Cooperative Research Centre for
Sustainable Rice Production

REMOTE SENSING OF RICE-BASED IRRIGATED AGRICULTURE: A REVIEW

Tom G. Van Niel and Tim R. McVicar

Program 1: Sustainability of Natural Resources
Project 1105: Remote Sensing of Irrigated Crop Types and its Application to Regional Water Balance Estimation

www.ricecrc.org

REMOTE SENSING OF RICE-BASED IRRIGATED AGRICULTURE: A REVIEW

Tom G. Van Niel and Tim R. McVicar

Program 1: Sustainability of Natural Resources

Project 1105: Remote Sensing of Irrigated Crop Types and its Application to Regional Water Balance Estimation

Rice CRC Technical Report P1105-01/01

ISBN 1 876903 02 3

CSIRO LAND and WATER

A PDF version is available at http://www.ricecrc.org

REMOTE SENSING OF RICE-BASED IRRIGATED AGRICULTURE: A REVIEW

Tom G. Van Niel[1,2] and Tim R. McVicar[1]

[1]CSIRO Land and Water,
PO Box 1666
Canberra, ACT 2601
email: thomas.van.niel@cbr.clw.csiro.au
tim.mcvicar@cbr.clw.csiro.au
http://www.cbr.clw.csiro.au/

[2]Cooperative Research Centre for Sustainable Rice Production
C/- Yanco Agricultural Institute
PMB Yanco, NSW 2703
email: thomas.van.niel@cbr.clw.csiro.au
http://www.ricecrc.org

TABLE OF CONTENTS

1 Introduction ... 1

2 Background of Remote Sensing ... 2

2.1 Reflective Remote Sensing ... 4
2.2 Microwave Remote Sensing ... 11
2.3 Thermal Remote Sensing ... 12
2.4 Integrating Remote Sensing with other Data Types in a Geographic Information System (GIS) ... 13

3 Remote Sensing in Rice-Based Agriculture ... 15

3.1 Crop Type Identification ... 18
3.2 Crop Area Measurement ... 21
3.3 Crop Yield ... 23
3.4 Crop Damage ... 25
3.5 Water Use and m_a Mapping ... 27
3.6 Water Use Efficiency ... 29

4 Limitations of Remote Sensing in Rice-Based Agriculture ... 33

4.1 Data Availability ... 33
4.2 Length of Recording Period ... 33
4.3 Limited Predictive Capability ... 33
4.4 Requirement of Expertise and Computer Facilities ... 34
4.5 Cost ... 34

5 Conclusions ... 36

6 Acknowledgements ... 37

7 References ... 37

1 INTRODUCTION

The 'Green Revolution' in rice farming of the late 1960's denotes the beginning of the extensive breeding programs that have led to the many improved rice varieties that are now planted on more than 60% of the world's riceland (Khush, 1987). This revolution led to increases in yield potential of 2 to 3 times that of traditional varieties (Khush, 1987). Similar trends have also been seen in the Irrigation Areas and Districts of southern New South Wales (NSW) as the local breeding program has produced many improved varieties of rice adapted to local growing conditions since the 1960's (Brennan et al., 1994). Increases in area of rice planted, rice quality, and paddy yield resulted (Brennan et al., 1994).

Increased rice area, however, has led to the development of high water tables and risk of large tracts of land becoming salt-affected in southern NSW (Humphreys et al., 1994b). These concerns have led to various environmental regulations on rice in the region, culminating in 1994 when restrictions on rice area, soil suitability, and water consumption were fully enacted (Humphreys et al., 1994b). Strict environmental restrictions in combination with large areas of land make the management of this region a difficult task. Land managers require, among other things, a way of regulating water use, assessing or predicting crop area and productivity, and making management decisions in support of environmentally and economically sustainable agriculture. In the search for more time and cost effective methods for attaining these goals, while monitoring complex management situations, many have turned to remote sensing and Geographic Information System (GIS) technologies for assistance.

The spectral information and spatial density of remote sensing data lends itself well to the measurement of large areas. Since the launch of LANDSAT-1 in 1972, this technology has been used extensively in agricultural systems for crop identification and area estimation, crop yield estimation and prediction, and crop damage assessment. The incorporation of remote sensing and GIS can also help integrate management practices and develop effective management plans. However, in order to take advantage of these tools, users must have an understanding of both what remote sensing is and what sensors are now available, and how the technology is being used in applied agricultural research. Accordingly, a description of both follows: first a description of the technology, and then how it is currently being applied. The applications of remote sensing relevant to this discussion can be separated into crop type identification; crop area measurement; crop yield; crop damage; water use/ moisture availability (m_a) mapping; and water use efficiency monitoring/mapping.

This report focuses on satellite remote sensing for broad-scale rice-based irrigation agricultural applications. It also discusses related regional GIS analyses that may or may not include remote sensing data, and briefly addresses other sources of finer-scale remote sensing and geospatial data as they relate to agriculture. Since a complete review of the remote sensing research was not provided in the rice literature alone, some generic agricultural issues have been learned from applications not specifically dealing with rice. Remote sensing specialists may wish to skip section 2.

2 BACKGROUND OF REMOTE SENSING

The following has been updated from McVicar and Jupp (1998).

Remote sensing is the acquisition of digital data in the reflective, thermal or microwave portions of the electromagnetic spectrum (EMS). Measurements of the EMS are made either from satellite, aircraft or ground-based systems, but it is characteristically at a distance (or "remote") from the target. Due to the large spatial extent of the areas considered for the CRC for Sustainable Rice Production Project 1.1.05, this report will focus on data gathered from satellite remote sensing systems.

Remotely sensed images are recorded digitally by sensors on board the satellites. An example of a satellite operation is shown in Figure 1. The satellites vary in height above the Earth's surface from approximately 700 km, which orbit the earth, to some 36 000 km, which are geostationary above the equator. The images can be manipulated by computers to highlight features of soils, vegetation and clouds. Each pixel, or picture element, contributing to the image is a measurement of a particular wavelength of electromagnetic radiation at a particular spatial scale for a particular location at a specific time. The most common display of remotely sensed data is a single overpass, which non-remote sensing specialists may think of as a 'satellite photo'.

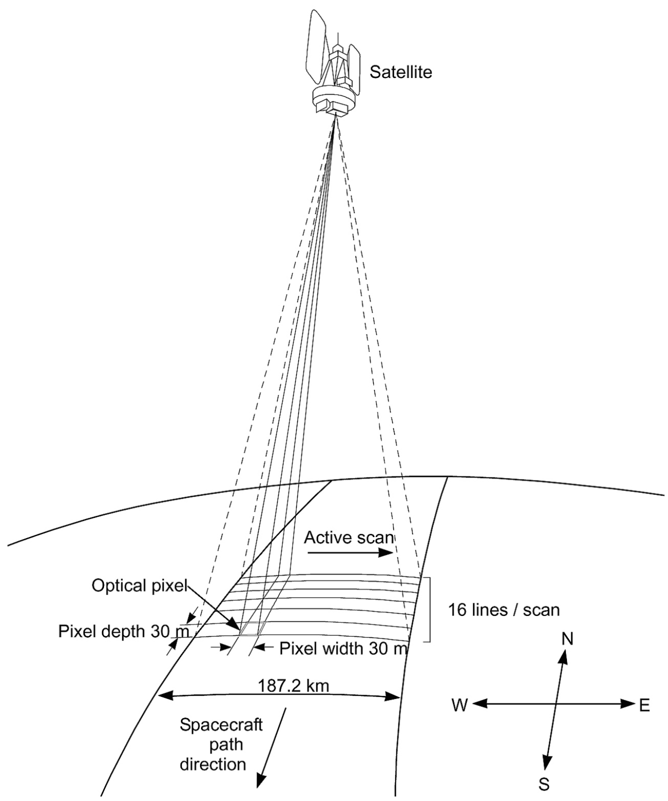

Figure 1. Schematic of satellite operation, specifically the LANDSAT satellite and the Thematic Mapper (TM) sensor. [Adapted from (Harrison and Jupp, 1989). Reproduced by permission of CSIRO Australia].

When dealing with remotely sensed images, the extent, resolution, and density of the spectral, spatial and temporal characteristics need to be considered. Spectral extent describes what portion of the EMS is being sampled (e.g., is it just visible or does the range extend into the thermal). Spectral resolution refers to the bandwidths in which the sensor gathers information. Spectral density indicates the number of bands in a particular portion of the EMS (e.g., hyperspectral sensors have higher spectral density than broadband instruments). Spatial extent is the area covered by the image, while spatial resolution refers to the smallest pixel or picture element acquired. Spatial density refers to the amount of area measured by the sensor, so the spatial density for remotely sensed data is complete, while the spatial density of, for example, rainfall stations which are sampled at explicit points, would be incomplete. This means, for the extent of the image, remotely sensed data are a ‘census’ at a particular spatial scale recorded at a specific time. Temporal extent is the recording period over which the data is available. For some systems, data has been recorded for over 25 years. Temporal resolution is the time that the data is acquired over. Remote sensors usually have a low temporal resolution (i.e., a matter of seconds), while rainfall data recorded at meteorological stations usually have a very high temporal resolution (i.e., they record almost continuously). Temporal density is the repeat characteristics of the satellite and, for some applications, greatly influences the availability of cloud free data.

Remote sensing of the land surface occurs at wavelengths of the EMS where the light can pass through the Earth’s atmosphere with no, or little interaction with the atmosphere. These bands of the EMS are called ‘atmospheric windows’ and refer to the spectral extent in which radiation reaching remote sensing instruments carries information about the Earth’s surface conditions. These ‘atmospheric windows’ are defined by the transmittance of the constituents of the Earth’s atmosphere. There are some gases, which absorb all electromagnetic radiation in certain wavelengths preventing these areas of the EMS being used for remote sensing. Figure 2 shows the divisions of the EMS briefly described in the next section.

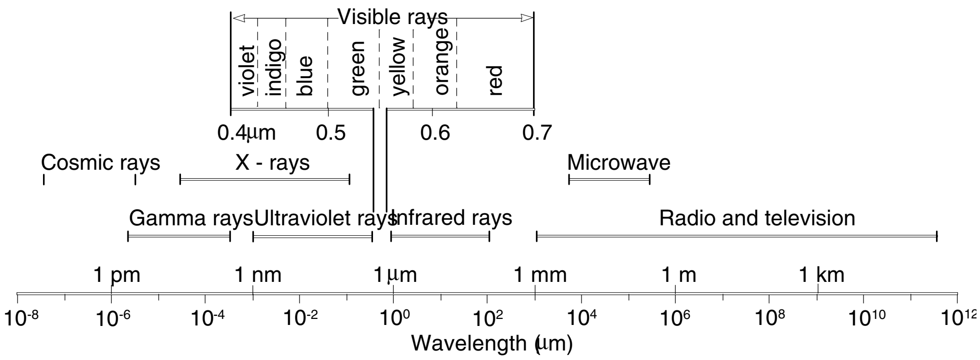

Figure 2. Breakup of electromagnetic spectrum. Note that the scale is logarithmic. [Adapted from (Harrison and Jupp, 1989). Reproduced by permission of CSIRO Australia].

One basis of remote sensing is that different land covers have different spectral properties. Figure 3 shows idealised reflectance plots for two vegetation, soils and water types, respectively. Different surfaces also have varying responses in the thermal and microwave atmospheric windows of the EMS. Image processing approaches utilise these differences to extract information relevant for rice-based irrigation systems.

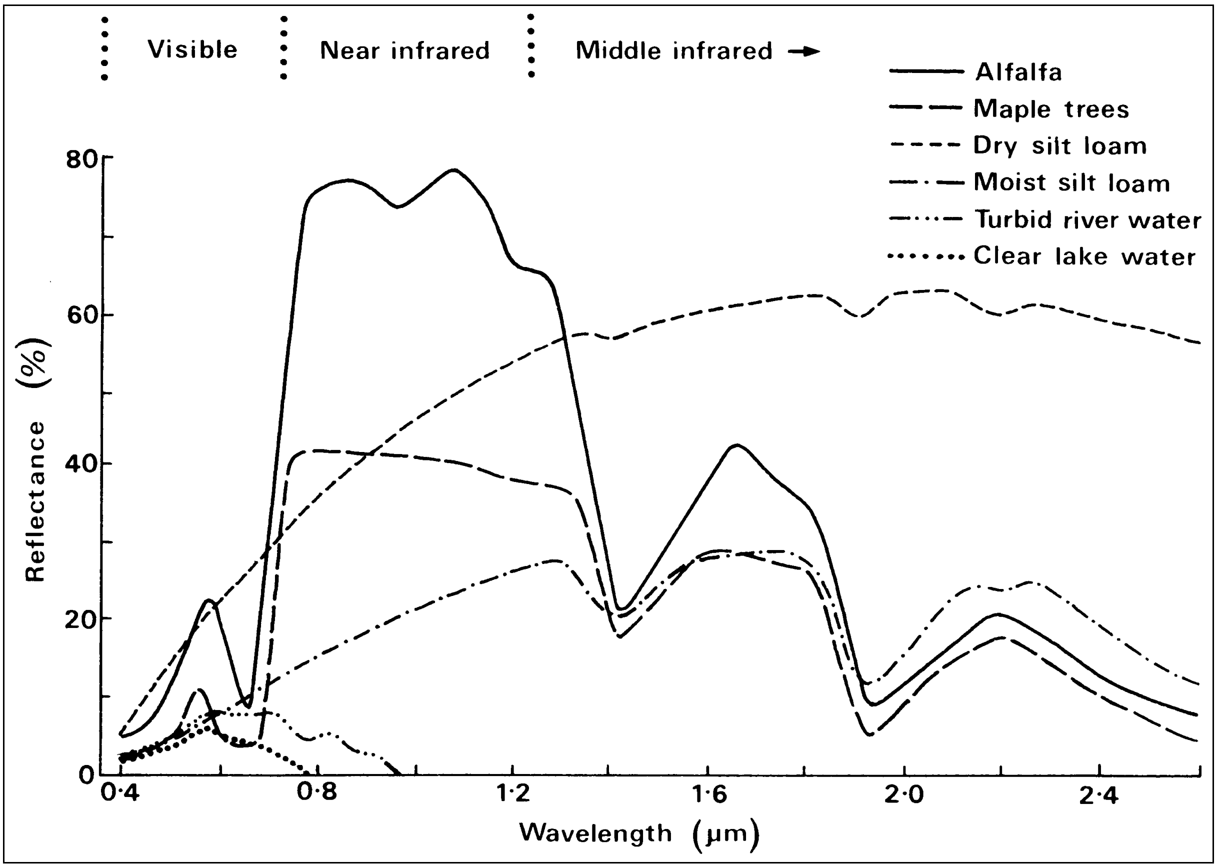

Figure 3. Idealised reflectance plots for different land cover types. [Adapted from (Harrison and Jupp, 1989). Reproduced by permission of CSIRO Australia].

2.1 Reflective Remote Sensing

The reflective portion of the EMS ranges nominally from 0.4 to 3.75 micro meters (μm). Light of shorter wavelength than this is termed ultraviolet. The reflective portion of the EMS can be further subdivided into the visible 0.4 to 0.7 μm, near infrared (NIR) 0.7 to 1.1 μm, and mid infrared 1.1 to 3.75 μm. It is in the visible portion of the EMS that we sense with our remote sensing device (eyes) which allow us to see. Different surface reflective properties allow us to distinguish colour in the visible region of the EMS.

Chlorophyll pigments that are present in leaves absorb red light. In the NIR portion, radiation is scattered by the internal spongy mesophyll leaf structure, which leads to higher values in the NIR channels. This interaction between leaves and the light that strikes them, often determined by their different responses in the red and NIR portions of reflective light, see Figure 4, is how vegetation is detected using remote sensing. The objective of vegetation analysis from spectral measurements, often, is to reduce the spectral data to a single number that is related to physical characteristics of vegetation (e.g. leaf area, biomass, productivity, photosynthetic activity, or percent cover) (Baret and Guyot, 1991, Perry and Lautenschlager, 1984, Huete, 1988), while minimising the effect of internal (e.g. canopy geometry, and leaf and soil properties) and external factors (e.g. sun-target-sensor angles, and atmospheric conditions at the time of image acquisition) on the spectral data (Baret and Guyot, 1991, Chavez, 1988, Gong et al., 1992, Huete et al., 1985, Huete, 1987, Huete and Warrick, 1990, Huete and Escadafal, 1991, Kimes, 1983, Li et al., 1993, Richardson and Wiegland, 1977, Slater and Jackson, 1982, Singh, 1989).

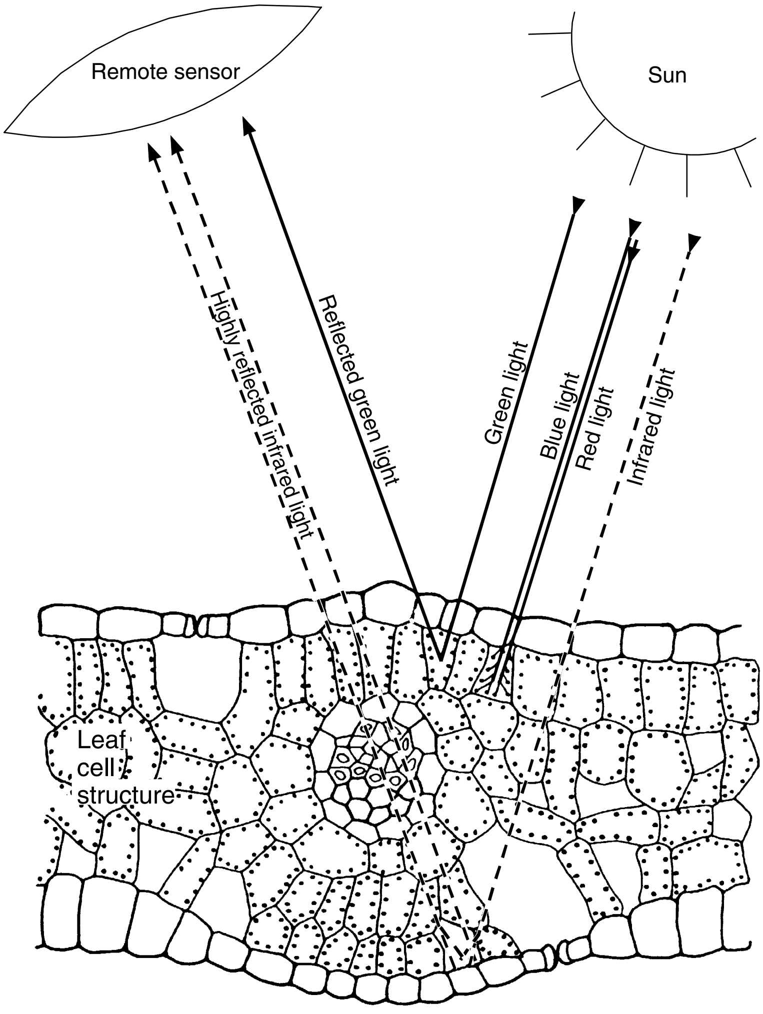

Figure 4. Schematic reflectance of a typical green leaf in cross section; chloroplasts reflect the green light and absorb red and blue light for photosynthesis. Near infrared light is highly scattered by water in the spongy mesophyll cells. [Adapted from (Harrison and Jupp, 1989). Reproduced by permission of CSIRO Australia].

