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REVIEW of REMOTE SENSING and WATER ACCOUNTING to support AGRICULTURAL WATER MANAGEMENT in SUBBASINS





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1 EXECUTIVE SUMMARY

During the mid-20th century there was an emphasis on water resource development with large irrigation projects funded from public investment and in the later 20th Century massive private investment in bores and submersible pumps. The “Green Revolution” had succeeded in reducing poverty and malnutrition but was not uniform. The 21st century is now characterised by much of the world experiencing water scarcity with an estimated 1.2 billion people living in basins with water scarcity. It is projected that up to two-thirds of the world’s population could experience water scarcity due to population growth, changing diets, economic growth and changing climates

To improve water resource management particularly in the agricultural sector, the largest water consumer requires good data to inform decision making. Typically, in low/middle income countries, in situ monitoring of water resources such as river flows, groundwater levels, and water consumption by irrigated agriculture, is limited. The investment required for in situ monitoring infrastructure and capacity, particularly for groundwater, can be prohibitive. Consequently, there is often a paucity of detailed and robust data upon which to generate information to assist with decision making. At basin and larger scales, inroads are being made to address this gap through harnessing the latest in big data and applying remote sensing (RS) and earth observation (EO) data products. However, the potential for such data and associated products to assist with sub-basin scale water management is not known.

In many Asian countries the historic rapid expansion of irrigated agriculture has impacted on both surface and groundwater resources. There is now increasing competition for water between different economic sectors within basins. This has meant significant changes, over the last several decades, to agricultural water management in terms of its scope and direction. There are two prevailing approaches to agricultural water management, the first ‘classical’ approach is about irrigation development and improving irrigation efficiency. The pursuit of increased agricultural water use efficiency without supporting governance changes has resulted increased water usage not less as expected. The second ‘neoclassical’ agricultural water management approach is to manage water resources at the basin level, balancing water availability with needs. It also involves focusing on water consumption or depletion, tracking where the water being used. The ‘classical’ approach is often entrenched within government agencies, and the ‘neoclassical’ approach is being pushed by agricultural development agencies such as FAO and IWMI. This can lead to tensions.

Consequently, due to these different approaches, agricultural water management is either occurring at the larger basin or irrigation area scales, often funded by external donors. There is little activity occurring at smaller sub-basin scales. Agricultural water management at smaller sub-basins is also hampered by complex governance arrangements, with different levels of government and agencies all having roles and often competing. Any hydrological data collected is often siloed and of limited duration.

Doner funded studies have shown remote sensing and water accounting frameworks can provide crucial hydrological data to help improve agricultural water management in data poor areas at larger basin scales and irrigation areas. It has not been used at smaller sub-basin scales. Part of the problem moving from larger basins to smaller basins are scaling issues, with many of the tools and approaches developed for larger basins not suitable for smaller basins. Water Accounting Plus (WA+) is designed for use with remote sensing data to calculate water balances for basins. However, it is a depletion-based water accounting system that tracks where water is being used, not where it flows. So, outflow data in WA+ can have a high degree of uncertainty. To overcome this a hydrologic model was built into the Water Accounting Plus framework to track surface and groundwater flows and to support water resource planning. Though the model needs to be calibrated with terrestrial discharge data often unavailable in smaller subbasins. The model is complex to set up, and lack of calibration data limits the model usage within smaller sub-basins.

Remote sensing data is available for most hydrological parameters needed to determine water balances, rainfall, evapotranspiration and changes in storage (GRACE). GRACE data though is coarse (~300 km) and only available for larger basins. There are multiple satellite-derived datasets that are increasingly open-access available for use smaller sub-basins. New missions are being developed that will increase data availability. Although, many datasets are now free, they are delivered in formats that lack user-friendly interfaces, require advanced processing, or are at unsuitable spatial and temporal resolutions. Advanced processing also requires significant computing power, internet connectivity, and licensing of specialized software that may not be available. This creates a gap between data availability and data use.

It has been shown that remote sensing and water accounting can help fill hydrological data gaps to lift water productivity and reduce poverty as seen in India. However, remote sensing cannot completely replace terrestrial data, though it has an important role in augmenting terrestrial data sources as in the case of China.

2 INTRODUCTION

The mid 20th century was characterised by water availability with an emphasis on water resource development with large irrigation projects funded through public investment. These large surface water irrigation schemes consisted of dams and reservoirs which provided water to irrigation command areas with extensive networks of canals and drains. This expansion of irrigated agriculture was driven by rapid population growth and demand for food (Karimi, 2014; Turrall et al., 2011).

The public investment in surface water irrigation started in the 1960s, peaked during the 1970s and had declined by the 1990s (Giordano et al., 2019; Karimi, 2014; Turrall et al., 2011). The reasons for the decrease of public investment in surface irrigation, were multifaceted. The “Green Revolution” had succeeded in reducing poverty and malnutrition but was not uniform (Turrall et al., 2011; Vincent and Hussein, 1999). The success of earlier schemes had increased global food supplies reducing the imperative for further investments in irrigation. Additionally, despite the success in increasing food production, large scale irrigation schemes were viewed as failing to live up to their potential and required continuous injections of outside capital for operations and maintenance. There was also a rising awareness of the impacts of irrigated agriculture on aquatic and riparian ecosystems due to the large-scale diversion of water (Giordano et al., 2019; Turrall et al., 2011).

Since the 1980s, coinciding with the decline in investment in surface water irrigation, there was a significant increase in private investment in groundwater irrigation due to the availability of cheap pumps, power and well construction methods. This has led to the overexploitation of groundwater and falling water tables (Batchelor et al., 2014; Karimi, 2014; Turrall et al., 2011).

The 21st century is now characterised by much of the world experiencing water scarcity with an estimated 1.2 billion people living in basins with water scarcity (Food and Agriculture Organisation, 2012; Karimi, 2014). It is projected that up to two-thirds of the world’s population could experience water scarcity due to population growth, changing diets, economic growth and changing climates (Food and Agriculture Organisation, 2012; Karimi, 2014; Turrall et al., 2011).

To improve water resource management particularly in the agricultural sector, the largest water consumer requires good data to inform decision making (Van Opstal et al., 2021; Whiting et al., 2023). Typically, in low/middle income countries, in-situ monitoring of water resources such as river flows, groundwater levels, and water consumption by irrigated agriculture is limited. The investment required for in situ monitoring infrastructure and capacity, particularly for groundwater, can be prohibitive. Consequently, there is often a paucity of detailed and robust data upon which to generate information to assist with decision making. On basin and larger scales, inroads are being made to address this gap by harnessing the latest in big data and applying remote sensing (RS) and earth observation (EO) data products. However, the potential for such data and associated products to assist with sub-basin scale agricultural water management is not known.

The report will review:

- i) What hydrological data is being used in sub-basin agricultural water management
- ii) Identify a suitable conceptual model of water governance maturity
- iii) Water accounting and water balance methodologies with a focus on the use of remote sensing

- iv) Review of remote sensing data available for water accounting and improve decision making in agricultural water management

3 DATA INFORMED WATER RESOURCE MANAGEMENT

3.1 HYDROLOGICAL DATA USAGE IN AGRICULTURAL WATER MANAGEMENT AT SUBBASIN IN THE ASIA PACIFIC

INTRODUCTION

The mid 20th century, was characterised by water availability, with significant public and private investment in irrigated agriculture, though by the 21st Century much of the world experienced water scarcity (Karimi, 2014; Turrall et al., 2011). This meant significant changes, over the last several decades, to agricultural water management in terms of its scope and direction as well as implications for data collection. Due to these changes there have been a substantial number of reviews into agricultural water management practices and data (Batchelor et al., 2014; Carmody and Turrall, 2023; Ghimire et al., 2023; Giordano et al., 2017; Giordano et al., 2019; Molden et al., 2010; Pérez-Blanco et al., 2020; Perry, 2007; Perry, 2011; Perry, 2012; Perry and Steduto, 2017; Perry et al., 2009; Seckler, 1999; Seckler et al., 2003; Van Opstal et al., 2021) covering hundreds of articles and reports. The main findings the reviews are summarised in the following sections.

CHANGES TO AGRICULTURAL WATER MANAGEMENT OUTLOOKS AND PRACTICES

The mid 20th century, with water availability, saw extensive public investment in large surface water irrigation schemes, consisting of dams and reservoirs providing water to irrigation command areas with extensive networks of canals and drains (Giordano et al., 2019; Karimi, 2014; Turrall et al., 2011). These investments started in the 1960s, peaked during the 1970s and had declined by the 1990s (Giordano et al., 2019; Karimi, 2014; Turrall et al., 2011).

The design, building, operation and maintenance of these large irrigation schemes had led to the development of specialist agencies within many Asian governments such as the Royal Irrigation Department in Thailand and similar ‘hydraulic bureaucracies’ in other countries such as Cambodia, Laos PDR and Vietnam (Bruns, 2017; Lebel et al., 2020; Pahl-Wostl, 2019; Suhardiman et al., 2012). The role of these ‘hydraulic bureaucracies’ traditionally has been to support the development of irrigated agriculture. Additionally, while water was plentiful during the mid-20th Century, international agricultural development and research organisations such as the Food and Agriculture Organisation of the United Nations (FAO), International Irrigation Management Institute and the International Commission on Irrigation and Drainage (ICID) also had a similar roles in supporting the development of irrigated agriculture (Perry, 2007; Seckler, 1999; Seckler et al., 2003; Suhardiman et al., 2012; Van Opstal et al., 2021).

The prevailing views during this period were that irrigation systems were to satisfy the water requirements of crops and the role of agricultural water management was essentially to deliver sufficient to water to the rootzones of crops for optimal growth (Allen et al., 1998; Perry, 2007). However towards the beginning of the 21st Century, the global water situation, including Asia, had changed to one of water scarcity (Food and Agriculture Organisation, 2012; Karimi, 2014; Turrall et al., 2011). Also, within the Asian region, agriculture had become less important to national economies, with industrial expansion and relocation of rural populations to urban areas in search of work (Sikka et al., 2024). This resulted in increased competition for water within basins and aquifers between

agriculture, power generation (surface water), environmental services and water supplies for municipal and industrial purposes (Giordano et al., 2017; Lebel et al., 2020; Pahl-Wostl, 2019; Sikka et al., 2024; Wang et al., 2025).

Consequently, there was a major shift the perceived role of agricultural water management, particularly amongst agricultural research and development agencies such as the International Irrigation Management Institute and ICID. They were moving away from improving the delivery of water from irrigation systems to crops to “analysing water use in the context of the water balance of the river basin” (Perry, 2007; Seckler, 1999). This shift also involved the International Irrigation Management Institute changing its name to the International Water Management Institute (IWMI) to reflect this change. They were also moving agricultural water management away from focussing on water withdrawals for irrigation to focussing on better understanding areas of water depletion, where water was being used and consequently becoming unavailable to other users (Perry, 2007; Perry, 2011; Seckler, 1996; Seckler et al., 2003). Depletion may be losses through evapotranspiration, unrecoverable flows to sinks, incorporation into products or degradation of quality to render it unusable for its intended purposes (Karimi, 2014; Perry, 2007).

This has resulted in two distinct approaches to agricultural water management, the traditional ‘classical’ approach that focuses on irrigation development and crop growth and the newer ‘neoclassical’ approach, analysing water depletion, as defined by Seckler et al. (2003). The ‘classical’ approach can still be entrenched within agricultural/agronomic industries and ‘hydraulic bureaucracies’ while the ‘neoclassical’ approach is being promoted by international agricultural research and development agencies, such as FAO and IWMI, and donor organisations creating tensions (Perry and Steduto, 2017; Van Opstal et al., 2021).

These alternate approaches often operate at different scales, with different data needs and outcomes in terms of water management (Giordano et al., 2017; Van Opstal et al., 2021). The key decision makers, along with their data needs and motivations for change, vary with scale from farm to irrigation district to basin – Table 3.1 (Giordano et al., 2017; Van Opstal et al., 2021). The ‘classical’ approach mainly operates at the farm and irrigation scheme scales but has impacts at the basin scales, while the ‘neo-classical’ operates mainly at basin scales but is applicable to all scales. These will be explored further in the next section.

TABLE 3.1 DECISION MAKERS AND DATA NEEDS, AS WELL AS THE OPERATIONAL RELEVANCE OF AGRICULTURAL WATER MANAGEMENT APPROACHES, AT DIFFERENT SCALES (AFTER GIORDANO ET AL .2017)

Scale	Crop / field/ farm	Irrigation system	Basin
Decision makers	Grower – occupier or owner	Scheme managers, Irrigation companies, Water User Associations, government authorities	Planners and policy makers (national and /or provincial governments)
Data needs / purpose	Water availability and timing, water usage, crop yield and productivity	Assessing irrigation system performance, if uneven distribution of water and timing, groundwater over-abstraction	Assessment of water usage / allocation including economic value of water usage by agriculture as compared to other sectors
Motivations for change	Increasing reliable farm income	Problems with water distribution through network or aquifer depletion	Need to manage water resources at basin scale
‘Classical’			

3.2 MANAGEMENT OUTCOMES OF THE DIFFERENT AGRICULTURAL WATER MANAGEMENT APPROACHES

INTRODUCTION

To discuss some of the issues around the ‘classical’ approach to agricultural water management it is first necessary to understand one of the key performance measures, irrigation efficiency. Irrigation efficiency is the ratio of the irrigation water used by crops to the water diverted or withdrawn from the source (Perry, 2007). Crop water demand for optimum growth is measured by evapotranspiration (ET_a). The amount of irrigation water required for the crop (NET) is the crop water requirement less the amount provided by rainfall to the rootzone, effective rainfall (P_e) – Equation (i) (Allen et al., 1998; Seckler, 1999)

$$NET = ET_a - P_e \quad (i)$$

The ratio of irrigation water needed or used by the crop (NET) to the amount of water withdrawn from a specific irrigation source and delivered to the field (D_s) is known as *application efficiency* - E_a (Seckler, 1999)

$$E_a = \frac{NET}{D_s} \quad (ii)$$

Related to this is the concept of water productivity which is the amount of crop yield per unit of water applied (i.e. kg/m³) or economic output per unit of water applied (i.e. USD/m³) (Perry, 2007; Perry et al., 2009; Seckler et al., 2003).

