SATELLITE BASED YIELD - WATER USE RELATIONSHIPS OF PERENNIAL HORTICULTURAL CROPS

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A thesis submitted in total fulfilment of the requirements of the degree of Doctor of Philosophy

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Abstract

Drought and several seasons of historically low water allocations in the period, 1996 – 2010, created demands for reliable data relating yield and water requirement of perennial high value horticultural crops grown in the Murray Darling Basin of Australia.

To cope with drought, irrigators were required to decide whether to buy or sell water on the water market, and to answer basic agronomic questions concerning the viability of crops and the amount of water to be applied to crops. The drought established the demand for detailed data describing the dependence of yield on water supply. This study focused on apple, peach, nectarine, pear, apricot, plum and wine grape crops grown in the Goulburn Valley Irrigation Region of northern Victoria.

Doorenbos and Kassam (1979) produced a simple yield-water use relationship where relative yield is related to relative crop water use. Relative yield is measured as actual yield/$Y_{\text{MAX}}$, where $Y_{\text{MAX}}$ is maximum attainable yield. Relative water use is measured as $\text{ET}/ET_{\text{MAX}}$, where ET is actual evapotranspiration and $ET_{\text{MAX}}$ is evapotranspiration for standard conditions with no water stress (Crop Water Requirement; CWR).

This thesis applied the Doorenbos and Kassam model, subject to the condition that increases in yield are constrained to the region, $\text{ET} \leq \text{CWR}$. The approach required estimates of $Y_{\text{MAX}}$ and CWR for each crop. Implementations of the Doorenbos and Kassam model are commonly based on the assumption that regional crop-specific estimates of $Y_{\text{MAX}}$ and CWR apply.

However, the major variables in the Doorenbos - Kassam model (actual yield, ET, $Y_{\text{MAX}}$ and CWR) depend on crop vegetation cover. The yield-water use relationship of each crop/field therefore depends on the site-specific vegetation cover.

Vegetation cover can be estimated using on-ground measures of fractional radiation interception ($f$) and/or derived from Normalised Difference Vegetation Index (NDVI) measured by satellites. NDVI data facilitate the extension of field scale findings to regional and industry scales. A model of vegetation cover was assumed whereby vegetation cover was maintained at its maximum value over a prolonged period in the
midseason which encompasses yield processes and crop water use (Palmer et al. 2002).

Yield can be estimated using the radiation use efficiency approach of Monteith (1977), whereby yield is related to growing season radiation interception. CWR depends on evaporative demand and the crop coefficient ($K_c$). Many reports have shown that $K_c$ varies directly with vegetation cover. Field studies related yield to intercepted growing season radiation using the vegetation cover model applied to commercial crops grown in the Goulburn Valley. Estimates of $Y_{\text{MAX}}$ were derived from the upper range of yield observations in those data.

CWR was derived from analysis of satellite-based estimates of ET (METRIC; Allen et al. 2005a) and their relationship with NDVI (Tasumi et al. 2005a). The basal crop coefficient ($K_{cb}$) estimates of Tasumi et al. (2005a) were used in the derivation of CWR estimates in this study. In situ measures of $f$ were linearly related to midseason satellite-derived measures of NDVI. Relationships conformed to responses reported for broad acre crops. Intra-seasonal variation in NDVI was also assessed, and found to conform with the adopted model for vegetation cover.

The thesis successfully combined field studies and remote sensing approaches to produce water production functions for major horticultural crops grown in the Goulburn Valley. Satellite-derived measures of NDVI were found to provide an affordable, repeatable and reliable alternative to impractical ground-based observations of vegetation cover.

This study implies a central role for NDVI in water productivity of perennial high value horticultural crops. Maps of NDVI thereby provide estimates of $Y_{\text{MAX}}$ and CWR for all major horticultural crops in a region and irrigators can therefore access the data required for irrigation scheduling and undertake objective water management strategies based on the range of crop options available to the grower. The water production functions provide the ability to diagnose low water productivity providing direction for improved land and water management outcomes at farm and industry scales.
Declaration

I certify that this thesis is less than 100,000 words in length (exclusive of tables, figures, bibliographies and appendices) and contains completely my own work except for the literature and data cited from the various sources given in the list of references. The content of this dissertation has not been published and submitted for another degree at any university.

Mark Glenn O’Connell
August 2011
Statements

This study was undertaken while I was employed by the Department of Primary Industries in my capacity as a research scientist and based at Tatura, Victoria, Australia during the period: September 2007 – August 2011.

I was a member of a team working on the project, ‘Measurement, Monitoring and Reporting Systems for improved management of Farm and Regional Water Resources in Australia’, supported by Department of Primary Industries, Victoria, Department of Sustainability and Environment, Victoria, National Water Commission, and the CRC for Irrigation Futures. The project team consisted of spatial science and remote sensing specialists, hydrologists and agronomists.

Author contributions to project publications relevant to the thesis but not forming part of it:


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Dr Desmond Whitfield from Department of Primary Industries, Tatura and Professor David Connor and Associate Professor Gregory Dunn from The University of Melbourne were the supervisors of this thesis. I would like to thank Des, David and Greg for providing valuable comment and support in the preparation of this thesis. I particularly thank Des for his advice and guidance throughout my research, and David and Greg for their assistance, encouragement and continuous improvement of the thesis. Thanks to Helen and Mark Toman for the use of premises to conduct periodic meetings with Des and David during the course of the study.

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Finally, I would like to thank my wife Sharon and my children: Andrew, Cameron, Alyse and Benjamin for their support.
Abbreviations

ARVI  Atmospherically Resistant Vegetation Index
ATV   All Terrain Vehicle
CIMEC Calibration using Inverse Modelling at Extreme Conditions
CRC   Cooperative Research Centre
CWR   Crop water requirement
CWS   Crop water supply
CWSI  Crop Water Stress Index
CWU   Crop water use
DD    Deep drainage
DMC   Dry matter content
ET    Crop evapotranspiration
ET_o  Short reference crop evapotranspiration
ET_R  Tall reference crop evapotranspiration
ET_REF Reference crop evapotranspiration
EVI   Enhanced Vegetation Index
f     Fractional radiation interception
f_0900 Fractional radiation interception at 0900 h
f_1230 Fractional radiation interception at 1230 h
f_1600 Fractional radiation interception at 1600 h
FAO   Food and Agriculture Organisation of the United Nations
f_MAX Maximum fractional radiation interception
g     Gram
G     Soil heat flux
GEMI  Global Environment Monitoring Index
GIS   Geographic Information System
GL    Gigalitre
h     Harvest index
H     Sensible heat flux
Ha    Hectare
I     Irrigation
K_c   Crop coefficient
K_eb  Basal crop coefficient
K_e   Soil evaporation coefficient
K_s   Stress coefficient
k_y   Evaporation-yield extinction coefficient
LIDAR Light Detection and Ranging
METRIC Mapping EvapoTranspiration at high Resolution with Internalized Calibration
MJ    Megajoule
ML    Megalitre
mm    Millimetre
n     Number of observations
NASA  National Aeronautics and Space Administration
NDVI  Normalized Difference Vegetation Index
NIR   Near-infrared radiation
PAR   Photosynthetically active radiation
PAR_T Transmitted photosynthetically active radiation
R     Rainfall
RED   Visible (red) radiation
R_n   Net radiation flux
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<td>RO</td>
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<td>SAVI</td>
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Chapter 1 Introduction

1.1 Water scarcity
Globally, water reserves are over allocated in many agricultural regions and strong competition exists for limited water supply (Fischer et al. 2007). Crop water productivity (yield/water use) must be increased to ensure food security (Fereres et al. 2003) at a time when agricultural production faces increased pressure from predicted future global food needs (Lotze-Campen et al. 2008).

In Australia, approximately 13,700 GL of water is diverted annually to irrigation districts in the Murray Darling Basin (MDBA 2010). The basin suffers declining water resources due to increasing agricultural demand, that is aggravated by uneven spatial and temporal distribution of surface and groundwater reserves, and leaky, ageing water delivery infrastructure (MDBA 2010; NVIRP 2010).

1.1.1 Water policy
The demand for the limited water resources in the Murray Darling Basin has led to a greater emphasis on environmental water allocations, increased water trading and large scale investments to improve infrastructure and delivery systems (DSE 2004a,b; NWC 2007, 2009; DEWHA 2010; MDBA 2010).

The newly developed ‘Basin Plan’ for the Murray Darling Basin (MDBA 2010) introduces environmental sustainable limits (known as sustainable diversion limits, SDLs) that are predicted to come into effect in 2014. SDLs set caps on the amount of water that can be diverted for agricultural use within each river catchment. The result will be less water available to all farming systems. The introduction of SDLs, combined with the recent drought, declining terms of trade (ABARE 2010) and changing climate (CSIRO 2007) provide stimuli for innovative change in water management to increase crop productivity and water-use efficiency. At the farm level, water management decisions will require balancing available water supply against crop area and requirements of particular crop types.

In Victoria, new water trading rules also include the unbundling of water entitlements from land, and new ‘reserve’ and ‘carryover’ policies (www.g-mwater.com.au). The carryover policy provides ability to ‘carryover’ water between irrigation seasons. The
‘reserve’ policy provides for water to be held back and stored in catchment reservoirs (e.g. Lake Eildon) each year. Together these two policies improve stability in water supply and its economic value (Hughes and Goesch 2009).

New irrigation infrastructure and reconfiguration upgrades (e.g. $2 billion ‘food bowl’ northern Victoria modernisation project) of irrigation supply channels and on-farm irrigation water metering are expected to deliver water savings to agriculture, including horticultural growers (DSE 2007; NVIRP 2010). These developments aim to reduce water loss by seepage and evaporation from delivery systems; improve water measurement and monitoring while, at the same time, dramatically reducing maintenance costs compared with the existing irrigation infrastructure (NVIRP 2010). These developments provide a catalyst to improve water productivity and regional water-use efficiency (DSE 2007).

1.2 Perennial horticulture in the Murray Darling Basin
The main horticultural districts of the Murray Darling Basin are the Murrumbidgee, Goulburn Valley, Sunraysia and Riverland irrigation regions. Perennial crops dominate horticultural production in these regions, whereas the tomato fresh market and processing sector dominates annual horticultural crops. Figure 1.1 illustrates location of the Murray Darling Basin and the scale and extent of perennial horticultural industries that are predominately located along the Murray River.
1.2.1 Perennial horticulture in Victoria

In northern Victoria, a diverse range of perennial high value horticultural crops is cultivated in two major irrigation regions: Sunraysia and Goulburn Valley (Fig. 1.1). Crop types include:

i. Deciduous tree fruits (pome fruit, stone fruit, nut),

ii. Evergreen tree fruits (olive, citrus) and,

iii. Grapes (wine, dried vine fruit, table).

Taken together, these crops provide important fruit, nut, wine and edible oil products. Deciduous fruit trees (e.g. apple, pear, peach, nectarine, apricot, plum) dominate the Goulburn Valley, while evergreen fruit and grape crops are commonplace in Sunraysia.

In northern Victoria, crops require irrigation due to low summer rainfall and high evaporative demand. Irrigation systems are relatively well developed. Delivery systems are predominately pressurised, providing flexibility of frequency, rate and duration of irrigation inputs (Boland et al. 2001). Water is delivered to crops by drip, micro-jet or low-level sprinkler devices. In Victoria, horticultural crops accounted for 26% (312 GL/year) of water extracted in 2008/09 (ABS 2010).
Horticultural production systems provide important regional economic benefits including local employment opportunities in production, transport, support services and regional infrastructure. Economic return to each 100 ML of water used in horticulture has been valued at approximately $250,000 plus employment of four persons (Boland and Thompson 2008).

At the national level, productivity of apple and pear orchards is not highly competitive in international terms (APAL 2010). Australian apple orchard productivity of 15 t/ha (fruit fresh weight) lags well behind the world’s best, such as New Zealand at 55 t/ha and Italy at 35 t/ha (WAR 2010). Similarly, Australian pear orchard productivity of 25 t/ha also lags well behind the world’s better producers such as Chile at 44 t/ha and The Netherlands at 36 t/ha (WPR 2010).

1.2.2 Water availability for horticulture
Irrigated horticulture in northern Victoria has recently experienced over a decade of low rainfall that has further constrained availability of water for irrigation and increased the cost of tradable water. Despite good economic performance, horticulture faces increasing pressure on availability and security of water supply, primarily because river systems have been ‘over-allocated’ to irrigators. Reduced irrigation supply has arisen from recent droughts, competition between agriculture and the environment, increasing urban demand, and new horticultural and plantation developments in areas previously not irrigated (e.g. green field sites: almond, plum, wine grape, peach, cherry, olive, pistachio, walnut, timber). Climate change forecasts of higher evaporative demand and lower catchment-reservoir yields (DSE 2007) make water availability a high priority for horticultural industries.

Reduced rainfall and associated catchment water yield from prolonged drought, or a change to a drier regime, provide for speculation of early signs of climate change. The recent multi-year (1996-2010) drought gripping south eastern Australia, dubbed ‘The Big Dry’, was predominantly driven by the Indian Ocean Dipole ocean-atmosphere conditions rather than Pacific Ocean conditions (the El Niño-Southern Oscillation) (Ummenhofer et al. 2009). From 1961 to the ‘The Big Dry’, the Goulburn Valley irrigation supply system consistently delivered over 100 % of allocated water at low cost ($50/ML) (www.g-mwater.com.au). During ‘The Big Dry’ allocations were
reduced and water traded at record high prices in the 2002/03, 2006/07, 2007/08, 2008/09 and 2009/10 seasons that followed record low inflows into Lake Eildon (Fig 1.2).

**Figure 1.2** Relationship between price of traded water and seasonal water allocation in the Goulburn irrigation region of Victoria during the irrigation seasons 1998-2010. Data from Goulburn-Murray Water (www.g-mwater.com.au) and Watermove (www.watermove.com.au).

### 1.2.3 Water management strategies

Considerable opportunities and strategies exist to improve water productivity, but gains will only be achieved according to proper biophysical principles and appropriate socioeconomic considerations (e.g. Perry *et al.* 2009; Molden *et al.* 2010).

For the stone and pome fruit industry in the Goulburn Valley, Kaine *et al.* (2005) established that growers were driven by re-development upgrades and time-management savings rather than water saving or water productivity targets *per se*. Despite this lack of motivation to change irrigation management practices, White *et al.* (2006) suggests that large water saving opportunities (12 – 18 %) can be achieved through improvements in on-farm agronomy in the fruit industry.

During low allocation seasons, Goulburn Valley horticulturists have responded by implementing several water management strategies to cope with uncertain water availability:
i. Removal of old unproductive orchards (e.g. 50+-year-old pear crops) providing opportunity to transfer water to other crops.

ii. Replacing flood (surface irrigation) systems with new micro-irrigation infrastructure (e.g. drip or micro-jet) (Adem 2010) thus saving water for other crops.

iii. Implementation of tactical within-season management practices such as deficit irrigation strategies, including post-harvest deficit irrigation, able to save up to 3 ML/ha (Goodwin and Bruce 2009).

iv. Purchase of additional irrigation water through water trading markets to ensure optimum crop production (yield and fruit quality). Water has become available to horticulture because the local dairy industry based on summer active perennial pastures is not competitive when water price exceeds $300/ML (Mallawaarachchi and Foster 2009).

However, these revised water management strategies incur greater complexity and most a greater financial cost.

1.2.4 Economic, social and environmental water management

Future water management strategies for horticulture must aim to satisfy economic, social and environmental objectives at farm, industry and regional scale.

On-farm, horticultural enterprises can survive and prosper by improving financial return from water (i.e. increasing productivity per unit water used, $/ML), but with difficulty under uncertain conditions, including the effects of possible climate change. For growers, the major issue is economic, but with contributions to the industry wide requirements of social and environmental sustainability.

To prosper, the industry as a whole can maintain its licence to operate, and its appropriate share of land and water resources, by meeting social requirements for environmental responsibility. In particular, impacts on water, salt and nutrients extend beyond farm water management practices to include maintenance of irrigation infrastructure/systems and diversions to control and store surface drainage flows for re-use in irrigation.
Equity issues related to sharing of water (re-allocation and co-managing) with other water users (urban, environmental and agricultural sectors) to maintain environmental assets (e.g. health of riparian vegetation and wetlands) are the primary focus for horticulture at the regional/catchment scale in order to provide required economic, social and environmental outcomes.

Quantification of consumptive crop water use and knowledge of crop water requirement are keys to understanding performance of irrigation systems and management of water resources in agricultural catchments.

1.3 Components of the water balance
Crops are supplied with water (crop water supply, CWS), by rainfall (R) and irrigation (I) and lose it from the root zone by surface runoff (RO) and deep drainage (DD). Crop water use or evapotranspiration (ET), combines transpiration through the crop (T) and evaporation from exposed wet soil (E). These various relationships are specified in the following water balance equation, viz:

\[
ET = E + T \\
= I + R - RO - DD \\
= CWS - RO - DD
\]

1.1

The separation of E and T is important because crop growth (and yield) is strongly related to T (de Wit 1958; Penman 1962; Rijtema 1966, 1968) and only to ET when E is small relative to T. Water lost by ET must be replenished if plants are to maintain adequate water status for continuing productivity. The contribution of E depends on both agronomic and hydrologic factors. E depends on the exposed wetted surface area that decreases as vegetation cover increases. In mature micro-irrigated perennial horticultural crops, E is an order of magnitude smaller than ET (Bonachela et al. 2001; Silva et al. 2008; Flumignan et al. 2011).
1.3.1 Matching crop water supply to crop water requirement

In Australia, irrigators have commonly manipulated CWS in order to minimise effects of soil water deficits on yield. However, the liberal water use strategies that developed when water supplies were cheap, abundant, and reliable, often resulted in application of excess water, and harmful offsite outcomes.

Most evidence suggests that yield of perennial high value horticultural crops is not related to crop water supply. Callinan (2000) and Boland et al. (2005a), for example, showed that yields in pear, apple and peach/nectarine crops were unrelated to irrigation inputs in northern Victoria. Application of water in excess of crop water requirement, CWR, (i.e. overwatering) is most likely the result of inadequate understanding about soil water content and CWR, inaccurate perceptions of the relationship between yield and crop water use, and reliable availability of cheap and good quality water.

CWR is recognised as the level of CWS that minimises crop water stress, thereby achieving maximum yield and high water productivity. Irrigation management is regarded as optimal when CWS closely approximates CWR because E, RO and DD losses are small. Yield does not increase with greater CWS but rather may decrease at high levels that cause water logging. The only exception applies to irrigation with saline water for which some DD (the leaching fraction of CWS) is required to prevent build up of salt in the root zone. Leaching fractions of 5 – 10 % of CWS are commonly applied to perennial horticultural crops (McLean et al. 2008). The amounts of RO and DD in the water budget are dominated by farm irrigation practices, and their contributions are most readily minimised by good water management. In other words, CWS is sufficient to maximise yield, and the excesses that contribute to RO and DD losses are minimised.

Irrigators adapt CWS to account for weather (rainfall + evaporative demand), crop type and vegetation cover. CWS is readily measured or estimated as the amount of water delivered to the crop (irrigation + rainfall). The ability to match CWS to CWR therefore depends on the availability of appropriate values for CWR and tools to monitor crop water status. Despite availability of tools and knowledge for estimation of CWR and increasing pressure on limited water supply, very few (< 5 %)
horticulturalists use either method for objective irrigation scheduling to improve water management (Boland et al. 2001; Montagu and Stirzaker 2008).

CWS can be adjusted to CWR using crop water status indicators, either:

i. Plant or soil based water relations or,

ii. Weather based calculations of ET.

The former method uses field assessment of soil water deficit (e.g. soil matric potential or water content) (Goodwin et al. 1992; Charlesworth 2005) or plant based water stress indicators (e.g. leaf or stem water potential, foliage temperature, trunk shrinkage, fruit growth, sap flow) (Naor 2006; Conejero et al. 2010; Shackel 2011) to determine CWR.

The weather based approach to determine ET depends upon the water requirement of an unstressed reference crop of full cover and constant stature, known as the reference crop evapotranspiration (ET$_{\text{REF}}$), and coefficients ($K_c$) for individual crops, as in:

\[ \text{ET} = K_c \times \text{ET}_{\text{REF}} \quad \text{(1.2)} \]

Crop coefficients, $K_c$, have been widely employed to account for effects of crop type, crop vegetation cover and growth stage on the ET of crops that differ from the reference canopies used to determine evaporative demand (ET$_{\text{REF}}$).

Evaporative demand (ET$_{\text{REF}}$) may be described by ‘short’ (grass) reference crop evapotranspiration (ET$_o$, FAO-56; Allen et al. 1998) or ‘tall’ (alfalfa/lucerne) reference crop evapotranspiration (ET$_R$, ASCE; Allen et al. 2005b). Pan evaporation and the Penman equation have also been used (FAO-24; Doorenbos and Pruitt 1977). Because the alfalfa reference ET$_R$ is greater than the corresponding international grass reference ET$_o$, the $K_c$ values calculated from ET$_R$ tend to be 15 – 30% smaller than those calculated from ET$_o$ (Allen et al. 2005b).

Estimates of $K_c$ in perennial horticultural crops are expensive and are made infrequently. Individual measurements provide specific detail on the water balance of individual crops, local management practices and climate regimes. Those
measurements are not applicable at regional or industry scales. Methods applied to fruit tree and grape crops include the use of:

i. Weighing lysimeters (Ayars et al. 2003; Williams and Ayars 2005),
ii. Drainage lysimeters (Mitchell et al. 1991; Boland et al. 1993),
iii. Sap flow techniques (Yunusa et al. 1997; Ferreira et al. 1997; Goodwin et al. 2006),
iv. Mass and energy balance measurements (Ferreira et al. 1997; Spano et al. 2008) and,
v. Water balance modelling (Green et al. 2003; Testi et al. 2006).

In response to paucity of local information, estimates of CWR used in perennial horticultural crops in Australia (e.g. Goodwin 1995; Mitchell and Goodwin 1996) are derived largely from overseas experience (FAO-56; Allen et al. 1998). The limited empirical ET studies in the local environment make estimation of CWR problematic for a range of perennial horticultural crops, locations and varied vegetation cover and management conditions. In particular, the differing biophysical and physiological characteristics of orchards and vineyards from location to location limit the applicability of ‘generic’ information, such FAO-56 $K_c$ (Allen et al. 1998).

Maximum crop evapotranspiration for standard conditions with no water stress, $ET_{\text{MAX}}$, provides an estimate of in-season CWR for perennial horticultural crops (Allen et al. 1998):

$$CWR = ET_{\text{MAX}} = K_c \cdot ET_{\text{REF}} \quad 1.3$$

to which an allowance for water requirement after harvest can be made as $0.3ET_{\text{MAX}}$ (Goodwin 2009) so that seasonal CWR can be expressed as:

$$CWR = \sum_{\text{pre–harvest}} (K_c \cdot ET_R) + 0.3 \cdot \sum_{\text{post–harvest}} (K_c \cdot ET_R) \quad 1.4$$

Accurate estimates of CWR and maximum yield ($Y_{\text{MAX}}$) are required to interpret yield and water use performance. A practical yield-water use framework is essential to improve agricultural water management. FAO-33 (Doorenbos and Kassam 1979) describe a simple, linear yield-water use relationship to emphasize that actual yield
(Y) and CWS must be assessed against $Y_{\text{MAX}}$ and CWR, respectively, in order to interpret yield-water use information.

1.4 Yield-water use framework

CWS and Y are relatively easily measured. CWR and $Y_{\text{MAX}}$ are more difficult to determine and vary among and between horticultural crops.

Factors known to influence ET and directly determine CWR are:

i. Crop vegetation cover,

ii. Crop type,

iii. Weather (rainfall + evaporative demand) and,

iv. Soil water availability.

Factors known to influence $Y_{\text{MAX}}$ are:

i. Crop vegetation cover,

ii. Crop type and,

iii. Radiation climate.

Crop vegetation cover is a major determinant of energy balance that directly influences important processes such as photosynthesis and transpiration (Ritchie 1972). In perennial horticultural crops cover is a function of canopy size, shape (e.g. Tatura trellis v. central leader), planting arrangement (planting density, row direction) and leaf area density (Goodwin 2004). Ground-based measurements of fractional radiation interception ($f$) are a common approach used to measure vegetation cover (Charles-Edwards and Thorpe 1976; Khemira et al. 1993; Iannini et al. 2002).

Crop type determines the length of growing season and that also varies widely among perennial horticultural crops in northern Victoria (ANFIC 2010). Fruit maturity (i.e. harvest date) ranges from late November for early season crops (e.g. apricot) to late April for late season crops (e.g. apple). In perennial horticultural crops of the Goulburn Valley, vegetation cover varies 3 – 4 fold during and between growing seasons (O’Connell and Goodwin 2005).

Both yield and CWS depend on vegetation cover and crop type. Therefore, any variation in $f$ and/or length of growing season clearly impacts water productivity. The
approach taken in the study reported in thesis exploits the joint, linear dependence of CWR and $Y_{\text{MAX}}$ on $f$. Hydrologic and production considerations of variation in $f$ are outlined below.

1.4.1 Dependence of crop water requirement on fractional radiation interception

Fruit tree and vine $K_c$ values have been linearly related to vegetation cover, including ground-based measurements of $f$ (Ayars et al. 2003; Williams and Ayars 2005; Consoli et al. 2006b,c,d; Goodwin et al. 2006). Therefore, inclusion of a measure of $f$ provides an adjustment on the T component of the water balance for horticultural crops of incomplete vegetation cover (Goodwin et al. 2006).

However, ground estimates of $f$ (e.g. by ceptometer or hemispherical radiation sensor) are extremely time consuming, costly and largely impractical because sampling must account for substantial spatial and temporal variability in vegetation cover and its effect on daily variation in $f$.

Models describing $f$ have been developed but require estimation and/or measurement of several canopy parameters (Palmer 1977, 1989). Again, the volume of work required has limited application of this approach to crop growth studies. In contrast, remote sensing from multi-spectral sensors mounted on satellites offers a cheap, simple, repeatable and spatially rich method to obtain field-scale vegetation cover across agricultural regions. Chapter 2 introduces the vegetation cover indicator, Normalised Difference Vegetation Index (NDVI), and describes its relationship to $f$. These are important techniques for the overall study in this thesis and so are described in detail in Chapter 2.

1.4.2 Dependence of maximum yield on fractional radiation interception

Yield-radiation response functions were first developed for crops growing under ‘ideal’ conditions by researchers in the 1970-1980’s (e.g. Gallagher and Biscoe 1978) and were soon applied to perennial horticulture (Monteith 1977; Palmer 1988). They showed how $Y_{\text{MAX}}$ can be expressed as a function of incoming solar radiation ($S$), fractional radiation interception ($f$) of photosynthetically active radiation, radiation-use efficiency ($\varepsilon$), harvest index ($h$) the fraction of total plant dry mass that is partitioned to fruit as:
Here, to account for differences in cultivar and maturity (individual crops and growing season length) and growing seasons, intercepted seasonal radiation is calculated progressively as (ΣfS) because both f and S vary during the growing season. Yield considerations of fruit quality (i.e. fruit size, skin colour) are not included, but in practice are often of equal concern to growers as is yield.

1.4.3 Crop water production function

The crop water production function describes changes in crop yield with increasing CWS for given agro-climatic conditions. It distinguishes yield limits imposed by water supply, climate, and other growing conditions, and thereby provides an objective framework for analysis and practical interpretation of yield/water use outcomes. Hypothetical water productivity response functions of yield to irrigation level have been proposed (Kijne et al. 2003; Naor 2006). A literature search reveals a distinct lack of available yield – water use data for perennial horticultural crops. However, Grimes and Williams (1990) provide a water production function for table grapes.

The simplest comprehensive crop water production function combines the:

i. FAO-33 yield-water use relationship (Doorenbos and Kassam 1979) with

ii. $Y_{\text{MAX}}$ that is achieved when CWS equals or exceeds CWR.