Vegetation Indices (VI's) were developed in an attempt to obtain this objective from remote sensors by taking advantage of the differences in the reflective responses of vegetation in the red and NIR wavelengths. Although VI's are often hampered by limitations in dealing with the complex nature of real-life vegetation canopy interactions (Baret and Guyot, 1991, Huete et al., 1985, Huete, 1987, Huete and Jackson, 1987, Huete, 1988, Huete and Warrick, 1990, Huete and Escadafal, 1991, Huete et al., 1992, Qi et al., 1993), they have gained widespread popularity due to the benefits of remote sensing's high spatial density and extent, and the value added to generic, rather coarse-scale vegetation modelling.

LANDSAT Thematic Mapper (TM) and the Système pour l'observation de la Terre (SPOT) sensors, and many other remote sensing instruments, have channels situated in the red and NIR, see Table 1 and Figure 2. For example, the red and NIR bands for LANDSAT TM are band 3 (630-690 nm) and band 4 (769-900 nm), respectively. Most vegetation indices are combinations of these two reflective bands. The most common linear combinations are the simple ratio (NIR/Red) and Normalised Difference Vegetation Index (NDVI) = (NIR-Red)/(NIR+Red). Previous research has shown positive correlations exist between foliage presence, including measurements of LAI (Tucker, 1979, McVicar et al., 1996b, McVicar et al., 1996c, McVicar et al., 1996a) and plant condition (Sellers, 1985), and vegetation indices such as the simple ratio and NDVI. For a comprehensive listing of vegetation indices refer to Tian (1989), Kaufman and Tanre (1992), Thenkabail et al. (1994b) and Leprieur et al. (1996).

TABLE 1: GENERAL DESCRIPTION OF CURRENT AND ANTICIPATED SATELLITE SENSORS.

Some satellite specifications are available on the internet at sites like the Canadian Centre for Remote Sensing (CCRS) satellite details page (http://www.ccrs.nrcan.gc.ca/ccrs/tekrd/satsens/sats/satliste.html).

Satellite: Sensor	Channel #	Spectral Resolution	Spatial Resolution	Sample Swath	Repeat Cycle	Lifetime
Current						
NOAA:AVHRR[1]	1	580-680 nm	1100	2700 km	12 hrs	1981 - present
	2	725-1100 nm	"			
	3	3.55-3.93 μm	"			
	4	10.3-11.3 μm	"			
	5	11.5-12.5 μm	"			
SPOT:VMI[2]	1	430-470 nm	1000	2000 km	26 days	1998- present
	2	500-590 nm	"			
	3	610-680 nm	"			
	4	790-890 nm	"			
	5	1.58-1.75 μm	"			
LANDSAT:MSS[3]	4	500-600 nm	80	185 km	16 days	1972- present
	5	600-700 nm	"			
	6	700-800 nm	"			
	7	800-1100 nm	"			
LANDSAT:(E)TM[4]	1	450-520 nm	30	185 km	16 days	1983- present
	2	520-600 nm	"			(1999-present)
	3	630-690 nm	"			
	4	769-900 nm	"			
	5	1.55-1.75 μm	"			
	7	2.08-2.35 μm	"			
	6	10.4-12.5 μm	120 (60)			
	(8)	(520-900 nm)	(15)			
SPOT:HRV(IR)[5]	1	500-590 nm	20	60 km	26 days	1986 - present

	2	610-680 nm	"			
	3	790-890 nm	"			
	4	510-730 nm	10			
	(4)	(1.58-1.75 μm)	20			
	(5)	(610-680 nm)	10			
IRS[6]	1	500-750 nm	5.8	70 km	22 days	1997 - present
	2	520-590 nm	23	140 km		
	3	620-680 nm	"			
	4	770-860 nm	"			
	5	1.55-1.70 µm	70			
	6	620-680 nm	188	800 km		
	7	770-860 nm	"			
IKONOS[7]	1	450-520 nm	4	13 km	3 days	1999-present
	2	520-600 nm	"			
	3	630-690 nm	"			
	4	760-900 nm	"			
	5	450-900 nm	1			
TERRA:ASTER[8]	1	520-600 nm	15	60 km	1-2 days	1999-present
	2	630-690 nm	"			
	3	760-860 nm	"			
	4	1.60-1.70 µm	30			
	5	2.145-2.185 µm	"			
	6	2.185-2.225 µm	"			
	7	2.235-2.285 µm	"			
	8	2.295-2.365 µm	"			
	9	2.360-2.430 µm	"			
	10	8.125-8.475 µm	90			
	11	8.475-8.825 µm	"			
	12	8.925-9.275 µm	"			
	13	10.25-10.95 µm	"			
	14	10.95-11.65 µm	"			
TERRA:MODIS[9]	1	620-670 nm	250	2330 km	1-2 days	1999-present
	2	841-876 nm	"			
	3	459-479 nm	500			
	4	545-565 nm	"			

	5	1.23-1.25 µm	"			
	6	1.628-1.652 µm	"			
	7	2.105-2.155 µm	"			
	8	405-420 nm	1000			
	9	438-448 nm	"			
	10	483-493 nm	"			
	11	526-536 nm	"			
	12	546-556 nm	"			
	13	662-672 nm	"			
	14	673-683 nm	"			
	15	743-753 nm	"			
	16	862-877 nm	"			
	17	890-920 nm	"			
	18	931-941 nm	"			
	19	915-965 nm	"			
	20	3.660-3.840 µm	"			
	21	3.929-3.989 µm	"			
	22	3.989-4.020 µm	"			
	23	4.020-4.080 µm	"			
	24	4.433-4.498 µm	"			
	25	4.482-4.549 µm	"			
	26	1.360-1.390 µm	"			
	27	6.535-6.895 µm	"			
	28	7.175-7.475 µm	"			
	29	8.400-8.700 µm	"			
	30	9.580-9.880 µm	"			
	31	10.78-11.28 µm	"			
	32	11.77-12.27 µm	"			
	33	13.185-13.485µm	"			
	34	13.485-13.785µm	"			
	35	13.785-14.085µm	"			
	36	14.085-14.385µm	"			
JERS:SAR[10]	1	1275 MHz	18 x 18	75 km	44 days	1992-1996
JERS:OPS[11]	1	520-600 nm	18 x 24	75 km		
	2	630-690 nm	"			
	3	760-860 nm	"			
	4	760-860 nm	"			
	5	1.60-1.71 µm	"			
	6	2.01-2.12 µm	"			

	7	2.13-2.25 μm	"			
	8	2.27-2.40 μm	"			
ERS:SAR[12]	1	5.3 GHz	<30	80-100 km	Varies	1991-present
RADARSAT[13]	1	5.3 GHz	28 x 25	100 km	24 days	1995-present
Anticipated						
EROS:A[14]	1	500-900 nm	1.8	12.5 km	2 days	2000
EROS:B[15]	1	500-900 nm	0.82	16 km	2 days	2000
QUICKBIRD-1[16]	1	450-900 nm	1	704 km	1-5 days	2000
	2	450-520 nm	4			
	3	520-600 nm	"			
	4	630-690 nm	"			
	5	760-890 nm	"			
ORBVIEW-3(4)[17]	*	Panchromatic	1	8 km	3 days	2000
	*	Multispectral	4			
	*	Hyperspectral	*	5 km		

1 NOAA:AVHRR refers to a series of satellites operated by the United State Federal Agency, NOAA, National Oceanographic and Atmospheric Administration. The Advanced Very High Radiometric Resolution (AVHRR) sensor operates on this platform. From 1978 to 1981 only the first 4 channels were acquired. The NOAA series of satellites are polar orbiting at a height of some 700km, similar to the height of the LANDSAT series of satellites. AVHRR data is acquired over a large swath width, compared to the LANDSAT data, due to the wide scan angle, $\pm$ 55°, of the AVHRR sensor. The Local Area Coverage (LAC) pixel size is 1100 m at the sub-satellite point, becoming 5400 m at the of edge of the swath. Global Area Coverage (GAC) data are also recorded by the AVHRR sensor. GAC is a sub-sampling of the LAC data and nominally has a 5 by 3 kilometre resolution. GAC data is recorded onboard the satellite and recorded at the NASA Goddard Space Flight Centre. AVHRR/3 onboard NOAA-15 has a time shared Channel 3 referred to as 3a and 3b. Channel 3a has a spectral resolution from 1.58-1.64 μm and records during the day. Channel 3b has a spectral resolution from 3.55-3.93 μn and records at night.

2 SPOT:VMI refers to the Vegetation Monitoring Instrument (VMI) aboard the Système pour l'observation de la Terre 4 (SPOT4) satellite. The satellite has been functional from March 24, 1998 to present.

3 LANDSAT:MSS refers to the MultiSpectral Sensor (MSS) onboard the LANDSAT series of satellites. From 1972 to 1983, for LANDSAT 1 - 3 the repeat cycle was 18 days. LANDSAT is a polar orbiting sun synchronous satellite, which passes a given latitude at the same solar time, it operates at a height of 700 km.

4 LANDSAT:(E)TM refers to the Thematic Mapper (TM) sensor onboard LANDSAT 4 and 5 and the Enhanced Thematic Mapper (ETM) sensor onboard LANDSAT 7. Channel and wavelengths are not ascending due to the late inclusion of channel 7. In LANDSAT 7, the addition of a panchromatic band with a 15 meter spatial resolution is a notable change to

previous LANDSAT sensors as is the increase in the thermal channel (6) spatial resolution to 60 meter. Daytime passes are at about 10:00 am local time, whereas night time passes are at about 10:45 pm.

5 SPOT:HRV(IR) refers to the Haute Resolution Visible (HRV) sensor aboard the Système pour l'observation de la Terre (SPOT) satellites 1-3 and the Haute Resolution Visible Infrarouge (HRVIR) aboard the SPOT 4 satellite. SPOT 1 lifetime is from February 22, 1986 to present. SPOT 2 has been transferring data from January 21, 1990 until present, and SPOT 3 was functional from September 26, 1993 to November 14, 1996 when the satellite was declared lost. There has been an addition of a new Channel between 1.58-1.75 µm with a 20 m spatial resolution and a change of the 10 m panchromatic Channel from 510-730 nm in SPOT 1-3 to 610-680 nm in SPOT 4. The satellite has been functional from March 24, 1998 to present. Text inside parenthesis represent the changes in SPOT 4.

6 IRS refers to the Indian Remote Sensing (IRS) satellite 1-D. The IRS-1D was launched into polar orbit on the 29th of September, 1997. It's payload has been activated since October, 1997. This satellite contains a panchromatic sensor, a LISS-III sensor detecting VIS, NIR, and SWIR, and a WiFS sensor collecting red and NIR.

7 IKONOS refers to Space Imaging's IKONOS satellite launched September 24, 1999

8 TERRA:ASTER refers to the Advanced Spaceborne Thermal Emission and Reflection (ASTER) radiometer instrument aboard the TERRA (EOS AM-1) satellite. ASTER is designed to obtain detailed maps of land surface temperature, emissivity, reflectance and elevation. ASTER is the only high spatial resolution instrument on the TERRA platform.

9 TERRA:MODIS refers to the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument aboard the TERRA (EOS AM-1) satellite. MODIS will view the Earth's surface every 1-2 days in 36 spectral bands. Spatial resolution varies from 250m to 1000m. MODIS is geared to global change models.

10 JERS:SAR refers to the Synthetic Aperature Radar (SAR) sensor on-board the Japan Earth Resources Satellite 1 (JERS-1) satellite. Satellite life was from February 11, 1992 to October 12, 1998. The first SAR image was recived on April 21, 1992. A cooling device failed in January of 1994 disrupting steady state transmission.

11 JERS:OPS refers to the Optical Sensors (OPS) on-board the Japan Earth Resources Satellite 1 (JERS-1) satellite. Channel 4 is for forward viewing (15.53°). Channel 3 and 4 make a stereo pair. Satellite life was from February 11, 1992 to October 12, 1998. The first SAR image was recived on April 21, 1992. A cooling device failed in January of 1994 disrupting steady state transmission.

12 ERS:SAR refers to the Active Microwave Instrumentation (AMI) sensor aboard the European Remote Sensing (ERS) 1 and 2 satellites. The information given in the table is for Synthetic Aperture Radar (SAR) in image mode (5.3 GHz C-Band). Repeat cycle has been variable: 3 day cycle from July 17, 1991 to March 1, 1992, 35 day cycle from March 2, 1992 to December 22, 1993, 3 day cycle from December 23, 1993 to April 9, 1994, 168 day cycle from April 10, 1994 to March 20, 1995, 35 day cycle from March 21, 1995 to present.

13 RADARSAT refers to the Canadian Space Agency's RADARSAT satellite in standard mode. RADARSAT collects Synthetic Aperature Radar (SAR) in the C-Band at an incidence angle of 20-49°, nominal spatial resolution of 30m, and swath of 100 km. There are 5 other operating modes including wide swath (20-45°, 30m, 150 km), fine resolution (37-47°, 8m, 45 km), extended coverage (52-58°, 18-27m, 75 km), scanSAR narrow (20-49°, 50m, 300 km), and scanSAR wide (20-49°, 100m, 500 km)

14 EOS:A refers to the 1.8 meter panchromatic satellite due to be launched in 2000 by West Indian Space.

15 EOS:B refers to the 0.82 meter panchromatic satellite due to be launched in 2000 by West Indian Space.

16 QUICKBIRD-1 refers to EarthWatch Inc.'s satellite due to be launched sometime in this year (2000). QuickBird is designed to have 1 meter panchromatic and 4 meter multispectral spatial resolution.

17 ORBVIEW-3(4) refers to Orbital Imaging's Orbview-3 and Orbview-4. Also meant to launch sometime in 2000, both will gather 1 meter panchromatic and 4 meter multispectral. Orbview-4 will also collect hyper spectral data in 200 wavebands. Some specific spectral and spatial information is unknown at this time (*).

While the amount of leaf is one determinant of the signal strength in the reflective portion of the EMS there are several other important factors which control the acquired value. These include the sun-target-sensor geometry. This will control the amount of shadow contributing to the signal; the shadow may be driven by insolation effects due to regional topography and may also be influenced by vegetation shadowing. This effect, termed the bidirectional reflectance distribution function (BRDF) (Burgess and Pairman, 1997, Deering, 1989), is characteristic of vegetation structure. Other effects in the reflective portion of the EMS include changes in soil colour and changes in the observed signal due to changes in the atmospheric component of the signal, including atmospheric precipitable water (Choudhury and DiGirolamo, 1995, Hobbs, 1997), atmospheric aerosols (e.g., dust), and changes in the response of the sensor over time.

Primarily, the reflective portion of the EMS has been used for:

1. identification of rice;
2. area estimation of rice;
3. estimation and prediction of crop yield; and
4. crop damage assessment

These are discussed more fully in section 3.1, 3.2, 3.3 and 3.4, respectively.

2.2 Microwave Remote Sensing

The microwave portion of the EMS ranges nominally from 0.75 to 100 centimetres. Radio signals have wavelengths that are included in these bands. These systems can either be active (the sensor sends its own signal) or passive (the background signal from the Earth's surface is observed). There are five smaller sections of this range which are used for remote sensing. These are :

P band	100 - 30 cm;
L band	30 - 15 cm;
S band	15 - 7.5 cm;
C band	7.5 - 3.75 cm; and
X band	3.75 - 2.4 cm.

RADAR (RAdio Detection And Ranging), is an active system based upon sending a pulse of microwave energy and then recording the strength, and sometimes polarisation, of the return pulses. The way the signal is returned provides information to determine characteristics of the landscape. RADAR has been used in the determination of near surface soil moisture, and the identification of rice crops based on the presence of standing water.

Primarily, the microwave portion of the EMS has been used in agriculture for:

1. identification of rice
2. area estimation of rice; and
3. estimation and prediction of crop yield.

These are discussed more fully in sections 3.1, 3.2, and 3.3, respectively.

2.3 Thermal Remote Sensing

The thermal portion of the EMS ranges nominally from 3.75 to 12.5 micro meters. The radiant energy observed by sensors is emitted by the surface, be it land, ocean or cloud top, and is a function of surface temperature. Models have been developed to allow surface temperature to be extracted from thermal remote sensing. Prata et al. (1995) review the algorithms and issues involved in the calculation of land surface temperatures, denoted T_s.

Thermal remote sensing is an instantaneous observation of the status of the surface energy balance (SEB). The SEB is driven by the net radiation at the surface. During the daytime this is usually dominated by incoming shortwave radiation from the sun, the amount reflected depending on the albedo of the surface. There are also up and down welling longwave components. At the ground surface, the net allwave radiation is balanced between the sensible, latent and ground heat fluxes. Over long periods of time the ground heat flux averages out, and the SEB represents the balance with the sensible and latent heat fluxes. During the day the measured surface temperature at the Earth's surface is, in part, dependent on the relative magnitude of the sensible and latent heat fluxes.

The surface energy balance at any instant is given by:

$$\boldsymbol{R_n = \lambda E + H + G} \tag{1}$$

where:

$\boldsymbol{R_n}$ is net all wavelength radiation (Wm^{-2});

λE is the latent heat flux (of evapotranspiration (ET)) (W m^{-2});
H is the sensible heat flux (W m^{-2}), or the energy involved in the movement of the air and its transfer to other objects (such as trees, grass etc); and
G is the ground heat flux into the soil or other storages (W m^{-2}).