Irrigation and application efficiencies are useful concepts when used for purposes for which they were developed, the design of irrigation systems and management of crop water requirements (Allen et al., 1998; Seckler, 1999). However, to understand its limitations in agricultural water management it is important to understand the original meaning of the term efficiency.

The term efficiency was originally developed in thermodynamics to describe how efficiently one form of energy is transformed into another under the second law of thermodynamics as energy is transformed from one form to another losses occur and efficiency is the ratio of output energy to input energy and provides a measure of losses (Dehli et al., 2023). For example, in hydropower generation, water moving under gravity due to changes in elevation, head pressure, results in generation of power. The efficiency measures how much of this change in head was transformed into electrical power. In this situation the change in water elevation, head losses, are unrecoverable forms of energy (Dehli et al., 2023).

As Perry (2007) noted about efficiency concepts;

- *“high efficiency reflects low losses;*
- *losses are a non-recoverable waste of resources;*
- *reductions in ‘losses’ will mean that more of the input is available for alternative uses;*
- *and, by implication high efficiency is ‘good’.”*

The above concepts, though true for thermodynamic efficiency, have been wrongfully applied to irrigation efficiency. There is the belief that irrigation is a profligate and wasteful user of water and improvements to irrigation management and efficiency will lead to increased agricultural production and reduced demand for water (Pérez-Blanco et al., 2020; Perry and Steduto, 2017; Perry et al., 2009; Van Opstal et al., 2021).

An example of how efficiency concepts are flawed when applied to irrigation are losses. Irrigation losses to the system may be recoverable and used elsewhere in the basin. (Perry, 2007; Seckler, 1999; Seckler et al., 2003). The irrigation losses can provide recharge to aquifers that are utilised for irrigation during the dry season or reused by other irrigators downstream (Batchelor et al., 2014; Perry, 2007; Seckler, 1999; Seckler et al., 2003; Simons et al., 2015). An alternative way to consider the so-called irrigation 'losses', from a hydrological perspective, is view them as a transfer in storage. For example, from a reservoir or canal to an aquifer. The irrigation or application efficiency for an irrigation scheme is typically around 45% but when accounting for recycling of water within a basin, the basin efficiency could be around 80% (Seckler, 1999; Seckler et al., 2003).

One of the key management interventions proposed to improve water availability and security is to improve irrigation efficiency and water productivity (Batchelor et al., 2014; Van Opstal et al., 2021). Some of the management interventions to improve water efficiency and water productivity have included the use of advanced technologies such as drip and sprinkler irrigation systems, changes to land management practices such as no tillage and laser leveling as well as changes to agronomic practices including use of high yield varieties and fertigation, fertilisers applied through the irrigation system (Batchelor et al., 2014; Giordano et al., 2017; Pérez-Blanco et al., 2020; Perry and Steduto, 2017).

Under the 'classical' approach data collection is mainly about measuring water supply to irrigated agriculture, water usage by crops and crop performance. The data collected has shown that the misapplication of the thermodynamic concept of efficiency has led to some disastrous management outcomes. When water conservation technologies were applied without other interventions it led to intensification of water use. Data such as water application rates, areas cropped, biomass per unit area, and crop yields, have shown that increased crop yields are often coupled with increased consumptive water use. Improved efficiency, productivity and profitability had encouraged farmers to increase the area cropped or cropping intensity, leading to increased water use not less as thought (Batchelor et al., 2014; Giordano et al., 2017; Pérez-Blanco et al., 2020; Perry and Steduto, 2017). Increased irrigation efficiency had also led to less water being available for other downstream users within the basin due to less recycling of water (Perry, 2011; Perry and Steduto, 2017; Perry et al., 2009).

The increase in water efficiency and water productivity leading to increased water consumption is known as 'Jevon's Paradox' (Van Opstal et al., 2021). Though the paradoxical effects of water conservation technologies leading to increased water consumption have been known for over a decade, water conservation technologies are still being proposed as solutions to improve efficiency leading to water savings particularly in within agriculture/agronomic industries and 'hydraulic bureaucracies' (Perry and Steduto, 2017; Van Opstal et al., 2021). A recent evaluation of the Asian Development Banks's Water Sector Policy and Program, 2011–2021 found though funded irrigation projects increased productivity and water efficiency it was unclear whether the water 'saved' resulted in increased environmental benefits or increased water consumption due to not measuring off-site effects (Asian Development Bank, 2022).

The continued assumptions that water conservation technologies saves water and increases water productivity are due to the confusion between local effects (on-farm water savings as opposed to basin scale water savings) and the focus on water applied and not water consumed as an indicator of water productivity (Perry and Steduto, 2017). Water conservation technologies have their place as part of a suite of water management measures but the potential effects need to be properly assessed at the broader hydrological, basin, and socio-economic scales (Giordano et al., 2017; Molden et al., 2010; Pérez-Blanco et al., 2020) which is currently not been done as the ADB evaluation has shown.

It was recommended by Perry (2007) that due the problems with irrigation efficiency, particularly as efficiency is a thermodynamic concept, that the term ‘fractions’ be used instead. Fractions are used in the Water Accounting (Molden, 1997; Molden and Sakthivadivel, 1999) and Water Accounting Plus frameworks (Karimi et al., 2013; Mul et al., 2020) which were designed to assess water productivity at the basin scales.

The assessment of water usage and productivity at the basin scales is the basis of the ‘neo-classical’ approach to agricultural water management particularly through water accounting methodologies. Associated with the basin scale water accounting is the concept of Integrated Water Resource Management - IWRM (e.g. (Michailovsky et al., 2020a). IWRM *“promotes the co-ordinated development and management of water, land and related resources, in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems”* (Global Water Partnership, 2000).

Though in practice IWRM covers activities ranging from the operational management of existing resources and the development of new resources along with planning and design of associated infrastructure. It also includes the early warning of hydrological risks (i.e. drought and flood) as well as the management and reduction of risks (Malthus and Zamyadi, 2024; Sheffield et al., 2018). For which information on resources and hazard risk is essential (Sheffield et al., 2018).

A range IWRM decisions benefit from hydrometeorological information that also includes land use land cover data. These include land management and water allocation at the basin scale for a range of related sectors (ecosystems, water supply, energy production, agriculture, plantation and forest management, etc.); environmental management and protection; irrigation, water supply, the design and operation of water infrastructure for hydropower, flood control, drought preparedness and mitigation, and wastewater treatment; management of water for agriculture, industry, energy production, natural resource management, and health applications; hydrological disaster risk management and reduction; and broader issues related to water resources development, planning policy, and governance (Sheffield et al., 2018). Table 3.2 provides a summary of the main IWRM decisions, the types of variables required, and how these are obtained traditionally. There are also many other decisions requiring information on water related variables, such as land use planning and environmental planning and management that are not covered (Sheffield et al., 2018).

Though IWRM is now a global paradigm for basin water management and has become institutionalised within most of the Asia- Pacific region, through incorporation into water law, implementation has proven more difficult (Duc et al., 2024; GWP and UNEP-DHI, 2021; Suhardiman et al., 2012; Zinzani and Bichsel, 2018). Part of the difficulties in implementing IWRM, and using hydrological data in decision making within basins has been the complexities of governance arrangements of basins at different scales (Bruns, 2017; Lebel et al., 2020; Suhardiman et al., 2012; Zinzani and Bichsel, 2018).

TABLE 3.2 WATER DATA THAT COULD BE USED IN DECISION MAKING (AFTER: SHEFFIELD ET AL., 2018)

Water resource management functions	Data used in decision making	Data sources
Planning and design		
Flood control – design (flood storage and mitigation)	Long term records of precipitation and streamflow (decades), Long term records of snow/ ice as snow water equivalent (SWE) where applicable	Rain gauge networks, stream gauge networks, snow courses and pillows
Hydropower - design	Long term records of precipitation streamflow (decades), Long term records of snow/ ice as snow water equivalent (SWE) where applicable	Rain gauge networks, stream gauge networks, snow courses and pillows
Irrigation systems – design (withdrawals, distribution and application)	Long term records of precipitation, streamflow and groundwater(decades), Crop water usage	Rain gauge networks, stream gauge networks, groundwater monitoring networks (piezometers, production bores), meteorological networks
Waste water treatment – design (collection, treatment and disposal)	Wastewater sources and water quality; Data from disposal sites (surface water, groundwater)	Flows in distribution network, Stream gauge networks, groundwater monitoring networks (piezometers, production bores),
Water supply - design	Records of precipitation, streamflow and groundwater	Long term records of precipitation, streamflow and groundwater(decades),
Downstream water needs / Transboundary water agreements (at broader scales)	Long term records of streamflow and groundwater(decades), water usage records and environmental flow requirements	Stream gauge networks, groundwater monitoring networks (piezometers, production bores),
Operation and management		
Water supply – operations	Real time precipitation. evapotranspiration and groundwater	Rain gauge networks, eddy-covariance towers and automated weather stations, stream gauge networks,

Water resource management functions	Data used in decision making	Data sources
		groundwater monitoring networks (piezometers, production bores),
Water supply - management (match water demand with available supply)	Real time precipitation, evapotranspiration, streamflow and groundwater	Rain gauge networks, eddy-covariance towers and automated weather stations, stream gauge networks, groundwater monitoring networks (piezometers, production bores),
Hydropower - operations (maximise power output within other management considerations)	Real time precipitation, evaporation and streamflow, precipitation forecasts.	Rain gauges, stream gauges, meteorological stations and automated weather stations, weather forecasts
Flood control – operations (control of dam infrastructure to manage floods)	Real time precipitation, streamflow and meltwater (snow water equivalent), precipitation forecasts.	Rain gauges, stream gauges, snow courses and pillows, weather forecasts
Wastewater - management (efficient treatment and disposal)	Records of feed sources, data from disposal areas	Stream gauges, groundwater monitoring (piezometers, production bores)
Irrigation systems – operations	Real time precipitation, streamflow, groundwater and soil moisture, evapotranspiration estimates	Rain gauge networks, stream gauge networks groundwater monitoring networks (piezometers, production bores), soil moisture probes, eddy-covariance towers and automated weather stations, meteorological stations
Ecosystem management	Recent data on precipitation, streamflow, water levels, soil moisture, water quality	Rain gauges, stream gauges including stage height, water quality sampling
Disaster management		

Water resource management functions	Data used in decision making	Data sources
Crop monitoring and food security (crop production and availability, early warning of food insecurity and famine)	Real time vegetation characteristics, crop water needs, soil moisture, precipitation forecasts	Crop field sampling, eddy-covariance towers and automated weather stations, meteorological stations, soil moisture probes, weather forecasts
Drought early warning and management	Real time precipitation, soil moisture, streamflow, groundwater, precipitation forecasts	Rain gauges, soil moisture probes, stream gauges, groundwater monitoring (piezometers, production bores), weather forecasts
Flood early warning and management	Real time precipitation, streamflow, precipitation forecasts	Rain gauges, stream gauges, weather forecasts
Health (water related) – monitoring and management of water quality, pollution and disease vectors	Real time precipitation, surface water, water quality parameters	Rain gauges, stream gauges including stage height, water quality sampling

This can be illustrated using the Lancang-Mekong Basin as an example. The Lancang-Mekong Basin spans five countries; the Peoples Republic of China (PRC), Myanmar, Lao People's Democratic Republic, Thailand, Cambodia and Vietnam (Figure 3.1).