That is, maximum crop evapotranspiration ($ET_{\text{MAX}}$) equates to CWR (Equation 1.3) and actual crop yield ($Y$) equates to $Y_{\text{MAX}}$ under adequate water supply (FAO-56; Allen et al. 1998). The influence of the magnitude and duration of water deficits on $Y$ relative to $Y_{\text{MAX}}$ ($Y/Y_{\text{MAX}}$) can be related relative to ET deficit using the FAO-33 yield response functions.

Figure 1.3 provides a schematic diagram of a ‘two stick’ water production function showing both the water- and climate-limited response regions and derivation of CWR. An offset on the X-axis is provided to represent post-harvest water requirement, i.e. between harvest and end-of-season. In general, post-harvest water requirement is a minor component of the seasonal water budget and varies mostly depending on fruit maturity date (Equation 1.4).
Figure 1.3 A crop water production function (red lines) for a perennial horticultural crop showing increase in water-limited maximum yield ($Y_{WL}$) with increasing crop water supply (CWS) in water-limited response region (CWS < CWR), and attainment of maximum yield ($Y_{MAX}$) in the climate-limited region (CWS > CWR). CWR occurs at the minimum CWS required to achieve $Y_{MAX}$ (green line). An X-axis offset is provided to represent post-harvest water use.

This approach is consistent with the FAO-33 functional model of Doorenbos and Kassam (1979) that describes the water limited yield response at low rates of water supply in the form:

$$\frac{Y}{Y_{MAX}} = k_y \cdot \frac{ET}{ET_{MAX}}$$  \hspace{1cm} \text{1.6}

Here, $Y$ is actual yield, $ET$ is actual crop evapotranspiration, $ET_{MAX}$ is maximum crop evapotranspiration and $k_y$ is a yield response factor (evapotranspiration-yield coefficient). Unfortunately, the FAO-33 report does not provide empirical data on $k_y$ for perennial horticultural crops.

Given that $ET_{MAX}$ can be equated to CWR (Equation 1.3), and assuming yield is proportional to water supply (i.e. $k_y = 1$), then under water-limited conditions (CWS < CWR and $Y < Y_{MAX}$), Equation 1.6 simplifies to:

$$\frac{Y}{Y_{MAX}} = \frac{ET}{CWR}$$  \hspace{1cm} \text{1.7}

When water is non-limiting, CWS ≥ CWR, yield of pest- and disease-free crops grown under optimal nutrient and soil conditions is determined by radiation and
temperature environments (e.g. Production Level 1: Penning de Vries 1982). In that climate limited response region, \( Y \approx Y_{\text{MAX}} \) and \( \text{CWS} \geq \text{CWR} \).

The simplest water production function is therefore formally described by:

\[
Y = \frac{\text{ET}}{\text{CWR}} \cdot Y_{\text{MAX}} \quad ; \quad \text{CWS} < \text{CWR} \quad 1.8
\]

\[
Y = Y_{\text{MAX}} \quad ; \quad \text{CWS} \geq \text{CWR} \quad 1.9
\]

In summary, at small CWS, yield is water limited but increases to a maximum \( Y_{\text{MAX}} \) as water shortage is relieved. Minimum CWS to sustain \( Y_{\text{MAX}} \) is referred to as CWR. CWS in excess of CWR does not increase yield, but contributes to hydrologic losses (E, RO and DD).

Vegetation cover influences both axes of the water production function. That is, ET, CWR, Y and \( Y_{\text{MAX}} \) have a dependence on vegetation cover. Therefore, water production functions adjusted for vegetation cover can provide growers with ability to compare actual yield with \( Y_{\text{MAX}} \) and CWS with CWR.

1.5 Yield estimation using crop simulation models
An increasing number of simulation models of biomass production and yield of horticultural crops are becoming available. Many models, however, simulate only part of the crop production system such as photosynthesis, respiration, assimilate partitioning, phenology/development. Photosynthesis-based models, for example, have been developed for apple (Lakso and Johnson 1990; Hester and Cacho 1997), peach (Grossman and DeJong 1994) and pear (Marsal and Stockle 2011) crops. Few are yet integrated in complete crop growth models (Gary et al. 1998; Marcelis et al. 1998). A literature search reveals that no readily available crop model deals with variable crop water supply, differences in vegetation cover and diversity of crop types grown in northern Victoria (e.g. pome and stone fruit, wine grape). Although the FAO-33 approach (Equation 1.6) provides a practical prediction of yield, the lack of \( k_y \) data for perennial horticulture crops currently restrict its application.
1.6 Water use efficiency appraisal of perennial horticulture

Existing farm and regional assessments of water use and water productivity performance and water accounting have failed to recognize the dependences of CWR and $Y_{MAX}$ on vegetation cover.

1.6.1 Irrigation benchmark surveys

In the Murray Darling Basin, various yield – water use surveys have identified horticultural crops of high water productivity (e.g. Skewes and Meissner 1997a,b; Giddings et al. 2002; Toll and Burrows 2006; Sommer and Pollock 2008a,b,c; Toll et al. 2008). These studies have considered water use efficiency ratio ($Y/CWS$) at field scale to benchmark industry water performance and ‘best management practice’. These irrigation surveys focus on individual commodity types and are often based on multi-year sampling of crop performance within a district.

Figure 1.4 presents data collected by Skewes and Meissner (1997a) showing a typical response, that of water productivity of orange orchards. These authors report a 7-fold range in water use efficiency (1 – 8 t/ML). However, without a metric for vegetation cover to independently assess $Y$ against $Y_{MAX}$ and $CWS$ against CWR, these water use efficiency values presented here offer little guidance to advance hydrologic and/or agronomic management.

![Figure 1.4 Histogram of water use efficiency (calculated as a 3-year weighted mean crop yield/irrigation input) of orange ($n = 39$) crops in the lower Murray region of Australia for the period 1993/94 to 1995/96. Data from Skewes and Meissner (1997a).]
1.6.2 Water accounting

In Victoria, water accounting reports utilize a spatial geographic information system (GIS) combining land use and crop type with estimated CWR and information on farm irrigation-water delivery (McAllister et al. 2009).

At the farm level, a water use appraisal performance indicator of water deliveries (total water supplied, TWS) against predicted CWR for an irrigation season can be applied to horticultural industries as in Figure 1.5. This figure shows the combined TWS – CWR relationship for the major horticultural industries in the Sunraysia Irrigation region of northern Victoria for season 2002/03. It reveals that irrigation water was commonly applied in excess of estimated CWR.

![Figure 1.5 Relationship between total water supplied (TWS) and estimated crop water requirement (CWR) of horticultural farms (n = 489) in the Sunraysia region of Victoria for the 2002/03 irrigation season. Line represents 1:1 line. Horticultural crops include grape, almond, citrus and vegetable. Data from McAllister et al. (2009).](image)

However, the estimates of crop-specific CWR in Figure 1.5 are derived from ‘generic’ tabulated FAO-56 $K_c$ values (Allen et al. 1998) and so fail to account for the wide variation in vegetation cover among crops that, as emphasized above, is known to directly impact ET and CWR. Furthermore, as a performance indicator of regional irrigation efficiency, the analysis pools all crop categories (grape, almond, citrus and vegetable) into one industry (‘horticultural’) sector.

At the regional level, water productivity for individual irrigated perennial horticulture crops/farms is not currently assessed in Victoria, due to difficulties in being able to relate yield data to water supply data.
1.7 Summary of problem

Improvements in water productivity require estimation of CWR and $Y_{\text{MAX}}$. Both CWR and $Y_{\text{MAX}}$ depend jointly on vegetation cover. Practical estimates CWR and $Y_{\text{MAX}}$ are largely unavailable for the diverse range of perennial horticultural crops cultivated in northern Victoria because:

i. Industry knowledge is subjective and unreliable,

ii. Empirical yield and water use data are rare and,

iii. Absence of suitable crop simulation model(s) capable of providing the yield response to variable CWS, vegetation cover, length of growing season and crop type.

1.8 Approach

The study presented in this thesis explains the development of a satellite-based water productivity framework for use in the appraisal of yield and water use relationships of high value, perennial horticultural crops in the Goulburn Valley irrigation region.

Satellites can provide affordable and repeatable data related to vegetative cover and crop water use of individual crops and regions. Because of the importance and newness of the approach, Chapter 2 will describe important recent advances in satellite technologies made in the estimation of vegetation cover, water use and yield. The vegetation cover indicator, Normalised Difference Vegetation Index (NDVI), is used to estimate fractional radiation interception ($f$) while crop water use (ET) can be directly derived from satellite data using energy balance algorithms and weather data. Together NDVI and ET allow estimation of crop water requirement (CWR). Chapter 2 also outlines the procedures used to obtain water productivity components, $Y_{\text{MAX}}$ and CWR, in perennial horticultural crops in the Goulburn Valley irrigation region of Victoria.

Field experiments were undertaken to support this approach. Chapters 3 and 4 investigate the dependence of $Y_{\text{MAX}}$ on $f$, and $f$ on NDVI, respectively. Chapter 5 analyses a time series of NDVI among several perennial horticultural crops. Chapter 6 explores the dependence of ET on NDVI. The overall objective was to compile crop- and site-specific estimates of water productivity components (CWR and $Y_{\text{MAX}}$) in several horticultural crops. The approach requires a combination of hydrologic and agronomic disciplines and spatial science (GIS) and remote sensing technologies.
Chapter 2 Estimation of maximum crop yield and water requirement from satellite derived data

2.1 Introduction
Satellite remote sensing provides objective, repeatable and affordable measures of vegetation cover and crop growth, yield and water use from farm to regional scales. Attempts to utilize these data have proliferated in recent years. Maas and Rajan (2008), for example, used Landsat data to estimate vegetation cover of field crops, while Bastiaanssen and Ali (2003) derived yield in several broad-acre crops, and Allen et al. (2005a) analysed evapotranspiration (ET) of irrigated potato crops in Idaho, USA.

Measures of vegetation cover, ET and yield using satellite remote sensing information provide the basic components for evaluation of water productivity. Chapter 1 explained the importance of estimates of maximum yield \( Y_{\text{MAX}} \) and crop water requirement \( \text{CWR} \) to assess the agronomic (actual yield \( \text{v.} \ Y_{\text{MAX}} \) and hydrologic (water inputs \( \text{v.} \ CWR \) performance of perennial horticultural crops.

2.2 Crop growth and water use
2.2.1 Vegetation cover
The remotely sensed indicator of vegetation cover, Normalised Difference Vegetation Index (NDVI), first proposed by Kriegler et al. (1969), provides data that can be used for estimation of crop growth and development and also of water use. Vegetation typically reflects energy in the near-infrared (NIR) (~ 0.8 – 1.1 µm) range and absorbs in the (visible) red (RED) range (~ 0.7 – 0.8 µm). NDVI is the ratio of the differences in reflectivities of NIR and RED radiation to their sum (Rouse et al. 1973):

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad 2.1
\]

As such, values range between – 1 and +1. Negative values indicate water or snow, while NDVI of vegetation typically ranges from 0.15 to 0.8, with higher values associated with greater vegetation cover.

Measurement of NDVI has been widely applied to broad-scale annual cropping systems and rangeland pastures (e.g. Tucker 1979; Wiegand et al. 1991; Pineiro et al.)
2006; Maas and Rajan 2008). By contrast, limited information and literature exists on remotely-sensed vegetation indices and their application to perennial horticultural crops. Exceptions are found in estimation of vegetation cover in wine grape canopies (Lamb et al. 2001; Johnson 2003; Hall et al. 2003; Johnson and Scholasch 2005).

2.2.2 Crop water use


Remotely sensed ET offers major advantages over traditional point-scale ground-based technologies. Point-based measurements (e.g. by lysimetry, Bowen ratio, scintillometry, surface renewal, eddy covariance) are expensive, often unreplicated and technically demanding. The spatial coverage of satellite derived estimates of ET make the approach affordable and readily repeatable and, overcomes the need to extrapolate from point measurements. Historically, these estimates have been inferred from relationships between canopy temperature and air temperature (Kustas and Norman 1996; Caselles et al. 1998), and canopy temperature and vegetation index (Moran 1994; Moran et al. 1994, 1997).

Neale et al. (1989), Choudhury et al. (1994), Bausch (1993, 1995) and Hunsaker et al. (2003, 2005) employed a spectral vegetation index as the independent variable to infer values of the crop coefficient ($K_c$) to derive ET in irrigation scheduling. Other work has applied semi-empirical techniques combining spectral vegetation data and in situ measurement of canopy properties (e.g. LAI, albedo, soil humidity, ground vegetation cover and fractional radiation interception, Consoli et al. 2006a,b,e; D’Urso et al. 2008). These approaches rely on a vegetation index to extrapolate water use measurements made at point/field scale to commercial crops.

Most recent satellite derived estimates of ET, however, use a land surface energy balance budget (Bastiaanssen et al. 1998, 2005; Allen et al. 2005a; Tasumi et al. 2005a,b). The two ET models that use this approach, Surface Energy Balance Algorithm for Land (SEBAL; Bastiaanssen et al. 1998) and Mapping Evapotranspiration at high Resolution and with Internalized Calibration (METRIC;
Allen et al. 2005a, 2007a,b), provide direct estimates of ET. METRIC places greater reliance than SEBAL on ground-based reference ET (ET\textsubscript{REF}) measurements for calibration (Allen et al. 2007a).

### 2.2.3 Yield

Ground-based and remotely sensed measurements are commonly used to estimate crop yield (Bouman 1995; Prasad et al. 2006). Yield estimation using satellites is based on physiological principles that relate biological and environmental variables to multi-spectral reflectance. Two approaches have been used to integrate remotely sensed data with crop growth models (Bouman 1995). In the first, measurements of fractional radiation interception (\(f\)) are estimated from optical sensors and used as forcing functions in models of the type described in Equation 1.5. The second, uses time series of remotely sensed data to progressively calibrate crop growth models during the growing season for improved yield prediction.

The relationship between vegetation productivity and NDVI is well established, especially in the domain of global vegetation modelling (Prince and Goward 1995; Myneni et al. 1997; Sellers et al. 1997; Yuan et al. 2010). Crop yield assessment models that apply NDVI as the indicator of vegetation cover use various approaches including field surveys, expert knowledge, trend analysis, regression analysis, statistical models and crop growth and agrometeorological models (Moran et al. 1997).

As an example, Prasad et al. (2006) report a non-linear, multi-variate optimization model to predict yield of corn and soybean using the remotely sensed variables NDVI, soil moisture and surface temperature in combination with rainfall and historical yield data. Taken together, the soil moisture, surface temperature and rainfall data allow estimation of ET.

A common approach to estimate yield applies principles of crop ecology with high temporal frequency monitoring of remotely sensed vegetation indices (e.g. NDVI) to describe crop development and growth. Growth and yield can be modelled using the radiation-use efficiency model (Monteith 1977) under optimal environmental conditions. Bastiaanssen and Ali (2003) estimated yield in broad-acre crops in this way using Equation 1.5. They estimated \(f\) from NDVI, and crop growth and yield
from published information on maximum radiation-use efficiency and harvest index, respectively. Similar approaches using constant (maximum) radiation-use efficiency (Equation 1.5) have been applied to estimate yield in rice (Huang et al. 2002), guava (Rodriguez-Moreno et al. 2007) and pistachio (Moazenpour et al. 2006) crops.

2.3 Water productivity components of horticultural crops in the Goulburn Valley

In the previous sections, examples of estimation of vegetation cover, ET and yield using satellite remote sensing data were identified. Chapter 1 emphasised the importance for water productivity components: maximum yield ($Y_{\text{MAX}}$) and crop water requirement (CWR) to assess the agronomic and hydrologic performance of perennial horticultural crops that differ in vegetation cover. The joint dependence of $Y_{\text{MAX}}$ and CWR on vegetation cover establishes it as the key variable for estimating crop production and water use, and identifying potential improvements in water productivity.

Chapter 1 also described how perennial horticultural crops have discontinuous canopies, variable stages of canopy (leaf area) development and hence seasonal patterns of vegetation cover. When combined, these factors provide challenges for the interpretation of remotely sensed vegetation and water use information. The following subsections describe estimation of components of water productivity using vegetation cover, ET and yield, all derived from satellite data.

2.3.1 Fractional radiation interception

NDVI data derived from satellites provide an established metric for vegetation cover that can differentiate between crops, fields, farms and enterprises. The link between NDVI and fractional radiation interception is well documented, both theoretically (Kumar and Monteith 1981; Sellers et al. 1992; Myneni and Williams 1994; Myneni et al. 1995) and empirically (Asrar et al. 1984; Bartlett et al. 1990; Daughtry et al. 1992; Gamon et al. 1995; Joel et al. 1997; Myneni et al. 1997; Yang et al. 2008).

Fractional radiation interception ($f$) is monotonic and a near-linear function of NDVI (Asrar et al. 1992). Bastiaanssen and Ali (2003) describe an average $f$– NDVI relationship using ground-based measurements for broad-acre crops reported as:
\[ f = 1.26 \cdot \text{NDVI} - 0.16 \]

predicting a NDVI value of \( \approx 0.13 \) for bare ground (i.e. zero vegetation cover, \( f = 0 \)) and a maximum of \( \approx 0.85 \) for high vegetation cover (i.e. \( f \geq 0.8 \)). There are, however, no published empirical relationships between \( f \) and NDVI for horticultural tree and vine crops. Accordingly, this study conducted ground-based measurements of \( f \) for several high value perennial horticultural crops in the Goulburn Valley region and compared them with NDVI derived from satellite data.

### 2.3.2 Crop water use

The METRIC model applies a one-layer resistance (surface and aerodynamic) model to estimate ET fluxes (Allen et al. 2007b) as a residual of the surface energy balance, the energy consumed in evaporation for each recorded pixel of the satellite data:

\[
\text{LE} = R_n - G - H
\]

In this equation, \( \text{LE} \) = latent heat flux, \( R_n \) = net radiation flux at the surface, \( G \) = soil heat flux, and \( H \) = sensible heat flux to the air. LE is converted into ET by dividing by the latent heat of vaporisation. The primary inputs for the model are short-wave and long-wave (thermal) images from a satellite.

This direct ET (METRIC) method has several benefits because it calculates radiative properties of land/crop surfaces thereby eliminating the need to identify crop type and developmental stage, soil cover and soil wetness. Comparisons of performance with ground-based ET measurements (e.g. by Bowen ratio, eddy correlation, scintillometry, lysimetry) show high levels of robustness and accuracy (Bastiaanssen et al. 2005; Barbagallo et al. 2009; Choi et al. 2009).

The METRIC model was chosen for estimation of ET and hence crop water requirement (CWR) of perennial horticultural crops in the Goulburn Valley because it provides a direct measure of ET at field- and regional-scales and can be adjusted to local evaporative demand (ET\text{REF}) using ground-based weather station measurements (e.g. Allen et al. 2005a; Tasumi et al. 2005a).
2.3.3 Crop water requirement

Estimation of CWR, as described in Chapter 1, is a necessary development in understanding water productivity. There, it was explained how CWR can be estimated from well-watered crops (ET\textsubscript{MAX}) and can be related to reference evaporative demand (ET\textsubscript{R}) using the crop coefficient (K\textsubscript{c}), i.e. CWR = K\textsubscript{c} \cdot ET\textsubscript{R}; Equation 1.3.

FAO-56 (Allen \textit{et al.} 1998) also describe ET under non-water stress conditions by the ‘dual’ K\textsubscript{c} approach, in terms of the basal crop coefficient (K\textsubscript{cb}), and dimensionless water stress (K\textsubscript{s}) and soil evaporation (K\textsubscript{e}) coefficients:

\[ K\textsubscript{c} = K\textsubscript{s} \cdot K\textsubscript{cb} + K\textsubscript{e} \quad 2.4 \]

In the absence of water stress, K\textsubscript{s} = 1, Equation 2.4 simplifies to:

\[ K\textsubscript{c} = K\textsubscript{cb} + K\textsubscript{e} \quad 2.4 \]

In what follows, CWR is estimated from ET – NDVI relationships using the hydrologic and vegetation interpretive framework reported by Whitfield \textit{et al.} (2011) (Appendix 1). In this approach, paired satellite-derived ET – NDVI data provide crop- and site-specific CWR for horticultural crops in a framework, described below, that is able to distinguish water-stressed from well-watered crops.

2.3.3.1 Hydrologic and vegetation framework to detect water stress

This framework developed by Whitfield \textit{et al.} (2011) is based on the ET – NDVI responses of irrigated broad-acre crops reported by Tasumi \textit{et al.} (2005a). Those authors described how satellite-derived ET changed with NDVI during growth of potato and sugar-beet crops (Figure 2.1).

The data in Figure 2.1 show that potato crops with low vegetation cover (NDVI < 0.3) had the most variable ET (0 < K\textsubscript{c} < 0.9). These were crops at the commencement of the growing season (3\textsuperscript{rd} June) that differed in ET – NDVI response due to varied planting schedules that effected crop emergence and associated ‘start-up’ water management practices. In other words, when vegetation cover was sparse following crop establishment, ET was highly variable from field to field across the region. As the season progressed (19\textsuperscript{th} June), however, and crop canopies developed, both NDVI
and ET ($K_c$) increased. As the crops matured, ‘full’ vegetation cover conditions prevailed (21st July), and all crops had high vegetation cover (NDVI > 0.65) and high, but less variable, ET ($K_c > 0.8$).

The key piece of information arising from the study of Tasumi et al. (2005a) on annual crops in Idaho, USA, is the rising edge (green line) in Figure 2.1 that describes the linear increase in crop transpiration capability (basal crop coefficient, $K_{cb}$) as NDVI increases from the lower bound of ET – NDVI observations.

The green $K_{cb}$ baseline is interpreted as the lower, threshold rate of ET that Idaho growers adopted to trigger irrigation of their crops. Points above this baseline represent crops with high water availability while points below the baseline represent crops with inadequate water supply (i.e. water stress conditions).

![Figure 2.1](image)

**Figure 2.1** Relationship between crop water use indexed to local evaporative demand ($ET/ET_R = crop coefficient, K_c$) and vegetation cover measured as NDVI of irrigated potato crops ($n = 717$) during the growing season (sowing to maturity) in 2000, Idaho, USA. Data from Tasumi et al. (2005a). The green line forms the basal crop coefficient ($K_{cb}$; Equation 2.6).

Practically, the $K_{cb}$ line equates to an ‘irrigation refill line’ and can be quantified as:

$$K_{cb} = 1.33 \times NDVI - 0.13$$

2.6
The limits of NDVI are again approximately 0.15 and 0.85 in crops (c.f. Bastiaanssen and Ali 2003; Fig. 2.1). Given that estimates of $f$ and $K_{cb}$ are practically equivalent based on Equations 2.2 and 2.6, respectively, $f$ is established as an effective estimator for $K_{cb}$.

In summary, Figure 2.2 presents the hydrologic-vegetation framework in a practical way to identify well watered from water stressed crops. ET is calculated using METRIC and related to local ‘alfalfa’ reference crop evapotranspiration ($ET_R$), from which evaporation ratio ($ET/ET_R = K_c$) is related to NDVI.

Deviations of $ET/ET_R$ measurements above and below the green line reveal magnitudes of excess or inadequate water supply to maintain CWR. At small NDVI, large deviations above the line reflect water loss from wetted soil (e.g. start of season, 3$^{rd}$ June in Figure 2.1). Observations below the $K_{cb}$ line represent water stressed crops. Those at NDVI $\leq 0.15$ identify bare soil (zero vegetative cover).

*Figure 2.2 Theoretical ET – NDVI response diagram appropriate to irrigated crops depicting the basal crop coefficient ($K_{cb}$) and vegetation cover (NDVI) relationship (green line; Equation 2.6) of irrigated broad-acre annual (potato and sugar-beet) crops grown in Idaho, USA (after Tasumi et al. 2005a). The green line forms a diagnostic water stress reference baseline to compare satellite-derived ET and NDVI data for other crops and regions.*
To derive CWR, $K_c$ was estimated by $K_{cb}$ plus the contribution of surface evaporation ($K_e$) depending on the mean frequency of surface wetting within the sample population of ET – NDVI data (after Whitfield et al. 2011):

$$K_c = K_{cb} + dK_{cb} \quad 2.7$$

Here, $dK_{cb}$ is the sample mean displacement (offset) in excess of the $K_{cb}$/irrigation refill line (Equation 2.6) subject to the caveats that $K_s = 1$, $K_{cb} \leq ET_R$ and $K_c \leq 1.05 ET_R$ (Allen and Pereira 2009). Thus, CWR is obtained by:

$$CWR = \frac{(K_{cb} + dK_{cb})}{ET_R} \quad 2.8$$

Therefore, the regional derivation of crop specific NDVI-dependent estimates of $K_c$ provides site-specific estimate of CWR for each orchard/vineyard field (Equation 2.8).

### 2.3.4 Maximum yield

Chapter 1 explained the lack of reliable estimates of maximum yield ($Y_{MAX}$) data for the diverse range of perennial horticultural crops in the Goulburn Valley. Yield-radiation response functions to estimate $Y_{MAX}$ for crops were presented in Equation 1.5. Accordingly, to derive $Y_{MAX}$ in this study, estimates of maximum radiation-use efficiency were undertaken by relating ground-based measurements of $f$, seasonal radiation climate and phenophase information to the upper range of observations of commercial yield data in orchard and vineyard crops.

### 2.4 Thesis aim

The principal objective of this study is to formulate a satellite-based yield-water use framework applicable to management of water supply to high value perennial horticultural crops in northern Victoria.

### 2.5 Thesis overview

Chapter 3 describes estimation of maximum yield ($Y_{MAX}$) using field measurements of fractional radiation interception ($f$), radiation climate and phenophase information in the major perennial horticultural crops of the Goulburn Valley irrigation region.
Chapter 4 describes the dependence of ground-based measures of \( f \) on NDVI derived from Landsat data for apple, apricot, pear, peach, nectarine, plum and wine grape crops in the Goulburn Valley.

Chapter 5 examines the temporal stability in NDVI using a collage of Landsat imagery that span an irrigation season for the major fruit tree crops in the Goulburn Valley.

Chapter 6 develops NDVI-dependent estimates of CWR from relationships of ET and NDVI for the major horticultural crops in the Goulburn Valley. ET and NDVI were determined from Landsat data using the METRIC model and related to the NDVI-dependent basal crop coefficient \( (K_{cb}) \) described by Tasumi et al. (2005a).

Chapter 7 explores effects of vegetation cover and length of growing season on water productivity in peach crops. Additionally, CWR is derived using estimates of \( Y_{\text{MAX}} \) from irrigation benchmarking survey data of apple, peach/nectarine and pear crops for which vegetation cover is not measured. As an application of findings from this study reported in this thesis, NDVI-dependent water productivity parameters, \( Y_{\text{MAX}} \) and CWR, are mapped for horticultural crops of the Goulburn Valley.

Chapter 8 summarizes the conclusions from this study and their implications. Deficiencies of the study and recommendations for further research in relation to improved knowledge and understanding of yield-water use relationships in perennial high value horticulture are discussed.
Chapter 3 Field based estimates of maximum yield of perennial horticultural crops in the Goulburn Valley

3.1 Introduction
Chapter 1 described the dependence of crop yield (Y) on radiation use efficiency (ε), harvest index (h), fractional radiation interception (f) and solar radiation (S) (Equation 1.5). In the absence of specific measures of h, that rely on destructive sampling or complicated measurement (e.g. Hall et al. 1989), for many purposes yield can be related to cumulative intercepted radiation (ΣfS) by means of an effective radiation use efficiency, ε*, by:

\[ Y = \varepsilon^* \cdot \Sigma fS \] 3.1

where \( \varepsilon^* = \varepsilon \cdot h \).