λE denotes the amount of energy needed to change a certain volume of water from liquid to vapor, either by transpiration or evaporation. The combination of these two fluxes is called evapotranspiration. The net available energy (AE) at the Earth's surface, which is available for conversion to other forms, can be written as:

$$\boldsymbol{AE = R_n - G = \lambda E + H} \tag{2}$$

where the terms are defined as above. A key factor determining the observed surface temperature is the partitioning of the ***AE*** into the latent and sensible heat fluxes. This is governed by the amount of water available and the ease with which it is transferred from the surface to the atmosphere, via λE. See Eymard and Taconet (1995), and the reference list therein, for a review of methods to infer surface fluxes from satellite data. These techniques provide the opportunity to map the actual λE flux, denoted λE_a. For given meteorological conditions there will also be a potential λE, denoted λE_p, which could occur if water was not limiting. The ratio of λE_a to λE_p is termed the moisture availability (m_a).

Thermal remotely sensed data can also be recorded at night. During the night the SEB is dominated by the release of heat from the ground, which was absorbed during the daylight hours. The release of heat during the night is governed by how much was absorbed during the day and, the rate at which it is released after sunset. This is a function of the environment's capacity to store heat, which also depends on the amount of water stored in the environment.

The thermal portion of the EMS has been used to determine:

1. surface temperature estimation (including water temperature); and
2. moisture availability (m_a) mapping.

These are discussed more fully in sections 3.4 and 3.5.

2.4 Integrating Remote Sensing with other Data Types in a Geographic Information System (GIS)

Remotely sensed data (visible, thermal, microwave), GIS data layers (soils, geology), point based measurements (rainfall, soil moisture, biomass) or model outputs (biomass, soil moisture) all have spatial and temporal attributes associated with the data attribute, and can be integrated. Economic situations and social indicators will have a time and may have a space associated with the data attribute and can also be integrated. The integration of several data types will allow factors such as crop types, yield estimates, and water use to be determined more objectively.

Many GIS data layers cover entire regions. However, these are often produced from the spatial interpolation of point samples; this is especially the case for some meteorological surfaces. Some physical parameters, such as soil water holding capacity, which are assumed to be time in-variant, only need to be mapped once. Remote sensing provides repeated measurements, at a particular spatial scale and electromagnetic wavelength, which allows dynamic environmental conditions, such as soil moisture and vegetation cover, to be monitored.

The data structure in the GIS can be conceptualised as being pancakes of remotely sensed data (TM or SPOT), which are intersected at right angles by skewers of point based data (Bureau of Meteorology (BOM) rainfall and air temperatures). In the data, two dimensions (the pancakes) are spatial, latitude and longitude, and the third (the skewer) is time. For some issues (e.g., groundwater monitoring) it can be important to include elevation (or depth) as another dimension in the data structure. Both data sets (point based BOM and remotely sensed) often have vastly different spatial and temporal scales. For example, TM data are spatially dense, with a 30 metre spatial resolution, and are recorded over large areas in a matter of seconds at a specific time for specific wavelengths. This means, for the extent of the image, remotely sensed data are a 'census' (high spatial density) at a particular spatial scale recorded at a specific time. Depending on the amount of cloud coverage and the satellite repeat characteristics, optical remotely sensed data may only be available monthly (low temporal density). On the other hand, meteorological data are recorded at specific points, which may be separated by tens to hundreds of kilometres (low spatial density). Meteorological variables are usually recorded daily (high temporal density), as either integrals (e.g., rainfall and wind-run totals), or extremes (e.g., maximum and minimum air temperatures). Thus, remotely sensed data are spatially dense but temporally sparse, while meteorological data are spatially sparse but temporally dense.

Data of varying degrees of spatial and temporal density can be incorporated into a GIS. Spatial and temporal resolutions of the data will vary, depending on, among other things, the issues being addressed. See Langran (1992), Peuquet (1994), Peuquet (1995) and Mitasova et al. (1995), for detailed discussions of both the theoretical and the technical aspects of data integration arising from the inclusion of time in GIS.

The advantages of using time series of several data sets, including those not observed remotely, is illustrated in the following example from Barrs and Prathapar (1994) and Barrs and Prathapar (1996). An irrigation company may want to estimate crop area in order to plan for the marketing of specific crops. To get an early estimate of rice production, a November image was acquired, in which standing water was used to estimate rice area. Standing water can be easily identified in the NIR portion of the EMS where it has a low reflectance (see Figure 3). In order to map other crop types and to delineate standing water areas on which rice was not grown, a March image well into the rice growing season was then acquired. This image was used to refine the end of season yield prediction by 'fine-tuning' the irrigated area estimation from the first image. By determining areas that were still standing water, they could ascertain that these were either failed crops or permanent water bodies. The later image was also used to classify other summer crop types, with varying confidence. Other GIS data, like field delineations and known water bodies, could also have been used to adjust the classification. Errors of omission as well as errors of commission can be corrected, increasing classification accuracy. For example, in a land use map, if 90% of a known field is classified as rice, it makes sense to assume the whole field is rice, thus fixing some errors of omission. However, in a land cover map, knowing, for example, that 10% of the paddock planted with rice did not grow successfully can be valuable information for estimating yields, thus fixing some possible errors of commission. The difference between land use and land cover should be noted as these should not be combined in thematic classes.

It should be noted that some data likely to be used in spatial modelling will not have a precise spatial reference associated with it, for example economic factors such as interest rates and grain prices. However, the temporal nature of these variables can be incorporated into larger information systems, of which remotely sensed data are but one component.

3 REMOTE SENSING IN RICE-BASED AGRICULTURE

A basic understanding of rice physiology is essential to the success of remote sensing applications in rice-based agricultural systems. This knowledge can play a critical role in the planning stages of a remote sensing project (e.g., identifying optimum acquisition dates for the purchase of imagery) as well as in the final stages of analysis (e.g., aiding in the delineation of rice paddies or the estimation of growth stages) (Ribbes and Toan, 1999, Le Toan et al., 1997). The growing cycle of rice can be separated into two stages with respect to most analyses of remotely sensed data: vegetative and reproductive (Casanova, 1998, Ribbes and Toan, 1999).

The vegetative stage includes the part of the growth cycle where the plant develops and grows, starting after sowing and ending when the plants start to reproduce. This stage is characterised by a steady increase in plant height and biomass. The reproductive stage starts when the plant stops growing taller and ends after maturity and includes panicle and grain development (Ribbes and Toan, 1999). It may be beneficial at times to further split the reproductive stage into two categories: reproductive pre-heading and reproductive post-heading. Reproductive pre-heading defines the period from panicle primordia initiation to heading and post-heading refers to the period from heading to maturity (Casanova, 1998).

The length of the growth cycle of rice can vary from 3 to 6 months for different varieties (Casanova, 1998), and can also be categorised into two main groups for many remote sensing applications: tropical and temperate. Growth cycles for tropical rice varieties last about 110-120 days, while those of temperate varieties usually last around 140-150 days (Le Toan et al., 1997). However, this duration can vary based on cultivar. For example, short duration varieties have been bred with growth cycles less than 90 days (Senanayake et al., 1994). These differences in growth cycle length are due to differences in vegetative stage duration: the vegetative stage can be anywhere from 40 to 120 days in length (Senanayake et al., 1994).

Irrespective of cultivar, reproductive pre-heading duration is about 23-25 days, while reproductive post-heading duration lasts 30-35 days (Senanayake et al., 1994). During the reproductive stage, plant height and biomass typically remain stable at around 100 cm and 2000 gm^{-2}, respectively (Ribbes and Toan, 1999). The vertical characteristics of the rice plant also change as the plants grow, with stem inclination decreasing and the leaf angle increasing (Ribbes and Toan, 1999).

For different locations, the timing of the growth cycle of rice varies depending on local climate, management, and cultivar planted. Consequently, the timing of rice for a particular site of interest should be known. Australian rice varieties have changed over the past 40 years with Caloro dominating the 1960's, Calrose in the 1970's to mid 1980's and Amaroo from the mid 1980's into the 1990's (Brennan et al., 1994). This has been associated with development of long-grain, fragrant and Spanish varieties to meet higher priced markets (Brennan et al., 1994). Short duration varieties are generally desirable because they can be competitive with weeds, require less pesticides and herbicides, utilise less irrigation water, and allow for double cropping in tropical environments (Khush, 1987). In a temperate environment like southern NSW, short duration varieties are also desirable because they can allow more leeway for sowing and harvesting between the limitations of cold springs and autumns (Reinke et al., 1994). Timing of rice in southern NSW is summarised as:

1. placed under permanent flood and aerially sown in late September/early November;
2. canopies emerging during late October/late November;
3. flowering by late January/early February;
4. de-watered in late February/March; and
5. harvested in March/May.

Other summer crops in NSW include corn, sorghum, and soybeans, while winter crops include wheat, barely, oats, and canola. Pasture is grown in both seasons. Citrus, stone fruits, and grapes are also grown in the area. Some of these crops may use remnant soil moisture after a flooded rice crop, whereas others are furrow or drip irrigated.

There is an interest in monitoring other crops than rice within the irrigation areas of southern NSW from remote sensing. Of these other crops, there is a good potential for remote monitoring of corn and soybeans. The spectral reflectance characteristics of corn and soybeans along the EMS are slightly different in shape and amplitude (Thenkabail et al., 2000) allowing for differentiation between these two crops (Badhwar et al., 1982). Multitemporal remote sensing data has been used to estimate soybean and corn crop characteristics such as yield, LAI, biomass, plant height (Thenkabail et al., 1994a, Thenkabail et al., 1994b), development stage (Badhwar and Henderson, 1985), and crop proportion (Badhwar, 1984b, Badhwar, 1984a). For single date imagery, however, the timing of image acquisition can greatly influence classification results since confusion between spectral signatures can occur due to differences in crop growth stages. That is, on the day of image acquisition, the two crops could look spectrally similar.

Moderately high correlations (from 0.7 to 0.85) have been reported between several soybean and corn crop characteristics when related to VI's. Soybean was correlated to standard NIR and red-based VI's , whereas corn crop characteristics were more highly correlated with VI's that include at least one MIR band (Thenkabail et al., 1994b, Thenkabail et al., 1994a). Mature soybean crops have higher reflectance in the NIR and lower reflectance in the red portions of the EMS than corn, resulting in detectably higher standard VI values for soybeans (Tucker et al., 1979). This means that three of the main summer crops (rice, corn, and soybeans) can potentially be discriminated from each other using remote sensing. However, to do this, more than one image throughout the growing season might be needed in order to take advantage of spectral differences due to the phenology of these crops.

Remote sensing based applications, then, will not only take advantage of both the characteristics and timing of growth cycle, but will also consider the spectral reflectance of different crops. Since rice is the focus of this report, the basic spectral patterns of rice must be understood. The reflectance from rice, like all green vegetation, can be summarised by a generalised vegetation response as seen in Figure 3. It is the differences in this basic vegetation response that allow discrimination between vegetation types. However, these vegetative-type responses are harder to differentiate between each other than a non vegetative-type response like soil or water. This is true since non vegetative-type features usually reveal drastically different response curves when compared to vegetation (Figure 3).

As irrigated rice fields are flooded, the spectral characteristics of water can be used to distinguish potential rice paddocks and provide an early estimate of rice area (Barrs and

Prathapar, 1996, McCloy et al., 1987). Inaccuracies result, however, when this early estimate is not adjusted by a later image, which can aid in elimination of permanent water bodies and other irrigated crops from the classification (Barrs and Prathapar, 1996, McCloy et al., 1987). The visible and near infrared wavelength response of rice, once the vegetation starts to cover the water in flooded paddocks, is much the same as other crops (Martin and Heilman, 1986). However, rice was found to be more distinguishable from other crops due to its water absorption characteristics by including middle infrared (MIR) wavelengths in the crop discrimination(Martin and Heilman, 1986, Thenkabail et al., 1994b).

It is also very important to understand the interaction of the reflectance of vegetation in key bandwidths of the EMS to relevant vegetation characteristics such as biomass or leaf area index (LAI). Since most studies relating vegetation to biomass or LAI use VI's of NIR and red EM portions, these interactions, specifically should be understood. NIR reflectance of rice is directly related to green biomass. It continues to increase from early tillering, where NIR reflectance is about 15%, to heading where it reaches a maximum of about 50% (Casanova, 1998). Post-heading NIR reflectance decreases to about 33% as rice crop green biomass decreases due to death and loss of leaves (Casanova, 1998). Red reflectance of rice is inversely related to green biomass, where it decreases from about 10% at emergence to 2% at flowering, and then increases to about 18% at maturity due to senescence (Casanova, 1998). Some VI's perform better than others, but in general, these interactions result in better correlations between VI's and biomass in the vegetative and pre-heading stages than in the post-heading stage, where VI's tend to saturate (Casanova, 1998).

The saturation of VI's results in a notable limitation to the usefulness of remote sensing in estimating crop biomass, LAI, and, therefore, yields in rice-based irrigated agricultural systems. This saturation is mainly due to the inability to detect the accumulation of biomass that takes place well after crop canopy cover reaches 100% (Thenkabail et al., 2000). After canopy closure, NIR reflectance continues to increase significantly, while red reflectance may only change slightly, resulting in minimal changes in a VI (Thenkabail et al., 2000). Since NIR is typically the numerator of a VI ratio, and red is the denominator, it takes an inordinately large increase in NIR to increase the overall VI after heading (Thenkabail et al., 2000). This is demonstrated in the saturation of NDVI above LAI's of 2.5 to 3 (Thenkabail et al., 2000) and fraction of intercepted photosynthetically active radiation ($fPAR$) above 94% (Casanova, 1998). In irrigated agriculture, LAI's often exceed 3, which decreases the accuracy of yield measurements from remote sensing. However, this is somewhat offset by the fact that growth stage information received from remote sensing is often useful and that microwave remote sensing measurements can provide structural measurements after LAI's exceed 3.

The applications of remote sensing relevant to this discussion can be separated into 6 main categories as determined by the bulk of the current rice-based remote sensing literature. These are:

1. crop type identification;
2. crop area measurement;
3. crop yield;
4. crop damage;
5. water use/ moisture availability (m_a) mapping; and
6. water use efficiency.

A discussion of each follows.

3.1 Crop Type Identification

The most commonly practiced application in remote sensing of agriculture is mapping land cover to identify crop types. This process primarily uses the spectral information provided in the remotely sensed data to discriminate between perceived groupings of vegetative cover on the ground. The spatial (Atkinson and Lewis, 2000) and temporal information included in single date and time series data, respectively, usually play a secondary role, but can also aid in the classification procedure. Discrimination of crops is usually performed with 'supervised' or 'unsupervised' classifiers. The basic difference between these types of classification is the process by which the spectral characteristics of the different groupings are defined. Common clustering algorithms include maximum likelihood, minimum distance to mean, and parallel piped (Jensen, 1986).

Unsupervised classification relies upon a computer algorithm to define natural groupings of the spectral properties of the pixels in an image. After initial classification, the analyst attempts to assign the perceived groupings *a posteriori* (after the fact). Problems arising from using this methodology are related and include classification of meaningless groupings, idiosyncratic definition of initial number of classes, and subjectivity involved in combination of similar classes. However, if land cover classes are spectrally well separated, adequate results may be obtained.

Because the unsupervised classification algorithm will automatically output the often arbitrarily defined number of classes input to it, the resulting classes are frequently non-representative or meaningless. That is, the initial classification can be drastically different based on the number of classes the analyst originally requests. Some of the classes generated may have little meaning with respect to reality because they contain more than one functional or 'on the ground' class. Others are too specific (i.e., several spectral classes form one functional class) and need to be recombined. Spectral classes that contain more than one functional class are frequently harder to deal with because the analyst will need to reprocess them. The recombination of overly specific classes can also be problematic since the process is often subjective. This subjectivity is regularly expressed by results that are not easily duplicated and non-standardised (often represented by abrupt land cover changes at management boundaries).

The advantage of an unsupervised approach, however, is that no *a priori* (before the fact) knowledge is needed. This can be beneficial when every crop type in a study site may not be known, or when attempting to discriminate between groups of crop vigour (Barrs and Prathapar, 1994). Unsupervised classification also avoids problems with the user biasing the classification with improper or poorly represented training data, which can be the case in supervised classification.

Supervised classification, which is the most common classification method in agricultural areas, requires *a priori* knowledge. It relies on the analyst to define the perceived groupings by identifying homogeneous areas, called training sites, from either *in situ* collection or directly from the image. These training sites are statistically analysed and then used to assign every pixel in the image to the group in which it has been determined a member. Problems may arise when defined training sites are a poor representation of the group's spectra. For example, training data with multiple modes in the training class histogram suggests that there are at least two different types of land cover within the training area. Also, positive spatial autocorrelation exists among pixels that are contiguous or close together (i.e., adjacent pixels have a high probability of having similar brightness values), which can cause a reduction in variance between adjacent pixels (Campbell, 1981). This reduction in variance can make large clumps of contiguous training pixels less representative of a particular cover type over the extent of an entire image and is why several single-pixel training sites located spatially apart from each other can result in better classifications than large clumps of contiguous training pixels (Medhavy et al., 1993, Campbell, 1981). Spatial autocorrelation also means that pixels in a remotely sensed image should not be thought of as entirely discrete features independent of their neighbours, but rather a set of continuos features influenced by their neighbours (Campbell, 1981).

Therefore, care must be taken to collect representative and non-autocorrelated training data. When such care is taken, classification for crop identification can be quite effective. Many authors report classification accuracies exceeding 90% for rice identification and other crops (Aplin et al., 1998, Barbosa et al., 1996, Le Hegarat-Mascle et al., 2000, McCloy et al., 1987, Medhavy et al., 1993, Kurosu et al., 1997, Panigrahy et al., 1999). However, the map user should be aware that not all accuracy assessments are equivalent.

In general, classification accuracy assessment involves sampling classes of the thematic map to summarise the amount of overlap between the classified map and what is present on the ground, although the performance of the classifier can also provide information on map accuracy (Richards, 1996). The 'ground truth' information is usually gathered from existing maps, aerial photography, or field surveys using any number of sampling schemes (e.g., simple random sample, stratified random sample, or systematic sample to name a few). However, because of differences in the accuracy of the 'ground truth' source and the sampling scheme used to gather the information, a certain amount of ambiguity is present in any classification accuracy summarisation.