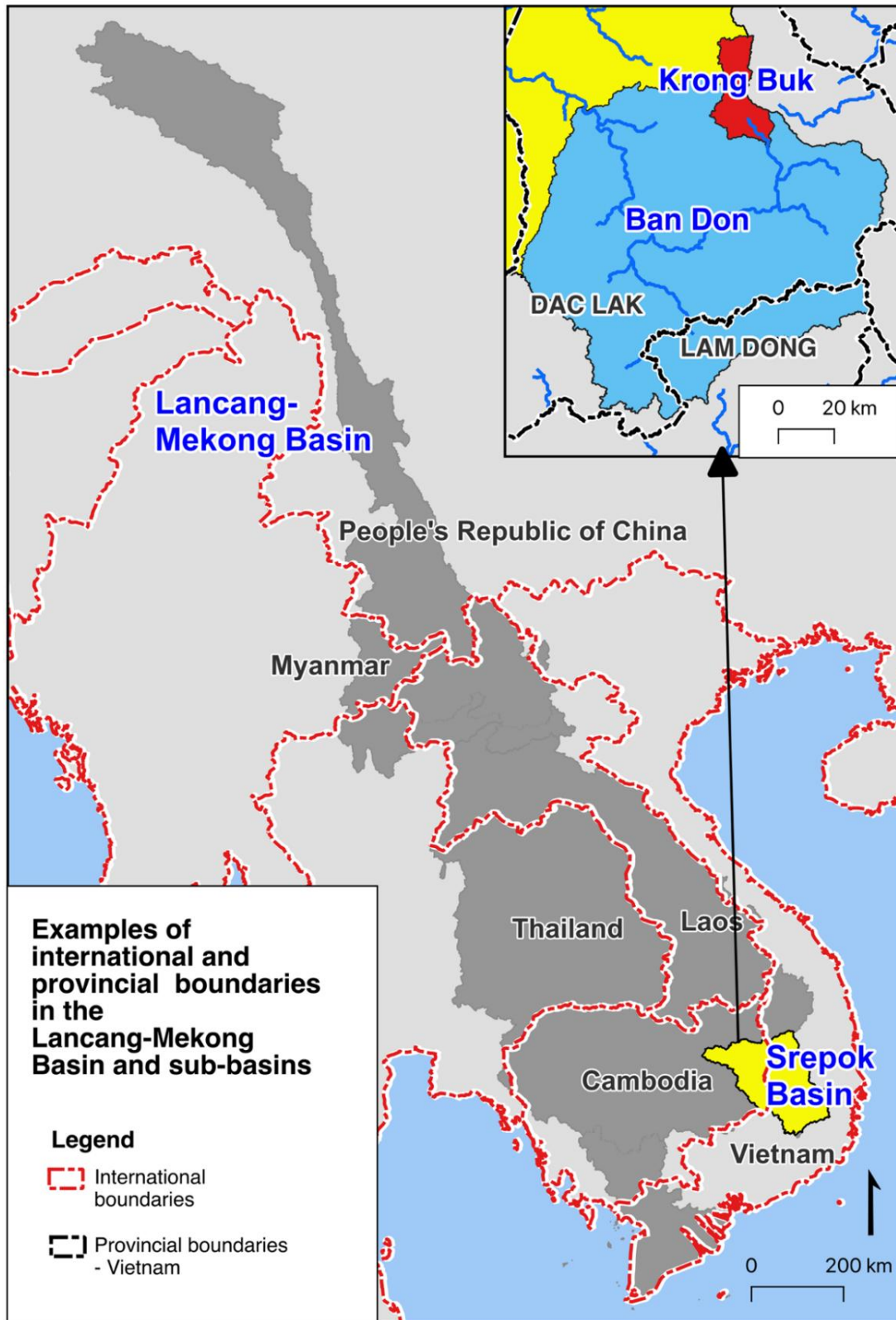
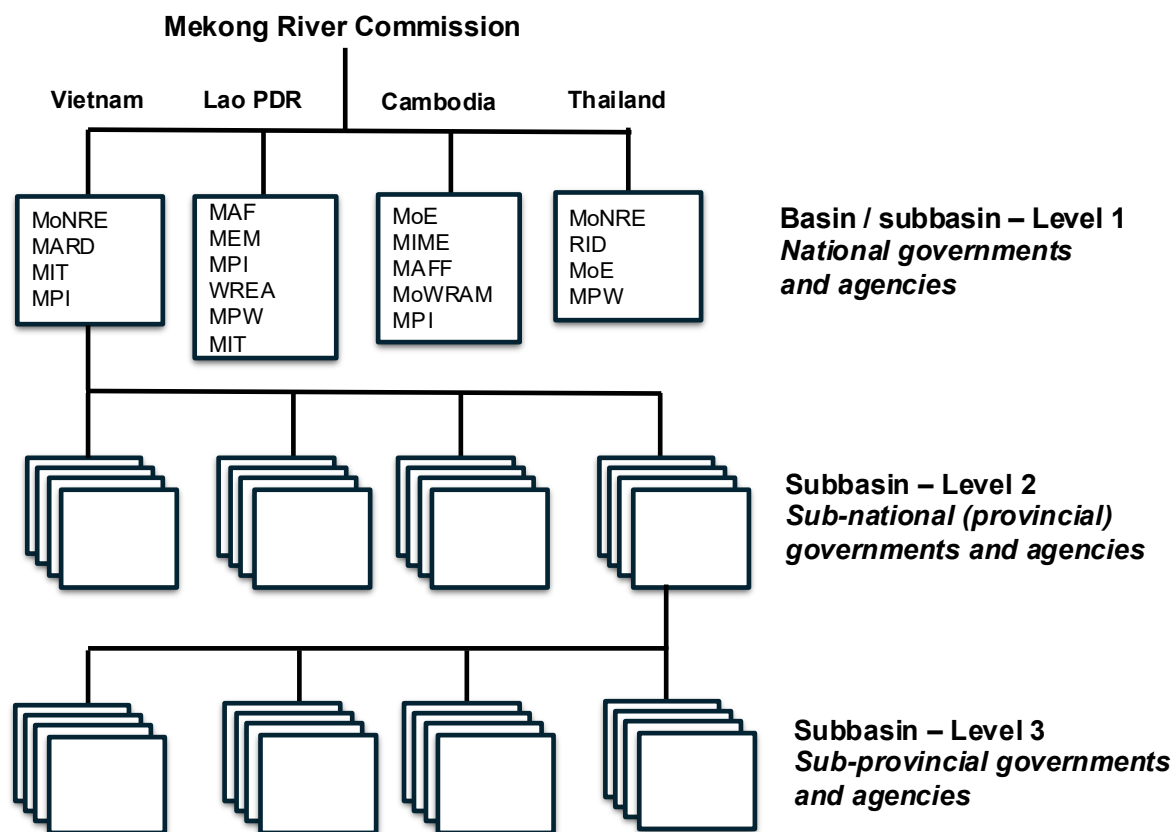


FIGURE 3.1 BASINS AND SUB-BASINS CAN BE ADMINISTERED BY NATIONAL AND SUB-NATIONAL GOVERNMENTS DEPENDING ON THE SCALE BEING CONSIDERED.

The Mekong River Commission has been setup to help manage transnational water issues for the lower Mekong and includes representation from four countries in the lower Mekong region – Figure 3.2 (Suhardiman et al., 2012).



Vietnam,

MoNRE - Ministry of Natural Resources and Environment
MARD - Ministry of Agriculture and Rural Development
MIT - Ministry of Industry and Trade
MPI - Ministry of Planning and Investment

Cambodia

MoE - Ministry of Environment
MIME - Ministry of Industry Mining and Energy
MAFF - Ministry of Agriculture Fisheries and Forestry
MoWRAM - Ministry of Water Resources and Meteorology
MPI - Ministry of Planning and Investment

Lao PDR

MAF - Ministry of Agriculture and Forestry
MEM - Ministry of Energy and Mines
MPI - Ministry of Planning and Investment
WREA -Water Resources Environment Agency
MPW - Ministry of Public Works
MIT - Ministry of Industry and Trade (MIT). In

Thailand

MoNRE - Ministry of Natural Resources and Environment;
RID -Royal Irrigation Department
MoE - Ministry of Energy
MPW - Ministry of Public Work

FIGURE 3.2 ACTORS INVOLVED IN DECISION MAKING FOR THE MEKONG RIVER BASIN AT DIFFERENT SUB-BASIN SCALES (AFTER LABEL ET AL., 2020, SUHARDIMAN ET AL., 2012).

Within the national governments of the MRC there are multiple agencies responsible for the management of water (Figure 3.2). Only Vietnam and Thailand have good hydrological gauging networks, while Thailand is the only country that has a centralised hydrological database, though lacks subnational data (Carmody and Turrall, 2023; Ghimire et al., 2023). River Basin Organisations (RBOs) have been set up to help coordinate water management between national agencies however competition between the agencies prevents them from working cooperatively together on water management, particularly allocation issues, including sharing of data, limiting the effectiveness of RBOs (Carmody and Turrall, 2023; Lebel et al., 2020; Suhardiman et al., 2012).

The smaller subbasins of the Mekong range in size from the SrePok subbasin (30,700 km²), which is a transnational subbasin, to the Ban Don sub basin (10,800 km²) and the Krong Buk (464 km²) – Figure 3.1. For the smaller sub-basins water management becomes the responsibility of sub-national provincial and district governments. Subbasins can span multiple provinces and rivalry between the levels of government also complicates water management (Lebel et al., 2020; Suhardiman et al., 2012; Zinzani and Bichsel, 2018). The Vietnamese Mekong sub-basins cover 26 provinces and 159 districts (Table 3.3)¹.

TABLE 3.3 THE NUMBER OF PROVINCES AND DISTRICTS THAT COVER VIETNAMESE MEKONG SUBBASINS.

Mekong sub-basin	Provinces #	Districts #	Area of sub-basin (km ²)
Delta	14	107	32900
Mekong	1	3	1400
Se Bang Hieng	1	1	700
Se Kong	3	3	800
Se San	2	15	11200
Siem Bok	1	2	400
Sre Pok	4	28	18300
Grand Total	26	159	65700

Hydrological data may be collected by different agencies for specific purposes, with data collection often funded by external sources. The data though often remains siloed within the agencies and not shared limiting its role in decision making (Karimi et al., 2013; Lebel et al., 2020; Suhardiman et al., 2012). Carmody and Turrall (2023) concluded *‘hydrometric data across Asia is patchy at best and typically has poor spatial coverage and short time series whereas local data with good spatial and temporal resolution ... tends to be lacking’*. The availability of hydrological data depended on the maturity of water governance in the country. Therefore, a water governance maturity framework was developed to help understand the use of hydrological data within countries discussed in the next chapter.

Concluding, there are two approaches to agricultural water management, the ‘classical’ approach which is concerned with maximising the efficiency of water delivery to irrigation areas, with all its limitations, and the second, ‘neoclassical’ is concerned with assessing water usage and depletion at basin scales. This would explain why the hydrological data and studies were at either the basin or irrigation scales. For example, due to the lack of available hydrological data for decision making at the basin and irrigation district scales, the Asian Development Bank funded a series of Water Accounting studies that used remote sensing data to fill gaps in hydrological data for basins (Michailovsky et al., 2020a; Michailovsky et al., 2020b; Salvatore and Mul, 2020; Seyoum and Mul, 2020) and irrigation districts (Khan and Rebelo, 2020; Matheswaran and Rebelo, 2020; Velpuri et al., 2020a; Velpuri et al., 2020b). There has been little work with smaller sub-basins. Water accounting methods will be looked at more detail in a later chapter.

3.3 REFLECTING ON AGRICULTURAL WATER MANAGEMENT EXPERIENCES IN INDIA AND CHINA

To understand the possible trajectory of agricultural water management in Asia, its helpful to look to India and China that have the largest extents of irrigated agriculture in the Asia, as well as globally, at 7040 km² and 6294 km², respectively (Sikka et al., 2024). Both India and China have well developed space programs

¹ Since the analysis was completed, the Vietnamese sub-national governments have been restructured removing the district level of government as well as reducing the number of provincial governments.

and both have launched specific satellite missions to help manage natural and water resources (Li et al., 2025; Rajagopalan and Stroikos, 2024). India has recently launched the NISAR satellite in collaboration with NASA with part of the mission scope to help manage irrigation (NASA, 2025). China has launched the Gaofen (GF) satellites as part of the China High-definition Earth Observation System (CHEOS) (Li et al., 2025). This demonstrates the importance of remote sensing in the management of water and natural resources.

In India water management is mainly the responsibility of the state governments with the national government having a role in the coordination of water management and trans-jurisdictional basins (Ho, 2019; Labhsetwar, 2024). India has made significant progress towards food self-sufficiency, but still experiences poverty and starvation depending on the regions (Labhsetwar, 2024). Water management and hydrological data collection are variable. There are irrigation areas with low water productivity in India and through better use of water resources there is scope to reduce poverty and increase nutrition with remote sensing playing an important role (Chatterjee et al., 2025; Chatterjee et al., 2024; Ho, 2019; Labhsetwar, 2024).

China has stronger governance structures than India (Ho, 2019) so has fewer issues with malnutrition, though there are nutritional disparities between rural and urban populations (Ping and Ruoxi, 2024). China also has decentralised water governance arrangements but has stronger legal and administrative structures for basin water management than India (Carmody and Turrall, 2023; Ho, 2019; Wang et al., 2025).

In China, the national Ministry of Water Resources sets the overall water use limits, known as total amount control (TAC), which are then developed into water allocation plans and under those plans, sectoral water use quotas at the basin and sub-national administrative scales are set. The TAC, allocation plans, and sectoral quotas are designed to balance average water resources availability with demand. Higher priority in these instruments is given to water supplies for domestic, industry, power and environmental flows. The residual water availability is allocated to agriculture and quotas are set for irrigation water user associations and individual users, who are required to have valid water abstraction permits (Carmody and Turrall, 2023; Ho, 2019). China is looking to introduce water metering for all users (Carmody and Turrall, 2023; Ping and Ruoxi, 2024). This demonstrates that remote sensing has a role in augmenting but not replacing terrestrial data.

China also has a history of using pilot projects to test the validity of a particular water policy frameworks before committing to broader regulatory change (Carmody and Turrall, 2023). The experiences in basin water management can provide salient insights. Water to the Zhanghe Irrigation District in Hubei Province was reduced so it could be reallocated to other sectors. To support the growers, a suite of interventions was also introduced such as water conservation policies, like quotas and pricing mechanisms and water conservation technologies. Though the water allocated to growers was reduced, crop yields increased due to the interventions. In another example, surface water was reduced to the Liuyuankou Irrigation District, though without the supporting interventions and the growers augmented water supplies with groundwater not included in official water allocation plans (Giordano et al., 2017). Therefore both changes in governance and interventions need to be effectively coordinated to get reductions and increased efficiencies in agricultural water management.