ε is dependent on light, temperature, vapour pressure deficit and factors inherent to plant species (Loomis and Connor 1992). It is therefore important to maximise ΣfS and avoid water stress, which is known to decrease seasonal ε, to obtain high yields. Similarly, Lakso et al. (1999) emphasises that maximum yields (Y\text{MAX}) depend on large vegetation cover (high f) over a long period (high ΣS) to produce fruit (Y) with high ε, and to partition a large proportion of dry matter to fruit (high h) in high yielding apple orchards.

Modern commercial perennial horticultural plantings in the Goulburn Valley region aim for maximum yields in the third year after establishment. Orchard managers have effectively sought greater fruit yields increasing f achieved by extending tree canopies into the inter-row space (alleyways) with V- or Y-shaped trellis systems (e.g. Tatura Trellis, Open Tatura) and high plant densities within rows compared to traditional wide spaced isolated tree planting arrangements. Modern pressurised irrigation systems are widely used to minimise water stress required for high yields.

Maximum values, \( \varepsilon \approx 1.0 \text{ g above ground dry biomass/MJ solar radiation} \), have been reported for C3 annual crops grown under optimal conditions (Gallagher and Biscoe 1978; Kiniry et al. 1989; Bastiaanssen and Ali 2003). Reported ε values of non-horticultural tree species range between 0.5 and 1.5 g total dry biomass/MJ solar
radiation (Linder 1985; Cannell et al. 1988; Wang et al. 1991; Mariscal et al. 2000). For apple, \( \varepsilon \) values of 0.88 – 0.95 g total dry biomass/MJ solar radiation have been reported (Palmer 1988; Palmer et al. 2002). In terms of yield, reported values for \( \varepsilon \) range from 0.16 to 0.62 g fruit dry weight/MJ solar radiation in apple (Palmer 1989; Robinson and Lakso 1989, 1991; Wagenmakers and Callesen 1995; Palmer et al. 2002). Despite the above mentioned studies, a literature search reveals a distinct lack of available \( \varepsilon \) data for most of the perennial horticultural crop types grown in the Goulburn Valley.

Equation 3.1 suggests that yield is largely determined by source limitations imposed by vegetation cover (\( f \)) and length of growing season (\( \Sigma S \)), that is the photosynthetic (carbohydrate) capacity through adequate leaf area (‘source’ strength). However, sink limitations may also be important in yield outcomes (e.g. DeJong 1998; Marcelis et al. 1998), that is yield is directly related to fruit number. Orchardists manipulate fruit number (‘sink’ size) by tree pruning and/or fruit thinning management practices that target large fruit size to improve marketable yield in some crops. Grower manipulation of fruit number (i.e. crop load targets) therefore potentially impacts \( h \) and consequently yield.

Biomass distribution to determine \( h \) is poorly understood and documented in perennial horticultural crops. Available estimates of \( h \) range approximately 2-fold in fruit trees. For peach, Chalmers and van den Ende (1975) reported \( h \) values between 0.30 and 0.65. For apple, reported \( h \) varies widely, 0.33 < \( h \) < 0.73, depending on rootstock (Moore 1978; Palmer 1988, 1992; Strong and Azarenko 2000; Palmer et al. 2002).

O’Connell and Goodwin (2005) reported that vegetation cover varied 3 – 4 fold in peach crops in the Goulburn Valley. Differences in \( f \) have direct implications on yield (Equation 3.1). Yield has been linearly associated with midseason \( f \) in apple (Barritt 1989; Wünsche and Lakso 2000), peach (Iannini et al. 2002), sour cherry (Flore and Layne 1990), macadamia (Olesen et al. 2007) and lychee (Olesen et al. 2007). Similarly, short-term measures of leaf gas exchange have shown linear relationships between net carbon assimilation and intercepted radiation in almond, hazelnut, walnut, olive, peach and eggplant (DeJong and Doyle 1985; Hampson et al. 1996; Rosati et al. 2002; Rosati and DeJong 2003; Rosati et al. 2004; Gregoriou et al. 2007).
A limited number of overseas studies on horticultural crops have shown that yield is generally well correlated to $\Sigma f_S$ (Equation 3.1) in apple (Palmer et al. 2002), Cape gooseberry (Salazar et al. 2008) and garlic (Rizzalli et al. 2002).

The study reported in this Chapter sought to derive estimates of $\varepsilon^*$ from field measures of yield and seasonal fractional radiation interception in perennial horticultural crops. Estimates of maximum regional yield were made by attempting to identify high yielding crops in the Goulburn Valley region of Victoria.

3.2 Materials and Methods

3.2.1 Site selection

The study was carried out on commercial mature micro-irrigated orchard and vineyard crops in the Goulburn Valley region of Victoria during the 2007/08 and 2008/09 irrigation seasons. Crops included apple, apricot, pear, peach/nectarine, plum and wine grape. These crops collectively account for approximately 96% of the area occupied by perennial horticulture in the region ($\approx$ 10,000 ha). Sites were selected based on ‘best practice’ irrigation and agronomy. All crops were assumed to be free of water stress.

3.2.2 Sampling strategy

A diverse range in growing season radiation interception ($\Sigma f_S$) was achieved by targeting a wide range of maximum vegetation cover (measured as midseason daily fractional radiation interception, $f_{\text{MAX}}$) and/or available incoming radiation energy ($\Sigma S$), the latter determined by length of growing season in sampled crops.

Crop boundary information for each site was mapped by recording GPS coordinates of the horticultural block margins using a hand-held GPS (model 12CX, Garmin International Inc., Olathe, Kansas, USA). Boundary coordinates were then used to derive 10 random sampling locations (trees/vines) within each site using GIS software (ArcMap v. 9.2; Economic and Social Research Institute Inc., Redlands, California, USA). These sub-locations were then uploaded onto a GPS unit. Individual trees/vines at each of the 10 sampling points were tagged for subsequent measurement of fractional radiation interception and fruit number.
3.2.3 Model of vegetation cover

A model of seasonal changes in vegetation cover was used to describe crop growth and development to estimate yield (after Palmer et al. 2002). This model connects vegetative growth – phenophase data to seasonal photosynthate accumulation for fruit growth and development.

The diagram in Figure 3.1 describes the vegetation cover model used in this study by identifying the canopy development phases in a crop cycle for perennial deciduous tree and vine crops. Overall, vegetation cover varies from a minimum of zero until the time of leaf emergence in spring (point A; Fig. 3.1) to a maximum in late spring/early summer (point B; Fig. 3.1). That follows a long-lived (> 4-months, points B to D) period of maximum vegetation cover ($f_{\text{MAX}}$) that is common to all temperate fruit tree and vine crops in the Goulburn Valley.

![Schematic diagram showing temporal changes in daily fractional radiation interception ($f$) reflecting leaf area development and vegetation cover dynamics during the crop cycle in deciduous perennial horticultural crops in the Goulburn Valley, Victoria.](image)

In summary, the appearance of 1st leaf (point A) is followed by a rapid leaf area development phase (points A to B) to achieve maximum vegetation cover (point B). Maximum vegetation cover ($f_{\text{MAX}}$) remains relatively stable and dominates most of the irrigation season (points B to D), including harvest (point C) until commencement of leaf senescence (point D), when vegetation cover falls to a minimum at completion of leaf fall (point E).
For each site, the timing of canopy development phases (points A, B, D and E; Fig. 3.1) were obtained from on-site observations of foliage development. Crop maturity (point C; Fig. 3.1) was sourced from grower records.

### 3.2.4 Fractional radiation interception

Daily fractional radiation interception \( (f) \) was determined on clear sky days from measures of instantaneous photosynthetically active radiation (PAR) above and below the canopies at 0900 h, 1230 h and 1600 h using a ceptometer (Model SF80; Decagon Devices Inc., Pullman, Washington, USA). The measurements permit estimation of instantaneous \( f \), denoted \( f_{0900} \), \( f_{1230} \) and \( f_{1600} \), respectively were calculated as:

\[
f = 1 - \frac{\text{PAR}_T}{\text{PAR}}
\]

where, PAR is the incident flux of PAR measured above the canopy (≈ 1.5 m above ground level in an open region within the orchard/vineyard), and \( \text{PAR}_T \) is the transmitted flux of PAR measured below the canopy. Measurements were conducted during the period of maximum vegetation (foliage) cover (e.g. points B – C; Fig. 3.1). Instantaneous \( f \) was adjusted to the planting square (plant and row spacing) at each site.

Accurate estimation of daily \( f \) requires a measure of radiation interception environment throughout the day to account for variation in solar position and its interaction with canopy structure (row spacing and leaf area density) (Charles-Edwards and Lawn 1984; Grossman and DeJong 1998; Goodwin et al. 2006). This interaction is especially apparent in tall hedgerow canopies in north-south rows where instantaneous \( f \) at solar noon significantly underestimates daily \( f \) by as much 2 – fold (Charles-Edwards and Thorpe 1976; Khemira et al. 1993; Iannini et al. 2002). Accordingly, midseason (maximum) daily radiation interception \( f_{\text{MAX}} \) was calculated as the mean of \( f_{0900} \), \( f_{1230} \) and \( f_{1600} \) values (after Goodwin et al. 2006) as:

\[
f_{\text{MAX}} = \left( f_{0900} + f_{1230} + f_{1600} \right) / 3
\]
3.2.5 Cumulative growing season radiation interception
Cumulative growing season radiation interception (ΣfS) was calculated from commencement of full vegetation cover (point B, Fig. 3.1) to crop maturity (point C, Fig. 3.1), representing the main period of photosynthate accumulation to the fruit:

$$\Sigma fS = \sum_{B}^{C} (f_{MAX} \cdot S)$$

Estimates of daily solar radiation (S, MJ/m²) were obtained from the Bureau of Meteorology (www.bom.gov.au/climate/data) weather station at Tatura (36.7° S, 145.5° E, elev. 114 m).

3.2.6 Yield
Commercial crop yields (fresh weight) from the designated sample areas (site/block) were obtained from grower records after harvest using either: (1) weighbridge fruit deliveries to local cannery/winery or, (2) fruit bin count and fruit weight.

Dry weight yield was calculated by adjusting fresh weight yield by the sample mean values of fruit dry matter content for each crop species (see sub-section 3.2.8).

3.2.7 Fruit number
Fruit number (FN) was determined from the number of fruit per tree (or grape bunches per vine) measured prior to fruit maturity. FN data was adjusted to the planting square (plant and row spacing) at each site to derive total fruit number per hectare.

3.2.8 Fruit dry matter content
For dry matter content (DMC) determination, a random bulk sample of fruit (≈ 20 fruit or ≈ 10 vine bunches per site/block) was obtained at harvest time. Fruit DMC was derived from fresh weight and dry weight measurement after drying in a fan-forced oven at 75 °C to constant weight. For stone fruit, fruit flesh was separated from the stone and for vine crops, berries were separated from stalk/stems before oven drying.
3.2.9 Radiation use efficiency

Effective radiation use efficiency ($\varepsilon_{\text{MEAN}}$) was estimated for each crop as the fitted slope of the linear relationship linking yield ($Y$, dry weight) to cumulative seasonal fractional radiation interception during maximum vegetation cover to harvest ($\Sigma f/S$, Equation 3.4) forced through the origin (Equation 3.1). Similarly, maximum effective radiation use efficiency ($\varepsilon_{\text{MAX}}$) was determined from frontier analysis ($95^{\text{th}}$ percentile) of $Y - \Sigma f/S$ responses.

Table 3.1 provides a summary of the extent of data collected for yield – radiation interception analysis.

<table>
<thead>
<tr>
<th>Crop</th>
<th>$f_{\text{MAX}}$</th>
<th>$\Sigma f/S$</th>
<th>$Y - \Sigma f/S$</th>
<th>$Y - FN$</th>
<th>DMC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>51</td>
<td>51</td>
<td>49</td>
<td>35</td>
<td>30</td>
</tr>
<tr>
<td>Apricot</td>
<td>17</td>
<td>17</td>
<td>14</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Pear</td>
<td>55</td>
<td>55</td>
<td>61</td>
<td>26</td>
<td>20</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>63</td>
<td>63</td>
<td>55</td>
<td>29</td>
<td>22</td>
</tr>
<tr>
<td>Plum</td>
<td>16</td>
<td>16</td>
<td>13</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>Wine grape</td>
<td>27</td>
<td>27</td>
<td>25</td>
<td>13</td>
<td>20</td>
</tr>
</tbody>
</table>

3.3 Results

3.3.1 Fractional radiation interception

Table 3.2 shows mean and standard deviation of midseason daily fractional radiation interception, $f_{\text{MAX}}$, for each crop. Mean values of $f_{\text{MAX}}$ were highest in tree crops (44 – 61 %) compared to wine grape (27 %). Among orchard crops, $f_{\text{MAX}}$ varied 4 – fold from 20 to 81 % while, wine grape ranged within the limits, 16 % < $f_{\text{MAX}}$ < 40 %.

Table 3.2 Summary statistics of midseason daily fractional radiation interception ($f_{\text{MAX}}$) of major horticultural crops in the Goulburn Valley, Victoria.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>0.50</td>
<td>0.13</td>
</tr>
<tr>
<td>Apricot</td>
<td>0.59</td>
<td>0.11</td>
</tr>
<tr>
<td>Pear</td>
<td>0.44</td>
<td>0.13</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.59</td>
<td>0.12</td>
</tr>
<tr>
<td>Plum</td>
<td>0.61</td>
<td>0.10</td>
</tr>
<tr>
<td>Wine grape</td>
<td>0.27</td>
<td>0.06</td>
</tr>
</tbody>
</table>
### 3.3.2 Cumulative growing season radiation interception

Table 3.3 shows mean and standard deviation of cumulative growing season radiation interception ($\Sigma f_S$) measured for each crop. Mean values were high for apple and plum ($\approx 1,800$ MJ/m$^2$), intermediate for pear and peach ($\approx 1,200 – 1,400$ MJ/m$^2$) and low for apricot and wine grape ($< 750$ MJ/m$^2$).

<table>
<thead>
<tr>
<th>Crop</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>1,844</td>
<td>566</td>
</tr>
<tr>
<td>Apricot</td>
<td>613</td>
<td>176</td>
</tr>
<tr>
<td>Pear</td>
<td>1,154</td>
<td>533</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>1,374</td>
<td>451</td>
</tr>
<tr>
<td>Plum</td>
<td>1,806</td>
<td>560</td>
</tr>
<tr>
<td>Wine grape</td>
<td>745</td>
<td>249</td>
</tr>
</tbody>
</table>

### 3.3.3 Fruit dry matter content

Table 3.4 shows mean and standard deviation in dry matter content (DMC) measured for each crop. Apple, pear, peach and plum had similar mean DMC values (DMC $\approx 16 – 17\%$). Values in apricot (DMC $\approx 14\%$) were lower than in wine grape (DMC = 25\%).

<table>
<thead>
<tr>
<th>Crop</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>16.7</td>
<td>1.7</td>
</tr>
<tr>
<td>Apricot</td>
<td>13.8</td>
<td>1.4</td>
</tr>
<tr>
<td>Pear</td>
<td>16.2</td>
<td>1.3</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>15.5</td>
<td>2.0</td>
</tr>
<tr>
<td>Plum</td>
<td>17.4</td>
<td>3.3</td>
</tr>
<tr>
<td>Wine grape</td>
<td>25.0</td>
<td>3.2</td>
</tr>
</tbody>
</table>

### 3.3.4 Yield and cumulative growing season radiation interception relationships

Figure 3.2 presents the dry weight yield responses for individual crops to cumulative seasonal intercepted radiation ($\Sigma f_S$) while the mean effective radiation use efficiency ($\epsilon_{\text{MEAN}}$) values derived from them are presented in Table 3.5. Significant positive
linear yield – radiation interception relationships were observed for all crops (Fig. 3.2 and Table 3.5).

### Table 3.5 Summary statistics of mean effective radiation use efficiency ($\epsilon_{\text{MEAN}}$, g fruit dry weight/MJ solar radiation) of major horticultural crops in the Goulburn Valley, Victoria.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Mean</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>0.314***</td>
<td>0.022</td>
</tr>
<tr>
<td>Apricot</td>
<td>0.355***</td>
<td>0.035</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.284***</td>
<td>0.014</td>
</tr>
<tr>
<td>Pear</td>
<td>0.317***</td>
<td>0.025</td>
</tr>
<tr>
<td>Plum</td>
<td>0.175***</td>
<td>0.027</td>
</tr>
<tr>
<td>Wine grape</td>
<td>0.315***</td>
<td>0.029</td>
</tr>
</tbody>
</table>

***$P \leq 0.001$.

Maximum dry weight yield was highest in apple (≈ 12 t/ha), followed by pear and peach (≈ 9 t/ha), plum (≈ 7 t/ha), wine grape (≈ 6 t/ha) and apricot (≈ 3 t/ha). Maximum $\Sigma/S$ values of ≈ 2,900 – 3,100 MJ/m$^2$ were observed in apple, plum and peach. Pear had intermediate values of ≈ 2,200 MJ/m$^2$ compared to values of ≈ 900 and 1,300 MJ/m$^2$ for apricot and wine grape, respectively.

Apricot had high $\epsilon_{\text{MEAN}}$ (≈ 0.36 g fruit dry weight/MJ solar radiation) compared to other crops ($\epsilon_{\text{MEAN}}$ ≈ 0.12 – 0.32 g fruit dry weight/MJ solar radiation) (Table 3.5). $\epsilon_{\text{MEAN}}$ varied across all crop categories (Fig. 3.2).

Table 3.6 shows maximum effective radiation use efficiency ($\epsilon_{\text{MAX}}$) values derived from frontier analysis of yield-radiation interception relationships presented in Figure 3.2. High $\epsilon_{\text{MAX}}$ was recorded in pome fruit (pear and apple; $\epsilon_{\text{MAX}}$ ≈ 0.8 – 0.9 g fruit dry weight/MJ solar radiation) compared to $\epsilon_{\text{MAX}}$ ≈ 0.6 – 0.7 g fruit dry weight/MJ solar radiation for peach/nectarine, apricot and wine grape crops. Estimated $\epsilon_{\text{MAX}}$ for plum was ≈ 0.4 g fruit dry weight/MJ solar radiation.

### Table 3.6 Maximum effective radiation use efficiency ($\epsilon_{\text{MAX}}$, g fruit dry weight/MJ solar radiation) of major horticultural crops in the Goulburn Valley, Victoria.

<table>
<thead>
<tr>
<th>Crop</th>
<th>$\epsilon_{\text{MAX}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>0.80</td>
</tr>
<tr>
<td>Apricot</td>
<td>0.72</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.53</td>
</tr>
<tr>
<td>Pear</td>
<td>0.92</td>
</tr>
<tr>
<td>Plum</td>
<td>0.41</td>
</tr>
<tr>
<td>Wine grape</td>
<td>0.62</td>
</tr>
</tbody>
</table>
Figure 3.2 Relationships between yield and cumulative seasonal intercepted radiation ($\Sigma fS$) of the major perennial horticultural crops in the Goulburn Valley, Victoria. Lines represent mean and maximum effective radiation use efficiency ($\varepsilon_{\text{MEAN}}$, Table 3.5 and $\varepsilon_{\text{MAX}}$, Table 3.6).
### 3.3.5 Yield, cumulative seasonal radiation interception and fruit number relationships

Maximum fruit number of ≈ 380,000 fruit/ha was recorded in plum, compared to ≈ 300,000 fruit/ha for apple, pear and peach/nectarine and ≤ 200,000 fruit/ha for apricot. For wine grape, maximum fruiting levels were ≈ 85,000 bunches/ha.

Table 3.7 presents statistical summary of yield response expressed as a function of ΣfS and fruit number (FN). For apple and peach, ΣfS and FN jointly influenced yield. For pear, FN did not improve yield determination beyond ΣfS. No clear ΣfS – FN response was evident in apricot.

<table>
<thead>
<tr>
<th>Crop</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>0.196 (0.043)**</td>
<td>17.16 (4.15)***</td>
</tr>
<tr>
<td>Apricot</td>
<td>0.219 (0.114)</td>
<td>4.59 (5.06)</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.168 (0.041)***</td>
<td>11.35 (4.90)**</td>
</tr>
<tr>
<td>Pear</td>
<td>0.194 (0.069)*</td>
<td>9.37 (5.44)</td>
</tr>
</tbody>
</table>

***P ≤ 0.001, **P ≤ 0.05, *P ≤ 0.01

### 3.4 Discussion

This chapter presented and analysed relationships between fruit yield and seasonal intercepted solar radiation, Y – ΣfS, for commercially grown apple, pear, peach/nectarine, apricot, plum and wine grape crops in the Goulburn Valley. In all cases, yield was positive linearly related to ΣfS, in agreement with Monteith’s radiation use efficiency model (Equation 3.1). Radiation use efficiencies for fruit production were established for individual crops. Mean values (ε\text{MEAN}) were obtained from all data while maximum values (ε\text{MAX}) were obtained from the yield frontier taken as the 95th percentile of yield – radiation responses. These estimates of radiation use efficiency allow calculation of average and maximum (attainable) yield in relation to intercepted solar irradiance of vegetation cover assuming that growth is not limited by water stress (e.g. deficit irrigation), nutrient shortage (e.g. fruit growth disorders associated with nutrient related deficiencies), cultural practices (e.g. fruit number manipulation via fruit thinning) or adverse climatic conditions (e.g. bud/floral desiccation or fruit drop via frost damage or heat stress).
For apple, reported $\varepsilon_{\text{MAX}}$ values of 0.48 – 0.62 g fruit dry weight/MJ solar radiation (Palmer 1988, 1989; Robinson and Lakso 1989, 1991; Wagenmakers and Callesen 1995) and 0.88 – 0.95 g total dry biomass/MJ solar radiation (Palmer 1988; Palmer et al. 2002) compare favourably to $\varepsilon_{\text{MAX}}$ measured across the diverse range of perennial deciduous fruit and vine crops (Table 3.6) in this study.

The lower $\varepsilon_{\text{MAX}}$ observed in stone fruit (peach/nectarine, plum, apricot) compared to pome fruit (apple, pear) crops (Fig. 3.2 and Table 3.6) are likely due to the additional metabolic costs of the kernel and seed (stone) shell containing high energy synthesis compounds, protein and oil (Lieth 1968; McDermitt and Loomis 1981; Loomis and Connor 1992). Low $\varepsilon_{\text{MAX}}$ observed in wine grape may be due to mild water stress induced by deficit irrigation practices aimed at improved fruit/wine quality, especially in red varieties (e.g. Wample and Smithyman 2002).

This study used commercial yield data and did not attempt to derive total plant biomass production. Consequently, the $\varepsilon^*$ values reported in Table 3.5 ($\varepsilon_{\text{MEAN}}$) and Table 3.6 ($\varepsilon_{\text{MAX}}$) include the $h$ term of Equation 3.1. Further, commercial yield is expected to be less than total fruit yield because of pre-harvest losses in the field and rejection of some fruit for quality reasons. Such bias would result in smaller estimates of district average yield ($Y_{\text{MEAN}}$) relative to the maximum yield ($Y_{\text{MAX}}$). For a given crop type, if water stress is not the cause of large variation in $\varepsilon^*$ obtained from $Y - \Sigma f S$ data (Fig. 3.2), then variation in $h$ is likely to be responsible for variation in $\varepsilon_{\text{MEAN}}$ (Table 3.5).

Published data on yield of perennial horticultural crops in the Goulburn Valley region are limited. For peach, reported $Y_{\text{MAX}}$ of 104 – 110 t fresh weight/ha from experimental plots (Chalmers et al. 1978) exceeds the commercial, field-scale yields data obtained in this study by $\approx$ 2-fold ($Y \leq 8$ t/ha dry weight @ 15.5% DMC; Fig 3.2, Table 3.3). On the other hand, highest yielding orchards of pear and apple presented in Figure 3.2 are close to reported commercial crop values of $Y_{\text{MAX}}$ of 55 – 70 t fresh weight/ha and 80 – 110 t fresh weight/ha, respectively (Callinan 2000). Grape yields measured in this study were also similar to reported commercial production levels in south eastern Australia (Dunn and Martin 2004; Dunn et al. 2005; Clingeleffer 2010).
Fruit size is a primary driver in fresh market quality of perennial deciduous tree crops (e.g. apple, pear, peach, nectarine, apricot, plum). High marketable yield is achieved by orchard growers targeting large fruit size by tree pruning and manipulation of fruit number by flower and/or fruitlet thinning. Fruit thinning increases the assimilation (carbohydrate) capacity (source strength) relative to fruit number (sink strength). Interpretation of whether yield is ‘source’ or ‘sink’ limited in the crops analysed in this study was confounded by the poor relationship between $\Sigma f_S$ and FN (Table 3.7). For apple and peach, data suggest that yield was jointly ‘source’ and ‘sink’ limited, while for pear and apricot, FN did not contribute statistically to the estimation of $Y_{\text{MAX}}$ or $Y_{\text{MEAN}}$. This means that variation in FN confounded yield determination.

This study applied the model of Palmer et al. (2002) to derive estimates of $\Sigma f_S$ based on measurement of $f_{\text{MAX}}$ as representing seasonal photosynthate accumulation to the fruit during the maximum vegetation cover period (Fig. 3.1, Equation 3.4). This simple model of vegetation cover incorporating the ‘plateau $f_{\text{MAX}}$ response’ in midseason fractional radiation interception is well supported by empirical studies in apple (Palmer 1988; O’Connell and Goodwin 2007b; O’Connell et al. 2008; Auzmendi et al. 2011; Casadesus et al. 2011), pear (O’Connell and Goodwin 2007a) and wine grape (McClymont 2006). Further, the model of vegetation cover aligns closely to the crop growth and development stages described in FAO Irrigation and Drainage Paper 56 (Allen et al. 1998).

High variation (2 – 4 fold) in $f_{\text{MAX}}$ was measured in all crops (Table 3.2). Differences in $f_{\text{MAX}}$ are primarily due to varying dimensions in row and alley spacing, crop height and also row orientation. Alleyways provide access for crop management practices (e.g. spraying, harvesting) and reduce the deleterious effects of canopy shading (Ryugo et al. 1980; Lakso et al. 1999; Wünsche and Lakso 2000). They also reduce vegetation cover in horticultural systems to $f_{\text{MAX}} \approx 60 – 70 \%$ (Lakso et al. 1999; Wünsche and Lakso 2000; Middleton et al. 2002; Palmer 2007). Here, adequate radiation distribution within the canopy secures fruit quality as shading leads to reduced fruit weight and fruit immaturity (increased firmness, lower colour and decreased soluble solids) (Lakso 1994; Corelli-Grappadelli et al. 1996).

A large range in growing season radiation environment ($\Sigma f_S$) was measured for each orchard and vineyard crop (Fig. 3.2 and Table 3.3). Differences in $\Sigma f_S$ arise from the
combination of leaf area development phases in a crop cycle, midseason maximum vegetation cover ($f_{\text{MAX}}$), and length of the growing season to intercept available solar radiation ($\Sigma S$), for a given location (e.g. latitude) (Fig. 3.1, Equations 1.2 and 3.4). A marked (3-fold) difference between species in maximum values of $\Sigma S$ was evident between early maturing crops (e.g. apricot, $\Sigma S \leq 900 \text{ MJ/m}^2$) compared with long-season crops (e.g. peach and apple, $\Sigma S \leq 3,000 \text{ MJ/m}^2$) (Table 3.3). By comparison, low seasonal fractional radiation interception ($f_{\text{max}} \leq 40 \%$) was commonplace in wine grape crops, resulting in maximum $\Sigma S$ values $\leq 1,200 \text{ MJ/m}^2$.

Fruit DMC values (Table 3.4) were consistent with reported values for apple (Palmer 1988; Robinson and Lakso 1991; Salunkhe and Kadam 1995), peach (Salunkhe and Kadam 1995; Quilot et al. 2004), wine grape (Cozzolino et al. 2008) and the National Nutrient Database published by the United States Department of Agriculture (www.ars.usda.gov/ba/bhnrc). For stone fruit crops (apricot, peach/nectarine and plum), the fraction of assimilate partitioned between the flesh and stone were similar to data of Kamel and Kakuda (1992).

