Model-data fusion for land-atmosphere coupling: Remote sensing evapotranspiration and soil moisture dynamics in Murrumbidgee catchment

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ABSTRACT

Increasing stress on the world’s fresh water resources demands improvements to be made in increasing water productivity and encouraging efficient use of this limited resource. Global scale land surface models help us understand and predict the behaviour of terrestrial, atmospheric, climatic and hydrological processes that govern the ability to continuously update environmental policies. Irrigated agriculture is the largest consumer of the world’s fresh water resources and is a key component of the terrestrial water cycle. Global food security, which greatly depends upon irrigated agriculture, is facing serious threats due to limited fresh water availability. One of the most important factors for sustainability of irrigation in the future, under water stress circumstances, is the effort towards developing a better understanding of the land-atmosphere coupling processes that govern the hydrological principles and lead to effective use of water with better model predictions. Quantification of evapotranspiration is one of the vital components for water budgeting, efficient irrigation scheduling, cropping practices and water regulation in an irrigation system. Many remote-sensing algorithms have been developed over the years to model spatial actual evapotranspiration for larger areas to help improve water balances. More recently, efforts to derive surface soil moisture information to improve agricultural monitoring quality through remote sensing have also increased with the advancements in microwave sensing and retrieval models.

Continuous efforts over the past few years to model soil moisture and relate it to point- and remote-sensed observations have led to
somewhat improved availability and quality of surface soil moisture datasets. As a result of increased availability of microwave soil moisture datasets, it is now recommendable to test the potential of estimating root-zone soil moisture from remote sensing derived surface soil moisture to understand its spatial distribution. This study aims to explore the coupling of microwave derived soil moisture with surface energy balance components, and investigate the potential of estimating root-zone soil moisture by using a practicable, simplified assimilation technique in the Murrumbidgee catchment.

The study can be categorised into three stages. In the first stage, a Large Aperture Scintillometer (LAS) was installed over a horticultural farm near Leeton, NSW, to provide ground calibration for remote sensing energy balance modelling. LAS scintillation data was used to calculate sensible heat flux for the entire half-hourly time-series data. The latent heat flux was then estimated by solving an energy balance of fluxes measured by net radiometer and soil heat flux, and $H$ calculated using LAS. The LAS performed very well for the purpose of heat flux estimation for energy balance closure, provided the data was filtered for bad or missing values generated by various meteorological conditions or sensor errors. A network of meteorological stations enabled the testing of sensitivity of micro-meteorological variations occurring within the path-length of the LAS on sensible heat flux calculations. One-way between groups ANOVA analysis and Tukey’s HSD analysis suggested that moving the AWS further along the stretched path length will generate statistically significant differences in sensible heat flux, and eventually influence the whole energy balance closure i.e. meteorological conditions differed enough towards the centre of
the LAS beam to produce a mean difference of $\sim 14 \, \text{W/m}^2$ in the sensible
heat flux. The difference in the instantaneous estimate of $H$ reached up to
100 W/m$^2$ in some instances. A 50–100 W/m$^2$ difference in sensible heat
flux can result in a 1.25–2.5 mm.d$^{-1}$ error in daily evapotranspiration flux
and affect the entire water balance for large regions. Further, energy
balance modelling over the Murrumbidgee catchment was performed using
Terra/MODIS data for year 2010/11. The results revealed that SEBS
overestimated soil heat flux for higher values while it underestimated net
radiation for higher values.

Later, root-zone soil moisture dynamics were modelled using an
exponential filter (Wagner et al., 1999) using an AMSR-E surface soil
moisture dataset over six ground calibration sites. Time-step-based
statistical analysis between SEBS-derived actual evapotranspiration was
analysed with in-situ observations of surface soil moisture. Weak negative
correlation was observed between moisture and actual evapotranspiration,
which was not seen while relating surface fluxes to AMSR-E-derived
moisture at these sites. Finally, cross-correlation analysis was carried out
between measured surface and measured root-zone moisture time-series
with a time lag of 1 day to match Aqua/AMSR-E temporal resolution. A
strong positive correlation was found between the observed surface
moisture ($SM_{SL}(t)$) and observed root-zone moisture of next ($SM_{RZ}(t+1)$). An
exponential filter was applied on the AMSR-E soil moisture time-series to
calculate sub-surface moisture. The model performed poorly in estimating
root-zone moisture from AMSR-E data. A maximum correlation of 0.4681
with a low Nash-Sutcliffe coefficient value of -1.23 was observed. The
applied exponential filter model-DA showed potential for root-zone
moisture extraction, but the accuracy observation serves as a pre-requisite to base our understanding of spatial distribution of moisture and its coupling with actual evapotranspiration on it. Improvements in remotely sensed soil moisture observations will act as the cornerstone in enhancing understandings in land-atmosphere coupling by facilitating an operational assimilation scheme for estimating spatial root-zone soil moisture that is representative of the actual moisture state.


CERTIFICATE OF AUTHORSHIP

I hereby declare that this submission is my own work and to the best of my knowledge and belief, understand that it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at Charles Sturt University or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by colleagues with whom I have worked at Charles Sturt University or elsewhere during my candidature is fully acknowledged.

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1. INTRODUCTION

1.1. BACKGROUND

In the world today, water scarcity is rapidly becoming a serious concern for developed and developing nations alike, and could lead to a severe crisis at the global scale (IWMI, 2009b). There has been a 40% rise in food costs resulting from the 2008 world food crisis (Ullah, 2011). One of the main causes of the recent food crisis was the increase in water scarcity triggered by competing demands among traditional water consumers, namely agriculture, industry and cities, for available water resources, together with the effects of climate change (IWMI, 2009b). Many researchers in various parts of the world have already reported that there is an urgent need to improve water use efficiency in all sectors (Khan et al., 2008, Ullah, 2011). Hence, the stress on the world’s water resources will intensify due to a continuously increasing population (Gourbesville, 2008; Teixeira, 2008). Today, many parts of the world face physical water scarcity, mostly resulting from agriculture-driven issues like over-allocated supplies, reduction in river flows and depleting groundwater levels. Regions with plentiful resource are now facing economic-driven scarcity and have limited access due to non-development of water resources. In addition, the world’s population has doubled over the last four decades and is projected to be more than 9 billion by 2050 (IDB, 2011).

The pressures to meet growing water demands have also resulted in greater competition between regions or countries for access to water, and tension is rising due to the fact that growing water demand is not
synchronised with increased resources (Pulido-Calvo et al., 2007). Irrigated agriculture is the largest consumer of fresh water, accounting for 70% of global water withdrawals, while industry and urban uses are 20% and 10% respectively (Ullah, 2011, UN-Water, 2006). It is becoming difficult to maintain sufficient water of agriculturally usable quality due to climate change and reduced precipitation. To keep pace with the growing demand for food, it is estimated that in the next 30 years, 14% more freshwater will be required for agricultural purposes (Ullah, 2011). Therefore, irrigated agriculture now faces the dilemma of meeting the increases in food demand related to a growing world population, while ensuring the sustainable use of an already scarce water resource (Santos et al., 2008).

Australia is the largest and driest inhabited continent in the world where extreme variability of rainfall and droughts are a common occurrence. Here, the climate varies noticeably within small geographical distances. Therefore, the productivity of Australian agricultural production is highly dependent upon irrigation water supply. Diverse climatic conditions and terrain make water resources of Australia highly variable. In addition, in terms of development, water resources range from highly regulated rivers and groundwater resources, through to rivers and aquifers in almost immaculate condition (NWC, 2011).

The distribution of water in Australia is governed by the State and Territory governments. These allow the consuming sectors to access water for a variety of purposes, including for irrigation, mining and other industrial uses, and for servicing rural and urban communities. One of the major challenges faced by Australia today is balancing extraction for irrigation and
other uses while sustaining appropriate environmental and river health. Chartres and Williams (2006) stated that, by the second half of last century, it was clear that this natural equilibrium necessary for healthy functioning of the natural resource base had been disturbed by over-exploitation of natural resources. The National Land and Water Resources Audit (NLWRA) of 2001 indicated that 26% of Australia’s surface water management areas and some groundwater management units were either close to, or overused, compared with sustainable flow regimes (Ullah, 2011). An intergovernmental agreement National Water Initiative (NWI) was signed to increase the productivity and efficiency of Australia’s water use, acknowledge the need to service rural and urban communities, and to ensure the health of river and groundwater systems (NWC, 2011). Important Australian Government water policy initiatives were built on the foundation of reform developed under the NWI, and a comprehensive package of reforms was introduced for water entitlements, trading and sustainable use (NWC, 2011). These resulted in establishment of an independent Murray-Darling Basin (MDB) Authority for preparing a Basin Water Resources Plan, and Water for the Future program, to invest $12.9 billion over 10 years to address four priorities, which include taking action on climate change, using water wisely, securing water supplies, and supporting healthy rivers and waterways (DSEWPC, 2011). In Australia, 0.5% of the agricultural land is irrigated and consumes 65% of the water (Ullah, 2011). The MDB – the largest catchment for irrigation activities – covers 1,060,000 square kilometres (14% of Australia’s landmass). It accounts for 46% of the gross value of Australian irrigated agricultural production and 31% of total agricultural production (ABS, 2011). Hence, irrigation water is of immense importance to the Australian agricultural economy. Irrigated agriculture in
the MDB consumed around 68% of all irrigated water used for agriculture in Australia in 2010–2011, which was 37% increase on the previous year (ABS, 2011).

Under increasing water scarcity circumstances, irrigated agriculture will be required to produce more with less water in the future, which entails the best use of available water (Molden and Sakthvadivel 1999). Improvements in water management of irrigated areas and the assessment of irrigation performance are a critical task. These activities are needed not only to improve water productivity, but also to increase the sustainability of irrigated agriculture and to improve irrigation efficiency (Santos et al., 2008). Improvement inefficiency requires complete understanding of all terms of the water balance at various scales i.e. farm to basin levels (Khan and Hafeez, 2007). Hence, the quantification of water balance components is fundamental for a clear understanding of various hydrological processes (evapotranspiration, rainfall, runoff, soil moisture, seepage etc) and different factors (land use changes) affecting these hydrological processes, both spatially and temporally. To cope with water scarcity and the economic pressure on water resources, a holistic understanding of processes involved in land-atmosphere coupling serves as the basis for development of tools and techniques that may guarantee a sustained availability of fresh water.

One of the greatest challenges in modelling land-atmosphere local interactions is the soil moisture-evapotranspiration coupling from irrigated agricultural land. The quantification of evapotranspiration ($ET$) is one of the vital components for water budgeting, efficient irrigation scheduling; cropping practices and water regulation in any irrigation system. A lot of
uncertainties are involved in measurement of ET. Traditional approaches to estimate ET used point-based meteorological data to calculate reference evapotranspiration ($ET_o$) and multiplying it by a crop coefficient ($K_c$), determined according to the crop type and the crop growth stage (Allen et al., 1998). These conventional techniques employ point measurements to estimate the components of energy balance and are only representative of local scales and cannot be extended to large areas because of the heterogeneity of the land surface and the dynamic nature of heat transfer processes. Moreover, the determination of the crop coefficient is also debatable due to other factors, for example, whether crops grown compare with the conditions represented by $K_c$ values, especially in water scarce areas (Neale et al., 2005). Remote-sensing techniques can provide representative measurements of several relevant physical parameters at scales from a point to the global scale and are essential when dealing with processes that cannot be represented only by point measurements (Su and Jacobs, 2001).

Energy balance models concentrate on ET; they do not extend through soil to include water and heat exchanges. A key component of land surface interactions is the soil moisture-evapotranspiration coupling. Soil moisture, in fact, is the core of the system that controls the hydrological interactions between soil, vegetation and climate forcing, and plays a key role in governing the water and energy balance between land surface and atmosphere. The significance of soil moisture is its role in the partitioning of energy at the ground surface into sensible and latent (ET) heat exchange with the atmosphere. The challenge of modelling soil moisture, which naturally varies at different scales, within operational environmental models
in a way that facilitates comparison with observed data is very important but challenging.

1.2. Problem Statement

*ET* studies have used the model-predicted top soil moisture patterns for early drought prediction, drought monitoring, and evaluation of drought impact on agricultural production, but with limited accuracy (Kwast, J., 2009). At present, it may be difficult to integrate sub-surface processes into energy balance models due to non-availability of direct moisture observations. However, recent advancements and availability of microwave-retrieved surface moisture datasets is opening up doors to fuse energy balance and microwave-derived model data in order to study the reflection of soil moisture limitation to *ET* flux, and model spatial distribution of root-zone moisture on a large scale.

Observational efforts to understand the spatial and temporal variability of soil moisture over day-to-season and inter-annual time scales represent the basis for understanding soil moisture-atmospheric interactions and are essential to underpin improved process-based understanding (Jason et al., 2009). Spatio-temporal soil moisture patterns are currently derived from field measurements, process-based modelling or remote-sensing data. Microwave remote sensing provides a means to quantitatively describe the water content of a near-surface soil layer. In hydrological and meteorological modelling, root-zone soil moisture dynamics is a key variable that needs to be understood properly. Since there is only a weak link between near-surface and root-zone moisture through
the diffusion process, assimilation algorithms have allowed the retrieval of somewhat acceptable root-zone moisture using surface observations at the field. Entekhabi et al., (1994), Houser et al., (1998), Calvet and Noilhan, (2000), and Walker et al., (2001a,b) have shown some examples of how data assimilation techniques can sometimes produce reasonable moisture profiles. Several authors concluded that the Kalman Filter, an optimal sequential assimilation method extensively used in various environmental problems, is well suited for profile soil moisture estimation (Walker et al., 2001b). Other assimilation techniques such as 1-D Variational (1DVAR) also provide good results under controlled conditions (Sabater et al., 2007).

However, the lack of high quality information on the model parameters at a global scale (soil properties, atmospheric forcing) and the uncertainties related to the physical description of the water and energy balance are a disadvantage for data assimilation methods. Different assimilation methods (Kalman and Ensemble Kalman Filters) have shown potential in extracting the root-zone moisture dynamics, but all of these desktop studies such as Albergel et al., (2008) included either synthetic data or direct point-based observations at the field. With the increase in availability of calibrated microwave soil moisture datasets, it is now feasible to test the potential of estimating root-zone soil moisture from remote-sensing-derived surface soil moisture, which has not previously been applied to study the temporal dynamics of root-zone soil moisture. Therefore, this study aims to explore the interfacing between microwave-derived soil moisture with surface energy-balance-derived actual $ET$, and investigate the potential of estimating root-zone soil moisture by using a practicable, simplified exponential filter model.
1.3. Thesis Objectives

The specific objectives of this thesis are:

- To test the application of Large Aperture Scintillometer (LAS) for estimation of sensible heat flux and energy balance closure in hydrological settings of irrigated agriculture.
- Estimate the catchment-scale actual evapotranspiration using a surface energy balance model (SEBS), and investigate the coupling of actual evapotranspiration with in-situ and microwave-derived surface soil moisture data.
- Test the applicability of exponential filter model-DA to estimate spatially distributed root-zone soil moisture at catchment scale.

1.4. Thesis Outline

Chapter 2 provides a detailed overview of the study area and its salient features and characteristics. Chapter 3 reviews various traditional and state-of-the-art methods for estimation of ET with particular focus on the LAS technique and remote-sensing-based ET algorithms. The last section of Chapter 3 presents a review of modelling and assimilation methods focused on studying root-zone moisture. Chapter 4 discusses the data used and the methodology adopted for energy balance calculations from LAS, remote-sensing-based flux estimation using the energy balance model (SEBS) with Terra/MODIS data, and the assessment of an exponential filter in estimating root-zone soil moisture from microwave-based surface soil moisture time-series. Chapter 5 presents the results of the surface flux estimation from the scintillometer method in comparison with SEBS-
modelled fluxes using Terra/MODIS data. Chapter 6 presents the results of exponential-filter-based root-zone soil moisture retrieval from AMSR-E time-series, and assesses the performance of the model against observed data. Chapter 7 summarises the findings of this study and presents conclusions and recommendations for future research.
2. Study Area

2.1. General Overview

The Murray-Darling Basin (MDB) covers more than 1 million square kilometres of mainland Australia and encompasses parts of Queensland (QLD), New South Wales (NSW), Victoria (VIC), South Australia (SA) and all of the Australian Capital Territory (ACT). The MDB (Figure 2.1) is bound by the Great Dividing Range in the south and east and is defined by the catchment areas of the Murray and Darling Rivers and their many tributaries. The Basin is a place of great national significance, with many important social, economic and environmental values, and is home to over two million people. The Basin's floodplains, forests and wetlands provide habitats for diverse and unique native plant and animal species, and its water resources directly and indirectly support millions more. The Murray-Darling Basin Authority (MDBA) was established under the federal Water Act 2007 as an independent, expertise-based statutory agency under the Ministry of Water. It undertakes activities that support the sustainable and integrated management of the water resources of the MDB in a way that best meets the social, economic and environmental needs of the Basin and its communities (MDBA, 2012).
Figure 2.1: The Murray-Darling Basin (MDBA, 2012).

Figure 2.2: Murrumbidgee Valley and location of major irrigation areas (CSIRO, 2008).

The Murrumbidgee River within the MDB has the most important catchment, with annual agricultural production exceeding $1.9 billion. The Murrumbidgee catchment (Figure 2.2) has an area of 84,000 square kilometres, which is equivalent to about 11% of the total land area of New
South Wales, and 8% of the MDB (CSIRO, 2008). The river originates in the alpine area of Kosciuszko National Park and flows through the Monaro High Plains and the low-lying plains of the western Riverina, joining the Murray River south of Balranald. In the upper reaches of the Murrumbidgee River, main tributaries include the Tumut, Queanbeyan, Yass and Cotter Rivers, and Tarcutta Creek downstream of the Tumut junction. Other key tributaries include Jugiong, Muttama, Adelong, Kyeamba, Adjungbilly, Gilmore and Billabong Creeks, and Goobarragandra River. With a length of 1,600 kilometres, the Murrumbidgee River is the third-longest of the rivers that traverse the Basin.

The Murrumbidgee catchment extends across 34 local government areas. The largest city in the catchment is Canberra (population of 314,000), followed by Wagga Wagga, which is the largest inland city in NSW, with a population of 57,000 (ABS 2008). Other major urban centres and towns in the catchment include Griffith, Leeton, Hay, Yass, Gundagai, Narrandera and Jerilderie. These urban centres and surrounding rural areas rely on the water resources of the catchment to support rural industries like irrigated and dry-land agriculture.

Murrumbidgee catchment comprises two main irrigation areas. The Murrumbidgee Irrigation Area (MIA) occupies an area of approximately 3,624 square kilometres on the northern side of the Murrumbidgee River. Established in 1912 as a government irrigation scheme, it is now privately owned and operated by Murrumbidgee Irrigation Ltd. It is fed by two canals receiving diverted water from the river – the Main Canal and the Sturt Canal. The Main Canal receives water diverted at Berembed Weir to serve
the Yanco, Leeton and Griffith areas and can accommodate flows of up to 6,500 ML/day, while the Sturt Canal receives water diverted at Gogeldrie Weir to supply the Whitton and Benerembah areas, and can accommodate flows of up to 1,700 ML/day. Excess flows from much of the channel system escape to Mirrool Creek, where they can be pumped by irrigators, diverted back into the channel system or stored in Barren Box Swamp. Virtually all drainage escape flows are directed to Barren Box Swamp to support operational water demands, except for a few which return to the Murrumbidgee River. Barren Box Swamp is used as an on-line storage, primarily to provide capacity to supply irrigation, stock and domestic users further to the west in the catchment. Second is the Coleambally Irrigation Area (CIA) which covers an area of over 790 square kilometres on the southern side of the Murrumbidgee River. Originally, it was also established as a government scheme in 1960 but is now privately owned and managed by Coleambally Irrigation Co-operative Limited (CICL). Water is diverted to the irrigation area from the river through 41 kilometres of main canal and 477 kilometres of supply channels. Figure 2.2 shows the Murrumbidgee catchment area and the irrigation regions falling within it.

2.2. CLIMATE AND WEATHER

Rainfall in the region varies across the catchment, declining from east to west (1,700 millimetres in the east to 350 millimetres in the west). Average annual rainfall based on 112 years of records (1989–2011) is 528 mm/yr. Summers in the Murrumbidgee catchment are relatively hot, with average maximum January temperatures of 30°C. At higher altitudes, January temperatures generally remain below 20°C. Winters are cool to
mild, with average maximum July temperatures of 12°C, but averaging only 4°C at higher altitudes. Frosts are common in the catchment. Peak precipitation occurs during winter, and the variability in rainfall from one year to the next is high. The western area of the catchment, which experiences a much drier climate than the eastern catchment, comprises a series of complex interconnected channels that traverse a vast inland delta. Average evaporation varies from less than 1,000 millimetres per year in the south-east, to over 1,800 millimetres per year in the west. Evaporation in the Murrumbidgee is also strongly seasonal, varying from 1 millimetre per day during July at Wagga Wagga to 9 millimetres per day during January (Figure 2.3).
Figure 2.3: Mean rainfall (mm) and mean daily pan evaporation (mm) at Wagga Wagga station (Source: BOM).

Figure 2.4 below shows a map of spatial distribution of evaporation across the Murrumbidgee catchment.


2.3. WATER DIVERSION AND ALLOCATIONS

The primary users of water in the region are the two major irrigation districts (MIA and CIA) in the catchment. Irrigation also occurs around Hay and Balranald and in eastern parts of the catchment, including around Wagga Wagga. Burrinjuck and Blowering Dams provide regulated water. Burrinjuck Dam is situated in the upper catchment on the Murrumbidgee River and Blowering Dam is situated on the Tumut River. Collectively, these storages have a capacity of 2,654,000 ML. Management of the water resources within the Murrumbidgee River catchment occurs according to the Water Sharing Plan for the Murrumbidgee Regulated River Water. This water-sharing plan is currently being amended to include the Lowbidgee region. Important hydrologic regions within the catchment are: Mirrool Creek system, Murrumbidgee River channel, Mid-Murrumbidgee River Wetlands, Lower Murrumbidgee Floodplain, and Floodplain wetlands.
between Balranald and the Murrumbidgee River junction with the Murray River and Yanco Creek system.

The Murrumbidgee is a heavily regulated river with 26 dams as well as weirs and irrigation canals. Storages include those in the Snowy Mountain Hydro-electric scheme, those forming the ACT Water Supply System and the major NSW irrigation dams (Blowering Dam and Burrunjuck Dam). The Murrumbidgee River includes seven weirs that are used to manage water levels for diversion. These are Berembed, Yanco, Gogeldrie, Hay, Maude, Redbank and Balranald Weirs. The weirs contain relatively small storage volumes (1,000 to 13,000 ML) and have limited capacity for re-regulation of flow. There is also an off-river en-route storage (Tombullen) with a capacity of 11,000 ML that offers limited re-regulation opportunity. Most of the flow in the Murrumbidgee River comes from the upper portion of the catchment, and is delivered by the main tributary rivers: Yass, Molongolo, Queanbeyan, Bredbo, Numerall, Cotter, Goodradigbee and Tumut. Several tributaries located immediately downstream of the dams contribute significant inflows, including Adelong, Adjungbilly, Gilmore, Hillas, Tarcutta, Kyeamba, Jugiong, Muttama, Billabong and Houlghans Creeks, and Goobaragandra River. The middle and lower portions of the catchment do not contribute significant inflows.

Figure 2.5 shows annual general security allocations for Murrumbidgee valley since 1982/83 to 2011/12. In contrast to the drought conditions that have impacted on water availability since 2002/03, well above average rainfall in the catchment during the period 2010–12 have resulted in full irrigation allocations. Heavy rainfall, particularly from
October 2011 to March 2012 which saw higher than average flow levels in the Murrumbidgee River and associated flooding in lagoon systems adjacent to the River, was the primary causal factor for MI river drains backing up in some instances (MIL, 2012). The heavy rainfall resulted in a significant increase in channel supply and drainage waters, resulting in additional drainage to wetlands associated with the Murrumbidgee River (Burrell et al., 2012). Flooding again occurred in March 2012, adding to an already increased groundwater table, partially inundated wetlands and a productive irrigation area at full allocation. The 2012 floods posed many implications in the management and movement of excess water across the irrigation network (Burrell et al., 2012).

![Graph showing annual general security allocations (% for Murrumbidgee (CICL, 2012).](image)

**Figure 2.5:** Annual general security allocations (%) for Murrumbidgee (CICL, 2012).
2.4. SOILS

Soils in the Murrumbidgee region vary from sand to clay. Extensive soil studies have been conducted over the years in areas of Coleambally, Murrumbidgee and Murray Irrigation. Thacker J et al. (2008) stated that across the region, soils have developed primarily on fluviatile material and fluviatile sediments were deposited by prior streams in the region more than 35,000 years ago. Deep sands and sands over clays are found in or near the elevated stream beds that often have been changed by wind erosion. Clay has been deposited on the flood plain to form self-mulching and hard-setting clays. Based on prominent soil characteristics, CSIRO (2008) classified soils into five groups. These were clays, red brown earths, transitional red brown earths, sand over clays, and deep sands. Typical properties of these groups are given in Table 2.1.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Self-mulching clays</th>
<th>Hard setting clays</th>
<th>Red-brown earths</th>
<th>Transitional red brown earths</th>
<th>Sands over Clay</th>
<th>Deep sands</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topsoil</td>
<td>Clay</td>
<td>Loam to clay</td>
<td>Loam to sandy loam</td>
<td>Loam to clay loam</td>
<td>Sand to loam</td>
<td>Sand</td>
</tr>
<tr>
<td>Depth</td>
<td>5-15 cm</td>
<td>5 cm or less</td>
<td>10-25 cm</td>
<td>Less than 10 cm</td>
<td>25-100 cm</td>
<td>100 cm or more</td>
</tr>
<tr>
<td>Subsoil</td>
<td>Heavy clay with lime</td>
<td>Heavy clay</td>
<td>Heavy clay</td>
<td>Heavy clay</td>
<td>Cemented clayey sand above a mottled medium clay</td>
<td></td>
</tr>
<tr>
<td>Deep subsoil (1-2m)</td>
<td>Medium clay with concretionary lime</td>
<td>Medium clay, often with crystalline gypsum</td>
<td>Sandy clay, often micaceous</td>
<td>Medium clay, often with crystalline gypsum</td>
<td>Medium clay sometimes becoming more sandy with depth</td>
<td></td>
</tr>
</tbody>
</table>
A comprehensive analysis of soil groups is presented by Thacker J et al., (2008). Figure 2.6 shows a catchment scale map of soil texture produced by the Bureau of Rural Sciences, Australia.