4 WATER GOVERNANCE MATURITY - USE OF WATER-RELATED DATA TO SUPPORT WATER RESOURCES MANAGEMENT

Water resources management (WRM) requires frequent and regular decision-making, at scales from daily through to decadal, and irrigation schemes to basins. Many factors need to be considered, spanning economic, social and environmental considerations. Understanding the status of water resources is critical to support these decisions. The current status helps to guide decisions about how, how much, and where to use and protect water resources now and in the future.

The effective application of water-related data to support evidence-based WRM requires water-related data products to be tailored to suit their intended application. To assist in assessing and identifying opportunities to strengthen the use of water-data, and to guide the development of water-related data products, an understanding of the current status of WRM and use of data can be helpful.

PURPOSE AND SCOPE OF THE FRAMEWORK FOR MATURITY OF WATER RESOURCES MANAGEMENT AND THE USE OF WATER-RELATED DATA

The purpose of this framework is to support the strengthening of evidence-based, sub-basin water management by *identifying opportunities to strengthen the use of water-related data in water management decisions*. Identifying the management functions that already use water-related data indicates the existing ‘maturity’ of the water management regime operating at sub-basin levels. It also enables identification of management functions not currently informed, or incompletely informed, by water-related data – these represent opportunities to strengthen the water management regime.

The specific objectives of the framework are to:

- identify the many ways that water-related data can usefully inform sub-basin level water management
- be used as a basis for a conceptual framework against which the maturity of water management of any sub-basin, basin, province or country can be determined.
- enable stakeholders working in or supporting sub-basin water management to understand the extent to which this is already underpinned by water-related data, and the scope for and opportunities to further strengthen evidence-based sub-basin water management.

The focus of the framework is on water management and operations that are best made with hydrological data – that is, decisions about what actions to take to ensure sustainable and resilient water supplies to meet all agreed needs, including the environment. It does not include assessing institutional arrangements or governance processes (how and who to be involved in making decisions).

As outlined above, the focus is also on management decisions best made using hydrological or related data. Using relevant environmental data to inform decisions is good water management practice. Understanding the water and environmental situation is an essential step in developing basin plans and guiding sub-basin operations and determining and monitoring ongoing management decisions. However, water management decisions should not be made solely based on water-related data; data forms an important evidence-base to be considered during decision-making, alongside other factors such as social and environmental values and data, which should be considered through a participatory governance process.

This research project is interested in sub-basin water management. As such, this framework incorporates sub-basin level management tasks and decisions, though does not exclude basin or other levels, as they will influence sub-basin management.

The Framework does not attempt to diagnose the reasons for the results, for example, resource limitations, capacity gaps, accessibility of data.

Additionally, having access to and the capability to use water-related data on its own, cannot achieve the full range of water management functions / tasks possible; other management instruments are required, such as policies, plans, regulations, stakeholder communications, and participatory decision-making.

ASSESSMENT APPROACH

FRAMEWORK DEVELOPMENT

Through a review of literature relating to agricultural water management and water resources management more broadly, a list of typical water resources management (WRM) tasks was identified (refer to Box 1. The key resources drawn on included Sheffield et al. (2018), CapNet (2008), AWP (2020) and BoM (2013).

This was reviewed and updated by our expert team, and further refined following a review of water management policy in Viet Nam, in an effort to ensure key water resources management tasks relevant to Viet Nam were identified. The workshop activities described below further refined the framework.

Box 1: WATER RESOURCES MANAGEMENT TASKS, ORGANISED BY HIGH-LEVEL FUNCTIONAL CATEGORIES

PLANNING

- Water resources assessments to inform capacity for future / additional economic development / productivity in specific sub-basins
- Water resources capacity assessments to guide investment and design of water infrastructure
- Designing irrigation systems
- Designing water supply systems (community, towns, cities)
- Input to (environmental, drinking) water quality guidelines (alongside other ecosystem health, human health & values-based inputs)
- Determining water discharge license conditions and fees
- Designing flood control works
- Basin / Sub-basin level allocations for major water use groups (sub-basin level totals for each water user type e.g. agriculture, hydroelectricity, forestry, mining, industry, urban/domestic, environment, etc)
- Annual license allocations for major individual water users (agriculture, industry, hydroelectricity), including extraction locations
- Informing/forecasting Urban / domestic water supply service levels; Guiding (urban) demand management need & actions
- Measuring and predicting impacts of externalities such as climate change, population growth, industrial changes (à forecasting future water resource regimes)
- Determine groundwater/SW extraction licensing fees

MANAGEMENT & OPERATIONS

- Enforcing extraction allocations / compliance monitoring
- Guiding water infrastructure operations decisions e.g. opening or closing storage regulators, timing of pumping or irrigation or irrigation headworks operations, or access restrictions
- Identifying pollution problems for attention (evidence base for managers and polluters; spatial and temporal scale important)
- Compliance monitoring enforcing pollution requirements
- Monitoring sustainability/appropriateness of water allocations (comparing actual to projected balances to identify adjustments)
- Inform water markets / trading
- Determine location and number of groundwater extraction points

RISK & DISASTER MANAGEMENT

- Monitoring crop productivity (early warning food insecurity)
- Drought early warning and management
- Flood early warning and management

It is anticipated that not all tasks are undertaken in every place, depending on the complexity of the system (e.g. simple systems not requiring all of these), capacity and resourcing, basin/land use activities and scale. The framework thus includes some tasks that are more sophisticated/mature versions of others in the same list.

WRM tasks were categorised into 3 high-level functional categories, for easier interpretation by stakeholders. These groupings followed the lead of Sheffield et al (2018) but were modified to the specific list of WRM tasks in this framework. The 3 functional categories of WRM tasks are:

- Management and operations
- Planning
- Risk and disaster management

These three are not mutually exclusive, and some WRM tasks will contribute to all of these functional needs; the categorisation was only a guide to assist in interpreting the nature of the WRM task by stakeholders.

The list of WRM tasks above, are used as the basis of the framework, which is structured to encourage stakeholders to self-assess, for each WRM task:

- The current status of implementation / actioning of each task in the country (using a rating of green, yellow and red)
- The spatial and temporal scales at which each task is conducted
- The agencies involved
- How well water data is used to support this task (using a scoring of 1-5)
- The types of water data that is used

APPLYING THE FRAMEWORK TO ASSESSING STATUS OF WATER DATA USE (MATURITY OF DATA-INFORMED WATER MANAGEMENT).

The WRM framework above provides a systematic structure to assess, with stakeholders, the maturity of data-informed water management. The proposed method, which will be applied and refined through the Vietnam pilot study, involves stakeholders firstly reviewing the WRM framework to ensure it represents the scope of WRM in Vietnam. And Secondly, for each WRM task, discussing and identifying the following:

1. Spatial and temporal scales
2. Agencies/ organisations involved
3. Types of water-related data being used
4. Comments on use of data
5. Rating of use of water data to support WRM task

The fifth component, the rating of the use of water data to support each WRM task, is a semi-qualitative, self-assessment by stakeholders. Its rating should be determined by a diversity of stakeholders from different agencies, and the process involves discussion, in particular about items 1-4 in the above list. The proposed method involves determining a rating of 1-5; this could be agreed through consensus, or an average (or other appropriate measure) of individual, or group-based ratings. The specific method should be appropriate to the professional culture of the location and agencies involved, while ensuring a diversity of voices and inputs is considered.

SUMMARY

Understanding of the current status of Water Resources Management (WRM) and use of data can be helpful in assessing and identifying opportunities to strengthen the WRM regime, improve the use of water-data, and guide the development of water-related data products.

WRM will be implemented differently in different places, depending on governance systems, environmental, especially water situations, social systems and resources available for WRM. However, a list of typical WRM tasks that would be conducted in a strong – or mature – water resource management regime, can be identified from literature. The potential for this WRM framework to be used as the basis of a framework to identify opportunities to strengthen WRM and data use in any place, will be tested through a pilot application in Vietnam.

Most importantly, the framework has the potential to offer (i) a structured process to guide stakeholder discussions helps to ensure constructive and focused discussions around the current status of water resources management and opportunities to strengthen it, and (ii) guidance to water data product developers about the end use of data products and tools. Both are important outcomes to improving evidence-based water resources management, for agricultural and broader economic and social development and environment protection.

5 WATER ACCOUNTING METHODS

5.1 REVIEW OF WATER ACCOUNTING METHODS

WATER ACCOUNTING BACKGROUND

During the mid-20th century there was an emphasis on water resource development with large irrigation projects funded from public investment and in the later 20th century massive private investment in bores and submersible pumps (Batchelor et al., 2014; Karimi, 2014). The “Green Revolution” had succeeded in reducing poverty and malnutrition but was not uniform (Turrall et al., 2011; Vincent and Hussein, 1999). The 21st century is now characterised by much of the world experiencing water scarcity with an estimated 1.2 billion people living in basins with water scarcity (Food and Agriculture Organisation, 2012; Karimi, 2014). It is projected that up to two-thirds of the world’s population could experience water scarcity due to population growth, changing diets, economic growth and changing climates (Food and Agriculture Organisation, 2012; Karimi, 2014; Turrall et al., 2011).

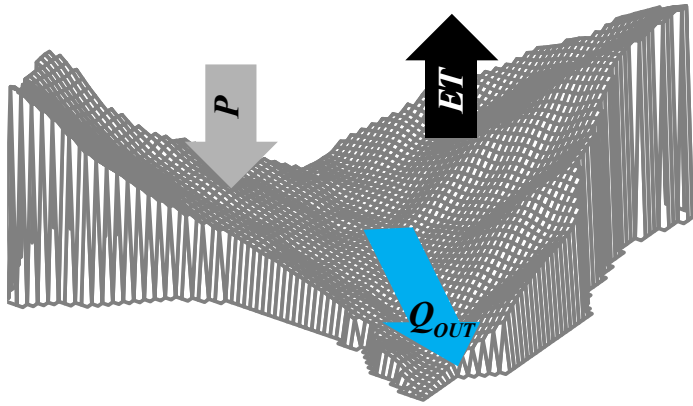
The management of water resources involves policy makers, economists, hydrologists, engineers, lawyers amongst others; all from different cultures, backgrounds and education levels which can lead to misconceptions and misinterpretations (Perry, 2007). An example of a term that can have multiple meanings is ‘closed basin’. In the agricultural water management literature a ‘closed basin’ is where all the water within a basin is fully utilised and no water is available for other purposes examples being the Indus River (Pakistan/ India) and Yellow River (China) (Karimi, 2014). Whereas in the broader hydrology discipline, a closed basin refers to an internally drained or endorheic basin. Depending on the context it could lead to confusion as to what is meant. Effective water governance requires timely and reliable data with a common set of terms that can be used and understood by different decision and policy makers which led to the development of water accounting frameworks (Giordano et al., 2017; Perry, 2007; Vardon et al., 2025).

Water accounting is defined as “the systematic study of the current status and trends in water supply, demand, accessibility and use in domains that have been specified” (Batchelor et al., 2017; Food and Agriculture Organisation, 2012)². At the foundation of all water accounting frameworks is developing water balances for the areas of interest. The main difference between water balances and water accounting is water accounting is not only concerned with the current status but also trends.

The conservation of mass is used to derive water balances as illustrated using a conceptual basin or catchment where inflows (In) plus changes in stocks or storages (ΔS) equals outflows (O) – Equation (iii).

$$O = In + \Delta S \quad (iii)$$

² Water auditing goes one step further than water accounting by placing trends in water supply, demand, accessibility and use in the broader context of governance, institutions, public and private expenditure, legislation and the wider political economy of water of specified domains.



The water balance for a small headwater basin or catchment (Figure 5.1) is where the change in storage (ΔS) equals inflows, precipitation (P) minus outflows evapotranspiration (ET) and runoff or discharge (Q_{OUT}) – Equation (iv)

FIGURE 5.1 A WATER BALANCE FOR A SMALL HEADWATER BASIN (AFTER HORNBERGER ET AL 1998).

$$\Delta S = P - ET - Q_{out} \quad (iv)$$

If averaged over years, then it can be assumed that $\Delta S=0$ and discharge is equal to precipitation minus evapotranspiration (v)

$$Q_{out} = P - ET, \Delta S = 0 \quad (v)$$

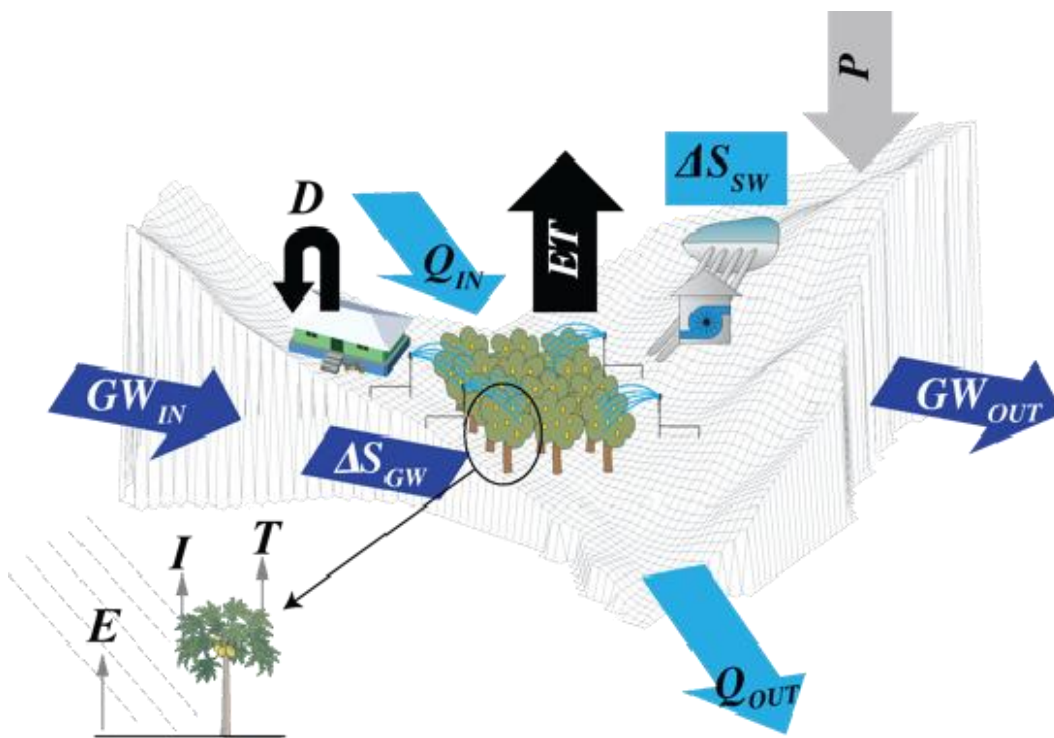


FIGURE 5.2 COMPONENTS OF A BASIN WATER BALANCE.