Chapter 1 identified the poor production performance of commercial pear and apple crops reported by the National industry body (APAL 2010). This study suggests that yield of fruit tree crops in the Goulburn Valley is well below the international performance. Low vegetation cover ($f_{\text{MAX}} \leq 40 \%$) was common in all crops and this limits radiation capture ($\Sigma S$) reducing the possibility of high yield (Equation 3.1).

The practical significance of $\varepsilon_{\text{MEAN}}$ and $\varepsilon_{\text{MAX}}$ (Tables 3.5 and 3.6) are to provide direction to advance yield outcomes by understanding maximum yield ($Y_{\text{MAX}}$) and gaps between attainable, district average yield ($Y_{\text{MEAN}}$) and actual (grower) yield. In the first instance, practical improvements in the production of perennial high value horticultural crops in the Goulburn Valley can be measured as the difference between $Y_{\text{MAX}}$ and $Y_{\text{MEAN}}$. Assuming fruit number limitations are not the major cause of yield determination, this yield gap is likely to be a result of a varied combination of abiotic (e.g. drought, nutrient deficiency) and biotic (e.g. pests and diseases) stress that limit crop growth and highlight the complexity of yield development. Monteith (1977) reported that ‘...more work is needed to identify the factors responsible for the large differences between average commercial and record yields’. It seems that the situation has changed little to the present time.
3.5 Conclusion

Estimates of maximum ($Y_{\text{MAX}}$) and average ($Y_{\text{MEAN}}$) regional yield in apple, pear, peach/nectarine, apricot, plum and wine grape crops in the Goulburn Valley region of Victoria was derived from yield – radiation interception relationships. Maximum yield was found to be highly dependant on seasonal radiation capture in agreement with Monteith’s radiation use efficiency model.
Chapter 4 Relationship between radiation interception and NDVI of perennial horticultural crops in the Goulburn Valley

4.1 Introduction
Vegetation cover is a major determinant of crop water requirement (Ayars et al. 2003; Williams and Ayars 2005; Goodwin et al. 2006), yield potential (Monteith 1977; Chapter 3) and water productivity in perennial horticultural crops. Taken together, vegetation cover and length of growing season determine yield potential and crop water requirement (Chapter 1). Equation 3.1 described yield as the product of radiation use efficiency, fractional radiation interception \((f)\) and radiation climate during the growing season. Earlier in Chapter 1, it was explained that crop water requirement can be determined from estimates of \(f\) and length of growing season together with evaporative demand calculated from weather observations.

At the regional level, variation in vegetation cover between crops may be due to differences in phenological development, age, canopy size and shape, and leaf area density. Canopy size, shape, and leaf area density are influenced by orchard/vineyard design (e.g. plant and row spacing, row direction, trellis structure) and during productive years by canopy management practices (e.g. tree training, pruning).

Direct measurement of vegetation cover \((f)\) from field measurements is onerous and costly (Chapter 1). Satellite based estimates therefore offer advantages of affordability and repeatability, providing both site-specific detail and an extensive regional coverage. It is, however, important to establish that measures of remotely sensed vegetation cover provide sufficiently accurate assessments for interpretation of yield, water use and water productivity.

Linear relationships have been established between (plot-scale) ground-based paired data sets of \(f\) and Normalized Difference Vegetation Index (NDVI) for annual row crops (corn, soybeans, sunflower and cereals: Asrar et al. 1984; Daughtry et al. 1992; Joel et al. 1997; Yang et al. 2008). In contrast, there are no published reports comparing NDVI derived from satellite against ground-based measures of \(f\) for any vegetation type.
This chapter investigates relationships between ground-based measures of $f$ and measures of NDVI derived from Landsat imagery for major horticultural tree and vine crops in the Goulburn Valley. To achieve this, paired $f$ – NDVI data for apple, apricot, peach/nectarine, plum, pear and wine grape crops are compared to the Bastiaanssen and Ali (2003) relationship of $f$ on NDVI for broad-acre crops reported as $f = 1.26 \cdot \text{NDVI} - 0.16$ (Equation 2.1).

4.2 Material and Methods

4.2.1 Study area

This study was conducted in the Goulburn Valley horticultural region of Victoria during the 2008/09 irrigation season. Ground-based measures of orchard and vineyard daily $f$ were related to NDVI derived from remotely-sensed Landsat data. A total of 70 sites were analysed including apple, apricot, peach/nectarine, plum, pear and wine grape. A small composite subset ($n = 70$) of potential sites at which $f$ was measured during the 2007/08 and 2008/09 irrigation seasons and previously presented in Chapter 3 (Table 3.1), was available for analysis in this study. These sites meet the requirement for:

i. Synchronous measurement of ground-based $f$ and satellite derived NDVI and,

ii. Cloud free Landsat data during the midseason period that coincides with maximum foliage cover (see Fig. 3.1).

4.2.2 Comparison of fractional radiation interception with satellite-derived NDVI

Ground-based field observations included crop type, row and plant spacing and daily $f$. Daily $f$ was measured, by methodology described in Chapter 3 (Equation 3.4), within 20 days of the satellite overpass.

Cloud-free satellite imagery (scene size = 170 km x 185 km) taken by Landsat-5 Thematic Mapper (TM) on 23 Jan 2009 (path/row: 93/85) was acquired from the United States Geological Survey (USGS) Earth Explorer website (http://earthexplorer.usgs.gov). The satellite overpass was at 10:30-11:00 a.m. local standard time. The image had received Level 1T processing and geo-referencing by USGS prior to delivery and had a pixel size of 30 m.
The TM bands 1–5 and 7 provided surface reflectance data for visible and near infrared radiation. Using these bands, NDVI was calculated on a per pixel basis according to Rouse et al. (1973) as:

\[
NDVI = \frac{(NIR - RED)}{(NIR + RED)}
\]

4.1

Here, NIR is near infrared radiation (Band 4) and RED is visible radiation (Band 3) (Allen et al. 2007a). Both RED and NIR are sensitive to solar elevation and azimuth so surface-reflectance irradiances of target crops varies within a growing season due to interactions with canopy geometry and associated shadows (e.g. row direction, trellis design). Accordingly, the method of Chander and Markham (2003) was used to apply radiometric correction to the digital count values of RED and NIR data to account for the intervening atmosphere and the sun-sensor geometry. NDVI was calculated on a pixel-by-pixel basis and averaged for each site, avoiding pixels at field edges.

Estimates of daily \( f \) and NDVI were averaged and paired at field scale in order to conduct \( f \) – NDVI analyses using GenStat 10 (VSN International Limited, Oxford, UK). Paired ground and remote observations were compared to the published \( f \) – NDVI relationship of Bastiaanssens and Ali (2003) for broad-acre crops (Equation 2.1).

### 4.3 Results

Figure 4.1 shows the relationships between daily \( f \) and NDVI for apple, apricot, pear, peach/nectarine, plum and wine grape crops in the Goulburn Valley region during the 2008/09 irrigation season. Daily \( f \) increased positively and linearly with NDVI.

Composite crop data showed minimum and maximum daily \( f \) values were \( \approx 15 \% \) and \( \approx 85 \% \), respectively. NDVI ranged within the limits, \( 0.25 < NDVI < 0.7 \). Figure 4.1 shows that grape crops had low vegetation cover (\( NDVI \leq 0.43, f \leq 39 \% \)) compared to the wide spectrum of vegetation cover measured for pear, apple, apricot and peach/nectarine crops. Plum crops had highest vegetation cover (\( NDVI \geq 0.57, f \geq 50 \% \)).

Summary statistics of the linear regression of paired \( f \) – NDVI data for crops with sufficient replication (\( n \geq 8 \)) and a composite response for all crops (\( n = 70; R^2 = \))
Values of the intercept ($a$) or slope ($b$) were significantly different from the composite response for apple, peach/nectarine and wine grape. Individual analyses of NDVI against morning $f$ and midday $f$ did not improve the $f$–NDVI response (data not shown).

In broad terms, the composite (apple, apricot, pear, peach/nectarine, plum and wine grape) $f$–NDVI relationship compared reasonably well to that of Bastiaanssen and Ali (2003) (Equation 2.1; red line, Fig. 4.1) across a wide range of NDVI.

Table 4.1 Coefficients, $a$ and $b$, of the linear relationship, $f = a + b \cdot \text{NDVI}$, for major perennial horticultural crops in the Goulburn Valley irrigation region in 2008/09.

<table>
<thead>
<tr>
<th>Crop</th>
<th>$a$</th>
<th>$b$</th>
<th>$R^2$</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>0.382 (0.145)*</td>
<td>0.283 (0.250)</td>
<td>0.04</td>
<td>23</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>-0.180 (0.196)</td>
<td>1.185 (0.335)**</td>
<td>0.45</td>
<td>15</td>
</tr>
<tr>
<td>Pear</td>
<td>0.112 (0.308)</td>
<td>0.589 (0.538)</td>
<td>0.15</td>
<td>10</td>
</tr>
<tr>
<td>Plum</td>
<td>-0.204 (0.480)</td>
<td>1.354 (0.763)</td>
<td>0.31</td>
<td>8</td>
</tr>
<tr>
<td>Wine grape</td>
<td>-0.220 (0.223)</td>
<td>1.347 (0.635)**</td>
<td>0.50</td>
<td>12</td>
</tr>
<tr>
<td>All crops</td>
<td>-0.069 (0.059)</td>
<td>1.027 (0.107)**</td>
<td>0.58</td>
<td>70</td>
</tr>
</tbody>
</table>

Standard errors of the regression coefficients are shown in parenthesis, * $P<0.05$, ** $P<0.001$. 48
4.4 Discussion

This chapter presented and analysed relationships between NDVI derived from satellite against ground-based measures of $f$ for apple, apricot, peach/nectarine, plum, pear and wine grape crops in the Goulburn Valley region. The composite dataset showed a linear $f –$ NDVI response ($R^2 = 0.58$, Table 4.1) and was consistent with that of Bastiaanssen and Ali (2003) (Equation 2.1, Fig. 4.1). In general, pear crops fell close or below the Bastiaanssen and Ali relationship, whereas apricot had values above it. Relationships for wine grape, plum, peach/nectarine and apple crops were scattered across the relationship. Even though ground-based $f$ measurements were conducted close to the date of the satellite overpass and both ground and remote observations were made at comparable field scales, not all the variation in $f$ was explained by NDVI. Overall, however, these observations reveal that the Bastiaanssen and Ali relationship provides a useful determinant for vegetation cover and overcomes the need for on-ground site specific measurement of $f$.

No published reports are available on ground-based measures of $f$ against satellite-derived NDVI for any vegetation type, although relationships between remotely sensed NDVI and leaf area index, shaded area and canopy cover in horticultural crops have been reported. In grape crops, strong linear responses between NDVI and leaf area index ($R^2 = 0.92$, Johnson (2003)) and NDVI and shaded area (Johnson and Scholasch 2005) suggest accurate capability in remote sensing of vegetation cover. In recent study, Trout et al. (2008) reported strong linear relationships between NDVI and canopy cover ($R^2 = 0.95$) in eleven different annual and perennial horticultural crops. In that case, however, perennial (pistachio, almond and grape) crops ($n = 10$) had little or no understorey vegetation (i.e. bare soil) and only two sites had canopy cover exceeding 50 %. By comparison, the current study examined six perennial horticultural crops, and included a wide range in vegetation cover ($15 \% \leq f \leq 85 \%$) and understorey conditions.

For a given crop, variation in vegetation cover across the region is likely to provide a wide range in NDVI (and $f$) due to differences in age, canopy geometry, planting arrangement (i.e. low v. high plant density) and canopy management practices. No crop in the $f$ - NDVI data (Fig. 4.1) covered the entire range of vegetation cover experienced in the region (see Table 3.2 and Chapter 5), nor the range of NDVI represented by the Bastiaanssen and Ali relationship. For example, plum crops
represented in Figure 4.1 had a narrow range in NDVI and grape crop NDVI values did not exceed 0.45. Therefore, further improvement to the current study requires measurements of \( f \) and NDVI across the full range of vegetation cover to understand if crop type and orchard/vineyard configuration result in different \( f \)– NDVI responses.

Conditions, when combined, that would confound \( f \)– NDVI comparisons include early season, sparse crops, with green understorey and a satellite view line down the planting (tree, vine) row.

Variation in understorey conditions and/or inter-row management practices among orchards and vineyards in the Goulburn Valley appears to have contributed to the scatter in the composite \( f \)– NDVI response (\( R^2 = 0.58; \) Table 4.1) reported here. Green understorey conditions provide higher NDVI values relative to on-ground \( f \), as was the case for some pear, apple and peach/nectarine crops (Fig. 4.1). For example, a notable outlier in Figure 4.1, with low \( f \) (29 \%) and high NDVI (0.63) can be explained by the presence of a dominant (3.5 m wide) green understorey (grass) cover crop in a sparsely vegetated apple orchard. In that case, trees were widely spaced at 2.5 m in E-W rows that were 5 m apart. They were 4.2 m tall and pruned to a central leader system with a canopy diameter of 2.2 m. These foliage dimensions give a vertical cover of 30 \% that equates closely to ground-based measured \( f \).

Further explanation to why some paired \( f \)– NDVI observations of orchard/vineyard crops fell below the Bastiaanssen and Ali relationship (red line, Fig. 4.1) are:

i. Penetration of near infrared radiation (NIR) deeply into tall, narrow, vertically trained (hedgerow) canopies of high leaf area density,

ii. Narrow, north-south row orientated canopies and,

iii. Non-vertical view angle of Landsat (\( \leq 7.5^\circ \) off-nadir) imagery at the scene margins (swath width 185 km).

The \( f \)– NDVI relationship is driven by different optical properties of green leaves in the RED (high absorption) and NIR (high reflection) bands (Equation 4.1). NIR has a greater optical depth into foliage than RED. Other vegetation indices may offer improved prediction of \( f \) among the diverse range in vegetation cover and canopy structures of orchard and vineyard crops. For example, Enhanced Vegetation Index (EVI) offers ability to provide ‘3D vegetation structure’ because it accounts for the
transmission of NIR and RED (Huete et al. 2002) and therefore should be tested in perennial horticultural crops. Discrepancies due to view angle effects were avoided as target areas are located in the centre of the Landsat image and diminish as vegetation cover increases (Epiphonio and Huete 1995).

Nevertheless, despite these above mentioned uncertainties, this study has shown that NDVI derived from satellite data can be used to make good estimates of vegetation cover of a wide range of perennial horticultural crops with discontinuous canopies. The low-cost and high repeat cycle (16 days) of Landsat data and relative simplicity of this vegetation cover procedure (Equation 4.1) should facilitate the quantification of vegetation and yield, water use and water productivity in agricultural regions at field, farm and regional scale.

4.5 Conclusion

This study provided relationships between ground-based measures of \( f \) and NDVI derived from satellite for the major perennial horticultural tree and vine crops in the Goulburn Valley region of Victoria. At the practical level, the \( f – \) NDVI relationship of horticultural crops compared well to published data for broad-acre crops. Satellite-based NDVI may be used to estimate \( f \) to derive and map vegetation cover information of perennial horticultural crops with minimal requirement for supporting information.
Chapter 5 Satellite derived estimates of NDVI of horticultural crops in the Goulburn Valley

5.1 Introduction
The Normalized Difference Vegetation Index (NDVI) is a vegetation cover indicator (Kriegler et al. 1969; Tucker 1979). Horticultural applications to assess vegetation cover using remote observations of NDVI have been reported for almond, grape and pistachio crops (Lamb et al. 2001; Johnson 2003; Johnson and Scholasch 2005). Chapter 2 described the derivation and advantages of estimation of vegetation cover using NDVI derived from satellite data.

Figure 3.1 presented a model of vegetation cover for perennial horticultural crops in which leaf area increases rapidly early in the growing season and vegetation cover reaches a long-lived (> 4 months) maximum until leaf fall. Chapter 4 showed that the fractional radiation interception \( f \) – NDVI relationship for broad-acre crops (Bastiaanssen and Ali (2003), Equation 2.1) adequately described \( f \) as a function of NDVI during the midseason period of several perennial horticultural crops in the Goulburn Valley. However, it is important to establish that NDVI derived from satellites provides sufficiently accurate assessments of the temporal trends in vegetation cover in order to interpret yield, water use and water productivity.

This chapter examines the temporal stability in satellite-derived NDVI for apple, apricot, peach/nectarine, plum, pear and wine grape crops during an irrigation season in the Goulburn Valley. This chapter aims to test the validity of the vegetation cover model described by Figure 3.1 using a collage of Landsat imagery.

5.2 Material and Methods
5.2.1 Study area
This study was conducted in the Goulburn Valley horticultural region of Victoria during the 2008/09 irrigation season. A total of 10,934 sites (fields) were analysed including apple, apricot, peach/nectarine, plum, pear and wine grape. These crops represent approximately 96 % of total crop area designated as horticultural land use in the region (= 10,000 ha). The proportion of fields classified as immature (<4 years-old) crops was less than 5 % of the total number of orchard and vineyard fields, and were therefore included in the study.
5.2.2 Measurement of NDVI using satellite remote sensing
Clear-sky Landsat5-TM images (path/row: 93/85) of the Goulburn Valley, Victoria, were obtained from the US Geological Survey EarthExplorer website (http://edcsns17.cr.usgs.gov/EarthExplorer) for five days during the 2008/09 irrigation season. The dates were 3 November 2008, 21 January 2009, 23 February 2009, 27 March 2009 and 12 April 2009, hereafter denoted as NOV, JAN, FEB, MAR and APR, respectively. These dates cover the growing season period of the major perennial horticultural crops in the Goulburn Valley region.

The images were analysed by the method described in Chapter 4 to evaluate NDVI of each orchard/vineyard field on each occasion of measurement. Crops were identified from local irrigation district surveys of land use and crop type conducted in 2006 across the Goulburn Valley region, and available from SPC Ardmona Pty Ltd (www.spcardmona.com.au). These land use data formed a GIS database layer to isolate and define unique horticultural crop (field) location, boundary (shape file) and field identification using ArcGIS (ArcMap v 9.3; Economic and Social Research Institute Inc., Redlands, California, USA).

Correlations between Landsat imagery dates for each orchard/vineyard field and crop category were used to assess the temporal variation in vegetation cover measured as NDVI by regression analysis using GenStat 10 (VSN International Limited, Oxford, UK).

5.3 Results
5.3.1 Seasonal variation of NDVI in apple
Temporal progression of vegetation cover measured as NDVI during the 2008/09 irrigation season for apple crops is depicted in the box plot diagram in Figure 5.1. Variation in NDVI was large for all periods (NOV to APR) with NDVI values ranging between 0.14 and 0.75. Similar minimum and maximum NDVI values were recorded on each occasion. Median NDVI values measured in NOV and APR were smaller than those in the mid- (JAN and FEB) and late-season (MAR) periods.
Figure 5.1 Box plots of vegetation cover measured as NDVI derived from Landsat data in apple crops (n = 2,023) during the 2008/09 irrigation period in the Goulburn Valley, Victoria. Each box contains the 25th – 75th percentiles, solid lines within the boxes show medians (50th percentile), T-bars show the bounds of the 10th and 90th percentiles and circles depict outliers (minimum and maximum NDVI values).

Individual analyses of NDVI distributions for pear, peach/nectarine, apricot, plum and wine grape crops showed similar temporal trends and distributions to apple during the 2008/09 irrigation season (NOV – APR) (data not shown). Crop NDVI was found to be independent of orchard/vineyard field area (data not shown).

5.3.2 Midseason NDVI for apple, peach, pear, apricot, plum and wine grape crops

The distribution of midseason (JAN) NDVI values representing maximum vegetation cover for apple, peach, pear, apricot, plum and wine grape crops in the Goulburn Valley region is presented in Figure 5.2. Variation in NDVI was large for all crop categories, with NDVI values ranging between 0.14 and 0.76. Respective median midseason NDVI values were 0.54, 0.53, 0.56, 0.50, 0.53 and 0.47 for apple, peach/nectarine, pear, apricot, plum and wine grape.

For all crops, the 10th percentile NDVI values were ≥ 0.30. Apricot and wine grape had low median, 1st and 3rd quartile NDVI values compared to other tree crops. By comparison, pear had a higher median NDVI value and a narrower inter-quartile range (Fig. 5.2).
Figure 5.2 Box plots of midseason vegetation cover measured as NDVI derived from Landsat data in apple \((n = 2,023)\), peach/nectarine \((n = 2,596)\), pear \((n = 4,547)\), apricot \((n = 873)\), plum \((n = 825)\) and wine grape \((n = 71)\) crops in the Goulburn Valley, Victoria in January 2009. Each box contains the 25\(^{th}\) – 75\(^{th}\) percentiles, solid lines within the boxes show medians (50\(^{th}\) percentile), T bars show the bounds of the 10\(^{th}\) and 90\(^{th}\) percentiles and circles depict outliers (minimum and maximum NDVI values).

5.3.3 Stability in NDVI distribution during the irrigation season

NDVI on the various dates is analysed for temporal stability by linear regression. Results are presented in Table 5.1, with scatter plots for apple on key dates in Fig. 5.3.

Slopes of the linear regressions (Table 5.1) are close to unity (slope \(\approx 1.0\)) and with low error (SE \(\leq 0.005\)) for all crops categories. Correlation coefficients, included in Table 5.1 reveal that comparisons between early- (NOV) and mid-season (JAN or FEB) periods were the most variable (0.56 < \(R^2\) < 0.71).

Highest goodness-of-fit values (0.72 < \(R^2\) < 0.91) occurred during the mid- (JAN or FEB) and end-of-season (MAR or APR) periods. This feature is explored further for apple in Figure 5.3. There, strong linear relationships are evident among mid- (JAN v. FEB) and late-season (FEB v. MAR, MAR v. APR) NDVI as indicated by high goodness-of-fit values (\(R^2 > 0.81\), Table 5.1). By comparison, correlation was weaker (\(R^2 \approx 0.64\)) between the start- (NOV) and mid-season (JAN) periods (Table 5.1 and Fig. 5.3). This weaker response was due to a small proportion of apple orchards having low start-of-season and high midseason NDVI values (NOV v. JAN; Fig. 5.3). Very few crops showed differences in NDVI during the mid- and late-season periods (JAN v. FEB, FEB v. MAR, MAR v. APR; Fig. 5.3).
Table 5.1 Summary statistics of linear relationships of NDVI derived from Landsat data for horticultural tree crops in the Goulburn Valley during the 2008/09 irrigation season. Image date: Time 1 = x axis, Time 2 = y axis.

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<th>Time 2</th>
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<th>SE</th>
<th>$R^2$ (%)</th>
<th>Number of orchards</th>
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Figure 5.3 Relationship between satellite derived NDVI in apple crops ($n = 2,023$) during the key vegetation cover – phenophase phases, early- (NOV), mid- (JAN and FEB) and late-season (MAR and APR) periods of the 2008/09 irrigation season in the Goulburn Valley, Victoria.

5.4 Discussion
This study quantified temporal variability in vegetation cover measured as satellite derived NDVI of apple, apricot, peach/nectarine, plum, pear and wine grape crops during an irrigation season in the Goulburn Valley. Strong temporal consistency in midseason NDVI was measured in these major perennial horticultural crops. Results support the model of vegetation cover for perennial deciduous crops adopted in this study, where vegetation cover is maximal, long-lived and stable for the midseason period (see Fig. 3.1). This temporal consistency in NDVI response offers the potential for satellite-derived NDVI maps to measure vegetation cover at reduced cost compared to ground-based approaches.

Overall, irrespective of crop category, higher NDVI values occurred midseason compared to the early-season period. Temporal variation in NDVI was least during
mid- (JAN – FEB) and late- (MAR) season periods as shown by regression relationships and correlation analysis (Fig. 5.2 and Table 5.1) and a tighter distribution of NDVI in box plot data (narrower inter-quartile range; Figs 5.1 and 5.2). The temporal (early-, mid- and late-season) trends in NDVI were similar for apple, pear, peach, apricot, plum and wine grape crops during the irrigation season. Similar temporal progression and strong midseason stability in NDVI has been reported in wine grape crops (Johnson 2003).

Midseason NDVI ranged between 0.14 and 0.76, representing bare ground (i.e. abandoned crop) and near ‘full’ vegetation cover, respectively. Most crops had NDVI values greater than 0.3, representing sparse vegetation as the minimum level of vegetation cover. Maximum NDVI measured in Goulburn Valley fruit tree crops (NDVI ≤ 0.76) was consistent with incomplete cover (i.e. discontinuous canopies). At the regional level, high (4 – fold) within-population variability in NDVI among all crop categories endorses the wide range in fractional intercepted radiation measured in Chapters 3 and 4, and aligns with earlier reports of wide distribution in vegetation cover (O’Connell and Goodwin 2005) and published values of fractional radiation interception of orchards (O’Connell et al. 2006, 2008) and vineyards (McClymont 2006) in the Goulburn Valley.

The likely explanation for outliers presented in Figure 5.3 showing low NDVI values in NOV (start-of-season) compared to high NDVI in JAN (mid-season) is a delay in leaf area development of late-maturing apple crops.

Sources of uncertainty in estimation of vegetation cover using NDVI include sun angle, characteristics of the understorey (i.e. cover crop), land use change and, management practices that use white reflective material. The temporal effect of sun angle (i.e. solar elevation and azimuth) was corrected for in each Landsat image (see Chapter 4). However, the effect of sun angle on surface-reflected irradiance of target crops (tree/vine canopy, shadows and cover crop) varies within a growing season due to interactions with canopy geometry (e.g. row direction, canopy size and shape). Under conditions of low vegetation cover and high levels of green cover crop, radiometric indices are likely to over estimate vegetation cover of the target crop. Conversely, management practices aimed to manipulate the radiation environment within canopies using white reflective material effectively lower NDVI values by
reducing the reflectance in both NIR and RED spectral bands (Equation 4.2). These practices aim to provide price premiums for uniformly ripened fruit and colour development, especially in apple, plum and nectarine crops. White reflective materials used in orchards include:

i. Calcium carbonate or kaolin clay applied to fruit and foliage (e.g. Surround®; Glenn and Putterka 2005; Rosati et al. 2006; Villanueva and Walgenbach 2007),

ii. A woven mulch cloth placed across the inter-row space (e.g. Extenday™; George et al. 2005) and,

iii. Above-canopy netting (George et al. 2005).

Industry data on these management practices is limited. However, orchard netting constitutes less than 5 % of total horticultural crop area in the region (M. Crisera, pers. comm. 2011).

Another source of uncertainty in intra-season NDVI could result from changes in land use during the period of the study. Tree removal, replanting and redesign of orchard infrastructure and layout (i.e. conversion from flood systems to micro-irrigation, trellis, high-density planting systems) or re-grafting new varieties has occurred in recent seasons in response to low irrigation allocations, drought and poor market conditions (Chapter 1). Pear and peach crops form the major portion of land use change in horticultural enterprises in the Goulburn Valley region (www.spcardmona.com.au).

Despite the above mentioned issues, results reveal that Landsat data provided accurate and useful field-scale NDVI information on the temporal distribution of vegetation cover in perennial horticultural crops. The observed diversity (4 – fold) in vegetation cover highlights the need to provide crop- and site-specific production and water use targets so growers can benchmark their irrigation and production performance and identify agronomic and water management practices for improvement in water productivity.

5.5 Conclusion
This study quantified temporal variability in vegetation cover during an irrigation season using NDVI derived from a collage of satellite images for several major
perennial horticultural crops in the Goulburn Valley. For a given crop type significant variation in NDVI was measured, reflecting differences in vegetation cover. Low temporal variation in crop NDVI occurred during the midseason period compared to the early-season rapid leaf development period. The strong temporal stability in NDVI response support the simple model of vegetation cover used in this study and suggest a single midseason satellite image is adequate to assess maximum vegetation cover. Overall, the low cost and performance of Landsat data make satellite-derived NDVI a robust, repeatable and valuable tool for estimation of vegetation cover in horticultural crops at the field scale.
Chapter 6 Satellite derived estimates of crop water requirement of perennial horticultural crops in the Goulburn Valley

6.1 Introduction
Observations reported in Chapter 5 revealed significant variation in vegetation cover measured as NDVI among horticultural crops in the Goulburn Valley. Such data imply large diversity in crop water requirement (CWR) and therefore have direct implications on water management (e.g. irrigation scheduling) and water productivity.