![Soil Texture Classification Map](image)

**Figure 2.6:** Soil texture classification across the Murrumbidgee catchment (Source: BRS).

### 2.5. Surface Water Availability

The average surface water availability in the Murrumbidgee is 4,270 GL/yr with approximately one-tenth sourced from inter-basin transfers from the Snowy Mountains Hydro-electric scheme (CSIRO 2008). This is an average amount, so there is capacity to retain more water during wet years. The Regulated Murrumbidgee River has a long-term extraction limit of 1,890 GL/yr, thus approximately 57% of the mean annual flow contributes to maintenance of basic ecosystem health. In the 2009/10 financial year, there were approximately 1,888,070 general security shares, 356,846 high security shares and 198,779 supplementary shares in the Regulated Murrumbidgee.
(Green et al., 2011). The Murrumbidgee and Coleambally Irrigation Areas are located downstream of Wagga Wagga and are responsible for approximately three-quarters of the irrigation diversions. The MIA is supplied by the Main Canal, which diverts water from the Berembed Weir pool and Sturt Canal which diverts water from the Gogeldrie Weir pool. The CIA is also supplied by a canal which diverts water from the Gogeldrie Weir pool. Flows into Yanco Creek are regulated by Yanco Weir. Diversions into the Nimmie-Caira portion of the Lowbidgee wetland are taken from the Maude Weir pool, while diversions into South and North Redbank are taken from the Redbank Weir pool. Since 2010, improvements in resources and continuation of wet regime allowed maximum water availability in 2011–2012 for all category licences. Figure 2.7 shows the water availability as a percentage of entitlement for different categories of licences from 2004–2012.

Figure 2.7: Murrumbidgee water availability (Burrell et al., 2012).
2.6. **GROUNDWATER**

Groundwater is an important source of water for industry and agriculture in the Murrumbidgee catchment. The connectivity between surface and groundwater systems varies with respect from seasonal, to longer term or permanently disconnected. The factors that influence surface-groundwater interactions are climate, flood frequency and duration, and surface and/or groundwater use. Most of the upland streams in Murrumbidgee receive flow from fractured rock aquifers. Use of groundwater in the catchment is controlled to some extent by the quality of water available for extraction. The water in the aquifers of mid and lower alluvial areas is predominantly fresh, and is suitable for most purposes including irrigation. Generally, water quality deteriorates from brackish to super saline water westward within the catchment. Groundwater management is implemented in Murrumbidgee catchment and other Groundwater Management Areas (GMA) in NSW.

*Figure 2.8: Groundwater Management Areas of the Murrumbidgee catchment (Green et al., 2011).*
Groundwater Management Areas of the Murrumbidgee catchment are shown in Figure 2.8. Out of the seven GMA’s, Mid Murrumbidgee and Lower Murrumbidgee contain close to 90% of the total groundwater entitlement for the entire catchment. Mid Murrumbidgee GMA narrow floodplains overlying bedrock and relatively high rainfall produce shallow alluvial water tables and strong hydraulic connections between river and aquifer. The area gains significant quantities of water from the aquifer for many months following major flood events. The Mid Murrumbidgee GMA has a long-term average extraction limit of 89,000 ML/yr, and most of it is town water supply. Within the Lower Murrumbidgee GMA, the Basin contains three main regional aquifers that have a maximum combined thickness, in the east, of about 170 metres and about 400 metres at the western extent. The shallowest and least productive of these is the Shepparton Formation. The most significant supplies come from the underlying Calivil Formation and the Renmark Group (Green et al., 2011).

2.7. LAND USE AND CROPPING PATTERN

Land use mapping in Australia is carried out under a national initiative called Australian Collaborative Land Use and Management Program (ACLUMP), which provides national and catchment scale land use mapping information. Figure 2.9 shows the current catchment scale land use map produced for Murrumbidgee catchment. Land use in the Murrumbidgee catchment is predominantly agricultural. The steeper regions are dominated by a mixture of native eucalypt forests and exotic forestry plantations. Agricultural land use varies greatly in intensity and includes pastoral, more intensive grazing, broad-acre cropping, and
intensive agriculture in irrigation areas along the mid-lower Murrumbidgee. Most of the irrigation activity in the region occurs in Coleambally and Murrumbidgee areas. These areas typically support a broad range of irrigation activities; the more important are rice, cereal crops, grapes, citrus, vegetables, pasture and hay production.

Figure 2.9: Land use in the Murrumbidgee catchment.

In 2011/12, the area under cropping within CIA was 68,715 ha while in the previous year it was 60,829 ha. The major crops were rice, wheat, corn, cotton and canola, and the areas under such planting increased due to
wetter seasons and increased allocations. Rice was the major crop, with 16,745 ha and 62% of water supplied by CICL being devoted to its production (CICL, 2012). Figure 2.10 shows the area covered under different crops for CIA in 2011/12. In the MIA, rice covered 27,255 ha, while irrigation supply to rice cropping accounted for a large 42% of total deliveries. Winter cereals, vines, cotton, citrus and pasture were amongst the other major crops reported in MIA covering 44,972 ha, 18,985 ha, 10,038 ha, 7,616 ha and 9981 ha respectively (Burrell et al., 2012). Figure 2.11 shows the area covered under different crops in the 2010/11 reporting year.

**Figure 2.10:** Cropped area (ha) of 2011/12 in CIA.

**Figure 2.11:** Cropping pattern (ha) of 2010/11 in MIA.
3. LITERATURE REVIEW

This chapter presents a literature review of various traditional and state-of-the-art methods for estimation of ET. Focus is particularly given to a detailed discussion about the LAS technique and remote-sensing-based ET algorithms, keeping in mind the scope of this study. The last section of the chapter presents a review of soil moisture modelling, with particular focus on data assimilation techniques for root-zone moisture studies.

3.1. EVAPOTRANSPIRATION

The combination of two separate processes whereby water is lost by evaporation from the soil surface and through transpiration by plants is referred to as evapotranspiration (ET) Allen et al., (1998). The estimation techniques are broadly subdivided into: (i) reference evapotranspiration (ET₀), (ii) crop potential evapotranspiration (ETₚ), and (iii) actual evapotranspiration (ETₐ).

3.1.1. REFERENCE EVAPOTRANSPIRATION

Crop reference ET or reference ET is the ET rate from a reference surface not short of water, which can be a hypothetical grass reference crop with specific characteristics (Allen et al., 1998). It is the evaporative demand of the atmosphere, independent of crop type, crop development and management practices. As the ET₀ expresses the evaporative power of the atmosphere at a specific time of the year and location, it does not consider
soil factors and characteristics. Climatic parameters are the only factors affecting $ET_o$ and can be computed from weather data. Numerous equations have been developed to estimate reference $ET$ by researchers and are described in Jensen et al., (1990). These methods have been broadly classified into three categories: Radiation methods, Temperature methods and Combination methods. A brief introduction to these classical techniques is given below. A comprehensive review of each of these methods can be found in Rabbani (2008) and Ullah (2011).

**3.1.1.1. Radiation Methods**

Empirical radiation equations for estimating $ET_o$ are generally based on energy balance variables. In humid climates where the aerodynamic term is relatively small, radiation methods give good results. Some examples for these methods would be Jenson Haise radiation method for $ET_o$ (Jensen and Haise, 1963) and the FAO radiation method presented by Doorenbos and Pruitt (1977).

**3.1.1.2. Temperature Methods**

Efforts to relate $ET$ to air temperature began in the 1920s. Many temperature methods were developed to use for situations where radiation, humidity and wind data is missing. These methods remain empirical and require local validation to achieve satisfactory results, and hence very rudimentary as compared to methods being used today. The only exception is the Hargreaves method, which has shown reasonable $ET_o$ results with a
global application (Allen et al., 1998). The Thornthwaite method, SCS Blaney-Criddle method and Hargreaves method are the most prominent examples of temperature methods.

3.1.1.3. Combination Methods

There are several combination methods for $ET_0$. Penman (1948) was the first to introduce a combination equation that incorporated a vapour removal mechanism. This became the basis of many improved methods to emerge later on, including 1963 Penman, 1982 Kimberly Penman, Priestly-Taylor, ASCE Penman-Montieth and FAO-56 Penman-Montieth. The FAO-56 Penman-Montieth is the most standard $ET_0$ estimation method today. Allen et al., (1998) derived this equation by simplifying its predecessor, the ASCE Penman-Montieth. They utilised some assumed constant parameters for a clipped grass reference crop that is 0.12 metres tall and is defined as “a hypothetical reference crop with an assumed crop height, a fixed surface resistance of 70 (s/m) and an albedo of 0.23”.

In 2005, the Environmental and Water Resources Institute (EWRI) within the ASCE established a standardised reference $ET$ computation equation called the ASCE-EWRI equation. In this modification, two reference surfaces were adopted for standardized $ET_{REF}$ i.e. short crop with a height of 0.12 metres (similar to full cover clipped grass) and tall crop with a height of 0.50 metres (similar to full cover alfalfa) with fixed surface resistance. The standardised $ET_{REF}$ for a short crop and long crop was denoted by $ET_{OS}$ and $ET_{RS}$ respectively. The final equation derived by ASCE-EWRI is given below.
\[ \frac{0.408A(R_n - G) + \gamma \frac{c_n}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + C_n u_2)} \]  
Equation 1

Where \( ET_o \) = Reference Evapotranspiration (mm.d\(^{-1}\)), \( R_n \) = net radiation at crop surface (MJ.m\(^{-2}\).d\(^{-1}\)), \( G \) = soil heat flux density (MJ.m\(^{-2}\).d\(^{-1}\)), \( T \) = mean daily air temperature at 2 metres height (\(^{\circ}\)C), \( u_2 \) = wind speed at 2 metres height (m.s\(^{-1}\)), \( e_s \) = saturation vapour pressure (kPa), \( e_a \) = actual vapour pressure (kPa), \( e_s - e_a \) = saturation vapour pressure deficit (kPa), \( \Delta \) = slope vapour pressure curve (kPa.\(^{\circ}\)C\(^{-1}\)). \( C_n \) and \( C_d \) are the numerator and denominator constants that change with reference type and calculation time-step.

3.1.2. CROP POTENTIAL EVAPOTRANSPIRATION

Crop potential evapotranspiration (\( ET_c \)) is referred to as the maximum \( ET \) from disease-free, well-fertilised crops, grown in large fields, under optimum soil water conditions, that are achieving full production under the given climatic conditions (Allen et al., 1998). Crop \( ET \) is calculated by the single crop coefficient or double crop coefficient approach. In the single crop coefficient approach, the effect of crop transpiration and soil evaporation are combined into a single \( K_c \) coefficient. The coefficient integrates differences in the soil evaporation and crop transpiration rate between the crop and the grass reference surface. In the dual crop coefficient approach, the effects of crop transpiration and soil evaporation
are determined separately in the basal crop coefficient ($K_{cb}$) and the soil water evaporation coefficient ($K_e$) (Allen et al., 1998).

\[
ET_c = K_c \times ET_o \quad \text{Equation 2}
\]

\[
ET_c = (K_{cb} + K_e) \times ET_o \quad \text{Equation 3}
\]

Where $ET_c$ is potential $ET$ of the crop, $K_c$ is the single crop coefficient, $K_e$ = soil water evaporation coefficient, $K_{cb}$ = crop transpiration coefficient and $ET_o$ is reference $ET$. The dual procedure is best for real time irrigation scheduling, for soil water balance computations, and for research studies where effects of day-to-day variations in soil surface wetness and the resulting impacts on daily $ET_c$, the soil water profile, and deep percolation fluxes are important (Allen et al., 1998).

### 3.1.3. Actual Evapotranspiration

Actual evapotranspiration ($ET_o$) is the $ET$ from crops grown under sub-optimal crop management and environmental conditions. This real crop $ET$ differs from $ET_p$ for a crop cultivated in the same field due to non-optimal conditions that affect crop growth and limit $ET$. These conditions include low soil fertility, salt toxicity, soil water logging, pests, diseases and root-zones with hard and impenetrable soil horizons, among others (Allen et al., 1998). There are three commonly used methods for the estimation of $ET_o$, classified according to their scale as: (i) hydrological methods, (ii) energy balance methods using micrometeorological instruments and (iii) energy balance methods using remote sensing.
3.1.3.1. HYDROLOGICAL METHODS

The most commonly used hydrological approaches are soil water balances, lysimeters and water balance-based hydrological models. Soil water balance is an indirect method of measuring $ET_a$, and can be determined as a residual term by measuring the different components of the soil water balance equation (Rana and Katerji, 2000).

$$ET = I + R - RO - DP + CR \pm \Delta SF \pm \Delta SW$$  \hspace{1cm} \text{Equation 4}

Where, $I$ is irrigation, $R$ is the rainfall, $RO$ is surface runoff, $CR$ and $DP$ is the vertically transported through capillary rise and deep percolation, $\Delta SF$ is the horizontal transport in the root zone by subsurface and $\Delta SW$ is the change in soil water content for a specific period of time (Ullah, 2011).
Lysimeters are isolated tanks filled with either disturbed or undisturbed soil, in which crops are grown under natural conditions to assess evaporation and transpiration (Yang and Zhang, 2009). This method is most often used to study climatic effects on $ET_a$, and for the evaluation of estimating procedures, because it provides a direct measurement of $ET_a$. Lysimeters also help in determining the different terms of the soil water balance equation by isolating the root zone of a crop from its environment, and controlling key processes (Ullah, 2011).

$ET_a$ from point to basin scale is also estimated with hydrological models. Several hydrological models based on the water balance approach have recently been developed for $ET_a$ measurement. An example of the widely used point-scale hydrological model is the SWAP model (van Dam et al., 1997). The physically based simulation model SWAP (Soil, Water, Atmosphere, Plant) calculates potential $ET$ by using the Penman-Monteith algorithm for three different conditions (bare soil, dry crop, and wet crop) by adjusting parameters for albedo, crop height, and crop resistance. Actual crop transpiration and soil evaporation may be simulated by taking into account the crop development stage as well as limitations in soil moisture. The model may be applied for many combinations of crop and soil to simulate the overall performance of irrigation schemes (Droogers et al., 2000). SLURP (Semi-distributed Land Use-based Runoff Processes) on the other hand is a basin-scale model that conceptualises the complete hydrological cycle and also includes features such as reservoirs, diversions and extractions, and irrigation schemes (Kite 1997). The model divides a basin into many smaller sub-basins using topographic analysis. Each sub-basin is again subdivided into areas of different land use forming a matrix.
Each element of the matrix is simulated by nonlinear reservoirs representing canopy interception, snowpack, rapid runoff, and slow runoff. The model routes precipitation through the physical processes and generates outputs (evaporation, transpiration, and runoff) and changes in storage (canopy interception, snowpack, soil moisture, and groundwater).

3.1.3.2. Micrometeorological Methods

So far, the most direct approach to measure $ET_a$ uses modern micrometeorological instruments based on the energy balance method that considers all the sources and losses of energy available for vaporising water (Drexler et al., 2004). Mathematically, energy balance is written as:

$$ R_n = G + H + \lambda E $$

Equation 5

Where $R_n$ is the net radiation, $G$ is the heat flux transfer to and from the soil, $H$ is the sensible heat flux density, and $\lambda E$ is the latent heat flux. The main hydrological intention to solve and energy balance is to either measure or estimate latent heat flux to derive $ET$. The key to accurate $ET_a$ results from energy balance methods is the accuracy in measurement of micrometeorological parameters. The most commonly used methods are the Bowen Ratio method, Aerodynamic method, Eddy Covariance method and the Large Aperture Scintillometer (LAS) technique.
a. **Bowen Ratio Method**

Bowen (1926) proposed an approach to estimate ET which is now one of the most well-known energy balance methods used for ET calculations. Starting with the basic energy balance equation, dividing both sides by \( \lambda E \) and solving the equation gives:

\[
\lambda E = \frac{R_n - G}{1 + \beta}
\]

Equation 6

Where \( \beta \) is the Bowen Ratio i.e. the ratio of sensible to latent heat flux (Bowen, 1926). Bowen used this ratio to estimate evaporation. The above equation is most accurate when \( \beta \) is small (Brutseart, 1982, Angus and Watts, 1984). \( \beta \) is measured experimentally using Bowen Ratio apparatus which determines the temperature and humidity gradients over a height interval \( \delta z \). The Bowen Ratio \( \beta \) is defined as \( H/\lambda E \) and can be related to the temperature and humidity differences. (Oke, 1987):

\[
\beta = \frac{H}{\lambda E} = \gamma \left( \frac{\partial T}{\partial z} / \frac{\partial e}{\partial z} \right)
\]

Equation 7

Bowen Ratio apparatus is required to accurately measure small differences in temperature and humidity over a small height interval above the evaporating surface. Traditionally, the equipment features a net radiometer and a pair of rotating precision aspirating psychrometers. Figure 3.2 shows a typical Bowen Ratio apparatus as used for high precision evaporation measurement. The requirement for placement above the evaporating surface with adequate upwind fetch applies similarly because
its theory of operation is related to that of Penman-type AWS systems and, as illustrated, very high accuracy hygrometers/psychrometers are required. For this reason, the Bowen Ratio is usually regarded as a research-only technique.

![Figure 3.2: Bowen ratio system (left and right) with radiation sensor (middle).]

Unlike the Penman-type deduction of the evaporative flux, the Bowen Ratio method requires simultaneous measurements of temperature and humidity at two adjacent levels. The differences in temperature and humidity can then be used to ‘partition’ (i.e. split up) the total available energy (measured simultaneously) between that which is heat moving upward from the surface (sensible heat flux), and that energy which is moving upward with the water vapour (latent heat flux, $\lambda E$).
Figure 3.3: Theoretical variation of sensible heat flux $H$ and evaporative flux $\lambda E$ at a change of surface (Rabbani, 2008).

Figure 3.3 illustrates the significance of a change in evaporating surface, from ‘dry surface’ to ‘wet surface’, which may be open water or irrigated cropping. Although the sum $H + \lambda E$ may change only a little (increasing over the wet surface where the water is more ‘available’), the partitioning between $H$ and $\lambda E$ changes vary greatly within the first few metres – indeed $\lambda E$ is greatly increased just downwind of the boundary, using more energy than is provided by radiation alone (the extra energy is extracted from the airflow). The requirement for adequate fetch ensures that the airflow has been able to re-establish equilibrium over the new surface.

Because of the fetch requirement, the applicability of the Bowen Ratio method to the present application is similarly limited, unless the experimentation site is very large, or very small scale apparatus can be constructed. Therefore, the Bowen Ratio method is unlikely to be cost-effective, even as a research tool (Craig and Hancock, 2004).
b. **THE AERODYNAMIC METHOD**

In the aerodynamic method, latent heat is determined directly by means of the scaling factors of friction velocity ($u^*$) and humidity ($q^*$). It assumes that flux density can be related to the gradient of concentration in the atmospheric surface layer (Rana and Katerji, 2000).

$$\lambda E = \rho \lambda u^* q^*$$

Equation 8

Where $\rho$ is density of air and $u^*$ and $q^*$ are derived from wind profile measurement and humidity profile measurement respectively. Since accurate measurement of different heights above the crop is difficult, Rana and Katerji (2000) proposed simplified versions of the aerodynamic method based on the measurement of wind speed and temperature at two heights only. However, Ullah (2011) reported that this method, both in its complete and simplified form, does not produce accurate enough results for tall crops.

c. **EDDY-COVARIANCE METHOD**

The measurement of vertical transfer of heat and water vapour by eddies was first described by Swinbank (1951). Since then, micrometeorologists have long held that eddy correlation techniques offer the most promise for providing accurate measurements of evaporative flux with a sound theoretical basis. The method offers an attractive alternative to other more implicated methods such as the Bowen Ratio.
Recent developments in electronics have resulted in new sensors with the required speed and accuracy for Eddy Covariance (EC). EC theory describes the turbulent transport of properties such as momentum flux, sensible heat flux and latent heat flux. The method relies on accuracy of measurement of the fluctuations in airspeed, temperature and humidity. Each parameter can be partitioned into a mean value plus an instantaneous deviation from the mean. The instantaneous deviations of air density and latent heat of vaporisation can be assumed to be zero. The long-term mean vertical wind velocity over a flat uniform surface can be assumed to have a value of zero. Applying these assumptions, the mean vertical flux for an averaging period longer than a few seconds becomes:

\[ \lambda E = \rho \lambda \bar{w} q \]

Equation 9

Where \( \lambda E \) is the instantaneous latent heat flux (W.m\(^{-2}\)), \( \rho \) is the instantaneous air density, \( \bar{w} q \) is the covariance of vertical wind speed and specific humidity. Thus, over a level, uniform surface, the latent heat is entirely due to eddy transport, with no contribution from mean vertical flow. A similar analysis can be applied to the sensible heat flux, yielding the equation:

\[ H = \rho C_p \bar{w} T \]

Equation 10

Where, \( H \) is the mean sensible heat flux (W.m\(^{-2}\)), \( C_p \) is the specific heat of air (J/kg\(^{-1}\)K\(^{-1}\)), \( \rho \) is density of air and \( \bar{w} T \) is the covariance of vertical airspeed and temperature (Km.s\(^{-1}\)) (Monteith and Unsworth, 1990).
The ‘vehicle’ for this transport is the arrangement of turbulent eddies caused by the friction (drag) between the surface and the prevailing wind blowing across it. This is illustrated in Figure 3.4. (The difference in concentration of the water molecules from high near the water surface, through to lower up in the evaporative plume, is the basis for the Bowen Ratio method, the Dalton Formula, and also the theory on which all combination equations are based.)

![Diagram of turbulent eddies](image)

**Figure 3.4:** A representation of turbulent eddies over a surface (driven by a horizontal wind with speed $u$) and how water molecules (black dots) are eventually transported away. The humidity (concentration of water molecules) in upward versus downward moving air is compared to give the humidity flux (evaporation) ($\text{Rabbani, 2008}$).

With sufficiently miniature (centimetre-sized) and fast response (milliseconds) sensors, it is possible to measure within individual eddies. If instantaneous humidity and airspeed (eddy rotation) are repeatedly measured, statistical correlation techniques can be used to deduce the evaporative flux in units of (fraction of) millimetres per second. Once again, these values can be summed up over time to produce the daily value. (This is one application of the general ‘eddy correlation’ technique: the same approach can be used to deduce the flux of any quantity transported via the turbulent eddies.)
In general, EC theory describes the turbulent transport of properties such as momentum flux, sensible heat flux and latent heat flux. The EC method relies on accurately measuring the fluctuations in airspeed, temperature and humidity, and only in recent years, developments in sensor science and electronics have resulted in new sensors with the required small size, speed of response and accuracy for this application. Likewise, developments in microprocessor technology have permitted the logging and immediate real-time processing of the large volumes of data generated.

### d. Scintillometer Method

Over the years, many research studies – including Wesely (1976b), Green and Hayaschi, De Bruin et al., (1995), Hill (1997), Meijninger and DeBruin (2000), Hemakumara and Moene (2003), Meijninger et al., (2006) and others – have demonstrated that the scintillation technique is a reliable and suitable method for surface flux estimation. Two of the processes that distort the electromagnetic radiation (EM) propagating in the atmosphere
are scattering and absorption by gasses and atmospheric particles, thus causing the beam to attenuate. The most important of the mechanisms that influences the propagation of EM radiation is small fluctuations in the refractive index of air \((n)\). These turbulent refractive index fluctuations cause the intensity of the radiation beam to fluctuate. These intensity fluctuations are known as scintillations. These turbulent fluctuations can regularly be observed in image dancing and blurring above hot surfaces, and the twinkling of stars.

The most important mechanism for transport of scalar quantities (heat, water vapour) in our atmosphere is turbulence. Turbulence is defined as three-dimensional movements of the air known as eddies. The size of these eddies may range between millimetres to tens of metres, depending upon various land and atmospheric characteristics and conditions. The refractive index of air is a function of the temperature \((T)\) and to a lesser degree the humidity \((Q)\) of the air and the density of the air \((\rho)\) (Meijninger and DeBruin, 2000). Hence, the difference in refractive index of the air to its surroundings are caused by eddies, resulting in scintillations.

A scintillometer is an instrument that consists of a light source (transmitter) and a detector (receiver) that measures intensity fluctuations. Because the measured variance of intensity fluctuations is a measure of the turbulent behaviour of the atmosphere, it can indirectly be related to the transport of certain quantities. Depending on the configuration of the scintillometer, e.g. the aperture size, wavelength and the number of receivers the fluxes of heat, water vapour and momentum can be derived. A schematic of a scintillometer setup is shown in Figure 3.6.
Figure 3.6: Schematic of a scintillometer setup where the EM beam emitted by the transmitter is scattered by turbulent eddies in the atmosphere (Meijninger and De Bruin, 2000).