Or for a more complex basin (Figure 5.2)

$$Q_{OUT} + GW_{OUT} + ET = P + Q_{IN} + GW_{IN} + \Delta S_{SW} + \Delta S_{GW} \quad (vi)$$

Where for **Outflow (vi)**, ET is evapotranspiration, Q_{OUT} is surface water flow out of study area and GW_{OUT} is groundwater flow out of the study area. For **Inflow**, P is precipitation, Q_{IN} is surface water flow into the study area and GW_{IN} is groundwater flow into the study area. With **Changes in storage**, ΔS_{SW} is change in

surface water storage (lakes, dams etc.) and ΔS_{GW} is the change in groundwater storage. Domestic water supplies (D) withdrawn for households and other users, except agriculture, are assumed to be recycled and included in storage and outflow terms; ET , ΔS_{GW} , Q_{OUT} and GW_{OUT} .

Evapotranspiration can be further separated into transpiration (T), water transpired by plants for photosynthesis, evaporation (E), water evaporated directly from soil and water, and interception (I), rainfall intercepted by plants and evaporated before reaching the ground (vii).

$$ET = T + E + I \quad \text{(vii)}$$

5.2 WATER ACCOUNTING FRAMEWORKS

Over recent decades water accounting as a relatively new discipline has gained more importance in the management of water with several international and national organisations such as the United Nations - Statistical Division, International Water Management institute (IWMI) and the Australian Government Bureau of Meteorology developing water accounting frameworks (Godfrey and Chalmers, 2012). The water accounting frameworks based on how they define and measure water resources can be divided into two classes; flow accounting methods and depletion accounting methods (Karimi, 2014).

FLOW ACCOUNTING METHODS

Flow accounting methods are based on actual measured data including river discharges, diversions, allocations and abstractions. The accounting includes assets or stocks (e.g. reservoirs or aquifers) and flows (e.g. rivers, irrigation canals, evapotranspiration) that occur in natural and engineered systems (Karimi, 2014; United Nations, 2012b; Water Accounting Standards Board, 2012).

The System of Environmental- Economic Accounting for Water (SEEA) is a water accounting framework for linking economic and hydrological information. SEEA provides a set of standard tables for presenting hydrological and economic information, that show the interaction between water and the economy as well as water resources in the environment. SEEA links hydrological data to the System of National Accounts (SNA) which is used to derive gross domestic product - GDP (United Nations, 2012a; United Nations, 2012b; Vardon et al., 2012).

A conceptual view of SEEA framework is shown Figure 5.3 where the physical flows of water within the environment and the economy are represented as two separate boxes. Stocks or assets of water are stores of water such as aquifers, lakes or reservoirs. Flows of water within the environment or between the environment and the economy result in changes in stock. Flows are quantified and are added or subtracted from a stock during a specific period of time, the reporting period either calendar or water year. Water use and water consumption are also reported. Water use is where the water is still available to other components of the system whereas water consumption is the amount of water lost to the economy during use through incorporation into products etc (United Nations, 2012b; Vardon et al., 2012). SEEA in most circumstances would not be applicable as the data required for the framework is unlikely to be available. Additionally, SEEA does not cover natural processes and agriculture which are typically the major water users in river basins (Perry, 2012).

The Australian Water Accounting Standards resulted from the National Water Initiative (Water Accounting Standards Board, 2014). Under the Australian Constitution water management is devolved to the sub-national, state and territory, governments which was an impediment to the management of the trans-jurisdictional basins like the Murray-Darling Basin where water demand exceeded availability. There was a strong interest in water from both government and the public during the intense drought of the early 21st

century, known as the 'Millenium Drought'. This led to the development of the National Water Initiative (NWI) through the Council of Australian Governments (CoAG), which consisted of the heads of subnational and the national governments. The NWI was developed to ensure consistent and coordinated

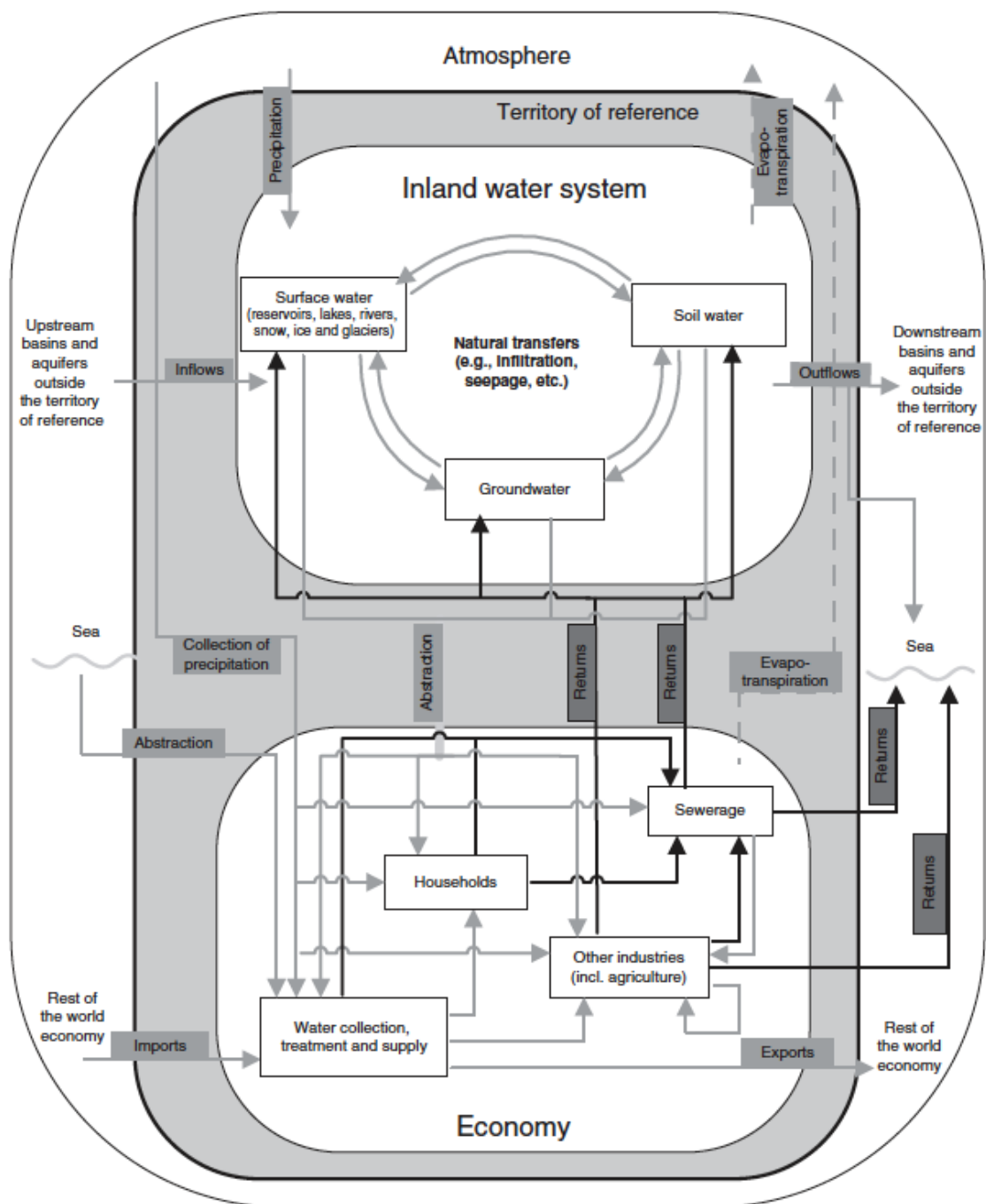


FIGURE 5.3 ELEMENTS OF THE SEEWA FRAMEWORK SHOWING THE MAIN WITHIN AN INLAND WATER SYSTEM AND THE ECONOMY (SOURCE: VARDON ET AL 2012).

water reform across the country with the national government taking over responsibilities for water management in exchange for financial rewards (Batchelor et al., 2017; Vardon et al., 2007). The NWI required the development of water resource accounting to ensure that *'adequate measurement, monitoring and reporting systems are in place in all jurisdictions, to support public and investor confidence in the amount of water being traded, extracted for consumptive use, and recovered and managed for environmental and other public benefit outcomes'* (Water Accounting Standards Board, 2014).

This led to the development of the Australian Water Accounting Standards which were uniquely based on financial reporting standards and both shared commonalities in reporting requirements. The first water accounting standard, finalised in 2012, was the *Australian Water Accounting Standard 1: Preparation and Presentation of General Purpose Water Accounting Reports*. The purpose of these General Purpose Water Accounting Reports (GPWARs) is to “provide information useful to users of that report for making and evaluating decisions about the allocation of resources” (Water Accounting Standards Board, 2012).

The GPWARs contain the following components; Contextual Statement, Accountability Statement, Statement of Water Assets and Water Liabilities (SWAWL), Statement of Changes in Water Assets and Water Liabilities (CSWAWL), Statement of Water Flows and note disclosures. The Contextual Statement is to provide information about the entity preparing the report, the water resources contained in the report and factors such as climatic conditions and legal obligations that could impact on the management of the water resource. The Accountability Statement is to demonstrate that the report was prepared in accordance with the Australian Water Accounting Standards (Water Accounting Standards Board, 2012).

The Statement of Water Assets and Water Liabilities (SWAWL) contains data on water assets, water liabilities and net water assets. It is the functional equivalent to a financial Balance Sheet. The Statement of Changes in Water Assets and Water Liabilities (CSWAWL) contains information about water asset increases and decreases, water liability increases and decreases, and changes in net water assets. It is the equivalent to a financial Profit and Loss Statement. The Statement of Water Flows includes information on water inflows and outflows, changes in water storage and opening and closing water storage balances. The CSWAWL and the Statement of Water Flows are often presented together (Water Accounting Standards Board, 2012).

The GPWARs contains information about the total resource including the amount available for withdrawals, water rights (liabilities) and actual withdrawals for social, cultural, economic and environmental benefits for the area of reporting whether that be a basin, water service provider or mining operation (Karimi, 2014). Some of the greatest limitations of GPWARs is that they require measured data which is not always available. Additionally, natural processes are not covered in the reporting which can be some of the largest consumers of water in a basin (Adam Lillicrap, *Pers Com.*)³.

DEPLETION ACCOUNTING METHODS

Depletion accounting systems seek to track water depletion (consumption of water) rather than withdrawals like the flow-based accounting systems. Depletion refers to water unavailable to other users. Depletion may be losses through evapotranspiration, unrecoverable flows to sinks, incorporation into products or degradation of quality to render it usable for its intended purposes (Karimi, 2014; Perry, 2007).

During the 1990s there was a major shift in the paradigm for agricultural water management, particularly at the International Irrigation Management Institute moving away from improving the efficiency of irrigation systems to “analysing water use in the context of the water balance of the river basin” (Seckler, 1999). This shift also involved moving away from focussing on water withdrawals as in case of classic irrigation efficiency measurements to better understanding areas of water depletion (Seckler, 1996; Seckler et al., 2003). Consequently, leading to the development of the IWMI Water Accounting framework that was designed to be used at a range of scales from farm to irrigation district to basin scales (Molden, 1997; Molden and Sakthivadivel, 1999; Molden et al., 2001). The framework was based on developing water balances with a defined set of terminologies as well as provided a means to determine the output

³ The Australian Water Accounting Standards were used in the Water Accounting course for the Master of Integrated Water Resource Management, a joint program between Kabul Polytechnic University and Griffith University but proved difficult to use due to lack of hydrological data in Afghanistan because of the civil war

per unit of water effectively depleted without the need to account for all the related flows -see Table 5.1 and Figure 5.4 (Karimi et al., 2012; Molden, 1997; Molden and Sakthivadivel, 1999).

The IWMI WA framework was originally designed for irrigation schemes and extended to the analysis of basins. So, some of the components of the WA framework proved to be too generic for basin level studies. Water depletion in irrigation schemes only results from crop evapotranspiration while at the basin scale, sources of water depletion also include municipalities, industries, fisheries, forestry, dedicated wetlands and all other uses. These are not covered in the WA framework. IWMI developed the Water Accounting Plus (WA+) that uses similar concepts as WA but considers in more detail the processes and mechanisms at the basin scale for different land use classes (Karimi, 2014; Karimi et al., 2013; Karimi et al., 2012).

