area as a result of drought and low water allocation is easily seen. The rice cropping area decreased from 40% in 2001/02 to 9% in 2008/09. In contrast barley increased from 4% to 19% during this period. However, again, rice, wheat, barley pasture and corn have become the dominant crops in the CIA for the year 2010/11 as shown in Figure 2.7.

![Pie chart showing proportion of crop areas in the CICL area of operation in 2010/11 (CICL, 2011)](image)

**Figure 2.7: Proportion of crop areas in the CICL area of operation in 2010/11 (CICL, 2011)**
Table 2.3: The Crop Areas and Proportion of Water Delivery Variations of Six Major Crops (CICL, 2011).

<table>
<thead>
<tr>
<th>Season</th>
<th>Rice Area (ha)</th>
<th>Rice Proportion of delivery (%)</th>
<th>Soybean Area (ha)</th>
<th>Soybean Proportion of delivery (%)</th>
<th>Corn Area (ha)</th>
<th>Corn Proportion of delivery (%)</th>
<th>Wheat Area (ha)</th>
<th>Wheat Proportion of delivery (%)</th>
<th>Pasture Area (ha)</th>
<th>Pasture Proportion of delivery (%)</th>
<th>Canola Area (ha)</th>
<th>Canola Proportion of delivery (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/11</td>
<td>14,512</td>
<td>65.1</td>
<td>1,240</td>
<td>1.5</td>
<td>4,367</td>
<td>6.9</td>
<td>11,334</td>
<td>4.8</td>
<td>8,119</td>
<td>4.0</td>
<td>3,381</td>
<td>1.4</td>
</tr>
<tr>
<td>2009/10</td>
<td>3,668</td>
<td>46.0</td>
<td>495</td>
<td>1.0</td>
<td>311</td>
<td>2.0</td>
<td>10,635</td>
<td>10.0</td>
<td>6,903</td>
<td>12.0</td>
<td>2,523</td>
<td>2.0</td>
</tr>
<tr>
<td>2008/09</td>
<td>2,135</td>
<td>33.1</td>
<td>308</td>
<td>1.4</td>
<td>2,472</td>
<td>3.4</td>
<td>4,215</td>
<td>9.5</td>
<td>4,481</td>
<td>16.3</td>
<td>1,471</td>
<td>4.9</td>
</tr>
<tr>
<td>2007/08</td>
<td>90</td>
<td>1.4</td>
<td>152</td>
<td>0.7</td>
<td>941</td>
<td>1.2</td>
<td>6,575</td>
<td>0.2</td>
<td>5,004</td>
<td>0.2</td>
<td>1,584</td>
<td>0.1</td>
</tr>
<tr>
<td>2006/07</td>
<td>8,518</td>
<td>54.3</td>
<td>478</td>
<td>0.8</td>
<td>1,863</td>
<td>7.6</td>
<td>12,509</td>
<td>15.9</td>
<td>9,958</td>
<td>7.8</td>
<td>1,602</td>
<td>1.0</td>
</tr>
<tr>
<td>2005/06</td>
<td>18,025</td>
<td>62.8</td>
<td>2,106</td>
<td>2.9</td>
<td>3,306</td>
<td>7.0</td>
<td>13,610</td>
<td>8.4</td>
<td>15,440</td>
<td>8.7</td>
<td>1,748</td>
<td>0.9</td>
</tr>
<tr>
<td>2004/05</td>
<td>8,142</td>
<td>44.0</td>
<td>1,495</td>
<td>2.2</td>
<td>3,671</td>
<td>7.2</td>
<td>20,287</td>
<td>18.8</td>
<td>12,865</td>
<td>10.8</td>
<td>2,681</td>
<td>1.3</td>
</tr>
<tr>
<td>2003/04</td>
<td>12,597</td>
<td>55.8</td>
<td>1,938</td>
<td>3.5</td>
<td>3,545</td>
<td>5.7</td>
<td>21,192</td>
<td>15.0</td>
<td>12,131</td>
<td>7.5</td>
<td>1,763</td>
<td>0.7</td>
</tr>
<tr>
<td>2002/03</td>
<td>11,395</td>
<td>46.0</td>
<td>1,788</td>
<td>1.0</td>
<td>4,788</td>
<td>9.3</td>
<td>21,346</td>
<td>20.4</td>
<td>10,183</td>
<td>7.4</td>
<td>2,095</td>
<td>1.7</td>
</tr>
<tr>
<td>2001/02</td>
<td>27,493</td>
<td>67.5</td>
<td>3,297</td>
<td>3.4</td>
<td>3,808</td>
<td>4.2</td>
<td>21,103</td>
<td>9.2</td>
<td>11,581</td>
<td>6.1</td>
<td>2,191</td>
<td>0.6</td>
</tr>
<tr>
<td>2000/01</td>
<td>30,440</td>
<td>73.9</td>
<td>4,551</td>
<td>5.9</td>
<td>4,074</td>
<td>5.7</td>
<td>14,276</td>
<td>4.6</td>
<td>11,998</td>
<td>4.7</td>
<td>2,153</td>
<td>0.4</td>
</tr>
<tr>
<td>1999/00</td>
<td>24,138</td>
<td>77.7</td>
<td>2,185</td>
<td>3.9</td>
<td>1,178</td>
<td>3.1</td>
<td>12,649</td>
<td>6.1</td>
<td>7,485</td>
<td>4.4</td>
<td>2,152</td>
<td>0.7</td>
</tr>
<tr>
<td>1998/99</td>
<td>24,491</td>
<td>73.8</td>
<td>4,339</td>
<td>5.7</td>
<td>1,059</td>
<td>1.3</td>
<td>13,963</td>
<td>1.7</td>
<td>13,879</td>
<td>8.1</td>
<td>2,184</td>
<td>1.7</td>
</tr>
<tr>
<td>1997/98</td>
<td>24,624</td>
<td>70.4</td>
<td>4,998</td>
<td>7.5</td>
<td>1,678</td>
<td>2.4</td>
<td>14,943</td>
<td>7.4</td>
<td>9,964</td>
<td>6.1</td>
<td>2,053</td>
<td>0.4</td>
</tr>
</tbody>
</table>
2.6.2 Crop yield

As the cropping areas of each crop improved during the period after recovery from drought, there was an improvement in total yield for all winter and summer crops mainly because of water availability. Wheat production increased from 12,000 tonnes in 2007 to 90,000 in 2011 in the area and a similar trend could be observed for all other major winter crops in the CIA. Table 3.5 shows the statistics of the main summer crops production in the CIA for the five years from 2006/07 to 2010/11. It is evident that rice is the main summer crop in the area while corn and soybean are the second and third most important crops during the season. The highest production in 2010/11 was obtained from rice, corn and soybeans of 146,218, 55,000, and 3,600 tonnes respectively. These high production of crops are attributed mainly to an increase in harvest area after recovery from drought.
Table 2.4: The Crop Areas and Yield of Major Winter Crops in the CIA from 2007 to 2011 (Scot, 2011).

| Year   | Wheat Harvest area (ha) | Wheat Tonnes | Wheat Yield (t/ha) | Barley Harvest area (ha) | Barley Tonnes | Barley Yield (t/ha) | Oats Harvest area (ha) | Oats Tonnes | Oats Yield (t/ha) | Triticale Harvest area (ha) | Triticale Tonnes | Triticale Yield (t/ha) | Canola Harvest area (ha) | Canola Tonnes | Canola Yield (t/ha) |
|--------|-------------------------|--------------|--------------------|--------------------------|------------------------|------------------|---------------------|-----------------------|-----------------|-------------------|-------------------------|------------------|------------------------|-----------------------|----------------|-------------------|
| 2007   | 4,000                   | 12,000       | 3.00               | 6,000                    | 15,000                 | 2.50             | 100                 | 100                   | 1.00            | 50                 | 50                      | 1.00            | 200                    | 200                   | 1.00            |
| 2008   | 8,000                   | 40,000       | 5.00               | 10,000                   | 40,000                 | 4.00             | 500                 | 1,000                 | 2.00            | 250                | 750                     | 3.00            | 1,300                  | 2,600                 | 2.00            |
| 2009   | 7,000                   | 35,000       | 5.00               | 9,000                    | 36,000                 | 4.00             | 0                   | 0                     | 0               | 200                | 600                     | 3.00            | 1,000                  | 2,500                 | 2.50            |
| 2010   | 40,000                  | 200,000      | 5.00               | 10,000                   | 40,000                 | 4.00             | 500                 | 1,000                 | 2.00            | 400                | 2,400                    | 6.00            | 3,000                  | 6,300                 | 2.10            |
| 2011   | 30,000                  | 90,000       | 3.00               | 10,000                   | 25,000                 | 2.50             | 500                 | 1,000                 | 2.00            | 400                | 1,200                    | 3.00            | 3,000                  | 6,000                 | 2.00            |

Table 2.5: The Crop Areas and Yield of Major Summer Crops in the CIA from 2007 to 2011 (Scot, 2011).

<table>
<thead>
<tr>
<th>Year</th>
<th>Rice Harvest area (ha)</th>
<th>Rice Tonnes</th>
<th>Rice Yield (t/ha)</th>
<th>Corn Harvest area (ha)</th>
<th>Corn Tonnes</th>
<th>Corn Yield (t/ha)</th>
<th>Soybeans Harvest area (ha)</th>
<th>Soybeans Tonnes</th>
<th>Soybeans Yield (t/ha)</th>
<th>Sorghum Harvest area (ha)</th>
<th>Sorghum Tonnes</th>
<th>Sorghum Yield (t/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006/07</td>
<td>8,096</td>
<td>83,399</td>
<td>10.30</td>
<td>1,500</td>
<td>15,000</td>
<td>10.00</td>
<td>200</td>
<td>760</td>
<td>3.80</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2007/08</td>
<td>602</td>
<td>5,448</td>
<td>9.05</td>
<td>3,020</td>
<td>36,240</td>
<td>12.00</td>
<td>225</td>
<td>675</td>
<td>3.00</td>
<td>100</td>
<td>800</td>
<td>8.00</td>
</tr>
<tr>
<td>2008/09</td>
<td>2,188</td>
<td>17,680</td>
<td>8.80</td>
<td>1,200</td>
<td>12,000</td>
<td>10.00</td>
<td>440</td>
<td>1232</td>
<td>2.80</td>
<td>50</td>
<td>400</td>
<td>8.00</td>
</tr>
<tr>
<td>2009/10</td>
<td>4,231</td>
<td>45,652</td>
<td>10.79</td>
<td>700</td>
<td>7,700</td>
<td>11.00</td>
<td>400</td>
<td>1,400</td>
<td>3.50</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2010/11</td>
<td>14,786</td>
<td>146,218</td>
<td>9.89</td>
<td>5,000</td>
<td>55,000</td>
<td>11.00</td>
<td>1,200</td>
<td>3,600</td>
<td>3.00</td>
<td>50</td>
<td>400</td>
<td>8.00</td>
</tr>
</tbody>
</table>
2.6.3 Crop water use

Crops within the region are irrigated from both surface and groundwater sources, but surface water is the main water source used in the area (Marsden Jacob Associates et al., 2010). Coleambally as one of the major rice production areas in Australia consumes the majority of irrigation water to the area (Watt, 2008). Even though there was a rapid decline of rice growing area during the drought, rice was still the major water consumer in the area in that period. Rice was the major water consumer in 2010/11 accounting for 66% of the total irrigation water. This is relatively a high percentage given that the rice growing area is relatively low at 23.8% (CICL, 2011).

Table 2.3 (above) shows the areas and proportion of water delivery of the six major crops in the CIA from 1997/98 to 2010/11. According to the table, water supplied by the CICL is mainly used to grow rice crops. The areas used to produce soybeans, corn, wheat, pasture and canola have varied throughout the history in response to the availability of water and changes in commodity prices (CICL, 2011).
3 LITERATURE REVIEW

3.1 Overview

Estimation of crop yield is becoming more important throughout the world because it is paramount in policy planning and decision making in agriculture. The need for crop yield modelling is increasing due to climate change and emerging issues in food security resulting from rapid population growth (Teixeira, 2008). Crop yield is a key factor in rural development and indispensable for national food security because it underpins the determination of policies for the food trade including pricing and transportation (Bastiaanssen & Ali, 2003). In addition, it is beneficial for farmers to make their marketing plans in advance and thus it is important to obtain timely information for optimum management of crop production (Horie et al., 1992).

There have been a number of crop yield models such as ORYZA2000, MACROS and LINTUL developed and applied in the estimation of yield and the analysis of yield gaps in the past few decades (Van Ittersum et al., 2003). However, these models have been applied on a farm scale rather than in the forecasting of crop yield on a regional or national scale. The main reason for not being able to apply these models on a regional or national scale has been the non-availability of input data such as soil type, crop varieties and farming practices on a regional or national scale (Samarasinghe, 2003). In the late 1970s, satellite remote sensing was identified as an economical, more reliable and rapid method of investigating the biological activity of green vegetation and considerable progress has been made in developing biophysical models to estimate crop production using satellite spectral data. These models are mostly based on Absorbed Photosynthetically Active Radiation (APAR) and above ground biomass (Samarasinghe, 2003). For the application of any yield estimation or forecasting model, assessment of various parameters such as Leaf Area Index (LAI), evaporative fraction and harvest index as well as information about land use are prerequisites which are also discussed in this chapter.
3.2 Leaf Area Index (LAI)

Leaf Area Index (LAI), defined as the one-sided green leaf area to unit ground area (m$^2$ green leaf area/m$^2$ ground area), is a dimensionless vegetation biophysical parameter (Zheng & Moskal, 2009). Its retrieval over diverse types of agricultural landscapes is crucial in determining biomass, photosynthesis and evapotranspiration (ET) in order to feed these parameters into crop yield modelling (Aparicio et al., 2000; Cheng, 2008; Doraiswamy et al., 2005; Mo et al., 2005) and also in determining crop water productivity (Liu et al., 2007; Mo et al., 2005) as it provides an understanding of dynamic changes in crop growth, development and productivity.

There are two widely used methods for estimating LAI: the direct (or destructive) method and the indirect method. The details of these methods are given in the following sections.

3.2.1 Direct measurement of LAI

Estimating LAI using the direct method involves leaf collection and area measurement of leaves (Zheng & Moskal, 2009). Different approaches have been tested and applied for the collection of leaves and determination of their area. Leaf collection can be carried out using either the harvesting method or non-harvesting litter traps to collect fallen leaves. Determination of the area of the leaves is usually made using planimetric and gravimetric techniques which are based on the measurement of individual leaf area and the dry weight of leaves respectively. In both methods the ratios of leaf area to ground area and leaf mass per unit ground area are determined in order to estimate the LAI (Zheng & Moskal, 2009).

This direct destructive method has been used in some studies to compare to indirect LAI estimates (Stroppiana et al., 2006) due to its highly accurate nature. Stroppiana et al., (2006) used the direct method to investigate the reliable range of indirect LAI measurements for paddy rice. In their study they used an LAI-2000 optical instrument to obtain indirect LAI measurements. The direct method involved the measurement of the
area of leaves using a more advanced technique than the conventional planimetric method. The leaves were photographed using a Canon PowerShot S70 Digital Camera and an unsupervised classification procedure was carried out to derive the actual area of the leaves. Plant density was estimated by counting the number of plants in a quarter of a square meter of the paddock plot and the calculated mean value was taken as the paddock’s plant density. The LAI was estimated as the product of the plant density of the plot and the average plant’s leaf area.

The direct method is believed to be the most accurate method in LAI estimation. However, applying this method has a number of drawbacks. As this method involves manual leaf collection, area measurement and the weighing of leaves, it is not economical and it is labour intensive. Moreover, it is not reliable and is time consuming to apply over large agricultural areas which have rapidly changing natures.

### 3.2.2 Indirect measurement of LAI

The indirect method is the most frequently used and the most convenient procedure for estimating LAI (Wang et al., 2010). The indirect method of LAI measurement either involves optical instruments or is based on the correlation between LAI and spectral vegetation indices. Vegetation indices can be defined as a measure of the greenness of the plant biomass (Huete et al., 2002). They are developed in terms of reflectance measurements of the canopy (Huete et al., 2006) extracted from satellite data (Gilabert et al., 2002). They have been developed to control external background effects such as soil brightness, soil colour, atmospheric effects, environmental effects and sensor characteristics (Jackson et al., 1983) while highlighting particular properties of the canopy such as photosynthetic and non-photosynthetic vegetation components, chlorophyll, leaf and canopy layers. They do this by combining the chlorophyll-absorbing red spectral region with the non-absorbing near infra-red region (Huete et al., 2006).

These spectral vegetation indices are widely used in estimating biophysical variables such as LAI, fraction of APAR, chlorophyll content and biomass, and they are very useful in ET estimation in order to assess
crop growth and calculate crop yield (Aparicio et al., 2000; Casanova et al., 1998; Huete et al., 2002; Huete et al., 2006). Moreover they are needed in different spatial and temporal scales for the monitoring, mapping, estimating and management of vegetation dynamics, biogeochemical and hydrologic processes, and for the assessment of climate variability (Huete et al., 2006). The most commonly used spectral vegetation indices are, the Normalised Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Deneralised Soil Adjusted Vegetation Index (GESAVI), Simple Ratio (SR), Difference Vegetation Index (DVI), Perpendicular Vegetation Index (PVI), Enhanced Vegetation Index and Ratio Vegetation Index. All these spectral vegetation indices are well correlated with LAI (Fernandes et al., 2004; Sonnentag et al., 2007; Wang et al., 2010) and allow effective indirect estimation of LAI. The most commonly used vegetation indices for the indirect estimation of LAI are explained in Table 3.1 below. These indices, based on the spectral signature of vegetation, are either derived using optical instruments or from remote sensing data. A detailed description of these indirect LAI measurement methods is given in the following section.

3.2.2.1 LAI measurement with optical instruments

Optical instruments are based on the canopy-gap fraction and radiation transmission and they are readily available for effective LAI measurement. Optical instruments such as plant canopy analysers like the LI-COR LAI-2000 (LI-COR Inc, 1992) and the SunScan system (Potter et al., 1996) are being generally used to retrieve LAI indirectly. These instruments calculate LAI by measuring incoming radiation as a function of intercepted light below the canopy compared to the above canopy reflectance based on the canopy-gap fraction. The amount of intercepted light depends on the structure (gap fraction) of the canopy (Stroppiana et al., 2006). The features and functions of these instruments are as follows:
3.2.2.1.1 LAI-2000 Plant Canopy Analyser

The LAI-2000 Plant Canopy Analyser (Figure 3.1) is one of the most widely used optical instruments for the non-destructive measurement of LAI in different vegetation types (Stroppiana et al., 2006). It measures the diffuse sunlight at five different zenith angles (7°, 23°, 38°, 53°, 68°) simultaneously (LI-COR Inc, 1992). By taking a number of measurements above and below the vegetation canopy, the attenuation can be obtained and it is used to compute LAI. Normally a higher number of below canopy readings are obtained to increase the accuracy of the measurements. Because the measurements of the LAI-2000 are taken at five different zenith angles above and below the canopy, there are ten final measurements. The measurements can be made using one of three operating modes: one sensor mode, two sensor mode or remote mode depending on the canopy height and sky conditions (LI-COR Inc, 1992).

Figure 3.1: LAI-2000 Plant Canopy Analyser

The accuracy of the measurements can be increased by considering different factors that may lead to erroneous readings. The LAI
measurements should be taken under diffuse sky conditions at dusk or dawn to avoid possible extra reflections from direct sunlight. If the sky and the canopy conditions are not ideal during the measurements, adjustments in measurements are required. A suitable view cap should be introduced to limit the sensor's horizontal field of view in order to mask out the influence of operator, adjacent plots and large gaps in a dense canopy (Stroppiana et al., 2006). In addition, multiple below canopy readings may be taken to achieve an accurate spatial average when the sky conditions are not favourable and canopy density is not homogeneous (LI-COR Inc, 1992). The analyser computes the amount of foliage (i.e. LAI) and its orientation based on the measurements of transmittance at the five zenith angles.

In order to correctly estimate the amount of foliage and its orientation, there are some assumptions to be made:

1. The foliage is black. In other words, no radiation measurements such as reflections or transmittance are included in the below canopy readings. If these assumptions are violated, it will affect the absolute value of calculations.

2. The foliage is evenly distributed and within the vegetation cover and there are no gaps due to row crops, isolated bushes, grass or deciduous forest.

3. The leaf width is small compared to the distance from canopy to sensor. Normally this distance should be at least four times the leaf width.

4. If wide angle view caps are used, it is assumed that the foliage is azimuthally randomly oriented.

However, in reality there are very few canopies that can meet with all the above assumptions and often the foliage deviates from the ideal situation (LI-COR Inc, 1992).

The FV-2000 program is a computer program used with LAI-2000 data to edit LAI field measurements. The program is capable of editing the LAI data by deleting bad readings, discarding required rings as necessary,
introducing correct canopy models appropriately and recalculating LAI into a new file. It is possible to detect extreme readings by looking at above canopy readings. If above canopy readings are inconsistent from one to another, it indicates unfavourable sky conditions, poor operating techniques involving failure to shade the instrument from direct sunlight or malfunctioning of the instrument due to electrical problems or erroneous calibration. Sensor calibration is only important when employing two-sensor mode or remote mode as two sensors are involved in both of these modes. It is necessary to know the comparison procedure under the same operating and environmental conditions. In single sensor mode, the calibration values are cancelled when the below canopy reading is divided by the above canopy reading in order to compute the transmittance (LI-COR Inc, 1992).

Even though this method of collecting LAI by employing the LAI Plant Canopy Analyser is time-consuming, laborious and only covers a very limited area, the instrument has been widely used in many studies for indirect measurements as these measurements are believed to be reasonable enough for LAI estimation and easy to obtain compared to direct retrieval.

Stroppiana et al., (2006) conducted a study to assess the reliability and adequacy of LAI-2000 Plant Canopy Analyser measurements for paddy rice by comparing to direct destructive measurements in Northern Italy. The result showed that the LAI-2000 estimates were more reliable and were in agreement with direct destructive measurements when LAI > 1 and LAI measurements were derived without wide angle readings (fifth ring with 68°). They concluded that, at the early stage, the low density (when LAI < 1) of the rice canopy affects the LAI-2000 measurements because there was no agreement with the direct destructive measurements.

3.2.2.1.2 SunScan Canopy Analysis System

The SunScan Canopy Analysis System (Figure 3.2) can be used to measure ecological parameters such as LAI and PAR above and beneath the plant canopy simultaneously and also it makes it possible to measure the intercepted solar radiation of the canopy. The instrument operates
automatically to observe diurnal changes in the total solar radiation (Shi et al., 2005). The best results can be obtained if the measurements are taken within the three hours before and after midday, depending on the season of the year and the location (Potter et al., 1996).

The SunScan Canopy Analysis System is a convenient and portable instrument which has a great number of possible applications (Potter et al., 1996). SunData software is able to calculate LAI based on a number of readings such as average PAR within the canopy and above canopy, the ratio of direct to total radiation, leaf angle distribution and leaf PAR absorption. Further, these calculations require information of solar zenith angles estimated from the time of day and corresponding latitude and longitude of the area. However, some types of canopy do not confirm reasonable results for the estimation of LAI using the SunScan Crop Canopy Analyser. For low and uniform canopies such as cereal crops and trial plots, reasonable LAI values can be estimated whereas for isolated trees or bushes such as orchard trees and sparse vegetation like scrub plots, extracting reasonable LAI values are not possible. The instrument could also be used in high, uniform and non-clumped trees such as timber plantations, but it is practically impossible due to the difficulties in obtaining high and above canopy references (Potter et al., 1996).

![Figure 3.2: SunScan Crop Canopy Analyser (Potter et al., 1996)](image-url)

Figure 3.2: SunScan Crop Canopy Analyser (Potter et al., 1996)
3.2.2.2 Estimation of LAI using spectral vegetation indices

Table 3.1: Information of Spectral Vegetation Indices used for Retrieval of LAI

| Normalised difference vegetation index | The Normalised Difference Vegetation Index (NDVI), an indicator of fresh and vigorous green biomass (Aguilar et al., 2012), is one of the most widely used vegetation indices in ecological studies (Pettorelli et al., 2005; Yi et al., 2008). It is generally estimated from satellite data by measuring the reflected red and near infra-red radiation of vegetation. The pigments of the leaves absorb the visible red and the cell structure of leaves reflects the near infra-red of the electromagnetic spectrum. These two regions of the spectrum are incorporated in defining NDVI and it is defined as the ratio of the difference between near infra-red and red reflectance to their sum (Bastiaanssen & Ali, 2003), represented in Equation 3.1. 

\[
NDVI = \frac{NIR - R}{NIR + R}
\]

where NIR and R represent the reflectance of the near infra-red and red bands respectively. Red and near infrared reflectance is very effective in discriminating soil from vegetation due to their high spectral differences. This spectral property is taken into consideration in identifying different surfaces on the earth. For example NDVI for bare soil takes a low value while it is high for green vegetation. The NDVI ranges from -1.0 to 1.0 indicating the amount of green biomass (Doraiswamy, 1995). |

Soil adjusted vegetation index

The Soil Adjusted Vegetation Index (SAVI) is a modified version of NDVI which is designed to correct the influence of the background soil effect where the vegetation cover is lower with a high influence of soil. In order to correct this influence, SAVI was developed to include a soil brightness correction factor (L) (Huete, 1988). L is a function of canopy density and varies between 0 and 1 according to the vegetation cover. For example, in very high vegetation regions, L is 0 and SAVI is equal to NDVI (Bannari et al., 1995). SAVI can be defined by Equation 3.2.

\[
SAVI = \frac{(NIR - R)}{(NIR + R + L)}(1 + L) \tag{3.2}
\]

where NIR and R represent the reflectance of the near infra-red and red bands respectively.

SAVI was used in the development of crop classification maps for yield estimation for four irrigated crops - wheat, rice, cotton and sugarcane - in the Indus Basin, Pakistan (Bastiaanssen & Ali, 2003). The SAVI was used in some other studies (Bausch, 1995; Ray & Dadhwal, 2001) for the estimation of the crop coefficient, Kc, for corn and wheat crops. However, the main limitation of this index is the factor L. To employ SAVI in crop growth and yield assessment models, prior knowledge of L (vegetation canopy density) is essential (Huete, 1988).
| Generalised soil adjusted vegetation index | This vegetation index is a member of the SAVI family and can be defined in terms of parameters such as soil line. GESAVI is less sensitive to soil background features such as colour and brightness, thus gaining popularity as a very effective vegetation index in monitoring the earth’s vegetation cover (Gilabert et al., 2002). Generally SAVI family indices (SAVI, OSAVI, MSAVI and TSAVI) which have low reactions to soil background perform better than the traditional vegetation indices. Although the GESAVI was found to be the most reliable member of the SAVI family and correlates significantly with LAI for a wide range of LAI, it requires the definition of soil line in order to obtain soil line parameters and soil adjustment factors for each study in advance, as there is no existing universal soil line (Gilabert et al., 2002). GESAVI is defined by:

\[
GESAVI = \frac{NIR - (B \cdot R) - A}{R - Z}
\]

where NIR and R represent the reflectance of the near infra-red and red bands respectively, Z is the soil adjustment coefficient and A and B are soil line parameters. |

| Simple ratio | The simple ratio is one of the simplest vegetation indices most commonly used to characterise vegetation canopies on regional and global scales. It is the ratio between near infra-red and red reflectance measured from vegetation canopies (Equation 3.4). This ratio is higher when more leaves are present in the canopy due to the higher absorption of red than infra-red radiation by leaf pigments (Jordan, 1969). This index is mainly used to estimate LAI which is a key input parameter of |
biosphere processes. It is categorised as an intrinsic index as it only uses measured reflectance and does not account for any external parameters in its development. This index is well correlated with foliage cover but is sensitive to background parameters such as solar illumination geometry, sensor viewing conditions, background soil effects, atmospheric absorption and scattering effects (Rondeaux et al., 1996).

Colombo et al., (2003) estimated LAI in terms of SR by developing relationships between LAI and SR for five different vegetations in terms of reflectance measurements of IKONOS images which has a 1m spatial resolution. SR was estimated from raw Digital Numbers (DN), texture information and the combination of texture and geo-statistical parameters of the images. The relationships between LAI and SR showed weak correlation for combined vegetation cover but when the vegetation cover is stratified, the relationships showed better correlation. These relationships best fit for linear behaviour for a limited range of LAI. The relationships showed the high spatial variability within the field itself due to the high spatial resolution of the image, so the study recommends this type of image is more suitable for precision agriculture where LAI variation is crucial in management decisions. A similar type of study was carried out by Turner et al., (1999) using Landsat TM images for three temperate experimental zones. In their study, they derived various SRs including DNs, radiance, atmospherically corrected (surface reflectance) and non-corrected reflectance (top of atmospheric reflectance) which were related to ground-based LAI measurements. The behaviour of the relationship was analysed for a wide range of LAI (1 to 13m$^2$m$^{-2}$) and it was reported
that the relationships were stronger when atmospherically corrected reflectance was used to derive the vegetation index than when it was based on DN, radiance or top of atmospheric reflectance. Further, both studies, (Colombo et al., 2003) and (Turner et al., 1999), suggested stratifying the land cover classes individually in the development of LAI-SR relationships for better accuracy.