The transmitter emits a beam of light with a certain wavelength ($\lambda$). At a known distance $L$ from the light source, the receiver analyses the intensity fluctuations that are caused by the turbulent eddies. Also, a number of length scales are shown that play a role in scintillometry: the diameter of the beam ($D$), the different eddy sizes and the height of the scintillometer above the surface ($z$). This emitted radiation is scattered by the turbulent atmosphere and the intensity fluctuations/scintillations ($\sigma_{lnA}^2$) observed at the receiver end. These scintillations can be expressed as the structure parameter of refractive index of air ($C_n^2$). Wang et al., (1978) found the relationship between path-averaged $C_n^2$ and the variance of the logarithm of amplitude fluctuations ($\sigma_{lnA}^2$) as:

$$\left\langle C_n^2 \right\rangle = 1.12 \sigma_{lnA}^2 D^{1/3} L^{-3}$$

Equation 11
Wang et al., (1978) also reported that scintillations produced by turbulence near the centre of the beam contribute more to the path-averaged $Cn^2$ than scintillations produced near the transmitter and receiver. Both humidity and temperature fluctuations produce scintillations in the refractive index of air. Therefore, in the visible and infra-red region, assuming that temperature and humidity fluctuations are perfectly correlated, the structure parameter of temperature ($C_T^2$) can be expressed using $Cn^2$ as:

$$C_T^2 = C_n^2 \left( \frac{T^2}{-0.78.10^{-6} P} \right) \left( 1 + \frac{0.03}{\beta} \right)^2$$ \hspace{1cm} \text{Equation 12}

Sensible heat flux can be calculated by using the following Monin–Obukhov similarity theory (MOST) relationships of $C_T^2$.

$$(C_T^2(z_{LAS} - d)^{2/3})/T_s^2$$ \hspace{1cm} \text{Equation 13}

While the Obukhov length, temperature scale and friction velocity $u^*$ are defined as:

$$L_{Ob} = \frac{u^2}{g k T_s}, T^* = -\frac{H}{\rho c_p u_s}$$ \hspace{1cm} \text{Equation 14}

and

$$u_s = \frac{k \mu}{\ln \left( \frac{z - d}{z_0} \right) - \nu \left( \frac{z - d}{L_{Ob}} \right)}$$ \hspace{1cm} \text{Equation 15}
Where $\Psi_m$ is the Businger–Dyer correction, $g$ the gravitational acceleration, $k_v$ the von Kármán constant, $u^*$ the friction velocity and $T_*$ the temperature scale, $\rho$ the density of air, and $c_p$ the specific heat of air at constant pressure. The installed height of LAS being $z_{\text{LAS}}$, wind speed is measured at height $z$, $d$ is the zero-displacement height and $z_o$ the roughness length, $\theta$ is solved iteratively as proposed by Green and Hayashi (1998) using estimates of the net radiation ($R_n$) and soil heat flux ($G_s$), which are derived from global radiation data. The Bowen ratio term is a humidity correction term. The study by De Wekker (1996) showed that this term can be neglected whenever the Bowen ratio is greater than 0.6, which is generally the case in arid and semi-arid areas.

Since LAS provides a measure of the $C_n^2$, weighted over the path length ($L$), this path-weighting function is symmetrical bell-shaped, having a centre maximum and tapering to zero at the transmitter and receiver end. This means that the LAS/XLAS is most sensitive in the middle of its path (Hartogensis et al., 2003).

![Path-weighting function of LAS](image)

**Figure 3.7**: The path-weighting function of LAS (Kipp&Zonen, 2007).
When the scintillation intensity rises above a certain limit, the theory, on which the scintillation measurement method is based, is no longer valid. When this occurs, the relationship between the measured amount of scintillations ($\sigma_{\text{lin}}^2$) and $C_n^2$ fails (Kipp&Zonen, 2007). This phenomenon is known as saturation. Therefore, $C_n^2$ must stay below a certain saturation criterion ($S_{\text{max}}$), i.e. the scintillometer can operate only under weakly scintillating conditions. The dependence of $C_n^2$ on the optical wavelength ($\lambda$), the aperture diameter ($D$), the measurement height ($z_{\text{LAS}}$) and the path length ($L$) can be written as follows:

$$C_n^2(\lambda, D, z_{\text{LAS}}, L) < S_{\text{max}}$$

Equation 16

The path length and the measurement height are the only variables that can be adjusted in order to keep $C_n^2$ below the saturation criterion, because the diameter and the wavelength of the LAS are constant. If LAS is installed at a height close to the Earth’s surface, it will see more scintillations than an LAS installed high above the surface. As the path length increases, more scintillations will be observed. This means that over long distances (~ several kilometres), the LAS must be placed high above the surface in order to prevent saturation. Over short distances (~ several hundred metres), the LAS can be installed close to the surface. Furthermore, the measured amount of scintillations depends on the surface conditions (Kipp&Zonen, 2007). Over dry areas, the surface sensible heat flux is large, resulting in higher $C_n^2$ values than over wet surfaces where the sensible heat flux is small. Figure 3.8 shows the minimum height of LAS for different surface conditions as a function of the path length (250m – 4.5 km).
Measurements of surface fluxes of sensible heat and latent heat are required for agricultural, meteorological and hydrological purposes, particularly for water management. A disadvantage of the method is that it is based on the semi-empirical Monin–Obukhov similarity theory, while the EC method involves direct measurements. Since scintillometer path lengths are comparable to the pixel sizes of satellite images, they enable verification of remote sensing models, used to estimate evaporation of crops using satellite images, with ground truth data. Several authors have tested the LAS. Under unstable conditions and for Bowen ratios larger than 0.75 approximately, the method appears to be reliable over homogeneous fields, e.g. Chehbouni et al., (2000), Meijninger and De Bruin (2000), McAneny et al., (1995) and De Bruin et al., (1995). The majority of these experiments have been conducted in relatively dry and semi-arid areas. However, large-scale agriculture in these areas often involves the application of irrigation,
resulting in very high values of evaporation from fields surrounded by dry desert. It is important to assess the accuracy of the structure parameter method under these conditions, where knowledge of evaporation is of great importance for water management, but it is questionable whether the Monin–Obukhov similarity theory still applies. Green and Hayashi (1998) have questioned the applicability of the LAS over irrigated paddy rice fields.

The Monin–Obukhov similarity theory (MOST) has been tested by several scientists using the variance method. De Bruin et al., (1991) used an EC system over an irrigated terrain with a dry to wet transition (desert to irrigated grass); the temperature and the sensible heat flux were highly affected by the local advection caused by the step-change, while humidity and latent heat flux were little affected. The temperature variance was too large in relation to the heat flux. De Bruin et al., (1993) proposed that MOST was applicable for temperature but not for humidity over an arid area, due to the relative importance of large eddies that affect turbulence in the surface layer. De Bruin et al., (1999) explained that if in the surface layer the fluxes of one of the scalars generated by surface heating or surface evaporation are of the same magnitude as the fluxes generated by other non-local features (such as advection or entrainment), it appears that this scalar does not obey MOST. Andreas (1998) suggested that violation of MOST can occur due to the fact that surface sources for heat and water vapour are not the same, i.e. the so-called metre-scale heterogeneity (Hoedjes et al., 2002). Moene et al., (2005) have presented a good detailed review of the relationships describing the signal of LAS. They also suggested that one of the weakest links in determination of $H$ scintillometer data is the MOST relationship for $C_T^2$ used to express the sensible heat flux.
Several investigations have demonstrated the potential of using LAS to measure path-averaged sensible heat fluxes over path lengths which are similar to satellite pixel scale, i.e. several kilometres (Kohsiek, 1987; De Bruin et al., 1995; McAneney et al., 1995; Lagouarde et al., 1996; and Hartogensis, 1997). Figure 3.9 compares the temperature flux obtained from scintillation measurements with its value from EC (Hill 1991). The solid circles indicate those very non-stationary cases for which the scintillation variances changed by more than a factor of eight during the 20 minute data run. The slight overestimate by the scintillation method is caused by an overestimate of $C_n^2$ by the scintillometer.

![Figure 3.9](image)

**Figure 3.9:** Temperature flux obtained from scintillation measurements compared with values from eddy correlations (Hill, 1991).

Figure 3.10 shows the comparison of sensible heat flux measured by EC with LAS-derived $H$ done by Meijninger et al., (2002). Solignac et al., (2009) also showed $R^2$ of above 90% and maximum RMSE of 26 W/m$^2$ between EC-based $H$ and LAS-derived $H$. 
The use of LAS is becoming increasingly common after realisation in the scientific community about its potential in surface fluxes studies. Most recent studies like Asanuma and Iemoto (2007), Ezzahar et al., (2009), Yang et al., (2010), Liu et al., (2011), Samain et al., (2011) and Tang et al., (2011) have shown excellent LAS performance for energy balance closure over different terrain. Figure 3.11 and Figure 3.12 show some comparison of...

Figure 3.11: Comparison of LAS-derived sensible heat flux with EC measurement Liu et al., (2011).
Figure 3.12: Top) Energy balance closure with EC. Bottom) Comparison of $H$ from LAS and EC (Tang et al., 2011).
Figure 3.13: Comparison of LAS-derived H and latent heat flux with EC measurements (Yang et al., 2010).

The scintillometer technique has not been applied in irrigation systems in an Australian climate. However, Hafeez et al., (2006) concluded that there is considerable potential to apply LAS for measuring $ET_o$ in Australia by comparing sensible heat flux measurements from LAS with SEBAL-estimated sensible heat flux. Some recent studies like Tang et al.,
(2011) have presented good agreement between LAS-derived fluxes and energy balance models (SEBS, TSEB).

3.1.3.3. Energy Balance Methods using Remote Sensing

The techniques that use remote-sensing data to estimate atmospheric turbulent fluxes are essential when dealing with processes that cannot be represented only by point measurements. In the remote-sensing-based estimation of atmospheric turbulent fluxes, two basic physical principles, the conservation of energy and turbulent transport, must be considered. The rationale behind the energy balance approach is that evaporation is a change of state of water by demanding a supply of energy for vaporisation. The whole problem then reduces to determine all other sources and sinks for energy to leave evaporation as the only unknown (Su, 2002).

Turbulent transport recognises the importance of wind in transporting vapour away from the evaporating surface and, when successful, providing a direct estimate to evaporation. This is often called the aerodynamic approach and employs, typically, gradients of wind velocity, temperature, and water vapour density in the near-surface atmosphere where the measurements of these gradients are available (Su et al., 2001). Since the energy budget in the energy balance approach needs to be distributed between sensible heat and latent heat fluxes, which involves the principle of turbulent transport, a complete treatment of both the conservation of energy and turbulent transport processes becomes necessary for developing relevant remote sensing algorithms (Su, 2002).
Generally, remote sensing of turbulent heat fluxes and evaporation are distinguished as analytical versus (semi-)empirical. The former takes into consideration detailed physical processes at the scale of interest, but usually involves complex relationships and requires various input variables, including those that can be observed directly by radiometric measurements and meteorological variables at a proper reference height. The latter tries to employ empirical relationships and data available chiefly from remote-sensing observations. Many analytical and (semi-)empirical models of energy balance methods using remote sensing have been developed over the past two decades. Some of the most well-known models include ALEXI/DisALEXI, NLDAS, SEBAL, METRIC, TSEBS, SEBI, and SEBS models.

a. ALEXI MODEL

ALEXI (Anderson, et al., 1997) estimates hourly and daily ET at a spatial resolution of 10 x 10 km over the conterminous U.S. using Geostationary Operational Environmental Satellite (GOES) imagery as well as albedo and vegetation indices from AVHRR or MODIS, and a modicum of synoptic weather data. DisALEXI (Norman et al., 2003) disaggregates ET estimates from ALEXI to finer spatial resolutions using high spatial resolution sensors such as MODIS, ASTER, and Landsat for purposes of validation with respect to ground-based flux data. ALEXI appears to hold much promise for producing operational and reliable ET maps at the regional and continental scale. ALEXI applies to a wide assortment of land use types and has been validated in rangeland in Oklahoma, agricultural landscapes in Iowa, tallgrass prairie in Kansas, and semi-arid desert in Arizona. Typical root-mean-
square-deviations for instantaneous fluxes are about 40 W m$^2$ (15%) at the 30–120 metre scale (from DisALEXI) in comparison with tower and aircraft-based measurements of sensible and latent heat fluxes (Norman, et al., 2003).

b. **NLDAS Model**

The original multi-agency North American Land Data Assimilation Systems (NLDAS) project was designed to provide land surface models with continually updated, one-eighth degree fields of land-surface water and energy states over central North America (Mitchell et al., 2004). Based on the success of the NLDAS project, the Global LDAS (GLDAS) (Rodell et al., 2004) and the Land Information Systems (LIS) (Lidard P et al., 2004) projects were developed to expand upon the original goals of NLDAS, and they became major projects that are supported and maintained at NASA. Forcing data for these modelling efforts include GOES, Doppler radar, rain gauge, and ET-based datasets. Robock et al., (2003) evaluated NLDAS-simulated latent heat fluxes using in-situ observations over the southern Great Plains for the periods of May–September of 1998 and 1999. The NLDAS models do fairly well, but still differences exist in the surface energy partition between models and observations due to differences between model-specified soil types and vegetation, and those observed at the stations. Kumar et al., (2008) compared and evaluated the LIS model predictions using surface observations at five different locations worldwide during the period July 2001 to September 2001. The model predictions agreed well with field observations.
c. **SEBAL Model**

The Surface Energy Balance Algorithm for Land (SEBAL), an intermediate approach using both empirical relationships and physical parameterisations, was developed in Spain (Bastiaanssen et al., 1998). SEBAL is a thermodynamically based model and partitions sensible heat flux and latent heat of flux. Semi-empirical relationships are used to estimate emissivity and roughness length of the normalised difference vegetation index (NDVI). SEBAL has a lot of uncertainties induced from (a) the assumption that at hot/dry pixels all energy flux into the atmosphere is sensible heat and at cool/wet pixels all is latent heat; (b) an estimation of roughness; and (c) from extrapolating the ET predicted at the time of satellite overpass to a daily time period. After its establishment, a lot of field validations have been done in different areas, especially in arid and semi-arid areas. However, due to the difficulty in finding exactly the right pixel of dry and wet conditions in certain images, its application is limited to a certain degree (Su, 2005). To solve the related limitation of SEBAL, some corrections have been made by Su (2002) to make it more practicable, who remedied a theoretical problem on the SEBAL model and added a scheme to apply NWP fields with an up-scaling and down-scaling approach. Khan and Hafeez (2007) and Khan et al., (2008) estimated seasonal actual ET in the Liuyaunkou Irrigation System (LIS) in the Yellow River Basin of China from Landsat 5TM/7ETM+, Terra MODIS, Terra ASTER, and NOAA-AVHRR using SEBAL. Customisations and modifications of SEBAL are required to suit local geo-climatic conditions; otherwise, the results would lack accurate estimation of actual ET. Hafeez et al., (2006) compared the sensible heat flux using SEBAL and LAS over the Savanna Ecosystem in West Africa. It was
found that SEBAL over-estimates the sensible heat flux compared to the actual sensible heat flux measured using LAS.

The efforts to fit dry and wet cases present in the spatial radiometric data lead to the development of the Simplified Surface Energy Balance Index (S-SEBI), which showed reasonable success for application to semi-arid areas (Roerink et al., 2000). More recently, Allen et al., (2005) developed METRIC, minimising the uncertainties in SEBAL.

d. METRIC Model

The METRIC (Mapping Evapotranspiration with High Resolution and Internalized Calibration) model computes a complete energy balance for each pixel from any satellite with visible, near infrared, and thermal infrared bands. Allen et al., (2005) developed METRIC by modifying the European SEBAL model. The most significant modification is the incorporation of reference ET as computed by the US Bureau of Reclamation’s system of AgriMet stations. Initial application and testing of METRIC shows substantial promise as an efficient, accurate, and relatively inexpensive procedure to map actual ET from irrigated lands throughout a growing season. ET from satellite images may replace current procedures that rely on ground-based ET equations and generalised crop coefficients (Morse et al., 2004). The internal calibration of the sensible heat computation within METRIC eliminates the need for atmospheric correction of reflectance measurements using radiative transfer models (Tasumi et al., 2005). METRIC has been applied in several parts of the USA, but the bulk of the applications have been in Idaho, where the Idaho Department of Water Resources
(IDWR) and the University of Idaho have used METRIC to compute monthly and seasonal \( ET \) for a variety of applications in water resource planning and water rights administration including: 1) water budgets for hydrologic modelling, 2) monitoring compliance with water rights, 3) supporting water planning, 4) estimating aquifer depletion, and 5) estimating water use by irrigated agriculture (Morse et al., 2004).

e. **TSEBS Model**

Norman et al., (1995) and Kustas and Norman (1999) developed the two-source energy balance system (TSEBS), based on the two-source approach proposed by Shuttleworth and Wallace (1985) and Shuttleworth and Gurney (1990). It considers the energy balance of soil and vegetation components separately and estimated \( ET_a \) by combining both components. No additional meteorological information is required for the application of this method. It requires some assumptions to accommodate the difference between radiometric surface and aerodynamic temperatures to partition surface energy balance into soil and vegetation components using either a single view angle or from multiple view angles (Ullah, 2011). The resistance to heat and momentum is the basis for energy exchange in the soil-plant-atmosphere continuum, and sensible heat fluxes are estimated by the temperature gradient-resistance system. Iterative procedures are used for the derivation of radiometric temperatures, resistances, sensible heat fluxes of the canopy and soil components. These iterative procedures are constrained by composite directional radiometric surface temperature, vegetation cover fraction and maximum potential latent heat flux. Gowda et
al., (2008) reported that the performance of TSEBS is not influenced by regional advections.

f. SEBI Model

Menenti and Choudhary (1993) developed SEBI, which is principally based on the Crop Water Stress Index (CWSI) concept (Jackson et al., 1988; Moran et al., 1996). This model follows the principle that surface temperature varies with evaporation. It relates to a given surface albedo and a given set of boundary layer characteristics (potential temperature, humidity and friction velocity). The main assumption is that a dry limit has a zero surface ET. Hence, the sensible heat flux is equal to the surface available energy from which the maximum surface temperature can be derived (Ullah, 2011). The minimum surface temperature can be evaluated from the wet limit, where the surface is considered to evaporate potentially. This potential ET is calculated from the Penman–Monteith equation with a zero internal resistance. The actual relative evaporation fraction can then be calculated by weighted interpolation of observed surface temperature within the maximum and minimum surface temperature. The definition of the aerodynamic transfer between the surface and boundary layer (both with respect to the flux profile relations and the specifications of the surface roughness length for heat) is crucial for this method and can hamper reliable results (Van den Hurk, 2001). The increased ratio between roughness length for momentum and surface roughness length for heat from 10 to 100 has a significant effect on the calculation of maximum surface temperature. This ratio implicates a great sensitivity of calculated evaporative fraction. SEBI
results over the Aral Sea Region revealed that parameterisation was not universally applicable (Menenti et al., 2001).

g. **SEBS Model**

The Surface Energy Balance System (SEBS) was developed for the estimation of atmospheric turbulent fluxes using satellite Earth observation data more coherently. SEBS (Su, 2002) consists of a set of tools for (i) the determination of the land surface physical parameters i.e. albedo, emissivity, temperature, vegetation coverage from spectral reflectance, (ii) for the determination of the roughness length for heat transfer (Su et al., 2001) and (iii) a new formulation for the determination of the evaporative fraction on the basis of energy balance in limiting cases. In the application, SEBS requires three sets of input information i.e. land surface parameters (albedo, emissivity, temperature, fractional vegetation coverage and leaf area index, and the vegetation/roughness height), meteorological data (air pressure, temperature, humidity, and wind speed at a reference height of PBL) and downward shortwave and longwave radiation that can either be direct measurements, model output, or parameterisation.

In SEBS, friction velocity, the sensible heat flux, and the Obukhov stability length are obtained by solving the set Monin–Obukhov Similarity (MOS) functions given by Brutsaert (1999). By replacing the MOS stability functions with the Bulk Atmospheric Boundary Layer Similarity (BAS) functions proposed by Brutsaert (1999), the system equations can be used to relate surface fluxes to surface variables and the mixed-layer atmospheric variables provided either by radiosonde data or obtained from atmospheric
model fields. The determination of the evaporative fraction on the basis of energy balance at limiting cases is carried out, and, finally, the turbulent heat fluxes are determined by utilising the surface energy balance. Further, by utilising the conservative characteristics of the evaporative fraction, the daily evaporation can be determined, given the total daily available energy.

**Figure 3.14:** Typical structure of the atmospheric boundary layer. SEBS includes both surface scaling and PBL scaling (Su, 2002).

In order to derive the actual sensible heat flux $H$, use is made of the similarity theory. In SEBS, distinction is made between the PBL and the Atmospheric Surface Layer (ASL) similarity (Figure 3.14). ABL refers to the part of the atmosphere that is directly influenced by the presence of the Earth's surface and responds to the surface forcings with a timescale of an hour or less, while ASL refers to usually the bottom 10% of ABL but above the roughness sub-layer, i.e. the ASL is where turbulent fluxes and stress vary by less than 10% of their magnitude (Stull, 1988). The roughness sub-layer (or the interfacial layer) is the near-surface thin layer of a few centimetres where the molecular transport dominates over turbulent transport. The thickness of the roughness sub-layer is thought to be around...
35 times the surface roughness height, or three times the vegetation height (Katul and Parlange, 1992).

### 3.2. Remote Sensing and Soil Moisture

Earth’s climate is a result of the complex interactions between the atmosphere, cryosphere (ice), hydrosphere (oceans), lithosphere (land), and biosphere (life), fuelled by the non-uniform spatial distribution of incoming solar radiation. The greatest challenge in modelling these intricate climate and atmospheric components has been the lack of sufficient computational power to solve complex problems of meteorology, fluid dynamics, atmospheric circulation and land surface interactions. Over the past four decades there have been astounding advancements in numerical weather predictions. Atmospheric models have not only gone from rather primitive in the early 1960s to somewhat reliable over different spatial scales, but they also provide forecasts over longer periods of time. These developments are based on dramatic improvements in the models used for prediction, including the numerical methods applied to integrate the prediction equations and a better understanding of dynamics and physics of the hydrologic system.

Global climate models are based on the general principles of fluid dynamics and thermodynamics that are complex to solve. State-of-the-art climate models now include interactive representations of the ocean, the atmosphere, the land, hydrologic processes, terrestrial and oceanic carbon cycles, and atmospheric chemistry. Recently, Earth system models are an attempt to integrate even more components of the climate system with the
ultimate goal to represent the climate in all of its aspects. The solution of these climate models over regional or global scales is obtained by solving physical interactions on 3-dimensional grid basis to which the basic equations are applied and evaluated. At each grid point, e.g. for the atmosphere, the motion of the air (winds), heat transfer (thermodynamics), radiation (solar and terrestrial), moisture content (relative humidity) and surface hydrology (precipitation, evaporation, soil moisture, snow melt and runoff) are calculated as well as the interactions of these processes among neighbouring points. A key component of these land surface interactions is the soil moisture-evapotranspiration coupling. Soil moisture, in fact, is the core of the system that controls the hydrological interactions between soil, vegetation and climate forcing, and plays a key role in governing the water and energy balance between land surface and atmosphere (Global Climate Observing System, GCOS, 2010). The significance of soil moisture is its role in the partitioning of energy at the ground surface into sensible and latent (ET) heat exchange with the atmosphere, and the partitioning of precipitation into infiltration and runoff.

Most of the inferred impacts of soil moisture for the climate system are induced by its role for ET. Uncertainty in land-atmosphere coupling has implications for the reliability of the simulated soil moisture-atmosphere feedback. It tempers our interpretation of the response of the hydrologic cycle to simulated climate. There have been some assessments of the capacity of climate models to simulate observed soil moisture. Despite the tremendous effort to collect and homogenise soil moisture measurements at global scales (Robock et al., 2000), discrepancies between large-scale estimates of observed soil moisture remain.
The challenge of modelling soil moisture, which naturally varies at different scales, within climate models in a way that facilitates comparison with observed data is important. A multidisciplinary approach considering the integration of in-situ, satellite and modelling techniques of soil moisture estimation will overcome the drawbacks associated with each of these methodologies, furnishing a proper and effective monitoring system of soil moisture variability at different scales (Brocca et al., 2011). It is not yet clear how to compare climate-model-simulated soil moisture with point-based or remotely-sensed soil moisture, which makes the assessment of models-simulated soil moisture rather difficult. Nevertheless, updating soil moisture in a numerical weather model has shown to have led to an increase in precipitation forecast (Boussetta et al., 2008). Despite the difficulties, there have been continuous efforts to model soil moisture by relating the arguably most accurate estimates (ground observations) with somewhat crude remote-sensing-derived estimates. Houser et al., (2010) summarised the point-satellite linkage of soil moisture as: 'Ground measurements should be used for calibrating and testing hydrological models that provide information on horizontal and vertical soil moisture variation. Satellite data, covering wider areas with a daily (or even longer) revisit time, can be applied for calibrating, evaluating and periodically updating spatially distributed hydrologic models, as they offer a snapshot of the evolving processes at a given time.'
3.2.1. Observations and Modelling

Schmugge et al., (2002), Wigneron et al., (2003), Jackson (2005) and Wagner et al., (2007) have presented excellent reviews on microwave remote-sensing techniques for soil moisture observation, their current state, development and prospects. The launch of the Soil Moisture and Ocean Salinity (SMOS) satellite by the European Space Agency (ESA) on 5 November 2009, and the scheduling of the Soil Moisture Active and Passive (SMAP) program by National Aeronautics and Space Administration (NASA) for November 2014, makes the importance of accurate soil moisture estimates obvious.