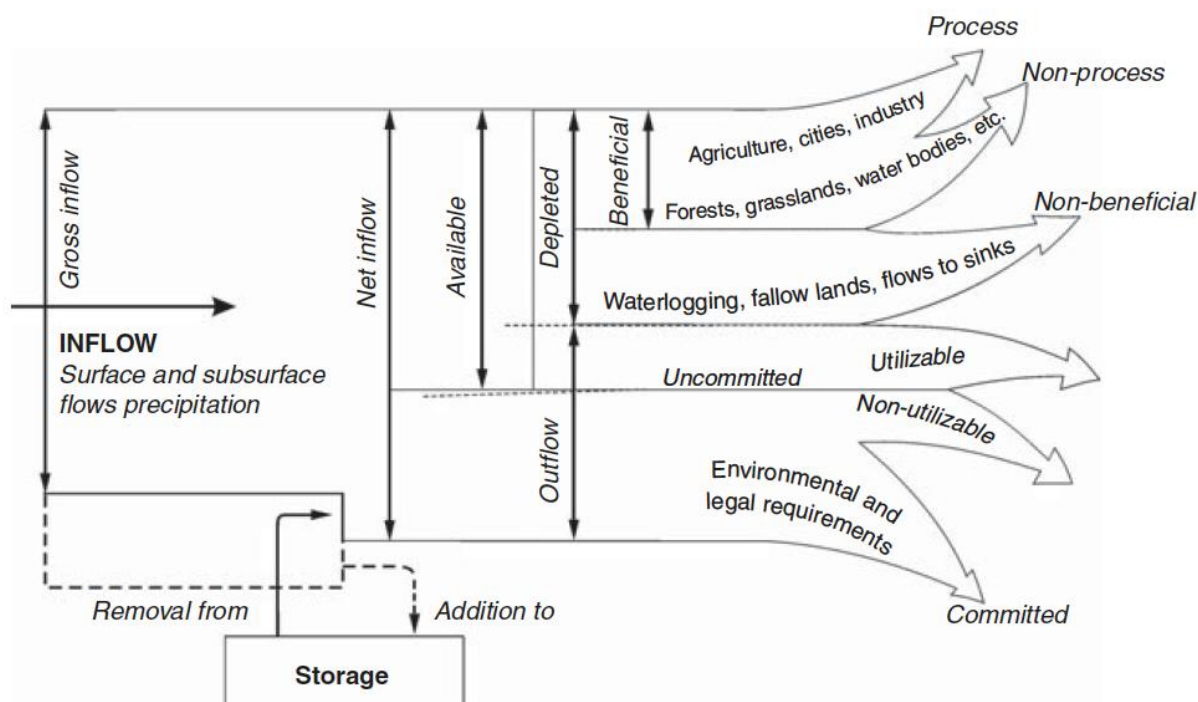


FIGURE 5.4 GENERALISED IWMI WATER ACCOUNTING FRAMEWORK (SOURCE: KARIMI ET AL 2012)

TABLE 5.1 DEFINITIONS OF TERMS USED IN THE IWMI WATER ACCOUNTING FRAMEWORK

Term	Definition
Gross inflow	the total amount of water that flows into the domain, including precipitation plus any inflow from surface or ground water sources.
Net inflow	the gross inflow plus any changes in storage. If water is removed from storage over the time period of interest, net inflow is greater than gross inflow; if water is added to storage, net inflow is less than gross inflow. Net inflow is either depleted or flows out of the water balance domain. Sustainability may be in question when net inflow differs from gross inflow over a long period of time.
Outflow	the water that leaves the domain and is further divided into committed and uncommitted outflows
Committed outflow	the part of outflow that is allocated to other uses such as downstream water rights or minimum stream flows to maintain aquatic ecosystems. It may also include a required outflow to be realised from an irrigated area.

Term	Definition
Uncommitted outflow	water that is available for a use but flows out of the domain due to lack of storage or operational measures. For example, waters flowing out to sea in excess of requirements for environmental or other beneficial uses are uncommitted outflows.
Available water	water that is available for use within the domain. It is the difference between Net inflow and committed outflow
Water depletion	a use or removal of water that makes it unavailable or unsuitable for further use.
Beneficial depletion	occurs when water is depleted in providing an input to produce a good such as an agricultural output, providing a need such as drinking or bathing water, or in any other manner deemed beneficial, such as supplying water for environmental uses. Beneficial depletion can be further classified as process or non-process depletion
Process depletion	is that amount of water diverted and depleted to produce an intended good. In industry, this includes the amount of water vaporised by cooling or converted into a product. For agriculture, it is crop-consumptive use plus that amount of water incorporated into plant tissues
Non-process depletion	occurs when no benefit or a negative benefit is derived from the depletion of water. Examples are evaporation from fallow land, discharge into sinks in excess of environmental requirements, deep percolation into saline aquifers or evaporation from waterlogged areas.
Non-process depletion	occurs when no benefit or a negative benefit is derived from the depletion of water. Examples are evaporation from fallow land, discharge into sinks in excess of environmental requirements, deep percolation into saline aquifers or evaporation from waterlogged areas.

5.3 WATER ACCOUNTING PLUS

Withdrawals and return flows data are often scarce and incomplete both at the local and river basin scales for different water sectors (Karimi et al., 2013). Evapotranspiration data though can be acquired from satellite derived datasets (Sheffield et al., 2018). Through the use of satellite derived data, the strength of Water Accounting Plus (WA+) is that it can provide quantified data on water depletion processes for every land use class (Karimi, 2014; Karimi et al., 2013; Karimi et al., 2012).

WA+ like all water accounting systems uses a water mass balance methodology. The total water balance in a basin in a given time period is:

$$P + (Q_{in}^{SW} + Q_{in}^{GW}) - ET - (Q_{out}^{SW} + Q_{out}^{GW}) + \Delta S = 0 \quad (\text{viii})$$

Where P is precipitation, ET is evapotranspiration, $(Q_{in}^{SW} + Q_{in}^{GW})$ are surface water and groundwater inflows, $(Q_{out}^{SW} + Q_{out}^{GW})$ are surface water and groundwater outflows and ΔS is change in storage.

The change in storage, ΔS , can be further divided into fresh (f) and polluted (p) stores:

$$\Delta S = \Delta S_f^{SW} + \Delta S_f^{GW} + \Delta S_p^{SM} + \Delta S_p \quad (\text{ix})$$

Where ΔS_f^{SW} is the change in surface water storage such as reservoirs and lakes, ΔS_f^{GW} is the change in groundwater storage (i.e. aquifers), ΔS_f^{SM} is the change in ice reserves (i.e. glaciers, permanent snow) and ΔS_p is change in contaminated or polluted water storages such as saline aquifers or inaccessible water (i.e. low yielding aquifers) (Karimi, 2014; Karimi et al., 2013).

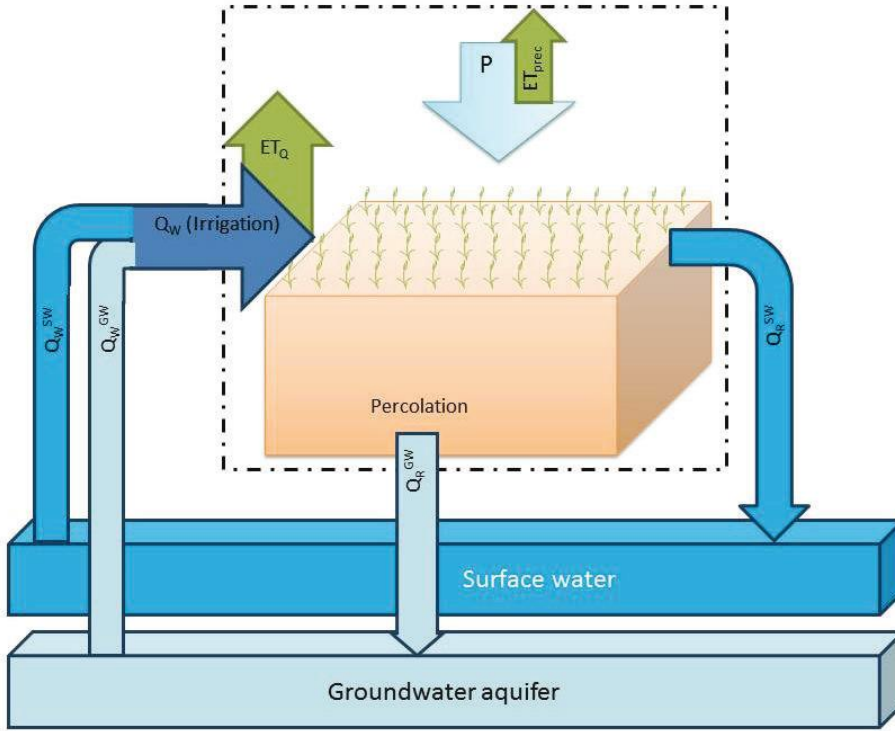


FIGURE 5.5 THE DERIVATION OF INCREMENTAL ET FROM THE DIFFERENCE BETWEEN GROSS AND NET WITHDRAWALS (SOURCE: KARIMI ET AL., 2013)

Water that is available to plants as soil moisture from rainfall is referred to as ‘green’ water and water that is applied to plants, through irrigation, to supplement rainfall is known as “blue water”. In areas where irrigation occurs and has withdrawals from either surface water, groundwater or both (Figure 5.5), the water balance equation is:

$$P + (Q_w^{SW} + Q_w^{GW}) - (ET_{prec} + ET_Q) - (Q_R^{SW} + Q_R^{GW}) = 0 \quad (\text{x})$$

Where $(Q_w^{SW} + Q_w^{GW})$ are withdrawals from surface water and groundwater, $(Q_R^{SW} + Q_R^{GW})$ are return flows to surface water and groundwater, ET_{prec} is the ET from precipitation (also known as ET_{green}), ET_Q is incremental ET and results from withdrawals only (and can also be known as ET_{blue}). ET_Q is the difference between withdrawals and return flows plus water incorporated into produce (i.e. plant tissues). ET from precipitation (ET_{prec}) can be formulated as:

$$ET_{prec} = P - Q_{Rprec} \quad (\text{xi})$$

Where Q_{Rprec} is return flow from rainfall only, which includes surface runoff, lateral subsurface drainage and recharge to groundwater. ET_{prec} can be derived from empirical equations for effective rainfall⁴, for example FAO, or other methods discussed later. ET_Q can be determined without having to measure flows (i.e. Q_w , Q_R) from:

⁴ Effective rainfall in agricultural water management refers to the component of rainfall remaining in the rootzone available for plant use, differing from the hydrological context where effective rainfall is the component of rainfall that contributes to runoff.

$$ET_Q = ET - ET_{prec} \quad (\text{xii})$$

Spatially distributed data on ET_Q is useful in ungauged (sub-) basins where withdrawals occur. Water depletion from natural processes and incremental ET can be tracked, both spatially and temporally by satellite derived ET data over discrete areas, for every land use class and water user. This approach forms the basis of WA+ framework to estimate water depletion in different land use management categories. WA+ originally summarised changes in water stocks, inflows and outflows for river basins in four sheets. These sheets are summarised in Table 5.2 (Karimi, 2014; Karimi et al., 2013).

TABLE 5.2 THE ORIGINAL WATER ACCOUNTING PLUS SHEETS (SOURCE: KARIMI ET AL., 2013)

Water sheets	Purpose	Bookkeeping sheets
Resource Base	Hydrological, manageable, utilisable flows, water security, sustainability	Assets & liabilities
Evapotranspiration	Beneficial and non-beneficial flows	Profit & loss/expenditure sheet
Productivity	Biomass returns, carbon sequestration, food security	Profit
Withdrawal	Management, regulation, allocations	Cash book

The main differences between the IWMI Water Accounting and Water Accounting Plus are:

- the link between land use and ET is made explicit in order to understand the impact of land use changes on exploitable water resources.
- manageable and non-manageable depletions are defined, and the processes are quantified for both geographical and atmospheric processes.
- surface and groundwater systems are differentiated as they have different management options
- incremental ET is computed for different land use categories and water user groups to assign benefits from managed water use.
- partitioning of consumed water (ET) into transpiration, evaporation and interception to determine beneficial ET (i.e. food, ecosystem services) and non-beneficial ET.
- input data for WA+ can be sourced from satellite derived datasets that can augment field data or replace if unavailable. Data inputs can become standardised and transparent. Though RS/EO data has its own short comings (Karimi, 2014; Karimi et al., 2013).

With the total basin or catchment inflows shown in Figure 5.2, only a fraction of the water resources can be controlled and regulated to provide water for human usage. This can include the installation of dams, bore fields and water supply infrastructure for agricultural, domestic and industrial use. Land use change (e.g. deforestation for agriculture, increasing hard surfaces through urban expansion) or altering land cultivation practices (e.g. no or minimum tillage, weed management) have a controlling effect on ET_{prec} . Therefore, land use, cultivation practices and water resources development are controlling factors of ET and effective rainfall (ET_{prec}) at the basin scale. Areas with a high degree of natural land cover are controlled by natural ecosystem processes rather than human activities and can also consume water as ET impacting on the water balance at the basin scale. Consequently, WA+ has four land use classes that reflect the degree of human influence of water resources in that class which include; *managed water use, modified land use, utilized land use, and conserved land use* (Karimi, 2014; Karimi et al., 2013).