Lobell et al., (2003) derived a linear relationship for fPAR (fraction of PAR) in terms of SR in order to determine the irrigated wheat yield in the Yaqui valley, Mexico, using Landsat 5 TM and Landsat 7 ETM+ images. They used different approaches to determine the wheat yield by incorporating fPAR which was derived in terms of NDVI and SR individually and by combining SR and NDVI. The estimated yield and cropping areas derived by incorporating individual vegetation indices with fPAR have shown under- and over-estimations while the combined approach showed more accurate results.

\[
SR = \frac{\text{NIR}}{\text{R}}
\]

where NIR and R represents the reflectance of the near infra-red and red bands respectively.
The Difference Vegetation Index is calculated from the difference between near infra-red and red reflectance as in Equation 2.5. A study was carried out (Anderson et al., 1993) to derive DVI from spectral measurements using a Landsat TM satellite and it was related to green dry biomass in order to investigate its level of association at different times during the cropping seasons in a semi-arid region in Colorado. The different approaches (ground-based, spectral classes derived from classification and greenness strata approach) were carried out to calculate dry green biomass and the relationships were then analysed. The correlation was poor for the ground-based approach due to the incorrect location of the ground sample point on the image and unmeasured variables in the sample area affecting the relationships negatively. In the spectral class approach, the derived relationship was significant only for one day when higher greenness was available. The results were significant for all the dates when DVI was related to biomass which was aggregated by the greenness stratum. This relationship indicated the possibility of calculating the green biomass in terms of vegetation indices.

\[
DVI = NIR - R
\]

3.5

where NIR and R represent the reflectance of the near infra-red and red bands respectively.
The Perpendicular Vegetation Index is developed by taking into account the background effect of bare soil (Bannari et al., 1995). The equation of PVI is defined as follows (Equation 3.6)

\[
PVI = \sqrt{((\text{NIR}_{\text{veg}} - \text{NIR}_{\text{soil}})^2 + (R_{\text{veg}} - R_{\text{soil}})^2)}
\]

3.6

where \((\text{NIR}_{\text{veg}} - \text{NIR}_{\text{soil}})\) and \((R_{\text{veg}} - R_{\text{soil}})\) are the reflectance differences between vegetation and bare soil in the near infra-red band and the red band respectively.

Casanova et al. (1998) estimated the PVI from in-situ reflectance measurements which were collected with a handheld multispectral radiometer in order to estimate LAI. Subsequently they estimated fPAR in terms of LAI and estimated the above ground biomass in order to monitor the rice crop status during the cropping season in the Ebro Delta, Spain. As the background effect of soil was addressed in this index, it showed less sensitivity to soil background and provided the best estimation for fPAR at different stages of the growing season.

However, in order to use PVI, prior knowledge of bare soil reflectance is required in advance and that is the main limitation of this index.
The Enhanced Vegetation Index (EVI) is available as a product of MODIS satellite data. It was developed by integrating the red, near infra-red and blue spectral bands in such a way as to minimise its sensitivity to the soil effect while improving its sensitivity to high biomass regions (Equation 3.7). But the use of long term EVI time series products are limiting their use as they generate problems due to the use of the blue spectral band (Zheng & Moskal, 2009). An EVI MODIS product which had coarse resolution was used by Colombo et al. (2003) in the Colombano region in Italy to estimate LAI for five different types of vegetation. This vegetation index showed the same behaviour as the NDVI and very similar behaviour to the other indices (SR, SAVI, PVI and ARVI) which were directly derived from reflectance measurements from an IKONOS satellite image.

\[
EVI = \frac{NIR - R}{NIR + RC_1 - BC_2 + C_3} G
\]

where NIR, R and B represent the reflectance of the near infra-red red and blue bands respectively, and \(C_1, C_2, C_3\) and \(G\) are coefficients of EVI.
The Ratio Vegetation Index was one of the first vegetation indices developed (Bannari et al., 1995; Pearson et al., 1972). This is a simple index which effectively represents canopy characteristics when the vegetation is dense. However, as it is very sensitive to atmospheric factors it is not effective for use when the vegetation cover is sparse. RVI is defined as follows (Equation 3.8):

$$RVI = \frac{R}{NIR}$$

where NIR and R represents the reflectance of the near infra-red and red bands respectively.

Many studies have been carried out to estimate LAI using vegetation indices derived from spectral and textural information, either from ground measurements or from satellite data. In order to develop relationships between the spectral measurements and the LAI of crops during the growing season, the reflectance measurements of the crop canopy are obtained either from remote sensing, a Multi-Spectral Radiometer (MSR) or an ASD spectroradiometer (Analytical Spectral Device) (Haboudane et al., 2004b). Red and near infra-red (NIR) wave bands should be included in the instrument’s spectral range in order to analyse absorbed and reflected spectral reflectance information of the crop canopy. This is because of the nature of the high reflectance of NIR and the high absorption of red by live plant tissues. The difference between NIR and red reflectance measurements is used as a simple tool for studying the reflectance data (Major et al., 1990; Wang et al., 2010). A number of SVIs have been developed based on the characteristics of NIR and red reflectance in order to estimate LAI using reflectance data.

Most vegetation indices are calculated from the combination of red (0.63–0.69µm), NIR (0.76–0.90µm), shortwave infra-red (1.55–1.75µm)
and middle infra-red bands (2.08–2.35µm) reflectance data using different algorithms. The reflectance data can be obtained from remote sensing data or can be collected from corresponding crops using hand held instruments such as the Multi-Spectral Radiometer (MSR) (CROPSCAN, 1995).

According to available literature the estimation of LAI using spectral vegetation indices can be divided in two categories:

1. Estimation of LAI using spectral vegetation indices derived from on-ground optical instruments; and
2. Estimation of LAI using spectral vegetation indices derived from remote sensing.

1. Estimation of LAI using spectral vegetation indices derived from on-ground optical instruments

Aparicio et al., (2000) carried out a field study to assess the potential for using spectral vegetation indices to provide accurate and indirect measurements of biophysical parameters in the estimation of crop yield in irrigated and rainfed wheat at two different test fields in north-eastern Spain. LAI was non-destructively estimated using a leaf area meter (a Delta-T device) and canopy reflectance was measured using a portable field spectroradiometer which was able to measure the visible and near infra-red reflectance of the electromagnetic spectrum. Several spectral vegetation indices - NDVI, Simple Ratio (SR) and Photochemical Reflectance Index (PRI) - were calculated from spectral measurements of wheat crops. All the spectral vegetation indices showed higher values under the irrigated conditions than the rainfed conditions. The study showed that LAI well correlated with the derived spectral vegetation indices. SR and PRI respectively were the best and worst spectral vegetation indices for determining the crop status and grain yield for wheat. The study further explained the usefulness of spectral vegetation indices for estimating the grain yield of wheat for different ranges of LAI.

A similar type of study was conducted by Haboudane et al. (2004b) for the prediction of LAI using different vegetation indices (NDVI,
Modified Second Soil-Adjusted Vegetation Index (MSAVI2), Modified Second Triangular Vegetation Index (MTVI2) derived from ground-measured reflectance data. The reflectance and LAI measurements of four crops - wheat, corn, soybeans and peas - were collected from experimental and commercial farms in Canada over a four year period. Ground reflectance measurements were collected with a spectroradiometer while LAI measurements were obtained both directly and indirectly by measuring the leaf area using an area meter (LI-3100) and an LAI-2000 plant canopy analyser respectively. The study showed that the relationships between the spectral vegetation indices and LAI are different from one index to another because the responses of the vegetation indices to the amount of chlorophyll and canopy characteristics vary as they are designed to measure vegetation chlorophyll content differently. Predictive equations developed from the relationships behave exponentially and the coefficient of determination varies with different vegetation indices and crop types.

2. Estimation of LAI using spectral vegetation indices derived from remote sensing

Obtaining ground-based LAI values at a regional level over dynamic and rapidly changing land cover is labour-intensive and expensive. Therefore, an alternative, rapid and reliable remote sensing-based method is required to accommodate the need for frequent readings over large areas. Numerous approaches and methodologies have been developed for LAI estimation based on remote sensing over a diverse range of landscapes for various crop types (Haboudane et al., 2004b; Qi et al., 2000).

Some vegetation indices are readily available as satellite products. For example, two MODIS vegetation indices, the NDVI and EVI, are such products which represent the biophysical status of vegetated surfaces on the globe (NASA, 2012) and provide 1km and 500m spatial resolution (Huete et al., 2002). The NOAA-AVHRR (Advanced Very High Resolution Radiometer on board the NOAA satellite) derived NDVI time series of 1km spatial resolution is another satellite product which is readily available and widely used in many applications (Cihlar et al., 1997; Goward et al., 1991;
A number of researchers have carried out studies on LAI estimation in different parts of the world and two of these are mentioned below.

Colombo et al.,(2003) developed a map of LAI in terms of different spectral and textural information for five vegetation types at test sites in the Colombano region of Italy by employing indirect measurement. Several vegetation indices including NDVI, SR, SAVI, PVI, Atmospherically Resistant Vegetation Index (ARVI) and EVI were derived using spectral and textural characteristics of IKONOS satellite images (1m spatial resolution). In-situ measurements of LAI were collected with an LAI-2000 plant canopy analyser. Single-sensor mode was employed with a 45° view-cap, all the measurements were taken under diffuse radiation conditions and all the measurements were taken under the assumption that the leaves of the canopy were randomly distributed. The LAI measurements were plotted against the derived vegetation indices and investigated the reliability of the relationships. The study showed a promising linear correlation between LAI and vegetation indices for individual vegetation types. However, the study suggested that it is difficult to define the most suitable vegetation index (from the tested indices) for the mapping of LAI.

A regional-scale study in a semiarid area in Morocco was carried out by Duchemin et al. (2006) and developed the relationship between NDVI and LAI. NDVI initially was estimated from field measurements and remote sensing measurements from a hand-held MSR87 multispectral radiometer and from Landsat-7/ETM+ satellite images. LAI was collected through direct destructive measurements by estimating the ratio of green leaf area to its ground area from metric and phenological observations. The relationship derived was found to be exponential and showed a low accuracy due to the saturation effect for well-developed canopies when the LAI value was between 2 and 6.
3.3 Land Use and Land Cover Classification

Land is defined as a delineable area of the earth’s terrestrial surface including all the attributes of the biosphere directly above or below it. It includes the climate of the surface, different terrain formations, soils, surface hydrological features, plant and animal populations, and human population patterns and the physical results of their present and past activities. In the light of the above definition, land can be divided into two domains: land cover and land use. Land cover explains the physical or biophysical status of the land including cropland, forest, wetlands and pastures while land use describes the modified condition of the land as a result of specific human activities (Ullah, 2011). There is a close relationship between land cover and land use, but they are not identical (Kashaigili & Majaliwa, 2010). For example, vegetation can be defined in terms of its characteristics and structure (grassland, forest or woodlands) in the domain of land class or it can be defined by its specific use (plantation or agriculture) in the domain of land use (Cihlar & Jansen, 2001).

Accurate and current Land Use and Land Cover (LULC) information is vital in agricultural regions due to the dynamic behaviour of irrigated fields. LULC types in these agricultural regions change rapidly both spatially and temporally and subsequently this affects ecological and hydrological processes, the climate and the economy. Therefore, detailed current crop maps must be developed in order to understand the spatial distribution of the present LULC patterns in a given region. Moreover, current LULC information plays an important role in many regional and global scale monitoring and modelling processes as it is used to retrieve LAI and other crop-related biophysical parameters which are key inputs of those processes, particularly in crop growth assessment and crop yield estimation models.

Satellite remote sensing offers remarkable opportunities for continuous monitoring of irrigated areas and related activities because of its synoptic nature, the prompt availability of images through archives and the availability of images in various spectral bands with temporal frequencies
that enable adequate monitoring of crop phenology and the estimation of harvests (Ozdogan et al., 2010). Remote sensing-based image classification has a long history and now is the most common method used to create LULC maps (Ouattara et al., 2004; Yan et al., 2006) due to its low cost and time effectiveness. It is an important tool for monitoring irrigated land, particularly the land’s physical and biophysical status, over time and space at a regional scale. The main steps involved in the classification procedure include the selection of satellite images, the determination of an appropriate classification technique, the collection of the correct number of training samples and the assessment of the accuracy of the LULC map. Accurate and current LULC maps can be obtained by utilising an effective remote sensing technique together with carefully selected image data. For example, a suitable classification technique for a specific application should be selected in accordance with the different image resolutions. Further, the user’s need, the extent of the study area, the strengths and limitation of the image data and economic conditions are key factors affecting the selection of remotely-sensed data (Lu & Weng, 2007).

In the past, LULC classification was carried out by visual interpretation of remote sensing images based on a number of visual interpretation techniques tailored from aerial photo interpretation techniques in order to prepare crop maps and to update the acreage of irrigated areas (Ozdogan et al., 2010). But recently LULC maps have been developed using advanced digital image classification techniques by incorporating images with high spatial resolutions.

3.3.1 Visual interpretation

LULC mapping based on visual interpretation was carried out using satellite hard copies in order to identify crop types, farm boundaries and their extents. At the very early stage, a traditional aerial photo interpretation technique was applied on temporal Landsat colour composite images to delineate the irrigated boundaries manually. In this technique, low cost time series available with several spectral bands including NIR offered useful
spectral information for correct identification and delineation of irrigated crops and boundaries (Ozdogan et al., 2010).

Later, this technique was automated and benefited from the strong spectral variations in the visible and NIR regions due to the different status of crops from irrigated to harvested and fallow fields. However, there are some disadvantages to the visual interpretation technique even though the technique develops classified crop maps accurately. The technique does not allow the discrimination of different irrigated crops accurately using a single date image. Further the technique is not economical to employ as classification is entirely dependent on a human analyst (Ozdogan et al., 2010).

3.3.2 Digital image classification

Even though image classification based on the conventional visual interpretation technique is highly accurate, most of the recent classification work has emphasised digital image classification techniques due to the shorter processing time and lower costs with acceptable accuracy. Based on the spectral and/or contextual information of a single pixel or a number of pixels of the image, they are assigned to various thematic classes in the real world. Among the many available classification procedures, conventional pixel-based classification still applies in many studies of irrigated agriculture using supervised, unsupervised and hybrid approaches.

With recent advancements in resolution of remotely-sensed images, various medium and high resolution satellite images are delivered by many sensors. With the development of technology, demand for new applications to utilise this reliable information has been stimulated and more efficient feature-extraction methods such as object-based image analysis techniques (Blaschke et al., 2000), artificial neural networks, fuzzy-sets and expert systems (Lu & Weng, 2007) have been developed.

In general, digital image classification techniques can be categorised into per-pixel, sub-pixel and per-field (object), or supervised and unsupervised, or parametric and nonparametric or hard and soft (fuzzy) classifications (Lu
& Weng, 2007). The categories are given in Figure 3.3 and a brief description of each category follows:

![Digital Image Classification Diagram](image)

**Figure 3.3: Different approaches of digital image classification techniques**

### 3.3.2.1 Pixel-based classification

Conventional pixel-based classification has also been carried out to create LULC classification maps in studies around the world (Akbari et al., 2006; Alexandridis et al., 2008; Cheema & Bastiaanssen, 2010) and in Australia (Ahmad et al., 1997; Khwaja et al., 2003) depending on the availability of data and resources and the user’s requirements. Pixel-based supervised image classification is used to create land cover maps on a single pixel basis (Yan et al., 2006). In this technique, the classifier identifies the single pixel’s position in a multi-dimensional feature space (spectral value), compares it with the prototype pixels of each class and assigns the corresponding thematic class (Yan et al., 2006). This technique uses only
the spectral value of the pixel to classify the image (Casals-Carrasco et al., 2000a; Rahman & Saha, 2008). Even though this technique is widely used and well developed with a number of sophisticated classifiers, it does not use the spatial, textural or conceptual characteristics of the image (Blaschke et al., 2000; Zhou & Robson, 2001). However, contextual information is crucial in accurate image classification (Blaschke et al., 2000; Zhou & Robson, 2001) in irrigated agriculture.

Pixel-based image classification is problematic because of the fact that it only takes into account the spectral values of pixels. Large areas which have similar spectral characteristics but consist of different vegetation cover or varying densities of tree cover would be difficult to classify by taking into account only the spectral characteristics as there is no method of analysing the structure of the cover. In other words, when different land cover classes have similar spectral characteristics, the classifier identifies them as one class as the classifier uses only the spectral information to identify the land cover class (Rahman & Saha, 2008) and this may lead to erroneous classification results. Another problem is that if the method is applied to the mapping of vegetation cover on a small scale, the spectral heterogeneity will create mixed pixels and a ‘salt and pepper’ effect will appear in the classified images (Blaschke et al., 2000). In addition, the pixel-based classification technique is problematic when applied to high resolution images in the mapping of community scale classes, as increased spectral heterogeneity within a small land cover class will lead to mixed pixels and thus lead to inaccurate classification results (Whiteside et al., 2011). Therefore, it is essential that contextual information be considered in order to identify meaningful image objects to obtain accurate image classification (Yan et al., 2006; Zhou & Robson, 2001).

A pixel-based classification technique works well with hyperspectral data as it compares the spectral values of particular pixels with several bands. However, it is does not work well with panchromatic or multispectral images (ENVI., 2009).
3.3.2.2 Object-based classification

Object-based classification was introduced in the 1970s and was based on high spatial resolution images (De Kok et al., 1999; Flanders et al., 2003) which had some limitations due to issues with hardware and software, low image resolution and inadequate explanation of theories (Flanders et al., 2003; Yan et al., 2006). However, since the mid-1990s, with improvements in hardware and software and the easy availability of high spatial resolution images, many studies have been carried out using of this technique (Benz et al., 2004; Das, 2009; De Kok et al., 1999; Herold et al., 2002; Yan et al., 2006).

Object-based classification is becoming more popular than pixel-based classification with the availability of high resolution multispectral images. In this technique the classifier takes objects into account instead of pixels. This means an object’s contextual information is taken into account whereas it is neglected in conventional classifications (Blaschke & Strobl, 2001). This technique is more appropriate for images that have high spatial resolution because very few high resolution image pixels are needed to cover the real world objects on the terrain (Geneletti & Gorte, 2003).

This technique consists of a number of sequential steps of segmentation and classification to create accurate LULC classification maps. Image segmentation is a crucial preliminary step in this technique. Image segmentation subdivides the image into a number of non-intersecting, homogeneous segments (Conrad et al., 2010; Dey et al., 2010; Geneletti & Gorte, 2003). The basic element of this approach is the image object and the smallest image object is one image pixel (Benz et al., 2004). Homogeneous objects are formed by grouping adjacent segments with similar characteristics of spatial, textural and spectral data.

The merging of segments is based on the homogeneity criterion which takes into consideration the similarities between and within adjacent segments. Adjacent segments which have the least difference are merged. This process progresses till the smallest difference in homogeneity exceeds the user-defined threshold (scale parameter). The scale level determines the
average image segment size (Rahman & Saha, 2008). The scale level should be selected very carefully as image segmentation is crucial in object-based classification because classification accuracy depends largely on good segmentation. If the scale level is too high, it allows more merging of the boundaries between segments and some features of interest will be lost. On the other hand, low scale levels perform over-segmentation leading to too many objects (ENVI., 2009; Rahman & Saha, 2008). Therefore good image segmentation using an appropriate scale level is important for image analysis and classification (Rahman & Saha, 2008; Yan, 2003). After the segmentation and merging phases are completed, meaningful image objects are formed and automatically assigned to a hierarchical network where each object knows its position within the network. These objects contain important contextual information which produce a quality classification (Rahman & Saha, 2008). The second step in the object-based image classification technique is the classification of image objects into thematic classes based on samples or rules or by combining both.

There are three commonly used segmentation techniques: threshold or clustering, edge-based and region-based (Fu & Mui, 1981). However as there are both advantages and disadvantages to these three techniques, no one method is suitable for all images and all methods are not suitable for a specific image (Pal & Pal, 1993). For example, the region-based method is widely used in many programs (Yan et al., 2006) and can be successfully applied in the extraction and classification of homogeneous regions but it is not suitable for images consisting of complex or noisy data.

One of the main limiting factors in object-based classification is the coarse spatial resolution of the image which affects the selection of suitable segmentation that is crucial in this technique.

3.3.2.3 Comparison of pixel-based and object-based classification

In conventional pixel-based classification, the basic unit is the pixel. A pixel-based classifier uses only the multispectral characteristics of the image pixels to classify the image into a class (Casals-Carrasco et al., 2000b) and does not make use of spatial characteristics (Blaschke et al.,
A commonly used algorithm for pixel-based classification is the Maximum Likelihood Classifier (MLC) (Dean & Smith, 2003; Lu & Weng, 2007). However, this classifier utilises only textural information, not spectral or contextual information (Zhou & Robson, 2001), which produces poor classification results (Angelo & Haertel, 2003). Objects in the real world are not represented by a single parameter but are defined by a number of characteristics and a range of contextual information. Normally, land cover types, especially vegetation, occur in more than one pixel in the real world. Hence, contextual information is important in order to increase the accuracy of conventional spectral classification by considering adjacent pixels. Therefore, spectral-contextual information is paramount in accurate image classification (Zhou & Robson, 2001) and has shown higher accuracy in results than traditional pixel-based classification in many studies (Blaschke, 2010; Geneletti & Gorte, 2003; Rahman & Saha, 2008; Yan et al., 2006).

One of the main advantages of the object-based approach is that it utilises knowledge which is beyond spectral information only and includes contextual information such as shape, texture and relationship along with ancillary data. Moreover, an object-based classification process has a greater possibility of using higher resolution images for classification and change detection than the pixel-based method (Whiteside et al., 2011). (Castillejo-González et al., 2009) showed that an object–based method outperformed several supervised classification algorithms such as parallelepiped, minimum distance, Mahanalobis distance classifier, spectral angle mapper and maximum likelihood classifier for crop mapping and measures related to the agro-environment. Some studies (Ouyang et al., 2011; Whiteside et al., 2011; Yan et al., 2006) have achieved higher accuracy in mapping land cover classes using object-oriented classification method than pixel-based approaches. The main specifications of pixel-based and object-based classification techniques are summarised and compared in Table 3.2.
Table 3.2: Main Specifications of Pixel and Object Based Techniques.

<table>
<thead>
<tr>
<th>Pixel-based Classification</th>
<th>Object-based Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mostly the spectral, and only rarely the textural, information is taken into account in the classification process.</td>
<td>In addition to spectral and textural information, contextual information and image hierarchy are also taken into account in the classification process.</td>
</tr>
<tr>
<td>Comparatively low accuracy is obtained.</td>
<td>Greater accuracy can be achieved.</td>
</tr>
<tr>
<td>There is no guarantee of enhancing the accuracy when using high resolution imagery due to its classification nature.</td>
<td>Object-based classification has great potential for improvement in accuracy owing to the use of higher resolution imagery in crop classification.</td>
</tr>
<tr>
<td>The process can be carried out using simple and inexpensive software packages.</td>
<td>Process needs sophisticated software which is comparatively expensive.</td>
</tr>
</tbody>
</table>

3.3.2.3.1 Supervised classification

Supervised image classification is one of the most widely undertaken classification procedures for qualitative analysis of remotely sensed data. It requires the use of suitably selected algorithms or class rules (Foody, 2004). Various algorithms are used in supervised image classification to allocate image pixels to one of the thematic classes. This approach requires human interaction to specify the definition or signature of the training samples to the algorithm in order to classify the spectral classes into real world thematic classes (Lu & Weng, 2007).

Three distinct steps are involved in supervised classification: image categorisation; allocation of a pixel or number of pixels (categories) to
thematic classes based on training statistics; and accuracy assessment of derived thematic classes. The output of this process is a thematic map which represents the spatial distribution of specific themes of interest such as land cover or land use (Foody & Mathur, 2004).

In supervised image classification, categorised image pixels need to be assigned to meaningful thematic ground classes. Representative samples for each category (called training data) need to be collected from the ground. Training data is normally obtained from the field, aerial photographs or from topographical maps. One of the key factors associated with the derivation of accurate thematic mapping is the training data. There may be a more considerable effect from training data on the classification accuracy than the classification technique adopted in the classification procedure (Hixon et al., 1980). The accuracy of the classification results depends not only on the collection strategies such as single pixel, seed and polygon but also the resolution of the satellite image and the complexity of the landscape (Lu & Weng, 2007). The collected training data is used in various statistical (parametric) and geometrical (non-parametric) algorithms to train the classifier. One of the most widely used parametric algorithms is the Maximum Likelihood Classification (MLC) algorithm which is based on statistical theory. The most commonly used non-parametric classification algorithms are parallelepiped, minimum distance, nearest neighbour and neural network (Kloer, 1994).

3.3.2.3.2 Unsupervised classification

In the unsupervised classification approach, human interaction is needed only to a small extent as training data is not utilised. Therefore this technique is more computer automated. In this method, different spectral clusters are formed in the feature space based on the inherent spectral characteristics of pixels using computer algorithms. Similar spectral properties of the pixels are determined based on statistically evaluated criteria (mean reflectance, standard deviation, covariance matrix and correlation matrix) and grouped into one spectral cluster. The spectral value
within a cluster should be similar, whereas the spectral values in different clusters should be reasonably distinct (Lillesand & Kiefer, 2000). The spectral clusters are subsequently compared with reference data such as paper maps or high resolution images to be labelled by a systems analyst in order to form classification maps consisting of real world thematic classes (Lillesand & Kiefer, 2000).

There are different clustering algorithms which can be used to form clusters in unsupervised classification. The most widely used forms are the k-means method and the Iterative Self Organising Data Analysis Technique (ISODATA) (Cheema & Bastiaanssen, 2010). Each has its own advantages and disadvantages.

In the k-means approach, the analyst defines the number of clusters to be formed in the dataset and the algorithm evaluates the locations of cluster centres in the multidimensional measurement space. Each image pixel is assigned to a cluster by taking into account its distance from the cluster centre. In this way, different clusters are formed and the land cover class identity for each spectral class is determined by the analyst by associating the reference data (Lillesand & Kiefer, 2000).

The ISODATA algorithm is one of most widely used, simple techniques in unsupervised image classification. It repetitively recalculates the statistics of cluster means and Euclidian distances for clusters throughout the entire classification and requires minimum user inputs to form spectrally homogeneous clusters. This algorithm calculates the means of each cluster with respect to the selected initial parameter and Euclidian distances to the cluster means for each cluster. Some of the clusters formed are merged by comparing the Euclidian distances of each cluster to cluster means. Identity is given to the resultant clusters based on reference data drawn from field surveys or old maps (Bahadur K.C., 2009).

3.3.2.3.3 Hybrid classification

There are some limitations in both supervised and unsupervised classification techniques in the development of accurate classification maps.
Supervised classification is the most widely used method for forming classification maps, however a sufficient number of quality training samples and their representations are a prerequisite for forming accurate land cover classes. The selection of a sufficient number of training samples with correct representativeness is a complicated procedure, especially for classification with fine-scale resolution images for heterogeneous landscapes. In other words, the quality of the training sample affects the accuracy of the classification (Lu & Weng, 2007) to a great extent. In contrast, in the unsupervised classification approach, there is no prior definition of classes required through field-collected training samples as this technique uses clustering-based algorithms to form spectral classes from the image (Lu & Weng, 2007). Benefited by its inherent characteristics the unsupervised classification approach has advantages over the supervised classification technique. However, unsupervised classification still has some drawbacks. For example, it may miss some specific and relevant details as the classifier strives for the best possible spanning of the entire dataset. Another disadvantage of the unsupervised classification technique is its dependency on classification parameters and the limitations of the clustering process. Further, the analyst has to select the optimum clustering parameters for a given dataset through numerous trials (Cihlar et al., 1998).

As there are drawbacks and limitations in both supervised and unsupervised classification techniques, some scientists have suggested various forms of hybrid classification techniques in order to improve accuracy and efficiency: a combination of a supervised and unsupervised approach (Cihlar et al., 1998; Lo & Jinmu, 2004); a combination of a supervised classification approach with additional empirical rules (Geneletti & Gorte, 2003); and a combination of a decision tree and a neural network approach (Liu et al., 2004).

3.3.2.4 Assessment of the accuracy of classification

In the past, photo interpretation was assumed to be 100% correct but without any accuracy assessment criteria this was not validated. The assessment of digital classification accuracy, mostly relying on photo
interpretation, may in fact lead to poor and inaccurate results (Congalton, 1991). Therefore it is necessary to validate the classification results before using them in any application. Accuracy assessment can be done effectively through an appropriate technique by choosing factors that can affect the process.

Accuracy assessment is normally carried out by testing the classification results against the reference data or ground samples. For this process, a set of pixels is selected from the classified image and compared with corresponding pixels of a known thematic class of pixels on the ground. This process is called the accuracy assessment.