Seneviratne et al., (2006a) presented the conceptual framework in classical hydrology for ET regimes in a climate model as a function of soil moisture, which was also highlighted by Koster et al., (2004a, 2009a) and Tueking et al., (2009). They highlighted the two main ET regimes, characterised by the evaporative fraction \( EF = \lambda E/R_n \) as: soil moisture limited and an energy-limited regime. In the energy-limited ET regime, corresponding to values of soil moisture lying above a given critical soil moisture \( \theta_{\text{CRIT}} \), evaporative fraction is independent of soil moisture content. Below \( \theta_{\text{CRIT}} \), soil moisture content provides a first-order constraint on ET. This is defined as the soil moisture-limited ET regime. Hence, three soil moisture regimes can be defined related to soil moisture-evapotranspiration coupling (Koster et al., 2004a). Wet \( (\theta > \theta_{\text{CRIT}}) \) and dry \( (\theta \leq \theta_{\text{WILT}}) \) regimes, where soil moisture does not impact ET variability, and transitional climate regime \( (\theta_{\text{WILT}} < \theta < \theta_{\text{CRIT}}) \), where soil moisture strongly constrains ET variability. However, microwave-based remote sensing provides means for quantitative
description the water content of a shallow flat soil surface. In short- and medium-range meteorological modelling and hydrological studies over vegetated areas, the variable of interest is the root-zone soil moisture content, which controls plant transpiration.

Li and Islam (2001) examined the feasibility of retrieving root-zone soil moisture and partitioning of surface fluxes through the model inversion technique using surface measurements. They showed that sensitivities of surface soil moisture to deeper layer soil moisture are different to those of surface fluxes. Also, the accuracy of soil moisture profile retrieval from surface measurements depends strongly on the initial surface soil moisture condition. For wet surface conditions, an initialisation based on remotely sensed surface soil moisture appears to be adequate for the retrieval of the soil moisture profile.

Bastiaanssen et al., (2000) statistically related the observed volumetric soil moisture to the evaporative fraction from the SEBAL model using optical-thermal satellite imagery. Despite the good agreement between soil water content and the evaporative fraction was observed, the method is entirely empirical and can only be indicative of actual soil moisture status.

In a similar study by Su et al., (2003), a theory for assessing relative soil moisture in the root-zone with remote-sensing data was proposed. Su et al., (2003) used optical-thermal satellite data with the energy balance model SEBS by Su (2002) to estimate relative ET and develop a relative soil moisture deficit index (Drought Severity Index, DSI).
Later, they related DSI with experimental data collected with a lysimeter in Northern China. Comparisons between the estimated DSI and the actual measurements of soil moisture confirm the validity and robustness of the proposed method. However, the derivation of DSI equations is based on assumptions which cannot be ignored if the method is to be experimented.

Varado et al., (2006) used the method presented by Ross (2003) to develop an unsaturated zone module for a large-scale hydrological model, the inclusion of a root extraction module and a formulation of interception. Two root water uptake modules, first proposed by Lai and Katul (2000) and Li et al., (2001), were included as the sink term in the Richards equation for movement of water in unsaturated soils. Their investigations using a Soil-Vegetation-Atmosphere-Transfer (SVAT) model as a reference showed that the vadose zone module was very accurate with errors of less than a few percent for cumulative transpiration. Soil evaporation was less accurately simulated, as it leads to a systematic underestimation of soil evaporation amounts. Varado et al., (2006) reported that under field conditions (soybean crop in Avignon, France), the accuracy of the vadose zone module is satisfactory, even when using potential ET instead of the comprehensive SVAT model, provided that a correct crop coefficient is defined.
There have been other efforts, such as those by Ross (2003), who developed a fast numerical method for solving the Richard's equation for water transport using Brooks-Corey expressions of soil hydraulic properties. Water fluxes were calculated using matric flux potentials combined with a novel spatial weighting scheme for the gravitational component. Flow across soil property interfaces was calculated by equating fluxes to and from the interface. Results showed an order of magnitude faster and more robust than an iterative scheme, typifying current practice. Execution time for the test problem with <3% error was 0.006s. Solutions for solute transport described by the advection-dispersion equation were obtained concurrently without a substantial increase in execution time, by assuming average water fluxes over several steps of the water transport solution.

Vidhya et al., (2009) combined optical and microwave remote-sensing data to generate a soil moisture index in Cumbum Valley, Tamil Nadu, India. Their results showed a good agreement of the dielectric constant with the soil moisture index. It was observed that an empirical relation between the dielectric constant and the soil moisture stress is possible to draw by correlation, but validation with critical field observed data is very important.

Starks et al., (2003) examined the feasibility of inferring root-zone soil water content by combining remotely sensed estimates of surface water content with the modelling techniques developed by Ragab (1995). Their results from a study conducted in a semi-arid environment of south-western Oklahoma, USA, suggest that it is feasible to infer root-zone soil water content in tall grass prairies by combining remotely sensed surface
observations into a soil water budget model, provided that remotely sensed data has not been corrupted by vegetation effects.

### 3.2.2. DATA ASSIMILATION FOR SOIL MOISTURE

Soil moisture is a complex variable to study. Assimilation schemes have shown great potential in studying the soil moisture dynamics, especially in the root-zone. These soil moisture estimation studies can be characterised into those according to: (i) problem size (small-scale vs large-scale), (ii) statistical rigour (optimal vs various sub-optimal methods), (iii) computational implementation (recursive vs non-recursive), or (iv) type of data to be assimilated.

In general, the larger the problem, the less statistical rigour can be applied, due to the computational requirements of statistically optimal techniques. Statistically optimal techniques mean that the estimations are a result of optimisation of an objective function, and that the model equations are derived through a consistent simplification such that the approximation error can be quantified. The computational implementation, being a very relevant topic, is less relevant from a hydrological viewpoint. Although there are many possibilities with regards to the type of data to be assimilated, nearly all existing studies use either direct measurements of soil moisture, or remotely sensed brightness data, which are very closely related to surface soil moisture.

Some prominent studies that applied statistical assimilation techniques used synthetic data (Entekhabi et al., 1994; Milly and Kabala,
small-scale field or laboratory data (Katul et al., 1993; Parlange et al., 1993; Galantowicz et al., 1999; Calvet et al., 1998; Castelli et al., 1999; Hoeben and Troch, 2000a). A second group considers large-scale field data sets (Houser et al., 1998, Reichle et al., 1999; Reichle, 2000). All studies integrate the data in spatially one-dimensional physical models and do not include any prior information other than model parameters i.e. no smoothness constraints or other regularising information.

3.2.2.1. **Optimal Estimation**

Optimal estimation techniques are applicable if the dimension of the soil moisture system is relatively small, e.g. a single vertical column. Algorithmically, the problem of optimal estimation can be solved by both recursive and non-recursive techniques. The recursive algorithm for optimal estimation is the Extended Kalman Filter, which has been used by many investigators (e.g. Entekhabi et al., 1994; Galantowicz et al., 1999; Hoeben and Troch, 2000b). The non-recursive technique, often called the variational approach (e.g. Bouyssel et al., 1999; Mahfouf, 1991; Reichle et al., 1999; Reichle, 2000) has been used much less in soil moisture data assimilation.

In cases where optimal estimation has been applied, the soil moisture system has been described as a simple linear multi-layer model (Milly, 1986), a nonlinear bucket model, obtained from the depth-integration of a one-dimensional version of Richards' equation (Katul et al., 1993; Parlange et al., 1993), or a multi-layer version—often in combination with the heat equation, and a model for the radiative transfer (Milly, 1986; Entekhabi et al., 1994; Galantowicz et al., 1999; Hoeben and Troch, 2000b). The
pioneering work in applying optimal estimation to soil moisture data assimilation has been done by Milly (Milly and Kabala, 1986; Milly, 1986). Milly and Kabala (1986) applied a Kalman Filter to determine the relative merits of the accuracy and the sampling frequency of the observations with a remote soil moisture sensor, using a linear soil moisture model. Milly (1986) demonstrated the use of an extended Kalman Filter in combination with a two-layer Richards' equation model and the heat equation.

Katul et al., (1993) used an extended Kalman Filter for the estimation of the soil moisture state in a simple bucket model derived from a one-dimensional Richards' equation. Katul et al., (1993) also estimated the two soil hydraulic parameters in their model: the initial estimation error variance, and the model error of the state-space formulation. Parlange et al., (1993) and Cahill et al., (1999) applied the same techniques to solve the diffusion equation linked with a water balance model. In this way they estimated diffusivity at field scale as well as the initial estimation error variance and the model error of the state-space formulation. Entekhabi et al., (1994) and Galantowicz et al., (1999) applied a multi-layer model of soil moisture and temperature dynamics, and used a Kalman Filter to update the temperature and moisture profile from brightness temperature observations. The spatially 1-dimensional model was entirely physically based on Richards' equation, heat equation, and radiative transfer equations. Entekhabi et al., (1994) are the first to show that it is possible to infer information about the temperature and moisture at depths below the penetration depth of microwaves. Entekhabi et al., (1994) also used synthetic data, representing a single soil column without vegetation. In their study, the updates of the brightness and infrared temperature data were
made hourly, which is not a very realistic situation. At this point, Hoeben and Troch (2000a,b) provided a follow-up, using synthetic data, as well as multi-frequency active microwave observations, to determine the observation interval whereby the algorithm breaks down. They arrived at similar conclusions to Entekhabi et al., (1994). Galantowicz et al., (1999) also concluded that updating the brightness temperature only once every three days is sufficient for the estimation of the soil moisture profile.

Draper et al., (2010) used ensemble Kalman Filter to assimilate near-surface soil moisture observations of AMSR-E into Interactions Soil-Biosphere-Atmosphere (ISBA). The EKF can translate near-surface soil moisture observations into useful increments to the root-zone soil moisture. To test the benefit of evolving the background error, the EKF was compared to a Simplified EKF (SEKF), in which the background errors at the time of the analysis are constant. They concluded that while the Kalman gains for the EKF and SEKF are derived from different model processes, they produce similar soil moisture analyses. Despite this similarity, the EKF is recommended for future work where the extra computational expense can be afforded.

Calvet et al., (1998) presented a comprehensive study on the feasibility of retrieving root-zone soil moisture from surface soil moisture or surface soil temperature observations. They used a French weather forecast system, which models soil moisture in a shallow surface layer and a deep reservoir. The assimilation technique is a strong constraint variational method. The uncertain parameter is the initial soil moisture of the deep reservoir. The data originated from two months of field observations in spring and autumn.
1995 in southern France. Their assimilation period was either a moving 15-day window or a moving 5-day window during the 30-day observation periods. In a series of assimilation experiments, observations are available to the estimation algorithm from twice-daily to once every four days. Calvet et al., (1998) stated that deep soil moisture can indeed be retrieved with reasonable accuracy from surface soil moisture observations once every three days, but conceded that soil moisture estimation from soil temperature measurements can at best work under dry conditions. They also concluded that the length of the assimilation window should not be shorter than 10 days.

Castelli et al., (1999) and Lakshmi (2000) used ground temperature observations for soil moisture estimation. In these studies, the input was treated as an uncertain time-dependent parameter called the soil moisture index. In both studies, a variational technique was applied whereby the surface energy balance was included as a physical constraint in the objective function. Mathematically, the estimation of the soil moisture index amounts to the estimation of a state-dependent model error term. And the estimates of the surface heat flux and the soil moisture index were derived from the FIFE experiment. Daily averages of the estimated surface heat flux compared well to independent latent heat flux observations. However, Castelli et al., (1999) concluded that there is a need to discriminate between soil moisture and aerodynamic contributions to the surface control over evaporation.

Walker et al., (2001) investigated the ability to retrieve the soil moisture and temperature profiles by assimilating near-surface soil moisture

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and surface temperature data into a soil moisture and heat transfer model. The desktop study using synthetic data showed that the Kalman Filter assimilation scheme is superior to the direct insertion assimilation scheme. It was also found that the profile retrieval could not be realised for direct insertion of the surface node alone, and that observations depth does not have a significant effect on profile retrieval time using the Kalman Filter technique. Walker et al., (2001) reported that Kalman Filter assimilation scheme was less susceptible to unstable updates if volumetric soil moisture was modelled as the dependent state rather than matric head, because the volumetric soil moisture state is more linear in the forecasting model. Many aforementioned studies like Entekhabi et al., (1994), Houser et al., (1998) and Calvet and Noilhan (2000) have also shown the potential of assimilation algorithms to retrieve root-zone soil moisture from observed surface values. However, the lack of high quality information on the model parameters at a global scale and the uncertainties related to the physical description of the water and energy balance are a disadvantage for data assimilation methods.

Calvet and Noilhan (2000) stated that in a land surface model, the conversion from surface to root-zone soil moisture may depend on multiple factors such as soil texture or vegetation coverage, and the analysed profile soil moisture is model-dependent. And Sabater et al., (2007) pointed out that the chosen assimilation method may also affect the results. Whereas Rechlie et al., (2008) demonstrated how poorly specified model and observation error parameters affect the quality of the assimilation products. In particular, soil moisture estimates from data assimilation are sensitive to observation and model error variances and, for very poor input error parameters, may even be worse than model estimates without data.
assimilation. Recently, Han E. et al., (2014) found that most of the benefits from the assimilation system to predict root-zone soil moisture are attributed to the initial remote-sensing observations, i.e. brightness temperature. The nonlinearities in the retrieval algorithm and the complexities in the EnKF marginally contribute to the predictive skills of the system.

### 3.2.2.2. **Sub-Optimal Estimation**

So far, the most comprehensive studies on soil moisture data assimilation have been carried out by Houser et al., (1998) and Reichle et al., (1999). Houser et al., (1998) modified and extended the TOPLATS land-atmosphere transfer scheme (Famiglietti and Wood, 1994a,b). TOPLATS is a spatially-distributed hydrological model to predict the diurnal dynamics of the water and energy fluxes at the land surface as well as the local vertical recharge into the underlying aquifer. The basic components of TOPLATS are water balance equations for the canopy and the soil and an energy balance equation at the surface. The original model describes the unsaturated zone with two layers, a root zone and a transmission zone. Houser et al., (1998) added a shallow, third soil layer at the top, the moisture content of which can potentially be inferred from remotely-sensed microwave observations. The soil moisture dynamics are based on an approximate analytical solution of Richards' equation using infiltration and exfiltration capacities. Horizontal flow exists only in the underlying saturated layer. In the unsaturated zone, lateral flow is completely neglected. The model was applied to the Walnut Gulch watershed in south-eastern Arizona, USA. Houser et al., (1998) applied five different data assimilation methods (from simple to more
complex): direct insertion, statistical corrections, two forms of nudging and optimal interpolation in combination with two ways of data reduction.

A more advanced data assimilation study to a large study domain has been performed by Reichle and co-workers (Reichle et al., 1999, Reichle, 2000). They applied a model of coupled moisture and heat transport, using six layers in the vertical direction. For computational efficiency, the force-restore method (Hu and Islam, 1995), rather than the full heat equation, was used to describe temperature dynamics. In addition, a vegetation sub-model was used analogous to the Simplified Biosphere Model by Xue et al., (1991). The downward flux out of the bottom soil layer is described by gravitational drainage. The brightness temperature is related to the system states with the Radiative Transfer model described by Galantowicz et al., (1999). As in the study of Houser et al., (1998), these studies also neglect lateral unsaturated horizontal moisture and heat transport, assuming that in the relatively flat study area the vertical fluxes dominate in the unsaturated zone. For the soil parameters and the meteorological forcings, the error covariances are assumed to be correlated exponentially in space as well as in time.

Montaldo and Alberton (2001) presented an operational framework for assimilating surface soil moisture remote-sensing measurements into a SVAT model using the force-restore assimilation technique for robust prediction of root-zone moisture time-series. This framework uses biases between observed and modelled time rates of change of surface soil moisture to quantify biases between modelled and actual root-zone average soil moisture content. A study using datasets from Cork, Ireland, showed
that the framework performed uniformly robust over three orders of magnitude of misspecifications of saturated hydraulic conductivity. Later, Montaldo and Alberton (2003) applied this method to form a multi-scale assimilation approach, which provided improvements in the prediction of root-zone soil moisture in Cork, Ireland.

Das et al., (2006) also used data assimilation and remote sensing to investigate the spatio-temporal evolution of root-zone soil moisture in Arizona. Root-zone soil moisture was estimated via assimilation of aircraft-based, remotely sensed surface soil moisture into a distributed Soil-Water-Atmosphere-Plant (SWAP) model. The assimilation of remotely sensed soil moisture observations had limited influence on the soil moisture profile i.e. root-zone soil moisture depended mostly on the soil type. Comparisons showed that the ground-based soil moisture observations at various depths were within ±1 standard deviation of the modelled profile soil moisture.

3.2.2.3. SUMMARY

There is a very limited use of different data sources: nearly all studies only utilise field or remotely sensed brightness data. There have been many interesting investigations on soil moisture data assimilation from low-level atmospheric parameters such as air temperature and relative humidity at 2 metres above the ground (e.g. Bouyssel et al., 1999; Bouttier et al., 1993a,b; Hu et al., 1999; Mahfouf, 1991; Rhodin et al., 1999). However, these parameters are only weakly and indirectly related to surface soil moisture. In addition, the studies using these data are geared towards improving numerical weather prediction and treat soil moisture rather as a tuning
parameter. These studies contain interesting contributions that may be applied in other soil moisture data assimilation studies. The reason for not including data such as catchment discharge, ET from different vegetation patches or groundwater levels is twofold. Firstly, the 1-dimensional models that have been applied so far do not lend themselves to the inclusion of any lateral fluxes. Secondly, no suitable data set has been compiled so far that includes such a variety of field and remote-sensing data, a problem previously noticed by Kostov and Jackson (1993). None of the above data assimilation studies has incorporated any regularising information. Regularisation is a generic term for mathematical techniques that enable one to solve an ill-posed problem by varying the problem resolution and including prior information in a structured and objective way. Such techniques were not required until now, simply because the 1-dimensional problems were not ill-posed. Nonetheless, a clear-cut regularisation technique will be required for solving higher dimensional problems to decide which prior information to utilise, how to weigh it against (posterior) observations and, most importantly, how to vary the resolution of the modelling problem.

The present data assimilation studies concentrate on the mathematical and computational implementation of the proposed techniques, and on the relationship between remote-sensing brightness data and surface soil moisture. Much less effort has gone into the redesign of hydrological models or the extension to more spatial dimensions. In addition, no advantage has been taken of the existing work, which has quite successfully related soil moisture to static soil and terrain properties with statistical techniques (e.g. Greminger et al., 1985; Schiffler and Bårdossy,
In some of these studies, systematic components have been identified and linked to topographic characteristics, (e.g. Moore et al., 1991; Hanna et al., 1982; Hairston and Grigal, 1991), soil morphological features (e.g. Kreznor et al., 1989), or chemical and physical attributes (Brubaker et al., 1993). The integration of both systematic and stochastic components has partially been achieved by conditioning geo-statistical techniques with secondary data such as topographic indices via (indicator) co-kriging (e.g. Lehmann, 1995; Western et al., 1998, 1999). Especially these latter (geo-statistical) techniques closely fit into the data assimilation framework. The lack of this integration can be explained from a lack of suitable field studies. Very much related to the previous problem, the focus in assimilation studies has been on using only a single (presumably unbiased) model, and never on model ensembles. A consequence has been that the role of model error and bias has never been assessed, and techniques for building and using model ensembles have not been developed. In the meteorological and oceanographic disciplines the use of model ensembles to reduce model bias and estimate the forecast-error statistics is gaining acceptance since the work by Evensen (Evensen, 1992; Houtekamer and Mitchell, 1997). Recently, it has also been shown that, within a Kalman Filter framework, ensemble techniques can help to reduce the computational burden for realistic higher dimensional problems to a reasonable level (Mitchell and Houtekamer, 2000). Notwithstanding the availability of knowledge and technical means, the first operational application of soil moisture data assimilation has still to be made. On the one hand, a very valid argument is that it is still too early to ask for applications when the data assimilation techniques are still so immature and data not even operationally available. But on the other hand, it is quite
viable to state that data assimilation is pre-eminently a branch of science which should be application-driven, and that the availability of operational tools may stimulate the development of the appropriate observing systems. However, with more remote-sensing soil moisture observations becoming available, it is appropriate to start from simple operational models and data assimilation techniques, and enhance these stepwise, rather than first developing advanced models and data assimilation techniques while implementing these in an operational setting at a later stage.
4. **METHODODOLOGY**

This chapter discusses the data used and the methodology adopted for flux calculation from large aperture scintillometer (LAS), remote-sensing-based flux estimation using the energy balance model (SEBS) with Terra/MODIS data. Lastly, an assessment of exponential filter to estimate root-zone soil moisture from microwave-based surface soil moisture time-series.

4.1. **LARGE APERTURE SCINTILLOMETER**

4.1.1. **INSTRUMENT**

LAS are instruments designed for measuring the path-averaged structure parameter of the refractive index of air \((C_n^2)\) over horizontal path lengths from 250 metres to 4.5 kilometres. The LAS optically measures intensity fluctuations (or scintillations) using a transmitter and receiver, which can be expressed as \(C_n^2\). The light source of the LAS transmitter operates at a near-infrared wavelength of 880 nm. At this wavelength, the observed scintillations are primarily caused by turbulent temperature fluctuations. Therefore, together with standard meteorological observations e.g. air temperature, wind speed and air pressure, these structure parameter measurements received by the LAS receiver can be used to derive the surface sensible heat flux \((H)\).
4.1.1.1. **Transmitter**

The transmitter uses a high power infrared-emitting diode (LED) which emits at 880 nm. It consists of an oscillator which consists of a block of wave with a frequency of 7 kHz. This wave is used as an input signal for a power-amplifier. Depending on the input voltage, this amplifier generates a current of maximal 2A based on a 0.5 duty cycle. As a result, the light intensity of the LED can be set, depending on atmospheric conditions and path length. The LED is thus modulating at a frequency of 7 kHz, in order to distinguish the EM signal from background radiation. LED is placed in the focal point of a spherical concave mirror with a diameter and focal length of 0.152 metre to construct an incoherent light beam. The optical parts are protected against atmospheric influences by a transparent Plexiglas window.

![Image](image.png)

*(a) (b)*

**Figure 4.1**: LAS transmitter and receiver.

The technical specifications of Kipp&Zonen LAS transmitter are given in Table 4.1 below:
Table 4.1: Technical specifications of the LAS transmitter (Kipp & Zonen, 2007).

<table>
<thead>
<tr>
<th>Transmitter</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating temperature</td>
<td>-20°C to +50°C</td>
</tr>
<tr>
<td>Humidity</td>
<td>0 – 100% RH</td>
</tr>
<tr>
<td>Voltage</td>
<td>12 VDC nominal ($V_{min} = 10.5$ V; $V_{max} = 15$ V)</td>
</tr>
<tr>
<td>Power</td>
<td>0.5 A maximum (path length dependant), ~ 3 A maximum with heater on</td>
</tr>
<tr>
<td>Window heater</td>
<td>Self-regulating at ~ 55 °C</td>
</tr>
<tr>
<td>Optical wavelength of LED</td>
<td>880 nm (spectral bandwidth at 50% ~ 80 nm)</td>
</tr>
<tr>
<td>Optical power output of LED</td>
<td>maximum 80 mW ($I_F = 1$ A, $\bar{I}_F = 500$ mA, duty cycle 0.5)</td>
</tr>
<tr>
<td>Modulation frequency</td>
<td>~ 7 kHz (duty cycle 0.5)</td>
</tr>
<tr>
<td>Beam width</td>
<td>~ 1 m at 100 m distance</td>
</tr>
<tr>
<td>Aperture diameter</td>
<td>0.152 m (6 inch)</td>
</tr>
<tr>
<td>Focal length Fresnel lens</td>
<td>0.152 m (6 inch)</td>
</tr>
<tr>
<td>Effective diameter</td>
<td>0.145 m</td>
</tr>
<tr>
<td>Typical signal 1 ($U_{TH_TR}$, Thermistor)</td>
<td>0 V to 10 V</td>
</tr>
<tr>
<td>Typical signal 2 (7 kHz oscillator)</td>
<td>7 kHz, 0.5 duty cycle, Amplitude = - 7.8 V</td>
</tr>
<tr>
<td>Typical signal 3 (LED pulse)</td>
<td>7 kHz, 0.5 duty cycle, Amplitude = 0 V to 1 V</td>
</tr>
</tbody>
</table>

4.1.1.2. Receiver

In an LAS receiver, a square law detector is used to measure the intensity ($I$). It is placed in the focal point of a spherical concave mirror identical to the one used in the transmitter.

The technical specifications of the Kipp&Zonen LAS receiver are given in Table 4.2 below.
Table 4.2: Technical specifications of the LAS receiver (Kipp & Zonen, 2007).