Certainly, the resulting accuracy assessment will be influenced by the reliability of the 'ground truth' source. Validation data might be less reliable than the classification itself, yet is used as 'ground truth' because it has been traditionally the standard by which management decisions have been made. For example, agricultural census' of large areas in rural-based countries may be extremely generalised, yet are often used to 'ground truth' a classification of fine spatial scale (e.g., 30 metre) satellite imagery. In this case, the classified map is probably more accurate than the 'ground truth' making unclear as to what the discrepancies between the classified map and the 'ground truth' are attributed to.

Another source of confusion introduced by classification accuracies is the way in which the accuracies are reported. It is advisable to differentiate between what is loosely known as producer's accuracy and user's accuracy (Story and Congalton, 1986). Producer's accuracy, here, is a strict comparison of the number correctly classified on the map versus the number of that same class determined by the 'ground truth' (i.e., per cent correct). This measurement only considers errors of omission ('ground truth' points that were left out in the classification). User's accuracy, on the other hand, considers both errors of omission and commission (i.e., those that were misclassified by being wrongly omitted as well as wrongly included) (Story and Congalton, 1986, Congalton, 1991). User's accuracy is usually lower than producer's accuracy, which is why producer's accuracy is usually reported. This can be potentially problematic when comparing results of classifications between different studies, especially when classification accuracy methodologies are not explained well in publications or reports (which is often the case).

To achieve high classification accuracy, multitemporal (Kurosu et al., 1997, Panigrahy et al., 1997), multi-sensor (Le Hegarat-Mascle et al., 2000, Okamoto and Kawashima, 1999) or GIS (Aplin et al., 1998) data is often integrated into the classification procedure. However, incorporating these data into a classification does not necessarily improve all crop type accuracies. For example, Barbosa et al. (1996) attained higher accuracies for several crop types using single date imagery as opposed to multitemporal imagery. These results depended on both the timing of the single date image as well as the accuracy assessment methodology used (Barbosa et al., 1996). For example, rice crop identification using one single date spring image produced equivalent or higher accuracy than the multitemporal classification (Barbosa et al., 1996). This specific example could be related to the ease by which the water in flooded rice fields can be separated from other areas at the time of image acquisition. In contrast, some authors believe that the early (spring) estimate of rice crops can be improved by use of a later image, which can aid in elimination of permanent water bodies and other irrigated crops from the classification (Barrs and Prathapar, 1996, McCloy et al., 1987). The 'law of diminishing returns' is most likely at work in this situation; slight increases in the accuracy of rice crop identification may not be worth the cost of purchasing another remotely sensed image unless the impact of the assessment on management is relatively high or potentially costly (Pax-Lenney and Woodcock, 1997b).

The performances of different sensors for crop identification have been tested over varied geographic areas and crop types. These most commonly include broadband optical (e.g., LANDSAT, SPOT, and AVHRR), and microwave (e.g., ERS, RADARSAT, JERS) used alone or in combination in the form of either single or multiple date imagery. In general, multitemporal microwave imagery results in roughly equal classification accuracies as single date optical imagery when specifically considering rice (i.e., about 90%) (Kurosu et al., 1997) or other crops (Le Hegarat-Mascle et al., 2000). Because of the complementarity of the data, the fusion of both optical and microwave imagery has resulted in higher overall and individual crop classification accuracies (> 95%) than either produce alone (Le Hegarat-Mascle et al., 2000).

Higher crop classification accuracies have also been achieved by the combination of GIS and remotely sensed data (Aplin et al., 1998). This method of classification depends on accurate GIS data and is sensitive to missing boundary lines. By using GIS data, Aplin (1998) achieved greater classification accuracies in 'constrained' areas having well-defined boundaries (e.g., agricultural fields and urban areas). Conversely, the inclusion of GIS data decreased classification accuracy in 'unconstrained' areas or those areas having poorly defined boundaries (e.g., grassland and bare soil areas) (Aplin et al., 1998). Similarly, others have improved classification accuracy using the contextual or landscape information inherent in the imagery (Moody, 1997, Stuckens et al., 2000). These techniques require no *a priori* knowledge, and therefore, are more flexible because they do not rely on an updated and accurate GIS layer. However, the user has more control when using GIS data, which can result in very accurate results.

Finally, hyperspectral remote sensing allows for the classification of imagery using many narrow bands along the EMS. These narrow bandwidths permit the use of very specific spectral characteristics for optimising the categorisation of agricultural properties such as biomass and leaf area index (Thenkabail et al., 2000) as well as classification of crops and crop stress (Lelong et al., 1998). The narrow bands in hyperspectral data are often ordered sequentially along a wide bandwidth (e.g., every 10 nm from 470 – 2500 nm) providing continuos spectral information over that EM portion. This continuos nature of hyperspectral data can provide very valuable information that can increase classification accuracy and is why this data source will be frequently used in the future. However, the tremendous spectral information comes at a cost; the datasets are much larger than broadband datasets and thus are harder to maintain in terms of data management and processing. Also, in multi-temporal analysis, accurate atmospheric correction of the hyperspectral data will be more critical than for broadband data.

3.2 Crop Area Measurement

Crop area measurement is a very common practice in agriculture. Remote sensing is often used for this purpose because of its strengths in regard to spatial extent, temporal density, relative low costs, and potential for rapid assessment of spatial features. Many of the same issues concerning crop type identification also affect crop area measurement from remotely sensed data. This is because crop type identification is a necessary first step to area estimation. In many cases, though, crop type identification is more concerned with classifying all crop types from each other, where area estimation often is concerned with only a few target crops. In either case, these two applications are frequently performed in sequence: first crop identification and then area estimation. There are a few issues that are not exclusively related, but tend to more specifically pertain to crop area estimation, including positional accuracy, mixed pixels and pixel size, and a mismatch between individual and overall accuracies of the results.

Positional accuracy, here, can be defined as the difference in the position of a feature on a map compared to the feature's real world or 'true' position. As such, the position of boundary lines on the map, for instance, are most likely not where they are in the real world, but are more accurately represented as a belt or swath around that boundary line on the map. This swath contains the 'true boundary line' and has a width that is inversely related to the scale of the source (Van Niel and McVicar, 2000). For example, as the scale of the source gets smaller (area representation gets larger) the width of the swath around the line generally represents a larger distance, making the positional accuracy decrease (Van Niel and McVicar, 2000). In other words, as the swath gets wider, the relative certainty of the position of the 'real boundary' gets smaller and the error likely increases. Therefore, when attempting to estimate crop areas accurately, considerable thought should be given to achieving high positional accuracy of crop boundary lines if GIS data are used in conjunction with remote sensing. Ground validation points are extremely important, in this case, to quantify positional accuracy and thus spatial uncertainty. Knowledge of spatial uncertainty is essential in making appropriate managerial decisions on crop area measurements (Van Niel and McVicar, 2000). For example, if crop area estimation is performed in an attempt to monitor year-to-year land use, it is extremely important to know how much potential error is included in the estimate solely due to uncertainties. With this knowledge, the manager has a better idea if the year-to-

year difference in area is reliably measured from the remotely sensed data or if it is 'absorbed' by the inaccuracies of the dataset itself.
Pixel size of the remotely sensed data also affects positional accuracy of boundary lines in crop area estimates, and therefore should be considered for its appropriateness to a particular application. One prominent issue is the relation of the pixel size to the paddock size (or feature element) being measured (Woodcock and Strahler, 1987, Pax-Lenney and Woodcock, 1997a). Although for large areas AVHRR data is very attractive due to its spatial extent and high repeat cycle, the 1 km pixel size is often disproportionately larger than paddock sizes. This may not be an unsurmountable problem when monitoring areas with many contiguous smaller fields of the same crop type (Quarmby et al., 1993b), but at the same time, must be considered. In an attempt to either compensate for mismatched pixel-to-field sizes or to increase the accuracy of area estimations, the spectral characteristics of impure or 'mixed' pixels can be 'unmixed' by linear mixture modelling.

In linear mixture modelling, the analyst assumes that any mixed pixel's spectral signature is made up of a combination of pure spectral signatures of all the separate land cover types contained in that pixel in proportion to the area of which that cover type is found in the pixel (van Leeuwen et al., 1997, Maas, 2000, Quarmby et al., 1992). The spectral signatures resulting from a pixel containing only one cover type (pure pixel) are known as end members. Proper unmixing of mixed pixels relies upon the identification of good end member spectra (Quarmby et al., 1992). Different combinations and proportions of the end members are combined to best match the signature of the mixed pixel, supposedly allowing for a better estimate of crop areas. Problems can arise when end members are either not a good representation of a particular land cover class, or when a land cover class' end member is not collected. Even when numerous and representative end members are gathered, results can still be spurious due to confusion caused by mixed pixel spectra being explained by multiple possibilities of end member combinations. Also, green crops can produce very similar end members at certain times of the year, resulting in erroneous unmixing in agricultural systems.

As with identification of crop types, ground validation is also very important in area estimation. Traditional estimates of crop area have come from census data over rather large areas, and are usually rather gross and usually contain little specific spatial context. This means that there is often no explicit locational knowledge contained in the 'ground truth'. This leads to very ambiguous results where overall values may be closely related, but the analyst often has no idea what sort of spatial variation exists between the 'ground truth' and the estimates from the remotely sensed data, leaving the comparison less meaningful. It is important, then, to make sure that the 'ground truth' data is defensibly more reliable than the observation as well as spatially explicit, wherever possible.

Often, there exists in the validation of area estimations, a mismatch between reported overall and individual accuracies. Many authors represent areal accuracy as an overall summation of several paddocks or districts. This tends to reveal extremely accurate results, often exceeding 99% (McCloy et al., 1987, Quarmby et al., 1992, Fang et al., 1998, Okamoto and Kawashima, 1999). However, this can be misleading because there often exists large areal errors in the individual paddocks or districts that were added together to generate this statistic. Unfortunately, this mismatch between overall and individual areal accuracy is rarely discussed, revealing a perceived dichotomy in the results.

The discrepancy between the overall accuracy and individual district- or paddock-level accuracy is due to errors of underestimation and overestimation cancelling each other out (Van Niel and McVicar, 2000). That is, when several areas are added together, the overestimates are often almost exactly offset by the underestimates, resulting in a good overall estimation of area even though individual error is much larger (McCloy et al., 1987, Quarmby et al., 1992, Fang et al., 1998, Okamoto and Kawashima, 1999).

In a study at the CIA in southern NSW, this individual areal error was seen to drop considerably when just two areas were added together, and continued to approach zero as more areas were summed (Van Niel and McVicar, 2000). This phenomenon can be exploited for management purposes, but care must be taken to ensure that proper interpretation of areal accuracy is achieved for specific management situations (Van Niel and McVicar, 2000). That is, it is only appropriate to use the summed or overall areal accuracy when the overall area is the specific concern.

3.3 Crop Yield

Crop yield forecasts can greatly influence farm-level management decisions, such as fertiliser applications and water delivery, as well as provide a means for farm income assessment. Consequently, individual farmers and district-level land managers show great interest in producing rapid and accurate estimates of crop yield, both locally and regionally. In the past, the standard yield estimation procedure included the analysis of crop cuttings at randomly sampled ground plots during harvest (Murthy et al., 1996), or meteorological regression models using rainfall and past yield data (Karimi and Siddique, 1992). These methods often produce results that are either not timely nor spatially explicit. Though still used, these methods are being replaced by estimation of crop yields using remote sensing because of its ability to produce results quickly and spatially. Using this technology, it was found that spatially meaningful estimates of yield can be made as early as 1 to 3 months prior to harvest (Quarmby et al., 1993b, Rasmussen, 1997), thus impacting management reaction time to yield forecasts.

Positive correlations exist between measurements of LAI (Curran et al., 1992, Tucker, 1979, Nemani and Running, 1989a, McVicar et al., 1996a, McVicar et al., 1996b, McVicar et al., 1996c), plant condition (Sellers, 1985), and VI’s. Based on this relationship, and assuming that LAI (or biomass) is related to yield, there are 3 main approaches used to forecast yield. These are: 1) correlate yield with NDVI (Maselli et al., 1992, Smith et al., 1995); 2) correlate yield with integration under the NDVI curve, denoted ∫NDVI (Benedetti and Rossini, 1993, Quarmby et al., 1993a, Rasmussen, 1997, Rasmussen, 1998a, Rasmussen, 1998b, Pinter Jr. et al., 1981, Honghui et al., 1999); or 3) simulate yield with crop models (sometimes using remotely sensed inputs) (Rosenthal et al., 1998, Inoue et al., 1998, Maas, 1988). For a detailed review of crop yield modelling using remote sensing, see McVicar and Jupp (1998). A brief summary of all three approaches follows.

Both regressions of VI and ∫NDVI studies generally attempt to estimate yield using remotely sensed data alone. A direct comparison of VI response to yield can result in highly correlated regression equations. For example, Harrison et al. (1984) achieved correlation coefficients (r) as high as 0.9 for calrose rice and 0.79 for Inga at the CIA using the greenness ratio of MSS7/MSS5. This study developed the yield model based on imagery acquired when the crop was at booting stage, the time when rice displays green leafy surfaces (Harrison et al., 1984). Promising correlation coefficients were also shown between reflective bands of TM imagery and harvested grain yield (up to 0.92 for band 7) (Tennakoon et al., 1992). These relationships can be used to estimate rice yield at district levels with reasonable success. For example, Patel et al. (1991) was able to estimate district rice yield with an accuracy ranging from 86% to 98%.

Likewise, ∫NDVI studies have produced similar results with relation to rice yield. Rice yields have been estimated within 3% of official values for 3 consecutive years in one study (Quarmby et al., 1993b), while correlation coefficients have been reported as high as 0.93 for millet yield in another (Rasmussen, 1992). However, the ∫NDVI method is highly sensitive to remotely sensed data availability, which can result in gross yield underestimates when portions of the growing season are missing (Quarmby et al., 1993b). Until just recently, the only operational satellite sensor with a repeat cycle sufficient for ∫NDVI studies of crop yield has been NOAA AVHRR (Rasmussen, 1992). The most notable additions to this list are the TERRA (ASTER and MODIS sensors), and Ikonos satellites both launched in 1999 (Table 1). Anticipated sensors could also impact the usefulness of ∫NDVI studies by increasing the number of satellites with relevant repeat cycles. These include Quickbird-1, and Orbview 3 and 4 (Table 1). The definition of the proper time interval for ∫NDVI studies has been disputed, but shown to only be significant when integrated over the reproductive stage (for millet) (Rasmussen, 1992). For rice, where LAI usually exceeds 5, VI's saturate, limiting the usefulness of this approach, and suggesting that different methods might achieve better results. To date, the ∫NDVI method has mostly been used in dryland farming. In an attempt to achieve highly accurate yield estimates, many models have been developed which aim to simulate plant growth. Such plant growth models need to be validated to ensure that they meet a desired level of predictive capability. Plant growth models can be validated by comparing simulated and *in situ* measurements of vegetation parameters (e.g., biomass or yield). However, plant growth models may also be validated by comparing simulated reflectance with that measured by remote sensing. This can be achieved by inverting either empirically-based relationships, or physically-based radiative transfer models. This means that a plant growth model estimate of cover can be converted, through a radiative transfer model, to an estimate of reflectance, or recalibrated through the estimation of key crop variables like LAI or above ground biomass (Inoue et al., 1998, Fischer et al., 1996, Fischer et al., 1997, Maas, 1988). This recalibration of crop variables links well to simple growth models because they can be directly related to *fPAR* , a key variable in most of these models (Inoue et al., 1998).

Because the radiative transfer model approach can be complicated and necessitates many input variables, the recalibration of simple models is often preferable (Inoue et al., 1998). Recalibration is also, very often, a better method for yield estimation than either using the remotely sensed data as direct input to simulation models, or ∫NDVI because it is not as limited by the availability of remote sensing data (Inoue et al., 1998). The recalibration approach using remote sensing has also been shown to drastically improve non-calibrated simulation models (Inoue et al., 1998).

3.4 Crop Damage

Of great concern in agricultural systems is the loss of productivity due to crop damage and its negative impact on meeting the increasing demands for food globally (Fox Strand, 2000). Rice damage and subsequent yield reduction can occur for many reasons including, various pathogens, insects, and weeds and often possesses a complex interaction with cropping practices (Ennaffah et al., 1997, Islam and Karim, 1997, Savary et al., 1997). Cropping practices such as differences in water depth and fertiliser applications have been shown to affect crop production (Anbumozhi et al., 1998). Likewise, irrigation with wastewater can cause heavy metal contamination in soils, also resulting in crop damage and yield reduction (Cao and Hu, 2000). Natural variables, such as climate, can also cause damage from either seasonal temperature or precipitation (drought) variations, although irrigated systems are generally sensitive to cold temperature events only. In southern NSW, depth of ponded water is used to regulate plant temperature. The rice panicle is kept under water, where during the night it remains warmer than the surrounding air temperature. Rice leaf blast epidemics may be related to temperature as well, leading to model simulations of yield losses due to current global warming trends (Luo et al., 1998). Crop damage research using remote sensing can be simplified into two different categories: those that measure the source of damage (direct measurement), and those that measure the effect of the source of damage (indirect measurement). In certain situations, the source of crop damage can be measured directly from remote sensing. These studies include assessment of salinisation, weed infestations, and waterlogging.

Saline soils have been shown to have higher reflectance in both the visible and NIR wavelengths than non-saline soils from both ground and satellite radiometric measurements (Rao et al., 1995) allowing for mapping of salinisation (Sharma and Bhargava, 1988, Dwivedi, 1992, Wiegand et al., 1996, Yu-liang, 1996). It should be noted, though, that successful mapping of salinisation results only when salt scalds are clearly visible on the soil surface. This is not the case for all salt affected soils, which means that salinisation is not always easily mapped from remote sensing. Detection of water from dry land is uncomplicated spectrally leading to the classification of potentially waterlogged areas (Sharma and Bhargava, 1988). However, these areas should be integrated with an accurate land use map as permanent water bodies and natural wetlands could quite easily be included in the classification otherwise. Ground-based electromagnetic (EM-31) surveys (Hume et al., 1999) and airborne radiometrics (Cook et al., 1996) have also proven useful for mapping soil attributes.