An error matrix is a square array with an equal number of rows and columns which represent the reference data (ground truth) and the corresponding results of classification. Table 3.3 represents the format of the error matrix. Usually the columns represent the reference data and the rows represent the land cover category that is generated by the classifier. The error matrix represents the accuracies very effectively by describing both the errors of inclusion (commission) and exclusion (omission) which are present in the classification process (Lillesand & Kiefer, 2000).
The error matrix can be used to analyse results descriptively. The classified image pixels which are in agreement with the ground truth data are located in the cells of the major diagonal of the error matrix while the classified image pixels which are in disagreement with the ground truth data are located in the off diagonal cells (Potgieter et al., 2010). The overall accuracy is calculated using the ratio of the sum of the total number of pixels along the major diagonal (correct number of pixels) to the total number of all pixels in the error matrix (Equation 3.9). The accuracies for individual classes are computed by dividing the diagonal element by the total number of pixels in the corresponding column or row. These accuracies are defined as “producer” and “user” accuracies respectively (Lillesand & Kiefer, 2000). The producer accuracy explains how well the ground truth pixels of a specific cover are classified, while the user accuracy
describes the probability of a pixel classified to a specific cover type actually representing that cover type on the ground (Congalton, 1991).

\[
\text{Overall accuracy} = \frac{\sum_{i=1}^{N} x_{ii}}{\sum_{i=1}^{N} x_{ii}} = \frac{1}{N} \sum_{i=1}^{N} x_{ii}
\]

3.9

Another discrete multivariate technique for accuracy assessment is the Kappa Coefficient (KC) which measures the actual agreement and chance of agreement (Cohen, 1960; Lillesand & Kiefer, 2000). The accurate formation of a land cover class mainly depends on the sample points in the error matrix approach. However, an inadequate number of ground truthing points could also lead to the assigning of the correct class by chance (Foody, 2002). This chance agreement can be examined in terms of the Kappa coefficient (Cheema & Bastiaanssen, 2010; Cohen, 1960; Foody, 2002). The Kappa coefficient statistic is called K-HAT \((k^\cdot)\), representing the agreement percentages which are obtained after removing the agreement which is expected to happen by chance and are calculated by incorporating the off-diagonal elements to compute KC (Congalton, 1991) (Equation 3.10)

\[
k^\cdot = \frac{\sum_{i=1}^{N} x_{ii} - \sum_{i=1}^{N} (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^{N} (x_{i+} \cdot x_{+i})}
\]

3.10

However, many other factors such as ground data collection, classification scheme, spatial autocorrelation, sample size and sampling scheme should also be considered along with the actual analysis technique when performing an accuracy assessment. It is necessary to take into account at least one of the above factors to avoid serious shortcomings in the accuracy assessment process (Congalton, 1991).

The error matrix approach is one of the most commonly used methods for accuracy assessment (Foody, 2002) and many researchers have recommended the use of this approach to achieve classification accuracy in remote sensing image classification (Congalton, 1991; Dawbin & Evans, 1988; Dorren et al., 2003; Potgieter et al., 2010). According to Lu & Weng (2007), the error matrix approach is widely used for categorical classes
where map categories are mutually exclusive and comprehensive and each location represents only one category.

### 3.3.2.5 Land use and land cover classification approaches in irrigated agriculture in Australia

A Dynamic Land Cover Dataset (DLCD) of Australia has been developed by Geoscience Australia and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) and was presented in 2011 (Lymburner et al., 2011). The DLCD is accurately generated using MODIS imagery and is available seasonally or monthly. Its long term observations allow managers, decision makers and researchers to understand the dynamics of different land cover types such as forests, woodlands and rangelands as well as cropping systems. The availability of a reliable and thematically comprehensive dataset for a country is essential in order to address a range of natural resource challenges including sustainable farming practices, management of water resources and land use practices. The DLCD can be used in many moderate and coarse models to estimate groundwater recharge and discharge, ET and land surface processes. Although the 250m scale DLCD is very useful from a regional perspective, it does not provide small scale information such as areas under different crops in irrigated agriculture which is paramount in efficient water resource management (Lymburner et al., 2011). There are only a few studies related to LULC classifications carried out in Australia and they are discussed below.

Shunlin et al., (2003) have developed two algorithms to estimate two biophysical variables, LAI and surface broadband albedo using Advanced Land Imager (ALI) data. ALI is a multispectral satellite sensor on board the NASA Earth Observing 1 (EO-1). It has identical spatial resolution to the Landsat-7 Enhanced Thematic Mapper Plus (ETM+) with three additional (one blue and two near infra-red) spectral bands. The validation of these two biophysical variables was carried out at the Beltsville Agricultural Research Centre (BARC) in the USA and the CIA in Australia. The first
site had variable crop fields and the second had multiple small plots within large homogeneous crop fields. However, a direct comparison was not possible due to geo-location and registration uncertainties in the images and, thus, the average LAI values for each field were calculated for the validation of the algorithm in the CIA. The results have proven that these products generated from the new algorithms are very accurate and the additional three ALI bands have been helpful for the estimation of the two biophysical variables.

Van Niel and McVicar (2004b) conducted a study in the CIA to determine the temporal windows to differentiate groups of crops and individual crops and to compare simple combining methods of single-date results to achieve higher overall accuracy. They used seventeen Landsat-7 ETM+ images for the classifications of four major irrigated crops - rice, corn, sorghum and soybeans - grown in the 2001-02 summer season. Pixel-based classification was carried out using MLC and the accuracy assessment was determined using a standard error matrix approach. The analysis showed that the period of optimum overall classification accuracy for the four groups of crops was late February to mid-March. The best time periods for differentiating of single crops were also identified. These were November to early December, mid-February to mid-March, early April to early May and early January to mid-March for rice, corn, sorghum and soybean respectively, although these time periods may not be valid for every year because the sowing data differs from one year to another. Further, the overall classification accuracy for rice and soybean was over 95% which indicated that these two major crops can be classified more accurately than the other two crops in the CIA.

Van Niel et al., (2003) carried out a study to compare the accuracy of classifications derived from broadband moisture indices with normal supervised classification results in the CIA. A set of cloud free ETM+ images was acquired during the summer season of 2000-2001. Three spectral vegetation indices related to environmental moisture (Normalized Difference Infra-red Index (NDII), Moisture Stress Index (MSI) and depth of ETM+ band 5) and one spectral vegetation index related to ‘greenness’
(NDVI) were computed using reflective ETM+ bands for 12 atmospherically corrected images. Pixel-based supervised classification was carried out for all 12 images using MLC and derived indices. Both the classifications were carried out using the same training datasets, and accuracy assessments were tested on a separate dataset which was not used as training data in the classification process. The results showed that the classifications based on indices were more accurate than those based on MLC in the early cropping stage due to the selection of targeted spectral features but after that, MLC was more accurate than the indices-based classifications due to the contraction of the canopy with less moisture content in the environment. However, the study has shown that the index-based classification is simpler because the technique only uses mathematical functions and thus limits the requirement for sophisticated computer software. The study reveals the importance of selecting spectral vegetation indices of moisture when classifying rice.

3.4 Yield Estimation

Crop growth and development fluctuate over time due to different environmental factors resulting in variations in crop yield spatially and temporally. Therefore, it is important to forecast crop yield before the harvest in the interest of national food security, to enable farmers to draw up plans for marketing their products and for implementing crop management practices such as fertilising and application of chemicals and irrigation scheduling (Horie et al., 1992). The yield can be estimated at farm, regional, country or continental level weekly, monthly, seasonally, yearly or for any particular period. However, the dimensions of the spatial-temporal scale depend on the requirements and the objectives. For example, at national level, a forecast on a large scale both in time and space is required as this is relevant for national food security and agricultural policy making (Horie et al., 1992).

Crop yield has been estimated over the past few decades by means of remote sensing data, agro-meteorological simulation models, crop growth models and statistical sampling methods (Asseng et al., 2003; Bairagi &
Remote sensing is the most suitable means of estimating crop yield over large scale landscapes (Teixeira, 2008). Crop simulation models such as MaizeMan, ORYZA2000 and APSIM (Agricultural Production Systems sIMulator) are commonly used to estimate crop yield at farm or field level.

### 3.4.1 Crop yield estimation using crop simulation models

In modern agricultural research, crop modelling and system analysis are being recognised as essential tools in understanding crop performance (Bouman et al., 2001). Knowledge about crop growth and development can be compared with modelling results and experimental observations to pinpoint knowledge gaps. New experiments or models can then be designed to address these knowledge gaps and used to identify the ideal genotype of crops, investigate yield gaps, enhance crop water management strategies and investigate how climate change can influence crop growth (Bouman et al., 2001).

One of the main objectives of crop simulation models is to compute agricultural production or yield as a function of weather parameters, soil conditions and crop management systems. Primary weather parameters such as air temperature, precipitation and solar radiation are key inputs in these models (Hoogenboom, 2000). These crop growth models are designed based on the mechanisms of various physiological processes such as photosynthesis, respiration, phenology, leaf development and grain initiation. Therefore, they have limited or no ability to adjust for individual situations (Hodges et al., 1987).

A number of crop simulation models such as ORYZA1, CERES-Rice, TRYM, VSM, RICAM, rice-weed competition model and ORYZA2000 have been developed for the assessment of rice growth and estimation of rice yield (Wikarmpapraharn & Kositsakulchai, 2010). Other simulation models such as MaizeMan (Humphreys et al., 2008) and CERES-Maize for maize (Hodges et al., 1987), APSIM (McCown et al., 1996; Wang et al., 2002) and CERES–Wheat (Nain et al., 2004) for wheat, and CROPGRO for
soybean (Basso et al., 2001) were developed to assess crop growth and
development and also to estimate crop yield. Each have their own
objectives, advantages and disadvantages, underlying assumptions and
complexities (Wikarmppapraharn & Kositsakulchai, 2010). However, most
of these crop growth models cannot produce one model to simulate different
crops. Instead there is a collection of models for specific crops (Liu et al.,
2007). The most widely used crop growth models for corn, rice and wheat
are discussed below.

3.4.1.1 MaizeMan

The MaizeMan model was initiated by Prof. Wayne Meyer of the
Commonwealth Scientific and Industrial Research Organisation (CSIRO)
Land and Water, Australia. The model was simulated using weather data
obtained from two Australian weather stations and results have shown that
seasonal weather conditions have a great effect on maize crop yields.
MaizeMan is a decision-support computer software package designed to
evaluate the effect of sowing, soil type, water table and irrigation
management practices on maize crop production. It was designed from the
CERES-Maize and SWAGMAN Destiny models (Humphreys et al., 2008;
White et al., 2003). The MaizeMan model estimates the yield of a maize
crop under different management decisions, especially sowing, irrigation
and nitrogen management. Different yields estimated under different
parameters help maize growers to make better decisions in such areas as
irrigation scheduling. In addition, the model can be used to assess maize
crop performance from previous cropping seasons, examine the effects of
different management practices and investigate alternative options for the
successful growth of maize which is severely affected by climatic
conditions, seasonal weather parameters or site specific conditions such as
soil type and groundwater level (White et al., 2003). MaizeMan is useful in
the practice of simple management strategies such as irrigation scheduling
and is customised to different soil types which, in turn, helps to maximise
crop yield, profitability, water and nitrogen use efficiency and ultimately
helps to avoid soil salinity problems (Humphreys et al., 2008).
This model was evaluated by Humphreys et al. (2008) for irrigated maize under sprinkler and furrow-irrigation systems. It showed reliable estimates for maize yield and soil water parameters in the Coleambally Irrigation Area (CIA). The model input parameters were collected from the Griffith weather station and rainfall data was collected from the CIA which is located about 50km south of Griffith but presents very similar weather conditions to Griffith. The scientists showed that the ability of MaizeMan to estimate crop yield and soil water parameters in small scale studies was encouraging. Moreover, they acknowledged that the model has the capacity to review different options for increasing crop yield and water productivity under different irrigation practices.

However the model was not tested for a shallow water table or saline soil conditions and it required numerous hydraulic soil parameters together with weather data to initiate and run the model. The model genetic coefficients used in MaizeMan were computed from observations taken from the Murrumbidgee Valley and this should be taken into consideration when the model is applied in a different environment (Humphreys et al., 2008).

3.4.1.2 ORYZA2000 model

The International Rice Research Institute (IRRI) has developed various crop models such as IRRIMOD and RICEMODE since 1970 (Bouman et al., 2001). In collaboration with the Simulation and System Analysis for Rice Production (SARP) project, IRRI released the ORYZA model series: ORYZA1 for potential production, ORYZA-W for water-shortage production and ORYZA-N for nitrogen-shortage production. ORYZA2000 was the updated version of all these series. The model simulates crop growth, development and water balance under potential production conditions such as water restrictions and nitrogen limitations (Bouman et al., 2001; Wikarmpapraharn & Kositsakulchaisri, 2010). Several computer modules such as above ground biomass, evapotranspiration and soil–water balance are combined with ORYZA2000 in order to estimate rice yield and to simulate different production situations (Bouman et al., 2001).
The key inputs of the model are soil characteristics, average wind speed, crop management practices and daily climatic data such as sunshine hours, minimum and maximum temperature, early morning vapour pressure and rainfall. The model estimates the yield potentials by combining all the required inputs for different climatic scenarios.

Wikarmpapraharn & Kositsakulchai (2010), compared two growth models, ORYZA2000 and CERES-Rice to check their ability to determine potential crop growth and rice yield in the Central Plain of Thailand. Although ORYZA2000 was a comparatively new research tool in Thailand, CERES-Rice had been used for years, tested and applied in research studies. The field experiments were conducted in order to calibrate the ORYZA model and to compare it with the CERES-Rice model under potential growth conditions. As the two models were developed under different approaches, the study was carried out to compare the two models under similar conditions in order to avoid biased results. Crop data such as leaf area, days to initiate panicle, flowering and grain yields were collected from field experiments and used for the estimation of crop parameters in ORYZA as well as for simulation. The results confirmed that both models satisfactorily predicted results for leaf area, days to initiate panicle and flowering, and estimated crop yield. They concluded that ORYZA2000 was satisfactorily simulating rice growth and development and further it can also be used as a research tool in order to make management decisions in field scale studies in Thailand.

ORYZA2000 was further evaluated by Amri (2008) against a dataset taken from field experiments in a rice research institute in Iran. In this study, crop data such as LAI, the biomass of leaves, stems, panicles and overall aboveground biomass were compared with simulated and measured crop data. The results showed that all the simulated and measured crop variables correlated positively except LAI. The researcher did not estimate the rice yield however the study showed satisfactory results for the estimation of total biomass production.
### 3.4.1.3 APSIM model

The Agricultural Production Systems sIMulator (APSIM) model was developed by an Australian collaborative group from the Agricultural Production Systems Research Unit (APSRU), Commonwealth Scientific and Industrial Research Organisation (CSIRO) and various Queensland State Government agencies (Keating et al., 2003). APSIM is a generic cereal yield prediction and crop development model designed to estimate economic products such as grain yield and biomass for different crop varieties under diverse climatic and management conditions. It is a cropping system modelling environment which simulates the dynamics of soil, vegetation and management relations for a single crop or a cropping system (Wang et al., 2002). It consists of a series of plug-in/pull-out modules which facilitate the simultaneous simulation of multiple crops through its central interface. It simulates more than 20 crops, grasses and trees, and consists of a number of crop modules for different crops such as wheat, cowpea, maize, sunflower, cotton, peanut and sorghum (Wang et al., 2002). The existence of these different modules in the APSIM model is a result of the adaptation of the initially developed crop growth models (Wang et al., 2002).

APSIM has been widely used in various applications such as crop management and cropping systems, water balance studies, climate impact, crop species interactions, crop classifications, and physical and chemical soil component studies (Keating et al., 2003). Asseng et al., (1998) tested the APSIM-wheat model to ascertain its performance by simulating above and below ground biomass, crop yields and water and nitrogen uptake for wheat crops in Western Australia. The output results were tested and compared with field experiment data obtained from different rainfall zones, soil types and wheat genotypes. The field experiments were carried out for ten seasons with varying farming practices such as varying sowing dates, plant density, fertiliser and irrigation. The APSIM model predictions of above and below ground biomass, crop yield, and water and nitrogen uptake presented acceptable results. The wheat yield estimations were well-predicted with a high degree of accuracy despite some under-estimates.
during severe droughts. The study suggested that it is possible to simulate above and below ground biomass predictions and wheat yield estimations using the APSIM model in Western Australia. However, APSIM is not appropriate for simulation of rice crops as the rice parameters are not properly calibrated and are not included in the model (Keating et al., 2003; Liu et al., 2007).

3.4.2 Crop yield estimation based on remote sensing data

The task of obtaining reliable and accurate information from farm scale to regional scale, covering thousands of hectares of irrigated lands, is challenging. However researchers have shown that the potential use of remote sensing data is invaluable in obtaining precise, real-time information on land surface processes and conditions (Bastiaanssen et al., 2000). Satellite remote sensing measurements are capable of providing regular and real-time information on the agricultural conditions of vast areas of irrigated land. The available wide range of spatial (5-5000m) and temporal (0.5–24 days) remote sensing data is capable of identifying and monitoring crop growth information and other related biophysical factors from individual farmer fields to entire river basins. It is an indispensable tool which can be used for different types of agricultural applications such as the estimation of crop yield and evapotranspiration, crop stress assessment, determination of land use and land cover, and the estimation of area of irrigated lands (Bastiaanssen et al., 2000). Among these agricultural applications, rapid and reliable crop yield estimation and predictions are important and crucial to the global economy and society (Ferencz et al., 2004). Therefore it is essential to employ satellite remote sensing in order to achieve accurate yield predictions.

Crop parameters such as greenness, vegetation condition changes throughout the cropping season and spectral measurements based on satellite data are useful for the predictability of crop parameters (Doraiswamy, 1995). Tucker et al., (1981) have shown that spectral data has a high correlation with vigour and vegetation condition. Each crop type
has a unique temporal signature which represents the normal vegetation conditions for different seasons. However extreme changes in weather conditions and natural disasters such as floods or droughts can change the normal temporal signatures of the vegetation. The amount of deviation from normal conditions may help to understand whether crop growth and crop yield will be affected. Healthy crop production can be expected if the vegetation is vigorous and has rapid growth. For example, if crops such as corn and wheat show a low leaf area index (LAI) through remote sensing measurements, the grain yield of those crops will have a low value (Doraiswamy, 1995; Tucker et al., 1980; Wiegand et al., 1991).

There are normally two main approaches to the estimation of crop yield using remote sensing data: (a) relating crop yield to spectral vegetation indices; and (b) simulating crop yield with crop models using remote sensing inputs (Van Niel & McVicar, 2004a).

3.4.2.1 Crop yield estimation by correlating vegetation indices

The seasonal growth of biomass or green vegetation has a correlation with crop yield (Doraiswamy, 1995). This principle of crop physiology has been applied in many studies in order to estimate crop yield by employing empirical regression equations linking vegetation indices and crop yields (Doraiswamy, 1995; Sharma et al., 1993). Many studies have been carried out to estimate crop yield using an empirical approach (Aparicio et al., 2000; Bairagi & Hassan, 2002; Groten, 1993; Maselli et al., 1992; Quarmby et al., 1993; Rasmussen, 1997; Sharma et al., 2000; Smith et al., 1995). In these studies, vegetation indices were obtained through remote sensing measurements. From all the vegetation indices used to develop empirical relationships, the most commonly used is the Normalised Difference Vegetation Index (NDVI) (Bastiaanssen & Ali, 2003; Prasad et al., 2006).

Maselli & Rembold (2001) carried out a yield-forecasting study using a regression model approach in order to predict cereal crop yield in a number of Mediterranean African countries. The researchers used NOAA-AVHRR NDVI Maximum Value Composite (MVC) images for the early estimation of wheat yield. The NDVI MVC averages were regressed with
the annual wheat yield values for 13 points throughout the cropping season and repeated for each country. The analysis revealed important relationships between final crop yield and the NDVI time series and pinpointed the most suitable time period for wheat yield forecasting in terms of NDVI data. Further they confirmed the suitability of NOAA-AVHRR NDVI MVC images in yield forecasting as NDVI is a sensitive indicator that represents the vegetation condition during the cropping season and therefore can be related to crop yield estimation.

The same regression approach was carried out in some other studies ((Maselli & Rembold, 2001; Mkhabela et al., 2011) to estimate the final productivity of cereal crops by integrating NDVI with cereal grain yields. Teal et al. (2006) regressed the NDVI with crop yield and evaluated the relationship between the corn grain yield and early season NDVI sensor readings at the Oklahoma Research Station. They achieved a strong correlation between yield and NDVI measurements and concluded that the yield estimations for corn could be accurately predicted with NDVI measurements.

Even though NDVI values are well correlated with reported grain yields in semiarid regions, this approach requires field-specific regression relationships to predict crop yield accurately (Doraiswamy et al., 2004). The relationships of crop yield and NDVI may not generally be applicable in different field locations and conditions as the relationships vary with the location. The coefficients of regression equations normally vary with environmental and weather conditions, different cultivars, crop growth stage and agronomic technologies (Horie et al., 1992). Therefore regressed empirical relationships can only be applied to a given region where the conditions are similar to those in which it has been developed (Doraiswamy et al., 2005). Moreover this approach of developing statistical regression relationships between NDVI and crop yield data shows a strong empirical character but in some studies correlation coefficients of regression models are moderate to low (Groten, 1993; Sharma et al., 1993). These relationships can provide accurate crop yield estimations only for the early stage of the cropping season as NDVI tends to saturate after the crop canopy
cover approaches 100% in its mid-vegetation phase (Thenkabail et al., 2000). The saturation effect of vegetation indices seriously limits the usefulness of remote sensing in determining accurate crop yield estimations (Van Niel & McVicar, 2004a).

3.4.2.2 Crop yield estimation by remote sensing models

Remote sensing provides a great opportunity for monitoring and estimating regional yield production on irrigated lands. The international research community has made significant efforts to develop a biophysical model for yield production using satellite data. Above ground biomass development is one of the important parameters of these models (Samarasinghe, 2003). Biomass (B) growth varies during the growing season with the crop dependent harvest index (HI) and the water content of the crop product (Mo). Therefore the total above ground biomass production can be converted into crop yield (Y) by incorporating the harvest index (HI) and the moisture (Mo) content of the crop. It is described by Equation 3.11.

\[ Y = \frac{B \cdot HI}{1 - Mo} \]  

Equation 3.11

The estimation of the various parameters in Equation 3.11 is explained in the following section.

3.4.2.2.1 Estimation of biomass production

A number of remote sensing-based, production-efficiency model approaches such as the Carnegie-Ames-Stanford-Approach (CASA) and Global Production Efficiency Model (GLO-PEM) have been tested and used in a number of studies for the estimation of biomass development and subsequent cereal crop yield in the last few decades. CASA is widely used in the estimation of biomass production (Bastiaanssen & Ali, 2003; Lobell et al., 2003; Samarasinghe, 2003; Tao et al., 2005) at a regional scale. Below are the parameters of the CASA model.
\[ B = \sum A_{\text{PAR}} \cdot \varepsilon \cdot \delta t \] 3.12

**Photosynthetically Active Radiation (PAR)**

Photosynthetically Active Radiation (PAR) (0.4–0.7\(\mu\)m) which is a part of the short wave solar radiation (0.3–3.0\(\mu\)m) is the primary source responsible for biomass production. PAR is absorbed by chlorophyll for plant photosynthesis and regulates net primary production. PAR is a fraction of incoming solar radiation illustrated by Equation 3.13 (Bastiaanssen & Ali, 2003). The fraction is generally about 45–50\% of average solar radiation for a 24 hour period \(K_{24}\) (Moran et al., 1995) and the fraction depends mainly on visibility, optical depth and the amount of ozone.

\[ PAR = 0.48 K_{24} \] 3.13

\(K_{24}\) (average solar radiation for 24 hours) can be computed as follows:

\[ K_{24} = K_{\text{EXO}} \cdot \tau_s \] 3.14

where \(K_{\text{EXO}}\) (diurnal average sun exo-atmospheric radiation) can be computed from Equation 3.15 and \(\tau_s\) is the atmospheric single-way transmissivity which is considered as a constant for the day at 0.7.

\[ K_{\text{EXO}} = \frac{K_s \cdot R}{\pi \cdot d} \] 3.15

where \(K_s\) (the sun’s external atmosphere radiation) is a constant value, \(R\) is the solar angle range for the diurnal sun exposition and can be given by Equation 3.16 and \(d\) is the sun-earth distance which can be given by Equation 3.18.

\[ R = W_s \cdot \sin \delta \cdot \sin(LAT_y) + \cos \delta \cdot \cos(LAT_y) \cdot W_s \] 3.16

where \(W_s\) is the solar angle hour for diurnal exposition given by Equation 3.17, \(\delta\) is the solar declination and \(LAT_y\) is the latitude.
\[ W_S = A \cos[-\tan(Lat_y) \cdot \tan \delta] \]  
\[ d = 1 + 0.01672 \cdot \sin \left( \frac{2\pi(J - 93.5)}{365} \right) \]

where J is the Julian day.

Absorbed photosynthetically active radiation (APAR)

PAR (0.4-0.7µm) is a fraction of the incoming short wave solar radiation (0.3–3.0µm) which is captured by green plant pigments for photosynthesis (Bastiaanssen & Ali, 2003). The total amount of incoming PAR (PAR\text{incoming}) is not fully utilised by leaves for photosynthesis as the leaves transmit (PAR\text{trans}) and reflect (PAR\text{ref}) incoming radiation. In addition soil receives the transmitted solar radiation and reflects a portion (PAR\text{soil}) of PAR\text{trans} back to the lower side of the canopy. Therefore APAR can be calculated as a fraction of PAR as follows (Goward & Huemmrich, 1992):

\[ APAR = PAR\text{incoming} - PAR\text{trans} - PAR\text{ref} + PAR\text{soil} \]

The fraction (f) of PAR absorbed by chlorophyll for the assimilation of carbon dioxide to produce dry matter can be given by the next equation.

\[ APAR = f (PAR) \]

The APAR/fPAR varies non-linearly with LAI (Bastiaanssen & Ali, 2003; Goudriaan, 1977). A satellite measurement surrogate for LAI can be derived mathematically using spectral reflectance measurements in the red and near infra-red regions allowing the opportunity for direct estimation of the APAR/fPAR. It is an indicator of fresh vigorous biomass and can be expressed using the following equation where the gradient and the intercept have been determined experimentally in some other studies (Daughtry et al., 1992; Myneni et al., 1997). As NDVI can be computed from most multi-spectral satellite images, the maps of f can be generated at a regional scale using NDVI (Bastiaanssen & Ali, 2003).
The amount of solar radiation interception on crop canopies varies throughout the cropping season and different crop species absorb the intercepted radiation with different efficiencies and in different quantities (Teixeira et al., 2007; Tesfaye et al., 2006). The quantity of the absorbed radiation is influenced mostly by the canopy extinction coefficient and the life span of green leaf (Jeuffroy & Ney, 1997; Tesfaye et al., 2006). The canopy architecture, the spatial distribution of leaf angle and optical properties of the leaves also have a significant effect on the canopy energy conversion process. Under optimal growing conditions, plant dry matter varies linearly with the amount of intercepted solar radiation, especially with PAR (Monteith & Moss, 1977; Russel et al., 1989).

The energy required to produce a unit of dry matter can be defined as light use efficiency (ε) (Kiniry et al., 1989). Light use efficiency can be determined by the gradient of the linear regression relationship of biomass and the cumulative radiation interception of crops (Muchow & Sinclair, 1994; Tesfaye et al., 2006). In fact, it can be said that there is a considerable difference in ε particularly between C3 (wheat, rice, barley, sunflower, oats, alfalfa, pasture and grapes) and C4 (sorghum, millet, sugarcane and maize) crops due to different photosynthetic activity (Atwell et al., 1999). Studies reveal that C4 crops have higher ε than C3 crops due to the different photosynthetic processes of diverse species (Kiniry et al., 1989; Teixeira, 2008). However, ε is also affected by water-deficit conditions and tends to reduce in value (Hughes & Keatinge, 1983).

In many studies, different approaches have been used to analyse the performance of light use efficiency. As long as the crops are not water stressed, ε varies in C3 crops and C4 crops (Bastiaanssen & Ali, 2003; Monteith, 1972). This means that it is not necessary to identify a specific crop within each group in order to apply ε. Therefore the same ε can be used for all the C3 crops for conversion of biomass into crop yield. The

\[ f = \frac{APAR}{PAR} = (-0.161 + 1.257NDVI) \]  

**Light use efficiency (ε)**

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different ε values used for the conversion of dry matter for the estimation of biomass found in the literature are summarised in Table 3.4 – Table 3.6.

Table 3.4: Light Use Efficiency Values for Corn Crops.