Recent developments in satellite remote sensing permit the determination of CWR based on NDVI in combination with ground-based agro-meteorological (weather station) measurements (e.g. Allen et al. 2007a). Chapter 2 explained how the crop coefficient ($K_c$) can be obtained from remotely sensed ET and NDVI. Whitfield et al. (2011) have reported a recent application of this approach to derive site- and crop-specific NDVI-dependent CWR ($K_c$ values) for citrus, almond and grape crops in the Sunraysia irrigation region, Victoria, Australia. Potentially each satellite overpass provides an individual estimate of $K_c$. The Landsat satellite has a 16-day repeat cycle, therefore several independent estimates of $K_c$ values from ET – NDVI observations in an irrigation season are possible.

This chapter explores a series of ET – NDVI relationships of horticultural crops obtained during the 2008/09 irrigation season in the Goulburn Valley. Water allocation in that season was very limited due to drought (Chapter 1). To satisfy that estimates of $K_c$ were not influenced by water stress, the $K_{cb}$ – NDVI response of irrigated broad-acre annual (potato and sugar-beet) crops in Idaho, USA reported by Tasumi et al. (2005a) was used as a diagnostic baseline ($K_{cb} = 1.33 \cdot \text{NDVI} - 0.13$; Equation 2.6) as summarised in Figure 2.2 and also described by Whitfield et al. (2011).

The objective is to make satellite-based measures of ET and NDVI of apple, pear, peach/nectarine and apricot crops in the Goulburn Valley, and to explore the potential use of the resultant ET – NDVI relationships for estimation of CWR using the approach described by Whitfield et al. (2011). Potential application for weather based irrigation management is discussed.
6.2 Material and Methods

6.2.1 Land use classification: perennial horticultural crops

Orchard fields \((n = 10,038)\) were classified in major crop categories: apple, pear, peach/nectarine and apricot using land use methodology described in Chapter 5.

6.2.2 Estimation of evapotranspiration (ET), vegetation cover (NDVI) and local evaporative demand (ET<sub>R</sub>)

Processing of satellite images and calculations of Normalised Difference Vegetation Index (NDVI) followed the methods described in Chapter 4.

Specifically, the METRIC evapotranspiration (ET) model (Allen et al. 2005<sup>a</sup>, 2007) was applied to five Landsat-5 TM images (path/row: 93/85) taken on cloud-free days during the 2008/09 irrigation season in the Goulburn Valley as also described by Whitfield et al. (2011) (see Appendix 1). Landsat image dates were: 4 November 2008, 22 January 2009, 24 February 2009, 28 March 2009 and 13 April 2009, hereafter denoted NOV, JAN, FEB, MAR and APR, respectively.

In contrast to Allen et al. (2007), surface roughness, \(z_{0m}\), was estimated using the relationship of Teixeira et al. (2009):

\[
z_{0m} = \exp(0.26 (\text{NDVI}/\text{ALB}) - 2.21)
\]

6.1

Here, ALB was the pixel-wise METRIC estimate of surface albedo (Allen et al. 2007).

The internal calibration procedure of METRIC trains the surface energy balance to predict ET for two extreme conditions referred to as ‘cold’ and ‘hot’ pixels that respectively resemble a full-cover, well-watered ‘lucerne’ crop and a dry agricultural bare soil (fallow paddock). This procedure is referred to as ‘Calibration using Inverse Modelling at Extreme Conditions’ (CIMEC; Allen et al. 2008). Selection of these ‘hot’ and ‘cold’ anchors is made from a scatter plot of surface temperature against NDVI that may extend well beyond the specific horticultural landscape of interest. A ‘hot’ pixel has the combination of high surface temperature and zero vegetation cover (NDVI \(\approx 0.2\)) found within a fallow paddock, whereas, a ‘cold’ pixel is has the low surface temperature and full-cover of a ‘lucerne’ crop (NDVI \(\approx 0.8\)).
In the present analysis, satellite-derived ET estimates were scaled to local evaporative demand, calculated as alfalfa-based ‘tall-crop’ reference evapotranspiration ($ET_R$), and expressed as evaporation ratio ($ET/ET_R$) according to Allen et al. (2005b). $ET_R$ was calculated from meteorological observations taken at the Shepparton Airport ($36.6^\circ$ S, $145.7^\circ$ E, elev. 114 m), available from the Bureau of Meteorology (www.bom.gov.au/climate/data).

Table 6.1 presents the NDVI values for ‘cold’ and ‘hot’ anchor pixels, recent rainfall and calculations of $ET_R$ for each Landsat data image. No significant rainfall was recorded 14-days prior to any Landsat image acquisition.

<table>
<thead>
<tr>
<th>Image date</th>
<th>Previous 14-day rainfall (mm)</th>
<th>Hot anchor NDVI</th>
<th>Cold anchor NDVI</th>
<th>$ET_R$ (w/m$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOV</td>
<td>1.3</td>
<td>0.20</td>
<td>0.84</td>
<td>475</td>
</tr>
<tr>
<td>JAN</td>
<td>0.0</td>
<td>0.15</td>
<td>0.82</td>
<td>525</td>
</tr>
<tr>
<td>FEB</td>
<td>0.2</td>
<td>0.19</td>
<td>0.83</td>
<td>569</td>
</tr>
<tr>
<td>MAR</td>
<td>1.8</td>
<td>0.20</td>
<td>0.83</td>
<td>432</td>
</tr>
<tr>
<td>APR</td>
<td>0.0</td>
<td>0.17</td>
<td>0.81</td>
<td>361</td>
</tr>
</tbody>
</table>

Pixel-scale $ET/ET_R$ and NDVI estimates were categorised by crop type according to horticultural land use data (see Chapter 5) using ArcMap software (v. 9.3; ESRI Inc., Redlands, California, USA). Field-scale averages of paired data (NDVI and $ET/ET_R$) were calculated from pixel-scale data in order to calculate NDVI-dependent values of $K_c$. Daily $K_c$ was estimated as the ‘instantaneous’ ET ratio ($ET/ET_R$) value obtained at the time of the satellite image (Tasumi et al. 2005a; Allen et al. 2007a).

6.2.3 Determination NDVI-dependent crop water requirement using regional customised $ET/ET_R$ – NDVI relationships

Local estimates of CWR (Equation 2.8) appropriate to the main Goulburn Valley crops of apple, pear, peach/nectarine and apricot were derived from the respective $ET/ET_R$ – NDVI scatter plots, based on comparisons with the $K_{cb}$ – NDVI baseline (Equation 2.6) afforded by the irrigated annual (potato and sugar-beet) crops grown in Idaho, USA (Tasumi et al. 2005a) using the hydrologic and vegetation interpretive framework (Fig. 2.2) described in Chapter 2.
6.2.4 Statistical analysis

Statistical analysis was conducted using GenStat 10 (VSN International Limited, Oxford, UK).

6.3 Results

Figures 6.1, 6.2 and 6.3 show ET/ET$_R$ – NDVI relationships of apple, peach/nectarine and pear crops, respectively, in the Goulburn Valley region for the 2008/09 irrigation season. Irrespective of satellite image date or crop category, NDVI ranged between the limits, 0.14 < NDVI < 0.76, and ET increased linearly with NDVI.

The responses of these Goulburn Valley temperate fruit tree crops complied with the K$_{cb}$ line derived from potato and sugar-beet crops by Tasumi et al. (2005a). In general, minimum ET values (Figs 6.1, 6.2 and 6.3) were well-described by the rising edge of the potato/sugar-beet K$_{cb}$ data (green line) of Tasumi et al. (2005a). The incidence of ET – NDVI observations below this rising edge (green K$_{cb}$) baseline was particularly apparent in FEB and least common to MAR data.

The ET – NDVI data shown in Figures 6.1, 6.2 and 6.3 provide an extensive overview of the local irrigation industry during the 2008/09 season. They illustrate that crops exhibited a large range in ET for NDVI in the range, 0.3 < NDVI < 0.6. ET ranged from a minimum of ≈ 0.45 ET$_R$ to a maximum of ≈ 0.8 ET$_R$ for a NDVI value of 0.5. Few observations were recorded for NDVI < 0.20. ET was less than ET$_R$ for most crops although some observations of ET > ET$_R$ occurred in March.

The wide variation in NDVI and ET allows establishment of crop-specific ET – NDVI relationships for each image date. Here, the ET – NDVI responses that are parallel to the K$_{cb}$ line of Tasumi et al. (2005a) are depicted as yellow lines in Figures 6.1, 6.2 and 6.3. They describe the mean ET response to NDVI and represent the K$_c$ value (Equation 2.8).
Figure 6.1 Satellite derived field scale ET/ET$_R$ – NDVI relationships for apple in the Goulburn Valley irrigation region, during the 2008/09 irrigation season. Yellow lines show the K$_c$ that describes the mean population ET – NDVI response relative to the Tasumi et al. (2005a) K$_{ac}$/irrigation refill (green) line.
Figure 6.2 Satellite derived field scale ET/ET$_R$ – NDVI relationships for peach/nectarine in the Goulburn Valley irrigation region, during the 2008/09 irrigation season. Yellow lines show the $K_c$ that describes the mean population ET – NDVI response relative to the Tasumi et al. (2005a) $K_{cb}$/irrigation refill (green) line.
Figure 6.3 Satellite derived field scale ET/ET$_R$ – NDVI relationships for pear in the Goulburn Valley irrigation region, during the 2008/09 irrigation season. Yellow lines show the $K_c$ that describes the mean population ET – NDVI response relative to the Tasumi et al. (2005a) $K_c_{irr}$/irrigation refill (green) line.
Table 6.2 provides mean values of NDVI, ET/ET\textsubscript{R} and \(K_c\) offset (d\(K_{cb}\)) for apricot, apple, pear and peach/nectarine crops for each satellite image date during the 2008/09 irrigation season. The \(K_c\) offset (d\(K_{cb}\)) represents the parallel ET/ET\textsubscript{R} – NDVI relationship above the \(K_{cb}\) line (Equation 2.6) and describes the population mean ‘irrigation refill’ response.

Mean values of NDVI increased from NOV to JAN, were relatively constant during the mid- (JAN, FEB) and late- (MAR) season periods, and then decreased slightly at the end of the irrigation season (APR). Mean ET ratio, ET/ET\textsubscript{R}, ranged between 0.56 and 0.81 while the \(K_c\) offset, d\(K_{cb}\), ranged between 0.03 and 0.23. In general, irrespective of crop category, values of NDVI, ET ratio and d\(K_{cb}\) values were highest in MAR.

<table>
<thead>
<tr>
<th>Crop</th>
<th>NOV</th>
<th>JAN</th>
<th>FEB</th>
<th>MAR</th>
<th>APR</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apricot</td>
<td>0.46</td>
<td>0.48</td>
<td>0.47</td>
<td>0.48</td>
<td>0.46</td>
</tr>
<tr>
<td>Apple</td>
<td>0.49</td>
<td>0.52</td>
<td>0.52</td>
<td>0.53</td>
<td>0.51</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.48</td>
<td>0.51</td>
<td>0.51</td>
<td>0.52</td>
<td>0.50</td>
</tr>
<tr>
<td>Pear</td>
<td>0.50</td>
<td>0.54</td>
<td>0.53</td>
<td>0.53</td>
<td>0.51</td>
</tr>
<tr>
<td>ET/ET\textsubscript{R}</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apricot</td>
<td>0.59</td>
<td>0.63</td>
<td>0.56</td>
<td>0.72</td>
<td>0.61</td>
</tr>
<tr>
<td>Apple</td>
<td>0.62</td>
<td>0.69</td>
<td>0.64</td>
<td>0.80</td>
<td>0.69</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.59</td>
<td>0.67</td>
<td>0.59</td>
<td>0.76</td>
<td>0.65</td>
</tr>
<tr>
<td>Pear</td>
<td>0.64</td>
<td>0.71</td>
<td>0.66</td>
<td>0.81</td>
<td>0.70</td>
</tr>
<tr>
<td>d(K_{cb})</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apricot</td>
<td>0.12</td>
<td>0.12</td>
<td>0.07</td>
<td>0.22</td>
<td>0.14</td>
</tr>
<tr>
<td>Apple</td>
<td>0.11</td>
<td>0.12</td>
<td>0.08</td>
<td>0.23</td>
<td>0.15</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.08</td>
<td>0.13</td>
<td>0.03</td>
<td>0.19</td>
<td>0.13</td>
</tr>
<tr>
<td>Pear</td>
<td>0.12</td>
<td>0.13</td>
<td>0.08</td>
<td>0.23</td>
<td>0.15</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apricot</td>
<td>872</td>
<td>872</td>
<td>872</td>
<td>872</td>
<td>756</td>
</tr>
<tr>
<td>Apple</td>
<td>2,023</td>
<td>2,023</td>
<td>2,023</td>
<td>2,023</td>
<td>1,854</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>2,596</td>
<td>2,596</td>
<td>2,596</td>
<td>2,596</td>
<td>993</td>
</tr>
<tr>
<td>Pear</td>
<td>4,547</td>
<td>4,547</td>
<td>4,547</td>
<td>4,547</td>
<td>4,355</td>
</tr>
</tbody>
</table>

Table 6.2 Mean values of NDVI, ET/ET\textsubscript{R} and \(K_c\) offset (d\(K_{cb}\)) for apricot, apple, peach/nectarine and pear crops in the Goulburn Valley irrigation region, during the 2008/09 irrigation season.
6.4 Discussion

This study presented and analysed relationships between ET and NDVI for commercially grown fruit tree crops in the Goulburn Valley irrigation region from a collage of Landsat data spanning an irrigation season. The METRIC model was applied to derive ET. The series of ET – NDVI responses showed a large range of ET and NDVI in target crops. Strong linear ET – NDVI relationships permit the estimation of CWR ($K_c$ values) based on vegetation cover (NDVI) and local evaporative demand ($ET_R$). Therefore, the regional ET – NDVI information provided by this study provides irrigators with field- and crop-specific CWR data to derive water budgets and schedule irrigation.

No significant rain was recorded for the Goulburn Valley in the two weeks prior to days of analysis (Table 6.1). Maximum rates of ET coincided with the rate ascribed to full-cover ‘alfalfa’ reference crop employed as the cold anchor pixel in METRIC analyses ($ET = ET_R$; Figs 6.1, 6.2 and 6.3). Comparisons of Goulburn Valley crops with those of Tasumi et al (2005a) revealed that most ET observations exceeded the NDVI – dependent ET values that characterised the $K_{cb}$ (green) line of broad-acre crops grown in Idaho, USA. Accordingly, CWR ($K_c$ values) was established as the mean response of paired ET – NDVI data above the Tasumi $K_{cb}$ line using the constant $K_c$ offset slope ($dK_{cb}$) approach (Equation 2.8; Table 6.2). These $K_c$ regression (yellow) lines (Figs 6.1, 6.2 and 6.3) consequently describe the water use capability of target crops over the range of agronomic management options practised in the Goulburn Valley. Those lines thereby provide a more relaxed definition of $K_{cb}$ in target crops accounting for differences in crop structure, row orientation and irrigation system.

$ET/ET_R$ values furthest away from the $K_c$ values (yellow lines) provide upper and lower limits to the $K_c$ – NDVI space. These highest ET rates are likely to represent recently irrigated crops. Conversely, the lowest rates of ET are likely to be associated with crops at the end of their irrigation cycle, and then requiring irrigation. In the absence of rainfall, the relative contribution of soil/understorey ET ($K_e$, Equation 2.5) in micro-irrigated orchards depends on the level of fruit tree vegetation cover because shading determines the available energy for evaporation. High values of $K_e$ are likely to occur under conditions of sparse vegetation cover (low NDVI) compared to more dense crops (high NDVI). Irrespective of crop category or image date, for a given ET
ratio value (e.g. 0.6 ET/ET\textsubscript{R}), vegetative cover ranged by \(\approx 0.3\) NDVI units (i.e. 0.6 minus 0.3) (Figs 6.1, 6.2 and 6.3). This within population NDVI scatter suggests the presence of a green cover crop but requires further investigation. The relative contribution of soil/understorey ET (\(K_e\)) by cover crops could be more accurately described by varying the slope and intercept of the ET – NDVI response. An ET – NDVI analysis of sub-surface drip irrigated horticultural systems would improve the estimation of \(K_{cb}\), as \(K_e\) is likely to be negligible, making \(K_c \approx K_{cb}\) (Equation 2.5).

Results from this study demonstrate that crop water use and therefore irrigation requirement were primarily governed by vegetation cover. High NDVI values were accompanied by high ET values, representing high rates of transpiration resulting from frequent irrigation. Combining ET – NDVI observations with local climate data (ET\textsubscript{R}) provides a simple (irrigation management and scheduling) tool using the crop coefficient approach.

Results suggest, therefore, that a single ‘generic’ crop-specific FAO-56 \(K_c\) value (Allen \textit{et al.} 1998) is inappropriate. The data highlight a substantial range in vegetation cover, reinforcing the need for site-specific irrigation management strategies tailored to account for vegetation cover. Growers must account for this spatial variation in vegetation cover and match irrigation inputs to CWR if they are to improve water productivity in perennial horticultural crops in the Goulburn Valley.

These findings align with a recent study showing that \(K_c\) was strongly dependent on NDVI in almond, citrus and grape crops in the Sunraysia irrigation region of Victoria, Australia (Whitfield \textit{et al.} 2011). The current study also mirrors reports in pecan orchards showing wide range in vegetation cover (Wang \textit{et al.} 2007; Samani \textit{et al.} 2011) and seasonal ET (Sammis \textit{et al.} 2004; Samani \textit{et al.} 2007, 2009, 2011) and, a strong linear relationship between \(K_c\) and vegetation cover (Samani \textit{et al.} 2011).

The practical significance of improved irrigation management now available by the adoption of NDVI-dependent crop water use targets can be put in to context with the precision of existing water management (micro-irrigation) systems with the following examples.
First, consider a late-maturing crop (e.g. peach, apple) harvested in late-March that typically receives irrigation inputs totalling \( \approx 6 \) ML/ha (600 mm) (Boland et al. 2001). The seasonal local evaporative demand (\( \text{ET}_R \)), for the same 5-month period (Nov – Mar), calculated from local long-term weather data (www.bom.gov.au) is \( \approx 925 \) mm. Based on relationships shown in Figures 6.1, 6.2 and 6.3 and Table 6.2, a nominal (NDVI dependent) target \( K_c \) (ET/\( \text{ET}_R \)) value of 0.5, equates to a CWR of approximately 4.6 ML/ha (0.5 \( \times \) 925 mm = 460 mm). Given a crop water supply (CWS) of 6 ML/ha (600 mm) that can be applied with a precision of 10 % (\( \pm \) 60 mm), then actual CWR is 460 mm equates to a mismatch, and hence a potential water saving, of between 80 and 200 mm (0.8 – 2.0 ML/ha), equivalent to 13 – 33 % of CWS.

Second, a water use target (\( \approx 0.45 \) ET/\( \text{ET}_R \)) of a sparse (NDVI \( \approx 0.3 \)) crop is approximately one-half of that appropriate to crops with high vegetation cover (NDVI \( \approx 0.7 \), ET \( \approx 0.95 \) \( \text{ET}_R \)). Growers who employ high CWS on low NDVI crops are therefore likely to be using up to twice the amount of water needed to satisfy their water use capability. These practical examples highlight the ability to delineate the performance in irrigation (hydrologic) management for a specific crop/field and identify possible water savings using satellite platforms to determine CWR.

The ET/NDVI data presented in Figures 6.1, 6.2 and 6.3, suggest that some crops experienced mild water stress, especially during the midseason (FEB image) period when paired ET – NDVI data fell below the Tasumi baseline relationship. Further investigation regarding crop water status is required to assess if crops were irrigated below CWR (e.g. deficit irrigation). Firstly, an analysis of on-farm irrigation deliveries (CWS) indexed against evaporative demand is warranted, ideally at the same spatial scale as the ET – NDVI data. It is known is that water supply was restricted in the Goulburn Valley region during the 2008/09 irrigation season leading to a final irrigation allocation of only 33 % (www.g-mwater.com.au). The season was dry after early-season rainfall (\( \approx 89 \) mm) in November 2008 so that if they were to meet CWR, growers needed to purchase additional (temporary sales) water to irrigate their crops. Conditions of extreme evaporative demand that prevailed over a 3-week period commencing late January 2009 (21-day average \( \text{ET}_R \approx 8.9 \) mm/day) place further demands in effective irrigation scheduling to match CWS to CWR. The ET – NDVI observations suggest that many growers did not achieve the required CWS
because a greater proportion of apple, peach/nectarine and pear crops fell below the Tasumi baseline in FEB compared to the other Landsat image dates (NOV, JAN, MAR, APR; Figs 6.1, 6.2 and 6.3). It is probable, therefore, that some crops experienced periods of water stress during the 2008/09 irrigation season. A separate investigation is warranted to identify if ET/ET\textsubscript{R} – NDVI relationships developed in this study under drought conditions are consistent with the hydrologic and vegetation interpretive framework (Fig. 2.1, Whitfield et al. 2011) using satellite imagery and appropriate land use data in irrigation seasons with high (≥ 100 %) water allocation.

It should be noted that the land use data used in this study were established in 2006. Since then, drought conditions and irrigation seasons with low water allocations have led to the abandonment of some crops (Chapter 1), shown here by low ET – NDVI combinations on a limited number of fields (NDVI < 0.3; ET/ET\textsubscript{R} < 0.4, Figs 6.1, 6.2 and 6.3). The specific ET – NDVI water use relationships reported here must therefore be confirmed in order to ensure that the ET – NDVI relationships are repeatable and consistent over time before they are applied in practice. The extent to which findings are consistent with local knowledge and practice must also be established. Unusual or questionable observations may require formal experimental validation and testing.

This study confirms the usefulness of satellite technologies as a tool for ET (and K\textsubscript{c}) estimation and provides a framework to understand irrigation systems and improve agricultural water management. The approach that has been described and analysed provides the ability to deliver customised crop water use targets by sampling all crops within an irrigation district. Such local derived K\textsubscript{c} information has potential application for weather based irrigation management delivery for orchards (and vineyards) at farm to regional scales. Tools to deliver spatial and temporal water information to growers include web and/or mobile phone SMS based products (e.g. www.irrigateway.net).

6.5 Conclusion
Apparent crop water requirement was determined using satellite derived relationships of ET and NDVI of the major high value perennial horticultural crops in the Goulburn Valley, Victoria. The METRIC model was used to derive ET. Substantial within-population variability occurred in NDVI and ET. ET capability was strongly linked to
NDVI, shown by linear relationships between ET/ET_R and NDVI. Tree fruit crops complied with the basal crop coefficient (K_{cb}) response defined by the baseline ET – NDVI relationships of broad-acre annual crops reported by Tasumi et al. (2005a). Temporal trends in crop water status were evident during the irrigation season using the hydrologic and vegetative interpretive framework of Whitfield et al. (2011). This study has established that satellite remote sensing of ET and NDVI provides field-scale crop coefficients (K_c) for potential application of irrigation and agronomic management performance appraisal of perennial horticultural industries.
Chapter 7 Assessment of yield – water use outcomes based on vegetation cover

7.1 Introduction
Chapter 1 explained how maximum yield ($Y_{\text{MAX}}$) and crop water requirement (CWR) combine to form a crop water production function that, when adjusted for vegetation cover, provides important metrics to guide agronomic and/or hydrologic improvements in water productivity. Understanding yield response to water supply is critical due to the non-linearity in the water production function as shown in Figure 1.3. With that understanding, the water production function can provide growers with the ability to compare actual yield with $Y_{\text{MAX}}$ and crop water supply (CWS) with CWR and so improve the performance of their crops.

$Y_{\text{MAX}}$ and CWR jointly depend on vegetation cover and crop type (Chapters 3, 4 and 6). $Y_{\text{MAX}}$ can be estimated from vegetation cover, radiation use efficiency and length of growing season (Chapter 3) and therefore varies with crop type. CWR depends on evaporative demand, length of growing season and vegetation cover (Chapter 6). Vegetation cover and length of growing season provide the interacting links that determine $Y_{\text{MAX}}$ and CWR.

Perennial horticultural crops in the Goulburn Valley exhibited a 4 – fold range in vegetation cover (Chapter 5). Growers, therefore, must adapt CWS to vegetation cover if they are to optimise yield and water use outcomes. But estimation of vegetation cover is difficult. It may be obtained *in situ* from field measures of fractional radiation interception (Chapter 3) or remotely from measurement of NDVI (Chapter 5). Alternatively, vegetation cover may be estimated from $Y_{\text{MAX}}$ data (i.e. $f_{\text{max}} = Y_{\text{MAX}} / \epsilon_{\text{MAX}} \cdot \sum S$; Equation 3.1), an approach that requires information on radiation use efficiency, length of growing season and radiation climate as described in Chapter 3.

Data for benchmarking of irrigation performance of perennial horticultural crops have been collected routinely in the Riverland, Sunraysia and Goulburn Valley regions of the Murray Darling Basin for up to 10 years (Chapter 1). These data relate crop yield to CWS (irrigation + rainfall) on up to 20 farms per season. They have, however, been interpreted solely in terms of the water use efficiency ratio (yield/CWS). In the
absence of crop- or site-specific estimates of vegetation cover and consequent CWR, these analyses have limited ability to assist growers to improve hydrologic and/or agronomic management.

This chapter provides examples of the effects of length of growing season and vegetation cover on yield and water use in situations where site-specific measures of vegetation cover are available. It also explores the potential use of $Y_{\text{MAX}}$ to formulate estimates of maximum vegetation cover and maximum CWR in regional irrigation benchmarking. Finally, it assesses variability between and within crop categories in water productivity components ($Y_{\text{MAX}}$ and CWR) for apple, apricot, peach/nectarine and pear crops using the yield – water use relationships reported in earlier chapters of this thesis.

7.2 Material and Methods

7.2.1 Effects of vegetation cover and length of growing season on water productivity in peach

Effects of vegetation cover and length of growing season on $Y_{\text{MAX}}$ and CWR in peach crops in the Goulburn Valley, Victoria were calculated to illustrate yield – water use outcomes. Four combinations are evaluated, viz: low and high vegetation cover and short and long growing season.

Estimates of low and high vegetation cover were based on measures of maximum (midseason) daily fractional radiation interception ($f_{\text{MAX}}$) in peach orchards ($n = 63$) in the Goulburn Valley (Table 3.2). Low and high vegetation cover was taken as the 10th and 90th percentile $f_{\text{MAX}}$ values, respectively.

Growing season length for early and late maturity crops was determined from measured phenophase data in the above mentioned peach crops (Chapter 3). The phenophase data included the commencement of maximum vegetation cover (point B, Fig. 3.1), crop maturity (point C, Fig. 3.1) and post-harvest period (points C – D, Fig. 3.1).

Estimates of $Y_{\text{MAX}}$ and CWR were derived by methods described in Chapter 1. $Y_{\text{MAX}}$ depends on $f_{\text{MAX}}$, cumulative growing season solar radiation ($\Sigma S$) and radiation-use efficiency for maximum production ($\varepsilon_{\text{MAX}}$) (Equation 1.5):
\[ Y_{\text{MAX}} = \varepsilon_{\text{MAX}} \cdot \sum_{B}^{C} (f_{\text{MAX}} \cdot S) \]  

7.1

The value of \( \varepsilon_{\text{MAX}} \) was 0.53 g/MJ as reported in Table 3.4.