Weed infestations can also be directly measured with remote sensing if the weeds are prevalent prior to crop emergence (Lamb, 2000). In this case, the living vegetation (weeds) is easily identifiable from the background soil. These infestations are also detectable after crop emergence if their spectra are significantly different from the background soil and crop cover (Lamb et al., 1999). It was found that weed detection requires high spatial resolution and is sensitive to spatial registration and weed density, which can all affect the accuracy of the results (Lamb et al., 1999). This spatial resolution requirement limits the usefulness of most current satellite platforms for weed detection and is why most of these projects make use of airborne systems.

In most cases, however, it is impossible to measure the source of the damage directly using remote sensing. For example, the measurement of ducks or insects in a rice paddock is not feasible, whereas, the effects of these pests can potentially be detected through loss of above ground biomass or yield. In this sense, crop damage is almost always associated with crop yield, and therefore, there is much overlap with the previous section. This means that any of the multiple techniques that have been developed for estimating yield from remotely sensed data, can then be associated with losses due to various forms of crop damage. In specific cases, however, the indirect measurement is not necessarily associated with monitoring yield or biomass losses from a particular event (e.g., an insect infestation), but rather is an attempt to detect possible plant stress (Lelong et al., 1998) over a less discrete period of time.
It is well established that physiological stress in crops is related to incident reflectance from crop canopies and that this altered reflectance can be detected with remote sensing (Knipling, 1970, Thenkabail et al., 1994b). These changes in reflectance are prominent in both the visible and NIR regions of the EMS. An increase in leaf reflectivity in the visible light portion as a response to stress is caused by the metabolic sensitivity of chlorophyll resulting in less efficient absorption of light (increased reflection) (Knipling, 1970). NIR reflectance of leaves is more variable at the onset of stress (Knipling, 1970), but has been shown to increase steadily as stress continues in the form of dehydration (Gausman, 1974). NIR also looses distinctiveness in its spectral signature, especially in the water absorption regions, as the curve flattens (Gausman, 1974). These individual leaf responses are often seen at the crop level as losses in leaf area or foliar density in conjunction with increases in shadow and non-foliar surfaces (Knipling, 1970) if the stress continues long enough. Stresses due to dehydration will not generally be a problem in the irrigated areas of NSW, but will affect the surrounding dry-land agricultural systems. Also, the irrigated crops should have similar physiological/spectral responses to other stresses (e.g., disease). In either case, the major objective of such crop damage detection is the link to management decisions in a timely and cost effective manner in order to operate agricultural systems more efficiently

This is why so much of the current crop damage literature concentrates on precision agriculture. Precision agriculture is a process that heavily relies on observations describing within-paddock variability in order to implement dynamic management decisions that may result in higher crop production (Cook and Bramley, 1998). Another key component of precision agriculture is its reliance on technology such as Global Positioning Systems (GPS) and Variable Application Technology (VAT) (Cook and Bramley, 1998). These technologies, along with remote sensing, make the implementation of the procedure possible.

Critical spatial input to precision agriculture decision support systems include crop yield and soil properties. Several studies have shown how to generate these spatially variable inputs through analysis of ground samples (Bailey et al., 2001, Gandah et al., 2000), however, most prove to be both time and cost consuming, especially over large areas (Viscarra Rossel and McBratney, 1998). These limitations have made remote sensing an attractive alternate source of this spatially variable observational data (Moran et al., 1997, Lamb, 2000).

In general terms, the main benefits to the use of remote sensing in precision agriculture are associated with its strengths in mapping both time and space. Seasonal (temporal) and spatial variability of environmental characteristics, mainly crop and soil conditions (Moran et al., 1997), can be mapped efficiently with remote sensing. These data can then be used to implement timely management actions as the crops develop. Current limitations to the use of remote sensing in precision agriculture are mainly related to technology. Current satellite systems have fixed spectral bands, too coarse spatial resolutions, inadequate repeat cycles, and long delivery times (Moran et al., 1997). Airborne sensors overcome some of the spectral and spatial resolution problems associated with satellites, but these systems generate additional problems with radiometric and geometric correction making it hard to monitor large areas (Moran et al., 1997) as well as adding difficulty and time to image processing. Both systems (satellite and airborne) also tend to accumulate high costs associated with the large time-series of inter annual data that has to be acquired. Moran et al. (1997) discuss in detail the potential role of remote sensing in precision agriculture.

Benefits of precision agriculture not necessarily associated with remote sensing are increased efficiency, reduced risk of environmental hazards, and improved process control (Cook and Bramley, 1998). The limitations include cost and complexity of the system, training of users, and delivery of appropriate input data in a timely manner. As such, the potential usefulness of remote sensing in crop damage management, specifically for implementation in precision agriculture is high. However, the limitations of precision agriculture currently make it non-operational at a regional scale. As seen from various paddock-level studies, the process has merit, but is not yet routinely viable for most farmers or land managers. This is likely to change in the near future as some of these limitations disappear due to advances in technology and research methodologies.

3.5 Water Use and m_a Mapping

Knowing crop water use, both temporally and spatially, in irrigated areas allows water delivery to match agricultural demands. Crop water use can be determined either by crop specific empirical models or use of process based models. Both of these approaches require access to ground based meteorological data, usually with a daily time step. To perform either modelling approach over large irrigation areas will require access to a network of meteorological stations with a suitable spatial density and extent to characterise the spatial variation in observed meteorological variables.

A commonly used method to estimate crop water use is application of the Food and Agriculture Organisation (FAO) Guidelines for prediction of crop water use (Smith et al., 1991, Doorenbos and Pruitt, 1977, Frere and Popov, 1979). Class A Pan evaporation can be measured if such facilities exist and are properly maintained, or can be estimated from commonly observed meteorological data. The FAO method requires modification of crop coefficients; it does not require remotely sensed data. However, knowledge of different land uses are required to extend this approach spatially. Remote sensing is seen to be a timely and cost effective way to provide these maps to GIS models annually. A derivate of this method have been used by Kirk et al. (1999) to provide estimates of crop water use for farm-level irrigation water use efficiency for irrigation areas in South Australia. The location of paddocks was obtained from a GIS data base of paddock level cropping.

Many other water balance/plant growth models have been developed which require meteorological data, and soil and generic plant parameters to successfully run. These models can range from empirical to process based, however, as with the FAO approach, suitable maps of land use is required to take these estimates into the spatial domain. Given the issue of advection in irrigated environments (Humphreys et al., 1994a) the areal weighted up-scaling approach using GIS strata may introduce large errors in the regional crop water use calculation.

Regional remotely sensed T_s observations can be used in a resistance energy balance model (REBM, Monteith and Unsworth, 1990) to provide estimates of the $\boldsymbol{H}$. This allows the $\boldsymbol{\lambda E}$ to be estimated as the residual, obtained by rearranging Equ'n 1. REBMs require effective models for the resistances and other terms (including $\boldsymbol{R_n}$ and $\boldsymbol{G}$). Kustas and Norman (1996) review the use of remote sensing to estimate $\boldsymbol{\lambda E}$. REBMs describe the fluxes between soil and plant canopies and the atmosphere in terms of 'resistances'. The models are 'closed' by specified meteorological inputs defined at a reference height above the surface and some assumptions or models defined at or below the earth's surface. To solve a REBM at the time T_s is observed, several surface and near surface meteorological variables (either measured or estimated) are required. These include air temperature (T_a), relative humidity (h) or vapor pressure (e_a), solar radiation ($\boldsymbol{R_s}$) and wind speed (u) at some reference height above the surface and over a time limit of sufficient length for equilibrium to be assumed. The feasibility and effectiveness of providing such data when only standard daily meteorological data are available has been demonstrated (McVicar and Jupp, 1999a). REBMs also need surface information such as albedo and LAI (or percent vegetation cover) which may be obtained either from reflective remotely sensed data or *in situ* measurements.

During detailed experiments, when specific time-of-day meteorological data are collected, progress in REBM parameter formulation has been made. However, such experiments are limited to short times for small areas (e.g. Kustas et al., 1989, Kustas et al., 1990, Zhang et al., 1995, Raupach et al., 1997, Flerchinger et al., 1998). For operational regional irrigation water supply management, obtaining REBM estimates of fluxes at isolated points is of minimal use. Either model inputs or model outputs need to be spatially interpolated to the entire region of interest. The issue of 'interpolate then calculate (IC)' or 'calculate then interpolate (CI)' has received attention to spatially estimate moisture deficit (Stein et al., 1991), moisture availability (McVicar and Jupp, 1999b, McVicar and Jupp, 2000), global solar radiation (Bechini et al., 2000), and soil properties (Heuvelink and Pebesma, 1999, Bosma et al., 1994).

To avoid running a REBM at every point in the agricultural system, a number of methods have been developed. The methods are based on the link of the energy balance and water use. For example, leaf temperature can increase when the leaf is green, as stomatal closure to minimise water loss by transpiration results in a decreased $\boldsymbol{\lambda E}$. At the same time, due to the requirement of the energy balance, $\boldsymbol{H}$ usually increases.

Idso *et al.* (1981), Jackson (1982) and Jackson *et al.* (1981, 1983) pioneered methods using daytime T_s for assessing crop health and establishing irrigation scheduling at the field scale. These techniques, culminated in the development of the Crop Water Stress Index (CWSI) which has the form CWSI = 1 - m_{ad}, where the subscript d means the daily integral. The Normalised Difference Temperature Index (NDTI) directly maps m_a regionally. The high spatial density present in remotely sensed data is exploited by using this data as a covariate to spatially interpolate the NDTI in a CI approach (McVicar and Jupp, 1999b, McVicar and Jupp, 2000).

A number of approaches based on the negative correlation between T_s and NDVI (denoted T_s-NDVI) to provide a measure of environmental stress have developed. Goetz (1997) reported that the negative correlation between T_s and NDVI, observed at several scales (25 m^2 to 1.2 km^2), was largely due to changes in vegetation cover and soil moisture. For complete canopies, the slope of the T_s versus NDVI plot has been related to canopy resistance (Sellers, 1987, Hope, 1988, Nemani and Running, 1989b). Nemani et al. (1993) found the slope of T_s versus NDVI plot to be negatively correlated to a crop-moisture index. These empirical relationships defined from the slope of T_s-NDVI plots need to be acquired over a range of NDVI and T_s conditions, to allow the 'warm edge' to be calculated with any confidence. It also should be noted that the slope of T_s-NDVI plots is empirically related to m_a. For two different images, with different meteorological conditions, resulting in different atmospheric resistances, the relationship between the slope of T_s-NDVI plot and m_a can be non-unique.

Advances are currently being made that use the T_s versus NDVI plot combined with process based understanding to provide a more mechanistic interpretation of the remotely sensed data. There are two methods currently being put forward. The first, a progression of the slope of the T_s versus NDVI plot approach, describes the data as falling into a 'triangle' (Carlson et al., 1990, Carlson et al., 1994, Price, 1990, Gillies and Carslon, 1995, Gillies et al., 1997). The second, the Vegetation Index / Temperature Trapezoid (VITT) promotes the idea of data falling into a trapezoid (Moran et al., 1994, Moran et al., 1996, Yang et al., 1997). The VITT is an evolution of the CWSI. The unifying feature for both the 'triangle' and the 'trapezoid' is the appearance of the 'warm edge', the line between the dry bare soil point and the fully vegetated point (for the trapezoid its the fully vegetated stressed point). For any point, if both the vegetation cover and T_s can be measured, then m_a can be empirically defined for that image. The top side of the 'trapezoid' may collapse, forming a 'triangle', as a function of the remotely sensed spatial scale and the timing of acquisition during the growth cycle.

The main limiting factor for use of thermal remote sensing for operational management of irrigated areas is the repeat characteristics of remotely sensed data with suitable spatial resolution. Another difficultly in many irrigated rice growing areas is the measurement and specification of lateral energy flow (advection) from surrounding non-irrigated areas, which is usually not represented in REBMs. For example, in an advective environment, Dunin (1991, pp 45) states "the discrepancy (between lysimeter and Bowen ratio values of $\boldsymbol{\lambda E_a}$) reached 80 Wm^{-2} by noon and persisted in excess of 100 Wm^{-2} throughout the afternoon". This illustrates the difficulty in estimating $\boldsymbol{\lambda E_a}$ using models that don't include components for lateral flow of energy (as in most REBMs).

3.6 Water Use Efficiency

With population growth comes a decrease in living space (or global land area per capita) and thus, increased competition for land and water resources (Lund and Iremonger, 2000). These higher demands on water and land, among other things, result in a need for more efficient use of the resources. Assessing and improving Water Use Efficiency (WUE) in agricultural systems, then, will become exceedingly important as the demand for food production on these limited resources continues to increase. Water savings from these systems, in particular, could affect the regional and global water balances as the area of land placed under agriculture is expected to increase considerably in the near future (Lund and Iremonger, 2000).

WUE of the irrigated agricultural lands of southern NSW has become increasingly relevant, as the Snowy Water Inquiry into the environmental issues associated with the corporatisation of the Snowy Mountains Hydro-electric Scheme was initiated in 1998. Ninety-nine percent of the runoff from the Snowy Mountains is diverted inland to generate hydroelectric power, and irrigation water for agriculture (Gale, 1999). The Scheme provides an average of 1200 Gl per year to the Murray River and 1210 Gl per year to the Murrumbidgee (Gale, 1999). This water is used in the production of approximately A$1.5 billion per year worth of irrigated agricultural products (Gale, 1999).

Benefits of the scheme include electricity, increased urban water supply, recreation, dilution of salinity in the Murray River, stock watering, displacement of an estimated 5 million tonnes per year of carbon dioxide emissions to the atmosphere (the amount that would be produced if the same quantity of electricity was generated by coal-fired thermal power stations) (Gale, 1999), as well as providing the water for, among other crops, a 1.5 million tonnes of yield per year rice industry. Environmental impacts from the changes in flow and discharge regimes across these rivers include reduction in channel size, increases in groundwater levels, salinisation, erosion of river banks, changes in wildlife habitat, weed invasion, and a reduction of water quality (Gale, 1999).

The Snowy Water Inquiry was established by the Commonwealth, New South Wales and Victorian governments to determine how to best balance the environmental, electricity and irrigation interests of the region (Gale, 1999). Environmental issues of the inquiry included impacts on rivers, river channels, ecology, the lower Snowy River, and environmental flows (Gale, 1999). Economic issues included impacts on electricity generation, impacts on agriculture, and impacts on recreation and tourism (Gale, 1999). Social issues include the alteration of social values of heritage, culture, and community (Gale, 1999).

The final report delivered on 23 October 1998 presented 23 options for resolution, of which, composite option D was supported. Option D involves increasing the flow of the Snowy River below Jindabyne Dam to 15% of the pre-Scheme mean discharge (Gale, 1999). This option was chosen because it would provide environmental gains at minimal cost to agricultural, hydroelectric, and different government agencies (Gale, 1999). Whether the environmental gains of this option would be significant (Seddon, 1999, Erskine et al., 1999), or cost to agriculture minimal (Watson, 1999, Hoare, 1999) has been questioned. Also, it is questionable whether reducing one environmental problem is worth adding to another as increasing environmental flows in the Snowy River will translate into greater greenhouse emissions from subsequent thermal-powered electricity generation (Seaton, 1999).

The outcome of this inquiry will, no doubt, require irrigation managers to be more efficient with the water that is supplied to them. This increased WUE may occur through a combination of technology and changing management practices, and will most likely necessitate an analysis of WUE at different scales. Regional-scale analysis of WUE would be most helpful in defining gross efficiency relationships and help target areas that could potentially benefit from changes in management practice (McVicar et al., 2000). With this analysis, the baseline WUE could be determined and possibly whether or not plant breeding since the 1980's or 1990's has influenced WUE on a regional level. As such, regional WUE will be the focus of the following discussion.

Stanhill (1986) defined water use efficiency (WUE) both hydrologically and physiologically. Hydrological WUE is the ratio of evapotranspiration to the water potentially available for plant growth. It is expressed as a unitless percentage or fraction (0–1). Physiological WUE is a measure of the amount of plant growth for a given volume of water. The definition of physiological WUE can be defined for different measures of 'plant growth' and 'volume of water'. Turner (1986) notes that care is needed when defining WUE. For example, in some studies 'plant growth' has been measured in units of net biomass (including roots) (Ritchie, 1983, Tanner and Sinclair, 1983, Turner, 1997) or crop yield (Tanner and Sinclair, 1983, Turner, 1997). In various previous studies the units of 'volume of water' is either the total transpiration (Tanner and Sinclair, 1983, Turner, 1997, French and Schultz, 1984a, French and Schultz, 1984b), total evapotranspiration (Ritchie, 1983, Tanner and Sinclair, 1983, Turner, 1997), total water input (Sinclair et al., 1984), or the amount of precipitation plus initial soil water at the time of sowing (French and Schultz, 1984a, French and Schultz, 1984b).

Sinclair et al. (1984) introduced different time scales for several definitions of WUE. The temporal scales ranged from an instant, through daily, to a growing season. Intrinsically linked to a range in temporal scale is a range of spatial scale (Table 2), which can extend from a single leaf, through canopy, to field, farm level, and regional assessment. The scales are linked: for example, leaf WUE (in the order of 10's of cm^2) will usually be measured over a short time (e.g., a second to daily). On the other hand, farm-level and regional WUE (in the order of 10's to 1000's of km^2) will usually be measured over a longer time (e.g., a growing season). To date, there has been very little research focussing on farm level (Kirk et al., 1999, Tuong and Bhuiyan, 1999) or regional assessment (Schuepp et al., 1987, McVicar et al., 2000) of WUE.

TABLE 2: DIFFERENT SPATIAL SCALES OF PHYSIOLOGICAL WUE, CORRESPONDING TEMPORAL SCALES, AND SOME COMMON UNITS IN WHICH THEY ARE MEASURED.