<table>
<thead>
<tr>
<th><strong>Receiver</strong></th>
<th><strong>Operating temperature</strong></th>
<th>-20 °C to +50 °C</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Humidity</strong></td>
<td></td>
<td>0 – 100% RH (≈ IP 66)</td>
</tr>
<tr>
<td><strong>Voltage</strong></td>
<td></td>
<td>12 VDC nominal ((V_{\text{min}} = 11.3) V; (V_{\text{max}} = 15) V)</td>
</tr>
<tr>
<td><strong>Power</strong></td>
<td></td>
<td>0.2 A nominal, (~3) A maximum with heater on</td>
</tr>
<tr>
<td><strong>Window heater</strong></td>
<td></td>
<td>yes, self-regulating at (~55) °C</td>
</tr>
<tr>
<td><strong>Responsivity of photodiode at 880 nm</strong></td>
<td></td>
<td>0.6 A/W (spectral bandwidth at 50% ~ 60 nm)</td>
</tr>
<tr>
<td><strong>Aperture diameter</strong></td>
<td></td>
<td>0.152 m (6 inch)</td>
</tr>
<tr>
<td><strong>Focal length Fresnel lens</strong></td>
<td></td>
<td>0.152 m (6 inch)</td>
</tr>
<tr>
<td><strong>Effective diameter</strong></td>
<td></td>
<td>0.148 m</td>
</tr>
<tr>
<td><strong>Scintillation signal bandwidth of electronics</strong></td>
<td></td>
<td>0.2 Hz to 400 Hz</td>
</tr>
<tr>
<td><strong>Typical value signal 1 ((U_{\text{DEMOD}}) or signal strength (I))</strong></td>
<td></td>
<td>- 0.8 V to 0 V</td>
</tr>
<tr>
<td><strong>Typical value signal 2 ((U_{\text{CN2}}) or log (U_{\text{CN2}}) signal)</strong></td>
<td></td>
<td>- 5 V to 0 V</td>
</tr>
<tr>
<td><strong>Typical value signal 3 (7 kHz carrier)</strong></td>
<td></td>
<td>(~7) kHz, 0.5 duty cycle</td>
</tr>
<tr>
<td><strong>Typical value signal 4 ((U_{\text{TH}, R_t}) Thermistor)</strong></td>
<td></td>
<td>0 V to 10 V</td>
</tr>
<tr>
<td><strong>(Cn2) turbulent range</strong></td>
<td></td>
<td>(10^{-12}) to (10^{-17}) m(^{-2/3})</td>
</tr>
<tr>
<td><strong>Noise level of electronics ((U_{\text{DEMOD}}) (-0.8) V; LLAS (= 1184) m)</strong></td>
<td></td>
<td>(&lt;10^{-17}) m(^{-2/3})</td>
</tr>
</tbody>
</table>

The intensity of the incident EM radiation is proportional to the square of its amplitude \((x)\), and the variance of the log intensity is equal to four times the variance of log amplitude. Therefore, Wang et al., (1978) relation between \(C_n^2\) and variance of log amplitude fluctuations \((\sigma_{\text{log}}^2)\) can be written as:

\[
C_n^2 = 1.12 \sigma_{\text{log}}^2 D^3 L^3
\]  

Equation 18
Where \( D \) is the aperture diameter of the LAS and \( L \) the distance between the transmitter and the receiver i.e. the path length.

The receiver provides real-time \( C_n^2 \) values expressed in voltage \((U)\) as:

\[
C_n^2 = 10^{(U_{cn2}/12 + 1.15\times\text{Var}U_{cn2})} \tag{Equation 19}
\]

Since the relationship between \( U \) and \( C_n^2 \) is non-linear, the variance term \( \text{Var}U_{cn2} \) is used. The conversion from intensity fluctuations to \( C_n^2 \) involves a number of steps which are performed by the electronic circuitry of the receiver (Figure 4.2). Detail of these can be found in W.M.L Meijninger (2003).

![Figure 4.2: Flow chart of intensity fluctuations to \( U_{cn2} \) calculations (Kipp & Zonen, 2007).](image-url)
4.1.1.3. Experiment Setup

A comprehensive experiment was conducted in the MIA to investigate the potentials and the limitations of using LAS to infer path-average sensible heat flux. The study site is a horticulture farm with a consistent and uniform citrus crop located near the town of Leeton, NSW, Australia. The LAS transmitter and receiver were installed at a height of 4.3 metres above the ground, with a path length of 1400 metres. The path length of the LAS spanned over three horticulture properties, all having a citrus crop of similar height. Both transmitter and receiver were installed on rooftops of citrus processing sheds of same height above the ground, which is helpful while optically aligning the transmitter and receiver. Figure 4.3(a) shows a view of the transmitter installed over the study site. It is important that the transmitter (and receiver) has stable, secure mounting and that the transmitter beam is optimally aligned with the receiver. The alignment is performed by moving both transmitter and receiver (one at a time) until maximum signal is received. The transmitter was fixed on the specialised adjustable tripod which was affixed onto the rooftop to ensure maximum stability from wind, which can distort the signal and/or upset the alignment between transmitter and receiver.
Similarly, the receiver tripod was also affixed firmly after best alignment was achieved. This alignment needs to be checked and maintained over the length of experiment, in order to ensure redundancy in scintillation data. Figure 4.3(b) shows the signal strength maximum received at current alignment. Both the transmitter and receiver were powered using solar panels through 12V 200Ah/20HR batteries (Figure 4.4). The site receives long sunshine hours during most of the year, therefore it was experienced that the batteries remained fully charged most of the time while powering the LAS. However, it is important to have a sufficiently big battery to ensure power during consecutive cloudy days, especially in winter.

Figure 4.3: (a) LAS transmitter installed over the study site. (b) LAS receiver showing signal strength.

Figure 4.4: (a) Solar panel, and (b) Battery setup.
At the receiver end, a Campbell scientific micro-data logger CR-1000 was configured to read the scintillation data every second. Since LAS measures in the inertial-convective sub-range of frequencies, it provides statistically stable data within a minimum range of 10 minutes (Beyrich et al., 2002). The logger was programmed to sample half-hourly, i.e. to generate half-hour average tables containing $C_n^2$ information. A net radiometer (NR-Lite) and two soil heat flux plates (HFP015) were also installed at the site and configured with the receiver to record remaining energy balance components. A 3G modem was setup with data-logger that enabled real-time data acquisition from the site to the data server located in Charles Sturt University (Wagga Wagga, NSW), 145 kilometres south-east of the study site. Figure 4.5 shows the net radiometer and the data-logger setup for this experiment.

![Figure 4.5: (a) Net radiometer, NR-Lite. (b) Data-logger with 3G modem.](image)

In order to process scintillation data for sensible heat flux calculation, meteorological information (wind speed, air temperature, humidity, air pressure etc) is required. A set of automatic weather stations installed at the site are explained in the next section. Figure 4.6 shows a complete map of the LAS experiment setup with ancillary sensors.
Figure 4.6: Map of complete LAS experiment setup.

a. **Distributed Weather Sensors**

An automatic weather station (AWS) was installed at the receiver end to collect meteorological data required to calculate sensible heat flux from $C_n^2$ information. The AWS (Figure 4.7) consisted of an anemometer, temperature and humidity sensor, rain gauge and a pyranometer. The sensors were configured with a Campbell Scientific CR10X data logger programmed to save data into 10-mins and half-hourly tables onto a CF memory card.
The sensitivity of location of meteorological data along the stretch of path-length on calculation of sensible heat flux has not been analysed before. Therefore, a network of three Crossbow eKo PRO environmental wireless sensors network (WSN) was also installed within the line of sight of the receiver and the LAS transmitter. WSN consists of a wireless base station and wireless nodes that are distributed in multiple locations to read data from specific sensors (Figure 4.8). Data read by a WSN node is then transmitted back to the base station (or neighbouring node to be forwarded to base station). Each WSN node was equipped with an anemometer, rain bucket, air temperature and humidity and soil temperature and moisture sensor. These nodes are solar powered, which keeps the battery charged and helps avoid battery replacement in the field. The base station works at 2.4 GHz radio frequency, receiving data sequentially from the network and logging it onto USB memory device, and it is also transmitted to the data server via 3G connection. Figure 4.8(b) shows an example of such a WSN node being installed at the study site.
4.1.1.4. DATA ACQUISITION AND PROCESSING

The whole experiment was setup in October/November 2009 and consistent time series data was being logged from January 2010 till February 2011. LAS station data was initially downloaded through a 3G modem connected to the mobile phone network; later, a 3G VPN router was installed to improve bandwidth and throughput. Campbell Scientific provides LoggerNet software capable of communicating and programming the loggers. A scheduled download routine was setup with LoggerNet to download the data binary files onto the central server (Figure 4.9a). The CR1000 data loggers generate the data in Campbell Scientific’s proprietary binary data format, which needed to be converted to ASCII. Campbell Scientific’s Bailer software is capable of handling large amount of data files.
and can perform conversion/manipulation of data into required file size and format.

(a)

(b)

Figure 4.9: (a) A screenshot of LoggerNet software, (b) Screenshot of WINLAS input parameter window.

However, a preferred open-source alternative is the UNIX-based Camp2ascii utility (M. Bavay, 2007), which was used to convert all binary data into ASCII format. This allowed the basic text processing to be done in GNU/Bash shell. The ASCII data files from the AWS and three WSNs were also converted and merged together using shell scripting commands. LAS manufacturer Kipp&Zonen supply WINLAS (Figure 4.9b) software application to calculate sensible heat flux from $C_n^2$ information. LAS data were prepared and formatted according to the WINLAS software requirement. WINLAS requires scintillation data together with meteorological data (air temperature, humidity, air pressure and wind speed) to calculate sensible heat flux. Therefore, combining of LAS data and AWS was done based on time-steps. Similarly, a time-step-based combining of LAS data with WSN1, WSN2 and WSN3 meteorological data was also performed to generate four different input files containing the same $C_n^2$ data and different sets of
weather data. After preparation of input files, $H$ was calculated in WINLAS by using (i) LAS and AWS data, (ii) LAS and Eko1 data, (iii) LAS and Eko2 data, and finally (iv) LAS and Eko3 data. The results of $H_{LAS}$ are presented in the next chapter. Also in the next chapter, a comparison of $H$ calculated by varying location of weather data is presented. Later, energy balance was solved between net radiation, soil heat flux and $H_{LAS}$ to calculate $\lambda E$ in order to calculate instantaneous $ET$ comparable to remote-sensing-based modelled $H_{Sat}$ and $\lambda E$ from the SEBS model. A flow chart of sensible heat flux (and $\lambda E$) calculation from $C_n^2$ data is shown in Figure 4.10 below.

![Flow chart of sensible heat flux calculation from $C_n^2$ data](image)

**Figure 4.10:** Flow chart of flux calculation from $C_n^2$ (Kipp&Zonen, 2007).
4.2. Remote Sensing Derived Heat Fluxes Estimation

There are number of methods for estimating actual ET through remote sensing using optical-thermal satellites, as discussed in the previous chapter. The suitability of any particular method is dependent on the purpose and scale of its application. For this study, SEBS was the selected method because of its internal calibration scheme, which required minimal ground-based measurements. The current setup of SEBS requires three sets of inputs:

I. Remote-sensing-derived albedo, emissivity, temperature and NDVI to derive surface roughness parameters.

II. Meteorological parameters at a reference site.

III. Radiation data (downward solar radiation, downward longwave radiation).

Therefore, the semi-automated processing framework of SEBS makes it the most appropriate model to be implemented in this study.

4.2.1. Surface Heat Fluxes Estimation using SEBS

Recently, a number of models have been developed to model surface energy balance from satellite Earth observation data. These models can be characterised by varying complexity, e.g. SEBAL (Bastiaanssen, 1995), SEBS (Su, 2001), and TSEBS (Norman et al., 1995). Various energy balance models calculate the net radiation, soil heat flux and sensible heat flux separately. The latent heat flux, which links the soil water balance with the surface energy balance, is estimated as the residual of the energy balance equation.
\[ R_n = G_0 + H + \lambda E \]

Equation 20

Where \( R_n \) is the net radiation, \( G_0 \) is the soil heat flux, \( H \) is the sensible heat flux, and \( \lambda E \) is the latent heat flux (\( \lambda \) being the latent heat of vaporisation). The net radiation is calculated by:

\[ R_n = (1 - \alpha)R_{swd} + \varepsilon R_{lwd} - \varepsilon \sigma T_0^4 \]

Equation 21

Where \( \alpha \) is the albedo, \( R_{swd} \) and \( R_{lwd} \) are the downward shortwave and longwave radiation respectively. \( \varepsilon \) is the emissivity of the surface, \( \sigma \) is the Stefen-Boltzmann constant, and \( T_0 \) is the surface radiative temperature.

\( R_{lwd} \) is given by:

\[ R_{lwd} = \varepsilon_a \sigma T_a^4 \]

Equation 22

And \( R_{swd} \) is calculated as:

\[ R_{swd} = I_{sc} e_0 \cos \theta_z \exp(-m \tau) \]

Equation 23

Where \( I_{sc} \) is the solar constant (1367 W.m\(^{-2}\)), \( e_0 \) the eccentricity factor, \( \theta_z \) the solar zenith angle, \( m \) the air masses and \( \tau \) the optical thickness. \( T_a \) is the air temperature and reference height.

SEBS parameterises the soil heat flux as:

\[ G_0 = R_e \left[ \left( \Gamma_c + \left| \left( 1 - f_s \right) \left( \Gamma_s - \Gamma_c \right) \right| \right) \right] \]

Equation 24
Here the assumption is that the ratio of soil heat flux to net radiation for full vegetation canopy is $\Gamma_c = 0.05$ and for bare soil is $\Gamma_s = 0.315$. (Kustas and Daughtry, 1989).

Fractional canopy coverage, $f_c$, which can be calculated from remote-sensing data, is then used to perform an interpolation between these limiting conditions. Under the dry-limit, the latent heat becomes zero due to the limitation of soil moisture, and the sensible heat flux is at its maximum value $H_{dry}$. But under wet-limit, the $\lambda E$ is only limited by the available energy and $H$ is at its minimum value $H_{wet}$. Mathematically, the energy balance for these two limiting cases can be expressed as:

$$H_{dry} = R_n - G_0 \quad \text{Equation 25}$$

$$H_{wet} = R_n - G_0 - \lambda E_{wet} \quad \text{Equation 26}$$

The ratio between the latent heat flux for the actual $ET$ and the wet-limit latent heat flux, $\lambda E_{wet}$, is called the relative evaporation $\Lambda_r$. It is calculated as:

$$\Lambda_r = \frac{\lambda E}{\lambda E_{wet}} = 1 - \frac{\lambda E_{wet} - \lambda E}{\lambda E_{wet}} \quad \text{Equation 27}$$

Or

$$\Lambda_r = 1 - \frac{H - H_{wet}}{H_{dry} - H_{wet}} \quad \text{Equation 28}$$
It is clear that the actual sensible heat flux $H$, is confined between the $H_{wet}$ and $H_{dry}$. Using the above equations with some basic algebraic manipulation, the final evaporative fractions equation is obtained:

$$\Lambda = \frac{\lambda E}{H + \lambda E} = \frac{\lambda E}{R_n - G} = \frac{\Lambda \cdot \Lambda_{wet}}{R_n - G}$$ Equation 29

This formulated the basis of the SEBS model. Further, in SEBS, the actual sensible heat flux $H$ is obtained by solving a set of non-linear equations and is constrained in the range set by $H_{wet}$ and $H_{dry}$ (discussed in 4.2.1.1). By inverting the above equation for evaporative fractions, the actual $H$ and $\lambda E$ are obtained:

$$H = (1 - \Lambda) \cdot (R_n - G)$$ Equation 30

$$\lambda E = \Lambda \cdot (R_n - G)$$ Equation 31

When the evaporative fractions are known, daily evaporation can be obtained as:

$$E_{\text{daily}} = 8.64 \times 10^7 \times \Lambda_0^{24} \times \frac{R_n - G_0}{\lambda \rho_w}$$ Equation 32

Where $E_{\text{daily}}$ is the actual evaporation on a daily basis (mm.d$^{-1}$). $\Lambda_0^{24}$ is the daily average evaporative fraction estimated by SEBS. Here, $R_n$ and $G_0$ are daily net radiation flux and soil heat flux.
4.2.1.1. **DETERMINATION OF SENSIBLE HEAT FLUX**

SEBS makes use of similarity theory to derive sensible heat flux. A distinction is made between the planetary boundary layer (PBL) and the atmospheric surface layer (ASL) (shown in Figure 3.14). ABL is directly influenced by the presence of the Earth’s surface and responds to the surface forcings with a timescale of an hour or less, while ASL refers to the bottom 10% of the PBL but above the roughness sub-layer. The roughness sub-layer is the near-surface thin layer of a few centimetres where the molecular transport dominates over turbulent transport. The thickness of the roughness sub-layer is thought to be around 35 times the surface roughness height, or three times the vegetation height (Katul and Parlange, 1992).

The similarity principle in the ASL for mean wind speed $u$ and mean potential temperature ($\theta_0 - \theta_a$), are usually written in integral form as (Su, 2002):

$$
\begin{align*}
\frac{u}{u^*} &= \frac{1}{k} \ln \left( \frac{z - d_0}{z_{0m}} \right) - \Psi_m \left( \frac{z - d_0}{L} \right) + \Psi_m \left( \frac{z_{0m}}{L} \right) \quad \text{Equation 33}
\end{align*}
$$

$$
\begin{align*}
\theta_0 - \theta_a &= \frac{H}{ku_{0.5}C_p} \ln \left( \frac{z - d_0}{z_{0h}} \right) - \Psi_h \left( \frac{z - d_0}{L} \right) + \Psi_h \left( \frac{z_{0h}}{L} \right) \quad \text{Equation 34}
\end{align*}
$$

Where $z$ is the height above the surface, $u^* = (\tau_0/\rho)^{1/2}$ is the friction velocity, $\tau_0$ is the surface shear stress, $\rho$ is the density of air, $k = 0.4$ is the von Karman constant, $d_0$ is the zero plane displacement height, $z_{0m}$ is the
roughness height for momentum transfer, $\vartheta_0$ is the potential temperature at the surface, $\vartheta_a$ is the potential air temperature at height $z$, $z_{oh}$ is the scalar roughness height for heat transfer, $\psi_m$ and $\psi_h$ are the stability correction functions for momentum and sensible heat transfer respectively, $L$ is the Obukhov length defined as:

$$L = -\frac{\rho C_p u^* \vartheta_v}{kgH}$$  \hspace{1cm} \text{Equation 35}$$

Where, $g$ is the acceleration due to gravity, $\vartheta_v$ is the potential virtual temperature near the surface.

SEBS uses the criterion proposed by Brutsaert (1999) to determine if the MOS or the Bulk atmospheric boundary layer similarity (BAS) scaling is appropriate for a given situation. The above functions are valid for unstable conditions only. For stable conditions, the expressions proposed by Beljaars and Holtslag (1991) are used for atmospheric surface layer scaling and the functions proposed by Brutsaert (1982) for atmospheric boundary layer scaling. Here, friction velocity, sensible heat flux and the Obukhov stability length are obtained by solving the system of non-linear equations given by Broyden (Press et al., 1997). It is important to note that the derivation of the sensible heat flux using the above equations (Equation 33 - Equation 35) requires only the wind speed and temperature at the reference height as well as the surface temperature and is independent of other surface energy balance terms. This derived actual sensible heat flux is further subject to constraints in the range set by $H_{wet}$ and the $H_{dry}$. $H_{dry}$ is calculated with Equation 26 and $H_{wet}$ is derived from an equation similar to the Penman-Monteith combination method. Menenti (1984) derived the following
equation for $\lambda E$ by grouping the resistance terms into the bulk internal (or surface, or stomatal) resistances, $r_i$ (s/m), and the external (aerodynamic) resistances, $r_e$(s/m), under the assumption that roughness lengths for heat and vapour transfer are equal (Brutsaert, 1982):

$$
\lambda E = \frac{\Delta r_e (R_v - G_0) + \rho C_p (e_{sat} - e)}{r_e (\gamma + \Delta) + \gamma r_i}
$$  
Equation 36

Where $\Delta$ (Pa.K$^{-1}$) is the rate of change of $e_s$ with temperature, and $\gamma$=0.67 (PaK$^{-1}$) is the psychrometric constant. The variable $r_e$ depends on the Monin-Obukhov length $L$, which is also a function of friction velocity and $H$ (Equation 35). By solving $L$ and $u^*$ solved iteratively, $r_e$ is derived from Equation 34 as:

$$
r_e = \frac{1}{k u^*} \left[ \ln \left( \frac{z - d_0}{z_{0h}} \right) - \Psi_h \left( \frac{z - d_0}{L} \right) + \Psi_h \left( \frac{z_{0h}}{L} \right) \right]
$$  
Equation 37

Unlike Penman-Monteith, Equation 36 is valid for both vegetation and bare soils when $r_i$ is properly defined. Since $r_i$ is controlled by soil moisture content and SEBS does not include soil moisture data, $r_i$ cannot be used directly in SEBS. Because wet-limit $r_i$=0, $H_{wet}$ is derived from Equation 27, Equation 28 and Equation 36:

$$
H_{wet} = \frac{\left( R_v - G_0 \right) - \frac{\rho C_p (e_{sat} - e)}{r_{ew}}}{\gamma} \left( 1 + \frac{\Delta}{\gamma} \right)
$$  
Equation 38

Where $r_{ew}$ is the external resistance at wet-limit, which can be expressed similar to Equation 37:
Here, the wet-limit Obukhov length, \( L_w \) is derived from Equation 35, \( \Lambda_r \) is solved from Equation 27 and used in calculation of the evaporative fraction in Equation 29. Latent heat flux is then derived by inverting Equation 29:

\[
\lambda E = \Lambda_r (R_a - G_a)
\]

Equation 40

\( \lambda E \) is used to calculate actual \( ET \) flux \( E \) (m.s\(^{-1}\)) from Equation 41 below, and further used to estimate daily \( ET \) rate (mm.d\(^{-1}\)) from Equation 32.

\[
E = \frac{\lambda E}{\lambda \rho_w}
\]

Equation 41

Where \( \rho_w \) (kg.m\(^{-3}\)) is the density of water (e.g. 998 kg.m\(^{-3}\) at 25 ℃).

**a. Roughness Length for Heat Transfer**

In the calculation of MOS functions, roughness length for momentum \( (z_{0m}) \) and heat transfer \( (z_{0h}) \) are required. In SEBS, \( z_{0h} \) is derived using a simplified Lagrangian:
\[ z_{0h} = \frac{z_{0m}}{\exp(kB^{-1})} \quad \text{Equation 42} \]

Where \( B^{-1} \) is the inverse Stanton number (or Margoulis number). Many researchers (Verhoef et al., 1997; Troufleau et al., 1997) reported that \( kB^{-1} \) values are not representative of different land cover types and hence should be avoided in models. Su et al., (2001) improved the \( kB^{-1} \) concept to overcome the above mentioned issues. Therefore, SEBS used a modification to Massman (1999a), made by Su et al., (2001):

\[
kB^{-1} = \frac{kC_d}{4C_t u(h_c) (1-e^{-z_0/2})} f_s^2 + 2 f_s f_c^2 f_r^2 \left( \frac{k. u_s - z_{0m}}{u(h_c) h_c} \right) + kB_s^{-1} f_s^2 \quad \text{Equation 43}
\]

Where \( f_s \) is the fraction of un-vegetated soil \((1-f_c)\), \( C_d \) is the foliage drag coefficient \((0.2)\), \( C_t \) is the heat transfer coefficient of the leaf \((0.01)\), \( u(h_c) \) is the horizontal wind speed at the top of the canopy, \( h_c \) is the height of the canopy \((m)\), and \( C_t^* \) is the heat transfer coefficient of the soil, which is calculated with:

\[
C_t^* = Pr^{-2/3} . Re^{1/2} \quad \text{Equation 44}
\]

Where \( Pr \) is the Prandtl number \((0.71)\) and \( Re^* \) is the roughness Reynolds number calculated with:

\[
Re_* = \frac{h \mu_s}{\nu} \quad \text{Equation 45}
\]
Where \( h_s \) (m) is the roughness height of the soil, \( \nu \) is the kinematic viscosity of the air (\( Pa \cdot s \)), which is calculated with Massman, (1999b): \( kB_{s}^{-1} \) in Equation 53 is \( kB_{s}^{-1} \) for bare soil surface, which is calculated following Brutsaert (1982):

\[
kB_{s}^{-1} = 2.46(Re_s)^{1/4} \times \ln(7.4)
\]

Equation 46

The within-canopy wind speed profile extinction coefficient, \( n \), needed in Equation 53, can be calculated by:

\[
n = \frac{C_d \cdot LAI}{2u^2/|h(h_s)|^2}
\]

Equation 47

Where \( LAI \) is the Leaf Area Index. \( LAI \) is derived from NDVI (Su, 1996, 2000):

\[
LAI = \sqrt{\left( NDVI \cdot \frac{1 + NDVI}{1 - NDVI} \right)}
\]

Equation 48

Since the \( NDVI \) saturates at high \( LAI \) values, Equation 58 cannot be used for dense vegetation covers. It is preferred to use field measurements of \( LAI \) if available. Also, field measurements of \( z_{0m} \) can be used in Equation 42. When field data is not available, the following lookup table (Table 4.3) with literature (Su, 2000) values can be used.
Table 4.3: Land use classes and associated $z_{0m}$ values.