<table>
<thead>
<tr>
<th>Study area</th>
<th>ε (gMJ⁻¹)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>1.850-3.020</td>
<td>(Westgate et al., 1997)</td>
</tr>
<tr>
<td>China</td>
<td>3.916-4.227</td>
<td>(Tao et al., 2005)</td>
</tr>
<tr>
<td>USA</td>
<td>1.960</td>
<td>(Suyker &amp; Verma, 2012)</td>
</tr>
<tr>
<td>USA</td>
<td>2.726-3.706</td>
<td>(Wiegand et al., 1991)</td>
</tr>
<tr>
<td>USA</td>
<td>3.500</td>
<td>(Kiniry et al., 1989)</td>
</tr>
</tbody>
</table>

Table 3.5: Light Use Efficiency Values for Rice Crops.

<table>
<thead>
<tr>
<th>Study area</th>
<th>ε (gMJ⁻¹)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Philippines</td>
<td>2.200</td>
<td>(Kiniry et al., 1989)</td>
</tr>
<tr>
<td>Pakistan</td>
<td>1.800</td>
<td>(Bastiaanssen &amp; Ali, 2003)</td>
</tr>
<tr>
<td>Italy</td>
<td>2.900</td>
<td>(Boschetti et al., 2011)</td>
</tr>
</tbody>
</table>

Table 3.6: Light Use Efficiency Values for Wheat Crops.

<table>
<thead>
<tr>
<th>Study area</th>
<th>ε (gMJ⁻¹)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>2.800</td>
<td>(Kiniry et al., 1989)</td>
</tr>
<tr>
<td>Mexico</td>
<td>2.191</td>
<td>(Lobell et al., 2003)</td>
</tr>
<tr>
<td>Pakistan</td>
<td>2.500</td>
<td>(Bastiaanssen &amp; Ali, 2003)</td>
</tr>
</tbody>
</table>

Developments in light use efficiency

Monteith’s model for light use efficiency was further improved by Field, et al., (1995) by more comprehensively considering corrections for environmental conditions by adding soil moisture (W) and temperature (T1, T2) which significantly affect light use efficiency. They formulated equation 3.22 for ε and as follows:
\[ \varepsilon = \varepsilon^* \cdot T_1 \cdot T_2 \cdot W \] 3.22

where \( \varepsilon^* \) is described as the maximum light use efficiency for above ground biomass when environmental conditions are optimal. However, actual light use efficiency is lower than the maximum light use efficiency value because actual light use efficiency varies throughout the cropping season due to environmental stresses (Bastiaanssen & Ali, 2003). These stresses can be calculated mathematically in terms of correction scalars of temperature (T1, T2) (Equation 3.23) and water stress (W) (Equation 3.24) as follows:

\[ T_1 = 0.8 + 0.02T_{opt} - 0.0005T_{opt}^2 \] 3.23

\[ T_2 = \frac{1}{1 + \exp[0.2T_{opt} - 10 + T_{mean}]} \] 3.24

\[ X \frac{1}{1 + \exp[0.3(-T_{opt} - 10 + T_{mean})]} \] 3.24

where T1 represents the reduction effect on crop growth due to the temperature of cooler regions, while T2 represents the reduction effect on light use efficiency due to its deviation from the optimum temperature \( T_{opt} \) (Bastiaanssen & Ali, 2003). The optimum temperature \( T_{opt} \) is the monthly mean temperature in which the maximum leaf area index occurred and \( T_{mean} \) is the monthly mean temperature.

Field et al., (1995) calculated the water scalar (W) as a ratio of actual to potential evapotranspiration and applied a minimum value of 0.5 for W. However, Bastiaanssen et al., (1997) found that the evaporative fraction \( (\Lambda) \) is controlled by the soil moisture in the root zone. (Bastiaanssen & Ali, 2003) found in their studies in a semi-arid region that the \( \Lambda \) is non-linearly correlated with existing soil moisture for some of the irrigated crops and further confirmed that soil moisture changes are very gradual due to the continuous irrigation. Therefore W is assumed to be equal to the evaporative fraction \( (\Lambda) \) as below:
where $\lambda E$ is latent heat flux, $R_n$ is net radiation and $G$ is soil heat flux. The evaporative fraction ($\Lambda$) can be calculated by applying the well-known energy balance equation:

$$W = \Lambda = \frac{\lambda E}{R_n - G}$$

This equation represents the water exchange process to and from land and atmosphere. The partition of net radiation ($R_n$) is over the different fluxes such as soil heat flux ($G$), sensible heat flux ($H$) and latent heat flux ($\lambda E$) which are involved in the energy balance. Remote sensing measurements and ground meteorological measurements are used to calculate the three components $R_n$, $G$ and $H$ so $\lambda E$ can be estimated as a residual term. A detailed description of these components follows.

- **Net radiation ($R_n$)**

Net radiation ($R_n$) is defined as the difference between incoming and outgoing radiation for both shortwave (0.15-5μm) and longwave (3-100μm) solar radiation as follows:

$$R_n = (1 - \alpha_s)R_S + (\varepsilon_s\varepsilon_a\sigma T_a^4 - \varepsilon_s\sigma T_S^4)$$

where $\alpha_s$ is surface albedo, $R_S$ is incoming shortwave radiation, $\sigma$ is the Stefan-Boltzman constant, $\varepsilon_s$ is surface emissivity, $\varepsilon_a$ is atmospheric emissivity, $T_a$ is atmospheric temperature and $T_S$ is surface temperature. Net radiation is positive during the day while it is negative during the night. However the daily total value is normally positive except where there are extreme weather conditions at high latitudes (Allen et al., 1998). Net radiation is measured under field conditions using pyrgeometers and pyranometers or using net radiometers above the vegetated surface (Teixeira, 2008). According to Kustas & Norman (1996) there are a number of different remote sensing approaches to estimating net radiation but these
two approaches showed the least uncertainty of 5-10% compared to the field-based observations at meteorological time scales.

- **Soil heat flux (G)**

  Energy in the form of heat available during daylight hours warms up the land surface and subsurface. A temperature gradient between the two surfaces is formed and, consequently, a heat flux develops in the soil which can be expressed as follows (Teixeira, 2008):

  \[ G = \lambda_g \frac{\Delta T_g}{\Delta Z_g} \]  

  where \( \lambda_g \) is the thermal conductivity of the soil, \( T_g \) is the soil temperature and \( Z_g \) is soil depth. \( G \) largely depends on the thermal properties of the soil. In field conditions, soil heat flux (G) is calculated using flux plates or thermocouples buried in the soil surface. \( G \) can also be accurately estimated using remote sensing measurements (Li et al., 2009).

- **Sensible Heat Flux (H)**

  The process whereby heat energy is transferred to the atmosphere from the earth surface by conduction or convection due to the temperature difference is termed sensible heat flux. Sensible heat flux is the main cause of cool and warm air in the atmosphere. It can be expressed as follows:

  \[ H = \frac{\rho_{air} C_p \Delta T}{r_{ah}} \]  

  where \( \rho_{air} \) is air density, \( C_p \) is air specific heat at constant pressure, \( \Delta T \) is near-surface temperature difference and \( r_{ah} \) is the aerodynamic resistance to which the heat is transported to the boundary above the land surface. This equation has been applied in local and regional studies to estimate sensible heat flux over different vegetation types (Allen et al., 2005; Gokmen et al., 2012; Moran & Jackson, 1991).
Estimation of Latent Heat Flux (\(\lambda E\))

The latent heat flux is computed as the residual of the energy balance equation. Therefore it is required to estimate sensible heat flux \(H\), in order to estimate the residual \(\lambda E\). The temperature difference between air and surface due convection and conduction is defined as sensible heat flux. It is defined by Equation 3.29 (Bastiaanssen, 2000).

In this process, \(H\) and \(\Delta T\) are estimated through number of iterative process by selecting two hot and cold pixels. The main objective of iteration process is to determine a refined value for \(\Delta T\) as it is the most uncertain parameter which affects the value of \(H\). Aerodynamic resistance for heat transport and atmospheric air density are also recomputed in the iteration process with adjusted parameters. This process is repeated until the constant value for \(\Delta T\) and \(r_{al}\) for a hot pixel is stabilized. In the same way the fluctuations in \(H\) starts to decrease as the number of iterations increases. The variations in \(H\) become constant after a certain cycles of iterations (Tasumi & Allen, 2000).

The most widely used physical and or semi-physical remote sensing models for the estimation of \(E_{T_a}\) (actual evapotranspiration) on the basis of energy balance are: the Surface Energy Balance Algorithm for Land (SEBAL), Mapping Evapotranspiration at high Resolution and with Internalised Calibration (METRIC), Surface Energy Balance System (SEBS), Atmospheric Land Exchange Inverse (ALEXI) Model and Spatial Algorithm for Mapping Evapotranspiration (SAM-ET) (Ullah, 2011). Most of these models are less site specific and they do not require subjective intervention by the user as most of the algorithms only require the selection of hot and cold pixels within the image (Gokmen et al., 2012; Kustas & Anderson, 2009).

- **Surface Energy Balance Algorithm for Land (SEBAL)**

  The Surface Energy Balance Algorithm for Land (SEBAL), which based on an intermediate approach using empirical relationships and physical parameterisation-based analytical approaches, was formulated (Bastiaanssen et al., 1998a) and validated (Bastiaanssen et al., 1998b) in
Spain. This model is suitable for flat, heterogeneous, semi-arid regions and can be applied to diverse ecosystems as the model addresses the spatial variability of most agro-meteorological parameters (Bastiaanssen et al., 2008; Teixeira, 2008). SEBAL is based on the theory of thermodynamics (Hafeez & Khan, 2007). The algorithm requires routine climatic data along with spatially distributed visible, near infra-red and thermal infra-red data from remote sensing measurements.

The algorithm calculates $R_n$, $H$ and $G$ and acquires $\lambda E$ as a residual from the energy balance equation (Teixeira, 2008). Net radiation and soil heat flux are estimated using vegetation indices, LAI, and surface emissivity and albedo based on surface temperature and reflectance. SEBAL considers extreme hot and cold pixels for the development of a temperature gradient between aerodynamic surface temperature to air temperature and radiometric surface temperature (Ullah, 2011).

One of the main advantages of using SEBAL is that the tedious crop classification step can be omitted as thermal and infra-red imagery are used in the determination of ET$_a$ (Teixeira, 2008). Another advantage is that the algorithm requires a minimum amount of ground-based data and does not require correction for atmospheric effect on surface temperature because it performs an automatic internal calibration within the image (Li et al., 2009).

- **Mapping Evapotranspiration at high Resolution and with Internalized Calibration (METRIC)**

  The METRIC model is an advancement of SEBAL that can be applied in mountainous areas. It couples with the reference evapotranspiration, taking alfalfa as the standard surface, to estimate ET$_a$ (Allen et al., 2005). The model was developed on the same principals and techniques as the SEBAL model. It consists of multiple models and uses digital image data which records thermal, infra-red and near infra-red radiation together with quality weather data to estimate ET$_a$. ET$_a$ is calculated for the entire image on a pixel by pixel basis at the instant of the satellite overpasses. The process is based on the energy balance equation where ET$_a$ is estimated from the residual amount of the energy balance (Allen et al., 2007).
The METRIC model was applied to predict seasonal ET$_a$ for Landsat data in different parts of the USA and showed that the results have high accuracy and consistency throughout the cropping season (Allen et al., 2007). Applications of METRIC include hydrologic modelling for the estimation of water budgets, monitoring compliance with water rights, water resource management and planning, estimation of aquifer deletion, initiation of groundwater model calibration and computation of irrigated agriculture water use (Allen et al., 2007).

METRIC is a convenient algorithm for the estimation of ET$_a$ for many reasons. The algorithm can be used to estimate actual ET rather than potential ET and, therefore, it does not need knowledge of the crop type. Thus, tiresome crop classification can be avoided. Moreover, it is calibrated automatically using ground-based data (Allen et al., 2007). However, to use the model requires trained expertise and a thorough knowledge of energy balance and radiation physics together with some knowledge of vegetation characteristics. The quality of the result depends on the operator’s skills in selecting the correct hot and cold pixels in order to develop a temperature gradient.

- **Surface Energy Balance System (SEBS)**

The Surface Energy Balance System (SEBS) was developed and subsequently extended for greater coherence by Su (2001) for the estimation of turbulent fluxes of atmosphere and the evaporative fraction from remote sensing data in combination with meteorological information (Su, 2002). The model was developed with a set of tools to determine physical parameters of land surface compute the roughness length for heat transfer and estimate the evaporative fraction. Initially, the physical parameters of land surface such as albedo, surface temperature, emissivity and vegetation cover were determined from spectral reflectance and radiance (Su et al., 1999). The model was later extended by Su (2001) for the computation of roughness length for heat transfer and, from the new formulation of the
model, the evaporative fraction was determined on the basis of the energy balance approach to limiting cases.

At the final formulation stage, SEBS used three main sets of information for a more coherent development of the model and for its validation (Su, 2002).

The first set of information included land surface albedo, emissivity, surface temperature, fractional vegetation cover and leaf area index, and vegetation or roughness height. NDVI was used to substitute vegetation information when it was not clear or available. This information along with other information regarding the surface concerned could be derived by remote sensing means.

The second set of information consisted of air pressure, temperature, humidity and wind speed at a reference height. Reference height refers to the measurement height for the point of application or, in regional applications, it is the height of the planetary boundary layer (PBL). This data can be determined from a large scale meteorological model.

The last set included downward solar radiation and downward long-wave radiation. These inputs could be obtained directly by measuring, from a model or from parameterisation.

To determine the evaporative fraction, SEBS uses the energy balance approach at dry and wet limits (Su, 2002). In dry limit conditions, the latent heat becomes zero and sensible heat reaches its maximum due to the water limitations. In wet limit conditions, the evaporation occurs at its highest potential rate while sensible heat flux reaches its minimum value. By considering the values of sensible heat flux and latent heat flux at the two limits, the relative evaporative fraction can be calculated and, using all the derived values, the evaporative fraction can be determined (Su, 2002).

SEBS is advantageous to use for a number of reasons: prior knowledge of actual turbulent heat fluxes is not required in order to determine the turbulent heat fluxes; and uncertainty about surface temperature and meteorological data in SEBS can be overlooked as SEBS takes energy balance into account at wet and dry limits. However, this
model requires a number of parameters and relatively complicated solutions to turbulent heat fluxes which may lead to inconvenience in the absence of readily available data (Li et al., 2009).

### 3.4.2.2.2 Harvest index

The Harvest index (HI), an important biophysical parameter, is the ratio of dry grain mass to above ground biomass (Jianchang & Jianhua, 2010; Lobell et al., 2003) and can be expressed as in Equation 3.30. It is mainly used in the estimation of crop yield.

\[
HI = \frac{\text{Grain mass}}{\text{Above ground dry biomass}}
\]  

3.30

A variety of studies have proposed a number of different approaches to estimating HI. Kemanian et al. (2007) developed a simple method for estimating HI in cereal crops. The method was based on the fraction of biomass development during the post-anthesis phase (Fg). They proposed that HI is a linear or curvilinear function of Fg. The models were tested for three crops, barley, wheat and sorghum, in and outside of Australian environments. Both models showed a positive relationship, however the curvilinear model exhibited a better correlation than the linear model. The model developed for the estimation of HI was simple, straightforward and easy to parameterise.

Most other studies have adopted simple procedures for estimating the HI of different grain crops by integrating total biomass and grain weight obtained from the field. Diacono et al. (2012) estimated the HI of durum wheat under Mediterranean environmental conditions by integrating total biomass weight (g m\(^{-2}\)) and grain weight (g m\(^{-2}\)). They showed that the HI varies from year to year for wheat grain as a result of different environmental conditions such as climate, soil fertility and agricultural practice. In their studies, Hay and Gilbert (2001) confirmed that the HI of wheat and corn changed inconsistently with the season, management and environment conditions for two different regions - Mexico and Malawi.
The simple ratio of grain yield to above ground biomass has been adopted in many studies in order to estimate the HI as it is a widely used method and is straightforward and easy to apply. In this method, grain weight is incorporated with and without the moisture content of the grain. This simple approach for estimating HI was incorporated in different yield models such as CASA and Environmental Policy Integrated Climate (EPIC) to estimate crop yield (Bastiaanssen & Ali, 2003; Liu et al., 2007; Tao et al., 2005).

Some of the typical published values of HI found in the literature for different locations around the world are summarised in Table 3.7 - Table 3.9.

Table 3.7: Harvest Index Values for Irrigated Corn.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Harvest Index (%)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mexico</td>
<td>0.33-0.50</td>
<td>(Hay &amp; Gilbert, 2001)</td>
</tr>
<tr>
<td>Malawi</td>
<td>0.19-0.56</td>
<td>(Hay &amp; Gilbert, 2001)</td>
</tr>
<tr>
<td>China</td>
<td>0.45</td>
<td>(Hay, 1995; Tao et al., 2005)</td>
</tr>
<tr>
<td>USA</td>
<td>0.44-0.47</td>
<td>(Wiegand et al., 1991)</td>
</tr>
<tr>
<td>Argentina</td>
<td>0.22-0.36</td>
<td>(D’Andrea et al., 2008)</td>
</tr>
</tbody>
</table>

Table 3.8: Harvest Index Values for Irrigated Rice.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Harvest Index (%)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pakistan</td>
<td>0.25-0.50</td>
<td>(Bastiaanssen &amp; Ali, 2003)</td>
</tr>
<tr>
<td>Sri Lanka</td>
<td>0.45-0.50</td>
<td>(Samarasinghe, 2003)</td>
</tr>
<tr>
<td>Philippines</td>
<td>0.41-0.56</td>
<td>(Bueno &amp; Lafarge, 2009)</td>
</tr>
<tr>
<td>China</td>
<td>0.17-0.39</td>
<td>(Ju et al., 2009)</td>
</tr>
</tbody>
</table>
Table 3.9: Harvest Index Values for Irrigated Wheat.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Harvest Index %</th>
<th>Source of data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.230-0.390</td>
<td>(Perry &amp; Antuono, 1989)</td>
</tr>
<tr>
<td>Australia</td>
<td>0.100-0.500</td>
<td>(Richards &amp; Townley-Smith, 1987)</td>
</tr>
<tr>
<td>South Australia</td>
<td>0.290-0.350</td>
<td>(Richards &amp; Townley-Smith, 1987)</td>
</tr>
<tr>
<td>South Australia</td>
<td>0.280-0.350</td>
<td>(French &amp; Schultz, 1984)</td>
</tr>
<tr>
<td>Australia - NSW</td>
<td>0.170-0.420</td>
<td>(Stapper &amp; Fischer, 1990)</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.376</td>
<td>(Lobell et al., 2003)</td>
</tr>
<tr>
<td>China</td>
<td>0.310-0.450</td>
<td>(Yang et al., 2000)</td>
</tr>
<tr>
<td>China</td>
<td>0.330-0.530</td>
<td>(Zhang et al., 2008)</td>
</tr>
</tbody>
</table>

3.4.2.2.3 Moisture content

The moisture content of cereal grain is an estimate of the quantity of water in the product after harvesting or processing (Pixton & Warburton, 1971). It is one of the key characteristics for determining the quality of the product (Nelson et al., 2000). The moisture content is important in determining the correct time for harvesting the crop and making decisions about potential safe storage facilities. Moreover, it is a key factor in determining the market value of the product as grain containing moisture is of lower value because the drying cost for safe storage has to be taken into account. Moisture content plays an important role in the effective processing of grain for flour and other food products (Nelson et al., 2000). Some of the moisture content percentages used in different studies for corn, rice and wheat, in different countries are given in Table 3.10 – Table 3.12.

The standard method for estimating the moisture content of grain involves drying the grain for a specific time interval at a particular temperature (Austin et al., 2013; Nelson et al., 2000). The moisture content is determined on the measure of weight change on drying (Austin et al., 2013). Generally, the moisture content, \( m_c \), is expressed as a percentage and calculated using Equation 3.31 (Norimi et al., 2012).
where \( m_{\text{wet}} \) is the weight before drying the sample and \( m_{\text{dry}} \) is the weight of the dried sample.

### Table 3.10: Reported Moisture Content Percentages for Corn Crops.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Moisture %</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>15.5</td>
<td>(Westgate et al., 1997)</td>
</tr>
<tr>
<td>China</td>
<td>11.0</td>
<td>(Tao et al., 2005)</td>
</tr>
<tr>
<td>Australia</td>
<td>15.5</td>
<td>(Carberry et al., 1989; Vetsch &amp; Randall, 2002)</td>
</tr>
</tbody>
</table>

### Table 3.11: Reported Moisture Content Percentages for Rice Crops.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Moisture %</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pakistan</td>
<td>11.0</td>
<td>(Bastiaanssen &amp; Ali, 2003)</td>
</tr>
</tbody>
</table>

### Table 3.12: Reported Moisture Content Percentages for Wheat Crops.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Moisture %</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pakistan</td>
<td>11.0</td>
<td>(Bastiaanssen &amp; Ali, 2003)</td>
</tr>
</tbody>
</table>

#### 3.4.3 Yield estimation application in the world

The prediction of crop yield is crucial and has a direct impact on national economic policies and the international food trade (Hayes & Decker, 1996). Efforts have been made to develop various crop yield estimation models for different crops in different parts of the world. Crop growth models and remote sensing techniques are both used for the estimation and production of regional and national crop yields. Crop growth modelling was initiated in the Netherlands in the mid-sixties. There are a number of studies that have been carried out using both methods for
the estimation and prediction of crop yield around the world (Aparicio et al., 2000; Bastiaanssen & Ali, 2003; Doraiswamy et al., 2005; Liu et al., 2007).

A GIS-based EPIC crop growth model (GEPIC) was developed, tested and used to estimate wheat yield by Liu et al. (2007) at a grid resolution of 30’ on the land surface. Using this model, wheat yield was simulated and results were compared with (Food and Agriculture Organization) FAO statistical yields in 102 countries for 10 years and the model produced acceptable results. The model was used to simulate more than 100 different types of crops in a unified manner for various weather conditions and different soil properties in many countries.

Bastiaanssen and Ali (2003) developed a new crop yield forecasting model using remote sensing techniques to assess crop growth and to forecast the crop yield for irrigated crops in the Indus Basin, Pakistan. In their studies they integrated three models to develop the new model: Monteith’s model of PAR, the CASA model for light use efficiency and SEBAL. In their study, NDVI was calculated from an Advanced Very High Resolution Radiometer (AVHRR) on board the NOAA satellite and was applied in the estimation of PAR. The new model developed was successful for wheat, rice and sugarcane but less successful for cotton because the low spatial resolutions of NOAA pixels are difficult to distinguish in small scale cotton fields.

A similar type of study was carried out by Samarasinghe (2003) integrating the same models with NOAA-AVHRR satellite images to estimate the yield for irrigated rice and the biomass of rain-fed tea, rubber and coconut in Sri Lanka. This study did not provide completely accurate results due to the coarse spatial resolution of the satellite images but it did provide useful yearly crop yield information. Therefore, the author suggested using a combination of low and high satellite images to complement high spatial and temporal profiles in order to accommodate the small plots of vegetation found in the country and also to acquire data frequently.
3.4.4 Yield estimation applications in Australia

Australian grain production is relatively small compared to global production. However, compared to Australia’s population, the country contributes a significant portion of the world trade and generated $17.7 billion in foreign income in 2010 (ABARES, 2011) from the agriculture sector. The main agricultural areas in Australia include the Murray Darling Basin, the Western Australian wheat belt and the eastern coastal catchment including the Great Barrier Reef in Queensland (Nikolova et al., 2012). The main summer crops include rice, sorghum and corn while the main winter crops include wheat, barley, oats and canola. The total production and cropped area of the principal crops in the country in 2011 are shown in Figure 3.4 and Figure 3.5 respectively.

![Figure 3.4: Proportion of principal grain production in 2010-11 (ABS, 2011)](image-url)
In Australia, crop yield and production estimates are mostly calculated from climate-focused crop models and most are restricted to the main cereal crops (Nikolova et al., 2012). These models are combined with estimates of planted cropping areas and crop yield estimates derived from local expertise. These simple agro-climatic models are more suitable for regional scale yield estimation than more complex simulation models such as APSIM which require a higher level of input (Nikolova et al., 2012). However, a number of non-agro-climatic studies have been carried out in different parts of Australia to estimate crop yield and production for different crops such as wheat, rice, corn, sorghum and canola which include the above mentioned methodologies as well as some other techniques.

Asseng et al., (1998) applied the APSIM crop simulation model in Western Australia in order to simulate wheat yield, above and below ground growth, and water and nitrogen uptake. The model output results were compared with different field conditions of rainfall, soil types and wheat genotypes. Field data were obtained for ten seasons by varying the crop sowing date, plant density, nitrogen fertiliser, deep ripping and irrigation. The overall APSIM model outputs showed acceptable results and the wheat
yield predictions showed promising results with a coefficient of determination \( (r^2) \) of 0.77. The study indicated that it is possible to do simulation studies for the prediction of wheat yield on specific soil types and rainfall conditions in Western Australia.

However it cannot be applied over large scale studies as in remote sensing model approaches. This model was further used in Barellan Pucawan in New South Wales and in Warra in Queensland by Asseng et al. (2003) to evaluate how the wheat yield varied in accordance with the specific leaf area (SLA), an indicator of early vigour. They further used the APSIM model in five different locations (Miles in Queensland, Dalwallinu and Cunderdin in Western Australia, Kerang in Victoria and Wagga Wagga in New South Wales) in order to investigate the impact of temperature variability on wheat yield. The locations included winter-dominant (Mediterranean) and summer-dominant (subtropical) regions in high and low rainfall zones and warmer and cooler climatic regions and represented all Australian cropping regions. The temperature variations in the main wheat growing regions of the world are identical to the Australian conditions during the grain filling stage. The study analysed the effect of higher temperature on the reduction of grain yield and subsequent future challenges over global food security. Moreover, the study highlighted the need for adaptation strategies to prevent yield losses in wheat due to heat stresses.

Stephens et al., (1994) correlated shire wheat yields across the Australian wheat belt with a Weighted Rainfall Index (WRI) and analysed the average monthly correlation coefficient. Strong correlations were found between state and national yields and the weighted rainfall index throughout the country except in Western Australia. The model was validated with official Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) data and the Australian Bureau of Statistics. Yield predictions were equal or more accurate than the reported official statistics at the end of the tested years of 1990, 1991 and 1992.

Another forecasting system was developed by the Queensland Department of Primary Industries to forecast regional commodities in
Australia (Potgieter et al., 2001). The system was designed based on a shire-based, stress-index wheat model and climate forecasts. At the early stage of the cropping season, the system facilitates the investigation of the possibilities of exceeding shire-based, long term median yields associated with different types of seasons. The objectives of this system were to inform Queensland local governments about areas which might produce low yields in any year and to use this system to forecast regional commodities (Potgieter et al., 2001).

Many successful agro-climatic models for wheat have been developed in Australia during the last few decades (Potgieter et al., 2002; Stephens et al., 1994). A similar modelling approach was carried out successfully to forecast the sorghum yield in North East Australia. A simple agro-climatic model was developed by Potgieter et al. (2005) in order to forecast sorghum yield in the north east sub-tropical region of Australia for 32 shires accounting for 90% of the total sorghum production of Australia. Sorghum is the principal dry-land summer crop in this region, however during the previous decade, its market had changed from export to domestic and most of the sorghum products were currently consumed within the livestock industry (Potgieter et al., 2005). The estimations at regional scale were beneficial to many agricultural businesses because sorghum production fluctuates annually due to the variable climate in Australia (Hammer & Muchow, 1991). These agro-climatic models used a simple soil and crop water balance in order to compute the water stress index. The model was trained by applying actual shire yield data obtained from the Australian Bureau of Statistics (Potgieter et al., 2005).

The literature contains very few studies on the estimation of corn yield in Australia. One study was carried out by Humphreys et al. (2008) in the Coleambally Irrigation Area (CIA) in order to evaluate strategies for increasing irrigation water productivity for maize. For this study the researchers used the MaizeMan crop simulation model. In the model, rainfall input was measured in the CIA while other input parameters were obtained from the Griffith weather station which is about 50 km from the experimental site but has similar climatic conditions to the CIA. The study
suggested that MaizeMan is a useful tool to predict crop and soil-water parameters under both furrow and sprinkler irrigation systems. It also showed that the model was useful for assessing options for increasing crop yield and water productivity. However, the researchers acknowledged that the limited availability of field data would limit prediction capabilities (Humphreys et al., 2008).

The CERES-Maize model is a crop-growth and yield-simulation model requiring practically achievable input parameters and its predictions are reasonably accurate. The yield predictions of CERES-Maize were compared with field-observed data by Carberry et al., (1989) and validated using the STANDARD CERES-Maize simulation model. The study was carried out at the semi-arid Katherine Research Station in the Northern Territory of Australia. The researchers revised the CERES-Maize model by altering the parameters of the model which were specifically sensitive to climatic variations and different genotypes and achieved reasonably accurate results.

### 3.4.5 Summary and knowledge gaps

The key messages and research gaps arising out of a thorough literature review are discussed below.