Spatial scale	Temporal scale	Units
single leaf (10's of cm^2)	second – day – growth stage	$mgCO_2/gH_2O$ or μmol/mmol
canopy (1 to 10's of m^2)	second – day – growth stage	$mgCO_2/gH_2O$ or μmol/mmol
field (100's of m^2 to 10's of ha)	day – growth stage – season	mg/gH_2O or kg/ha.mm
farm (1 to 100's of ha)	growth stage – season – year	kg/ha.mm or tonne/km^2.TL
region (10's to 1000's of km^2)	season – year	kg/ha.mm or tonne/km^2.TL

Single-leaf WUE is commonly defined as the net CO_2 uptake per unit of transpiration. On a continuous basis – that is, at any instant within a day – it is expressed as the ratio of leaf net photosynthetic rate to leaf transpiration rate, or at the daily time-step it is expressed as the ratio of daytime CO_2 uptake to daytime transpiration. Canopy (or community) WUE is commonly defined as the ratio of the net CO_2 assimilation of crop canopy to crop canopy transpiration – that is, the ratio of the canopy CO_2 flux to the H_2O flux for canopy transpiration. Canopy WUE can be expressed continuously and at a daily time-scale, as above, and can also be calculated for specific growth stages. Field WUE can be defined as the ratio of grain yield per unit of water, hence the units would be kg/ha.mm; however the ‘plant growth’ and ‘water’ terms need to be explicitly defined. Regional WUE has similar definitions to field WUE except it applies to a larger area.

There are three main approaches available to assessing WUE regionally:
1. Remote sensing, which can estimate both evapotranspiration and CO2 exchange of large areas at specific times of day, can be used to present regional WUE estimates at specific times (Schuepp et al., 1987). This requires access to much ancillary ground based meteorological data and presents difficulties in extending this from the field sites to regions. There are also difficulties in temporally extending the data from specific times to entire growing seasons;
2. Using remotely sensed based estimates of yield and of λE. However, as has been discussed previously there is difficulty in estimating yield in irrigated environments where LAI is high. Methods exist for providing daily λE maps from specific time-of-day T_s observations, however, reliable estimates of λE are difficult to obtain in highly advective irrigated agricultural environments. Taking isolated daily observations to estimate growing season λE would again require access to ground based meteorological data; and
3. Regional databases of yield, precipitation, irrigation and initial soil water can be developed allowing an ‘input-output’ (Zoebl, 2000) definition of regional WUE (McVicar et al., 2000). ‘Input’ is the water available over the crop growing season and ‘output’ is the yield. This approach is well suited to spatial assessment of regional WUE. Coupling this approach with canopy and field-scale process understanding will allow identification of the regional data bases that are required to develop` a more process constrained regional WUE estimation.

For many of the variables that influence WUE, data are usually not regionally available, and hence they cannot be included in the development of regional WUE estimates. Factors varying both spatially and temporally include:
1. crop varieties, which includes plant breeding (Khush, 1987, Brennan et al., 1994, Brennan et al., 1997) and genetic modifications;
2. soil conditions (Christen and Skehan, 1999, So and Ringrose-Voase, 2000), including soil erosion, sodicity, salinisation, and waterlogging;
3. climate change (Loaiciga et al., 1996), including precipitation patterns and CO_2 concentration (Hunsaker et al., 2000);
4. agricultural practices, including the use of fertilisers (Anbumozhi et al., 1998), irrigation management (Pereira, 1999), crop rotation (So and Ringrose-Voase, 2000), planting density, and the use of mulch (Tolk et al., 1999) to reduce soil evaporation.

These interactions are complex, and largely unknown at the regional scale of southern NSW, making absolute measures of WUE difficult. The ‘input-output’ GIS definition of regional WUE, however, is most suited to the analysis of relative trends, both spatially and temporally. Such a GIS would rely on access to data recorded by irrigation companies and the RiceGrower’s Cooperative, all who are industry participants in the CRC for sustainable rice production.

4 LIMITATIONS OF REMOTE SENSING IN RICE-BASED AGRICULTURE

Remote sensing is a valuable source of data in rice-based agriculture, especially when regional-scale issues are the concern. However, there are some limitations of remote sensing regarding agricultural applications including:

1. Data availability;
2. Length of recording period;
3. Limited mapping capability;
4. Requirement of expertise and computer facilities; and
5. Cost

A very brief discussion of these topics follows.

4.1 Data Availability

Non-availability of remotely sensed data may be due, among other things, to rocket launch, satellite operational problems or political issues. Events such as these will continue to occur and operational systems must pre-determine the influence of any data stream becoming non-available. Satellites have different repeat cycles (Table 1). This means that certain satellites will provide only 2 images per month, for example, whereas others can produce an image every

day. This can have considerable impact on agricultural applications since repeat cycle characteristics of satellites are one of the determinants for forecasting yield with the ∫NDVI approach, for example. Also, these high repeat cycle platforms usually have lower spatial resolution, impacting the appropriateness of its data to fine-scale applications. Another major cause of optical data unavailability is cloud coverage. This could be problematic when timing of image acquisition is critical as in crop identification. This may be avoided by using either microwave or airborne remote sensing. However, processing of these data can be a problem due to the scientific expertise needed for analysis of microwave data and the data management associated with large area airborne acquisitions.

4.2 Length of Recording Period

The period over which remotely sensed data are available has little impact on agricultural applications. Most agricultural research and management is interested in current or future concerns. However, for the few agricultural projects dealing with historical context, the recording period could be restricting. Remote sensing, unlike meteorological data, has not been recorded for a century. The longest time series currently available of free to ground remotely sensed data covering Australia at monthly time steps is AVHRR at 15 years. LANDSAT data has been recorded since 1972, but can be quite expensive when acquiring a long time series

4.3 Limited Mapping Capability

The limited capability of remote sensing to map certain agricultural variables has been discussed in detail in section 3. Specifically, remote sensing is limited to mapping single crops to slightly higher than 90% accuracy when multi-date, multi-sensor, or GIS data is also used. Remote sensing alone, however, is more limited at discrimination of multiple crops to this level of accuracy. Yield predictions are also limited from remotely sensed data because of the saturation problem discussed in section 3.3. Remote sensing is also often unable to detect direct sources of crop damage (section 3.4). These limitations may decrease in the future as spatial and spectral resolutions, and repeat cycles increase. However, the resolutions needed for this type of detection will probably not be available for some time. Finally, although remote sensing from satellites has high potential for providing spatially variable data needed for precision agriculture, the limitations of fixed spectral bands, too coarse spatial resolutions, inadequate repeat cycles, and long delivery times (Moran et al., 1997) make it non operational at this time.

4.4 Requirement of Expertise and Computer Facilities

Agricultural research with remote sensing requires a moderate level of expertise and computing support. The processing of remotely sensed data requires an investment in training of personnel as well as adequate computers and data storage. Computer *hardware* and *software* are important, but perhaps more important is *mindware* to ensure the correct use of remote sensing to assist in the decision making process.

4.5 Cost

Cost of remote sensing projects can be prohibitive, especially when fine detail is needed over large areas. However, this depends on the application and the appropriate remote sensing platform. Much agricultural research has been accomplished with free NOAA AVHRR data. Yet, AVHRR data is not appropriate for many applications. With the launch of the TERRA satellite in 1999, came a new era in remote sensing: no cost moderate to fine resolution data. The spatial resolution of the ASTER and MODIS sensors is appropriate for many different agricultural applications. However, some remote sensing data is currently expensive for large areas of land (e.g., 1,000 km^2), including very high spatial resolution data (e.g., IKONOS or airborne systems), and hyperspectral data.

The cost estimates for specified common commercially available remotely sensed data is summarised in Table 3 by each irrigation area in southern NSW. These estimates are intended to give potential users of remotely sensed data a general idea of the costs involved, and by no means are meant as a precise cost. Values in this table are most useful when viewed in the relative context of prices by sensor and by irrigation area. Figure 5 provides the spatial context of the extent of two popular sensors ((E)TM and SPOT) for the study site.

TABLE 3: COST ESTIMATES FOR SPECIFIED REMOTELY SENSED DATA

Irrigation Area	TM	ETM	SPOT PAN	SPOT X	IKONOS[1]
CIA[2]	$750	$600	$1,530	$1,430	$11,172
MIA[3]	$2,375	$2,200	$7,600	$6,800	$63,468
MIL[4]	$3,025	$2,400	$9,500	$8,500	$97,176

1 IKONOS column represents the price for either 1m panchromatic or 4m multispectral data.

2 CIA estimates for TM and ETM, were based on one prices for one ninth scene (up to 3,600 sq km) (map oriented price). SPOT PAN and SPOT X costs are based on one half scene (up to 1,800 sq km) (map oriented price), and IKONOS costs are based on price per area (931 sq km * $12 AUS/sq km = $11,172).

3 MIA cost estimates for TM and ETM are based on one full scene and one ninth scene (full scene is path image price and ninth scene is map oriented price). SPOT PAN and SPOT X costs are based on 4 full scenes (path image price), and IKONOS estimates are based on price per area (5,289 sq km * $12 AUS/sq km = $63,468).

4 MIL estimates for TM and ETM are based on one full scene, one ninth scene and one small scene (path image price for full and map oriented price for ninth and small). SPOT costs are based on 5 full scenes (path image price), and IKONOS costs are based on price per area (8,098 sq km * $12 AUS/sq km = $97,176).

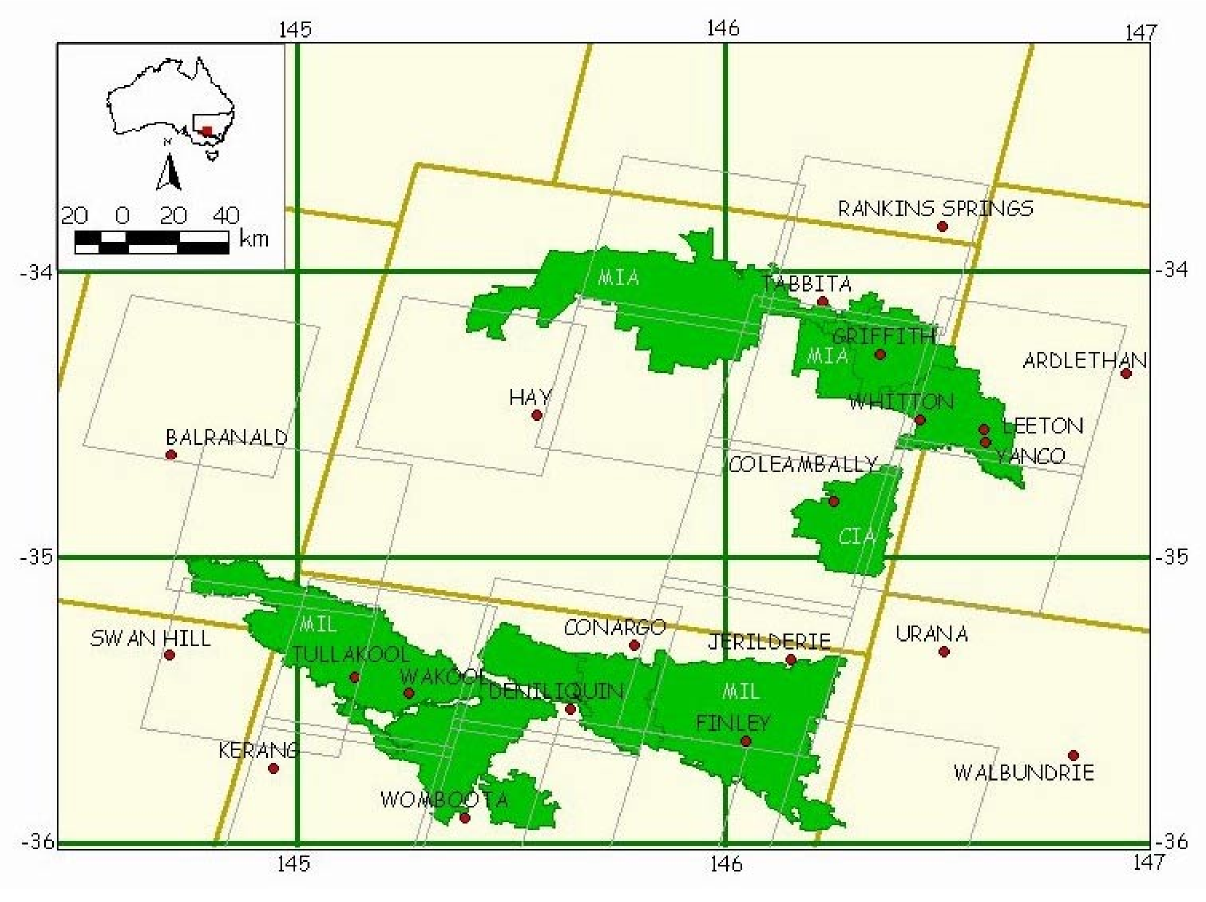

Figure 5. SPOT and (E)TM satellite 'footprints' for the study site. TM footprints are the large rectangles represented with heavy lines. Selected SPOT footprints are the smaller rectangles represented with light lines. The ETM image on the front cover is for the top centre ETM 'footprint'.

5 CONCLUSIONS

Remote sensing is a valuable source of data that can provide a synoptic perspective critical for understanding biophysical relationships at a regional scale. Because of this, remote sensing has been a popular tool readily accepted into agricultural research and management. Since the launch of LANDSAT-1 in 1972, scientists and managers have been using remote sensing for crop identification, area measurements, yield prediction, and crop damage assessment. More recently, remote sensing has been seen as a source of spatial data for precision agriculture, although currently these systems are not widely operational. Remote sensing along with climate data and GIS technology can also be used for modelling λE and m_a for regional analyses of water use efficiency. As fine to moderate remotely sensed data is now available free of cost, the use of remote sensing in agricultural management is more appealing than ever. The current availability of very fine spatial resolution data as well as the anticipation of hyperspectral data also broadens the scope of remote sensing and its usefulness regarding agricultural management.

The common thread in crop type identification applications is an attempt to achieve greater accuracy from remotely sensed data. In order to accomplish this, researchers have looked into various alternatives. Most of these alternatives have to do with the type of sensor (i.e., optical or microwave), number of images (i.e., single-date or multi-date), timing of the imagery, or processing technique. Although these characteristics certainly make a difference in the results attained, the trait that seemed to be most relevant was an appropriate use of the spatial data in combination with process understanding. Appropriate ground validation data and accuracy assessment is also critical for testing and reporting results.

Area measurement of crops from remote sensing is largely straightforward. However, positional accuracy and pixel size can both affect the results attained in this procedure. The scale of the remote sensing data, therefore, should be appropriate for the level of accuracy desired. This means that clear management objectives should be outlined prior to areal measurements. Individual areal measurements may vary more widely and be less accurate than summed (overall) measurements because errors of underestimation are offset by errors of overestimation when a number of areas are added together.

Strong correlations can exist between single date VI's or multi-date cumulative or integral VI's and crop yield. This relationship can provide early estimates of crop yield as well as allow for the assessment of crop damage. However, these remote sensing techniques are fairly limited because VI's tend to saturate rather quickly. They also are heavily dependant on the timing of the imagery acquired in relation to the physiological stage of the crop and can be influenced greatly by a lack of data due to things like cloud cover. The alternative crop simulation models can also provide fairly good predictions of crop yield alone. These models, however, usually simulate crop yield well for 'normal' seasons, whereas variations from normal can create rather large errors. This is why using remote sensing to recalibrate simple growth models is often preferred over using either approach separately.

Thermal remote sensing can be linked with meteorological data, through resistance energy balance models, to estimate crop water use. For operational management of irrigated areas, having access to data with the required spatial resolution at the required frequency is an issue. Mapping m_a prior to the irrigating of furrow or drip irrigated crops (i.e. those other than rice in southern NSW), would allow irrigation amounts to be better targeted. Regional estimates of WUE appear to be best developed using a regional GIS data 'input-output' definition. Required data sets include rainfall, water application, and yields. These data sets are measured in NSW; for some, the main issue is their availability.

6 ACKNOWLEDGEMENTS

This research was funded by the Cooperative Research Centre for Sustainable Rice Production and CSIRO Land and Water.

7 REFERENCES

Anbumozhi, V., Yamaji, E. and Tabuchi, T. (1998). Rice crop growth and yield as influenced by changes in ponding water depth, water regime and fertigation level. *Agricultural Water Management* **37,** 241-253.

Aplin, P., Atkinson, P. M. and Curran, P. J. (1998). Identifying missing field boundaries to increase the accuracy of per-field classification of fine spatial resolution satellite sensor imagery. 27th International Symposium on Remote Sensing of Environment, Tromso, Norway, 399-402.

Atkinson, P. M. and Lewis, P. (2000). Geostatistical classification for remote sensing: an introduction. *Computers and Geosciences* **26,** 361-371.

Badhwar, G. D. (1984a). Automatic corn-soybean classification using Landsat MSS data. I. Near-harvest crop proportioin estimation. *Remote Sensing of Environment* **14,** 15-29.

Badhwar, G. D. (1984b). Automatic corn-soybean classification using Landsat MSS data. II. Early season crop proportioin estimation. *Remote Sensing of Environment* **14,** 31-37.

Badhwar, G. D., Carnes, J. G. and Austin, W. W. (1982). Use of Landsat-derived temporal profiles for corn-soybean feature extraction and classification. *Remote Sensing of Environment* **12,** 57-79.

Badhwar, G. D. and Henderson, K. E. (1985). Application of Thematic Mapper data to corn and soybean development stage estimation. *Remote Sensing of Environment* **17,** 197-201.

Bailey, J. S., Wang, K., Jordan, C. and Higgins, A. (2001). Use of precision agriculture technology to investigate spatial variability in nitrogen yields in cut grassland. *Chemosphere* **42,** 131-140.

Barbosa, P. M., Casterad, M. A. and Herrero, J. (1996). Performance of several Landsat 5 Thematic Mapper (TM) image classification methods for crop extent estimates in an irrigation district. *International Journal of Remote Sensing* **17,** 3665-3674.

Baret, F. and Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment* **35,** 161-173.

Barrs, H. D. and Prathapar, S. A. (1994). An inexpensive and effective basis for monitoring rice areas using GIS and remote sensing. *Australian Journal of Experimental Agriculture* **34,** 1079-1083.

Barrs, H. D. and Prathapar, S. A. (1996). Use of satellite remote sensing to estimate summer crop areas in the Coleambally Irrigation Area, NSW. CSIRO, Division of Water Resources Consultancy Report 96/17, pp. 35.

Bechini, L., Ducco, G., Donatelli, M. and Stein, A. (2000). Modelling, interpolation and stochastic simulation in space and time of global solar radiation. *Agriculture, Ecosystems and Environment* **81,** 29-42.

Benedetti, R. and Rossini, S. (1993). On the use of NDVI profiles as a tool for agricultural statistics: the case study of wheat yield estimate and forecast in Emilia Romagna. *Remote Sensing of Environment* **45,** 311-326.