<table>
<thead>
<tr>
<th>Land use class</th>
<th>$z_{0m}$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Grass</td>
<td>0.0340</td>
</tr>
<tr>
<td>2 Maize</td>
<td>0.4966</td>
</tr>
<tr>
<td>3 Potatoes</td>
<td>0.0639</td>
</tr>
<tr>
<td>4 Beets</td>
<td>0.0639</td>
</tr>
<tr>
<td>5 Cereals</td>
<td>0.4966</td>
</tr>
<tr>
<td>6 Other crops</td>
<td>0.0639</td>
</tr>
<tr>
<td>7 Greenhouses</td>
<td>0.4066</td>
</tr>
<tr>
<td>8 Orchards</td>
<td>0.6065</td>
</tr>
<tr>
<td>9 Bulbs</td>
<td>0.0639</td>
</tr>
<tr>
<td>10 Deciduous forest</td>
<td>1.2214</td>
</tr>
<tr>
<td>11 Coniferous forest</td>
<td>1.2214</td>
</tr>
<tr>
<td>12 Heather</td>
<td>0.0408</td>
</tr>
<tr>
<td>13 Other open spaces in natural areas</td>
<td>0.0408</td>
</tr>
<tr>
<td>14 Bare soil in natural areas</td>
<td>0.0012</td>
</tr>
<tr>
<td>15 Fresh water</td>
<td>0.0002</td>
</tr>
<tr>
<td>16 Salt water</td>
<td>0.0002</td>
</tr>
<tr>
<td>17 Continuous urban area</td>
<td>1.1052</td>
</tr>
<tr>
<td>18 Built-up area in rural area</td>
<td>0.5488</td>
</tr>
<tr>
<td>19 Deciduous forest in urban area</td>
<td>1.2214</td>
</tr>
<tr>
<td>20 Coniferous forest in urban area</td>
<td>1.2214</td>
</tr>
<tr>
<td>21 Built-up area with dense forest</td>
<td>1.2214</td>
</tr>
<tr>
<td>22 Grass in built-up area</td>
<td>0.0334</td>
</tr>
<tr>
<td>23 Bare soil in built-up area</td>
<td>0.0012</td>
</tr>
<tr>
<td>24 Main roads and railways</td>
<td>0.0035</td>
</tr>
<tr>
<td>25 Buildings in rural areas</td>
<td>0.5488</td>
</tr>
</tbody>
</table>

SEBS uses the empirical relationship of $z_{0m}$ with NDVI (Su, 2001):

$$z_{0m} = 0.005 + 0.5 \cdot \left( \frac{NDVI}{\text{max}(NDVI)} \right)^{2.5} \quad \text{Equation 49}$$

Where $\text{max}(NDVI)$ is the maximum NDVI in the study area. The height of canopy, $h_c$, and the displacement height, $d_0$, are calculated with Brutsaert, (1982) relationships.
\[ h_c = \frac{z_{0w}}{0.136} \]  
\[ d_0 = \frac{2}{3} h_c \]

**Equation 50**

**Equation 51**

**b. Meteorological Parameters**

Standard meteorological parameters of air temperature, air pressure, relative humidity and incoming solar radiation are required as SEBS inputs. From these parameters the model derives saturation vapour pressure, potential temperature, virtual potential temperature, specific humidity and air density and distributes these parameters spatially.

Saturation vapour pressure \( e_s \) (kPa) is calculated with (Kwast, J. 2009):

\[ e_s = 0.611 e_s^\frac{17.502 t_o}{e_s^{\frac{1}{2}} + 240.97} \]

**Equation 52**

Where \( t_o \) is the air temperature (°C). Actual vapour pressure \( e_o \) is calculated by multiplying relative humidity \( H_f \) with \( e_s \). The potential temperature \( \theta \) is calculated with (Kwast, J., 2009):

\[ \theta = T \left( \frac{P_o}{p} \right)^{0.286} \]

**Equation 53**
Where $T$ is the air temperate, $p$ (mbar) is the air pressure and the reference pressure, $p_o = 1013$ mbar. The virtual potential temperature, $\theta_v (K)$ can now be calculated with:

$$\theta_v = (1 + 0.61q) \theta$$

Equation 54

Where specific humidity, $q$ (kg/kg), is defined as:

$$q = \left( \frac{R_d}{R_v} \right) \frac{e_a}{p}$$

Equation 55

In this equation, $R_d=271.1$ (J.kg$^{-1}$) and $R_v=461.5$ (J.kg$^{-1}$) are the specific gas constants for dry air and water vapour respectively. Now, the air density (kg/m$^3$) is calculated with:

$$\rho_a = \frac{p}{R_a \theta_v}$$

Equation 56

The moist air density $\rho_w$ (kg/m$^3$) is calculated using mixing ratio $\varpi$:

$$\rho_w = \rho_a \varpi$$

Equation 57

$$\varpi = 0.622 \frac{e_a}{p - e_a}$$

Equation 58

4.2.2. DATA PROCESSING AND SEBS MODELLING

SEBS uses a set of calculation procedures for (i) the determination of the land surface physical parameters i.e. albedo, emissivity, temperature,
vegetation coverage from spectral reflectance, (ii) for the determination of the roughness length for heat transfer (Su et al., 2001) and (iii) a new formulation for the determination of the evaporative fraction on the basis of energy balance in limiting cases (Su, 2002). In the application, SEBS requires three sets of input information i.e. land surface parameters (albedo, emissivity, surface temperature, fractional vegetation coverage and leaf area index, and the vegetation/roughness height), meteorological data (air pressure, temperature, humidity, and wind speed at a reference height of PBL) and downward shortwave and longwave radiation that can either be obtained from direct measurements, model output, or parameterisation. Figure 4.11 shows the flowchart of ET modelling processes in SEBS as described by Kwast, J. (2009).

Karssenberge et al., (2007) implemented the SEBS algorithm using the PCRaster Python Library which can be downloaded from ‘http://pcraster.geo.uu.nl/projects/applications/sebs/’. The library is capable of running SEBS on a variety of satellite sensors i.e. MODIS, Landsat, ASTER etc. Kwast, J. (2009) reported that various other researchers, who have implemented SEBS in PCRaster, checked and reported it as a robust modelling framework for running SEBS. In this research, since high temporal resolution was required (comparable to daily LAS fluxes), Terra/MODIS data was used to model surface fluxes. In the next sub-section, the acquisition and preparation of input data for SEBS is explained.
4.2.2.1. **LAND-SURFACE PARAMETERS FROM MODIS**

MODIS sensor onboard the Terra satellite has been designed to provide improved monitoring for land, ocean and atmosphere research. The design of the land imaging component combines characteristics of the Advanced Very High Resolution Radiometer (AVHRR) and the Landsat Thematic Mapper, adding spectral bands in the middle and longwave infrared (IR) and providing a spatial resolution of 250 metres, 500 metres, and 1 kilometre. Spectral channels for improved atmospheric and cloud characterisation have been included to permit both the removal of atmospheric effects on surface observations and the provision of atmospheric measurements (Justice C.O. et al., 1998). MODIS views the entire Earth surface every 1 to 2 days, scanning the Earth with a swath of 2000 square kilometres and acquiring data in 36 spectral bands with spatial resolution spanning from 250 metres to 1000 metres.
In order to use MODIS data as an input for SEBS, different data products provided by NASA’s Land Processes Distributed Active Archive Center (LPDAAC) were used. LPDAAC processes the raw data to remove radiometric and geometric errors to produce products at different processing levels. There are five levels of MODIS land products in order of increasing level of processing (Justice C.O. et al., 1998). Level-3 (L3) products are spatially re-sampled, averaged and/or temporarily composited to produce a single estimate of a geophysical variable for each grid location. Three types of MODIS L3 version 5 land products, namely MOD11A1, MOD43A3 and MOD13Q1, were acquired for the study year of 2010/11.

MODIS Land Surface Temperature and Emissivity (LST/E) products provide per-pixel temperature and emissivity values at 1000 metres resolution. Temperatures are extracted in Kelvin with a view-angle dependent algorithm applied to direct observations. This method yields 1 K accuracy for materials with known emissivities. The view angle information is included in each LST/E product. Emissivities are estimates derived from applying algorithm output to database information. The LST/E algorithms use MODIS data as input, including geolocation, radiance, cloud masking, atmospheric temperature, water vapour, snow, sea ice, vegetation indices and land cover. The temperature products in turn are key inputs to many of the high level MODIS products and provide data for global temperature mapping and change observation. The MOD11A1 product comprises the following Science Data Set (SDS) layers for daytime and night-time observations: LSTs, quality control assessments, observation times, view zenith angles, clear sky coverages, and bands 31 and 32 emissivities from
land cover types. The LST and emissivity data layers along with data quality (QC) information layers were extracted from MOD11A1 products and projected from native sinusoidal projection to geographic projection (GDA94) using GDAL (Geospatial Data Abstraction Library) command line tools in GNU/Linux shell scripting environment. GDAL is an open-source geospatial library for reading and writing raster geospatial data formats which presents a single abstract data model to the calling application for all supported formats. It may also be built with a variety of useful command-line utilities for data translation and processing. The QC science data set provides information on algorithm results that are viewable in a spatial context for each pixel. The QC information indicates if the algorithm results were nominal, abnormal, or if other defined conditions were encountered at the pixel level. The QC data was then used to check quality flags for LST and emissivity data to discard pixels of undesired quality.

Similarly, vegetation index data for SEBS input was prepared from MODIS vegetation indices product (MOD13Q1). MODIS vegetation indices products are designed to provide spatial and temporal comparisons of vegetation conditions. Blue, red, and near-infrared reflectances, are used to determine the MODIS daily vegetation indices. MODIS also includes a new Enhanced Vegetation Index (EVI) that minimises canopy background variations and maintains sensitivity over dense vegetation conditions. The EVI also uses the blue band to remove residual atmosphere contamination caused by smoke and sub-pixel thin clouds. The MODIS NDVI and EVI products are computed from atmospherically corrected bi-directional surface reflectances that have been masked for water, clouds, heavy aerosols, and cloud shadows. LPDAAC provides MOD13Q1 data every 16
days at 250-metre spatial resolution as a gridded L3 product in the Sinusoidal projection. Version-5 MOD13 vegetation indices are Validated Stage 2, meaning that accuracy has been assessed over a widely distributed set of locations and time periods via several ground-truth and validation efforts. MOD13Q1 data contains SDS layers on NDVI, EVI, blue, red, near-infrared and middle infrared reflectances, sun zenith angle, view angle and pixel quality. The NDVI and QC SDS layers were extracted and projected into geographical projection using GDAL tools. QC layer was then used to remove pixels of unwanted or bad quality.

Similarly, albedo data was prepared from MCD43A3 albedo product. MCD43A3 provides 500-metre data describing both directional hemispherical reflectance (black-sky albedo) and bi-hemispherical reflectance (white-sky albedo). MCD43A3 product contains 16 days of data provided in a level-3 gridded dataset in Sinusoidal projection. In preparation of MCD products, both Terra and Aqua data are used providing the highest probability for quality input data. MCD43A3 contains SDS layers on black-sky and white-sky albedos (BSA and WSA) for individual bands, and a broadband shortwave albedo. Data quality information associated with MCD43A3 product can be obtained from MCD42A2, which contains SDS layers BRDF albedo quality, snow albedo and BRDF albedo ancillary information. The SDS layer of shortwave albedo from MCD43A3 and BRDF albedo quality from MCD43A2 were extracted and projected from sinusoidal to geographic GDA94 system. Using the QC layers, the albedo data was prepared by any low quality of bad data value pixels. Figure 4.12 shows the flowchart of pre-processing steps for MODIS.
These pre-processed land surface parameters were then used to run the SEBS model. Additionally, meteorological data required by SEBS i.e. temperature, humidity, pressure, wind speed, was from the AWS installed near the LAS receiver at the study site. The output of the SEBS model consists of maps of soil heat flux, sensible heat flux, latent heat flux, relative evaporation, evaporative fraction and actual ET flux at the moment of satellite overpass. The results of remote-sensing-based flux modelling and comparison with LAS-derived fluxes is presented in the next chapter.
4.3. REMOTE-SENSING-BASED ROOT-ZONE SOIL MOISTURE

4.3.1. EXPONENTIAL FILTER

Microwave-based remote-sensing sensors (e.g. Aqua/AMSR-E, SMOS/MIRAS,) can provide some quantitative description of near-surface soil water content \( w_g \). However, in short-range and medium-range meteorological and hydrological modelling, root-zone soil moisture content \( w_2 \) is the main variable of interest which is often well related to the surface layer soil moisture through diffusion processes. However, no clear relationship between the regression coefficients and the characteristics of the site could be identified (Jackson, 1986). Assuming that hydrologic equilibrium conditions are satisfied, and provided soil properties are known, it is possible to estimate the profile soil moisture content from instantaneous surface observations. Many assimilation studies (reviewed in Chapter 3, section 3.2.2) have shown the potential of retrieval of \( w_2 \) from \( w_g \) observations. Albergel et al., (2008) provided some quality insights into the use of semi-empirical approach developed by Wanger et al., (1999) to retrieve the root-zone soil moisture from surface soil moisture simulations in France. In this objective, the possibility of using the exponential filter (Wagner et al., 1999) to model the root-zone soil moisture from remotely sensed surface soil moisture time-series of AMSR-E over the Murrumbidgee catchment is explored.

In a simplified two-layer water-balance approach, the \( w_2 \) can be estimated by convoluting the surface soil moisture time series with an exponential filter. Here, the remotely sensed surface-layer moisture is regarded as \( w_g \) and the second layer \( w_2 \) is considered as a ‘reservoir’ below.
With an assumption that the water flux between those two layers is proportional to the difference in soil moisture content between the two layers, a connection between \( w_2 \) and \( w_g \) can be established with the following equation:

\[
L \frac{d w_2(t)}{d t} = C \left[ w_g(t) - w_2(t) \right] \quad \text{Equation 59}
\]

Where \( L \) is the depth of the second layer, \( t \) represents time and \( C \) is an area-representative pseudo-diffusivity constant. Considering \( T=L/C \), \( w_2 \) can be expressed as follows:

\[
w_2(t) = \frac{1}{T} \int_{-\infty}^{t} w_g(\tau) \exp \left[ -\frac{t-\tau}{T} \right] d\tau \quad \text{Equation 60}
\]

Here, \( T \) represents characteristic time length. This parameter is considered as a surrogate parameter for all the processes affecting the temporal dynamics of soil moisture. \( T \) represents the time scale of soil moisture variation, in units of day. Since large time series are related in this approach, it is assumed that the soil hydraulic conductivity is constant while it may vary in reality. Remotely sensed data provide measurements at irregular time intervals, thus the continuous formulation of Equation 60 is replaced by a discrete equation (Wagner et al., 1999):

\[
SWI_m(t_n) = \frac{\sum_{t} ms(t_i) e^{-\frac{t_n-t_i}{T}}}{\sum_{t} e^{-\frac{t_n-t_i}{T}}} \quad \text{Equation 61}
\]
Where \( ms(t_i) \) is surface soil moisture estimated from remote sensing at time \( t_i \). Here, Wagner et al., (1999) replaced the discontinuous time series with the continuous parameter \( w_g(t) \). The quantity \( w_g(t) \) is replaced by the Soil Water Index (\( SWI_m \)). The \( SWI_m \) at time \( t_n \) is calculated if there is at least one measurement in the time interval \((t_n-T, t_n)\) and at least four measurements in the interval \((t_n-3T, t_n)\) (Pellarin et al., 2006). \( SWI_m \) is a trend indicator ranging from 0 to 1. Ceballos et al., (2005) validated Equation 61 against in-situ measurements in the semi-arid region of the Duero Basin in Spain. They found a statistically significant coefficient of determination \((R^2=0.75)\) and an RMSE of 0.022 \( m^3.m^{-3} \) when comparing the plant available water content values derived from scatterometer and area-averaged field measurements (0–100 centimetres). If a recursive formulation based on Stroud (1999) is applied, the exponential filter can be written as:

\[
SWI_{m(n)} = SWI_{m(n-1)} + K_n (ms(t_n) - SWI_{m(n-1)}) \quad \text{Equation 62}
\]

Where the gain \( K \) at time \( t_n \) is given by:

\[
K_n = \frac{1}{1 + \sum_{i} e^{\frac{(t_i-t_n)}{T}}} \quad \text{Equation 63}
\]

Or;

\[
K_n = \frac{K_{n-1}}{K_{n-1} + \sum_{i} e^{\frac{(t_i-t_{n-1})}{T}}} \quad \text{Equation 64}
\]

Here, the gain \( (K) \) ranges from 0–1. In presence of extensive temporal data gaps, Equation 64 tends toward unity. In that case, the
previous estimates are disregarded when new observations are obtained, and the new estimate takes on the value of the new observation. The recursive formulation can handle data more easily than the original exponential filter (Equation 61), as the only requirement for an update of the $SWI_m$ is the availability of a new $ms(t_n)$ observation and the time interval since the last observation $(t_n-t_{n-1})$.

4.3.2. DATA ACQUISITION

4.3.2.1. AMSR-E INSTRUMENT

The Advanced Microwave Scanning Radiometer (AMSR-E) instrument is a modified version of the AMSR instrument developed for the Japanese Advanced Earth Observing Satellite-II (ADEOS-II). AMSR-E is one of the six instruments (Figure 4.13) onboard the Aqua satellite, which was launched on 4 May 2002. AMSR-E is a passive microwave radiometer which measures radiation at six frequencies in the range 6.9–89 GHz with dual polarisation. It scans conically at a fixed incidence angle of 54.8 degrees across a 1445-kilometre swath, providing near-global coverage in two days or less. The spatial resolution at the surface varies from approximately 60 kilometres at 6.9 GHz to 5 kilometres at 89 GHz. The orbit of Aqua is sun-synchronous with equator crossings at 1:30 P.M. and 1:30 A.M. local solar time.
The main characteristics of the AMSR-E instrument are given in Table 4.4 below:

Table 4.4: AMSR-E instrument characteristics.

<table>
<thead>
<tr>
<th>Centre frequencies (GHz)</th>
<th>6.92</th>
<th>10.65</th>
<th>18.7</th>
<th>23.8</th>
<th>36.5</th>
<th>89</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth (MHz)</td>
<td>350</td>
<td>100</td>
<td>200</td>
<td>400</td>
<td>1000</td>
<td>3000</td>
</tr>
<tr>
<td>Sensitivity (K)</td>
<td>0.3</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
<td>1.1</td>
</tr>
<tr>
<td>IFOV (km)</td>
<td>76 x 44</td>
<td>49 x 28</td>
<td>28 x 16</td>
<td>31 x 18</td>
<td>14 x 8</td>
<td>6 x 4</td>
</tr>
<tr>
<td>Sample spacing (km)</td>
<td>10 x 10</td>
<td>10 x 10</td>
<td>10 x 10</td>
<td>10 x 10</td>
<td>10 x 10</td>
<td>5 x 5</td>
</tr>
<tr>
<td>Integration time (ms)</td>
<td>2.6</td>
<td>2.6</td>
<td>2.6</td>
<td>2.6</td>
<td>2.6</td>
<td>1.3</td>
</tr>
<tr>
<td>Main beam efficiency (%)</td>
<td>95.3</td>
<td>95</td>
<td>96.3</td>
<td>96.4</td>
<td>95.3</td>
<td>96</td>
</tr>
<tr>
<td>Beamwidth (deg)</td>
<td>2.2</td>
<td>1.4</td>
<td>0.8</td>
<td>0.9</td>
<td>0.4</td>
<td>0.18</td>
</tr>
<tr>
<td>Antenna diameter (m)</td>
<td>1.6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scan period (s)</td>
<td>1.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Antenna offset angle (deg)</td>
<td>47.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earth-incidence angle (deg)</td>
<td>54.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orbit altitude (km)</td>
<td>705</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Swath width (km)</td>
<td>1445</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orbit type</td>
<td>Sun-synchronous, 98.2 inclination, 1:30 pm equator crossing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orbit period (min)</td>
<td>98.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
For AMSR-E, global swath coverage is achieved every two days or less, separately for ascending and descending passes, except for a small region near the poles. However, at the equator, any point on the surface falls within a descending AMSR-E swath approximately every other day, with occasional daily or every third day sampling (Figure 4.14).

![AMSR-E coverage](http://aqua.nasa.gov)

Figure 4.14: AMSR-E coverage (http://aqua.nasa.gov).

### 4.3.2.2. AMSR-E Soil Moisture Data

The AMSR-E soil moisture algorithm operates within the overall AMSR-E processing scheme (Joint AMSR Science Team, 2001). AMSR-E raw data are received in the USA and transmitted to the NASDA Earth Observations Center (EOC) in Japan for Level 1A processing, and then routed to the US AMSR-E Science Information Processing System (SIPS) for calibration and higher level product generation. At the SIPS facilities, the data are converted into geophysical data products that are achieved at the
National Snow and Ice Data Center (NSIDC) Distributed Active Archive Center (DAAC) in Boulder, CO. In Level 2A processing, the data are quality checked, co-registered, resolution-matched at four resolutions referred to as Res 1, 2, 3, and 4, and output as half-orbit data file granules. The Level 2A data contain as a subset the original Level 1A data. These Level 2A data are used in soil moisture algorithm processing to generate output Level 2B and Level 3 soil moisture and ancillary data products written in HDF-EOS format (Figure 4.15). The input Level 2A data are quality controlled and remapped to an Earth-fixed grid. The output Level 2B soil moisture data consist of half-orbit data granules that are composited in the Level 3 processing into daily global grids, separately for ascending and descending half-orbits. The grid used is the 25-kilometre Equal-Area Scalable Earth-grid (EASE-grid), with a global cylindrical, equal-area projection true at 30 N and 30 S. This is one of a family of grids defined by the NSIDC. The EASE-grid is used for the AMSR-E soil moisture products for continuity of format with the historical global gridded Special Sensor Microwave/Imager (SSM/I) data archived at the NSIDC.

Daily AMSR-E-derived Level 3 soil moisture data were acquired for a period of three years (2007–2011) from NSIDC. Each HDF-EOS file contains core metadata with QA metadata flags that are set by SIPS at the Global Hydrology and Climate Center (GHCC) prior to delivery to NSIDC. Three levels of quality assessment (QA) are conducted with the AMSR-E Level 2 and 3 products: automatic, operational, and science QA. If a product fails QA, SIPS does not send the granule to NSIDC until it is reprocessed. Level 3 products that fail QA are not delivered and archived at NSIDC.
Figure 4.15: Soil moisture algorithm processing flow (Njoku et al., 2005).

The AMSR-E soil moisture algorithm uses Polarisation Ratios (PR), sometimes called normalised polarisation differences of the AMSR-E channel brightness temperatures. PR is the difference between the vertical and horizontal brightness temperatures at a given frequency, divided by their sum. This effectively eliminates or reduces surface temperature effects, which is necessary since no dynamic ancillary surface temperature data are input into the algorithm. The algorithm first computes a vegetation/roughness parameter \( g \) using PR 10.7 GHz and PR 18.7 GHz, plus three empirical coefficients. Soil moisture is then computed using departures of PR 10.7 GHz from a baseline value, plus four additional coefficients. The baseline values for PR 10.7 GHz are based on monthly minima at each grid cell over an annual cycle (Njoku and Chan, 2005).

The vegetation/roughness parameter \( g \) incorporates effects of vegetation and roughness together, because both have the same functional form (exponential) in their influence on the normalised polarisation
differences in the simplified model used in the retrieval algorithm. The parameter $g$ may be interpreted as equivalent vegetation water content with units of kg.m$^{-2}$. In a desert with no vegetation, any value of $g$ greater than zero is due to roughness only. The value of $g$ reflects the influence of roughness on the polarisation ratio as if equivalent vegetation of amount $g$ (kg.m$^{-2}$) were present. If the surface were smooth everywhere, then $g$ would equal the vegetation water content in kg.m$^{-2}$, since the roughness contribution would be zero. Vegetation water content and roughness cannot be determined independently from $g$, and it is computed primarily as a lumped correction factor for the soil moisture retrieval (Njoku and Chan, 2005).

### 4.3.2.3. In-Situ Observations

To explore the potential of root-zone soil moisture estimation from surface data time series using an exponential filter, an increased density of long-term observations is required. For this purpose, in-situ observations from selected sites from Murrumbidgee Soil Moisture Monitoring Network (MSMMN) were used (Smith et al., 2012). MSMMN is a network of soil moisture and micro-meteorology monitoring sites for calibration and validation of soil moisture remote sensing, modelling and data assimilation (Figure 4.16).
In 2003, the Murrumbidgee Soil Moisture Monitoring Network evolved into an extensive soil moisture monitoring experiment with 38 monitoring sites (Walker et al., 2008). Due to a change in technology, the CS615 water content reflectometers installed at earlier sites and calibrated for Murrumbidgee soils (Western et al., 2000) were not available at the time of network expansion. The Campbell Scientific CS616 water content reflectometer that replaced the CS615 sensor was therefore used in its place. Consequently, the CS616 sensors required a site-specific calibration for the Murrumbidgee soils as the manufacturer’s calibration (Campbell Scientific Inc., 2002) was found to be insufficient, with errors as large as 15% v/v. Therefore, a detailed calibration of sensors was performed and results reported by Yeoh N. et al., (2008). The CS616 sensors are observing data on three different depths (0–30 cm, 30–60 cm, 60–90 cm).