Leaf area index (LAI) is a key biophysical parameter and its determination is crucial for the estimation of foliage cover and the prediction of crop yield and monitoring of crop growth. However, spatial, temporal and ground-based estimation is tedious and time consuming. LAI is functionally associated with canopy spectral reflectance and its retrieval using remote sensing data has prompted many investigations and research studies into biophysical processes in crops. Common and widely used approaches to the estimation of LAI have identified empirical relationships developed using spectral vegetation indices (Chen & Cihlar, 1996; Haboudane et al., 2004a). A number of relationships have been established for the quantification of LAI using different vegetation indices including the
most commonly and widely used Normalised Difference Vegetation Index (NDVI).

During the past few decades, many efforts have been made to improve NDVI as well as to develop and introduce new vegetation indices by reducing the soil background effects (Bannari et al., 1996; Broge & Leblanc, 2001) and the atmospheric effects (Jiang et al., 2008; Karnieli et al., 2001). Even though these external factors such as soil background and atmospheric effects have been taken into account, the vegetation indices still have inherent limitations due to specific vegetation parameters such as plant geometry and chlorophyll content. Thus, it is not possible to design or use a specific vegetation index which is sensitive to a particular vegetation parameter but not sensitive to others (Govaerts et al., 1999). Therefore, different vegetation indices are suitable and have been designed for different applications (Haboudane et al., 2004a). However, no such empirical model has been developed to estimate ground-based LAI for the three irrigated crops, corn, rice and wheat in Australia.

Accurate and up-to-date land use and land cover (LULC) classification maps are crucial for regions where agriculture dominates. As irrigated land is changing rapidly, land cover types and patterns are frequently modified. The acquisition of up-to-date land cover information of irrigated land on a regional or national scale is a demanding task due its rapidly changing nature along its temporal and spatial scales. Remote sensing plays a vital role in the derivation of accurate and current LULC maps over various spatial and temporal scales (Abd El-Kawy et al., 2011).

Traditionally, LULC maps were derived by interpreting hard copies of satellite and aerial photos visually. Later, this traditional interpretation was replaced by digital image classification techniques because of their speed, accuracy and cost effectiveness. However, with the availability of high-resolution satellite images, the advancement of digital-image processing techniques, and convenient classification and analysis techniques, many avenues were opened for researchers to develop more accurate, economical and current LULC classification maps to produce much valued information about irrigated agriculture. In the process of developing LULC maps,
satellite images, classification procedures, training samples and accuracy assessment methods and techniques must be selected with great care in order to fulfil the requirements of the application. The literature search revealed that image classification was traditionally carried out based on a single pixel (pixel-based) classification. However, it can be done more accurately using the object-based image analysis technique. Both pixel-based and object-based image classification techniques can be performed using supervised, unsupervised and hybrid techniques depending on the suitability and purpose of classification and the availability of data. Consideration should also be given to the need to use time-series data or a single date image after taking into account the requirements and availability of satellite images.

Irrigated agriculture is the major consumer of fresh water in the world, and faces the challenge of requirement to produce more food with less water. This critical situation can be improved only by increasing crop water productivity. Crop yield is an important indicator of crop response to water resource management. Therefore, it is necessary to monitor crop growth and development in order to assess the relationships between crop yield and irrigation performance. In addition, crop yield estimation is an index of national food security as well as being important in the food trade industry.

There are different approaches to estimating crop yield mainly based on computer simulation models and remote-sensing approaches. Computer simulation models require more input data and they can only be applied to farm scale studies. However, remote sensing models are more commonly applied for the estimation of crop yield at regional and national scales. There are two main approaches to estimating crop yield: the development of an empirical relationship between crop yield and vegetation indices; and the development of crop yield estimation models based on photosynthetically active radiation (PAR), light use efficiency and surface energy balance. The empirical relationship approach requires extensive field data which is time consuming and laborious. Further, it has not been successfully used in large scale studies. However, crop yield estimation models based on PAR, light
use efficiency and surface energy balance can be applied successfully at local to regional scales.

On the basis of the literature review, the following key research gaps were identified and research has been carried out to address these gaps in irrigated agriculture in Australia.

Firstly, it was discovered that a method has not been developed in order to estimate ground-based LAI using remotely-sensed vegetation indices for corn, rice and wheat in Australian irrigated agriculture. Secondly, an accurate LULC classification technique incorporating high and moderate spatial scale satellite images has not been developed to identify seasonal summer and winter irrigated crops. Finally it was noted that for the three study crops, corn, rice and wheat, there was no crop yield estimation method using remote sensing data integrating PAR, light use efficiency and energy balance developed in this country.
4 METHODOLOGY

This chapter describes the methodology adopted in the current study to achieve the objective of the research. It explains the development of remote sensing biophysical models to estimate LAI, an LULC classification technique for irrigated crops and the development of yield models to estimate crop yield for three different crops in the study area: rice, corn and wheat.

Rice and corn are the predominant summer crops while wheat is the major winter crop. Because of the economic importance of these three crops in the study area and because they are widely grown in Australia they were selected for this study.

In Australia, crop yield is estimated in a number of different ways. Among them, climate-focused complex crop growth and simulation models such as APSIM, MaizeMan and CERES-Maize are widely used to estimate cereal grain yield at farm level. The input parameters of these models mainly depend on meteorological data and soil characteristics on a field or farm scale. However, these models cannot be used for regional scale studies as they are designed and developed for farm or field scale studies. Further, these models are quite complex and for regional scale studies input parameters are not widely available and are demanding. In addition, these traditional models are not able to account for spatio-temporal variations in crop growth and development in order to estimate accurate cereal yields at the regional level. In the CIA, there is an absence of advanced technologies to effectively carry out the crop yield estimations.

For the current study, a remote sensing approach was adopted in a GIS environment to estimate the crop yield of the three main cereal crops in the CIA. The study was carried out to estimate crop yields of three different seasonal cereals in the winter and summer seasons of 2010/11. The main rationale for selecting this period was the availability of real time, accurate ground and satellite data. In addition, the Coleambally Water Smart Australia project (CWSA) was operating in parallel to the current study and made a lot of rich data available for the yield estimation in this PhD study.
The validation of satellite data was carried out with data from a flux tower and other micro-metrological instruments installed under this project. High spatial resolution satellite images and accurate ground truthing data for LAI model development and for LULC classification were also available under the CWSA project.

4.1 Data collection

As outlined previously, there are two main cropping seasons in the CIA, winter and summer. Usually, winter and summer crops are sown in April/May and October/November while harvested in October/November and March/April respectively. Based on the crop genotype, the sowing dates and the harvesting dates may vary by a few weeks.

At the start of the study, the data required to carry out this study was identified through the literature review and subsequently data was collected from different sources. To meet the objectives of the study, various ground-based measurements were also required. For this purpose, comprehensive field campaigns were carried out to collect field measurements of leaf area index (LAI), reflectance, harvest index and training sample data for two seasons, winter 2010 and summer 2010/11, on various rice, corn and wheat farms in the CIA. The procedure adopted for the collection of various parameter data is described below.

4.1.1 Remote sensing satellite data

Various types of remote sensing satellite data are available for environmental monitoring over agricultural areas, and each type of data has different characteristics due to its spatio-temporal resolution. The required remote sensing data is selected based on their resolutions, cost factor, requirement and the availability. There are four types of resolution that can be defined for satellite imagery in remote sensing: spectral; spatial; temporal; and radiometric.
4.1.1.1 Spectral resolution

Spectral resolution is the wavelength interval size and the number of segments that the sensor measures. These segments are intervals of wavelengths of the electromagnetic spectrum. In order to estimate the vegetation indices, vegetation type, LULC and evapotranspiration (ET), it is necessary to have red and near infra-red bands (segments) among other spectral bands.

4.1.1.2 Spatial resolution

Spatial resolution is the pixel size of a satellite image and represents the size of the surface which is measured on the ground in square meters. For farm level studies, it is necessary to have a high spatial resolution to reduce the effect of mixed land cover types on spectral data. But unlike precision agriculture, it is not necessary to have very high resolution satellite image data (Colombo et al., 2003).

4.1.1.3 Temporal resolution

Temporal resolution is the time gap between the capturing of two images at a given location. The temporal resolution has to be high enough to coincide with the important phenological development stages of the crops. This helps in the development of regression models as well as the formation of accurate classification maps.

4.1.1.4 Radiometric resolution

Radiometric resolution is the number of gray scale levels of the sensor and it is normally expressed as 8-bit, 11-bit, 12-bit or 16-bit. Less consideration was given to radiometric resolution in this study as farms were very homogeneous. However, almost all the ground sample points were established at the very mid-points of farms in order to extract the pixel value information under homogeneous conditions. Therefore, it was essential to consider textural information such as tone values or spatial variation in places where spectral information was heterogeneous or patchy.
The proper selection of remote sensing imagery to meet the study’s needs is a matter of prime importance. Among the numerous multispectral images used in crop assessment and crop production, high spatial resolution images such as IKONOS, SPOT 5 HRG and RapidEye are mainly used in field scale applications, while Landsat TM/ ETM+ and Terra ASTER medium scale satellite images are widely applied in regional scale studies and coarse spatial resolution images such as MODIS, AVHRR and SPOT images are preferable in continental or global scale studies (Lu & Weng, 2007). Even though various remote sensing images are available for vegetation monitoring in irrigated agriculture, it is necessary to give careful consideration to selecting the most appropriate satellite images in order to meet the study requirements. Due consideration was given to the selection of satellite images in this study with cost effectiveness, coverage area and resolution effects being taken into account.

Satellite data with different spatio-temporal characteristics were selected as required, dependant on the study’s objectives. Landsat 5 TM images of the area are nominally available every 16 days and qualify for time-series remote sensing applications. Landsat was used for the development of biophysical models to estimate LAI and to develop the crop yield models in the current study. In addition, a set of RapidEye images was obtained and used in the classification process as the methodology adopted for the classification process required high spatial resolution images.

**4.1.1.5 Landsat 5 TM**

Landsat 5 TM was launched in March 1984. The main objective of the program is to provide a global archive which consists of Landsat images. It is managed by the United States Geological Survey (USGS). Since its launch, Landsat 5 TM images have been widely used for many applications and studies in the agriculture discipline. The satellite orbits the earth every 16 days in a near polar, sun-synchronous orbit at an altitude of 705km. The satellite employs an oscillating mirror with a ground swath extending 185km perpendicular to both directions of its orbital track and records data
in 7 spectral bands. The spatial resolution is 30m for bands 1-5 and 7 (the visible regions) and it is 120m for band 6 (thermal band). Table 4.1 illustrates the wavelength regions of corresponding spectral bands.

Landsat 5 TM has been widely used in various regional scale studies for the derivation of empirical relationships between leaf area index (LAI) and spectral vegetation Indices (SVIs) (Colombo et al., 2003; Casanova et al, 1998; Haboudane et al., 2004; González-Sanpedro et al., 2008; Baret and Guyot, 1991) and for crop classification in irrigated agriculture (Julien et al., 2011; Larrañaga et al., 2011; Ullah, 2011; Van Niel & McVicar, 2004b).

Table 4.1: Spatial and Spectral Characteristics of TM Sensor.

<table>
<thead>
<tr>
<th>Band number</th>
<th>Spectral range (µm)</th>
<th>Spectral information</th>
<th>Spatial resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45-0.52</td>
<td>Visible Blue</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>0.52-0.60</td>
<td>Visible Green</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>0.63-0.69</td>
<td>Visible Red</td>
<td>30</td>
</tr>
<tr>
<td>4</td>
<td>0.76-0.90</td>
<td>Near Infra-red</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>1.55-1.75</td>
<td>Mid Infra-red</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>10.40-12.50</td>
<td>Thermal Infra-red</td>
<td>120</td>
</tr>
<tr>
<td>7</td>
<td>2.08-2.35</td>
<td>Mid Infra-red</td>
<td>30</td>
</tr>
</tbody>
</table>

The CIA contains approximately 95,000ha of total land area. This area is completely covered by two overlapping east-west Landsat 5 TM images which have a cover of approximately 170km north/south and 183km east/west which is sufficient to cover the whole study area (Figure 4.1). A set of cloud free Landsat 5 TM satellite images coinciding with field data collection dates were downloaded for the current study for winter and summer as described in Table 4.2 and Table 4.3 respectively.
Figure 4.1: The CIA which falls within the overlap of two Landsat 5 TM images (Van Niel & McVicar, 2004b)

Table 4.2: Landsat 5 TM Image Acquisition Dates and Ground Data Collection Dates for the Winter Season.

<table>
<thead>
<tr>
<th>Field data collection dates</th>
<th>Satellite overpass dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/09/08</td>
<td>2010/09/06</td>
</tr>
<tr>
<td>2010/09/27</td>
<td>2010/09/22</td>
</tr>
<tr>
<td>2010/10/22</td>
<td>2010/10/24</td>
</tr>
<tr>
<td>2010/11/05</td>
<td>2010/11/02</td>
</tr>
<tr>
<td>2010/11/18</td>
<td>2010/11/18</td>
</tr>
<tr>
<td>2010/12/06</td>
<td>2010/12/04</td>
</tr>
</tbody>
</table>
Table 4.3: Landsat 5 TM Image Acquisition Dates and Ground Data Collection Dates for the Summer Season.

<table>
<thead>
<tr>
<th>Field data collection dates</th>
<th>Satellite overpass dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/11/05</td>
<td>2010/11/02</td>
</tr>
<tr>
<td>2010/11/18</td>
<td>2010/11/18</td>
</tr>
<tr>
<td>2010/12/06</td>
<td>2010/12/04</td>
</tr>
<tr>
<td>2010/12/21</td>
<td>2010/12/27</td>
</tr>
<tr>
<td>2011/01/10</td>
<td>2011/01/05</td>
</tr>
<tr>
<td>2011/01/20</td>
<td>2011/01/28</td>
</tr>
<tr>
<td>2011/02/09</td>
<td>2011/02/06</td>
</tr>
<tr>
<td>2011/02/28</td>
<td>2011/03/01</td>
</tr>
<tr>
<td>2011/03/17</td>
<td>2011/03/26</td>
</tr>
<tr>
<td>2011/04/04</td>
<td>2011/04/02</td>
</tr>
</tbody>
</table>

4.1.1.6 RapidEye images

RapidEye is a German geospatial information provider having a constellation of five satellites launched in 2008. Each satellite contains identical sensors located in the sun-synchronous orbital plane at an altitude of 630km and is capable of imaging any point on the earth every day. It has an image capture capacity of four million square kilometres per day with a ground sampling distance of 6.5m. The spectral range of this image is 16-bit per band. The images have 5m spatial resolution and are capable of recording five spectral bands as shown in Table 4.4.

As RapidEye provides multi-spectral bands with high spatial resolution of 5m, it is ideal for use in regional scale crop classification studies. In addition these images work well with object-oriented classification techniques where the technique requires high spatial resolution satellite images. Further, the image gives more opportunity for accurate classification of irrigated crops as it has a red-edge band in addition to the red band. Both fall in the visible region of the electromagnetic spectrum. For these reasons, RapidEye images are suitable for the classification technique selected for the current study.
High spatial resolution RapidEye images were purchased for the CWSA project, and after using them in that project, the images were freely available for the use in current study. However, these images which were appeared on 17th and 30th of January 2011 and were able to be used only for the summer crop classification in 2010/11 and not for the winter crop classification. Because of budget limitations it was not possible to buy high resolution RapidEye images for the classification of the winter crops.

Table 4.4: Spatial and Spectral Characteristics of RapidEye Images.

<table>
<thead>
<tr>
<th>Band number</th>
<th>Spectral range (µm)</th>
<th>Spectral information</th>
<th>Spatial resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.44-0.51</td>
<td>Visible Blue</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>0.52-0.59</td>
<td>Visible Green</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>0.63-0.68</td>
<td>Visible Red</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>0.69-0.73</td>
<td>Visible Red edge</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>0.76-0.85</td>
<td>Near Infra-red</td>
<td>5</td>
</tr>
</tbody>
</table>

4.1.1.7 MODIS satellite images and products

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an advanced optical sensor launched in December 1999 which has Terra and Aqua satellites on board. The sensor provides daily global coverage with 36 spectral bands between 0.415 and 14.235µm. Seven of the spectral bands are capable of vegetation and land surface monitoring as they belong to visible, near infra-red and shortwave infra-red regions. The characteristics of MODIS images are given in Table 4.5.
In parallel to providing images, the MODIS sensor provides a number of MODIS-products for the observation and biophysical monitoring of the global environment. These products derived from spectral bands with spatial resolutions of 250m to 1000m are available to users mainly as radiation balance products, vegetation products and land cover products (Justice et al., 2002).

The MOD15A2 is a level 4 MODIS Leaf Area Index (LAI) and fraction of photosynthetically active radiation product (fPAR). It has 8 days temporal and 1000m spatial resolution. In this study the MOD15A2 product was used in place of a ground-based LAI of rice crops in the CIA. Some studies have used this product successfully in different applications in rice growing areas (Cheng, 2008).

### 4.1.2 Climatic data

The climatic data for two seasons of summer and winter was obtained from the two Automatic Weather Stations (AWS) located in the CIA. The weather stations were located at CSIRO Griffith and the Bureau of Meteorology (BoM) weather station at Coleambally. Climatic variables such as maximum and minimum temperatures, wind speed, net radiation and relative humidity were collected for the estimation of ET of selected crops.

---

**Table 4.5: Spatial and spectral characteristics of MODIS images.**

<table>
<thead>
<tr>
<th>Band number</th>
<th>Spectral range (µm)</th>
<th>Spectral information</th>
<th>Spatial resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.459-0.479</td>
<td>Visible Blue</td>
<td>500</td>
</tr>
<tr>
<td>2</td>
<td>0.545-0.565</td>
<td>Visible Green</td>
<td>500</td>
</tr>
<tr>
<td>3</td>
<td>0.620-0.670</td>
<td>Visible Red</td>
<td>250</td>
</tr>
<tr>
<td>4</td>
<td>0.841-0.875</td>
<td>Near Infra-red-1</td>
<td>250</td>
</tr>
<tr>
<td>5</td>
<td>1.230-1.250</td>
<td>Near Infra-red-2</td>
<td>500</td>
</tr>
<tr>
<td>6</td>
<td>1.628-1.652</td>
<td>Short Wave Infra-red-1</td>
<td>500</td>
</tr>
<tr>
<td>7</td>
<td>2.105-2.155</td>
<td>Short Wave Infra-red-2</td>
<td>500</td>
</tr>
</tbody>
</table>
4.1.3 Field data

Required ground measurements were collected from a number of different farms in the CIA. Every seven to ten days during the cropping seasons, field visits were planned to coincide with important phenological development stages of the crops, satellite overpass days and favourable weather conditions in order to guarantee cloud-free satellite images of important crop growth stages. The ground-based measurements of crop reflectance, LAI measurements, above ground biomass and ground truth data were collected at different rice, wheat and corn farms in the CIA for each study crop in both seasons. Figure 4.2 shows the ground-based LAI and reflectance for data collection farms in the CIA during the winter and summer seasons of 2010/11.

![Figure 4.2: Locations of LAI and MSR data collection farms in the CIA](image)

4.1.3.1 Reflectance measurements

The development of empirical relationships between ground-based NDVI and LAI is one of the research objectives of the current study. Therefore, ground reflectance measurements for the three irrigated crops were measured in order to estimate ground-based NDVI. Reflectance measurements for the three crops were made with a hand-held Multi-
Spectral Radiometer (MSR) shown in Figure 4.3 (CROPSCAN, 1995). The instrument consists of two sensors facing upwards and downwards to measure both incoming radiation from the sky and outgoing radiation reflected from the canopy, nearly simultaneously. After measuring incoming and outgoing radiation with optical sensor bands, the MSR calculates the percentages of reflectance of the canopy. The MSR16R model normally can accommodate up to 16 sensor bands, however, only 11 sensor bands were available with the MSR16R hand-held instrument which was used in the current study. The sensor bandwidths of MSR16R are similar to the selected MODIS, Landsat 5 TM and Landsat 7 ETM+ bandwidths (Table 4.6).

Figure 4.3: Multispectral radiometer and accessories
Table 4.6: Information on CROPSCAN - MSR16R Model.

<table>
<thead>
<tr>
<th>Satellite Equivalent</th>
<th>Sensor Name</th>
<th>Centre wavelength (nm)</th>
<th>Half Peak Bandwith (nm)</th>
<th>Pass Band range (nm)</th>
<th>Transmission</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODIS B3</td>
<td>467</td>
<td>4675</td>
<td>8.5</td>
<td>463-472</td>
<td>46</td>
</tr>
<tr>
<td>Landsat 5 B2</td>
<td>485</td>
<td>4905</td>
<td>66</td>
<td>458-524</td>
<td>78</td>
</tr>
<tr>
<td>MODIS B12</td>
<td>550</td>
<td>5503</td>
<td>8.9</td>
<td>546-555</td>
<td>57</td>
</tr>
<tr>
<td>Lanst 7 B8</td>
<td>560</td>
<td>5612</td>
<td>71.8</td>
<td>525-597</td>
<td>89</td>
</tr>
<tr>
<td>MODIS B1</td>
<td>650</td>
<td>652</td>
<td>11.1</td>
<td>646-658</td>
<td>55</td>
</tr>
<tr>
<td>Lanst 7 B3</td>
<td>660</td>
<td>662</td>
<td>57.3</td>
<td>636-691</td>
<td>89</td>
</tr>
<tr>
<td>Landsat 5 B4</td>
<td>830</td>
<td>832.5</td>
<td>348.6</td>
<td>760-906</td>
<td>/ /</td>
</tr>
<tr>
<td>MODIS B2</td>
<td>855</td>
<td>855.5</td>
<td>9.6</td>
<td>851-860</td>
<td>57</td>
</tr>
<tr>
<td>MODIS B5</td>
<td>1240</td>
<td>1240.7</td>
<td>10.3</td>
<td>1236-1246</td>
<td>53</td>
</tr>
<tr>
<td>MODIS B6</td>
<td>1640</td>
<td>1641.6</td>
<td>14.9</td>
<td>1634-1649</td>
<td>52</td>
</tr>
<tr>
<td>Landsat 5 &amp; 7 B5</td>
<td>1650</td>
<td>1669</td>
<td>195</td>
<td>1752-1760</td>
<td>/ /</td>
</tr>
</tbody>
</table>

In this study three MSR scans per GPS point were taken for row crops such as corn. One scan was taken directly above the plant, another, at a half plant, half inter-row space, and the third directly above the inter-row space. The average values were calculated from these measurements. By using this strategy, sampling bias was reduced and a more accurate representation of the canopy reflectance was gathered. For the non-row crops of rice and wheat, only one scan was obtained per GPS measurement point. These were taken at 30m intervals at each site, along transects to represent the Landsat 5 TM image resolution of 30m.

At every important phenological stage, 50 MSR measurements were taken along two parallel transects (>30m apart) at 30m intervals in corn farms. Similarly, 10m interval reflectance measurements were taken along single transects in wheat and rice farms. The coordinates of all the sample GPS points were collected using a hand held GPS during the field work.

**4.1.3.2 LAI measurements**

Ground-based LAI measurements are require in developing empirical relationships with NDVI. These relationships were paramount in obtaining ground-based LAI by means of satellite-based NDVI and also in the classification phase in the current study. A hand-held, LAI-2000 Plant Canopy Analyser (LI-COR Inc., 1992) as shown in Figure 4.4 was
employed to collect LAI ground measurements for the three crops in the different paddocks in the study area.

The instrument simultaneously measures diffuse sunlight at five zenith angle ranges with midpoints of 7°, 23°, 38°, 53° and 67°. By taking measurements above and below the vegetation canopy, attenuation can be obtained, and this can be used to ascertain the amount of foliage, LAI, of the corresponding crop. Normally a higher number of below canopy readings are obtained to increase the accuracy of the measurements. For one above canopy reading the optimal numbers of below canopy readings are determined based on the 95% confidence that the true LAI mean is within +/- 10% of measured leaf area. In this study, four below canopy LAI measurements were taken. Single sensor mode and 45° view cap was employed under overcast conditions at dawn or dusk to avoid possible over-reflections from the sun and erroneous results. LAI measurements were also taken at the same points, as MSR measurements taken for the three study crops.

Figure 4.4: LAI-2000 Plant Canopy Analyser (a) and its optical sensor (b)
4.1.3.3 Harvest Index data

Ground-based data for the three study crops were collected in the CIA in order to estimate crop-specific HI. Field samples of above ground biomass were collected at final physiological maturity of the three crops. Ground samples of 1m$^2$ were collected randomly at different rice, corn and wheat farm locations. For rice and corn, ten samples were collected and, for wheat, it was reduced to five due of its uniform growth. The samples were harvested manually and for all the harvested samples, wet biomass was weighed. The wet biomass was oven-dried at 70°C for 24 hours and the final weights of above ground dry biomass and grain yields were estimated. Moisture content was established by calculating the weight difference of the total wet and dry matter. Subsequently, the harvest index and the effective harvest index (HI$_{eff}$) were estimated by incorporating the above ground biomass, grain mass and moisture content using Equation 4.1 and Equation 4.2 respectively.

\[
HI = \frac{\text{Grain mass}}{\text{Above ground dry biomass}} \quad 4.1
\]

\[
HI_{eff} = \frac{\text{harvest index}}{1 - \text{Moisture content}} \quad 4.2
\]

As recommended by most studies (Li et al., 2011; Lobell et al., 2003), only the above ground biomass without roots was used in estimating the harvest index. Further, the effective harvest index was used in yield modelling instead of the normal harvest index. It is more suitable for irrigated crops than the normal harvest index in estimating crop yield, as it usually carries higher yields for irrigated crops (Bastiaanssen & Ali, 2003).

4.1.3.4 Ground truth data and training samples

A sufficient number of high quality training samples are a prerequisite for the creation of accurate classification maps in order to assign the image pixels to a meaningful thematic feature class on the ground. Generally, training data is collected through field campaigns, from high spatial satellite images or from air photographs. The training samples are normally
collected by visiting the field during the cropping season on or near the overpass day of the satellite which is used for the creation of the classification map (Alexandridis et al., 2008). Training data is needed to train the classification algorithms as well as to validate the resulting classification maps.

In this study, training samples were collected from different farm plots in the CIA through a number of field trips. Special attention was given to collecting field samples at important phenological stages of the crops during the summer and winter cropping seasons. The positions of the training locations were obtained in the field using a hand held GPS instrument with 15m of instrument XY positioning accuracy. Sample points are shown in Figure 4.5 on a false colour composite of bands 4, 3 and 2 of the Landsat 5 TM image. For each recorded sample point, crop type, irrigation condition, and crop height were recorded as auxiliary information. The training data was collected from all land cover types at the different fields in the study area. The main land cover types found in the area for the winter season were wheat, oats, barley, canola and pasture and in summer they were rice, soybeans, maize (corn), grapes, prunes, sunflowers, lucernes and pasture.

Figure 4.5: Ground truth points taken in the CIA shown on a false colour composite of a Landsat 5 TM image
After the importing of these vector data to ArcGIS software, they were polygonised and rasterised. For each land cover type two sets of polygons were delineated within the farms. One set was used as training data while the other set was used to assess the accuracy of the classified map. To avoid the mixed-pixel effect on classification accuracy, the polygons were selected from the middle of each farm.

4.2 Development of Empirical Models for LAI Estimation

LAI is an important biophysical parameter for determining vegetation health, biomass, photosynthesis and ET for the modelling of crop yield. Ground measurement of this parameter is tedious and time-consuming due to the heterogeneity across the landscape over time and space. For this study, extensive field data collection campaigns were carried out in the CIA in order to collect ground-based LAI and reflectance measurements which were used to estimate NDVI. Co-relationships between satellite and ground measured reflectance were developed and regression analysis was carried out to analyse the LAI and NDVI regression models. The analysis showed that the atmospheric correction process significantly improved the relationship between LAI and NDVI for Landsat 5 TM images.

4.2.1 Processing of reflectance measurements

Reflectance measurements taken with the MSR16R portable crop scanner were checked and cleaned for erroneous readings. Ground-based NDVI (NDVI_G) was calculated from the equivalent red (band 6 - central wave length 662nm) and near infra-red (band 7 - central wave length 832.7nm) bands of MSR using Equation 4.3.

\[
NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}
\]

where \( \rho_R \) and \( \rho_{NIR} \) are corresponding red and infra-red wavelengths from the MSR16R instrument.
4.2.2 Processing of leaf area index measurements

LAI measurements collected with the LAI-2000 were downloaded using the program FV-2000 and the data was analysed. The program was further used to recompute the average value for sample points by eliminating erroneous readings of extreme LAI measurements. Rings of the detector and the canopy models were interactively changed for better accuracy of the measured LAI.

4.2.3 Satellite data pre-processing

Pre-processing of images is needed prior to model formulation in order to rectify any distortions in images which may occur due to sensor, platform and atmospheric conditions. This operation includes geometric rectification, radiometric calibration, topographic correction and atmospheric correction. The Landsat 5 TM and RapidEye images were pre-processed for these corrections.