Bosma, W. J. P., Marinussen, M. P. J. C. and van der Zee, S. E. A. T. M. (1994). Simulation and areal interpolation of reactive solute transport. *Geoderma* **62,** 217-231.

Brennan, J. P., Lewin, L. G., Marshall, G. R. and Reinke, R. F. (1994). An economic assessment of rice breeding in New South Wales. *Australian Journal of Experimental Agriculture* **34,** 889-896.

Brennan, J. P., Singh, I. P. and Lewin, L. G. (1997). Identifying international rice research spillovers in New South Wales. *Agricultural Economics* **17,** 35-44.

Burgess, W. and Pairman, D. (1997). Bidirectional reflectance effects in NOAA AVHRR data. *International Journal of Remote Sensing* **18,** 2815-2825.

Campbell, J. B. (1981). Spatial correlation effects upon accuracy of supervised classification of land cover. *Photogrammetric Engineering and Remote Sensing* **47,** 355-363.

Cao, Z. H. and Hu, Z. Y. (2000). Copper contamination in paddy soils irrigated with wastewater. *Chemosphere* **41,** 3-6.

Carlson, T. N., Gillies, R. R. and Perry, E. M. (1994). A method to make use of thermal infrared temperatures and NDVI measurements to infer soil water content and fractional vegetation cover. *Remote Sensing Reviews* **9,** 161-173.

Carlson, T. N., Perry, E. M. and Schmugge, T. J. (1990). Remote Estimation of Soil Moisture Availability and Fractional Vegetation Cover for Agricultural Fields. *Agricultural and Forest Meteorology* **52,** 45-69.

Casanova, D., Epema, G.F. and Goudriaan, J. (1998). Monitoring rice reflectance at field level for estimating biomass and LAI. *Field Crops Research* **55,** 83-92.

Chavez, P. S. (1988). An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data. *Remote Sensing of Environment* **24,** 459-479.

Choudhury, B. J. and DiGirolamo, N. E. (1995). Quantifying the effect of emissivity on the relation between AVHRR split window temperature difference and atmospheric precipitable water over land surface. *Remote Sensing of Environment* **54,** 313-323.

Christen, E. W. and Skehan, D. (1999). Design and management of subsurface drainage for improved water quality: a field investigation. CSIRO Land and Water Technical Report 6/99, pp. 65.

Congalton, R. G. (1991). A Review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* **37,** 35-46.

Cook, S. E. and Bramley, R. G. V. (1998). Precision agriculture - opportunities, benefits and pitfalls of site-specific crop management in Australia. *Australian Journal of Experimental Agriculture* **38,** 753-763.

Cook, S. E., Corner, R. J., Groves, P. R. and Grealish, G. J. (1996). Use of airborne gamma radiometric data for soil mapping. *Australian Journal of Soil Research* **34,** 183-194.

Curran, P. J., Dungan, J. L. and Gholz, H. L. (1992). Seasonal LAI in Slash Pine Estimated with Landsat TM. *Remote Sensing of Environment* **39,** 3-13.

Deering, D. W. (1989). Field measurements of bidirectional reflectance: In *Theory and Application of Optical Remote Sensing* (Ed, Asrar, G.) John Wiley and Sons, New York, pp. 14-65.

Doorenbos, J. and Pruitt, W. O. (1977). Guidelines for predicting crop water requirements: In *FAO Irrigation and Drainage Paper*, Vol. No. 24 Rome, pp. 34.

Dunin, F. X. (1991). Extrapolation of 'point' measurements of evaporation: some issues of scale. *Vegetatio* **91,** 39-47.

Dwivedi, R. S. (1992). Monitoring and the study of the effects of image scale on delineation of salt-affected soils in the Indo-Gangetic plains. *International Journal of Remote Sensing* **13,** 1527-1536.

Ennaffah, B., Bouslim, F., Benkirane, R., Ouazzani Touhami, A. and Douira, A. (1997). *Helminthosporium spiciferum*, foliar parasite of rice in Morocco. *Agronomie* **17,** 299-300.

Erskine, W. D., Turner, L. M., Terrazzolo, N. and Warner, R. F. (1999). Recovery of the Snowy River: politics and river rehabilitation. *Australian Geographical Studies* **37,** 330-336.

Eymard, L. and Taconet, O. (1995). The methods for inferring surface fluxes from satellite data, and their use for atmosphere model validation. *International Journal of Remote Sensing* **16,** 1907-1930.

Fang, H. L., Wu, B. F., Liu, H. Y. and Huang, X. (1998). Using NOAA AVHRR and Landsat TM to estimate rice area year-by-year. *International Journal of Remote Sensing* **19,** 521-525.

Fischer, A., Kergoat, L. and Dedieu, G. (1997). Coupling satellite data with vegetation functional models: review of different approaches and perspective suggested by the assimilation strategy. *Remote Sensing Reviews* **15,** 283-303.

Fischer, A., Louahala, S., Maisongrande, P., Kergoat, L. and Dedieu, G. (1996). Satellite data for monitoring, understanding and modelling of ecosystem functioning: In *Global Change and Terrestrial Ecosystems* (Eds, Walker, B. and Steffen, W.) Cambridge University Press, Cambridge, pp. 566-591.

Flerchinger, G. N., Kustas, W. P. and Weltz, M. A. (1998). Simulating surface energy fluxes from radiometric surface temperatures for two arid vegetation communities using the SHAW model. *Journal of Applied Meteorology* **37,** 449-460.

Fox Strand, J. (2000). Some agrometeorological aspects of pest and disease management for the 21st century. *Agricultural and Forest Meteorology* **103,** 73-82.

French, R. J. and Schultz, J. E. (1984a). Water use efficiency of wheat in a Mediterranean-type environment. I. The relation between yield, water use and climate. *Australian Journal of Agricultural Research* **35,** 743-64.

French, R. J. and Schultz, J. E. (1984b). Water use efficiency of wheat in a Mediterranean-type environment. II. Some limitations to efficiency. *Australian Journal of Agricultural Research* **35,** 765-775.

Frere, M. and Popov, G. F. (1979). Agrometeorological crop monitoring and forecasting. FAO FAO Plant Production and Protection Paper 17, pp. 64.

Gale, S. J. (1999). The Snowy Water Inquiry: food, power, politics and the environment. *Australian Geographical Studies* **37,** 301-313.

Gandah, M., Stein, A., Brouwer, J. and Bouma, J. (2000). Dynamics of spatial variability of millet growth and yields at three sites in Niger, West Africa and implications for precision agriculture research. *Agricultural Systems* **63,** 123-140.

Gausman, H. W. (1974). Leaf reflectance of near-infrared. *Photogrammetric Engineering and Remote Sensing* **40,** 183-191.

Gillies, R. R., Carlson, T. N., Cui, J., Kustas, W. P. and Humes, K. S. (1997). A verification of the ‘triangle’ method for obtaining surface soil water content and energy fluxes from the remote measurements of the Normalized Difference Vegetation Index

(NDVI) and surface radiant temperature. *International Journal of Remote Sensing* **18,** 3145-3166.

Gillies, R. R. and Carslon, T. N. (1995). Thermal remote sensing of surface soil water content with partial vegetation cover for incorporating into climate models. *Journal of Applied Meteorology* **34,** 745-756.

Gong, P., Ledrew, E. F. and Miller, J. R. (1992). Registration-noise reduction in difference images for change detection. *International Journal of Remote Sensing* **13,** 773-779.

Harrison, B. A. and Jupp, D. L. B. (1989) *Introduction to remotely sensed data,* CSIRO Publications.

Harrison, B. A., Jupp, D. L. B., Ibrahim, A. A. and Angus, J. F. (1984). The use of Landsat data for monitoring growth of irrigated crops. Third Australasian Remote Sensing Conference, Queensland, 36-43.

Heuvelink, G. B. M. and Pebesma, E. J. (1999). Spatial aggregation and soil process modelling. *Geoderma* **89,** 47-65.

Hoare, C. P. (1999). Murrumbidgee Irrigation Limited. *Australian Geographical Studies* **37,** 322-324.

Hobbs, T. J. (1997). Atmospheric correction of NOAA-11 NDVI data in the arid rangelands of Central Australia. *International Journal of Remote Sensing* **18,** 1051-1058.

Honghui, L., Xiaohuan, Y. and Naibin, W. (1999). Remote sensing based estimation system for winter wheat yield in North China Plain. *Chinese Geographical Journal* **9,** 40-48.

Hope, A. S. (1988). Estimation of wheat canopy resistance using combined remotely sensed spectral reflectance and thermal observations. *Remote Sensing of Environment* **24,** 369-383.

Huete, A. R. (1987). Soil and sun angle interactions on partial canopy spectra. *International Journal of Remote Sensing* **8,** 1307-1317.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* **25,** 295-309.

Huete, A. R. and Escadafal, R. (1991). Assessment of biophysical soil properties through spectral decomposition techniques. *Remote Sensing of Environment* **35,** 149-159.

Huete, A. R., Hua, G., Qi, J., Chehbouni, A. and Leeuwen, W. J. D. v. (1992). Normalization of multidirectional red and NIR reflectances with the SAVI. *Remote Sensing of Environment* **41,** 143-154.

Huete, A. R. and Jackson, R. D. (1987). Suitability of spectral indices for evaluating vegetation characteristics on arid rangelands. *Remote Sensing of Environment* **23,** 213-232.

Huete, A. R., Jackson, R. D. and Post, D. F. (1985). Spectral response of a plant canopy with different soil backgrounds. *Remote Sensing of Environment* **17,** 37-53.

Huete, A. R. and Warrick, A. W. (1990). Assessment of vegetation and soil water regimes in partial canopies with optical remotely sensed data. *Remote Sensing of Environment* **32,** 115-167.

Hume, I. H., Beecher, H. G. and Dunn, B. W. (1999). EM to estimate groundwater recharge from rice growing. Rural Industries Research and Development Corporation RIRDC RIRDC-98, pp. 37.

Humphreys, E., Meyer, W. S., Prathapar, S. A. and Smith, D. J. (1994a). Estimation of evapotranspiration from rice in southern New South Wales: a review. *Australian Journal of Experimental Agriculture* **34,** 1069-1078.

Humphreys, L., Van Der Lely, A., Muirhead, W. and Hoey, D. (1994b). The development of on-farm restrictions to minimise recharge from rice in New South Wales. *Australian Journal of Soil and Water Conservation* **7,** 11-20.

Hunsaker, D. J., Kimball, B. A., Pinter, P. J. J., Wall, G. W., LaMorte, R. L., Adamsen, F. J., Leavitt, S. W., Thompson, T. L., Matthias, A. D. and Brooks, T. J. (2000). CO_2 enrichment and soil nitrogen effects on wheat evapotranspiration and water use efficiency. *Agricultural and Forest Meteorology* **104,** 85-105.

Idso, S. B., Jackson, R. D., Pinter Jr., P. J., Reginato, R. J. and Hatfield, J. L. (1981). Normalizing the stress-degree-day parameter for environmental variability. *Agricultural Meteorology* **24,** 45-55.

Inoue, Y., Moran, M. S. and Horie, T. (1998). Analysis of spectral measurements in paddy field for predicting rice growth and yield based on a simple crop simulation model. *Plant Production Science* **1,** 269-279.

Islam, Z. and Karim, A. N. M. R. (1997). Whiteheads associated with stem borer infestation in modern rice varieties: an attempt to resolve the dilemma of yield losses. *Crop Protection* **16,** 303-311.

Jackson, R. D. (1982). Soil moisture inferences from thermal infra-red measurements of vegetation temperatures. *IEEE Transactions on Geoscience and Remote Sensing* **20,** 282-286.

Jackson, R. D., Hatfield, J. L., Reginato, R. J., Idso, S. B. and Pinter Jr., P. J. (1983). Estimation of daily evapotranspiration from one time-of-day measurements. *Agricultural Water Management* **7,** 351-362.

Jackson, R. D., Idso, S. B., Reginato, R. J. and Pinter Jr., P. J. (1981). Canopy temperature as a crop water stress indicator. *Water Resources Research* **17,** 1133-1138.

Jensen, J. R. (1986) *Introductory digital image processing: A remote sensing perspective,* Prentice-Hall, Englewood Cliffs.

Karimi, M. M. and Siddique, K. H. M. (1992). The relationship between grain and yield of spring wheat and rainfall distribution in Western Australia using regression models. *Iran Agricultural Research* **11,** 1-23.

Kaufman, Y. J. and Tanre, D. (1992). Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote Sensing* **30,** 261-270.

Khush, G. S. (1987). Rice breeding: Past, present and future. *Journal of Genetics* **66,** 195-216.

Kimes, D. S. (1983). Dynamics of directional reflectance factor distributions for vegetation canopies. *Applied Optics* **22,** 1364-1372.

Kirk, J. A., Miles, M. W. and Ralph, R. L. (1999). Monitoring and assessment of change in irrigation districts. Final report for the development of a GIS for Riverland Irrigation Districts. Information and Data Analysis Branch, Planning SA, Department for Transport, Urban Planning and the Arts and the Central Irrigation Trust Final Report pp. 289.

Knipling, E. B. (1970). Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. *Remote Sensing of Environment* **1,** 155-159.

Kurosu, T., Fujita, M. and Chiba, K. (1997). The identification of rice fields using multi-temporal ERS-1 C band SAR data. *International Journal of Remote Sensing* **18,** 2953-2965.

Kustas, W. P., Choudhury, B. J., Moran, M. S., Reginato, R. J., Jackson, R. D., Gay, L. W. and Weaver, H. L. (1989). Determination of sensible heat flux over sparse canopy using thermal infrared data. *Agricultural and Forest Meteorology* **44,** 197-216.

Kustas, W. P., Moran, M. S., Jackson, R. D., Gay, L. W., Duell, L. F. W., Kunkel, K. E. and Matthias, A. D. (1990). Instantaneous and daily values of the surface energy balance over agricultural fields using remote sensing and a reference field in an arid environment. *Remote Sensing of Environment* **32,** 125-141.

Kustas, W. P. and Norman, J. M. (1996). Use of remote sensing for evapotranspiration monitoring over land. *Hydrological Sciences Journal des Sciences Hydrologiques* **41,** 495-516.

Lamb, D. W. (2000). The use of qualitative airborne multispectral imaging for managing agricultural crops - a case study in south-eastern Australia. *Australian Journal of Experimental Agriculture* **40,** 725-738.

Lamb, D. W., Weedon, M. M. and Rew, L. J. (1999). Evaluating the accuracy of mapping weeds in seedling crops using airborne digital imaging: Avena spp. in seedling triticale. *Weed Research* **39,** 481-492.

Langran, G. (1992) *Time in geographic information systems,* Taylor and Francis, London.

Le Hegarat-Mascle, S., Quesney, A. and Vidal-Madjar, D. (2000). Land cover discrimination from multitemporal ERS images and multispectral Landsat images: a study case in an agricultural area in France. *International Journal of Remote Sensing* **21,** 435-456.

Le Toan, T., Ribbes, F., Wang, L., Floury, N., Ding, K., Kong, J. A., Fujita, M. and Kurosu, T. (1997). Rice crop mapping and monitoring using ERS-1 data based on experiment and modeling results. *IEEE Transactions on Geoscience and Remote Sensing* **35,** 41-56.

Lelong, C. C. D., Pinet, P. C. and Poilve, H. (1998). Hyperspectral imaging and stress mapping in agriculture: A case study on wheat in Beauce (France). *Remote Sensing of Environment* **66,** 179-191.

Leprieur, C., Kerr, Y. H. and Pichon, J. M. (1996). Critical assessment of vegetation indices from AVHRR in a semi-arid environment. *International Journal of Remote Sensing* **17,** 2549-2563.

Li, Y., Demetriades-Shah, T. H., Kanemasu, E. T., Shultis, J. K. and Kirkham, M. B. (1993). Use of second derivatives of canopy reflectance for monitoring prairie vegetation over different soil backgrounds. *Remote Sensing of Environment* **44,** 81-87.

Loaiciga, H. A., Valdes, J. B., Vogel, R., Garvey, J. and Schwarz, H. (1996). Global warming and the hydrologic cycle. *Journal of Hydrology* **174,** 83-127.

Lund, H. G. and Iremonger, S. (2000). Omissions, commissions, and decisions: the need for integrated resource assessments. *Forest Ecology and Management* **128,** 3-10.

Luo, Y., Teng, P. S., Fabellar, N. G. and TeBeest, D. O. (1998). Risk analysis of yield losses caused by rice leaf blast associated with temperature changes above and below for five Asian countries. *Agriculture, Ecosystems and Environment* **68,** 197-205.

Maas, S. J. (1988). Use of remotely-sensed information in agricultural crop growth models. *Ecological Modelling* **41,** 247-268.

Maas, S. J. (2000). Linear mixture modeling approach for estimating cotton canopy ground cover using satellite multispectral imagery. *Remote Sensing of Environment* **72,** 304-308.

Martin, R. D. J. and Heilman, J. L. (1986). Spectral reflectance patterns of flooded rice. *Photogrammetric Engineering and Remote Sensing* **52,** 1885-1890.

Maselli, F., Conese, C., Petkov, L. and Gilabert, M. (1992). Use of NOAA-AVHRR NDVI data for environmental monitoring and crop forecasting in the Sahel. Preliminary Results. *International Journal of Remote Sensing* **13,** 2743-2749.

McCloy, K. R., Smith, F. R. and Robinson, M. R. (1987). Monitoring rice areas using Landsat MSS data. *International Journal of Remote Sensing* **8,** 741-749.

McVicar, T. R. and Jupp, D. L. B. (1998). The current and potential operational uses of remote sensing to aid decisions on Drought Exceptional Circumstances in Australia: A Review. *Agricultural Systems* **57,** 399- 468.

McVicar, T. R. and Jupp, D. L. B. (1999a). Estimating one-time-of-day meteorological data from standard daily data as inputs to thermal remote sensing based energy balance models. *Agricultural and Forest Meteorology* **96,** 219-238.

McVicar, T. R. and Jupp, D. L. B. (1999b). Using AVHRR data and meteorological surfaces to spatially interpolate moisture availability in the Murray-Darling Basin. CSIRO Land and Water Technical Report 50/99 pp. 45.

McVicar, T. R. and Jupp, D. L. B. (2000). Using covariates to spatially interpolate moisture availability in the Murray-Darling Basin: a novel use of remotely sensed data. *Remote Sensing of Environment* **(In Print),** .