Figure 4.16: Soil moisture/temperature and suction observations sites in MSMMN.
The moisture data logged by the sensors is archived at the OZNet server and can be obtained from the data server. The metadata and ancillary information including soil laboratory analysis can also be acquired. Soil moisture time-series for the study period 2007–11 was downloaded from the archive. A description of the selected soil moisture measurement sites is given in Table 4.5. Observations are taken every 30 minutes, and these have been sub-sampled at the time of Aqua overpasses for Australia to make them comparable to soil moisture derived from the co-located AMSR-E pixel. In the next chapter, the results of the comparison between in-situ and AMSR-E-retrieved soil moisture are discussed in detail.
Table 4.5: Details of selected soil moisture measurement sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
<th>Latitude (WGS84)</th>
<th>Longitude (AHD)</th>
<th>Elevation (AHD)</th>
<th>Landuse</th>
<th>Soil Type</th>
<th>Annual Precip. (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M6</td>
<td>Hay AWS</td>
<td>-34.55</td>
<td>144.85</td>
<td>89</td>
<td>Grazing</td>
<td></td>
<td>368</td>
</tr>
<tr>
<td>Y13</td>
<td>Widgiewa</td>
<td>-35.09</td>
<td>146.31</td>
<td>121</td>
<td>Grazing</td>
<td></td>
<td>439</td>
</tr>
<tr>
<td>K12</td>
<td>Samarra</td>
<td>-35.23</td>
<td>147.49</td>
<td>220</td>
<td>Crop/Grazing</td>
<td>Silty Loam</td>
<td>596</td>
</tr>
<tr>
<td>M7</td>
<td>Griffith Aerodrome</td>
<td>-32.25</td>
<td>146.87</td>
<td>137</td>
<td>Grazing</td>
<td>Silty Loam</td>
<td>437</td>
</tr>
<tr>
<td>Y5</td>
<td>Dry Lake</td>
<td>-34.73</td>
<td>146.29</td>
<td>136</td>
<td>Cropping</td>
<td>Loamy Sand</td>
<td>435</td>
</tr>
<tr>
<td>Y6</td>
<td>Colleambally</td>
<td>-34.84</td>
<td>145.87</td>
<td>121</td>
<td>Irrigated Crop</td>
<td></td>
<td>411</td>
</tr>
</tbody>
</table>
5. **REMOTE SENSING FOR EVAPOTRANSPIRATION MODELLING**

In this chapter, the results of heat flux calculation and energy balance from large aperture scintillometer (LAS) are presented. Further, remote-sensing-based flux estimation using the energy balance model (SEBS) with Terra/MODIS data and the validation of the SEBS-derived fluxes is discussed.

**5.1. HEAT FLUXES ESTIMATION USING SCINTILLOMETER**

In order to calculate sensible heat flux for energy balance closure using LAS, scintillation data was prepared in combination with meteorological records from AWS and the three WSNs as described in Chapter 4, section 4.1.1.4. The sensible heat flux was calculated in WinLAS at a half-hour time-step. For solving the energy balance, soil heat flux measurements from a Huskeflux plate and net radiation from the net radiometer at the same time-step as the LAS were used (Figure 5.1). The latent heat flux was then estimated by solving an energy balance of fluxes measured by these instruments and $H$ calculated using LAS. Daily diurnal net radiation and soil heat flux series is presented in Figure 5.1 below. Summertime maximum net radiation peaks near 800 W/m$^2$, while the maximum wintertime net radiation peaks at 400–500 W/m$^2$. 
Figure 5.1: Daily daytime diurnal net radiation and soil heat flux from Jan 2010 till Feb 2011.
A continuous time-series of energy balance components \((R_n, G, H_{LAS})\) was therefore obtained for the entire experiment length. Figure 5.2 and Figure 5.3 show a signature sinusoidal trend of the variation of energy balance components during a typical summer (1 February 2010) and winter day (6 June 2010) respectively. The half-hourly net radiation, soil heat, sensible heat and latent heat flux (residual energy balance term) values describe the variation observed by these fluxes follows the theoretical sine curve. The grey areas of the plots indicate time before sunrise and after sunset when the atmosphere becomes stable and the derived turbulent fluxes become meaningless.

**Figure 5.2:** LAS-derived \(H\) in the energy balance cycle for 1 February 2010.
Figure 5.3: LAS-derived $H$ in the energy balance cycle for 6 June 2010.

The day time $H$ on 1 February 2010 ranges from $\sim 10$ to 298 W/m$^2$, having a mean value of 135 and standard deviation of 89. $R_n$ ranges from 162 to 781 W/m$^2$, with a mean value of 498 and standard deviation of 176. The latent heat flux varies from 153 to 483 W/m$^2$ with a mean value of 338 W/m$^2$, suggesting high latent flux on a summer day when the temperature was 37°C. Similarly, the day time $H$ on 6 June 2010 varies from 16 to 144 W/m$^2$ with a mean value of 77 W/m$^2$ and $R_n$ ranges from 89 to 322 W/m$^2$. This results in latent heat flux from 64 to 203 W/m$^2$ with a mean value of 155 W/m$^2$, suggesting a realistic flux value on a winter day (temperature of 15°C). The change in the intensity of fluxes between summer and winter seasons is also evident from the above figures. This valid energy balance closure suggests that for current configuration, the LAS has performed well for the purpose of heat flux estimation, provided the data is filtered for bad or missing values generated by various meteorological conditions (i.e. cloud cover, rainfall, etc) or sensor errors.
Figure 5.4 and Figure 5.5 show two graphs of $R_n$, $G$, $H$, and $LE$ for two separate weeks, in summer (December 2009) and winter (May 2010). During the summer week, average maximum net radiation is 780 W/m$^2$, while average maximum net radiation is 400 W/m$^2$ during the winter week. Both the graphs show consistent partitioning with $H$ being around 40% in summer and 35% in winter. A noticeable difference was observed between $G$ in summer (around 4–5%) and in winter (18%) due to factors such as excessive irrigation and high density of canopy in the summer. The increase in winter soil heat flux can also be observed in Figure 5.1 above. Similarly, the average maximum latent heat flux is observed to be about 56% during the week in summer and 47% during the week in winter. An example of complete LAS-derived energy balance is shown in Figure 5.6, while similar graphs for the entire length of the experiment are presented in Appendix-A.
Figure 5.4: Fluxes time-series for a week in summer (December 2009).

Figure 5.5: Fluxes time-series for a week in winter (May 2010).
Figure 5.6: A comparison of wintertime and summertime energy balance fluxes.
5.1.1. Sensitivity of Distributed Weather Data on Sensible Heat Flux

One common setting for an LAS-based experiment includes a meteorological station (AWS) usually installed at the receiver end to generate required ancillary data (Figure 4.5 and Figure 4.6), which is hereafter referred to as standard configuration. In this experiment, the addition of three wireless meteorological stations (as described in Chapter 4, section 4.1.1.4) along the path-length of the scintillometer allowed us to test the sensitivity of micro-meteorological variations occurring within the path-length of the LAS on sensible heat flux calculations. The three wireless stations equipped with similar sensors provided meteorological information at the same time-steps. The data from all three stations was collected and collated and processed with the same method as the AWS. After time-step-based joins were performed, $H$ was calculated three times by replacing the AWS reading (wind speed, temperature, humidity, pressure etc) with three WSN stations successively. In this way, the four $H$ results form a scenario where the effect of moving the weather station along the LAS path-length on the sensible heat flux calculations can be studied.

Since none of these $H$ values can be considered as absolute real, one-way between groups ANOVA was performed to check the significance of variances that occurred in resultant flux values owing to variation in the location of meteorological stations. Table 5.1 shows a highly significant effect of location of meteorological station on flux value at the $p<0.05$ level for the three conditions ($F(3, 18104) = 19.636, p = 0.000$). The systematic or explained variance in ANOVA analysis is the variable caused
due to independent variable i.e. path-length. The ‘Between Groups’ field in Table 5.1 shows that the variance between the groups of calculated $H$ is statistically significant.

<table>
<thead>
<tr>
<th>Flux Value</th>
<th>Sum Squares</th>
<th>of</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>568701.560</td>
<td>3</td>
<td>189567.187</td>
<td>19.636</td>
<td>.000</td>
</tr>
<tr>
<td>Within Groups</td>
<td>174775847.504</td>
<td>18104</td>
<td>9653.991</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>175344549.064</td>
<td>18107</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

It cannot be concluded that the means of which of these groups $H_{Eko1}$, $H_{Eko2}$ and $H_{Eko3}$ are significantly different from each other. Figure 5.7 shows the mean plot with 95% confidence interval. It can be seen that Eko2 WSN station data produced the greatest difference in $H$ results compared to the standard configuration of AWS. The means of $H_{AWS}$ and $H_{Eko2}$ appear to be approximately 10 W/m$^2$ apart, whereas no significant difference was observed between the means of $H_{AWS}$ and $H_{Eko1}$ and $H_{Eko2}$ and $H_{Eko3}$ independently due to the small variation in path-length. The standard deviations were relatively constant across the four scenarios.
Figure 5.7: Mean plot of $H_{AWS}$, $H_{Eko1}$, $H_{Eko2}$ and $H_{Eko3}$ with 95% confidence interval.

Hence, the location of the meteorological station along the path-length of the scintillometer can result in a huge variance in the sensible heat flux calculations. One automatic weather station may not be representative of the actual flux occurring in the field, especially for longer path-lengths. This implies that moving the AWS further along the stretched path-length will generate statistically significant differences in sensible heat flux and eventually influence the whole energy balance closure.

The F value shows that all four setups (locations of AWS) are not equally effective on the $H$ results, but it does not tell which of these four scenarios differ from one another. Tukey’s HSD (Honestly Significant Difference) test is a Post-ANOVA Pair-Wise comparison procedure that allows answering this question (Yandell, B.S., 1997). Table 5.2 shows the result of multiple comparisons between groups using Tukey’s test. The results show that the mean of sensible heat flux calculations from $H_{AWS}$
and $H_{Eko1}$ are not significantly different from each other ($p=0.423$). And, the means of $H_{Eko2}$ and $H_{Eko3}$ are also not significantly different from each other ($p=0.800$). Whereas, $H_{AWS} - H_{Eko2}$, $H_{AWS} - H_{Eko3}$, $H_{Eko1} - H_{Eko2}$ and $H_{Eko1} - H_{Eko3}$ are significantly different from each other ($p < 0.001$), while the standard deviations remained constant. These pairwise comparisons are plotted in Figure 5.8 below.
Table 5.2: Multiple comparisons using Tukey’s Post Hoc test.

<table>
<thead>
<tr>
<th>Value</th>
<th>Tukey HSD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(I)</td>
</tr>
<tr>
<td></td>
<td>Group</td>
</tr>
<tr>
<td>H_AWS</td>
<td>H_Eko1</td>
</tr>
<tr>
<td></td>
<td>H_Eko2</td>
</tr>
<tr>
<td></td>
<td>H_Eko3</td>
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<td></td>
<td>H_Eko2</td>
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<tr>
<td></td>
<td>H_Eko3</td>
</tr>
<tr>
<td>H_Eko2</td>
<td>H_AWS</td>
</tr>
<tr>
<td></td>
<td>H_Eko1</td>
</tr>
<tr>
<td></td>
<td>H_Eko3</td>
</tr>
<tr>
<td>H_Eko3</td>
<td>H_AWS</td>
</tr>
<tr>
<td></td>
<td>H_Eko1</td>
</tr>
<tr>
<td></td>
<td>H_Eko2</td>
</tr>
</tbody>
</table>

* The mean difference is significant at the 0.05 level.

The graphical representation (Figure 5.8) of the above table demonstrates that the variance is increased as we move away from the standard configuration and hence there is a greater need of capturing this micro-meteorological divergence. The plot implies that in this entire exercise, only Eko2 and Eko3, and, Eko1 and AWS stations result in no mean difference in the final sensible heat flux output. Therefore, it is adequate to use only one station (per case) in these cases, while all others will have a significantly different effect on the H results and cannot substitute each other.
Figure 5.8: Plot of pairwise comparison between ANOVA groups.

In this experiment (path-length 1400 metres), the meteorological conditions differed enough towards the centre of the LAS beam to produce a mean difference of $\sim 14 \text{ W/m}^2$ in the sensible heat flux. The level of under- and over-estimate can be seen in lower bound and upper bound columns of Table 5.2 above.

The standard configuration of one automatic weather station would produce a single flux result which may not be representative of the entire field’s conditions. To develop a graphical understanding of how much the sensible heat flux result diverges when the location of the
meteorological station is changed along the path-length, the difference of \( H \) resulting from the three Eko wireless stations and AWS are plotted in Figure 5.9 below.

![Figure 5.9: Difference in \( H \) by moving meteorological station.](image)

**Figure 5.9**: Difference in \( H \) by moving meteorological station.

Figure 5.9 shows the instantaneous difference between \( H \) resulting from Eko1, Eko2, Eko3 and AWS for the entire time-series. As the pairwise comparisons confirm, there is not a significant difference between the effect of Eko1 and AWS of sensible heat flux which can be seen in the plot. However, the underestimate of \( H_{AWS} \) from \( H_{Eko2} \) reached up to a 100 W/m\(^2\) in some instances. A 50–100 W/m\(^2\) difference in sensible heat flux can result in a 1.25–2.5 mm.d\(^{-1}\) overestimate in daily ET flux and affect the whole water balance. Similar to \( H_{Eko2} \), \( H_{Eko3} \) saw a difference as high as 50
$W/m^2$. This means that the standard configuration with one AWS at the corner of the field never represented the actual state of flux occurring in the field. Moreover, the difference is highly significant and cannot be ignored if the path length of the LAS experiment is stretched above a few hundred metres. The Eko2 WSN station was placed close to the centre of the beam and produced the largest difference in sensible heat flux output. Therefore, it is recommended to have an AWS placed at the centre of the beam, or preferably have a network of stations distributed along the stretch of large path-length.
5.2. **Actual Evapotranspiration using SEBS Model**

In order to model land surface fluxes from satellite data, Terra/MODIS imagery for the study period 2010/11 was used. The methodology of pre-processing raw MODIS data to compute land surface parameters (temperature, albedo, emissivity and NDVI) required for SEBS modelling was discussed in Chapter 4, section 4.2.2.1. After performing the quality flag test for pixels quality, 22 MODIS images were pre-processed for SEBS input. SEBS requires three sets of inputs: (1) land surface products derived from remote-sensing data, (2) meteorological parameters at a reference site, and, (3) radiation data. The LAS site had been instrumented with all the required sensors, therefore the second and third set of data for SEBS input were available for the study site. The algorithm was implemented in PCRaster Library (Karssenberg et al., 2007). Consequently, the energy balance terms, relative evaporation, evaporative fraction and ET fluxes were derived for the Murrumbidgee catchment.

The output of the SEBS model consists of maps representing net radiation, soil heat flux, sensible heat flux, latent heat flux, relative evaporation, evaporative fraction and actual ET flux at the moment of satellite overpass. Figure 5.10 and Figure 5.11 show spatial variation of sensible heat flux and latent heat flux over the Murrumbidgee catchment on 6 January 2011.
Appendix-B contains all maps of sensible heat flux and latent heat flux for the study period of 2010/11. The validation of these fluxes with LAS-derived surface fluxes will be discussed in the next section.

![Sensible heat flux over the Murrumbidgee catchment on 6 January 2011.](image)

**Figure 5.10**: Sensible heat flux over the Murrumbidgee catchment on 6 January 2011.

![Latent heat flux over the Murrumbidgee catchment on 6 January 2011.](image)

**Figure 5.11**: Latent heat flux over the Murrumbidgee catchment on 6 January 2011.

### 5.2.1. **Spatial Variation of Actual Evapotranspiration**

Spatial variation of actual $ET$ was obtained using SEBS for the entire study period of 2010/11. On 5 February 2010, the spatial actual $ET$
reached a maximum of 10 mm/d, while on 9 March it ranged from 0.3–7.7 mm/d with standard deviations of 1.98 and 1.74 respectively.

Similarly, the spatial variation of $ET$ across the catchment on 18 March and 19 April 2010 can be seen in Figure 5.13(a) and Figure 5.13(b) respectively. On 18 March 2010, the $ET$ ranged from 0.9–6.1 mm/d with a standard deviation of 1.42 and mean value of 2.1 mm/d. On 19 April 2010,
actual ET ranged from 0.1–6.2 mm/d with a 1.27 mean and a standard deviation of 0.97.

![Map of ET on 18 March 2010](image1)

![Map of ET on 19 April 2010](image2)

**Figure 5.13**: Daily actual ET on (a) 18 March 2010, and (b) 19 April 2010.

The spatial actual ET varied from 0.77–3.48 mm/d on 10 September 2010 having a mean value of 1.16 and standard deviation of 0.9. While on 15 September 2010, ET ranged from 0.56–3.76 mm/d with a standard deviation of 0.95 from the mean (0.98 mm/d). Figure 5.14 shows the maps of spatial actual ET on 10 and 15 September 2010 respectively.
Figure 5.14: Daily actual ET on (a) 10 Sep 2010, and (b) 15 Sep 2010.

The spatial map of actual ET on 10 and 19 October 2010 is presented in Figure 5.15 below. On 10 October 2010, the ET varied from 0.8–6.2 mm/d with a standard deviation of 1.44 from the mean value of 2.15 mm/d. And on 19 October 2010, daily ET ranged from 0.7–5.9 mm/d and had a mean value of 2.0 and standard deviation of 1.38.
Figure 5.15: Daily actual ET on (a) 10 Oct 2010, and (b) 19 Oct 2010.
Figure 5.16 shows the spatial map of actual ET on 6 and 13 December 2010. At the peak of summer, the actual ET ranged from 0.4–8.9 and from 1.2–10 mm/d on 6 and 13 December respectively. Statistics show the mean values of 3.5 and 4.05 mm/d and standard deviations of 1.98 and 2.2 for 6 and 13 December respectively.

Similarly, on 22 December 2010, the spatial actual ET ranged from 1.4–8.9 mm/d with a standard deviation of 2.18 from the mean value (3.9 mm/d). While on 4 January 2011, the maximum ET
reached 9.7 mm/d with a mean value of 3.9 mm/d and standard deviation of 2.14. Figure 5.17 shows the map for 22 December 2010 and 4 January 2011.

![Map showing actual ET values for 22 December 2010 and 4 January 2011.](image)

**Figure 5.17**: Daily actual ET on (a) 22 Dec 2010, and (b) 4 Jan 2011.

Actual ET maps for 7 January 2011, 11 January 2011, 20 January 2011, and 22 January 2011 are shown in Figure 5.18 below. On 7 January 2011, the spatial actual ET varied from 1.6–9.7 mm/d with a standard deviation of 1.63 from the mean ET value of 3.9. On 11 January 2011, the ET ranges from 0.4–9.5 mm/d with a standard deviation of 1.59 from the
mean value of 3.83. The maximum actual $ET$ on 20 January 2011 was 9.9 mm/d, while the mean $ET$ was 4.0 mm/d with a standard deviation of 2.18. Likewise, on 22 January 2011, the $ET$ varied from 1.6–8.96 mm/d across the catchment and had a mean value and standard deviation of 3.53 and 1.99 respectively.

Figure 5.18: Daily actual $ET$ on (a) 7 Jan 2011, (b) 11 Jan 2011, (c) 20 Jan 2011, and (d) 22 Jan 2011.

Figure 5.19 below shows the maps of actual $ET$ on 23 January 2011, 29 January 2011, 30 January 2011, and 15 February 2011. On 23 January 2011, the spatial actual $ET$ ranged from 1.0–9.9 mm/d with a standard deviation of 2.12 from the mean $ET$ value of 3.85. On 29 January 2011, the $ET$ ranged from 1.7–9.8 mm/d and had a standard deviation of 1.86 from the mean value of 3.95. The maximum actual $ET$ on 30 January 2011 was 7.76 mm/d while the mean $ET$ was 3.15 mm/d with a standard deviation of 1.38. Similarly, on 15 February 2011, the $ET$ varied from 1.6–8.2 mm/d and had a standard deviation of 1.84 from the mean value of 3.15 mm/d.
Statistics for all resulting maps of actual ET for the study period are shown in Table 5.3 below.

![Maps of actual ET](image)

**Figure 5.19**: Daily actual ET on (a) 23 Jan 2011, (b) 29 Jan 2011, (c) 30 Jan 2011, and (d) 15 Feb 2011.
<table>
<thead>
<tr>
<th>Date</th>
<th>MAX</th>
<th>MIN</th>
<th>MEAN</th>
<th>STD.Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>5/2/2010</td>
<td>10.0</td>
<td>0.2</td>
<td>4.7</td>
<td>1.98</td>
</tr>
<tr>
<td>9/3/2010</td>
<td>7.7</td>
<td>0.3</td>
<td>3.2</td>
<td>1.74</td>
</tr>
<tr>
<td>18/03/2010</td>
<td>6.1</td>
<td>0.9</td>
<td>2.1</td>
<td>1.42</td>
</tr>
<tr>
<td>19/04/2010</td>
<td>6.2</td>
<td>0.1</td>
<td>1.27</td>
<td>0.97</td>
</tr>
<tr>
<td>10/9/2010</td>
<td>3.48</td>
<td>0.77</td>
<td>1.16</td>
<td>0.9</td>
</tr>
<tr>
<td>15/09/2010</td>
<td>3.76</td>
<td>0.56</td>
<td>0.98</td>
<td>0.95</td>
</tr>
<tr>
<td>10/10/2010</td>
<td>6.2</td>
<td>0.8</td>
<td>2.15</td>
<td>1.44</td>
</tr>
<tr>
<td>19/10/2010</td>
<td>5.9</td>
<td>0.7</td>
<td>2.0</td>
<td>1.38</td>
</tr>
<tr>
<td>6/12/2010</td>
<td>8.9</td>
<td>0.4</td>
<td>3.5</td>
<td>1.98</td>
</tr>
<tr>
<td>13/12/2010</td>
<td>10.0</td>
<td>1.2</td>
<td>4.05</td>
<td>2.2</td>
</tr>
<tr>
<td>22/12/2010</td>
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<td>1.4</td>
<td>3.9</td>
<td>2.18</td>
</tr>
<tr>
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<td>0.8</td>
<td>3.9</td>
<td>2.14</td>
</tr>
<tr>
<td>7/1/2011</td>
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<td>1.6</td>
<td>3.9</td>
<td>1.63</td>
</tr>
<tr>
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<td>9.5</td>
<td>0.4</td>
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</tr>
<tr>
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<td>1.2</td>
<td>4.0</td>
<td>2.18</td>
</tr>
<tr>
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<td>1.6</td>
<td>3.53</td>
<td>1.99</td>
</tr>
<tr>
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<td>3.85</td>
<td>2.12</td>
</tr>
<tr>
<td>29/01/2011</td>
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<td>1.7</td>
<td>3.95</td>
<td>1.86</td>
</tr>
<tr>
<td>30/01/2011</td>
<td>7.7</td>
<td>0.6</td>
<td>3.15</td>
<td>1.38</td>
</tr>
<tr>
<td>15/02/2011</td>
<td>8.2</td>
<td>1.6</td>
<td>3.15</td>
<td>1.84</td>
</tr>
</tbody>
</table>

5.2.1.1. **Validation using Scintillometer-Derived Fluxes**

In order to gain confidence in the accuracy of remote-sensing-based \( ET_a \) modelling, the surface fluxes from the LAS experiment were used to validate the remote-sensing-derived fluxes. Since LAS provides path-averaged heat fluxes over an area comparable with satellite pixel scale, this provides an excellent basis for direct calibration and validation of remote-sensing-based energy balance components. The scintillometer data was recorded at half-hourly time stamps, while the remote-sensing
image provided instantaneous surface flux at the time of satellite overpass. Therefore, based on the overpass time of the Terra satellite, surface fluxes from LAS output were extracted for comparison purposes. The pixel values for all LE, H and ET images for 2010/11 were also extracted for the LAS location in the MIA (Chapter 3, Figure 4.6).

a. **Net Radiation and Soil Heat Flux**

Figure 5.20 shows the relationship between in-situ and SEBS-derived net radiation flux. Direct measurement values from net radiometer show a good correlation ($R^2$ of 0.667, RMSE = 74.2) with remote-sensing results. The discrepancies in SEBS-derived $R_{net}$ increase with higher net radiation values. The slope of the linear fit line in comparison with the 1:1 line shows that the underestimate from ground data increases with higher net radiation values.

![Figure 5.20: Linear fit between SEBS and in-situ net radiation.](image)

**Figure 5.20**: Linear fit between SEBS and in-situ net radiation.
Soil heat flux from heat flux plates showed a strong correlation ($R^2$ of 0.89, RMSE=10.17) with SEBS modelled $G_0$. The slope of linear fit line shows that SEBS overestimates soil heat flux as the soil heat flux increases. In-situ $G_0$ and $R_{net}$ from soil heat flux plates and net radiometers provide the most direct calibration/validation, therefore it is recommendable that a localised calibration and/or validation is performed especially for larger study areas in order to increase model performance. Nevertheless, the SEBS-derived $R_{net}$ and $G_0$ correlated very well with in-situ data, considering that net radiometers and heat flux plates only provide point values. Figure 5.21 shows the linear fit between SEBS and in-situ soil heat flux.

Figure 5.21: Linear fit between SEBS and in-situ soil heat flux.

b. SENSIBLE HEAT FLUX

Figure 5.22 shows the correlation plot of sensible heat flux obtained from SEBS and scintillation data-derived $H$. A good correlation ($R^2$ of 0.77, RMSE=33.1) was obtained for sensible heat flux. However, the residuals were comparatively higher due to model-induced errors in LAS
and SEBS methodologies. The strong correlation suggests that ground validation of large pixel-based energy balance is more recommendable with the LAS because of a better match between pixel size and path-length of LAS. In this study, the path-length of LAS was selected to compare well with the Terra/MODIS pixel size to get the best possible validation of sensible heat flux. The similarity of slopes of the 1:1 line and linear fit line in Figure 5.22 suggests that LAS provided valuable validation for sensible heat flux at MODIS pixel size.

![Figure 5.22: Linear fit between SEBS and LAS-derived sensible heat flux.](image)

**c. Latent Heat Flux and Daily Actual Evapotranspiration**

The LAS-derived latent heat flux showed a strong correlation ($R^2$ of 0.9122, RMSE=40.2) with SEBS modelled LE. Figure 5.23 shows the linear fit between SEBS and LAS-based LE. The slopes of the fit line and 1:1 show that SEBS performed very well in order to estimate latent heat flux. Since LE is a residual term in the energy balance, its accuracy is highly influenced...
by the accuracy of sensible heat flux estimation. Accurate sensible heat flux estimation resulted in latent heat flux with much improved accuracy.