CWR was estimated according to Equation 1.4 including an allowance (0.3 \( \text{ET}_{\text{MAX}} \)) for orchard maintenance during the post-harvest period (Goodwin 2009). That is,

\[ \text{CWR} = \sum_{B}^{C} (f_{\text{MAX}} \cdot \text{ET}_{R}) + 0.3 \cdot \sum_{C}^{D} (f_{\text{MAX}} \cdot \text{ET}_{R}) \]  

7.2

Water productivity (WP) was calculated as the ratio of \( Y_{\text{MAX}} \) to CWR:

\[ \text{WP} = \frac{Y_{\text{MAX}}}{\text{CWR}} \]  

7.3

Values were calculated for 2007/08 and 2008/09 irrigation seasons and average responses were derived to assess the effect of vegetation cover and length of growing season on \( Y_{\text{MAX}} \) and CWR in peach crops.

Estimates of daily solar radiation (\( S, \text{MJ/m}^2 \)) and ‘alfalfa’ reference crop evapotranspiration (\( \text{ET}_R, \text{mm} \)) were obtained from the Bureau of Meteorology (www.bom.gov.au/climate/data) weather station at Tatura (36.7° S, 145.5° E, elev. 114 m). Table 7.1 describes the agronomic parameters and weather data used in analysis of vegetation cover and length of growing season on water productivity in peach crops.

<table>
<thead>
<tr>
<th>Vegetation cover</th>
<th>Maturity</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>( f_{\text{MAX}} ) (%)</th>
<th>( \Sigma S ) (MJ/m²)</th>
<th>( \Sigma \text{ET}_R ) (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Early</td>
<td>324</td>
<td>5</td>
<td>90</td>
<td>44</td>
<td>1,181</td>
<td>836</td>
</tr>
<tr>
<td>Low</td>
<td>Late</td>
<td>305</td>
<td>56</td>
<td>90</td>
<td>44</td>
<td>2,919</td>
<td>933</td>
</tr>
<tr>
<td>High</td>
<td>Early</td>
<td>324</td>
<td>5</td>
<td>90</td>
<td>73</td>
<td>1,181</td>
<td>836</td>
</tr>
<tr>
<td>High</td>
<td>Late</td>
<td>305</td>
<td>56</td>
<td>90</td>
<td>73</td>
<td>2,919</td>
<td>933</td>
</tr>
</tbody>
</table>

Table 7.1 Agronomic parameters and weather data used in analysis of vegetation cover and length of growing season on water productivity in peach crops in the Goulburn Valley irrigation region. Commencement (B) and end (D) of the period of maximum vegetation cover and fruit maturity (C) are expressed as day of year.
7.2.2 Determination of crop water requirement from yield observations in irrigation benchmarking surveys of apple, peach/nectarine and pear in northern Victoria

Estimates of $Y_{\text{MAX}}$ of apple, pear and peach/nectarine crops grown in northern Victoria (Goulburn and Murray Valley) were determined from empirical yield and CWS irrigation benchmarking data (Table 7.2) as follows. For each crop, dry weight yield was calculated as fresh weight yield multiplied by fruit dry matter content previously determined in Chapter 3 (Table 3.3). $Y_{\text{MAX}}$ was estimated as the 95th percentile of yields observed for individual crop types in the surveys.

Length of growing season for the most common crop/variety combination grown in the region was determined from phenophase data measured in Chapter 3. The varieties were T204, Pink Lady and Packham for peach, apple and pear, respectively. The values of $\epsilon_{\text{MAX}}$ were 0.53, 0.80 and 0.92 g/MJ for peach, apple and pear, respectively as reported in Table 3.4.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>Boland et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>O’Connell et al. (2006)</td>
</tr>
<tr>
<td></td>
<td>O’Connell and Goodwin (2007b)</td>
</tr>
<tr>
<td></td>
<td>O’Connell (unpublished)</td>
</tr>
<tr>
<td>Pear</td>
<td>Boland et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>O’Connell and Goodwin (2007a)</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>Boland et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>O’Connell (unpublished)</td>
</tr>
</tbody>
</table>

CWR was estimated as the product of $f_{\text{MAX}}$ and growing season evaporative demand ($\Sigma E_{T_R}$), with adjustment for duration of the post-harvest period (Equation 7.2). The estimated levels of vegetation cover ($f_{\text{MAX}}$) were determined for each $Y_{\text{MAX}}$ using length of growing season, available solar radiation ($\Sigma S$) and radiation-use efficiencies for potential production ($\epsilon_{\text{MAX}}$):

$$f_{\text{MAX}} = \frac{Y_{\text{MAX}}}{\epsilon_{\text{MAX}}} \cdot \sum_{B}^{C} S$$

Weather data for Tatura, taken from the Bureau of Meteorology (www.bom.gov.au/climate/data), were used to calculate $\Sigma S$ and $\Sigma E_{T_R}$. Key dates of
vegetation cover development and, $\Sigma S$, $\Sigma ET_R$ and $\varepsilon_{\text{MAX}}$ values used in calculations of $f_{\text{MAX}}$ and CWR for apple, pear and peach/nectarine are presented in Table 7.3.

Table 7.3 Agronomic parameters and growing season solar radiation ($\Sigma S$) and evaporative demand ($\Sigma ET_R$) regimes, and maximum crop production ($\varepsilon_{\text{MAX}}$) parameters used to calculate vegetation cover ($f_{\text{MAX}}$) to derive crop water requirement (CWR) for apple, pear and peach/nectarine crops in northern Victoria. Commencement (B) and end (D) of maximum vegetation cover period and fruit maturity (C) dates expressed as day of year.

<table>
<thead>
<tr>
<th>Crop</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>$\varepsilon_{\text{MAX}}$ (g/MJ)</th>
<th>$\Sigma S$ (MJ/m$^2$)</th>
<th>$\Sigma ET_R$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>305</td>
<td>105</td>
<td>145</td>
<td>0.80</td>
<td>3,836</td>
<td>1,060</td>
</tr>
<tr>
<td>Pear</td>
<td>319</td>
<td>46</td>
<td>115</td>
<td>0.92</td>
<td>2,355</td>
<td>915</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>305</td>
<td>46</td>
<td>90</td>
<td>0.53</td>
<td>2,692</td>
<td>935</td>
</tr>
</tbody>
</table>

7.2.3 Variation in maximum yield and crop water requirement within and between crop categories

Spatial variation in $Y_{\text{MAX}}$ and CWR for apple, apricot, peach/nectarine and pear crops in the Goulburn Valley region were analysed for the 2008/09 irrigation season. $Y_{\text{MAX}}$ and CWR were determined from Equations 7.1 and 7.2, respectively, using NDVI derived from Landsat data (Chapter 5). Radiation use efficiency and ground-based crop phenophase information are as presented in Chapter 3, while radiation climate and evaporative demand data are from local weather observations (e.g. Table 7.3). Location and crop classification of orchard fields ($n = 10,039$) were sourced from SPC Ardmona Pty Ltd (www.spcardmona.com.au) as described in Chapter 4.

As a potential application for operational implementation to improve water productivity outcomes, maps of crop category, $Y_{\text{MAX}}$ and CWR for the Shepparton East district (36.41º S, 145.45º E, elev. 118 m) located in the centre of the Goulburn Valley irrigation region were generated using ArcGIS (ArcMap v 9.3; Economic and Social Research Institute Inc., Redlands, California, USA).

7.3 Results

7.3.1 Effects of vegetation cover and length of growing season on water productivity in peach

Estimated $Y_{\text{MAX}}$, CWR and WP for early and late maturing peach crops under low or high vegetation cover are shown in Table 7.4. Varying the level of vegetation cover and/or length of growing season resulted in substantial ranges in $Y_{\text{MAX}}$ (2.7 – 11.4 t/ha), CWR (2 – 6 ML/ha) and relatively smaller variation in WP (1.4 – 1.9 t/ML).
Both $Y_{\text{MAX}}$ and CWR increased under higher levels of vegetation cover. Similarly, later fruit maturity increased $Y_{\text{MAX}}$ and CWR.

Table 7.4 Maximum yield ($Y_{\text{MAX}}$), crop water requirement (CWR) and water productivity (WP) of peach crops under conditions of low and high vegetation cover and early and late fruit maturity in the Goulburn Valley irrigation region.

<table>
<thead>
<tr>
<th>Vegetation cover</th>
<th>Maturity</th>
<th>$Y_{\text{MAX}}$ (t/ha dry weight)</th>
<th>CWR (ML/ha)</th>
<th>WP (t/ML)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Early</td>
<td>2.7</td>
<td>2.0</td>
<td>1.4</td>
</tr>
<tr>
<td>Low</td>
<td>Late</td>
<td>6.8</td>
<td>3.6</td>
<td>1.9</td>
</tr>
<tr>
<td>High</td>
<td>Early</td>
<td>4.6</td>
<td>3.4</td>
<td>1.4</td>
</tr>
<tr>
<td>High</td>
<td>Late</td>
<td>11.4</td>
<td>6.0</td>
<td>1.9</td>
</tr>
</tbody>
</table>

The corresponding water production functions under scenarios of early and late maturing peach crops with low or high vegetation cover are presented in Figure 7.1. There, response of the water productivity parameters ($Y_{\text{MAX}}$ and CWR) to the above mentioned vegetation cover and length of growing season scenarios are clearly illustrated.

The CWS required to maintain tree health during the post-harvest period are also depicted as the X-axis intercepts in Figure 7.1. Early season crops had greater post-harvest water requirement (0.7 – 1.2 ML/ha) compared to late season crops (0.2 – 0.4 ML/ha), reflecting the duration between harvest and commencement of leaf fall. By comparison, vegetation cover played a reduced role in determining post-harvest water requirement compared to length of growing season. For example, the difference in post-harvest water requirement for early versus late maturing peach under high vegetation cover was 0.8 ML/ha (1.2 - 0.4 ML/ha; Fig 7.1).
Figure 7.1 Water production functions for early and late fruit maturity peach under (a) low and (b) high vegetation cover in the Goulburn Valley irrigation region of Victoria. Water production functions are derived from crop water requirement (CWR) and maximum yield (Y\textsubscript{MAX}) (see Table 7.4).
7.3.2 Determination of crop water requirement from yield observations in irrigation benchmarking surveys of apple, peach/nectarine and pear in northern Victoria

Observations of Y and CWS from the irrigation benchmarking surveys are plotted individually for apple, pear and peach in Figure 7.2. The survey data reveal a wide range in CWS and Y outcomes. Typically, CWS ranged 3 – 4 fold (c. 5–15 ML/ha) for highly variable yield (c. 3 – 20 dry weight t/ha).

Estimated $Y_{\text{MAX}}$ derived from benchmarking data was 19.9, 12.9 and 9.8 dry weight t/ha for apple, pear and peach, respectively (Table 7.5 and Fig. 7.2).

<table>
<thead>
<tr>
<th>Crop</th>
<th>$Y_{\text{MAX}}$ (t/ha dry weight)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>19.9</td>
</tr>
<tr>
<td>Pear</td>
<td>12.9</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>9.8</td>
</tr>
</tbody>
</table>

Estimated CWR were 6.8, 4.0 and 6.0 ML/ha based on maximum crop production conditions with $f_{\text{MAX}}$ of 67, 55 and 77 % for apple, pear and peach, respectively (Table 7.6 and Fig. 7.2).

<table>
<thead>
<tr>
<th>Crop</th>
<th>$f_{\text{MAX}}$ (%)</th>
<th>CWR (ML/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>67</td>
<td>6.8</td>
</tr>
<tr>
<td>Pear</td>
<td>55</td>
<td>4.0</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>77</td>
<td>6.0</td>
</tr>
</tbody>
</table>

The water productivity parameters ($Y_{\text{MAX}}$ and CWR) of the respective water production functions for apple, pear and peach are plotted in Figure 7.2. Most yields in the irrigation benchmark data are below $Y_{\text{MAX}}$ and CWS for many crops greatly exceed estimated CWR. The varying X-axis intercepts in Figure 7.2 represent the estimated CWS required to maintain tree health during the post-harvest period for apple (0.1 ML/ha), peach (0.5 ML/ha) and pear (0.5 ML/ha).
Figure 7.2 Water productivity responses for apple ($n = 12$), pear ($n = 34$) and peach/nectarine ($n = 56$) based on empirical irrigation benchmarking data of yield and crop water supply (see Table 7.2). Red lines show estimated water production functions derived from crop water requirement (CWR, green line; Table 7.6) and maximum yield ($Y_{\text{MAX}}$, black line; Table 7.5).
7.3.3 Variation in maximum yield and crop water requirement within and between crop categories

Figure 7.3 shows maps of crop- and site-specific estimates of $Y_{\text{MAX}}$ and CWR for apple, apricot, peach/nectarine and pear crops in the Shepparton East district within the Goulburn Valley for the 2008/09 irrigation season. This spatial data reveals a wide range in CWR and $Y_{\text{MAX}}$ estimates. Typically, CWR ranged 3 – 4 fold ($c.$ 2 – 8 ML/ha) with highly variable $Y_{\text{MAX}}$ ($c.$ 3 – 25 dry weight t/ha) predictions.

At the regional level, Table 7.7 provides a summary of the range in vegetation cover (NDVI), $Y_{\text{MAX}}$ and CWR for these major tree crops. NDVI ranged within the limits, 0.24 < NDVI < 0.72. Irrespective of crop category, $Y_{\text{MAX}}$ and CWR ranged approximately five fold.

Table 7.7 Range in satellite-derived midseason vegetation cover (NDVI), maximum yield ($Y_{\text{MAX}}$) and crop water requirement (CWR) of apple, apricot, peach/nectarine and pear crops in the Goulburn Valley irrigation region during 2008/09.

<table>
<thead>
<tr>
<th>Crop</th>
<th>NDVI</th>
<th>$Y_{\text{MAX}}$ (t/ha dry weight)</th>
<th>CWR (ML/ha)</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>0.24 - 0.72</td>
<td>4.9 - 25.7</td>
<td>1.4 - 7.5</td>
<td>2023</td>
</tr>
<tr>
<td>Apricot</td>
<td>0.25 - 0.70</td>
<td>1.7 - 7.8</td>
<td>0.9 - 4.4</td>
<td>873</td>
</tr>
<tr>
<td>Peach/nectarine</td>
<td>0.24 - 0.72</td>
<td>2.3 - 12.0</td>
<td>1.1 - 5.8</td>
<td>2596</td>
</tr>
<tr>
<td>Pear</td>
<td>0.24 - 0.72</td>
<td>3.3 - 17.5</td>
<td>1.0 - 5.4</td>
<td>4547</td>
</tr>
</tbody>
</table>
Figure 7.3 Map of location and extent and, estimated site- and crop-specific maximum yield ($Y_{\text{max}}$, t dry weight/ha) and crop water requirement (CWR, ML/ha) of apple, apricot, peach/nectarine and pear crops in the Shepparton East district within the Goulburn Valley irrigation region for the 2008/09 irrigation season.
7.4 Discussion

This chapter presented and analysed yield – water use outcomes based on vegetation cover in a range of perennial horticultural crops. First, a case study for peach crops examined the effects of length of growing season and vegetation cover on yield and water use where site-specific measures of vegetation cover were available. Second, in the absence of direct estimates of vegetation cover, yield – water use relationships were used to derive maximum vegetation cover and maximum CWR in regional irrigation benchmarking data for apple, peach and pear. Third, variability between and within crop categories was presented by mapping water productivity components (Y\textsubscript{MAX} and CWR) derived from satellite NDVI data for apple, apricot, peach/nectarine and pear crops.

7.4.1 Effects of vegetation cover and length of growing season on water productivity in peach

Results demonstrate that variation in vegetation cover and length of growing season has substantial implications for Y\textsubscript{MAX} and CWR. Both Y\textsubscript{MAX} and CWR directly relate to the level of vegetation cover and fruit maturity date. CWR, the crop water supply where yield reaches a maximum (Y\textsubscript{MAX}), ranged three fold, while Y\textsubscript{MAX} varied four fold (Table 7.4). WP was 1.4 and 1.9 t/ML under early and late maturing peach, respectively. Therefore, knowledge of vegetation cover and length of growing season is critical to interpret water management and productivity outcomes.

The implications of variation in vegetation cover and/or length of growing season on Y\textsubscript{MAX} and CWR were clearly highlighted using the water production function approach (Fig. 7.1). For example, for a given level of vegetation cover, early maturing peach had lower CWR and Y\textsubscript{MAX} compared to later maturing crops.

When vegetation cover and crop type are known, site- and crop-specific appraisal of yield and water use outcomes can be determined from CWR and Y\textsubscript{MAX} information. Site- and crop-specific yield and water use targets can then be used to compare actual yield and actual CWS (irrigation + rainfall) to facilitate irrigation management and guide growers to improve water productivity.
7.4.2 Determination of crop water requirement from yield observations in irrigation benchmarking surveys of apple, peach/nectarine and pear in northern Victoria

Regional irrigation benchmarking data have been collected routinely and extensively, but without corresponding information on vegetation cover. Linear regression line analysis of these yield – CWS data in the form of Y/CWS ratio values (e.g. Fig. 1.4) offers misleading water productivity information as this model implies yield continually increases with additional water inputs (irrigation + rainfall). Rather, proper interpretation of these data requires knowledge of CWR and YMAX to provide agronomic and/or hydrologic management advice.

The power of the water production function is emphasised by the need to evaluate CWS against CWR and actual yield against YMAX in attempts to identify management options for improved water productivity. Comparison of agronomic or water management options as discussed below explain why benchmarking crops solely in terms of a value of the water use indicator (Y/CWS) ratio has limited ability to assist growers improve management.

The potential use of YMAX to formulate estimates of maximum vegetation cover and maximum CWR in regional irrigation benchmarking data provides a novel approach to obtain region- and crop-specific yield and water use information. It seems that yield is the most defensible measure taken in empirical benchmarking data. The analyses used here combined information on crop productivity and length of growing season (Chapter 3) using the joint dependence of yield and crop water use on vegetation cover.

Applying potential radiation use efficiency (εMAX) gave values of maximum vegetation cover (fMAX) of 67, 55, and 77 % for apple, pear and peach, respectively (Table 7.5). These are realistic, fall within bounds of measured fMAX (Chapter 3), align well with district scale estimates of vegetation cover derived using satellite NDVI (Chapter 5), and local knowledge. Although values of YMAX do exceed measured yields for apple and pear recorded in Chapter 3, such high yields, apple ≈ 100 t fresh weight/ha and pear ≈ 80 t fresh weight/ha are obtained in commercial orchards (B. van den Ende, pers. comm. 2008), obviously with optimum agronomic (i.e. fruiting level, pest/disease, water, nutrient) management. In other words, high harvest index combined with large vegetation cover and maximal radiation use efficiency are
required for such large yields (Equation 3.1). Derived values of CWR of 6.8, 4.0 and 6.0 ML/ha for apple, pear and peach, respectively (Table 7.5 and Fig. 7.2) align well with satellite remote sensed estimation (Chapter 6), current irrigation ‘best’ practice recommendations (Boland et al. 2002) and also with local experience.

Figure 7.2 shows that the best growers achieved $Y_{\text{MAX}}$ in the absence of production limiting factors (e.g. pest/disease, nutrient deficiency) and weather extremes (e.g. hail, frost) in accordance with the potential production principles (Production Level 1: Penning de Vries 1982). The analysis emphasizes, therefore, that $Y_{\text{MAX}}$ is achievable by reducing irrigation inputs towards CWR, so in most cases there is no need to increase CWS. Crop yields below the $Y_{\text{MAX}}$ line were common and these orchards may have had low vegetation cover but at high CWS these crops greatly exceeded the nominated CWR. This suggests that these crops are likely to need both hydrologic (e.g. irrigation scheduling) and agronomic/crop husbandry (e.g. fruiting level, fertilizer, herbicide, pesticide) management changes to improve their water productivity. They were also likely to have suffered hydrologic losses (i.e. drainage, runoff, soil/surface evaporation; Equation 1.1).

Depending on vegetation cover, peach crops in the CWS < CWR zone in Figure 7.2, were potentially subjected to water stress (i.e. deficit irrigation). In the absence of vegetation cover information, it is not possible to distinguish the effects of water stress on low yield outcomes. In general, the irrigation benchmarking data reveal very few crops in the CWS < CWR zone, suggesting most crops were grown under conditions in which irrigation water was readily available and inexpensive (Chapter 1).

The water production functions derived here for apple, peach and pear (Fig. 7.2) offer needed practical guidance at an industry level. Using peach as an example, and referring to Figure 7.2, the water production function suggests that CWS > 6 ML/ha is excessive. For peach, using the scenario of high vegetation cover and late fruit maturity, similar water productivity parameters ($Y_{\text{MAX}}$ and CWR) were obtained in benchmarking data (Fig. 7.2) compared to the water productivity analysis for known vegetation cover (Fig. 7.1). For the peach crops shown in Figure 7.2, efficient irrigation management would adjust CWS, both in time and space, to available soil wetted volume, estimated CWR and irrigation system design (Mitchell and Goodwin
1996). It is important to record, however, that matching CWS to CWR within individual seasons requires appropriate irrigation scheduling to minimise (soil/surface evaporation, runoff, drainage) losses. Some losses may be unavoidable given irrigation method and associated infrastructure, soil type, and/or irrigation scheduling practices including irrigation run time and interval.

Empirical benchmarking surveys suffer from a small sample size to represent district practice and a bias towards high vegetation cover, high yields and high CWR when attempting to identify high water productivity. By comparison, principles of crop- and site-specific water productivity, based on $Y_{\text{MAX}}$ and CWR, can be derived for each field using vegetation cover derived from satellite NDVI measurement (Chapter 5), ground-based evaporative demand, and crop phenology information to estimate length of growing season (Chapters 3 and 6).

The formation of crop- and site-specific water production functions provide a useful tool to guide irrigation scheduling, estimation of water requirements for maximum yield, determination of high water productivity, allocation of water at farm and regional levels and hold potential to assist economic analyses in water productivity.

### 7.4.3 Variation in maximum yield and crop water requirement within and between crop categories

Figure 7.3 and Table 7.7 highlight the large variation in vegetation cover and therefore water productivity components that exists among the major horticultural crops in the Goulburn Valley region. Mapping of CWR and $Y_{\text{MAX}}$ provides spatial information and a tool to compare actual yield and irrigation input data between individual crops at farm and regional scales. The satellite-based NDVI-dependent water production function approach makes for reliable and consistent field/farm scale agricultural water management information to aid decisions related to irrigation, water policy and regional water resource and land use management.

### 7.5 Conclusion

Variation in vegetation cover and length of growing season of horticultural crops in the Goulburn Valley irrigation region has large implications for yield potential and crop water requirement, and therefore directly impacts water productivity assessment. In the absence of information on vegetation cover from which CWR and $Y_{\text{MAX}}$ can be
estimated, benchmarking crops solely in terms of the water use efficiency ratio (yield/CWS) is misleading. Knowledge of vegetation cover and associated CWR and \( Y_{MAX} \) is needed to assist growers to improve hydrologic and/or agronomic management. This can be done effectively by applying a vegetation cover dependent water production function that permits objective water productivity performance evaluation and mapping by comparison of actual yield and crop water supply to crop- and site-specific yield and water use targets.
Chapter 8 Conclusions

This thesis combined field based and satellite derived data to develop a water productivity framework applicable for high value perennial horticultural crops in the southern Murray Darling Basin, Australia.

The dual approach produced estimates of crop water requirement (CWR) and maximum yield ($Y_{\text{MAX}}$) in a water production function based on the model of Doorenbos and Kassam (1979) for apple, peach, nectarine, pear, apricot, plum and wine grape crops.

Estimates of CWR and $Y_{\text{MAX}}$ in the water production function were based on their mutual dependence on vegetation cover. The most commonly used ground-based method to estimate vegetation cover requires measurement of fractional radiation interception ($f$). Satellite platforms that measure NDVI provide the ability to estimate $f$ at field, farm and regional scales. Vegetation cover was found to maintain a maximum over a prolonged period in the midseason, following the model of Palmer et al. (2002). Ground or remote vegetation cover measurement provided satisfactory estimates to derive site-specific values of CWR and $Y_{\text{MAX}}$.

$Y_{\text{MAX}}$ was estimated using the radiation use efficiency model of Monteith (1977) where observations of yield were related to field measures of intercepted growing season radiation on commercial crops (Chapter 3). Remotely sensed NDVI was found to be a suitable estimator for $f$ among tree and vine crops (Chapter 4). Chapter 5 showed that intra-seasonal remote measures of NDVI complied with the basic assumption of stable maximum vegetation cover. Estimates of CWR were derived from satellite based ET – NDVI observations (Chapter 6). ET was estimated from Landsat data using the METRIC model. Sensitivity analysis demonstrated important effects of length of growing season and vegetation cover on resultant water production functions (Chapter 7). Chapter 7 showed the water production function was a valuable tool for the interpretation and analysis of published yield – water use relationships. Key data for crop- and site-specific estimates of CWR and $Y_{\text{MAX}}$ (i.e. crop- and site-specific water production functions) can be derived from maps of NDVI supplemented by weather data and phenology information.
In addition this study demonstrated very large variability in vegetation cover among crops. Therefore knowledge of crop type *per se* is not sufficient to define crop- and site-specific water production functions for management purposes. The establishment of regional water use efficiency benchmarking depends on the availability of ancillary measures of vegetation cover (e.g. NDVI).

The following sections summarise the results and conclusions drawn from this study and their implications to improvement of performance of horticultural crops of the region. Deficiencies of the study and future research directions in relation to yield – water use relationships of high value perennial horticultural crops are discussed.

### 8.1 Summary of outcomes

#### 8.1.1 Yield dependence on cumulative fractional radiation interception

Chapter 3 showed how orchard and vineyard yield was highly dependant on cumulative fractional radiation intercepted during the growing season. Estimates of maximum ($Y_{\text{MAX}}$) and average ($Y_{\text{MEAN}}$) regional yield were determined from intercepted radiation measured in apple, apricot, peach, nectarine, pear, wine grape and plum crops by applying the radiation use efficiency model (Equation 3.1). Testing of fruit number as an additional variable in yield determination showed varied crop responses between crop categories.

Despite restricted water supply due to drought (Chapter 1), the study assumed that experimental sites used for yield – radiation interception relationships in the 2007/08 and 2008/09 irrigation season constituted ‘well watered’ crops (Chapter 3, section 3.2.1). Figure 8.1 presents the relationship between ET ratio ($ET/ET_R$) and NDVI, measured from Landsat data (January 2009) for experimental sites in the 2008/09 irrigation season reported in Chapter 3.

Figure 8.1 reveals that ET of all experimental crops studied in 2008/09 equalled or exceeded the lower ET/NDVI boundary defined by Tasumi *et al.* (2005a) for broad-acre crops (Equation 2.4 and Fig. 2.2). This suggests that crops studied in Chapter 3 were irrigated adequately.
Figure 8.1 Satellite derived field scale ET/ET<sub>R</sub> – NDVI relationships for apple (n = 23), apricot (n = 2), peach/nectarine (n = 16), plum (n = 8), pear (n = 11) and wine grape (n = 13) crops used for field assessment of maximum yield in the Goulburn Valley, Victoria in the 2008/09 irrigation season. Data are from Landsat imagery taken on 22 January 2009. Green line shows the Tasumi et al. (2005a) K<sub>th</sub> - NDVI response (Equation 2.4).

At the regional scale, the widespread use of supplementary sales water across the horticultural industry to meet irrigation requirements (Chapter 1; sub-section 1.2.3) is reinforced by the collage of ET – NDVI responses above the Tasumi baseline measured in apple (Fig. 6.1), peach/nectarine (Fig. 6.2) and pear (Fig. 6.3) crops. Therefore, it appears despite the drought, irrigation management was apparently successful in satisfying CWR.