Managed water use represents land uses that have had the highest degree of human impact where water is actively managed for use such as irrigation systems, drinking water supply schemes, hydropower and

canals where water levels are maintained for navigation. It includes any areas where water is applied such as irrigated agriculture, golf courses and urban parks (see Table 5.3 for more examples). *Modified land use* refers to landscapes where the natural hydrological cycle been significantly perturbed by human activities such as dryland or rainfed agricultural systems, improved pasture, urban areas including parks that are rainfed (see Table 5.3 for further examples). *Utilised land use* represents areas that are utilised by human activities but have had little disturbance to the natural hydrological cycle such as areas used for grazing, firewood collection and hunting (see Table 5.3 for more examples). *Conserved land use* relates to the environmentally sensitive land uses and natural ecosystems that are set aside for protection, including protection from sea (Karimi, 2014; Karimi et al., 2013).

TABLE 5.3 EXAMPLES OF WATER ACCOUNTING PLUS LAND USE CLASSES (AFTER KARIMI ET AL., 2013)

Managed water use	Modified land use	Utilised land use	Conserved land use
Irrigated pastures	Plantation trees	Closed natural forests	Reserves or national parks
Irrigated crops	Rainfed pastures	Tropical rain forest	Areas set aside for conservation
Irrigated fruits	Rainfed crops	Open natural forest	Glaciers
Irrigated biofuels	Rainfed fruit	Woody savanna	Coastal protection sites
Reservoirs & canals	Rainfed biofuels	Open savanna	
Greenhouses	Rainfed recreational parks	Sparse savanna	
Aquaculture	Fallow land	Shrub land	
Urban and peri-urban	Dump sites	Natural pastures	
Industrial areas	Oasis & wadis	Deserts	
Irrigated recreational parks	Roads and lanes	Mountains	
Managed wetlands & swamps	Peri-urban areas	Rocks	
Inundation areas		Flood plains	
Mining		Tidal flats	
Evaporation ponds		Bare land	
Waste water treatment beds		Waste land	
Power plants		Moorlands	
		Wetlands & swamps	
		Alien invasive species	
		Permafrosts	

SHEET 1 RESOURCE BASE SHEET

The sheet shows the volumes of water in the domain during the period of interest. The sheet uses similar definitions to the IWMI WA framework but they are restricted to available water (Figure 5.6). A new term is introduced, *exploitable water*, which represents the volume of water in the domain available for use by the different sectors; agriculture, domestic, industrial and the aquatic environment (Karimi, 2014; Karimi et al., 2013).

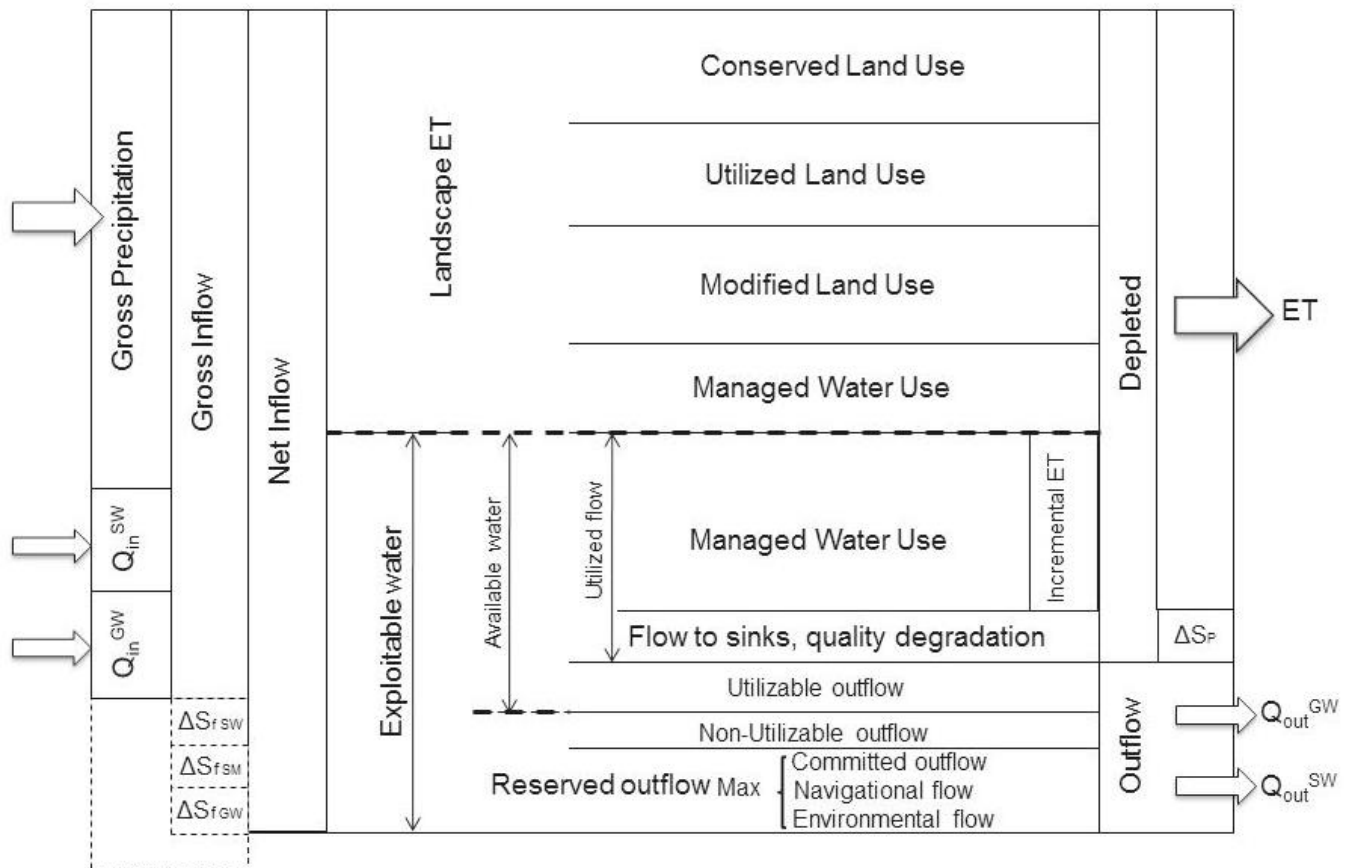


FIGURE 5.6 THE RESOURCE BASE SHEET

An example of a resource base sheet showing annual flows for the Litani River Basin, Lebanon during the period 2010-2016 is shown in Figure 5.7 (FAO and IHE Delft, 2019).

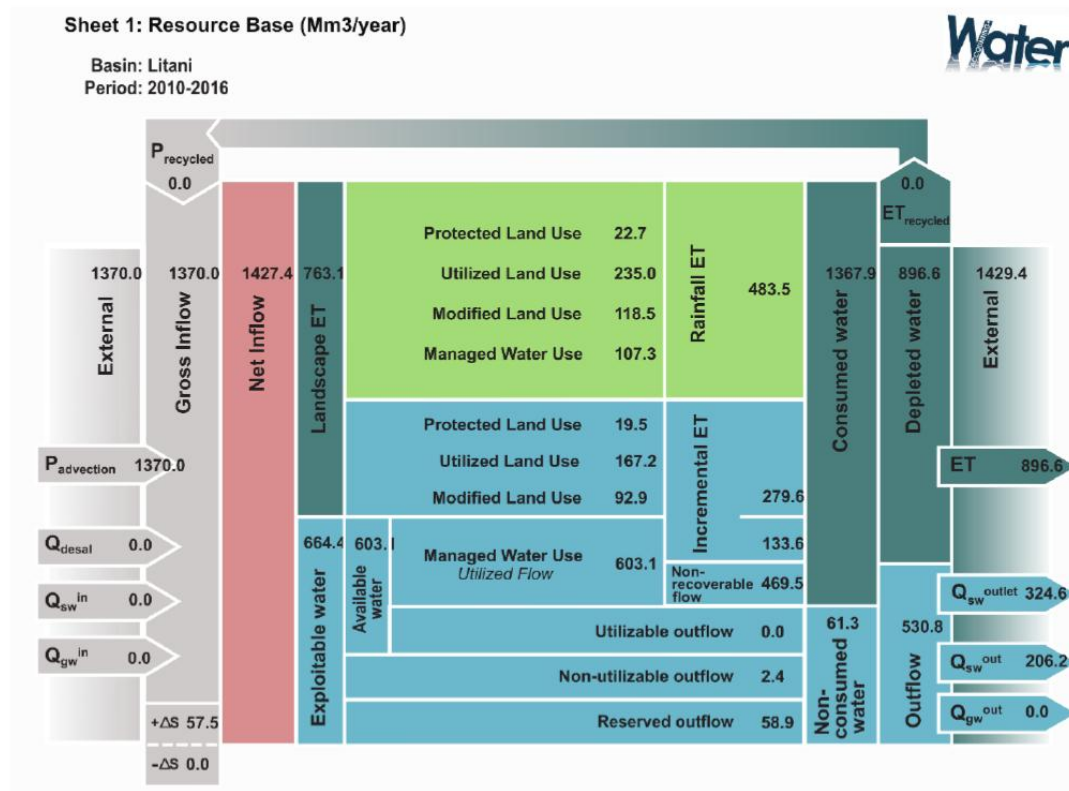


FIGURE 5.7 SHEET 1: RESOURCE BASE SHEET FOR THE LITANI BASINS (SOURCE: FAO AND IHE DELFT, 2019)

A series of performance indicators for the Resource base sheet were proposed in Karimi et al (2013). The first is the *Exploitable water fraction (xiii)*, the part of the net inflow that is not lost to the landscape ET processes. For the Litani Basin the *Exploitable water fraction* would be 0.46

$$Exploitable\ water_{fraction} = \frac{Exploitable\ water}{Net\ inflow} \quad (xiii)$$

The *Storage change fraction* defines the degree of dependency on change in freshwater storage change (ΔS_{fw}). For the Litani Basin the *Storage change fraction* is -0.09. Negative values represent depletions in storage (*Gross inflow – Net Inflow*) or more simply, that during the period of interest more water is being used than is available.

$$Storage\ change_{fraction} = \frac{\Delta S_f}{Exploitable\ water} \quad (xiv)$$

The *Available water fraction* describes the portion of exploitable water that is available for withdrawals within a basin. For the Litani Basin the *Available water fraction* is 0.91.

$$Available\ water_{fraction} = \frac{Available\ water}{Exploitable\ water} \quad (xv)$$

The *Basin closure fraction* describes to what extent available water is already depleted in a basin or domain. A closed basin is where all available water is used. A closed basin can still have substantial discharge, but all outflow is reserved for downstream users or environmental flows. For the Litani Basin the *Basin closure fraction* is 1 meaning it is a closed basin with no water available for further use. Any water required from one sector needs to come from another sector of the economy. There is 469.5 Mm³/yr being discharged as non-recoverable flow as the water quality is unsuitable for further use. Improving water quality would free up water resources for other uses.

$$Basin\ closure_{fraction} = \frac{Utilised\ flow}{Available\ water} \quad (xvi)$$

The *Reserved outflows fraction* indicates if the *Committed* or *Reserved outflows*, for both surface water and groundwater, are being met. For the Litani Basin the *Reserved outflows fraction* is 0.96. However, most of the surface water outflow, 206.2 Mm³/yr, is too degraded in water quality for beneficial use.

$$Reserved\ outflow_{fraction} = \frac{Reserved\ outflows}{Q_{out}^{SW} + Q_{out}^{GW}} \quad (xvii)$$

SHEET 2 EVAPOTRANSPIRATION SHEET

The sheet describes which parts of ET processes are managed, manageable or non-manageable. Manageable areas are areas that are utilised but are not actively managed. ET is split into “beneficial” and “non-beneficial” based on value judgments (Karimi, 2014; Karimi et al., 2013). The Sheet 2 Evapotranspiration for the Litani Basin is shown in Figure 5.8 (FAO and IHE Delft, 2019).