![Linear Fit Between SEBS and LAS-Derived Latent Heat Flux](image)

**Figure 5.23:** Linear fit between SEBS and LAS-derived latent heat flux.

Similarly, the resulting daily actual ET from SEBS showed a very strong correlation with LAS-derived ET ($R^2$ of 0.91, RMSE=0.8). Figure 5.24 shows the linear fit between SEBS and LAS-based ET. The similarity of slopes of the linear fit and 1:1 line suggest that the model performed very well in comparison with path-averaged ET from LAS. The strong correlation is due to the fact that LAS-derived flux values are areally-averaged to the MODIS pixel size, which helped in accurate sensible heat flux estimation. Consequently, the entire energy balance improved significantly enough to result in a strong correlation of 0.91.
Figure 5.24: Linear fit between SEBS and LAS-derived daily evapotranspiration.
6. MODELLING ROOT-ZONE SOIL MOISTURE WITH AMSR-E

In this chapter, results and discussions are presented on the performance of the simplified exponential filter model for root-zone soil moisture using AMSR-E-derived surface moisture dataset.

6.1. CALIBRATING EXPONENTIAL FILTER MODEL WITH IN-SITU DATA

To explore the potential of extracting root-zone moisture dynamics using an exponential filtering on AMSR-E-retrieved surface soil moisture, six ground calibration sites scattered across the Murrumbidgee catchment were selected (see Chapter 4, section 4.3.2.3). The local soil moisture observations at depths ranging between 20–50 centimetres are significantly correlated to root-zone moisture integrated over the whole profile (Albergel et al., 2008). Therefore, soil moisture observations at the study sites were acquired for surface layer and a deeper layer of 30 centimetres. The data is recorded at half-hourly time-steps by Campbell Scientific CS615/CS616 sensors. Similarly, daily AMSR-E-derived Level3 soil moisture data was acquired for a period of three years (2007–2011) from NSIDC data achieve. The AMSR-E pixels values for the entire time-series were extracted for each ground station site. Based on the overpass time of Aqua satellite, the in-situ (half-hourly) data was also sub-setted and a time stamp-based join for the entire data series was performed.
Figure 6.1 shows the plot of AMSR-E-derived soil moisture plotted against surface layer moisture measured at all sites. The red line represents the measured moisture while the green dots represent the corresponding AMSR-E pixel value for the particular site.
Figure 6.1: Plot of AMSR-E-retrieved soil moisture series with surface layer moisture at six selected sites.
Figure 6.2: Volumetric soil moisture at surface layer and 30 cm observed at six selected sites.
6.1.1. **Cross-Correlation Between Surface and Root-Zone Moisture**

The surface soil moisture is often well correlated with root-zone moisture which can be observed in Figure 6.2 above. How well the surface soil moisture feeds the root-zone depends upon various factors including terrain, soil type and texture, vegetation context, soil water availability, ET rate etc. Before estimating root-zone soil moisture from ASMR-E surface soil moisture, a cross-correlation analysis was applied between measured surface and measured root-zone moisture time-series.

Cross-correlation is a measure of similarity between two waveforms as a function of time lag applied to one of them. Cross-correlations help identify variables which are leading indicators of how much one variable is predicted to change in relation to the other variable. There are three possible outcomes in the Pearson’s correlation r; Positive correlation (r = +1), where as one variable rises the other variable is predicted to rise at a similar rate at the specified time-lag; Zero (r = 0) or no correlation whatsoever; or Negative correlation (r = -1), where as one variable rises the other falls at the specified time-lag. Since AMSR-E has a temporal resolution of one day, a lag-time of one day was selected for cross-correlation analysis between soil moisture at surface layer ($SM_{Sl}$) at time $t$ with the root-zone moisture ($SM_{RZ}$) at time $t+1$ day.

Figure 6.3 shows the cross-correlation between surface soil moisture time-series and root-zone moisture with one day time lag.
Figure 6.3: Cross-correlation between surface layer and 30 cm soil moisture at six selected sites.

A strong positive correlation between $SM_{SL}(t)$ and $SM_{RZ}(t+1)$ was observed as shown in Figure 6.3 above. All sites showed a strong correlation at a lag of one day, meaning the root-zone soil moisture is well correlated to surface moisture of the previous day. Table 6.1 indicates a minimum correlation of 0.6768 was obtained for site Y13 and the strongest correlation (0.88) was found for sites M7 and K12. The strong correlations in these sites can be related to the fact that these sites are non-irrigated rain-fed grazing land with no agricultural activity. Therefore, the sinusoidal wetting and drying root-zone with respect to changes in the surface layer soil moisture are more prominent. Figure 6.4 shows the RMS of residuals from the cross-correlation analysis for all sites. The long-term trend of the $SM_{SL}(t)$ dynamics is well correlated with the $SM_{RZ}(t+1)$, which can be seen in high correlation
values. However, the residual error was high for most of the sites. The surface soil moisture variations are sensitive to factors such as rainfall, temperature changes, evaporation or irrigation. It can be seen in Figure 6.4 that site M7 with non-irrigated grazing land cover has the minimum residual error amongst all six time-series.

![Image: Magnitudes of residual error from cross-correlation between $SM_{SL}(t)$ and $SM_{RZ}(t+1)$.

**Figure 6.4:** Magnitudes of residual error from cross-correlation between $SM_{SL}(t)$ and $SM_{RZ}(t+1)$.

**Table 6.1:** Correlation between $SM_{SL}(t)$ and $SM_{RZ}(t+1)$.

<table>
<thead>
<tr>
<th>Site</th>
<th>$R$</th>
<th>Model</th>
<th>RMS of Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>M6</td>
<td>0.7472</td>
<td>$0.7722^*x+0.1366$</td>
<td>0.0417316</td>
</tr>
<tr>
<td>Y13</td>
<td>0.6768</td>
<td>$0.7975^*x+0.104$</td>
<td>0.0691184</td>
</tr>
<tr>
<td>K12</td>
<td>0.88</td>
<td>$0.6824^*x+0.0911$</td>
<td>0.0334974</td>
</tr>
<tr>
<td>M7</td>
<td>0.88</td>
<td>$0.9735^*x+0.0073$</td>
<td>0.014777</td>
</tr>
<tr>
<td>Y5</td>
<td>0.7235</td>
<td>$0.4413^*x+0.1098$</td>
<td>0.0326172</td>
</tr>
<tr>
<td>Y6</td>
<td>0.7688</td>
<td>$0.5373^*x+0.0638$</td>
<td>0.0414493</td>
</tr>
</tbody>
</table>
6.1.2. Assessment of Exponential Filter Performance on AMSR-E Soil Moisture

The analysis in the above section indicated that $SM_{SL}$ and $SM_{RZ}$ are significantly correlated. The recursive formulation of the exponential filter was then applied to model the deeper layer soil moisture from 2007–2011. The results of 30 centimetre soil moisture derived using AMSR-E time-series are presented in Figure 6.5 below. For all of the sites, the AMSR-E-derived root-zone soil moisture showed trends comparable to the observed data. However, the exponential filter model overestimated for most of the sites, which can be explained by a high residual error found between $SM_{SL}(t)$ and $SM_{RZ}(t+1)$. Site M7, with minimum RMSE (Figure 6.4) shows best match with minimal overestimation. Whereas, for site Y13 with maximum RMSE (Figure 6.4), the model failed to produce comparable root-zone soil moisture estimates.
Figure 6.5: Figure soil moisture probe time-series at 30 cm with AMSR-E-derived root-zone moisture with exponential filter.
In order to assess the performance of the exponential filter, the correlation coefficient (R), root mean square error (RMSE) and the Nash-Sutcliffe coefficient (N) (Nash and Sutcliffe, 1970) were calculated.

\[
N = 1 - \frac{\sum_{t=1}^{T} (Obs_t - Sim_t)^2}{\sum_{t=1}^{T} (Obs_t - \overline{Obs})^2}
\]  

Equation 65

The Nash–Sutcliffe model efficiency (Equation 65) coefficient is used to assess the predictive accuracy of models. Nash-Sutcliffe efficiencies can range from $-\infty$ to 1. An efficiency of 1 corresponds to a perfect match of modelled to the observed data. An efficiency of 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas efficiency less than 0 occurs when the observed mean is a better predictor than the model. Essentially, the closer the model efficiency is to 1, the more accurate the model is.

Figure 6.6 shows the comparison of measured 30 centimetre soil moisture against the modelled 30 centimetre soil moisture using AMSR-E data for station M6. A correlation of 0.2789 was found between modelled and observed values. The Nash-Sutcliffe coefficient of -0.74 suggests that the model simulated the 30 centimetre moisture values that are closer to but less accurate than the mean of the observed data.
Figure 6.6: Exponential filter performance for site M6.

Figure 6.7 shows the comparison of measured versus modelled 30 centimetre soil moisture for site Y13. A correlation of 0.2646 was found between modelled and observed data. The Nash-Sutcliffe coefficient of -0.05 suggests that the model performance in simulating the deeper layer soil moisture was the same as the previous site (M6). The modelled values are as accurate as the mean of the 30 centimetre soil moisture observation at the site.
Similarly, at site K12, the model’s performance in simulating 30 centimetre soil moisture was not better than the mean of the observed data. Here, a relatively better correlation of 0.4422 was found between modelled and observed root-zone moisture. Figure 6.8 shows the comparison plot of measured versus simulated moisture at site K12.

Figure 6.7: Exponential filter performance for site Y13.

Figure 6.8: Exponential filter performance for site K12.
A good correlation of 0.4681 was seen for site M7. The relatively weaker N value (-1.23) indicates that the exponential filter failed to predict the root-zone moisture comparable to the observed mean. Figure 6.9 shows the comparison plot for site M7.

**Figure 6.9:** Exponential filter performance for site M7.

Figure 6.10 shows the plot of modelled versus observed data for site Y5. A correlation of 0.3094 was obtained while a low N value (-0.74) suggests that the modelled output is somewhat comparable to the mean of the observed data.
Figure 6.10: Exponential filter performance for site Y5.

Figure 6.11 shows the comparison of measured 30 centimetre soil moisture against the modelled 30 centimetre soil moisture using AMSR-E data for station Y6. A correlation of 0.2161 was found between modelled and observed values. The Nash-Sutcliffe coefficient of -0.96 suggests that the model simulation was less accurate than the mean of the observed data. Table 6.2 shows the summary of the performance assessment of the exponential filter in estimating root-zone layer soil moisture from AMSR-E surface moisture data.
Figure 6.11: Exponential filter performance for site Y6.

Table 6.2: Performance assessment of exponential filter.

<table>
<thead>
<tr>
<th>Site</th>
<th>T</th>
<th>R</th>
<th>RMSE</th>
<th>N for T=1 day</th>
</tr>
</thead>
<tbody>
<tr>
<td>M6</td>
<td>1</td>
<td>0.2789</td>
<td>0.0593</td>
<td>-0.74</td>
</tr>
<tr>
<td>Y13</td>
<td>1</td>
<td>0.2646</td>
<td>0.0523</td>
<td>-0.05</td>
</tr>
<tr>
<td>K12</td>
<td>1</td>
<td>0.4422</td>
<td>0.0346</td>
<td>-0.34</td>
</tr>
<tr>
<td>M7</td>
<td>1</td>
<td>0.4681</td>
<td>0.0335</td>
<td>-1.23</td>
</tr>
<tr>
<td>Y5</td>
<td>1</td>
<td>0.3094</td>
<td>0.0491</td>
<td>-0.74</td>
</tr>
<tr>
<td>Y6</td>
<td>1</td>
<td>0.2161</td>
<td>0.0642</td>
<td>-0.96</td>
</tr>
</tbody>
</table>

6.2. Discussion

This study has revealed some valuable insights into the use of a semi-empirical exponential filter (Wagner et al., 1999) for estimating root-zone soil moisture dynamics using AMSR-E-derived remote-sensing surface soil moisture time-series. Across the full dataset, the performance of the filter for T=1 day was rather poor (N < 0) compared to that reported in the study by Albergel et al., (2008). However, it has to be noted that this study focused on estimating root-zone moisture dynamics over
Aqua/AMSR-E’s data, and therefore the quality of this mathematical technique cannot be questioned on this basis alone. In this experiment, a maximum Nash-Sutcliffe coefficient value of -0.05 was observed, suggesting a weak correlation between modelled and observed deeper layer soil moisture, even when strong cross-correlation between the observed surface and observed deeper layer data was seen. The lower Nash-Sutcliffe values suggested that the exponential filter failed to predict the next-day root-zone moisture value that is considerably better than the mean of the observed data. The low correlation along with negative NSE resulted from the overestimation and high residual error as seen in Figure 6.5.

The main source of error that can affect the accuracy of root-zone soil moisture extraction is the accuracy of surface soil moisture itself. AMSR-E measurements of soil moisture are directly sensitive only to the top 1 centimetre of soil averaged over approximately a 60 kilometre spatial extent. Therefore, significant uncertainty can occur when these measurements are compared against point-derived in-situ data, due to differences in sampling depth and spatial extent between satellite and in-situ observations (Jackson et al., 2010). Measurements of AMSR-E soil moisture are most accurate in areas of low vegetation (Crow et al., 2010). Attenuation from vegetation increases the retrieval error in soil moisture (Njoku et al., 2005). Njoku et al., (2005) reported that the retrieval algorithm for AMSR-E surface soil moisture does not explicitly model effects of topography, snow cover, clouds and precipitation. Other potential error sources include anomalous inputs from bad radiometric data and low-level processing errors. Also, the soil moisture retrievals
represent averages over the horizontal footprint area and vertical sampling depth in the top \( \sim 1 \) centimetre of soil. The actual sampling depth varies with the amount of moisture in the soil (Njoku, 1999). Soil moisture deeper than \( \sim 1 \) centimetre below the surface may not be sensed by AMSR-E. Another possible error source may be the Radio Frequency Interference (RFI) in the 6.9 GHz channel, since it is shared with mobile communication services. The soil moisture algorithm uses the help of the 10.7 GHz channel to compensate for the RFI.

**Figure 6.12:** Scattergram of scaled in-situ surface soil moisture with normalised actual ET derived from remote sensing.

Climate and soil characteristics are other important parameters with a potential impact on the model performance, especially at regional and local scales. Daily weather variations can significantly influence the soil water availability by altering ET rates. Figure 6.12 shows a scattergram
of normalised in-situ surface soil moisture with remote-sensing-derived actual ET using the SEBS model. The negative correlation between ET and surface soil moisture can be observed at all observation sites, which was not seen when the AMSR-E surface moisture dataset was used (Figure 6.13). In order to interface the calibrated exponential filter model with energy balance ET, accuracy of remotely sensed surface soil moisture is a prerequisite, or else the modelled root-zone soil moisture dynamics may not be representative of the actual moisture state in the deeper layer.

![Figure 6.13: Scattergram of scaled AMSR-E surface soil moisture with normalised actual ET derived from remote sensing.](image)

Factors like soil texture, bulk density and organic matter content can influence the infiltration capacity of the soil and can therefore affect the model’s performance. Figure 6.14 shows the fraction of clay, silt and sand at sites K12 and Y5.
Table 6.2 shows that site K12 has shown a relatively stronger NSE than site Y5. This shows a trend of decreasing correlation between surface and root-zone with the increase in sand fraction. Albergel et al., (2008) also reported that sandy soils tend to result in weaker model performance. A detailed soil texture analysis for each site was not available. Nonetheless, remote-sensing-derived surface soil moisture datasets spread over large areas and the availability of a comprehensive soil characteristics dataset from in-situ observations for the whole catchment of the Basin is unworkable. The exponential filter therefore shows the potential of extracting root-zone soil moisture dynamics from remote-sensing-derived surface soil moisture time-series provided a good ground-calibrated moisture dataset is available. Similar to Albergel et al., (2008), this study has also shown that root-zone soil moisture extraction is
highly localised, and implementation of a localised methodology over a spread of remote-sensing data will reveal unrealistic results. Various studies that yielded good results (discussed in section 3.2.2) either utilised a synthetic dataset or were point-based, which cannot result in spatially distributed root-zone moisture that is representative of the actual moisture state. At present, the accuracy of soil moisture sensors limit the ability to achieve acceptable model accuracy on which a holistic understanding of root-zone moisture distribution of the catchment can be established.
7. CONCLUSIONS AND RECOMMENDATIONS

One of the greatest challenges in modelling land-atmosphere local interactions is from irrigated agricultural land. The quantification of ET is one of the most vital components for water budgeting, efficient irrigation scheduling, cropping practices and water regulation in any irrigation system. Over the last two decades there has been a large amount of energy balance modelling from satellite remote sensing specialising in ET of agricultural areas. Lately, efforts to derive surface soil moisture information to improve agricultural monitoring quality through remote sensing have also increased with the advancement in microwave sensing and retrieval algorithms. The challenge of modelling soil moisture, which naturally varies at different scales, in a way that facilitates comparison with observed data is important. Boussetta et al., (2008) state that the assessment of models-simulated soil moisture is difficult due to ambiguity in comparing model-simulated soil moisture with point-based or remotely sensed soil moisture. Nevertheless, the continuous efforts over the past few years to model soil moisture and relate it to point- and remote-sensed observations have led to the availability of relatively improved surface soil moisture datasets. ET studies concentrate on ET and energy balance models do not extend to include sub-surface processes. This study aimed to explore the potential of extracting root-zone soil moisture dynamics from microwave-based surface moisture data, and attempt to explain the coupling between energy balance-derived ET and remote-sensing-derived soil moisture in the Murrumbidgee catchment.
The study can be categorised into three stages. In the first stage, a Large Aperture Scintillometer (LAS) was installed over a horticultural farm near Leeton, NSW. Along with the ancillary sensors (Net radiometer and soil heat flux plate), the LAS provided ground calibration for remote-sensing energy balance modelling. Also, the LAS setup provided robust datasets and the opportunity for continuous flux monitoring over the site. LAS scintillation data was used to calculate sensible heat flux for the entire half-hourly time-series data. The latent heat flux was then estimated by solving an energy balance of fluxes measured by the net radiometer and soil heat flux, and $H$ was calculated using LAS. Results presented in Rabbani et al., (2011) and section 5.1, demonstrate that LAS performed very well for the purpose of heat flux estimation for energy balance closure, provided the data was filtered for bad or missing values generated by various meteorological conditions or sensor errors.

Sensible heat flux calculation using LAS requires a meteorological station to record the required ancillary information. In this experiment, three replica wireless meteorological stations were installed along the path-length of the LAS. This enabled the testing of sensitivity of micro-meteorological variations occurring within the path-length of the LAS on sensible heat flux calculations. One-way between groups ANOVA analysis was used to test the significance of variances that occurred in resultant sensible heat flux owing to variations in the locations of meteorological stations. A highly significant effect of location of meteorological station on sensible heat flux was found. The results of Tukey’s HSD analysis in Chapter 5, section 5.1.1, suggested that moving the AWS further along the stretched path-length will generate statistically significant differences in
sensible heat flux and eventually influence the whole energy balance closure. The multiple comparisons using Tukey’s test suggested that in estimation of sensible heat flux, a highly significant difference occurred when the meteorological station was placed closed to centre of the beam. This means that the meteorological conditions differed enough towards the centre of the LAS beam to produce a mean difference of \( \sim 14 \text{ W/m}^2 \) in the sensible heat flux. The difference in instantaneous estimate of \( H \) reached up to a \( 100 \text{ W/m}^2 \) in some instances. A 50–100 W/m\(^2\) difference in sensible heat flux can result in a 1.25–2.5 mm.d\(^{-1}\) error in daily ET flux and affect the entire water balance for large regions. Therefore, it is recommended to capture this meteorological variation by placing the AWS at the centre of the beam, or having a network of stations distributed along the stretch of large path-length as exercised in this experiment.

In the second stage, energy balance modelling over the Murrumbidgee catchment was performed using Terra/MODIS data for year 2010/11. The SEBS algorithm was implemented with the PCRaster Python library. SEBS calculates the energy balance terms, relative evaporation, evaporative fraction and ET flux for all pixels of a remote-sensing image, using its optical and thermal bands, in combination with meteorological measurements, radiation measurements and additional field data. Chapter 5, section 5.2.1, presents the results of actual ET modelling while the sensible heat flux and latent heat flux maps are shown in Appendix-B

The SEBS-derived values were validated using LAS-calculated fluxes. The in-situ net radiometer showed a good correlation (\( R^2 \) of 0.667)
with remote-sensing-derived net radiation. And soil heat flux from heat flux plates showed a strong correlation ($R^2$ of 0.89) with the SEBS-model-derived value. The results revealed that SEBS overestimated soil heat flux for higher values while underestimated net radiation for higher values. Therefore, it is recommendable that a localised calibration and/or validation are performed especially for larger study areas in order to achieve good model performance. For sensible heat flux, a strong correlation ($R^2$ of 0.77) was obtained but the residuals were comparatively higher due to model-induced errors. The strong correlation suggests that ground validation of large pixel-based energy balance is more recommendable with an LAS because of a better match between pixel size and path-length of the LAS. Similarly, the latent heat flux and daily actual ET shows a very strong correlation ($R^2$ of 0.9) with SEBS-modelled output. Being a residual energy balance term, the accuracy of latent heat flux is highly dependent upon sensible heat flux estimation. Since LAS has provided areally-averaged flux estimations comparable to the MODIS pixel size, it has proved to be a very desirable flux monitoring and energy balance calibration/validation tool.

In the third stage, root-zone soil moisture dynamics were modelled using an exponential filter (Wagner et al., 1999) using an AMSR-E surface soil moisture dataset over the Murrumbidgee catchment. Six ground calibration sites across the Basin were selected to be used with AMSR-E level 3 data product. Time-step-based statistical analysis between SEBS-derived actual ET with in-situ observations of surface soil moisture was performed. Surface moisture data from the six calibration sites showed a weak but negative relationship between moisture and actual ET, which
was not seen while relating surface fluxes to AMSR-E-derived moisture for the study locations. The most significant limiting factors that need addressing prior to exploring spatial distributions of coupling strengths are differences in spatial and temporal scales of moisture retrievals and energy balance model biases.

Further, cross-correlation analysis was carried out between measured surface and measured root-zone moisture time-series with a time lag of one day to match Aqua/AMSR-E temporal resolution. A strong positive correlation was found between observed surface moisture \( SM_{sl}(t) \) and observed root-zone moisture of next \( SM_{rz}(t+1) \). All sites showed a strong correlation at a lag of one day, indicating strong root-zone and surface moisture coupling. Later, the exponential filter was applied on AMSR-E soil moisture time series to calculate sub-surface moisture for the next day. The Nash-Sutcliffe model efficiency method was used to assess the quality of the exponential filter’s estimates for each of the six calibration sites. Across the full dataset, the model performed poorly in estimating root-zone moisture from AMSR-E data. The maximum correlation of 0.4681 was obtained for site M7 with a poor Nash-Sutcliffe coefficient value of -1.23. The low Nash-Sutcliffe value suggested that the exponential filter failed to predict a next-day root-zone moisture value that was comparable to the mean of the observed data.

Major error source affecting the accuracy of root-zone soil moisture extraction is the accuracy of surface soil moisture itself. AMSR-E’s sensitivities and coarse spatial resolution are major factors contributing to weak model performance. Also, significant uncertainties in
AMSR-E are caused by factors like attenuation from vegetation, effects of topography, snow cover, clouds, precipitation and radio frequency interferences. Application of the exponential filter model-DA to estimate spatial root-zone moisture using unreliable input will provide an unrealistic spatial representative of actual root-zone moisture at the catchment scale. Therefore, accuracy of remotely sensed soil moisture observations is a prerequisite to studying its coupling with energy balance-modelled fluxes at catchment scale. Improvements in remotely sensed soil moisture observations will act as the cornerstone in enhancing understandings in land-atmosphere coupling by facilitating an operational assimilation scheme for estimating spatial root-zone soil moisture that is representative of the actual moisture state.
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APPENDIX-A

APPENDIX-B

Sensible heat flux and latent heat flux maps derived from SEBS over the Murrumbidgee catchment.

Sensible heat flux using SEBS (2/5/2010)

Latent heat flux using SEBS (2/5/2010)

Sensible heat flux using SEBS (3/18/2010)

Latent heat flux using SEBS (3/18/2010)
Sensible heat flux using SEBS (3/20/2010)

Latent heat flux using SEBS (3/18/2010)

Sensible heat flux using SEBS (4/19/2010)

Latent heat flux using SEBS (4/19/2010)
Sensible heat flux using SEBS (12/6/2010)

Latent heat flux using SEBS (12/6/2010)
Sensible heat flux using SEBS (12/13/2010)

Latent heat flux using SEBS (12/13/2010)
Sensible heat flux using SEBS (1/4/2011)

Sensible heat flux using SEBS (1/7/2011)

Latent heat flux using SEBS (1/7/2011)
Sensible heat flux using SEBS (1/9/2011)
Sensible heat flux using SEBS (1/20/2011)

Latent heat flux using SEBS (1/20/2011)
Sensible heat flux using SEBS (1/22/2011)

Latent heat flux using SEBS (1/22/2011)
Sensible heat flux using SEBS (1/25/2011)

Latent heat flux using SEBS (1/25/2011)
Sensible heat flux using SEBS (1/30/2011)

Latent heat flux using SEBS (1/30/2011)
Sensible heat flux using SEBS (1/25/2011)

Latent heat flux using SEBS (1/25/2011)
APPENDIX-C

AMSR-E-derived surface soil moisture maps over the Murrumbidgee catchment.
AMSR-E Surface Soil Moisture: 11/17/10

AMSR-E Surface Soil Moisture: 11/18/10

AMSR-E Surface Soil Moisture: 11/19/10

AMSR-E Surface Soil Moisture: 11/20/10