McVicar, T. R., Jupp, D. L. B., Reece, P. H. and Williams, N. A. (1996a). Relating LANDSAT TM vegetation indices to in situ leaf area index measurements. CSIRO, Division of Water Resources Technical Memorandum 96.14, pp. 80.

McVicar, T. R., Jupp, D. L. B. and Williams, N. A. (1996b). Relating AVHRR vegetation indices to LANDSAT TM leaf area index estimates. CSIRO, Division of Water Resources Technical Memorandum 96.15, pp. 33.

McVicar, T. R., Walker, J., Jupp, D. L. B., Pierce, L. L., Byrne, G. T. and Dallwitz, R. (1996c). Relating AVHRR vegetation indices to in situ leaf area index. CSIRO, Division of Water Resources Technical Memorandum 96.5, pp. 54.

McVicar, T. R., Zhang, G., Bradford, A. S., Wang, H., Dawes, W. R., Zhang, L. and Lingtao, L. (2000). Developing a spatial information system to monitor regional agricultural water use efficiency for Hebei Province on the North China Plain. CSIRO Land and Water Technical Report 31/00 pp. 55.

Medhavy, T. T., Sharma, T., Dubey, R. P., Hooda, R. S., Mothikumar, K. E., Yadav, M., Manchanda, M. L., Ruhal, D. S., Khera, A. P. and Jarwal, S. D. (1993). Crop classification accuracy as influenced by training strategy, data transformation and spatial resolution of data. *Journal of the Indian Society of Remote Sensing* **21,** 21-28.

Mitasova, H., Mitas, L., Brown, W. M., Gerdes, D. P., Kosinovsky, I. and Baker, T. (1995). Modelling spatially and temporally distributed phenomena: new methods and tools for GRASS GIS. *International Journal of Geographic Information Science* **9,** 433-446.

Monteith, J. L. and Unsworth, M. H. (1990) *Principles of Environmental Physics,* Edward Arnold, London.

Moody, A. (1997). Using landscape spatial relationships to improve estimates of land-cover area from coarse resolution remote sensing. *Remote Sensing of Environment* **64,** 202-220.

Moran, M. S., Clarke, T. R., Inoue, Y. and Vidal, A. (1994). Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sensing of Environment* **49,** 246-263.

Moran, M. S., Inoue, Y. and Barnes, E. M. (1997). Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of Environment* **61,** 319-346.

Moran, M. S., Rahman, A. F., Washburne, J. C., Goodrich, D. C., Weltz, M. A. and Kustas, W. P. (1996). Combining the Penman-Monteith equation with measurements of surface temperature and reflectance to estimate evaporation rates of semiarid grassland. *Agricultural and Forest Meteorology* **80,** 87-109.

Murthy, C. S., Thiruvengadachari, S., Raju, P. V. and Jonna, S. (1996). Improved ground sampling and crop yield estimation using satellite data. *International Journal of Remote Sensing* **17,** 945-956.

Nemani, R. R., Pierce, L. L., Running, S. W. and Goward, S. N. (1993). Developing satellite derived estimates of surface moisture status. *Journal of Applied Meteorology* **32,** 548-557.

Nemani, R. R. and Running, S. W. (1989a). Estimation of regional surface resistance to evapotranspiration from NDVI and thermal-IR AVHRR data. *Journal of Applied Meteorology* **28,** 276-284.

Nemani, R. R. and Running, S. W. (1989b). Testing a theoretical climate-soil-leaf area hydrologic equilibrium of forests using satellite data and ecosystem simulation. *Agricultural and Forest Meteorology* **44,** 245-260.

Okamoto, K. and Kawashima, H. (1999). Estimation of rice -planted area in the tropical zone using a combination of optical and microwave satellite sensor data. *International Journal of Remote Sensing* **20,** 1045-1048.

Panigrahy, S., Chakraborty, M., Sharma, S. A., Kundu, N., Ghose, S. C. and Pal, M. (1997). Early estimation of rice area using temporal ERS-1 synthetic aperture radar data-a case study for the Howrah and Hughly districts of West Bengal, India. *International Journal of Remote Sensing* **18,** 1827-1833.

Panigrahy, S., Manjunath, K. R., Chakraborty, M., Kundu, N. and S.Parihar, J. (1999). Evaluation of RADARSAT standard beam data for identification of potato and ice crops in India. *ISPRS Journal of Photogrammetry and Remote Sensing* **54,** 254-262.

Patel, N. K., Ravi, N., Navalgund, R. R., Dash, R. N., Das, K. C. and Patnaik, S. (1991). Estimation of rice yield using IRS-1A digital data in coastal tract of Orissa. *International Journal of Remote Sensing* **12,** 2259-2266.

Pax-Lenney, M. and Woodcock, C. E. (1997a). The effect of spatial resolution on the ability to monitor the status of agricultural lands. *Remote Sensing of Environment* **61,** 210-220.

Pax-Lenney, M. and Woodcock, C. E. (1997b). Monitoring agricultural lands in Egypt with multitemporal Landsat TM imagery: how many images are needed? *Remote Sensing of Environment* **59,** 522-529.

Pereira, L. S. (1999). Higher performance through combined improvements in irrigation methods and scheduling: a discussion. *Agricultural Water Management* **40,** 153-169.

Perry, C. R., Jr. and Lautenschlager, L. F. (1984). Functional equivalence of spectral vegetation indices. *Remote Sensing of Environment* **14,** 169-182.

Peuquet, D. J. (1994). It's about time: A conceptual framework for the representation of spatiotemporal dynamics in geographic information systems. *Annals of the Association of American Geographers* **84,** 441-461.

Peuquet, D. J. (1995). An event-based spatiotemporal data model (ESTDM) for temporal analysis of geographical data. *International Journal of Geographic Information Science* **9,** 7-24.

Pinter Jr., P. J., Jackson, R. D., Idso, S. B. and Reginato, R. J. (1981). Multidate spectral reflectance as predictors of yield in water stressed wheat and barley. *International Journal of Remote Sensing* **2,** 43-48.

Prata, A. J., Caselles, V., Coll, C., Ottle, C. and Sobrino, J. (1995). Thermal remote sensing of land surface temperature from satellites: Current status and future prospects. *Remote Sensing Reviews* **12,** 175-224.

Price, J. C. (1990). Using spatial context in satellite data to infer regional scale evapotranspiration. *IEEE Transactions on Geoscience and Remote Sensing* **28,** 940-948.

Qi, J., Huete, A. R., Moran, M. S., Chehbouni, A. and Jackson, R. D. (1993). Interpretation of vegetation indices derived from multi-temporal SPOT images. *Remote Sensing of Environment* **44,** 89-101.

Quarmby, N., Milnes, M., Hindle, T. and Silleos, N. (1993a). The use of multi-temporal NDVI measurements from AVHRR data for crop yield estimation and prediction. *International Journal of Remote Sensing* **14,** 199-210.

Quarmby, N. A., Milnes, M., Hindle, T. L. and Silleos, N. (1993b). The use of multi-temporal NDVI measurements from AVHRR data for crop yield estimation and prediction. *International Journal of Remote Sensing* **14,** 199-210.

Quarmby, N. A., Townshend, J. R. G., Settle, J. J., White, K. H., Milnes, M., Hindle, T. L. and Silleos, N. (1992). Linear mixture modelling applied to AVHRR data for crop area estimation. *International Journal of Remote Sensing* **13,** 415-425.

Rao, B. R. M., Ravi Sankar, T., Dwivedi, R. S., Thammappa, S. S. and Venkataratnam, L. (1995). Spectral behaviour of salt-affected soils. *International Journal of Remote Sensing* **16,** 2125-2136.

Rasmussen, M. S. (1992). Assessment of millet yields and production in northern Burkina Faso using integrated NDVI from AVHRR. *International Journal of Remote Sensing* **13,** 3431-3442.

Rasmussen, M. S. (1997). Operational yield forecast using AVHRR NDVI data: reduction of environmental and inter-annual variability. *International Journal of Remote Sensing* **18,** 1059-1077.

Rasmussen, M. S. (1998a). Developing simple, operational, consistent NDVI-vegetation models by applying environmental and climatic information: Part I: Assessment of net primary productivity. *International Journal of Remote Sensing* **19,** 97-117.

Rasmussen, M. S. (1998b). Developing simple, operational, consistent NDVI-vegetation models by applying environmental and climatic information: Part II: Crop yield assessment. *International Journal of Remote Sensing* **19,** 119-139.

Raupach, M. R., Finkele, K. and Zhang, L. (1997). SCAM: A soil-canopy-atmosphere model: description and comparisons with field data. CSIRO Centre for Environmental Mechanics Technical Report 132, pp. 81.

Reinke, R. F., Lewin, L. G. and Williams, R. L. (1994). Effect of sowing time and nitrogen on rice cultivars of differing growth duration in New South Wales 1. Yield and yield components. *Australian Journal of Experimental Agriculture* **34,** 933-938.

Ribbes, F. and Toan, T. l. (1999). Rice field mapping and monitoring with RADARSAT data. *International Journal of Remote Sensing* **20,** 745-765.

Richards, J. A. (1996). Classifier performance and map accuracy. *Remote Sensing of Environment* **57,** 161-166.

Richardson, A. J. and Wiegland, C. L. (1977). Distinguishing vegetation from soil background information. *Photogrammetric Engineering and Remote Sensing* **43,** 1541-1552.

Ritchie, J. T. (1983). Efficient water use in crop production: generality of relations between biomass production and evapotranspiration: In *Limitations to Efficient Water Use in Crop Production* (Eds, Taylor, H. M., Jordan, W. R. and Sinclair, T. R.) American Society of Agronomy, Madison, pp. 29-44.

Rosenthal, W. D., Hammer, G. L. and Butler, D. (1998). Predicting regional grain sorghum production in Australia using spatial data and crop simulation modelling. *Agricultural and Forest Meteorology* **91,** 263-274.

Savary, S., Srivastava, R. K., Singh, H. M. and Elazegui, F. A. (1997). A characterisation of rice pests and quantification of yield losses in the rice-wheat system of India. *Crop Protection* **16,** 387-398.

Schuepp, P. H., Desjardins, R. L., Macpherson, J. I., Boisvert, J. and Austin, L. B. (1987). Airborne determination of regional water use efficiency and evapotranspiration: present capabilities and initial field tests. *Agricultural and Forest Meteorology* **41,** 1-19.

Seaton, P. L. (1999). Sins of the fathers, opportune for the sons. *Australian Geographical Studies* **37,** 328-329.

Seddon, G. S. (1999). Saving the throwaway river. *Australian Geographical Studies* **37,** 314-321.

Sellers, P. J. (1985). Canopy reflectance, photosynthesis and transpiration. *International Journal of Remote Sensing* **6,** 1335-1372.

Sellers, P. J. (1987). Canopy reflectance, photosynthesis and transpiration. II. The role of biophysics in the linearity of their interdependence. *Remote Sensing of Environment* **21,** 143-183.

Senanayake, N., Naylor, R. E. L., De Datta, S. K. and Thomson, W. J. (1994). Variation in development of contrasting rice cultivars. *Journal of Agricultural Science, Cambridge* **123,** 35-39.

Sharma, R. C. and Bhargava, G. P. (1988). Landsat imagery for mapping saline soils and wet lands in north-west India. *International Journal of Remote Sensing* **9,** 39-44.

Sinclair, T. R., Tanner, C. B. and Bennett, J. M. (1984). Water-use efficiency in crop production. *BioScience* **34,** 36-40.

Singh, A. (1989). Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing* **10,** 989-1003.

Slater, P. N. and Jackson, R. D. (1982). Atmospheric effects on radiation reflected from soil and vegetation as measured by orbital sensors using various scanning directions. *Applied Optics* **21,** 3923- 3931.

Smith, M., Allen, R., Monteith, J. L., Perrier, A., Santos Pereira, L. and Segeren, A. (1991). Expert consultation on procedures for revision of FAO guidelines for prediction of crop water requirements. FAO Land and Water Development Division pp. 54.

Smith, R. C. G., Adams, J., Stephens, D. J. and Hick, P. T. (1995). Forecasting Wheat Yield in a Mediterranean-type environment from the NOAA Satellite. *Australian Journal of Agricultural Research* **46,** 113-125.

So, H. B. and Ringrose-Voase, A. J. (2000). Management of clay soils for rainfed lowland rice-based cropping systems: an overview. *Soil and Tillage Research* **56,** 3-14.

Stanhill, G. (1986). Water use efficiency. *Advances in Agronomy* **39,** 53-85.

Stein, A., Staritsky, I. G., Bouma, J., Van Eijsbergen, A. C. and Bgegt, A. K. (1991). Simulation of moisture deficits and areal interpolation by universal cokriging. *Water Resources Research* **27,** 1963-1973.

Story, M. and Congalton, R. G. (1986). Accuracy assessment: A user's perspective. *Photogrammetric Engineering and Remote Sensing* **52,** 397-399.

Stuckens, J., Coppin, P. R. and Bauer, M. E. (2000). Integrating contextual information with per-pixel classification for improved land cover classification. *Remote Sensing of Environment* **71,** 282-296.

Tanner, C. B. and Sinclair, T. R. (1983). Efficient water use in crop production: research or re-search ?: In *Limitations to Efficient Water Use in Crop Production* (Eds, Taylor, H. M., Jordan, W. R. and Sinclair, T. R.) American Society of Agronomy, Madison, pp. 1-28.

Tennakoon, S. B., Murty, V. N. and Eiumnoh, A. (1992). Estimation of cropped area and grain yield of rice using remote sensing. *International Journal of Remote Sensing* **13,** 427-439.

Thenkabail, P. S., Smith, R. B. and De Pauw, E. (2000). Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sensing of Environment* **71,** 158-182.

Thenkabail, P. S., Ward, A. D. and Lyon, J. G. (1994a). Landsat-5 Thematic Mapper models of soybean and corn crop characteristics. *International Journal of Remote Sensing* **15,** 49-61.

Thenkabail, P. S., Ward, A. D., Lyon, J. G. and Merry, C. J. (1994b). Thematic Mapper vegetation indices for determining soybean and corn growth parameters. *Photogrammetric Engineering and Remote Sensing* **60,** 437-442.

Tian, G. L. (1989). Spectral signatures and vegetation indices of crops. CSIRO Division of Water Resources Divisional Report 89/4, pp. 42.

Tolk, J. A., Howell, T. A. and Evett, S. R. (1999). Effect of mulch, irrigation, and soil type on water use and yield of maize. *Soil and Tillage Research* **50,** 137-147.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* **8,** 127-150.

Tucker, C. J., Elgin, J. H., McMurtrey, J. E. and Fan, C. J. (1979). Monitoring corn and soybean crop development with hand-held radiometer spectral data. *Remote Sensing of Environment* **8,** 237-248.

Tuong, T. P. and Bhuiyan, S. I. (1999). Increasing water-use efficiency in rice production: farm-level perspectives. *Agricultural Water Management* **40,** 117-122.

Turner, N. C. (1986). Crop water deficits: a decade of progress. *Advances in Agronomy* **39,** 1-51.

Turner, N. C. (1997). Further progress in crop water relations. *Advances in Agronomy* **58,** 293-338.

van Leeuwen, W. J. D., Huete, A. R., Walthail, C. L., Prince, S. D., Begue, A. and Roujean, J. L. (1997). Deconvolution of remotely sensed spectral mixtures for retrieval of LAI, fAPAR and soil brightness. *Journal of Hydrology* **188-189,** 697-724.

Van Niel, T. G. and McVicar, T. R. (2000). Assessing and improving positional accuracy and its effects on areal estimation at Coleambally Irrigation Area. Cooperative Research Centre for Sustainable Rice Production Technical Report 101/00, pp. 101.

Viscarra Rossel, R. A. and McBratney, A. B. (1998). Soil chemical analytical accuracy and costs: implications from precision agriculture. *Australian Journal of Experimental Agriculture* **38,** 765-775.

Watson, A. S. (1999). Murray Irrigation Limited. *Australian Geographical Studies* **37,** 325-327.

Wiegand, C., Anderson, G., Lingle, S. and Escobar, D. (1996). Soil salinity effects on crop growth and yield - illustration of an analysis and mapping methodology for sugarcane. *Journal of Plant Physiology* **148,** 418-424.

Woodcock, C. E. and Strahler, A. H. (1987). The factor of scale in remote sensing. *Remote Sensing of Environment* **21,** 311-332.

Yang, X., Zhou, Q. and Melville, M. (1997). Estimating local sugarcane evapotranspiration using LANDSAT TM image and a VITT concept. *International Journal of Remote Sensing* **18,** 453-459.

Yu-liang, Q. (1996). An application of aerial remote sensing to monitor salinization at Xinding Basin. *Advances in Space Research* **18,** 133-139.

Zhang, L., Lemeur, R. and Goutorbe, J. P. (1995). A one-layer resistance model for estimating regional evapotranspiration using remote sensing data. *Agricultural and Forest Meteorology* **77,** 241-261.

Zoebl, D. (2000). Patterns of input-output relations in agro-ecosystems. *Agriculture, Ecosystems and Environment* **79,** 233-244.

Rice CRC .... of growing importance

About the Rice CRC

The Rice CRC is strengthening the rice industry's research and development (R&D) effort through its focus on sustainability.

Its mission is to increase the environmental, economic and social sustainability of the Australian Rice Industry and enhance its international competitiveness through both strategic and tactical research and the implementation of practical, cost-effective programs.

The Centre uses the intellectual resources of some of Australia's peak R&D organisations to target five main program areas:

1. Sustainability of Natural Resources in Rice-Based Cropping Systems
2. Sustainable Production Systems
3. Genetic Improvement for Sustainable Production
4. Product and Process Development
5. Education, Skills Development and Techology Transfer

Rice CRC core participants are Charles Sturt University, NSW Agriculture, CSIRO, Department of Land and Water Conservation, University of Sydney, Ricegrowers' Co-operative Ltd and the Rural Industries Research and Development Corporation.

CRC AUSTRALIA

Established and supported under the Australian Government's
Cooperative Research Centres Program

Cooperative Research Centre for Sustainable Rice Production
C/- Yanco Agricultural Institute
Private Mail Bag
Yanco, NSW 2703
Telephone: (02) 6951 2713
Facsimile: (02) 6951 2533
Email: crc.rice@agric.nsw.gov.au
Website: www.ricecrc.org