4.2.3.1 Landsat 5 TM images

As this data source itself provides geometrically corrected images (level 1A images) it was not necessary to carry out geometric rectification. The accuracy of geometric locations was checked for several target points prior to use. Topographic correction was not required as the CIA is a flat terrain with 0° elevation, and the area consists mostly of irrigated crops where there is less chance of having shadows due to tall features. The images were initially calibrated for radiometric error by the provider; therefore radiometric correction was also not required.

Images are affected by atmospheric absorption and a scattering effect due to gases and aerosols in the atmosphere. Therefore it is necessary to consider the influence of this effect on satellite images. Several gases such as molecular oxygen, water vapour and ozone are most influential on the visible and near infra-red region of the solar spectrum. Therefore it is necessary to investigate the sensitivity of remote sensing data to these atmospheric effects.
In order to test this effect, the top-of-atmospheric spectral radiance was calculated from the Digital Numbers (DN) using calibration coefficients, and transformed to Top Of Atmospheric Reflectance (Toar) by taking into account the total incoming and reflected spectral radiance. The model Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) was then used to rectify the reflectance measurements for atmospheric error using the 6S (Second Simulation of Satellite Signal in the Solar Spectrum) code parameters of geometrical conditions, atmospheric model, aerosol model, aerosol concentration model (visibility), mean target elevation and sensor bands. This code converts DN to Toar and then to earth skin or surface reflectance (Surf).

4.2.3.2 RapidEye image

For this study, a level 3A (RapidEye Ortho product) images were obtained. These offered the highest level of pre-processing. Images were radiometrically and geometrically corrected and processed to remove terrain distortions by the producer. It was not necessary to rectify the atmospheric error as the image was used for single-date image classification (Song et al., 2001).

4.2.4 Model formulation

Two forms of NDVI maps, NDVI_{Toar} and NDVI_{Surf}, were created for each crop throughout the cropping season in order to develop regression models. Two different forms of reflectance, Toar and Surf derived from Landsat 5 TM images were used in the development of NDVI maps. The point values from NDVI_{Toar} and NDVI_{Surf} maps were then extracted at corresponding field GPS points where field data was collected. The extracted point values of NDVI_{Toar} and NDVI_{Surf} maps were plotted against the corresponding point values of NDVI_{G} and regression models were developed and the reliability of models were analysed. The most reliable model was selected by considering some statistical parameters such as coefficient of determination and the root mean square error.
Subsequently, a set of regression models were developed by integrating LAI and NDVI data. Corresponding GPS points’ values of ground-based LAI (LAI_G), were integrated with point values of three different forms of NDVI data, NDVI_G, NDVI_Tear and NDVI_Surf. Due consideration was given to the phenological growth of crops in selecting the trend lines between different datasets regardless of the best fit trend line. Statistical analysis was carried out for the evaluation of the performance of each model and thus each data product. MODIS LAI (MOD15A2) products were used to replace LAI_G in the development of the rice crop model. The models developed were validated over a new dataset which was collected from the CIA during the same cropping season and the reliability of the regression models created was analysed.

4.2.5 Quantitative evaluation of model performance

A large number of spectral vegetation indices have been developed around the globe to evaluate biophysical vegetation parameters such as LAI. Statistical techniques such as regression have been used to evaluate the performance of these indices. The most widely used regression-based statistical parameters are coefficient of determination ($r^2$) and root mean square error (RMSE) (Canisius & Fernandes, 2012; Colombo et al., 2003; Gilabert et al., 1996; Haboudane et al., 2004a; Qi et al., 2000; Wittamperuma et al., 2012). Generally for a bivariate regression model with a vegetation biophysical parameter as an independent variable and a vegetation index as a dependent variable, the best fit is measured with the coefficient of determination ($r^2$), mean squared error (MSE) or root mean squared error (RMSE). These are the indicators of the sensitivity of vegetation indices over biophysical parameters (Ji & Peters, 2007).

The coefficient of determination is popular among researchers as it defines the proportion of variability explained by each variable of the model and, further, $r^2$ ranges between 0 and 1 making it a standard measure of the best fit (Ji & Peters, 2007). However, caution is required when $r^2$ is used with non-linear regression models as it can produce a negative value. In the
current study, two indicators of sensitivity, $r^2$ and RMSE, were used to evaluate the model performance. RMSE and $r^2$ can be defined as follows:

\[
r^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}
\]

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}}
\]

where $\sum (Y_i - \hat{Y}_i)$ explains the deviations of observations from their predicted values $\hat{Y}_i$ and $\sum (Y_i - \bar{Y})$ explains the deviations of the observations $Y_i$ from their mean $\bar{Y}$ and $n$ is the number of observations.

### 4.3 Land Use and Land Cover Classification

Satellite remote sensing is the most suitable and widely used data source for mapping LULC patterns due to its repetitive data acquisition facility and its digital formatting nature which enable computer processing and accurate georeferencing (Abd El-Kawy et al., 2011; Chen et al., 2005). Image classification is one of the most important and widely used techniques for identifying different crops using remote sensing data (Akbari et al., 2006). It allows the gathering of more accurate information about total cropping areas together with crop types in irrigated agriculture. This technique is especially well suited to arid and semiarid environments where irrigated agriculture takes place. The availability of remote sensing images together with advanced image processing techniques enables scientists to extract more accurate information such as crop type, condition, area and growth in irrigated agriculture.

The selection of a suitable dataset for crop classification can be carried out by understanding the strengths and limitations of the characteristics of remote sensing data. In this study, the selection of satellite images for the classification was carried out with consideration for the characteristics of remote sensing data in different resolutions, area coverage and cost effectiveness as previously mentioned.
One of the objectives of the current study was to develop classification maps to calculate wheat, corn and rice cropping areas. An accurate crop classification map is vital for the temporal integration of biomass growth over the cropping period and for the assigning of corresponding harvest indices for different crops (Bastiaanssen & Ali, 2003). The conversion of accumulated above ground dry biomass into final crop yield can be calibrated through the crop-dependent harvest indices. Crop classification maps were developed for use in the crop yield estimation phase of the study and to represent the spatial distribution of crop yield for the three irrigated study crops.

The classification maps were created using single-date Landsat TM and RapidEye images acquired during the peak cropping seasons of summer and winter. A single-date image is sufficient for the classification of irrigated crops if the image is available during the peak cropping period (Ozdogan et al., 2010; Ullah, 2011). Single-date image classification accuracy can be improved and different crop types can be distinguished clearly with the help of time series data (Akbari et al., 2006; Ozdogan et al., 2010). It was possible to identify the peak cropping period by studying the time series data, cropping patterns, cropping calendar and accessing local expertise from the cropping area. If a single date image is used for the classification, application of atmospheric error is not required for the particular image (Song et al., 2001). Therefore, neither the selected single-date RapidEye nor the Landsat 5 TM images were corrected for atmospheric error.

The development of accurate classification maps required not only the selection of appropriate satellite images but also the employment of a good classification technique. In this study, an object-based classification technique was selected as it showed more accurate classification results in many studies (Geneletti & Gorte, 2003; Lu & Weng, 2007; Yan et al., 2006) than the conventional pixel-based classification technique. This technique works well with medium (10-30m) resolution images such as Landsat 5 TM images and fine (pixel size 2-10m) resolution images such as RapidEye (Whiteside et al., 2011). Therefore, an object-based, supervised, hybrid
classification technique was used in order to create high accuracy classification maps for the three irrigated crops in the CIA.

4.3.1 Object-based image classification

The object-based classification technique is a sequential process which consists of the segmentation of an image into homogeneous regions and the subsequent classification of the segmented objects into thematic classes (Whiteside et al., 2011). While this technique works well with high resolution multi-spectral images (Geneletti & Gorte, 2003), in some other studies (Dorren et al., 2003; Whiteside et al., 2011) acceptable results have been obtained for 5 TM images in the development of classified maps using an object-oriented classification technique.

In the feature-extraction workflow an object-based approach was employed to classify the images in this study. Medium-scale spatial resolution Landsat 5 TM images were used for classification of winter crops because of the unavailability of high spatial resolution imagery. For classification of summer crops, high-spatial RapidEye images were available. In the object-based approach, segmentation was carried out in an ENVI environment (using ENVI software) and classification was carried out using both developed LAI models and training samples. A confusion matrix was used to assess the accuracy of the developed classification maps in the two seasons.

4.3.2 Object-based supervised hybrid image classification

In this process, selected single-date Landsat 5 TM and RapidEye images were used as the base images to extract features. By analysing different scale levels interactively in the segmentation process, the most effective scale level was applied and formed the segments with the minimum mixed pixel effect. Also a number of homogeneous regions were formed based on spectral, spatial and texture information. The edge-based segmentation algorithm in the ENVI software was used and the algorithm performed iterative steps with a bottom-up segmentation approach (Figure
4.6). Starting with single pixels and merging a number of pixels into segments, homogeneous image objects were formed. In the merging phase, the segments were merged under the best possible merge scale to reduce over segmented and highly textured regions.

![Hierarchical levels of image objects](image)

Figure 4.6: Hierarchical levels of image objects (Benz et al., 2004)

The object-based classification technique initially required the recognition of meaningful image objects through the segmentation procedure in order to classify them into thematic classes. The identification of meaningful image objects can be done successfully using high spatial resolution images and consequently homogeneous segments will be produced leading to accurate classification results (Geneletti & Gorte, 2003). Landsat 5 TM images may not be as effective as RapidEye images in the production of very accurate homogeneous segments due to their medium spatial resolution which may lead to low accuracy of classification results. However, Whiteside et al. (2011) have shown that medium resolution Landsat 5 TM images also produce satisfactory results with the object-oriented classification technique.

The object-based, supervised, hybrid classification technique was performed by incorporating ground-based LAI values and subsequently introducing the ground truth data to train the image. LAI maps were created for the study crops using the empirical LAI models which were developed
in the first part of this study. The Landsat 5 TM and RapidEye images were used to create individual LAI maps for each season and they were staked as an additional band in the corresponding single date images which were selected for crop classification. For the three study crops, the LAI ranges corresponding to the image acquisition dates were extracted from the ground-based LAI measurements. Those LAI ranges were set as the thresholds and the crops holding those LAI value ranges were extracted from individual images. The extracted crops were further refined using ground truth (crop type) data and the final maps for each crop were obtained. For the rice crop, the corresponding LAI value ranges were extracted from the MODIS15A2 product appeared on 2\textsuperscript{nd} February, 2011 and which was the closest MODIS product to the single-date RapidEye image. Figure 4.7 illustrates the chronology involved in this classification process.
Figure 4.7: Schematic diagram of object-based, supervised, hybrid classification technique

4.3.3 Accuracy assessment

Assessment of the accuracy of the classified maps was carried out using ground truth data which was collected from the CIA during the summer and winter seasons. A number of sample points were randomly obtained from different corn, rice and wheat farms for the quantitative accuracy assessment of the classified maps. The confusion or error matrix, the most widely used method for accuracy assessment, (Foody, 2002; Lu & Weng, 2007) was employed to assess the accuracy in each class. The matrix provides measures for the overall accuracy of the produced map, and user and producer accuracy based on row and column calculations (Foody,
2002). Accuracies were obtained for corn, rice, wheat and the unclassified classes and the results were analysed.

4.4 Crop Yield Estimation

The main objective of this study was to forecast the crop yield of three irrigated crops in the CIA. This was achieved by applying the new model developed by (Bastiaanssen & Ali, 2003) as a combination of three originally developed models: the APAR model developed by Monteith (1972), the CASA approach for light use efficiency developed by Field et al. (1995) and the surface energy balance model of Bastiaanssen et al. (1998a). The estimated yields were validated over the reported crop yield statistics of the Department of Primary Industries, NSW, and spatial variations in the three study crops were investigated. All computations and estimations, including biomass and crop yield, were executed in the GIS environment. The methodology adopted for the estimation of various parameters for the crop yield model described in Equation 3.12 is further explained in following sections.

The classification maps for the two seasons, winter and summer were prepared on the basis of a hybrid classification technique and subsequently individual crop classification maps for corn, rice and wheat were generated. Using these maps, the raster maps of total above ground biomass development (B) were established and converted into final crop yield (Y) maps for the respective crops by assigning a crop-dependent effective harvest index. The effective harvest index was computed from field-based measurements of above ground biomass, dry grain mass and moisture content. In order to estimate the effective crop yield of each crop, the crop yields were masked out from developed yield maps.

4.4.1 Calculation of photosynthetically active radiation (PAR)

One of the most important parameters involved in biomass estimation is PAR. PAR was computed using a model for incoming solar radiation, $K_{24}$ as explained in Equation 3.1. $K_{24}$ was integrated with the time to obtain
the total PAR value for the time periods between two successive Landsat 5 TM images throughout the cropping season. The model parameters used to estimate $K_{24}$ are explained in Equations 3.1 through to 3.2.

4.4.2 Calculation of absorbed photosynthetically active radiation (APAR)

Raster maps of the NDVI for the three irrigated crops were generated for the CIA using available Landsat 5 TM satellite images for the whole cropping cycle. These NDVI raster maps were developed for each crop according to the relationships developed in the current study. These raster-based NDVI maps were applied for the computation of the fPAR according and subsequently the absorbed photosynthetically active radiation (APAR) was estimated by multiplying the two maps of fPAR and PAR.

4.4.3 Estimation of evaporative fraction through SEBAL model

The evaporative fraction was estimated using various heat fluxes derived by solving the energy balance equation. In order to estimate the evaporative fraction, the SEBAL model was applied to derive the heat fluxes. The SEBAL requires a minimum number of field measurements for the estimation of ET (Li et al., 2009; Ullah, 2011). The SEBAL has calibrated and validated farm and catchment scales for different climatic and vegetation settings worldwide (Bastiaanssen et al., 2009) and has already been applied in a number of studies in Australia (NWC, 2010). The SEBAL model computes instantaneous heat fluxes for the image overpass time as the image provides information only for the overpass time.

The raster maps of evaporative fraction $\lambda$ were developed using Equation 4.6 which explains the partitioning of net radiation into latent heat flux. This process varies extensively with surface wetness conditions (Bastiaanssen & Ali, 2003). The SEBAL was used to compute the evaporative fraction which is totally controlled by the soil moisture of the root zones (Bastiaanssen et al., 1997). The evaporative fraction was required in order to compute net radiation, latent heat flux and soil heat flux.
\[ \Lambda = \frac{\lambda E}{R_n - G} \]

where \( \lambda E \) is the latent heat flux, \( R_n \) is the net radiation and \( G \) is the soil heat flux.

### 4.4.3.1 Estimation of net radiation (\( R_n \))

Net radiation is defined as the balance of all incoming and outgoing electromagnetic radiation. It can be calculated from the surface radiation balance equation as follows (SEBAL, 2002):

\[ R_n = R_{s\uparrow} - \alpha R_{s\downarrow} + R_{L\downarrow} + R_{L\uparrow} - (1 - \varepsilon_o)R_{L\downarrow} \]

where \( R_{s\uparrow} \) is the incoming short-wave radiation (W/m\(^2\)), \( \alpha \) is the albedo, \( R_{s\downarrow} \) is incoming long wave radiation (W/m\(^2\)), \( R_{L\downarrow} \) is outgoing long wave radiation (W/m\(^2\)) and \( \varepsilon_o \) is the surface thermal emissivity.

The net short wave radiation \((1 - \alpha)R_{s\downarrow}\) is the quantity which is absorbed by the earth surface. It is a function of the surface albedo, \( \alpha \), which can be computed from narrow-band spectral reflectance for each band of the image. Incident angle and solar constant, earth-sun distance and broadband atmospheric emissivity are required to compute \( R_{s\downarrow} \). The incoming long-wave radiation, \( R_{L\downarrow} \), was computed with the modified Stefan-Boltzmann equation using both an atmospheric and a surface reference temperature. The outgoing long wave radiation, \( R_{L\uparrow} \), was computed as a function of surface temperature, surface emissivity and the Stefan-Boltzmann constant which is \( 5.67 \times 10^{-8} \). The surface temperature was obtained from the thermal radiance of the satellite image. Emissivity was computed as a function of a vegetation index. The term \((1 - \varepsilon_o)R_{L\downarrow}\) is a fraction of lost incoming long-wave radiation due to surface reflection.

### 4.4.3.2 Estimation of latent heat flux (\( \lambda E \))

The latent heat flux is computed as the residual of the energy balance equation. Therefore it is necessary to estimate sensible heat flux, \( H \), in order to estimate the residual \((\lambda E)\). The temperature difference between air
and surface due to convection and conduction is defined as sensible heat flux. It is defined by the following equation (Bastiaanssen, 2000).

\[
H = \frac{\rho_a \times C_p \times dT}{r_{ah}}
\]

where \(\rho_a\) is atmospheric air density (kg/m\(^3\)), \(C_p\) = specific heat of the air (J/Kg/K), \(dT\) is the vertical temperature difference between two heights (K), and \(r_{ah}\) is aerodynamic resistance for heat transport (sm\(^{-1}\)).

In the calculation of latent heat flux, \(H\) and \(dT\) were estimated through a number of iterative processes by selecting two hot and cold pixels. The main objective of the iteration process was to determine a refined value for \(dT\) as it was the most uncertain parameter affecting the value of \(H\). Aerodynamic resistance for heat transport and atmospheric air density were also recomputed in the iteration process with adjusted parameters. This process was repeated until the constant value for \(dT\) and \(r_{ah}\) for a hot pixel was stabilized. In the same way, the fluctuations in \(H\) started to decrease as the number of iterations increased. The variations in \(H\) became constant after several cycles of iterations (Tasumi & Allen, 2000).

### 4.4.3.3 Estimation of soil heat flux (G)

The amount of heat stored in the soil and vegetation is called the soil heat flux and this occurs due to conduction. Soil heat flux is given empirically in terms of net solar radiation, surface heating, albedo and NDVI as follows (Bastiaanssen, 2000):

\[
G_o = \frac{R_n \times T_s}{\alpha} \times (0,0038\alpha + 0,0074\alpha^2) \times (1 - 0,98 \times NDVI^4)
\]

where \(R_n\) is net radiation (W/m\(^2\)), \(T_s\) is the radiometric surface temperature (°C) determined from the thermal band of the Landsat 5 TM image, \(\alpha\) is surface albedo and NDVI is the Normalised Difference Vegetation Index computed from bands 3 and 4 of the TM images.
4.4.4 Light use efficiency

Monteith’s model for light use efficiency, which was further improved by Field et al. (1995), was used for light use efficiency. Raster maps of $\Lambda$, maximum light use efficiency ($\varepsilon^*$) obtained from published international literature, and maximum and minimum temperatures estimated through Equations 3.2 and 3.2 were used to generate the raster maps of light use efficiency for each Landsat 5 TM image.

4.4.5 Biomass production

Biomass growth during consecutive satellite acquisition days was calculated with temporal variation of light use efficiency ($\varepsilon$), APAR and with representative days of biomass development.

The annual crop cycle was split into several discrete time intervals to comply with the acquired Landsat 5 TM images in order to estimate the time steps for biomass development. These discrete intervals were formed by taking into account the sowing and harvest dates of the crops and the availability of Landsat 5 TM images. The time duration for biomass development was calculated carefully with effort made to maintain equal time durations of representative days for better accuracy. However, it was difficult to maintain equal time steps as cloud free images were not always available. The crop cycles were split into 9, 8 and 7 discrete time intervals for corn, rice and wheat respectively in order to accommodate available Landsat 5 TM images for each crop. Biomass growth during the intervening satellite days was calculated with daily variations in weather parameters and constant parameters for $\Lambda$, $\varepsilon^*$ and APAR.

Biomass calculations were repeated independently for each image for the corresponding number of discrete time intervals in each crop. There were 9, 8 and 7 raster maps of biomass generated for corn, rice and wheat respectively for the whole growing season of 2010/11 in accordance with the discrete time intervals of each crop. A total biomass approximation was carried out for the entire cropping season by integrating individual biomass development images.

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5  EMPIRICAL MODELS AND LAND USE AND LAND COVER CLASSIFICATION

This chapter presents the results obtained in different phases of the current study. The results are analysed with reference to local and international literature and various studies. Initially, regression models for the prediction of LAI for the three irrigated crops were developed using a novel remote sensing approach without physical interaction with the crop biomes. Next, LULC classification maps based on remote sensing data were developed using a hybrid object-oriented image classification technique. The accuracy of the classification was then determined and then the results were analysed in various ways including producer, user and overall accuracy through a confusion matrix.

5.1  Empirical Models for LAI Estimation

New empirical models were developed for the estimation of ground-based LAI as the basis of NDVI for three irrigated crops - corn, rice and wheat - in the CIA for the period of 2010/11. Ground-based NDVI (NDVI\textsubscript{G}) and satellite-based NDVI were plotted as a function of LAI, and the most accurate form of NDVI was selected in order to estimate LAI. This has necessitated a discussion of the reliability of different forms of NDVI.

A set of Landsat 5 TM satellite images was used for the remote estimation of NDVI for the whole cropping season. In order to analyse the sensitivity of remotely sensed NDVI with atmospheric effects, reflectance at the top-of-atmosphere was converted into top-of-canopy reflectance by applying an atmospheric correction. The two remotely-sensed NDVI datasets, based on the atmospherically corrected and uncorrected reflectance (the remotely-sensed NDVI datasets were NDVI at the ground surface (NDVI\textsubscript{Surf}) and NDVI at top of atmosphere (NDVI\textsubscript{Toar})), along with ground-based NDVI were used in regression with LAI. The best fit trend lines of
the regression models which were developed for the three different irrigated
crops were obtained by giving due consideration to the phenological growth
of the crops. The best fit trend line, in the form of a logarithmic function, is
presented below.

5.1.1 The relationships for corn

The ground-based NDVI and LAI data was collected during the
summer season of 2010/11 from several corn farms in the CIA through a
number of field campaigns. The ground data collection and the closest
Landsat 5 TM image acquired dates are shown in Table 5.1.

Table 5.1: Landsat 5 TM Image Acquisition Dates and Ground
Measurement Dates for Corn.

<table>
<thead>
<tr>
<th>Field data collection dates</th>
<th>Satellite overpass dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Reflectance and LAI measurements)</td>
<td></td>
</tr>
<tr>
<td>2010/11/05</td>
<td>2010/11/02</td>
</tr>
<tr>
<td>2010/11/18</td>
<td>2010/11/18</td>
</tr>
<tr>
<td>2010/12/06</td>
<td>2010/12/04</td>
</tr>
<tr>
<td>2010/12/21</td>
<td>2010/12/27</td>
</tr>
<tr>
<td>2011/01/10</td>
<td>2011/01/05</td>
</tr>
<tr>
<td>2011/01/20</td>
<td>2011/01/28</td>
</tr>
<tr>
<td>2011/02/09</td>
<td>2011/02/06</td>
</tr>
<tr>
<td>2011/02/28</td>
<td>2011/03/01</td>
</tr>
</tbody>
</table>

The satellite-based NDVISurf and NDVIToa were derived from Landsat
5 TM images. These two remotely-sensed NDVI datasets and the ground-
based NDVI measurements which were used in the development of
empirical models are presented in Figure 5.1 - Figure 5.3 below.
Figure 5.1: The relationship between LAI and NDVI\(_G\) for corn

\[
y = 0.2037\ln(x) + 0.652 \\
R^2 = 0.8306
\]

Figure 5.2: The relationship between LAI and NDVI\(_\text{Surf}\) for corn

\[
y = 0.16\ln(x) + 0.6227 \\
R^2 = 0.7427
\]
It is evident from the graphs and the statistics that ground-based NDVI relates with LAI more strongly than remotely-sensed NDVI for corn. NDVI$_G$, NDVI$_{Surf}$ and NDVI$_{Toar}$ correlate positively with LAI with high correlation coefficients of 0.86, 0.82 and 0.78 respectively. The coefficients of determination for these respective relationships were also positive with values of 0.83, 0.74 and 0.64 respectively.

5.1.2 The relationships for wheat

Empirical relationships for irrigated wheat were developed following a similar methodology to that used for the corn crop. Results have been presented in Figure 5.4, Figure 5.5 and Figure 5.6.
Figure 5.4: The relationship between LAI and NDVI$_G$ for wheat

Figure 5.5: The relationship between LAI and NDVI$_{Surf}$ for wheat
For wheat also, these relationships have shown promising results similar to corn. Ground-based NDVI correlated most highly with LAI with a correlation coefficient and coefficient of determination of 0.84. However, NDVI$_{Surf}$ and NDVI$_{Toar}$ also had relatively high correlation with LAI with correlation coefficients of 0.83 and 0.81 respectively and reasonably accurate coefficients of determination of 0.79 and 0.70 respectively.

5.1.3 The relationships for rice

Although the empirical relationships for irrigated rice were developed in the same way as for corn and wheat, the behaviour of the relationships was different than for those other crops (Figure 5.7).
As shown in Figure 5.7, the relationships were very poor showing a negative correlation coefficient of -0.37287 and a low coefficient of determination of 0.11 for the NDVI$_G$ – LAI$_G$ relationship. As there was no basic relationship between ground-measured NDVI and LAI, further empirical relationships such as LAI with NDVI$_{surf}$ and NDVI$_{Toar}$ for rice were not developed.

Ground-based NDVI and LAI measurements which were collected from the study area throughout the cropping season were compared with remotely-sensed data products and historical ground measurements from the CWSA project in order to investigate the reasons for the poor accuracy of the relationships for irrigated rice. The NDVI$_G$ was compared with remotely-sensed NDVI$_{Toar}$ and NDVI$_{surf}$ while ground-based LAI was compared with a MODIS LAI data product (MOD15A2) and historical measurements of LAI. The NDVI$_G$ correlated well with the remotely-sensed NDVI, however the ground-based LAI did not present any reasonable results when compared with MOD15A2 or with historical measurements. Therefore it is clear that the ground-based LAI data which was collected for the current study was problematic and it was not used to develop a relationship with NDVI$_G$ to form predictive equations for the estimation of the LAI of the rice crop.
The MOD15A2 extracted for the rice crop in 2009/10 was compared with the CWSA project’s LAI ground measurements for the same year. There was a medium coefficient of determination of 0.61 and a reasonably low RMSE of 0.26 between two of them. Further, MOD15A2 was also plotted as a function of NDVI\textsubscript{G} (Figure 5.8) and a higher correlation coefficient of 0.87 with a higher coefficient of determination of 0.87 was found. Therefore, MOD15A2 was found to be suitable for use in the next phases of the study in order to meet the various objectives of the study as it showed considerable accuracy over historical LAI values and NDVI\textsubscript{G}.

![Figure 5.8: Relationship between MODIS LAI product and NDVI\textsubscript{G} for rice](image)

Overall, the relationships between ground based LAI and NDVI for each crop were not the same and they showed different scatters due to chlorophyll content variation, the effects of canopy characteristics and the architecture of the different crops. Therefore, the predictive equations derived were also different because the crop canopy reflectance used to derive the predictive equations were crop type dependent. These are summarised in Table 5.2.
Table 5.2: Predictive Equations of Empirical Models.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Relationship</th>
<th>Predictive Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>LAI_G vs NDVI_G</td>
<td>( NDVI_G = 0.20 \ln LAI_G + 0.65 )</td>
</tr>
<tr>
<td></td>
<td>LAI_G vs NDVI_Surf</td>
<td>( NDVI_{Surf} = 0.16 \ln LAI_G + 0.62 )</td>
</tr>
<tr>
<td></td>
<td>LAI_G vs NDVI_Toar</td>
<td>( NDVI_{Toar} = 0.15 \ln LAI_G + 0.50 )</td>
</tr>
<tr>
<td>Wheat</td>
<td>LAI_G vs NDVI_G</td>
<td>( NDVI_G = 0.33 \ln LAI_G + 0.44 )</td>
</tr>
<tr>
<td></td>
<td>LAI_G vs NDVI_Surf</td>
<td>( NDVI_{Surf} = 0.28 \ln LAI_G + 0.39 )</td>
</tr>
<tr>
<td></td>
<td>LAI_G vs NDVI_Toar</td>
<td>( NDVI_{Toar} = 0.26 \ln LAI_G + 0.34 )</td>
</tr>
<tr>
<td>Rice</td>
<td>LAI_G vs NDVI_G</td>
<td>( NDVI_G = -0.38 \ln LAI_G + 0.84 )</td>
</tr>
<tr>
<td></td>
<td>LAI_MOD15A2 vs NDVI_G</td>
<td>( NDVI_G = 0.99 \ln LAI_{MOD15A2} - 0.313 )</td>
</tr>
</tbody>
</table>

5.1.4 Reliability of models developed for the study crops

From the above relationships developed for corn and wheat, it is evident that satellite-based NDVI and ground-based NDVI correlate with LAI with reasonable accuracy and, importantly, the ground-based measurements of NDVI correlate with LAI with a high degree of accuracy as shown in Table 5.3.