8.1.2 Satellite remotely sensed NDVI a suitable estimator of fractional radiation interception

This study established at a practical level good agreement between the low cost satellite-derived NDVI and ground measurements of orchard/vineyard f (Chapter 4). These relationships for a range of horticultural crops compared well with f – NDVI responses reported for broad-acre crops (Bastiaanssen and Ali 2003). These findings are supported by a recent report by Trout et al. (2008) showing strong linear relationships between satellite-derived NDVI and ground-based estimates of vegetation cover for annual and perennial horticultural crops. Likewise, recent examples of applications to assess vegetation cover using remote observations of
NDVI have been reported in grape crops (D’Urso et al. 2008; Hall et al. 2008; Hornbuckle et al. 2008).

8.1.3 Stability in midseason NDVI
Chapter 5 examined NDVI measured from satellite in apple, apricot, peach, nectarine, pear, grape and plum crops in the Goulburn Valley throughout an irrigation season. Stable estimates of NDVI were found to persist during the midseason period of maximum vegetation cover in agreement with the model of vegetation cover and phenological development described in Figure 3.1. Additionally, early- and end-of-season canopy development phases were detected in NDVI responses using the collage of Landsat imagery. Recently, Campos et al. (2010) reported similar stable midseason satellite-derived NDVI profiles in grape crops.

8.1.4 Derivation of NDVI-dependent crop water requirement using regional ET – NDVI observations
Chapter 6 demonstrated the feasibility, practicality and affordability of using METRIC, in combination with the diagnostic water stress baseline (Equation 2.6) for the formulation of customised irrigation water use targets at farm, industry and regional levels. Chapter 1 described that $K_c$ values fruit tree and vine crops are linearly related to vegetation cover. Chapter 6 examined a series of Landsat images to derive CWR from linear ET – NDVI functions for the major perennial horticultural crops in the Goulburn Valley during an irrigation season. Most ET – NDVI data corresponded with maximum water use described by a ‘full cover’ lucerne reference crop ($ET_R$, Allen et al. 2005b) and a baseline ET – NDVI relationship for broad-acre crops (Tasumi et al. 2005a).

Overall, these results confirm that crop coefficients can be derived from NDVI and local weather data once regional ET – NDVI relationships have been established. This approach provides a simple crop- and site-specific tool for the assessment of water requirements of irrigated crops. The $K_c$ – NDVI concept in conjunction with local evaporative demand provides improved irrigation scheduling information and is being widely accepted (Allen et al. 2011). Recently, Rafn et al. (2008) showed that NDVI-based $K_c$ estimates closely matched METRIC-based $K_c$ values for a wide range of irrigated broadacre crops.
The importance of vegetation cover on $K_c$ of perennial horticultural crops is highlighted in the review by Allen and Pereira (2009). The linear $K_c$ – vegetation cover responses have been further demonstrated by recent reports in grape (Campos et al. 2010; Whitfield et al. 2011), pecan (Wang et al. 2007; Samani et al. 2011), citrus (Consoli et al. 2006c,d; Whitfield et al. 2011), almond (Whitfield et al. 2011), vegetable (Trout and Johnson 2007; Brayla et al. 2010) and corn, soybean, sorghum and alfalfa (Singh and Irmak 2009) crops.

Recently, irrigation management guidelines to adjust CWS (and schedule irrigation) by vegetation cover have been provided by Cetin et al. (2008), Goodwin et al. (2009), Auzmendi et al. (2011) and Casadesus et al. (2011).

NDVI has also been recognised as an appropriate metric to adapt irrigation schedules in wine grape crops (D’Urso et al. 2008; Hornbuckle et al. 2008). Currently, IrriGATEWAY (www.irrigateway.net) offers NDVI-based $K_c$ maps for irrigation regions in south eastern Australia. However, this service extrapolates $K_c$ data from ET – NDVI relationships that are not specific to crop category or region.

Agronomic and water management applications are widening further (D’Urso 2001; D’Urso et al. 2010), with vegetation indices forming the biophysical backbone of commercial on-line services for agriculture (e.g. www.ariespace.com, www.fieldlook.com, www.pleiades.es).

### 8.1.5 Non-linearity of the water production function

Previous chapters have highlighted the important consequence of non-linearity in the water production function with increasing CWS. Recently, Montoro et al. (2011) report a curvilinear water production function for irrigated wheat, maize and poppy.

Chapter 7 showed without knowledge of vegetation cover, the simple empirical water use efficiency ratio (yield/CWS) commonly applied to benchmark perennial horticultural crops (e.g. Fig. 1.4) cannot distinguish need for improved irrigation water management (e.g. irrigation scheduling) to decrease water inputs to match CWR from need for improved crop agronomy (e.g. fertiliser management and/or pest-disease control).
The simple ‘two stick’ water production function used in this study provides a practical diagnostic agro-hydrologic framework to context the performance of grower practice (actual yield and irrigation supply) against water productivity metrics of Y_{MAX} and CWR. Therefore, field-specific water production functions that incorporate vegetation cover provide capability to diagnose areas for improvements in agronomy and water management and advance current irrigation performance assessment techniques.

Using the satellite-based water productivity framework, Chapter 7 demonstrated key steps towards the objective appraisal of water productivity by deriving and mapping Y_{MAX} and CWR from measures of vegetation cover supplemented by weather data and length of growing season information.

8.1.6 Derivation of regional maximum crop water requirement from maximum yield

For situations where measures of site-specific vegetation cover are not known, Chapter 7 applied a novel approach to formulate a crop-specific water production function using yield – radiation interception relationships. Chapter 7 described the derivation of CWR from estimates of regional maximum yield using irrigation benchmarking observations of yield and CWS in peach, apple and pear crops.

8.1.7 Farm to regional scale estimation of water productivity

Assessment of water productivity at farm to regional scales requires methods for estimating yield and water use (Chapter 1; Lorite et al. 2007; Montoro et al. 2011). Bastiaanssen and Bos (1999), Bastiaanssen et al. (2005) and Perry (2005) recommended the use of satellite remote sensing to satisfy data requirements for improved evaluation of irrigation performance.

As an application of findings from this study, Figure 7.3 demonstrated large variation in site- and crop-specific water productivity components derived from satellite data. Recently, similar satellite-derived water productivity approaches have been reported (e.g. Wesseling and Feddes 2006). Further, Santos et al. (2010) used Equation 1.8 as the basis of a water production function for broad-acre crops. They estimated Y_{MAX} from historical yield data and derived ET_{MAX} using the METRIC ET model. Similarly, EARS (2008) applied Equation 1.8 to derive regional yield estimates for coffee. Other satellite-based water productivity studies include industry-scale performance
assessment of grape and mango (Teixera et al. 2009), banana and sugar cane (Hellegers et al. 2009), wheat, rice and maize (Zwart and Bastiaanssen 2007), sugarbeet and cotton (Gonzalez-Dugo and Mateos 2008) and rice (Zwart and Leclert 2010) crops.

8.2 Implications

8.2.1 New irrigation management, yield and water productivity products from satellite data

Chapter 1 identified a lack of reliable local yield and CWR data and the associated confounding issue of large variation in vegetation cover among and between the diverse range of fruit tree and grape crops cultivated in northern Victoria.

This study showed that vegetation cover is key to understanding water productivity in perennial horticultural crops. Satellite derived measurement of NDVI provides a practical estimate of vegetation cover (Chapter 4). Vegetation cover varied 4–fold (Chapter 5), having large implications for irrigation management and production outcomes (e.g. Fig. 7.3).

The technique of using satellite-derived ET – NDVI observations from regional data to estimate site-specific crop water use targets (CWR, $K_c$ maps) and production targets ($Y_{\text{MAX}}, Y_{\text{MEAN}},$ yield maps) has several advantages including repeatability, large spatial extent, large sample size and affordability.

Water use targets derived from NDVI and local weather data offer objective irrigation management products to improve irrigation scheduling and water management. Yield targets derived from NDVI and climate and crop information provides data for production performance appraisal and insights to advance agronomic practices. Together, these satellite-derived agronomic and hydrologic variables permit evaluation of water productivity at field-, farm- and regional-scales.

The benefits of adoption of objective estimates of $Y_{\text{MAX}}$ and CWR offer improved ability to decide on:

i. Allocation of available water resources in water constrained seasons (e.g. low irrigation allocation induced by drought in water catchments),
ii. Water budget allocation among the mix of competing on-farm options (e.g. late maturing apple v. early maturing apricot) and,

iii. Management of stress levels under deficit irrigation (e.g. application of Regulated Deficit Irrigation).

In summary, the water productivity components, $Y_{\text{MAX}}$ and CWR, offer the ability to monitor, review and analyse:

i. Irrigation performance,

ii. Production performance,

iii. Irrigation scheduling,

iv. Water and production record keeping,

v. Farm water planning and,

vi. Seasonal water budgeting.

8.2.2 Information delivery systems for site-specific crop water requirement and maximum yield information

NDVI-dependent water production functions create the challenge to provide information to the next user (e.g. grower, agronomist, catchment manager) at field and regional scales.

Future production systems in perennial horticulture have the potential to integrate water use and yield targets, into an irrigation scheduling and/or production service. Such advice requires simple communication systems to deliver customised information to offer improvements in the economic value of water. Recently, Montoro et al. (2011) reported a highly successful and profitable irrigation scheduling service for broad-acre crops in central Spain.

Delivery of crop- and site-specific irrigation requirement (e.g. $K_c$ maps) and attainable production targets ($Y_{\text{MAX}}$) to the next user will most likely involve use of text communication service component by telephone, web, or mobile communication systems (e.g. SMS, smart phone, iPad) or web based communication platforms (e.g. D’Urso et al. 2008; Hornbuckle et al. 2008; www.irrigateway.net). Linking local evaporative demand/weather forecasts and/or market information (e.g. www.ausmarket.net.au) with yield – water use data may further assist decision making and farm planning, especially in water constrained seasons.
8.2.3 Linking water use targets to automated irrigation scheduling systems using wireless sensing networks

Application of water to crops should be synchronised with the needs of the crops for both economic and environmental reasons. However, the timing of irrigation applications and the CWR of perennial horticultural crops depend on vegetation cover, climate, and management, and are consequently highly variable.

There are two main options for precise irrigation scheduling. One is to schedule irrigations based on estimated CWR and replace the consumptive water use (Equation 1.3). A second is to measure plant water stress and irrigate according to known plant yield and quality responses. Linking options 1 and 2 is also possible.

Real-time irrigation management that continually adapts and ‘fine tunes’ irrigation inputs to NDVI-dependent CWR estimates (option 1, Chapter 6) using ‘feed-forward’ water stress irrigation scheduling systems (option 2) offers improved and precise water management (Miranda et al. 2005; Coates and Delwiche 2009). Water stress can be measured using real-time in situ plant/soil based auto-monitoring wireless sensor systems that guide (‘feed forward’) the irrigation control (solenoid) system to operate at fine temporal scales (e.g. hourly or daily) in order to match CWS to CWR.

Field testing of wireless soil-based sensors using ‘feed forward’ irrigation scheduling adjusted for vegetation cover in vineyard and orchard crops is currently being investigated by The University of Melbourne ‘Farms, Rivers and Markets’ project (www.frm.unimelb.edu.au).

Additionally, ‘feed back’ from in situ plant/soil sensor systems offers both automated control of water inputs and an independent performance assessment of irrigation scheduling. However, a search of the literature and web shows no examples of ‘feed back’ wireless sensor irrigation control systems in perennial horticultural crops. Therefore, further work is required to appraise ‘feed back’ irrigation scheduling systems in combination with site- and crop-specific CWR targets.
8.2.4 Vegetation cover to adjust agronomic inputs and inform management practices at field to farm scales

Agronomic inputs other than water can also be adjusted to vegetation cover. This strategy offers cost savings and efficiency gains when crops vary among and between fields. For example, the potential to target nutrient management geared to vegetation cover in pressurised irrigation systems (e.g. ‘open hydroponics’ fertigation, Boland et al. 2005b) with the use of NDVI – CWR information has yet to be rigorously investigated. Similarly, pest and disease management practices that adjust inputs (e.g. chemicals, biological control organisms) to vegetation cover need to be further explored.

8.2.5 Vegetation cover to guide water management and production inputs at the plant scale

The implications of within-field (plant scale) variation in vegetation cover on yield and water use warrant further research and development. Real-time crop and irrigation management at the plant scale using precision agriculture principles are becoming feasible with improved developments in irrigation infrastructure (e.g. solenoid and emitter) and remote sensing technologies.

Therefore, practical ‘precision agriculture’ applications of the above mentioned vegetation and water use remote sensing approaches using very high resolution imagery to examine the hydrologic and production performance to determine areas requiring improvement or intervention have yet to be realised. For example, Felderhof and Gillieson (2011) report the use of remote sensing vegetation indices that predict canopy health (nitrogen status) of individual trees to guide fertiliser requirement in macadamia crops.

With the same objective, McClymont et al. (2011a,b) provide a framework to analyse vegetation cover at the plant scale. Based on a water production function, the framework assesses the hydrologic (e.g. CWR, excess water) and agronomic (e.g. yield penalty) impact of uniform (field-scale irrigation management) water supply geared to deliver irrigation inputs at field mean and maximum vegetation cover derived CWR, respectively. Guidelines for irrigation (emitter output) distribution uniformity are also incorporated in the framework. In this way, irrigation management
and productivity inefficiencies due to spatial variation of plant-scale vegetation cover within a crop can be addressed using the McClymont framework.

As an example, based on the McClymont framework, micro-irrigated horticultural systems can adopt a row-based irrigation management strategy. This simple low cost modification of irrigation infrastructure can offer large water savings, avoid water stress on large (high vegetation cover) canopies and associated yield penalty, with resultant improved overall field water productivity (McClymont et al. 2011a).

8.2.6 Economic modelling of water and crop management for horticulture at farm to regional scales

Irrigation planning needs to combine water production functions with cost functions because identification of optimum irrigation strategies requires economic and risk modelling analysis of optional strategic and tactical management strategies (English et al. 2002).

Detailed financial and economic water productivity analysis is warranted to examine the implications of strategic farm options (e.g. crop/variety mix, new irrigation technologies) and tactical management practices (e.g. water trading, deficit irrigation, fruit thinning) by using the water production function concepts developed in this study.

Recently, The University of Melbourne ‘Farms, Rivers and Markets’ project (www.frm.unimelb.edu.au) has commenced a farm-scale economic study in orchards and vineyards to provide guidance to growers under limited and uncertain water supply. At the regional level, economic analysis for each of the major horticultural crop categories is also required to assess impacts of new water policies (e.g. SDLs) and water scarcity (see Chapter 1).

8.2.7 Water accounting for improving irrigation efficiency

Satellite derived CWR targets permit customised field- and farm-scale analysis of irrigation performance across regions/catchments. Using satellite approaches, Abuzar et al. (2008) and Santos et al. (2008, 2010) describe a ‘next generation’ water accounting and irrigation efficiency monitoring and reporting system that offers the capability to identify specific fields or crops experiencing problems in water
management. Such benchmarking programs can compare and map the match of CWS against CWR by using site-specific satellite-based ET (CWR) and irrigation water deliveries (CWS) between fields/farms both within and between irrigation seasons. This satellite based water accounting approach advances traditional regional-scale irrigation benchmarking methods previously outlined in Figure 1.5 (McAllister et al. 2009) and recent district statistical/modelling approaches (e.g. Garcia-Vila et al. 2008; Salvador et al. 2011). Advantages of the remote sensing approach over the traditional assessments include:

i. Most data is readily available,
ii. All water users are included,
iii. Groundwater extraction can be estimated,
iv. Cost effectiveness and,
v. ‘Near’ real time assessment/monitoring.

8.2.8 Potential application of satellite-based yield-water use framework to other crop and pasture industries

Application of satellite-based yield and water requirement principles developed in this study potentially offer advances to water and production outcomes to a diverse range of crop and pasture based industry sectors but is yet to be investigated rigorously. These industries include:

i. Irrigated annual crops (i.e. vegetables, tomato, rice, cotton, maize),
ii. Rainfed broad-acre crops (i.e. wheat, pulse, oilseed) and,
iii. Livestock pastures (i.e. dairy, lamb, beef).

8.2.9 Land and water resources management and catchment performance assessment

Field-, farm- and industry-scale actual water use, attainable production and land use information make for reliable and consistent agricultural water management decisions and are useful to a wide spectrum of industry players and stakeholders. These users include irrigators and growers, processing companies, agricultural consultants, food and water industry analysts, water providers and regulators and natural resource managers (e.g. Catchment Management Authorities).

Data on regional ET derived from satellite (e.g. METRIC, SEBAL) forms the backbone of performance assessment and water accounting and are important for
verification of regional irrigation models, irrigation delivery network performance appraisal and river basin/catchment models (Perry 2005; Droogers et al. 2010).

Spatially distributed water balance and crop information are essential for quantifying water productivity, irrigation system allocation requirements and water regulation, water and land resource planning and eco-site (e.g. native vegetation, riparian) health. Such approaches to aid water policy and decisions related to irrigation (e.g. water saving programs), regional water resource and land use management. In summary, improved water productivity information provides data for social, environment and economic performance analysis, including the ‘licence to operate’ (Chapter 1, section 1.2.4) and identification of vulnerable farms and/or industries especially in light of proposed SDLs under the Murray Darling Basin water reforms (Chapter 1, section 1.1.1). From a societal perspective, maximum benefits from irrigation must also consider water quality, employment and food security issues.

8.3 Further work
The estimation of $Y_{\text{MAX}}$ and CWR relied on yield and crop water use functions developed in this study. Additional information on yield – water use relationships is required to advance agronomic and/or water management and to accelerate operational implementation of improvements in water productivity in perennial horticultural crops.

8.3.1 Yield determination
Improved crop management in perennial horticulture requires, further understanding of yield determination, source – sink relationships, phenology, biomass growth and carbon partitioning in relation to local climatic and hydrologic conditions.

This thesis assumed yield processes were dominated by crop activity in the period of maximum vegetation cover up to crop maturity (Fig. 3.1). For this, the rapid ‘leaf-up’ phase and post-harvest period were excluded in the derivation of yield using the vegetation cover – phenophase model described in Chapter 3 (Equations 3.1 and 3.4). The adequacy of this approach requires testing as uncertainty remains with respect to the contribution of carbon assimilation during the post-harvest period to yield determination in the following season. Similarly, nor is the water requirement for carbon assimilation during that period well understood. The yield-water use
relationships under post-harvest deficit irrigation regimes for fruit tree crops in the Goulburn Valley region is currently under investigation by the Victorian Department of Primary Industries (Goodwin and Bruce 2009, 2011).

Maximum effective radiation use efficiency ($\varepsilon_{\text{MAX}}$) varied between crop categories (Table 3.6). Figure 8.1 suggests that water stress was unlikely to have been the cause of lower $\varepsilon_{\text{MAX}}$ measured in some crops. Remote sensing estimation of radiation use efficiency using the Photochemical Reflectance Index (Garbulsky et al. 2011), offers a new approach to assess production performance in horticultural crops (Equation 1.5) and warrants investigation.

Further studies to determine carbon partitioning to fruit organs and determination of harvest index among crops/varieties/rootstocks are required. Additional research is also required to improve the understanding of the effect of fruit number (e.g. crop load) on attainable yield and crop value (e.g. marketable yield, large fruit size) across the diverse range of crops and vegetation cover combinations (Gabino et al. 2007; Reginato et al. 2007; Best et al. 2008).

Finally, improved estimation of crop phenology using detailed time series analyses of NDVI to develop crop spectral response profiles of vegetation cover (Vincent and Pierre 2004; Nagai et al. 2009; Tuanmu et al. 2010) needs to be investigated in a range of perennial horticultural crops.

8.3.2 Water production function

Empirical data on water production functions and cost functions for perennial horticultural crops is unavailable (Chapter 1). This thesis adopted the simple practical analytical approach to model yield response to water supply (FAO-33 + $Y_{\text{MAX}}$, Fig. 1.3). Improved understanding of the response of yield to varied CWS, including deficit-, full-, post-harvest irrigation regimes, and their interactions with level of vegetation cover are critical to development of accurate prediction of $Y_{\text{MAX}}$ and CWR, and require further work (e.g. Fereres and Soriano 2007). However, new work by Gunduz et al. (2011) reports the yield response factor ($k_y$) for peach as 1.2 (Equation 1.6), suggesting peach productivity is sensitive to water shortage.
Understanding where the biophysical and economic functions of applied water coincide needs to be established. A valuable step could be, by comparison of the ‘two stick’ yield – crop water requirement model of the water production function with an economic ‘efficiency’ optimization model (English et al. 2002).

Nevertheless, the simple ‘two stick’ model has the great advantage that it permits estimation of the marginal rate of return per water input to guide management decisions in water constrained seasons. Knowledge of crop water requirement is essential, so that significant hydrologic losses of applied irrigation water by deep drainage and/or runoff can be estimated and accounted for in economic terms.

Recently, Naor (2006) and Clemmens and Molden (2007) have proposed a hypothetical ‘declining limb’ for water excess to the water production function. The purpose is to reduce yield at $\text{ca. CWS} \geq 1.8 \cdot \text{CWR}$ depending on soil hydraulic properties. The approach is sensible but so far lacks response data.

**8.3.3 Satellite remotely sensed NDVI a suitable estimator of vegetation cover**

This study relied heavily on NDVI as the measure of vegetation cover. Satellite-derived NDVI measurement is influenced by several factors:

1. Scale of the imagery,
2. Vegetation moisture,
3. Soil moisture,
4. Overall vegetative cover,
5. Differences in soil type and,
6. Crop management practices.

Additionally, the magnitude of the signal received at a satellite sensor is dependent on several factors, primarily:

1. Reflectance of the target (orchard or vineyard),
2. Nature and magnitude of atmospheric interactions,
3. Slope and aspect of the ground target area relative to solar azimuth,
4. Angle of view of the sensor, and
5. Solar elevation.
Several of the above mentioned signal magnitude phenomena (factors: ii, iii, iv and v) known to effect reflectance values can be discounted. Firstly, this study used Landsat data on specific targets (e.g. orchard/vineyard field) over the very flat (Riverine plains) landscape of the Goulburn Valley during summer months under clear sky conditions and high solar elevation. Additionally, Landsat has a near-vertical (nadir) view angle and radiometric corrections were applied to account for sun-sensor geometry effects (Chapter 4, section 4.2.2). Therefore, the target reflectance and aspect (canopy size/configuration) are the most likely causes of differences measured in NDVI (Chapters 4 and 5). That is, vegetation cover variation measured among orchards and vineyards are likely due to factors like canopy geometry, canopy size and row direction.

Potentially, there may be different $f$ – NDVI relationships (Chapter 4) between crop types and orchard/vineyard canopy configurations. Suggestions to improve the $f$ – NDVI relationship arise from:

i. Better discrimination between target (tree, vine) canopy and cover crop (grass) canopy,

ii. Analysis across the full range (sparse to ‘full’ cover) of orchard/vineyard vegetation cover experienced within the region,

iii. Larger sample size within a crop category,

iv. Comparable spatial assessment (measurement intensity) of daily $f$ relative to NDVI across entire fields and,

v. Site/crop specific analysis of canopy structural (leaf area density) effects of various orchard/vineyard configurations.

**8.3.3.1 Scale effects**

Ideally measures of $f$ and NDVI are made relative to the same area (field) and acquired simultaneously. This requirement raises further issues related to the spatial scale associated with the measurements, because satellite sensors always measure radiation quantities for areas substantially larger than those sampled by field point-scale instruments.

Custom designed mobile radiation interception measurement systems incorporating light sensors or solar panels (e.g. PowerFilm™, www.powerfilmsolar.com) mounted on a quad bike/ATV would address this spatial scale problem. Alternatively, two
simultaneous ground-based sensing platforms geared to measure paired \( f \) and NDVI (e.g. GreenSeeker\textregistered) data could further improve spatial capability, especially in crops with low foliage (e.g. grape). Guidelines provided by Duveiller and Defourny (2010) on spatial measurement intensity for remote sensing agriculture may assist choosing appropriate platform(s) to address these research questions.

8.3.3.2 Understorey crop and canopy management effects
Improving the ability to detect target crop foliage expansion and low vegetation cover crops in the presence of green understorey vegetation remains a challenging task. Further work to delineate the effect of a green cover crop and/or canopy management practices (e.g. reflective foliage sprays, reflective mulch) on estimation of vegetation cover using NDVI, especially in sparse perennial horticultural crops is warranted.

More precise NDVI measurement using higher resolution imagery obtained via satellite (e.g. SPOT, Quickbird, Ikonos, WorldView-2), manned airborne (Lamb et al. 2001; Johnson 2003; Hall et al. 2008) or unmanned aerial vehicle (Berni et al. 2009) platforms may improve \( f \) – NDVI relationships, albeit at a higher cost per hectare. Alternatively, improved image processing strategies to isolate and delete understorey signal (e.g. Lamb et al. 2001) can be adopted.

8.3.3.3 Soil emissivity and soil wetness effects
NDVI is sensitive to soil optical properties at low vegetation cover (Huete and Jackson 1988; Baret and Guyot 1991). NDVI increases under wet soil conditions without a change in vegetation cover as soils tend to darken after precipitation or irrigation. Orchard and vineyard fields under establishment are likely to have bare soil inter-row (understorey) conditions combined with sparse tree/vine vegetation cover compared to mature crops. Quantifying the importance of bare soils and understorey wetting regimes in sparse orchards and vineyards requires further investigation (Richardson and Weigand 1977). For example almond, citrus and grape crops common to Sunraysia irrigation region of northern Victoria (Fig. 1.1) are likely to have bare soils and those under furrow or overhead sprinkler irrigation systems a frequently wet understorey.
8.3.3.4 Alternative vegetation cover indicators

The NDVI is not the only vegetation index that has been developed. A number of
derivatives and alternatives to NDVI have been proposed in the scientific literature.
Other indices are available, each with its range of advantages and disadvantages, so
choice depends upon application.

Spectral bands from Landsat, other than those used to derive NDVI (Equation 4.1),
may provide better discrimination of vegetation cover in orchards and vineyards. The
simplest vegetation index is the Ratio Vegetation Index (RVI). More complex indices
include the Perpendicular Vegetation Index (PVI), the Soil-Adjusted Vegetation Index
(SAVI), the Atmospherically Resistant Vegetation Index (ARVI) and the Global
Environment Monitoring Index (GEMI). Each of these attempt to include intrinsic
correction(s) for one or more perturbing factors.

Alternative vegetation indices such as the PVI or SAVI known to be less sensitive to
interference of background soil reflectance than NDVI (Bastiaanssen 1998) may well
improve the $f –$ NDVI relationships derived in Chapter 4.

In addition to the influence of soil surface (soil emissivity and wetness) at the low
vegetation cover, NDVI also suffers from a loss of sensitivity to changes in amount of
vegetation under conditions of full cover. That is to say that as the amount of green
biomass increases, the relative change in NDVI diminishes. In these situations, it may
be advisable to use a vegetation index with better sensitivity to high-vegetation cover
such as the Enhanced Vegetation Index (EVI; Huete et al. 2002) or the Wide Dynamic
Range Vegetation Index (WDRVI; Gitelson 2004). EVI offers ability to provide
enhance ‘3D vegetation structure’ as it accounts for the transmission of near infrared
radiation (NIR) and visible radiation (RED) radiation. NIR has a greater optical depth
into foliage than does RED.

8.3.4 Crop growth/yield – water use simulation model for perennial horticultural
crops

Bio-physical crop models have an important role to improve the current state of
knowledge on crop production of high value perennial horticultural crops. However,
few examples from the suite of existing models provide a tool for analysis of whole
canopy photosynthesis and respiration processes, phenology and dry matter
partitioning (Grossman and DeJong 1994; Marcelis et al. 1998; Stockle et al. 2003). Most models ignore interactions between tree/vine architecture/geometry (i.e. vegetation cover), fruit number, water supply and carbon allocation (vegetative v. reproductive organs). Therefore, there is the need for crop growth – water use models that account for water supply, fruit number, harvest index, length of growing season (phenology), vegetation cover and crop type.