For the corn and wheat crops, the NDVI\(_G\) correlated positively with LAI\(_G\) with high correlation coefficients of 0.86 and 0.84 and high coefficients of determination of 0.83 and 0.84, respectively. For the respective crops, the correlation coefficient for the relationships between NDVI\(_{Surf}\) and LAI\(_G\) is also high and shows positive correlation coefficients of 0.81 and 0.81 and medium coefficients of determination of 0.74 and 0.77 respectively. The accuracy of NDVI\(_{Surf}\) – LAI\(_G\) is slightly lower compared to NDVI\(_G\) - LAI\(_G\) but higher than the accuracy of the NDVI\(_{Toar}\) - LAI\(_G\) relationships which still showed reasonably good correlation coefficients of 0.77 and 0.80 and coefficients of determination of 0.64 and 0.69 for corn and wheat respectively.
Table 5.3: The Accuracy of Relationships Developed Between LAI_G and NDVI_G, NDVI_Surf and NDVI_Toar for the Three Irrigated Crops.

<table>
<thead>
<tr>
<th>Crop</th>
<th>LAI_G vs NDVI_G</th>
<th>r²</th>
<th>Correlation coefficient</th>
<th>LAI_G vs NDVI_Surf</th>
<th>r²</th>
<th>Correlation coefficient</th>
<th>LAI_G vs NDVI_Toar</th>
<th>r²</th>
<th>Correlation coefficient</th>
<th>LAI_MOD15A2 vs NDVI_G</th>
<th>r²</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>0.83 0.86</td>
<td>0.74 0.81</td>
<td>0.64 0.77</td>
<td>-  -</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wheat</td>
<td>0.84 0.84</td>
<td>0.77 0.81</td>
<td>0.69 0.80</td>
<td>-  -</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rice</td>
<td>0.11 -0.37</td>
<td>-   -</td>
<td>-   -</td>
<td>0.87 0.87</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

For the rice crop, the relationships between ground-measured NDVI and LAI were very poor. However, the MOD15A2 (MODIS LAI product) showed good agreement with NDVI_G (Figure 5.8) as compared to the historical ground measurements of LAI. Therefore, it was reasonable to use MOD15A2 in the next phases of the study to meet the objectives of the study, as it showed considerable accuracy over historical LAI values and NDVI_G.

For the relationships developed above for corn and wheat crops, it can be seen that satellite-based NDVI and ground-based NDVI correlated with LAI with reasonable accuracies and importantly the ground-based measurements of NDVI correlates with LAI with a high level of accuracy. Therefore, ground-based measurements were more reliable for estimating ground-based LAI than satellite-based NDVI. As there was no remotely-sensed NDVI data to estimate LAI for rice as discussed above, LAI based on MODIS satellite and NDVI_G data was used to establish the relationships for rice.

5.1.5 Relationships of ground-based and remotely-sensed NDVI data

As explained above NDVI_G was more accurate for estimating LAI than satellite-based measurements but it is not often available at the required frequency or covering the required areas at regional and national scales due to the lack of cost effectiveness and the time consuming nature of performing the measurements. In contrast, remotely-sensed NDVI is more rapid and reliable and it can be accessed easily at minimal cost. Its
disadvantage is that it shows lower reliability compared to ground-based measurements. Therefore, in order to achieve high accuracy, timely access and economic value, ground-based and satellite-based measurements of NDVI were integrated for the estimation of LAI. Initially the two forms of satellite-based NDVI (NDVIToar and NDVISurf) were plotted as a function of NDVIG in order to develop empirical relationships for the corn and wheat crops. However, for the rice crop NDVIToar and NDVISurf did not have reasonable relationships with LAI and therefore they were not investigated. The empirical relationships between satellite-based and ground-based measurements of NDVI for the corn crop and wheat crop are given in Figure 5.9 - Figure 5.12.

![Figure 5.9: Comparison of atmospherically uncorrected NDVI with ground NDVI measurements for corn crop](image)

y = 0.6867x + 0.0577

R² = 0.6561
Figure 5.10: Comparison of atmospherically corrected NDVI with ground NDVI measurements for the corn crop

Figure 5.11: Comparison of atmospherically uncorrected NDVI with ground NDVI measurements for the wheat crop
Figure 5.12: Comparison of atmospherically corrected NDVI with ground NDVI measurements for wheat crop

The NDVI$_G$ of the two crops, corn and wheat, exhibited a high degree of variability throughout the cropping season due to variations in canopy characteristics starting from bare ground to full development of canopies and finally complete physiological maturity. Thus the relationships for the individual crops also varied considerably as shown above and presented in Table 5.4. The best fit trend lines of these relationships between NDVI$_{Toar}$ and NDVI$_{Surf}$ against NDVI$_G$ were plotted and the trend line for both crops behaved linearly. The linear equations obtained for each crop for estimation of NDVI$_G$ were subsequently used to determine LAI$_G$ by introducing the newly developed intermediate correlation developed for corn and wheat.

<table>
<thead>
<tr>
<th>Crop</th>
<th>NDVI$_{Toar}$ vs NDVI$_G$</th>
<th>NDVI$_{Surf}$ vs NDVI$_G$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>$NDVI_{Toar} = 0.6867 \times NDVI_G + 0.0577$</td>
<td>$NDVI_{Surf} = 0.7249 \times NDVI_G + 0.1582$</td>
</tr>
<tr>
<td>Wheat</td>
<td>$NDVI_{Toar} = 0.7568 \times NDVI_G + 0.0166$</td>
<td>$NDVI_{Surf} = 0.8327 \times NDVI_G + 0.0391$</td>
</tr>
</tbody>
</table>

The performance of the model was analysed in terms of statistical indices and showed promising results. After the application of atmospheric
correction for corn and wheat reflectance the coefficients of determination \((r^2)\) of NDVI (NDVI\(_{\text{surf}}\)) against NDVI\(_G\) relationships was improved from 0.66 to 0.76 for corn and from 0.77 to 0.80 for wheat and the root mean square error (RMSE) for the corresponding crops was reduced from 0.21 to 0.10 and from 0.18 to 0.10 respectively. Table 5.5 summarises these results for the two irrigated crops during the cropping season of 2010/11.

Table 5.5: Summary of the Model Performance Results for Corn and Wheat Crops.

<table>
<thead>
<tr>
<th>Crop</th>
<th>NDVI(_{\text{Toar}}) vs NDVI(_G)</th>
<th>NDVI(_{\text{surf}}) vs NDVI(_G)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(r^2)</td>
<td>RMSE</td>
</tr>
<tr>
<td>Corn</td>
<td>0.66</td>
<td>0.21</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.77</td>
<td>0.18</td>
</tr>
</tbody>
</table>

From Table 5.5 above, it is clear that remotely-sensed NDVI for irrigated crops was sensitive to atmospheric effects and model performance has improved accordingly after the application of atmospheric correction. Therefore it can be concluded that NDVI\(_{\text{surf}}\) correlated with NDVI\(_G\) more effectively than NDVI\(_{\text{Toar}}\) and therefore NDVI\(_{\text{surf}}\) was used to develop the intermediate relationship in the LAI determination process.

5.1.6 Predictive model of LAI in terms of ground-based and satellite based NDVI for irrigated corn

The models obtained for the corn crop can be summarised as follows:

\[
\text{NDVI}_G = 0.20 \ln \text{LAI}_G + 0.65
\]

\[
\text{NDVI}_{\text{surf}} = 0.72 \text{NDVI}_G + 0.16
\]

The model for the prediction of LAI for the corn crop can be deduced as follows:

\[
\text{LAI}_G = e^{\frac{\text{NDVI}_{\text{surf}} - 0.62}{0.19}}
\]
5.1.7 The predictive model for LAI in terms of both ground-based and satellite-based NDVI for irrigated wheat

The models obtained for the wheat crop can be summarised as follows:

\[ NDVI_G = 0.33 \ln LAI_G + 0.44 \]
\[ NDVI_{Surf} = 0.83 \cdot NDVI_G + 0.04 \]

The model for the prediction of LAI for the wheat crop can be deduced as follows:

\[ LAI_G = e^{\frac{NDVI_{Surf}-0.40}{0.27}} \]

The accuracy of these newly developed models for the two irrigated crops, corn and wheat, was determined by multiplying the two coefficients of determination (0.76 x 0.83 and 0.80 x 0.84) of the two separate models. These new models have shown considerably lower values of 0.63 and 0.67 for irrigated corn and wheat respectively. From these results it is evident that LAI\(_G\) estimation through NDVI\(_G\) and NDVI\(_{Toar}\) is not as accurate as it is estimated through NDVI\(_G\) and NDVI\(_{Surf}\). Therefore estimating LAI\(_G\) through NDVI\(_{Surf}\) is recommended as it has shown higher coefficients of determination of 0.74 and 0.77 for corn and wheat crops respectively.

5.1.7.1 Model validation

Different datasets for each crop, from the same cropping season but different farms during the crop cycle of 2010/11, were used for the validation of the predictive models. The results obtained are presented in Table 5.6.

Table 5.6: Model Validation Results for Corn and Wheat Crops.

<table>
<thead>
<tr>
<th>Crop</th>
<th>(r^2)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>0.80</td>
<td>0.75</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.68</td>
<td>0.62</td>
</tr>
</tbody>
</table>
5.1.8 Summary

LAI and NDVI values based on field and satellite measurements for different irrigated crops in the CIA vary with crop type due to the different canopy reflectance of the crops. Therefore the relationships developed between NDVI and LAI for corn and wheat are not uniform as they were crop type dependent. There were three different strategies involved in the estimation of ground-based LAI as discussed above: 1) estimation of LAI in terms of atmospherically corrected NDVI; 2) estimation of LAI in terms of atmospherically uncorrected NDVI; and 3) estimation of LAI using a combined approach of ground-based NDVI and atmospherically corrected NDVI. Of these three methods for both crops, the most accurate was the estimation of LAI in terms of atmospherically corrected NDVI. These results indicate that the models developed are reliable for the estimation of LAI for the two study crops in the CIA. However, the results obtained for the rice crop showed significantly different values. These discrepancies seem to have occurred as a result of problematic ground-based LAI. This may have been due to the different measurement capabilities of the handheld LAI-2000 Plant Canopy Analyser over different crop species and different structures of canopies. Further investigation is required for a thorough understanding of this problem. For the reasons outlined above, a predictive model for rice was not able to be developed in terms of ground-based measurements and therefore the MOD15A2 product was used to develop a predictive model for LAI to be used at different phases of the current study.

Importantly, the models developed for irrigated corn and wheat can be used to estimate LAI accurately, easily, rapidly and economically using only atmospherically-corrected satellite images with only a slightly lower accuracy than NDVI$_G$ without physical interaction with the crops.

5.2 Land Use and Land Cover Classification

Accurate crop classification maps are vital for the estimation of biomass over the cropping season and the assigning of harvest indices for
the estimation of crop yield in irrigated agriculture (Bastiaanssen & Ali, 2003). Due to a lack of fine detail in existing land cover databases for the study area, it was necessary to develop effective land use and land cover (LULC) classification maps of the CIA. The classification maps can be produced successfully with single date images acquired in the peak growing season. However, time series data is required in order to improve the classification results so that different crop types can be distinguished accurately. Vegetation indices also proved to be essential for identifying irrigated areas correctly (Ozdogan et al., 2010). In the current study, an LULC map was derived using single date Landsat 5 TM and RapidEye images. A Landsat 5 TM image for late September was selected for the winter classification map, while a RapidEye image from late January was selected for the summer classification map for the cropping seasons of 2010/11 in the CIA.

Even though a great number of winter and summer crop classes are found in the area, classification was carried out for only the three study crops and a few other significant crops in the area. All other minor crops were clustered under a one group as they were not dominant and not important for the present study. A hybrid classification technique was implemented which integrated an object-oriented classification technique and LAI thresholds. The LAI maps based on the predictive developed models were used to extract the correct crop types in the classification procedure. After the single date images were classified according to the corresponding LAI values of the selected crops, they were further refined using ground truthing data collected during the cropping seasons and the final classification maps were generated.

5.2.1 Winter crop classification

Crop classification for winter 2010 was carried out using single date Landsat 5 TM imagery from August 21, 2010. The main focus was to classify wheat as it was the principal winter crop in the current study. The mid-cropping season single date image was selected taking into account the
sowing and harvest dates for the wheat, which fell in mid April, 2010 and late November, 2010 respectively and with careful consideration of time series LAI data. Ground truthing data which was collected during several field campaigns and time series LAI maps based on the predictive models developed were used in order to develop an accurate LULC classification map. Several land cover types were found during the data collection period. However, only the main types of land cover, such as wheat, canola and pasture, were considered as land cover types for the classification. All other winter crops were classified under a common class labelled unclassified. The LULC analysis indicated that during winter 2010, a total area of 35,256ha was under crops, which included 14,809ha of wheat, 3,504ha of canola and 10,500ha of pasture. The area under all other crops was found to be 5,000ha. The classification map is shown in Figure 5.13.
5.2.1.1 Accuracy assessment

The usefulness of a LULC map depends on the accuracy of the developed LULC map (Cheema & Bastiaanssen, 2010). Therefore, an error matrix was generated for an accuracy assessment with a set of ground truthing data. A total of 226 ground truthing points were collected through the field campaigns for the generation of the error matrix. Feature space
plots were generated for different band combinations for the accurate identification of different crop types, and also for the matching of ground truthing samples with map classes. These scatter plots showed clear separability of available classes for each band combination. The classification map was trained with ground truthing data for accuracy assessment. Overall, producer and user accuracy were used as the accuracy measurements to check the reliability of the selected land cover classes in the classification map developed (Table 5.7).

Table 5.7: Error Matrix of Classification Map for Winter Crops.

<table>
<thead>
<tr>
<th></th>
<th>Canola</th>
<th>Wheat</th>
<th>Pasture</th>
<th>Unclassified</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canola</td>
<td>37</td>
<td>0</td>
<td>3</td>
<td>5</td>
<td>0.82</td>
</tr>
<tr>
<td>Wheat</td>
<td>6</td>
<td>38</td>
<td>3</td>
<td>2</td>
<td>0.78</td>
</tr>
<tr>
<td>Pasture</td>
<td>0</td>
<td>5</td>
<td>36</td>
<td>5</td>
<td>0.78</td>
</tr>
<tr>
<td>Unclassified</td>
<td>4</td>
<td>7</td>
<td>7</td>
<td>68</td>
<td>0.79</td>
</tr>
<tr>
<td>User accuracy</td>
<td>0.78</td>
<td>0.76</td>
<td>0.73</td>
<td>0.85</td>
<td></td>
</tr>
</tbody>
</table>

The results for the classification map were promising with an overall accuracy of 78% and average producer and user accuracies of 79% and 78% respectively. The producer and user accuracies for all the crops in this classification were relatively high. Wheat, a prominent crop in the CIA during the winter season and the winter crop selected for the current study, shows an acceptable level for both producer and user accuracy of 78% and 76% respectively.

5.2.2 Summer crop classification

LULC classification for the summer of 2010/11 was carried out with a single date 5m spatial resolution RapidEye image dated January 30, 2011. This image was selected with consideration for the same factors as the winter image selection, namely sowing and harvest dates. The image was taken within the peak period for the respective crop cycles and represented
the mid-season phenology of each crop. LAI time series, which were developed using Landsat 5 TM images, were utilised for clear identification of the mid-season of the crop cycles. A considerable number of land cover classes, including soybean, pasture, sorghum, sunflower, grapes and cotton in addition to rice and corn, were planted for the summer season in the CIA. However, only three crops - corn, rice and soybean - were considered for the classification process because of their dominance in the study area. All the other crops were clustered under a new class labelled unclassified. This classification was carried out in the same way as the winter classification. Ground truthing data was incorporated by investigating the LAI time series data to identify the correct land cover class as in the previous section. LULC analysis indicated that during the summer of 2010/11, a total area of 31,701 ha was under crops, which included 16,353 ha of rice, 3,836 ha of corn, 838 ha of soybean and, in the unclassified group, and 2,100 ha of other crops. The classification map developed for the summer of 2010/11 is shown in Figure 5.14.
Figure 5.14: Classification map for summer 2010/11

5.2.2.1 Accuracy assessment

For the accuracy assessment of the summer classification map, an error matrix was generated with 215 ground truthing data points. Since a large number of land cover classes were grouped under the ‘unclassified’ class, a larger number of ground truthing points were incorporated for this
newly formed class in order to improve accuracy. The error matrix for the summer crops is shown in Table 5.8. According to the confusion matrix, the overall accuracy of the classification was 82% while the average producer and user accuracies were 83% and 82% respectively.

Table 5.8: Classification error matrix for summer crops.

<table>
<thead>
<tr>
<th></th>
<th>Corn</th>
<th>Rice</th>
<th>Soybean</th>
<th>Unclassified</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>48</td>
<td>0</td>
<td>2</td>
<td>3</td>
<td>0.90</td>
</tr>
<tr>
<td>Rice</td>
<td>0</td>
<td>45</td>
<td>1</td>
<td>4</td>
<td>0.90</td>
</tr>
<tr>
<td>Soybean</td>
<td>2</td>
<td>1</td>
<td>32</td>
<td>7</td>
<td>0.76</td>
</tr>
<tr>
<td>Unclassified</td>
<td>3</td>
<td>3</td>
<td>12</td>
<td>52</td>
<td>0.74</td>
</tr>
<tr>
<td>User accuracy</td>
<td>0.90</td>
<td>0.92</td>
<td>0.68</td>
<td>0.79</td>
<td></td>
</tr>
</tbody>
</table>

Corn and rice show the highest producer accuracy of 90% and the highest user accuracy of 90% and 92% respectively. Soybean and the unclassified class show a lower producer accuracy of 76% and 74% and lower user accuracy of 68% and 79%, respectively. However, all the accuracy ratings fall within the acceptable level of accuracy.

5.2.3 Validity of land use and land cover classification

Classification maps can be derived from various forms of remotely-sensed data by employing different classification techniques. Accuracy assessment is generally accepted as a fundamental part of the classification process. An error matrix is the core of the accuracy assessment process and is often used in the classification procedure. The error matrix provides site-specific assessment of the relationship between the classified image and ground conditions (Foody, 2002).

The overall accuracies obtained in this research were 78% and 82% for winter and summer 2010/11, respectively. The average producer and user accuracy are 79% and 78% for winter and for summer are 83% and 82%. As there were enough ground truthing sample points for each crop
class for the generation of an error matrix, the need for the calculation of the Kappa coefficient did not arise.

The fact that the overall accuracy for the summer season was higher than for the winter season may have been caused by several factors. One factor is that the RapidEye image of 5m spatial resolution, used in the summer season, had a greater potential for the identification of crop areas and boundaries accurately and another factor is that the hybrid classification technique adopted was more effective with the high spatial resolution RapidEye images than the medium spatial resolution images of the Landsat 5 TM. Another advantage of the RapidEye image related to segmentation. With its high spatial resolution, the RapidEye image enabled improved segmentation results because, in the absence of mixed pixels, there was more accurate delineation of segments.

The accuracy for both the summer and winter crop classification were of a satisfactory level compared to the accuracy levels obtained in many other LULC classification studies. For example Cheema and Bastiaanssen (2010) obtained an overall accuracy of 77% for a land use classification carried out for water resource management studies. Bastiaanssen (1998) showed that average accuracy of 86% for classification could be achieved, however he has further shown that this accuracy could vary from 49% to 96% based on the spatial resolution of the satellite and the field size. Giri and Jenkins (2005) attained 77.3% accuracy from MODIS images with a 500m resolution in their land cover database preparation. Given the level of classification accuracy achieved in the studies mentioned above, the classification accuracy attained in the current study is reasonably acceptable.

The extents of some of the land cover classes were computed from the final classification map and statistics compared with data from CICL (2011). This is presented in Table 5.9. The areas computed from the classified map show considerable variation compared to the CICL data. Discrepancies between computed data and the information in the CICL database could be the reason for this variation. Farmers order water to irrigate crops at the beginning of the year. These water orders are saved in
the computer systems together with the corresponding planned cropping areas. However, later in the cropping season, farmers are free to change their plans and may grow a crop other than the planned crop or they may not grow a particular target crop for a whole cropping cycle. However the water orders which are already stored in the systems are not changed even though the actual water orders and crop areas have physically changed on the ground and are not as they were planned at the beginning of the year. As a result, erroneous water order data and crop areas can appear in the CICL system, thus creating inaccurate statistics. According to Ullah (2011), crop areas estimated through studies can be expected to have some discrepancies compared to the CICL published data. This could be the reason for the deviations in the computed crop areas in the current study from the published CICL data. It is reasonable to assume that the computed areas may be closer to reality than the CICL published data.

Table 5.9: Comparison of Estimated and Published Crop Areas of Different Crops.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Estimated crop area (ha)</th>
<th>Reported crop area (ha) (CICL, 2011)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>3,836</td>
<td>4,367</td>
</tr>
<tr>
<td>Rice</td>
<td>16,353</td>
<td>14,512</td>
</tr>
<tr>
<td>Wheat</td>
<td>14,809</td>
<td>11,334</td>
</tr>
<tr>
<td>Canola</td>
<td>3,504</td>
<td>3,381</td>
</tr>
<tr>
<td>Soybean</td>
<td>838</td>
<td>1,240</td>
</tr>
</tbody>
</table>

It can be concluded from the above results that the remote sensing based hybrid object-oriented classification technique provides accurate and rapid classification maps for classification of irrigated crops using single date imagery if a considerable range of time series data and sufficient number of ground truthing points are available.
6 ESTIMATION OF CROP YIELD

This chapter presents the results obtained in different phases of crop yield estimation process of the current study. The crop growth parameters which are needed for the estimation of crop yield were estimated and utilised for the estimation of yield of the three selected irrigated crops in the CIA. Further the obtained results of crop growth parameters and yields of corresponding crops are discussed and analysed for their validity. The results are analysed and compared with the local, and international literature and also with a number of different studies.

6.1 Yield Estimation

Regional estimation of crop production is crucial to water resource management, agricultural land management and food security. Remote sensing has great potential for the monitoring of crop production and the estimation of crop yield at regional and local levels. In this study high quality satellite data and field data together with crop parameters were used for the estimation and validation of crop yield for three irrigated crops in the CIA. The biomass production model of Monteith (1972) together with the light use efficiency model suggested by Field et al. (1995) and the surface energy balance (SEBAL) model of Bastiaanssen et al. (Bastiaanssen et al., 1998a), were used with some modifications in the estimation of yield in the area. The development of relevant crop parameters and the estimation of yield were executed in the environment of Geographic Information Systems (GIS).

Crop growth parameters such as photosynthetically active radiation (PAR), normalised difference vegetation index (NDVI), absorbed photosynthetically active radiation (APAR) and evaporative fraction (A) were developed as raster maps. These were integrated with the time duration in which biomass growth had occurred to estimate biomass production (B). For each study crop, a number of discrete time intervals were allocated for the estimation of above ground biomass growth within each time interval based on the crop lifecycle and the availability of cloud-
free satellite images. Each image was representative of an allocated time interval which was integrated with other crop growth parameters for the estimation of biomass development during each time interval. The final yield was estimated by incorporating the crop dependent harvest index with the total biomass accumulated throughout the cropping cycle.

6.1.1 Summer crop yield estimation

The yield estimation for two summer crops (corn and rice) was carried out by taking into consideration the corresponding summer crop growth parameters for each crop. All the crop growth parameters required for the estimation of biomass were executed for each crop in common raster maps except for light use efficiency. Light use efficiency varies with crop types as long as they are not water stressed. Rice is a typical C3 crop while corn belongs to the C4 category. Because the light use efficiency of these two study crops is different, the biomass estimates varied accordingly. The estimated representative time periods of these crops are shown in Table 6.1 and Table 6.2. The results of crop growth parameters of corn and rice for respective discrete intervals are discussed in the next sections.

<table>
<thead>
<tr>
<th>Image date</th>
<th>Representative days</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/11/02</td>
<td>27</td>
</tr>
<tr>
<td>2010/11/18</td>
<td>22</td>
</tr>
<tr>
<td>2010/12/04</td>
<td>21</td>
</tr>
<tr>
<td>2010/12/27</td>
<td>20</td>
</tr>
<tr>
<td>2011/01/05</td>
<td>23</td>
</tr>
<tr>
<td>2011/01/28</td>
<td>32</td>
</tr>
<tr>
<td>2011/03/01</td>
<td>35</td>
</tr>
</tbody>
</table>
Table 6.2: The Representative Periods for Rice in Relation to Landsat 5 TM Images.

<table>
<thead>
<tr>
<th>Image date</th>
<th>Representative days</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/11/18</td>
<td>13</td>
</tr>
<tr>
<td>2010/12/04</td>
<td>25</td>
</tr>
<tr>
<td>2010/12/27</td>
<td>20</td>
</tr>
<tr>
<td>2011/01/05</td>
<td>23</td>
</tr>
<tr>
<td>2011/01/28</td>
<td>28</td>
</tr>
<tr>
<td>2011/03/01</td>
<td>29</td>
</tr>
<tr>
<td>2011/03/26</td>
<td>22</td>
</tr>
</tbody>
</table>

6.1.1.1 Estimation of representative periods

Normally, corn was sown in mid-October 2010 and harvested in early April. In the current study, on the selected farm, Farm 34 in the CIA, the corn was sown on October 7, 2010 and harvested on April 4, 2011. There was a growth period of 180 days. The cropping cycle was split into seven discrete time intervals based on the availability of cloud-free Landsat 5 TM images with an average of 26 representative days for the time integration of biomass. The first Landsat 5 TM image utilised for the estimation of the various parameters fell on November 2 when there had been ample time for biomass development to be represented on the image. The last image used for the integration of biomass fell on March 1, 2011 which was approximately 4 weeks prior to the harvesting time.

Like corn, rice was sown in early November 2010 and harvested in mid April 2011 in the CIA. For the current study, the rice crop on Farm 208 in the CIA was sown on November 8, 2010 and harvested on April 16, 2011. It had a crop lifecycle of 160 days. The first image chosen for the representation of biomass development fell on November 18, 2010 and represented only 13 days of biomass development. Although there had been insufficient biomass growth during the initial 13 days, the first image had to be selected on November 18, 2010 because of the non-availability of cloud-
free satellite images. Consequently the NDVI representation on the image was extremely low as rice crops only start to emerge in early December. However it is accurate to have a low representative period of 13 days for the first image to represent its low biomass development. As with the first image, the timing of the last image acquired for the estimation of biomass was not optimal. It fell on March 26, 2011, which was approximately 3 weeks prior to the harvest. At 3 weeks to harvest, the crop had almost reached its full maturity and thus there was no rapid growth of biomass during this final period. Therefore it was reasonable to have comparatively few representative days for the last image to estimate the low biomass development.

6.1.1.2 Crop growth parameters for the estimation summer crop yield

6.1.1.2.1 PAR (Photosynthetically active radiation)

Daily incoming solar radiation ($K_{24}$) was incorporated for respective representative periods to obtain PAR. For each representative period PAR was estimated and used in the estimation of total biomass in the area. Figure 6.1 shows the estimated PAR for 20 representative days for the image taken on December 27, 2010. The average PAR obtained for this period was 99Wm$^{-2}$. However there was no significant variation of PAR in the image as $K_{24}$ was almost a constant value throughout the 20 day period during the summer.
Figure 6.1: Estimation of spatial variation in PAR over 20 day representative period from the Landsat 5 TM image of December 27, 2010.
6.1.1.2.2 NDVI (Normalised Difference Vegetation Index)

Raster maps of NDVI, which were required for the estimation of total biomass, were derived for each representative period. Figure 6.2 represents the NDVI raster map derived from the Landsat 5 TM image on December 27, 2010 for a 20 day representative period. For this period, the NDVI varied widely from 0.05 to 0.78, indicating the presence of very low to high vegetation density in the area. As winter crops were harvested a few weeks before this image acquisition date, the very low NDVI values can be explained by the presence of bare land on harvested farms. For instance wheat is normally harvested in late November and wheat farms in the area were completely bare by December 27. On the other hand, high NDVI values such as 0.78 were also present in the image. This was due to the presence of summer crops which were reaching the peak, or had already reached the peak, of the crop cycle. The two summer crops, corn and rice, which are normally sown in October and November, had completed one half and one third of their crop cycles respectively by the image acquisition date and biomass development thus varied accordingly. It is clear that the wide range of NDVI values can be explained by either the absence of biomass or the variation in biomass development in the area.
Figure 6.2: Estimation of spatial variation in NDVI over 20 day representative period from the Landsat 5 TM image of December 27, 2010

6.1.1.2.3 APAR (Absorbed Photosynthetically Active Radiation)

APAR is estimated by means of PAR and NDVI for each representative period. Figure 6.3 shows the raster image of APAR resulting
from PAR and NDVI from the December 27, 2010 Landsat 5 TM image. APAR varied widely ranging from 0.36 to 89.96 Wm$^{-2}$ for the 20 day period in the CIA. As PAR was almost a constant value for this 20 day period, it did not contribute to the variation in APAR therefore the only possible reason for the variation in APAR was the spatial variation in NDVI across the area. The low values of APAR can be explained as a consequence of low NDVI due to the presence of harvested bare lands and saline areas where less photosynthetic activity occurred. The high values of APAR could be from the high NDVI values shown in highly vegetated areas where the crops were more photosynthetically active.
Figure 6.3: Estimation of spatial variation in APAR over 20 day representative period from the Landsat 5 TM image of December 27, 2010

6.1.1.2.4 Evaporative fraction ($\Lambda$)

The evaporative fraction ($\Lambda$) was estimated using the SEBAL algorithm for each representative period. Figure 6.4 shows the spatial
variation of $\Lambda$ as a raster image estimated from the Landsat 5 TM image of December 27, 2010. For this date, $\Lambda$ varies considerably, between 0.20 and 0.82, throughout the area, revealing the soil moisture condition of root zones and indicating the growth of biomass in the irrigated area. The type of land cover has a significant effect on water consumption capacity from the catchment as well as the water holding capacity of root zones (Sen, 2004). During this summer period, various irrigated crops were present in the area and, therefore, $\Lambda$ could have varied as a result of differing evapotranspiration rates due to the different soil moisture conditions of the root zones. Normally, evapotranspiration is higher in cropped areas than in non-cropped areas. As a result of the presence of healthy vegetation as well as bare land in the area during this period, evapotranspiration could be high in some places and low in others. Therefore high and low spatial variation in $\Lambda$ during this period could be expected. Moreover during the hot summer months high evaporation can be expected due to high temperatures and the high values of $\Lambda$ can be explained as a result of high evapotranspiration. In summary, variations in $\Lambda$ can be explained by the variety of land cover classes, the different phenological stages of diverse crops, the cropping or non-cropping of certain crops and, importantly, the hot and cold climatic conditions of the CIA.
6.1.1.2.5 Light use efficiency ($\varepsilon$)

Light use efficiency was estimated from the Landsat 5 TM images by combining the raster maps of evaporative fractions which had been developed with the maximum light use efficiency of C4 crops. In the CIA,
estimated light use efficiency varies between 0.45 and 2.2 g MJ\(^{-1}\) in accordance with variations in soil cover and soil moisture (Figure 6.5). However, the obtained values in this study are lower than the maximum light use efficiency of 4.2 g MJ\(^{-1}\) taken for corn once all controlling factors are optimum. Maximum light use efficiency was not able to be calibrated at this stage due to time constraints and cost factors. Therefore the maximum light use efficiency was taken from the literature in order to formulate actual light use efficiency.
Figure 6.5: Estimation of spatial variation in light use efficiency over 20 day representative period for corn from the Landsat 5 TM image of December 27, 2010 in the CIA

Light use efficiency for rice was estimated as for the corn crop (Figure 6.6). The light use efficiency for rice also varied between 0.40 and 2.03 g MJ$^{-1}$ due to variations in the water content of the soil and the soil cover of
the area. However, the results obtained were lower than the maximum light use efficiency of 2.9g MJ⁻¹ for rice crops under optimal control conditions. Maximum light use efficiency was not able to be calibrated at this stage in the study due to time constraints and cost factors. Therefore the maximum light use efficiency was taken from the literature.
Figure 6.6: Estimation of spatial variation in light use efficiency over 20 day representative period for rice from the Landsat 5 TM image of December 27, 2010 in the CIA.
6.1.1.2.6 Biomass development

Biomass production was estimated based on solar radiation (APAR) and leaf development (NDVI) in conjunction with the light use efficiency for Landsat 5 TM images for each representative period. The total biomass development for the crop life cycle was estimated for the whole cropping season by integrating the individual biomass growth of each representative period. Figure 6.7 and Figure 6.8 represent biomass growth approximated from the Landsat 5 image on December 27, 2010 for corn and rice. Biomass growth per day varied between 0.15 and 8.21gm\(^2\) for corn and between 0.13 and 8.02gm\(^2\) for rice. This variation can be explained as the presence of low, medium and high biomass of different crops in the CIA.

The mid-season values obtained for both irrigated crops are reasonable for these irrigated crops when compared to the biomass development rates produced in some other studies. Bastiaanssen and Ali (2003) reported maximum biomass production of 7.53g/m\(^2\)/day for agricultural crops which were calculated for both C3 and C4 crops. They further pointed out that the values obtained for irrigated crops in their studies were generally low for the mid-season of the crop cycle in Pakistan. The biomass production rate of rice was also estimated by Samarasinghe (2003) in Sri Lanka. This study found that the average biomass production was 6.6g/m\(^2\)/day. Therefore it is evident that the biomass growth rates are in the range of 0.13 to 8.21 gm\(^2\) obtained in the current study and reasonably close to similar studies.
Figure 6.7: Spatial variation in biomass development in corn represented on the Landsat 5 TM image of December 27, 2010 in the CIA for a 20 day time period
Figure 6.8: Spatial variation in biomass development in rice represented on the Landsat 5 TM image of December 27, 2010 in the CIA for a 20 day time period

6.1.2 Estimation of summer crop yield

The final conversion of the total accumulated above ground biomass growth into crop yield varies with the effective harvest index and the
moisture content of the grain during the harvest. In the current study, the average harvest index for dry corn was 0.52 with the moisture content of the product at 12% during the harvest and the effective harvest index was found to be 0.59. For the rice crop the harvest index was 0.50 with a moisture content of 8% and the effective harvest index calculated was 0.54. These calibration parameters and their values for the two summer study crops are summarised in Table 6.3. The computed effective harvest indices were compared with international literature for rice and corn, and they fall in the upper range and slightly higher than the published values. However, this is acceptable for irrigated crops as the harvest index is generally higher for irrigated crops than it is for rain-fed crops (Bastiaanssen & Ali, 2003).

### Table 6.3: The Crop Parameters Used in Obtaining Crop Yield.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Harvest Index</th>
<th>Effective Harvest Index</th>
<th>Moisture Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>0.52</td>
<td>0.59</td>
<td>0.12</td>
</tr>
<tr>
<td>Rice</td>
<td>0.50</td>
<td>0.54</td>
<td>0.80</td>
</tr>
</tbody>
</table>

The crop yield for the two irrigated crops, rice and corn, was estimated in the CIA by integrating the effective harvest index and the moisture content. The yield of these two summer crops varied greatly across the area from one to another (Figure 6.9). The corn yield varied from 530 to 4,450 kg ha\(^{-1}\) with an average value of 3,920 kg ha\(^{-1}\), while rice yield varied from 5,100 to 12,450 kg ha\(^{-1}\) with an average of 7,935 kg ha\(^{-1}\) (Figure 6.10). There could be a number of reasons for the significant difference in yield volumes for corn and rice including the effects of farm conditions and water management practices, such as soil salinity, water logging, depth of the water table, differing number of irrigations applied per hectare at different farms and the salinity levels of irrigation water.
Figure 6.9: The spatial distribution of corn yield in the CIA for 2010/11
6.1.3 Winter crop yield estimation

The estimation of wheat yield was carried out in the same way as for summer crop yield estimation. Although the crop growth parameters and calibration parameters were different for the winter crops, the methodology adopted for estimation of crop yield in the current study was the same. Of the winter crops in the CIA, wheat was the only crop selected for the current research. The life cycle of the wheat crop was split into a number of discrete time periods to comply with available cloud-free Landsat 5 TM
images with each image representing a discrete time period. The raster data of PAR, APAR, Λ and NDVI were integrated for the estimation of biomass growth during each representative period as described previously. Wheat is a typical C3 crop, thus maximum light use efficiency was able to be drawn from published data relating to C3 crops. This was used to generate the raster maps of actual light use efficiency which varied throughout the cropping season. The harvest index and moisture content were computed using field-collected wheat samples and incorporated with total accumulated biomass to estimate the wheat crop yield.

6.1.3.1 Estimation of representative periods

In 2010 in the CIA, wheat started its crop cycle in late April or early May and was harvested in November. The wheat crop on Farm 34 had a 227 day lifecycle starting on May 18, 2010. In order to estimate crop biomass growth during the different stages of the crop lifecycle, appropriate representative time intervals were determined for each cloud-free Landsat 5 TM images falling during the cycle which are presented in Table 6.4. The number of representative days varied from 13 to 72 depending on the availability of cloud-free images. The average was 32 days. The first cloud-free satellite image appeared on May 1. However the time period between the first and the second images was considerable as a usable cloud-free second image was not available until August 21. Therefore a long representative time interval had to be taken into account in the estimation of biomass growth. The final image used to compute biomass fell on November 18 and approximately represented the last three weeks of the cycle. Despite its short duration, this time interval produced a realistic measure of low biomass growth as low NDVI normally exists in the final stage of crop growth.
Table 6.4: The Representative Periods in Crop Cycle of Wheat Compiled with Landsat Images.

<table>
<thead>
<tr>
<th>Image date</th>
<th>Representative days</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/05/01</td>
<td>54</td>
</tr>
<tr>
<td>2010/08/21</td>
<td>72</td>
</tr>
<tr>
<td>2010/09/06</td>
<td>20</td>
</tr>
<tr>
<td>2010/09/22</td>
<td>22</td>
</tr>
<tr>
<td>2010/10/08</td>
<td>23</td>
</tr>
<tr>
<td>2010/11/02</td>
<td>23</td>
</tr>
<tr>
<td>2010/11/18</td>
<td>13</td>
</tr>
</tbody>
</table>

6.1.3.2 Estimation of crop growth parameters for the estimation of winter crop yield

6.1.3.2.1 PAR (Photosynthetically active radiation)

PAR was estimated in terms of daily solar radiation by incorporating discrete corresponding time intervals. Figure 6.11 shows the raster image of PAR obtained for a period of 20 days represented by a Landsat image of September 6, 2010 where average PAR was 96Wm$^{-2}$. The PAR values obtained in the winter season were generally a little lower than those in summer. A possible reason for the low winter values could be the observed high daily solar radiation due to overcast or cloudy sky conditions.
Figure 6.11: Estimation of spatial variation in PAR over 20 day representative period from the Landsat 5 TM image on September 6, 2010

6.1.3.2.2 NDVI (Normalised Difference Vegetation Index)

Maps of NDVI for the estimation of the biomass growth of wheat at different stages were established in the same way as for the summer crops. Figure 6.12 represents the NDVI raster map for a 20 day time period
derived from the Landsat 5 TM image of September 6, 2010. NDVI varies widely from 0.09 to 0.73, indicating the presence of very low to high vegetation density in the area. The low NDVI values are explained by the bare and non-vegetated land resulting from the harvesting of the previous season’s summer crops. For instance, corn and rice are normally sown in October and November and harvested in March and April respectively. Before these sowing dates, the corn and rice fields were in the preparation stage in a completely bare condition. The high NDVI values, on the other hand, can be explained by the fresh and vigorous green biomass of the winter crops in the middle of their cropping cycle. The corresponding image fell at the peak of the winter crop cycle and therefore the high NDVI value of 0.73 is explained by the healthy and dense winter growth. Thus it can be seen that a wide range of NDVI values can occur at a given image date because of the fact that crops are at different stages in their respective cycles.
Figure 6.12: Estimation of spatial variation of NDVI over 20 day representative period from the Landsat 5 TM image on September 6, 2010

6.1.3.2.3 APAR (Absorbed Photosynthetically Active Radiation)

APAR was estimated in the same way as in the previous season as a function of NDVI and PAR. The raster map of APAR, estimated for a 20 day period in the winter season using the Landsat 5 TM image of September
6, 2010, is shown in Figure 6.13. APAR varied from 0.26 to 87.52Wm$^{-2}$ for this time period. These variations can be explained in terms of NDVI, which is an indicator of the vegetative condition on the ground at the image date as PAR was almost a constant value throughout the period. The low APAR values can be explained as the result of low NDVI due to the presence of bare harvested land and saline areas where less photosynthetic activity occurred. The high APAR values stem from high NDVI values occurring in heavily vegetated areas where crops were more photosynthetically active.
6.1.3.2.4 Evaporative fraction \( (\Lambda) \)

The evaporative fraction \( (\Lambda) \) for the estimation of the winter crop yield was also derived as in the summer season using the SEBAL algorithm for each representative period. Figure 6.14 shows the spatial variation of \( \Lambda \)
as a raster image estimated from the Landsat 5 TM image on September 6, 2010. For this date, $\lambda$ varied considerably between 0.11 and 0.61 over the area, indicating variations in soil moisture in the root zones and biomass growth in the CIA during the winter season. Both the lower and upper limits of $\lambda$ in winter are lower than those in summer due to the low evapotranspiration during the cold and rainy winter season. Further, there was sufficient water storage in the root zone following the wet winter season. Therefore, fairly high values of $\lambda$ could be expected in early September. Another possible reason for variations in $\lambda$ was the fact that different crops were at different stages in their cropping cycle. In most cases, evapotranspiration is higher in cropped areas than in non-cropped areas and in this case there were both cropped and non-cropped lands. In summary, the wide range of values for $\lambda$ can be explained by the variety in land cover classes, the different phenological stages of the crops, cropping and non-cropping circumstances and, importantly, the cool climatic conditions of the CIA.
Figure 6.14: Estimation of spatial variation of $\Lambda$ over 20 day representative period from the Landsat 5 TM image on September 6, 2010

6.1.3.2.5 Light Use efficiency ($\varepsilon$)

Actual light use efficiency, based on maximum light use efficiency, varied from 0.22 to 1.95 MJ$^{-1}$ as shown in Figure 6.15. However, this range is lower than the maximum light use efficiency of 2.8 MJ$^{-1}$ which
was used in the present study. The light use efficiency results obtained for the wheat crop in the winter cropping patterns give an indication of the water content of the soil during the winter season in the CIA. The wide variation can be explained by the different nutrient values on different farms in the irrigation area. In cooler weather, light use efficiency increases due to low biomass development and low temperature which both resulted in decreased maintenance respiration (Kiniry et al., 1989). However the light use efficiency obtained for the current study in the winter season was only a little lower overall than the summer values, revealing that the lower temperature has no significant effect on light use efficiency.
Figure 6.15: Spatial variation in light use efficiency of wheat over 20 day representative period estimated from the Landsat 5 TM image on September 6, 2010

6.1.3.2.6 Biomass production

Winter biomass production for different time intervals based on solar radiation (APAR) and leaf development (NDVI) in conjunction with light use efficiency was represented on Landsat 5 TM images as in the previous section. The total biomass development was estimated by integrating the
individual biomass growth at each time interval over the cropping season. Figure 6.16 represents biomass growth approximated for a 20 day time period on the Landsat 5 TM image of September 6, 2010. The biomass production of the wheat crop varied between 0.03 and 7.79g/m²/day. This variation can be explained by the presence of low, medium and high growth of biomass of various crops at diverse phenological stages in the CIA.

Compared with published international studies, the statistics for biomass growth were within an acceptable range. The results obtained in the current study are slightly higher than those achieved by Bastiaanssen and Ali (2003) which they believed were lower than the standard rates for the mid-summer cropping season for C3 and C4 crops.
6.1.3.3 Estimation of winter crop yield

The estimation of the winter wheat crop yield was carried out by integrating the total accumulated biomass, the harvest index and the moisture content, as outlined previously for summer crop yield estimation. All essential calibration parameters such as the harvest index, effective harvest index and moisture content were extracted from field samples and
utilised for the estimation of crop yield. These are summarised in Table 6.5. The average harvest index for oven-dried wheat was 0.48 with a moisture content of 11%. The effective harvest index was found to be 0.54. Compared with published literature, the harvest index falls in the upper range; however this is acceptable for irrigated wheat as the harvest index is generally higher for irrigated crops than it is for rain-fed crops (Bastiaanssen & Ali, 2003).

### Table 6.5: Calibration Parameters used for the Estimation of Crop Yield of Wheat.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Harvest Index (kg kg⁻¹)</th>
<th>Effective Harvest Index (kg kg⁻¹)</th>
<th>Moisture Content (kg kg⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td>0.48</td>
<td>0.54</td>
<td>0.11</td>
</tr>
</tbody>
</table>

The spatial variations in wheat yield during the winter season of 2010 in the CIA are shown in Figure 6.17. Wheat crop yield varied widely spatially from 1,020 to 5,840 kg ha⁻¹ across the irrigated area with an average value of 4,200 kg ha⁻¹. These variations in yield volumes reflected inconsistency in agro-economic practices in the area. The farm and water management issues impacting on yield may include soil salinity, water logging, depth of the water table, the quantity of irrigation water applied and the salinity level of irrigation water.
6.1.4 Summary of yield estimation

A combination of models for the estimation of biomass growth and crop yield were employed using Landsat 5 TM images to estimate the final crop yield of the study crops in the CIA. Even though the spatial resolution of the Landsat images was not as high as the RapidEye images, they were suitable for identifying farm boundaries and assigning the harvest index along with other relevant calibration parameters in order to estimate total yield. However, Landsat 5 TM images were not available at some
important phenological stages because of cloud cover and therefore, available cloud-free satellite images had to be used with longer representative periods than the designated 16 days in order to estimate the total biomass and, subsequently, the final crop yield. For example, only a small amount of growth had occurred when the first usable satellite image was taken on of May 1, 2010. When the next cloud-free image became available on August 21, it represented a 54-day time interval. However, the biomass growth estimated for 54 days based on the biomass represented in the image on May 1, 2010 was low compared to the real biomass growth in the area within that period.

The calibration parameters computed through field-collected data also showed slight discrepancies. The harvest index and the effective harvest index values were slightly higher for corn and rice but a little closer for wheat compared with the values in the published literature. The estimated moisture content for corn and wheat fell within the expected range but was a little low for the rice crop compared with published values.

Crop yield was estimated for the three irrigated crops by means of remote sensing models and statistics were subsequently compared with published data (Table 6.6). The estimated crop yield per hectare compared favourably to published data for the three irrigated crops although the total estimated yields for 2010/11 for the three crops deviated below the published figures.

Table 6.6: Estimated and Reported Crop Yields of Corn, Rice and Wheat in the CIA in 2010/11.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Estimated total crop yield (T/ha)</th>
<th>Reported total crop yield (T/ha)</th>
<th>Reported and estimated yield difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>10.20</td>
<td>11.00 (Scot, 2011)</td>
<td>7 %</td>
</tr>
<tr>
<td>Rice</td>
<td>9.80</td>
<td>10.79 (RMB, 2012)</td>
<td>9 %</td>
</tr>
<tr>
<td>Wheat</td>
<td>4.29</td>
<td>5.00 (Scot, 2011)</td>
<td>14 %</td>
</tr>
</tbody>
</table>
This way of forecasting agricultural productivity over large areas has the benefit of requiring less human interaction resulting in many advantages such as improved economic profitability and speed. In addition, it is a useful tool for planning strategies prior to the final harvesting stage of the cropping season.
7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

Demand for food is increasing and will continue to increase with the rapid growth of world population (Harkort, 2009). By 2030, cereal demand for human and animal consumption is expected to be 50% higher than in 2000 (Lobell et al., 2009). This increased quantity of food must be produced with little availability of water which offers a complex challenge for the agriculture industry (Serageldin, 1999b). The challenge of producing more food with less water in the agriculture industry can only be overcome by improving the water productivity (Harkort, 2009). In order to improve the productivity of water, it is necessary to assess the correlation between crop yield and hydrological processes. As crop yield is the ultimate key factor describing the agricultural reaction to water resource management, accurate crop yield estimation is of paramount importance in irrigated agriculture (Bastiaanssen & Ali, 2003; Molden & Sakthivadivel, 1999).

Being able to accurately estimate crop yield has the potential to impact significantly on the agriculture industry and on society more broadly. Meeting the increasing demand for food and water, resolving issues related to the food industry with regards to food pricing, managing food security and optimising agricultural management practices are inevitably bound to crop yield estimation in all major agricultural areas of the world. The early estimation of crop yield is also of paramount importance to the international food trade and to the planning and management of food transportation between countries (Bastiaanssen & Ali, 2003). Given the importance of crop yield estimation, it is crucial that Australian producers have access to technologies that can facilitate crop yield estimation. One such technology is remote sensing.

In many countries in the world, crop yield estimation studies have been carried out for various irrigated crops using remote sensing data in order to assess yield gaps, to estimate crop water productivity and for agricultural management practices (Ahmad et al., 2004; Bastiaanssen & Ali,
However, there have been very few studies carried out in Australia to estimate crop yield based on remote sensing data. In the CIA there have not been any yield estimation studies based on remote sensing data.

The current study was carried out in the CIA to estimate the crop yield of three irrigated crops prior to harvest. The estimation of yield prior to harvest not only benefits farmers in the CIA, but also enables better management of water allocation in the CIA. The study employed a new crop yield estimation model developed by Bastiaanssen and Ali (2003) based on three existing models: the absorbed photosynthetically active radiation model; the CASA approach for light use efficiency; and the surface energy balance algorithm for land, with some modifications. This model was calibrated for Australian conditions in the CIA for corn, rice and wheat. The model was able to predict crop yield accurately three to four weeks before harvest and produced comparable results to published studies. This unique model was tested against the effective harvest index which was estimated through site specific data, collected from the study area.

7.1.1 The predictive models for estimation of LAI

The current study presents novel algorithms for the estimation of field-based LAI measurements using spectral vegetation indices derived through Landsat 5 TM data for corn and wheat crops in the Coleambally region. Unfortunately, predictive models were not able to be developed for the rice crop as the ground-based LAI measurements could not be correlated properly with the vegetation indices. The reliability of the predictive models developed were analysed by means of regression analysis and showed a high degree of accuracy. The relationships between the vegetation indices and LAI for corn and wheat were unique because they were crop-type dependent. In addition, they demonstrated considerable scatter due to the chlorophyll content and the influence of different canopy characteristics. The degree of accuracy of the models was considerably improved when atmospherically corrected reflectance data were incorporated. The correlation coefficient and the coefficient of determination for wheat were lower than that of corn, but both models
showed acceptable accuracy. Importantly, these models are economical to use in the CIA and highly accurate in obtaining LAI field-based measurements with low cost images and without need for physical interaction with farm plots. Correlations for wheat were slightly lower than for corn but sufficiently strong to enable the use of the predictive models to estimate ground-based LAI.

The models developed in the current study, using a combination of ground-based and satellite-based data, were able to achieve increased accuracy, speed and reliability. Moreover, the validated results produced by the models proved to have a high level of accuracy, confirming that they could be used in the CIA region for the estimation of ground-based LAI.

### 7.1.2 Hybrid, object-oriented image classification

Accurate classification maps were needed for the crop yield estimation process. In the current study, single date RapidEye images with high spatial resolution were used in winter while Landsat 5 TM medium spatial resolution images were used for summer. A highly accurate hybrid technique was used to prepare the classification maps. The reason for this was that the object-oriented technique is more accurate than the pixel-based image classification technique (Oruc et al., 2004; Yan et al., 2006). In addition, the hybrid technique provides significantly more accurate results than traditional supervised and unsupervised techniques (Rozenstein & Karniel, 2011; Ullah, 2011). Further, the object-oriented classification technique is suitable to apply on medium to high spatial resolution data (Whiteside et al., 2011).

The use of single date images was expected to increase the overall classification accuracy as demonstrated by Van Niel and McVicar (2004b) who attained more than 95% accuracy for the classification of rice and corn crops in the Coleambally region using single date Landsat TM and Landsat ETM+ images.

The single-date RapidEye image used for the classification of the summer crops fell on January 30 and showed a dynamic cropping system
with bare land due to the harvest of some winter crops combined with the lush green of mid-season summer crops. It was easy to train the image using training data and thus to obtain accurate land cover classes. The overall accuracy of the winter and summer classifications in the current study were significantly high with 78% and 82% respectively. The accuracy of the summer classification was higher than the winter classification due to applying the same hybrid object-oriented technique but using high spatial resolution RapidEye images. The accuracy of the summer map was higher due to this high spatial resolution. However, there was no significant difference between the overall accuracy obtained for the two seasons. Further, the difference in the level of accuracy obtained for the summer classification was not significant compared with the very high spatial resolution images used in the classification process. Therefore, it can be concluded that medium-scale Landsat 5 TM images can also be used successfully with a hybrid object-oriented classification technique for the development of accurate classification maps.

In the object-oriented technique, the accuracy of segmentation contributes greatly to the accuracy of classification. In the current study, segmentation and merging underwent several iterations with different thresholds to delineate the homogeneous objects and this greatly improved the segmentation results. Therefore, this technique can be applied to create homogeneous objects in order to reduce spectral heterogeneity and thus to increase the accuracy of the classification.

The significantly high accuracy of the results for land use and land cover in this study suggests that the object-oriented classification technique has potential to extract land cover classes over irrigated agriculture in the Coleambally region of Australia. Further, the technique was successfully applied to medium spatial resolution Landsat 5 TM images which are freely available. Importantly, this technique has the capacity to use auxiliary data such as derivative data, other sensor data and existing GIS layers as well as context information which can be used as supplementary information to assist with the classification procedure. In the object-based classification technique, the utilisation of context information as well as the utilisation of
ancillary data plays a key role in the classification process. As explained in chapter 2, context information and ancillary data help to differentiate neighbouring pixels even if they have equal grey values. However, in the current study, context information was not taken into consideration. Rather ancillary data such as the LAI values of different crops at their peak growth stages were derived and incorporated with the Landsat 5 TM and RapidEye images as a different layer for the correct demarcation of land cover classes.

7.1.3 Crop yield estimation

The combination of production efficiency models based on remote sensing used in this study are potentially useful for the monitoring of net primary production and for yield forecasting at regional scales, but they can also be applied to national scale studies. In the current study, free-sourced Landsat 5 TM images were employed in the combined model for the estimation of net primary production and crop yield; however, any satellite sensors which have thermal infrared bands such as NOAA-AVHRR, ASTER and MODIS can be used. The model can be used to assess biomass production and consequently is useful for researchers in agricultural water management and food security.

This study estimated the average yields of three irrigated crops in the CIA for 2010/11 using remote sensing data. The yields for corn, rice and wheat were estimated at 10.20T/ha, 9.8T/ha and 4.3T/ha respectively. All these values were in agreement with the published data from the Department of Primary Industries (DPI), NSW (Scot, 2011; RMB, 2012). Corn and rice were in 92% and 91% agreement with the DPI data while the wheat yield showed 86% agreement with the published data. This was also close to published values even though the biomass production of the crops was relatively low. The low value of the biomass production may have been compromised by the high value of the effective harvest index, and the final yield of the wheat crop was similar to the values found in the literature. Spatial variations in the yield revealed that crop production varied across the region because of factors such as soil salinity, the availability of irrigation water in the area, different management practices and the depth of the
groundwater table. It is clear that crop yield has a relationship with the above mentioned factors and that crop yield estimation may help to provide better understanding and possible management of these circumstances.

Accurate and reliable agronomic information is vital for water resource management so that firm decisions to improve use of water resources and irrigation scheduling can be made. Crop yield is a strong reflection of and guide to water management practices. Therefore, accurate measurement of yield production in the CIA can significantly contribute to water policy. Remote sensing is a powerful and economically viable tool for monitoring of crop yields in the CIA.

### 7.2 Recommendations and the Way Forward

The new models developed for the estimation of LAI produced highly accurate regression analysis results, while validation results also showed a high degree of accuracy. These models were developed for two crops, corn and wheat, grown in the CIA under Australian conditions. It is recommended that these models be further validated for different datasets from different years both nationally and internationally.

Even though the image classification technique employed in this study is more suitable for high spatial resolution images, accuracy was not greatly improved by the use of RapidEye high spatial resolution images compared to Landsat 5 TM medium spatial resolution images in the current study. The overall accuracy was only slightly lower for the winter classification than for the summer classification, plausibly due to the spatial resolution of the images. However it does not seem worthwhile to use expensive high resolution RapidEye images to achieve such a small improvement in accuracy. ASTER images can also be used as they have a better spatial resolution at 15m than Landsat 5 TM, are not as expensive as RapidEye images, and in addition, they have thermal and infra-red bands. Another possibility for achieving economical classification maps is to integrate low cost, high spatial resolution aerial photographs with the Landsat 5 TM images using an image fusion technique to improve the accuracy and to obtain economical classification maps. However, further research is
required to determine whether ASTER images or aerial photographs integrated with the image fusion technique will improve the accuracy significantly beyond a level achievable with the free-sourced Landsat 5 TM images.

The estimated crop yield was validated using actual data and published data obtained from the Department of Primary Industry, NSW for the year 2010/11. However, further research is required to analyse crop yield estimation over a period of years and thus to confirm the reliability of the model.

For the estimation of biomass development over the cropping cycle, discrete time intervals of set lengths should be employed to represent the correct time integration of biomass during the crop cycle. Due to the non-availability of cloud-free satellite images, it was difficult in the current study to maintain consistent time intervals. However, by using other types of available sensor data or using cloud-filtering algorithms to filter the Landsat 5 TM images of existing cloudiness, this problem can be solved.

In this study, yield variations over the area were present for individual crops but the reasons for these variations have not been investigated at this stage. At a later stage, this model could be applied to estimate the crop yield of individual crops at each farm or node level in order to determine the correlation with different parameters such as water usage, soil salinity and groundwater depth for similar crop genotypes under equivalent management practices. Despite some limitations, this study can make a valuable contribution to explaining the spatial variation of yield over the area and to identifying the key factors affecting crop yield.
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