8.3.5 Linking bio-physical crop models to satellite technologies to inform water and crop management at farm to regional scales

This thesis shows that there is great scope to combine satellite remote sensing outputs with agronomic models. The satellite-based water productivity approach provides a basic entry point for application to more sophisticated bio-physical crop models.

Key challenges for operational crop monitoring and yield forecasting using crop models are to find spatially representative land use, soil type, crop type and meteorological input data. Studies that develop an integrated model, or combine models incorporating parameters from diverse sources, are more likely to advance water productivity outcomes.

But progress is being made. e-Science approaches used in annual cropping systems that integrate crop simulation modelling with satellite derived meteorological indices (e.g. CWSI, ET) and/or vegetation indices (i.e. NDVI) offer potential to inform water and crop management of perennial horticultural industries at farm to regional scales (e.g. Deleclole et al. 1998; Bastiaanssen and Ali 2003; de Wit and van Diepen 2008; Vazifedoust et al. 2009).

8.3.6 Next generation sensor systems and algorithms for detecting vegetation cover and crop water stress

Development of ultra-high resolution platforms to capture vegetation status offer improved capability in estimation of vegetation cover and water stress detection. Sensor systems mounted on unmanned aerial vehicles include thermal, multi- and hyper-spectral and Light Detection and Ranging (LIDAR) devices (e.g. Berni et al. 2009). These sensor platforms offer improved spatial and spectral resolutions and favourable revisit times compared to satellite or manned airborne platforms.
New generation state-of-the-art algorithms have taken advantage of the enhanced performance and characteristics of modern sensors, in particular their multi-spectral and multi-angular capabilities. Sensor specific formulae and coefficients to minimise the atmospheric, soil and angular affects of remotely sensed data have been formulated for application to ecosystem vegetation productivity modelling (e.g. www.nasa.gov, fapar.jrc.ec.europa.eu) warrant investigation.

8.3.7 Validation of satellite-derived crop water requirement

8.3.7.1 Agronomic and hydrologic validation of satellite derived evapotranspiration

Independent field scale evaluation of agronomic (yield and fruit quality) and hydrologic performance (Equation 1.1) from adoption of satellite derived irrigation management targets across key horticultural crops is required to gain confidence and industry acceptance of this new ET tool/technology.

The model METRIC estimates ET from the surface energy balance using satellite data, and rates of ET attributed to the ‘hot dry’ and ‘cold wet’ anchor pixels employed in the respective analyses (Chapter 6). One of the assumptions made in METRIC is that full hydrological contrast between the anchors is present in each Landsat image (Zhao-Liang et al. 2009). Verification of ET should therefore be based on equivalent measures of energy balance components, and reference crop ET (ET\text{REF}) made in the field.

Therefore, a combination of ground-based verification of energy balance and evaluation of on-farm water management outcomes (agronomic and hydrologic performance) according to CWR derived using the METRIC model require investigation. Given the impracticality of making comprehensive energy balance measures on a wide range of crop types, a strategic approach is recommended. Objective energy balance measures on land uses that approximate those used as ‘anchor’ pixels, would best provide ground-based data for direct comparison with the ‘anchor’ land uses employed in ET analyses. To quantify the energy balance, measurement systems comprising large aperture scintillometers (sensible heat flux, H), a net radiometer (net radiation flux, R\text{n}) and soil heat flux plates (soil heat flux, G) across a range of crops and vegetation cover situations could be established. The cold ‘wet anchor’ pixel is provided by well-watered (e.g. ‘full cover’ lucerne crop)
vegetation where, it is assumed, \( ET = 1.05 \cdot ET_R \). Conversely, very dry conditions at the hot ‘dry anchor’ pixel are met where \( H = R_n \) (i.e. \( ET = 0 \)) (Chapter 6).

### 8.3.7.2 Partitioning of evapotranspiration between target and understorey crops

The measurement of ET (and other energy balance terms: \( R_n \), G and H) among soil/vegetation mixes of tree/vine canopies and cover crops in micro-irrigated systems remains a difficult task. The use of more physically based (two- and three-source energy balance) ET models (Shuttleworth and Wallace 1985; Norman et al. 1995; Ortega–Farias et al. 2007; Poblete-Echeverría and Ortega-Farias 2009; Li et al. 2010) offer scope once parameterisation of the energy exchanges of the soil/substrate and vegetation (i.e. several input variables and resistance formulations) becomes robust for heterogeneous conditions. Alternatively, higher resolution remote sensing platforms combined with strategic on-ground measurement of components of the water balance (e.g. sap flow and micro-lysimetry) would provide more detail on ET partitioning between tree/vine and cover crop (e.g. Yunusa et al. 1997), therefore improving the estimation of irrigation requirements for the target crop.

### 8.3.7.3 Daily versus satellite time evapotranspiration

Further efforts are required to determine the appropriateness of ‘instantaneous’ (satellite image time) evaporation ratio (ET/ET\(_R\)) relationships relative to daily (24 h) ET for perennial horticultural crops. Data from weighing lysimetry studies on well watered short grass and sugar beet crops suggest that there is minimal temporal variation in hourly ET/ET\(_R\) for well watered crops (Allen et al. 2005a; Tasumi et al. 2005b). These lysimeter tests guided and supported the use of ET\(_R\) to define the ET at the ‘cold wet’ anchor pixel of METRIC and for extrapolation from the satellite image time to the full day and to days in between image dates (Allen et al. 2005a; Tasumi et al. 2005b). Likewise, Singh et al. (2011) report similar METRIC derived seasonal ET values from temporal Landsat data using different integration methods between image dates. However, sap flow data on fruit trees suggests temporal variability can occur at both diurnal and daily time scales in transpiration – evaporative demand relationships (Goodwin 2004). Likewise, variation in daily \( K_c \) values during the midseason have been reported using weighing lysimetry on fruit trees and grape vines (Ayars et al. 2003; Williams and Ayars 2005; Girona et al. 2011). Therefore, detailed water balance studies in perennial horticultural crops are needed to test the suitability of up-
scaling satellite time ET/\textit{ET}_R relationships to daily time scales and periods between consecutive satellite overpasses.

8.3.8 Spatial estimates of evaporative demand to improve water management

Weather station networks that provide daily reference crop ET (\textit{ET}_\text{REF}) located in major irrigation regions of the Murray-Darling Basin (Fig. 1.1) are required to take advantage of the ‘new-generation’ satellite derived NDVI and customised CWR (\textit{K}_c values) products. Recently, the Bureau of Meteorology has announced a new web-based mapping weather service (Forecast Explorer, www.bom.gov.au/watl) that will provide historical, recent and forecast (7-day) daily temperature, rainfall and evaporative demand (\textit{ET}_o, FAO-56; Allen \textit{et al}. 1998) data across Australia on a 6 x 6 km grid.

Better dissemination of water information to growers by linking field-specific NDVI-dependent CWR data to the new Bureau of Meteorology spatial weather service offers the opportunity to improve irrigation scheduling and water productivity.

8.4 Deficiencies

The issues identified here, and in other areas of agronomy and water management, will need to be addressed if the Goulburn Valley is to remain one of the most productive farming regions within the southern Murray Darling Basin, Australia.

8.4.1 Maximum yield

This thesis selected productive commercial orchards and vineyards to obtain estimates of maximum yield. Production performance in experimental crops was assumed to have optimal management of water and pest/disease and no allowance for growing conditions in previous seasons on current season (carbon assimilation) growth and yield (Fig. 3.1 and Equation 7.1) was made.

Factors that may have caused yield to be less than maximum include water stress and nutrition deficiency that were not directly investigated in this study. Better understanding of carbon allocation – yield responses to specific growing season periods warrants investigation. Further work on fruit number and interactions with water stress (e.g. Naor 2001) and/or vegetation cover on yield outcomes are needed. The opportunity for bio-physical crop models remains, whereby identifying the
limiting factors involved in yield determination should lead to new management strategies for improved production outcomes.

8.4.2 Post-harvest water requirement

Determination of the maintenance level of crop water use for the post-harvest period to secure yield in subsequent seasons requires further investigation. This is particularly important in early maturing crops/cultivars (e.g. apricot, peach) due to the long (≤ 5-month) post-harvest period. From a water budget perspective, substantial water savings are likely using post-harvest deficit irrigation strategies in early maturing crops.

8.4.3 Reliance on satellite data

This study utilised Landsat data to determine NDVI and ET. Launched in 1984, Landsat-5 is still operational two decades beyond its designed lifetime. Fortunately, the National Aeronautics and Space Administration (NASA) have a new replacement satellite, ‘Landsat-8’ (Landsat Data Continuity Mission), with a launch goal in December 2012. Landsat-8 will be equipped with long-wave (thermal) capability, a primary input to the METRIC ET model (Allen et al. 2005a). Considerations of the continuity of Landsat observations are provided by Wulder et al. (2011).

Satellite data is only available intermittently, depending on the source, cost, and weather. This thesis developed robust crop-specific regional customised ET – NDVI relationships from a collage of Landsat images to provide a sound basis for weather-based ET prediction of CWR ($K_c$ values), thereby removing the need to directly derive ET (within season) from satellite data. However, new crops, irrigation regions and/or irrigation systems/methods warrant new regional ET – NDVI relationships to be established. Here, analysis of ET – NDVI observations in seasons of high irrigation allocation is also warranted to examine the robustness of NDVI-dependent water use targets developed in Chapter 6. The extent that cover crop conditions influence satellite derived ET – NDVI data, especially in sparse orchards/vineyards, requires further consideration to avoid discrepancies and bias in vegetation cover and consequently, estimation of yield and water use.

Alternatives to satellite derived vegetation cover measurements include manned and unmanned airborne platforms equipped with vegetation index sensors. Ground-based
imagery systems and spot measurement of vegetation cover (i.e. ceptometer) are available, e.g. effective area of shade (Goodwin et al. 2009), but are more cumbersome and time consuming than the remote options described above.

8.4.4 Improved land use and land management spatial information

Up-to-date crop type and cultivar description data available on land use classification (GIS) systems would permit better estimation of crop phenology – vegetation relationships (e.g. length of growing season) to determine CWR and $Y_{\text{MAX}}$. Orchard and vineyard management practices such as netting against birds and hail, inter-row reflective mulch, reflective plastic crop covers and spray-on reflective crop protection agents (e.g. Kaolinite clay) pose a challenge to derivation of ET and NDVI using satellite techniques. Their identification and exclusion from satellite data needs testing to determine the effect on regionally derived yield – water use observations and estimates of water productivity.

8.5 Conclusion

This thesis developed and evaluated a satellite-derived crop- and site-specific framework for benchmarking water inputs and maximum yield of orchards and vineyards at field, farm, and regional scales. A combination of fieldwork, satellite remote sensing techniques and a simple widely used approach, advocated by Doorenbos and Kassam (1979) enabled this study to produce region- and crop-specific estimates of maximum yield and crop water requirement that underpin NDVI-dependent water production functions.

Variation in vegetation cover was the major variable that effects ET, CWR and actual yield and $Y_{\text{MAX}}$ in perennial horticultural crops. Methods developed in this thesis cope with variation in vegetation cover within a crop type and are valuable for irrigation management and yield appraisal. Irrigation benchmarking studies therefore need a measure of vegetation cover to appraise water use efficiency.

The NDVI-dependent water production function approach is the only tool of its type able to address water and productivity concerns at farm and regional scales in Australia. NDVI-dependent water production functions provide for improved understanding crop water use, irrigation requirement and crop production performance. The analytical tools and knowledge developed in this study place
perennial high value horticulture in a position to increase the economic outputs from water, improve water use, improve yield and manage diversity in a water scarce environment and an increasing competitive global market place.
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Appendix 1


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Abstract

The METRIC algorithm (Allen et al. 2007) was applied to a Landsat 5 image to assess the range of vegetation cover (measured as Normalised Difference Vegetation Index; NDVI), and rates of evapotranspiration (ET), of major horticultural crops grown in the Sunraysia Irrigation Region of SE Australia. The image represented the period of maximum foliage cover of horticultural crops grown in the Region. The range in mid-season NDVI of almond, grape and citrus crops almost matched the whole-of-season range reported for broad-acre irrigated annual crops grown in Idaho, USA. Alfalfa reference ET (ETr) constituted the upper limit to ET rate seen in Sunraysia crops. The range of ET and NDVI observations in this study therefore complied with limits on ET and NDVI seen in irrigated crops in Idaho, USA. ET - NDVI relationships seen in USA crops appear to provide a useful reference framework for well-watered irrigated crops in cases where ETr is the upper limit on ET. ET rates in Sunraysia crops were strongly related to NDVI. The dependence of ET rates on NDVI, combined with the large range in NDVI, meant that irrigation water requirement varied widely within and between crop types in the Sunraysia region: results support the use of NDVI measures to account for site-specific differences in crop water requirement attributable to vegetation cover. Findings suggest that satellite-based METRIC methods of ET estimation may be used to formulate region- and crop-specific estimates of the crop coefficients (Kcb, Ke, and Kc) required for optimal irrigation water management of horticultural crops.

INTRODUCTION

The Sunraysia Irrigation Region of SE Australia is a major producer of grape and citrus crops. Nut crops, including almond, have assumed increased importance in recent years.

Detailed investigations of the water use of well-watered crops (crop water requirement) of fruit, vine and nut species in Sunraysia are lacking because of the cost and difficulty of establishing and maintaining technical facilities to study long-lived perennial crops, and the impracticality of extending water use studies across a diverse range of cultivars, crops, and cultural methods. Satellite-based SEBAL-METRIC methods (Bastiaanssen et al. 1998; Allen et al. 2007) appeared to meet the need for an affordable comprehensive method of estimating water use, and crop water requirement, over the range of crops and cultural practices in the region.
Effects of crop type and weather on water use (evapotranspiration; ET) of ‘ideal’
well-watered crops have been widely studied in terms of a crop coefficient, Kc, and
reference crop evaporation, ETref:

$$ET = Kc \cdot ETref$$  \hspace{1cm} (1)

ETref accounts for effects of weather on ET, and Kc has been used to account for
the biophysical factors that differentiate ET rates of target and reference crops. Alfalfa is
the standard reference crop in western USA (ETref = ETr). More broadly, the ET
fraction, ETrF, where ETrF = ET/ETr, provides a general expression for measures of ET
made in relation to ETr (Allen et al. 2011).

SEBAL-METRIC procedures supply measures of ET and vegetation cover
(measured as NDVI) over large regions. The assumption that all irrigated crops in an
image meet the ‘ideal’ well-watered conditions implied by Equation 1 may therefore be
invalid, and satellite-based ET measures should preferably be gauged against ‘well-
watered’ criteria in order to derive estimates of Kc appropriate to the water use of well-
watered crops.

The dual crop coefficient approach has been widely used to describe ET rates of
‘non-ideal’ crops (e.g., Wright 1982; Allen et al. 1998, 2005), and is therefore appropriate
to the analysis of ET estimates derived from satellites. In that approach, rates of ET are
described in terms of an ‘adjusted’ Kc value that accounts for effects of soil water stress
on plant transpiration and the contribution of surface evaporation to ET. METRIC
measures of ETrF may therefore be described in terms of coefficients, Ks, Kcb and Ke, as
follows:

$$ETrF = ET/ETr = Ks \cdot Kcb + Ke$$  \hspace{1cm} (2)

Here, Kcb describes the contribution of transpiration to ET of well-watered crops. Ks
accounts for the decrease in transpiration due to soil water stress, and Ke accounts for
evaporation from wet soil and foliage surfaces at times when free water exists in the soil-
plant system.

Fractional vegetation cover (fV) is the major determinant of Kcb (Ritchie 1972;
Allen and Pereira 2009). Kcb is a maximum, Kcb = 1, at maximal fV (Allen and Pereira
2009). Kc therefore approximates Kcb in many full cover, well-watered crops when
surfaces are dry (fV = 1, Ke = 0, Ks = 1). More generally, Allen and Pereira (2009)
reported that fV is an effective surrogate for Kcb in well-watered crops with incomplete
cover (fV ≤ 1, Ke = 0, Ks = 1).

Effects of surface evaporation in rain-free periods are most pronounced at times
when foliage and soil surfaces are wet by irrigation. Ke contributions during dry periods
are therefore often expressed as short-lived spikes in ET following irrigation or rainfall,
and the magnitude of the short-term ET response to rain and irrigation has commonly
been employed to gauge the magnitude of Ke (e.g., Allen et al. 2005).

By contrast, Kcb contributions account for the major basal rates of ET that persist
throughout the irrigation cycle in mature crops. Goodwin et al. (2006), for example,
showed that transpiration rate in peach was directly related to fraction of shade on the soil
surface (i.e., fV). Allen and Pereira (2009) analysed the dependence of crop coefficients
on crop height and vegetation cover. They showed that Kcb was approximated by fV in
crops of height, h = 0.5 m. The relationship, Kcb = fV, constituted a lower bound to the
values of Kcb seen in taller crops (0.5 < h ≤ 4 m). In all cases, the maximum rate of ET
was ET\textsubscript{r} (Allen and Pereira 2009). Most Sunraysia crops are tall (h > 0.5 m) and their row structure results in incomplete canopy cover.

Tasumi and Allen (2007) applied the METRIC algorithm (Allen et al. 2007) to Landsat images to estimate ET of irrigated crops grown in Idaho, USA. Crops included alfalfa, peas, beans, corn, potato, sugar beets and cereals. Regional within-crop variability in ET\textsubscript{rF} was attributed to phenological differences in f\textsubscript{v} (measured as NDVI). Tasumi et al. (2005) had previously estimated K\textsubscript{cb} as the lower bound to METRIC measures of ET seen in irrigated potato and sugar beet crops grown in Idaho: K\textsubscript{cb} increased linearly with NDVI in the comprehensive range of NDVI derived from a collage of Landsat images that spanned the life cycle of crops grown in Idaho. Tasumi et al. (2005) assumed that crops in their study were well-watered, and the reported K\textsubscript{cb} line was adopted for empirical and analytical purposes in this study; their K\textsubscript{cb} line, referenced as the K\textsubscript{cb-I-NDVI} relationship, was described here by:

\begin{equation}
K_{\text{cb-I}} = 1.33 \times (\text{NDVI} - 0.1)
\end{equation}

This paper sought to quantify the range in NDVI, and to explore the dependence of METRIC-derived estimates of ET\textsubscript{rF} on NDVI in perennial horticultural crops grown in the Sunraysia Irrigation Region of SE Australia.

**MATERIALS AND METHODS**

ET was estimated using the METRIC algorithm (Allen et al. 2007) applied to a Landsat 5 image (5 Jan 2009; Path/Row 95/84) sourced from http://glovis.usgs.gov. The image was acquired during the peak period of summer irrigation activity in the Sunraysia region, when crop leaf area development was maximal.

In contrast to Allen et al. (2007), surface roughness, z\textsubscript{0m}, was estimated using the simple relationship derived by Teixeira et al. (2009) for a mix of agricultural and natural ecosystems:

\begin{equation}
z_{0m} = \exp(0.26 \times \text{NDVI/ALB}) - 2.21\end{equation}

Here, ALB was the pixel-wise METRIC estimate of surface albedo (Allen et al. 2007).

Estimates of ET\textsubscript{rF} were made according to:

\begin{equation}
\text{ETF} = \text{ET/ETr}
\end{equation}

ET\textsubscript{r} was computed at the time of satellite overpass using methods described by Allen et al. (1998, 2006) in conjunction with hourly weather data for Mildura airport (latitude 34.24°S, longitude 142.09°E) sourced from the Bureau of Meteorology.

Pixel-scale estimates of ET and NDVI were averaged at field-scale in order to conduct crop-specific ET-NDVI analyses. Citrus, grape and almond crops were located using land use data acquired from Sunrise21 Inc. (http://www.sunrise21.org.au).

ET\textsubscript{F} measures in Sunraysia crops were compared with K\textsubscript{cb} estimates of irrigated potato and sugar beet crops grown in western USA, by the use of a variable, dK\textsubscript{cb-I}, which measured the difference between observed values of ET\textsubscript{F}, and NDVI-dependent estimates of K\textsubscript{cb-I} (Equation 3):

\begin{equation}
dK_{\text{cb-I}} = \text{ETF} - K_{\text{cb-I}}
\end{equation}
RESULTS AND DISCUSSION

Rainfall

No rain was recorded in the two weeks prior to the satellite overpass. The water status of Sunraysia crops at the time of overpass was therefore attributable to regional irrigation practices.

ET-NDVI distributions in citrus, grape and almond crops

Mean NDVI in citrus, grape and almond was 0.40, 0.38 and 0.46, respectively, and mean ETrF was 0.55, 0.54 and 0.70, respectively.

Most NDVI observations were confined to approximate limits, 0.15 < NDVI < 0.75 (Fig. 1), and were therefore contained within the comprehensive range, 0.1 < NDVI < 0.85, reported for potatoes and sugar-beet by Tasumi et al. (2005), where vegetation cover varied from bare soil ($f_V = 0$) to full cover ($f_V =1$). Maximum values of NDVI in Sunraysia crops were therefore consistent with the incomplete cover of most horticultural crops. Nonetheless, the data described a wide range of vegetation cover in each of the Sunraysia crops.

Figure 1 also shows that NDVI-dependent estimates of KcbI (Equation 3) constituted a lower bound to METRIC estimates of ETrF in Sunraysia crops. Furthermore, the upper bound on ET in Sunraysia crops was described by ETr. Values of ETrF in Sunraysia crops were therefore largely confined to the range, KcbI < ETrF < 1.0, and NDVI was confined to the limits, 0.1 < NDVI < 0.85, as seen in irrigated broad-acre annual crops in Idaho. Those limits, depicted as red triangles in Figure 1, accounted for > 95% of ET-NDVI observations in mid-season citrus, grape and almond crops in Sunraysia.

Relationships between ETrF and NDVI in Sunraysia crops

Figure 1 shows that ETrF was strongly related to NDVI, and KcbI. However, there was considerable variability in ETrF for a given value of NDVI, especially in grape crops. Measures of dKcbI (Equation 6) were employed to study the species-dependent range in ETrF for a given NDVI.

In almond, for example, mean dKcbI was 0.22, with a standard deviation of 0.054. As all ETrF observations exceeded KcbI estimates (hypotenuse, red triangles in Figs. 1 and 2), regional almond Kc was approximated by the relationship, dKcbI = 0.22 (366 observations). ETrF in almond, as described by 95% confidence limits on dKcbI, corresponded to the range, +0.11 < dKcbI < +0.33.

Table 1 provides basic analogous statistics for grape and citrus. The wide confidence limits on dKcbI in grape and citrus showed that KcbI approximated Kc values reported by Tasumi et al. (2005). In fact, the lower confidence limits for dKcbI in grape and citrus included negative values for dKcbI, which suggested that a minor proportion of those crops was possibly more water-stressed than expected on the basis of KcbI.

Estimates of crop coefficients, Kcb, Ke and Kc

Upper confidence limits on dKcbI (Table 1) were assumed to represent rates of ET of recently irrigated crops. Similarly, the lower confidence limits on dKcbI were attributed to crops at the end of the irrigation cycle. The confidence levels on dKcbI in Table 1 thereby provided a simple statistical description of the NDVI-dependent upper
and lower rates of ETrF. Because rainfall made an insignificant contribution to the water availability of crops, it was assumed that the upper confidence limit represented the ET rate of recently-irrigated crops (ETrF = KcbI + 0.33 in almond; Fig. 2), and the lower confidence limit applied to crops just prior to irrigation (ETrF = KcbI + 0.11 in almond). The regional crop-specific NDVI-dependent estimate of Kcb in almond was therefore described by the relationship, dKcbI = 0.11.

Both Ke and Kcb contribute to the values of ETrF that occur during and soon after irrigation. After defining Kcb in terms of the lower confidence limit for dKcbI, mean regional crop-specific Ke was estimated as the ET response to irrigation, measured here as the increase in dKcbI between the lower to the upper confidence limit on dKcbI (see Table 1). The regional almond-specific estimate of Ke was therefore described by Ke = 0.22.

Table 2 summarises estimates of Kcb, Kc, and Ke derived from METRIC analyses of ET-NDVI relationships for almond, grape and citrus crops grown in Sunraysia Irrigation Region.

**CONCLUSIONS**

The range in NDVI of horticultural crops grown in Sunraysia was only slightly less than the whole-of-season range reported for irrigated annual crops in Idaho (Tasumi et al. 2005). The range in ETrF in Sunraysia generally matched that seen in Idaho crops. The maximum rate of ET in perennial horticultural crops in Sunraysia was similarly described by ETr. ET and NDVI observations in Sunraysia were therefore largely consistent with the range of ET-NDVI combinations seen in irrigated broad-acre crops grown in Idaho. Limits on NDVI and ETrF reported by Tasumi et al. (2005) appear to describe a two-dimensional ET-NDVI reference space appropriate to ‘tall’ well-watered irrigated crops.

In addition to the large range in mid-season NDVI seen in major perennial horticultural crops grown in Sunraysia, the study revealed that water use was strongly dependent on NDVI, as expected on the basis of experimental work in SE Australia (Goodwin et al. 2006), and analyses undertaken by Allen and Pereira (2009). The dependence of mean irrigation Kc on NDVI implies that irrigation water management should explicitly account for site-specific differences in vegetation cover/NDVI.

Finally, the study suggested that satellite-based METRIC methods of ET estimation may be used to formulate region- and crop-specific estimates of the crop coefficients (Kcb, Ke, and mean Kc) required for optimal water management in irrigated horticulture.

**ACKNOWLEDGEMENTS**

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**Tables**

Table 1: Mean, and upper and lower 95% confidence limits of $dK_{cbI}$, calculated as $dK_{cbI} = K_c - K_{cbI}$, in almond, grape and citrus crops grown in the Sunraysia Irrigation Region.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Mean</th>
<th>Lower confidence limit</th>
<th>Upper confidence limit</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Almond</td>
<td>+ 0.22</td>
<td>+ 0.11</td>
<td>+ 0.33</td>
<td>366</td>
</tr>
<tr>
<td>Grape</td>
<td>+ 0.18</td>
<td>– 0.05</td>
<td>+ 0.40</td>
<td>16846</td>
</tr>
<tr>
<td>Citrus</td>
<td>+ 0.15</td>
<td>– 0.03</td>
<td>+ 0.32</td>
<td>4522</td>
</tr>
</tbody>
</table>

Table 2: Estimates of $K_c$, $K_{cb}$ and $K_e$ derived from METRIC analyses of ET-NDVI relationships for almond, grape and citrus crops grown in the Sunraysia Irrigation Region.

<table>
<thead>
<tr>
<th>Crop</th>
<th>$K_c$</th>
<th>$K_{cb}$</th>
<th>$K_e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Almond</td>
<td>$K_{cbI} + 0.22$</td>
<td>$K_{cbI} + 0.11$</td>
<td>0.22</td>
</tr>
<tr>
<td>Grape</td>
<td>$K_{cbI} + 0.18$</td>
<td>$K_{cbI} – 0.05$</td>
<td>0.46</td>
</tr>
<tr>
<td>Citrus</td>
<td>$K_{cbI} + 0.15$</td>
<td>$K_{cbI} – 0.03$</td>
<td>0.36</td>
</tr>
</tbody>
</table>
Fig. 1. Field-scale ETrF – NDVI relationships of grape, citrus and almond crops in Sunraysia Irrigation Region in January 2009. Red triangles depict limits on NDVI and ETrF (0.1 ≤ NDVI ≤ 0.85; KcbI ≤ ETrF ≤ 1.0) reported for irrigated broad-acre crops grown in Idaho (Tasumi et al. 2005). The hypotenuse of the triangles represents KcbI (Equation 3).
Fig. 2. Lines depicting the mean (black), and upper (blue) and lower (grey) confidence limits on ET\textsubscript{r}F implied by values, dKc\textsubscript{bI} = 0.22, 0.33 and 0.11, respectively, in almond. Red triangle as in Fig. 1.
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