Sheet 2: Evapotranspiration (Mm3/year)

Period: 2010-2016
Basin: Litani

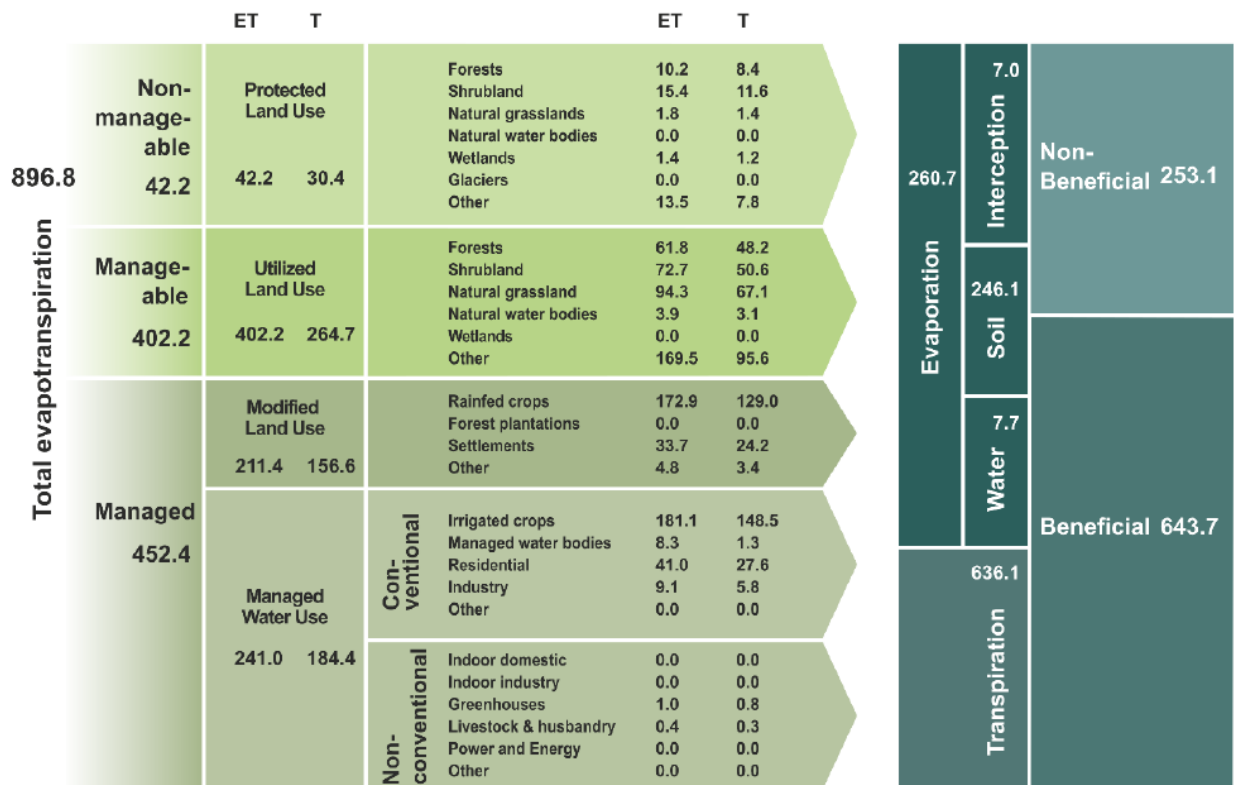


FIGURE 5.8 SHEET 2 EVAPOTRANSPIRATION SHOWING AVERAGE ANNUAL EVAPOTRANSPIRATION FOR THE LITANI BASIN BETWEEN 2010-2016 (SOURCE: FAO AND IHE DELFT, 2019)

The evapotranspiration sheet also has a series of recommended performance indicators (Karimi et al 2013). *Transpiration fraction* is the part of ET that is transpired by plants reflecting the impact of bio-physical processes. For the Litani Basin the *Transpiration fraction* is 0.71.

$$Transpiration_{fraction} = \frac{T}{ET} \quad (xviii)$$

The *Beneficial ET fraction* relates the proportion of beneficial E and T to the total ET in a basin. *Beneficial* means it can produce economic, social or environmental benefits (i.e. production of crops or evaporation from conservation wetlands). For the Litani Basin the *Beneficial ET fraction* is 0.72 which indicates most of the water depleted through ET is used beneficially.

$$Available\ water_{fraction} = \frac{Available\ water}{Exploitable\ water} \quad (xix)$$

The *Managed ET fraction* indicates the ET processes in a basin that could potentially lead to increased benefits through changes in management practices such as land use, cultivation practices and water withdrawals. This is 0.5 for the Litani Basin

$$Managed_{fraction} = \frac{ET_{managed}}{ET} \quad (xx)$$

The *Agricultural ET fraction* is the part of ET attributable to the agricultural production. The proportion of water depletion in the Litani Basin attributable to agriculture is 0.4

$$Agricultural ET_{fraction} = \frac{Agricultural ET}{ET} \quad (xxi)$$

3

SHEET 3 - AGRICULTURAL SERVICES

WA+ sheet 3 assesses agricultural water consumption, production and water productivity. The main purpose is to demonstrate to what extent water in the agricultural sector is used productively. The first part of WA+ sheet 3 describes consumptive water use by agriculture while the second part describes Land and Water productivity (FAO and IHE Delft, 2019; Mul et al., 2020). Sheet 3, Part 1 for the Litani Basin is shown in Figure 5.9. The sheets break downs usage by crop types which can help determine the relative economic value of the water being used for optimisation purposes.

Sheet 3: Agricultural services

Part 1: Agricultural water consumption (Mm3/year)

Basin: Litani

Period: 2010-2016



Crop											Agricultural water consumption	302.11
Cereals	Non-cereals				Fruit & vegetables			Oil-seeds	Feed crops	Beverage crops	Other crops	
15.28	3.64	17.54	-	-	5.85	55.49	-	28.16	-	-	-	ET rainfed 125.96
	Root / tuber crops	Leguminous crops	Sugar crops	Merged	Vegetables & melons	Fruits & nuts	Merged					
16.29	8.18	13.74	-	-	9.82	28.55	-	1.46	-	-	-	ET from rainfall irrigated 78.04
23.22	11.14	19.94	-	-	14.68	28.27	-	0.87	-	-	-	Incremental ET irrigated 98.11
39.51	19.32	33.67	-	-	24.50	56.82	-	2.33	-	-	-	Total ET irrigated 176.15

FIGURE 5.9 SHEET 3 AGRICULTURAL SERVICES - AGRICULTURAL WATER CONSUMPTION (PART1) FOR THE LITANI BASIN (SOURCE: FAO AND IHE DELFT, 2019)

In the Part 2 Land and water productivity, food production is estimated based on existing (coarse) global datasets for Net Primary Production (NPP) to calculate biomass production (kg/ha/yr). For higher resolution satellite datasets biomass production can be improved. The water productivity (kg/m³) is derived from dividing the biomass by the water consumed in Part 1 (FAO and IHE Delft, 2019; Mul et al., 2020). The sheets can indicate water savings and potential improvements in agricultural water management (Mul et al., 2020). The Land and water productivity for the Litani Basin is shown in Figure 5.10. In the Litani Basin rainfed cereals (wheat) had a higher water productivity than irrigated cereals (wheat) which indicates that improvements can be made to lift the productivity for irrigated cereals.

Sheet 3: Agricultural services

Part 2: Land productivity (kg/ha/year) and water productivity (kg/m3)

Basin: Litani

Period: 2010-2016



	Crop													
	Cereals	Non-cereals				Fruit & vegetables			Oil-seeds	Feed crops	Beverage crops	Other crops		
Land productivity	3568	35767	2492	-	-	21795	11989	-	99	-	-	-	Yield	rainfed
	2061	18508	1864	-	-	14627	10740	-	79	-	-	-	Yield from rainfall	} irrigated
	2062	17916	2046	-	-	15899	11256	-	29	-	-	-	Incremental yield	
	4123	36423	3910	-	-	30526	22009	-	107	-	-	-	Total yield	
Water productivity		Root / tuber crops	Leguminous crops	Sugar crops	Merged	Vegetables & melons	Fruits & nuts	Merged						
	0.74	6.74	0.72	-	-	4.86	4.31	-	0.03	-	-	-	WP	rainfed
	0.84	7.45	0.75	-	-	5.55	3.16	-	0.03	-	-	-	WP from rainfall	} irrigated
	0.60	5.37	0.57	-	-	4.11	2.66	-	0.02	-	-	-	Incremental WP	
	0.70	6.30	0.65	-	-	4.70	2.91	-	0.02	-	-	-	Total WP	

FIGURE 5.10 SHEET 3 AGRICULTURAL SERVICES - LANAD PRODUCTIVITY AND WATER PRODUCTIVITY (PART 2) FOR THE LITANI BASIN (SOURCE: FAO AND IHE DELFT, 2019)

SHEET 4 – UTILISED FLOW

The utilised flow provides an overview of all human-made withdrawals (Part 1) and estimates of natural withdrawals due to seasonal floods, shallow groundwater tables and groundwater dependent ecosystems such as forests (Part 2). The sheets describe surface water and groundwater contribution to total withdrawals. The sheets distinguish between consumed and non-consumed water as well as distinguishing between recoverable and non-recoverable flows (Mul et al., 2020). The recoverable flows show the impact of non-consumptive water use on downstream users (i.e. the recycling of water within the basin). The Sheet 4 Utilised Flow for the Litani Basin are shown in Figure 5.11 (Part 1 Human-made) and Figure 5.12 (Part 2 Natural land use)

Sheet 4: Utilized Flow

Part 1: Manmade (Mm3/year)

Basin: Litani

Period: 2010-2016

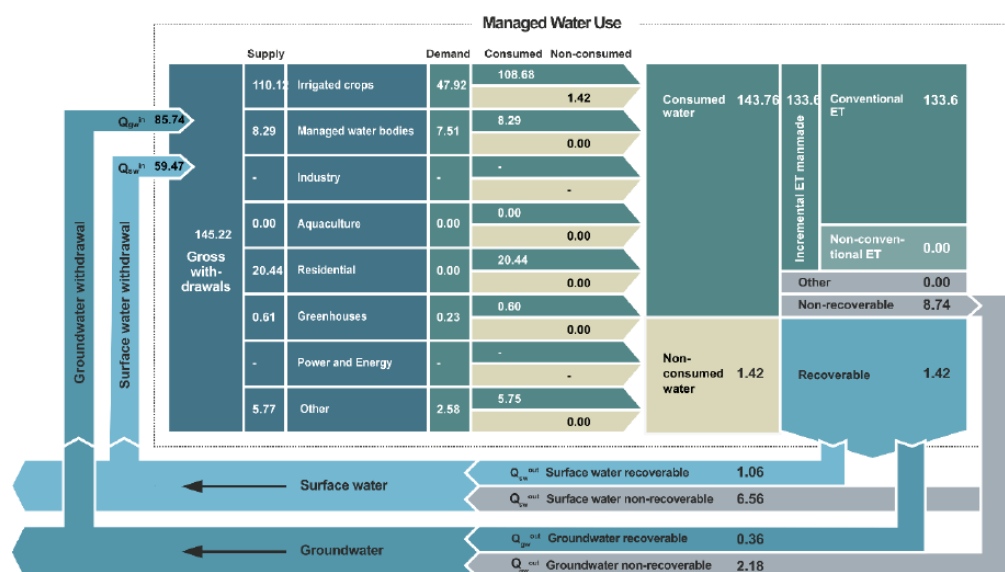


FIGURE 5.11 SHEET 4 UTILIZED FLOW PART 1 - HUMAN-MADE FLOWS FOR THE LITANI BASIN (SOURCE: FAO AND IHE DELFT, 2019)

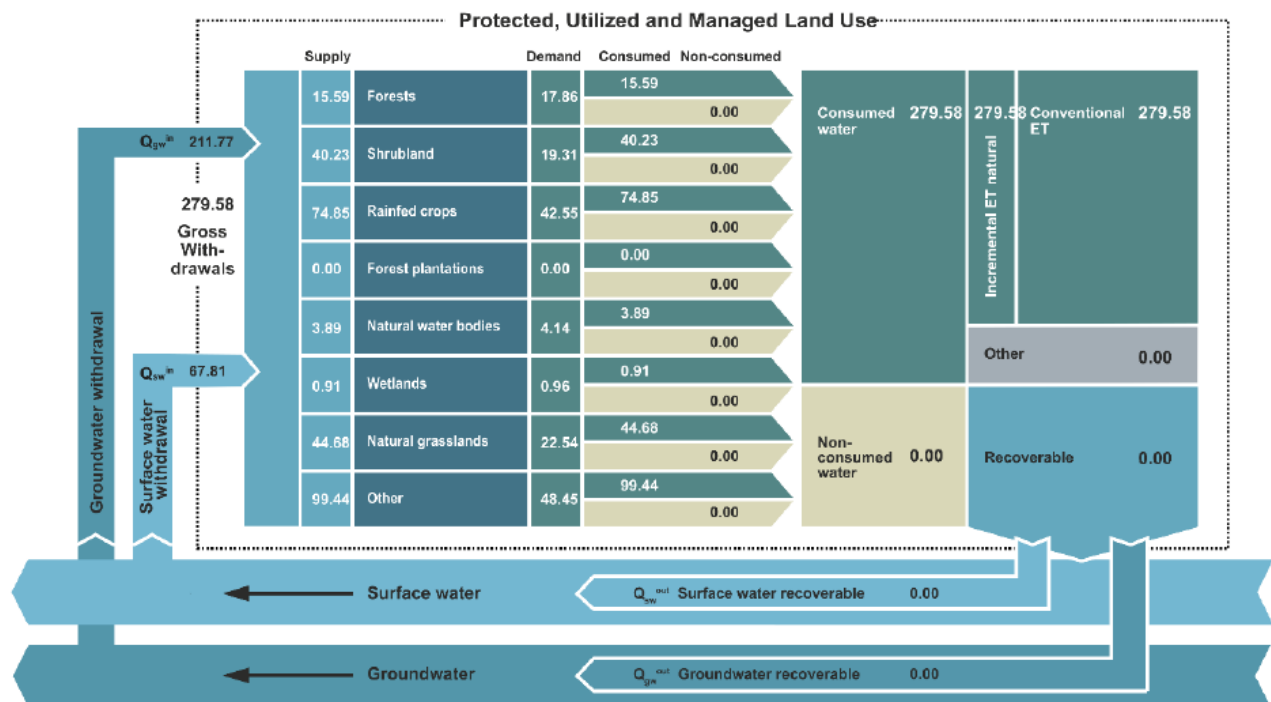


FIGURE 5.12 SHEET 4 UTILIZED FLOW PART 2 NATURAL LAND USE FOR LITANI BASIN (SOURCE: FAO AND IHE DELFT, 2019)

SHEET 5 SURFACE-WATER

This sheet has been added to the Water Accounting Plus framework since Karimi et al. (2013) and relies on a pixel-based water balance models using a 100 m grid. There have been different iterations of the pixel-based model which will be discussed later. The sheet quantifies the natural and actual river flows along a transect of tributaries. It also determines the surface water availability and utilizable withdrawals in any location in the river basin. The sheet is meant help with regulation, planning of infrastructure and water source development as well as the preparing of surface water allocation plans (Mul et al., 2020). An example of a Surface water sheet for the Litani Basin is shown in Figure 5.13.

Sheet 5: Surface Water (Mm3/year)

Basin: Litani

Period: 2010-2016

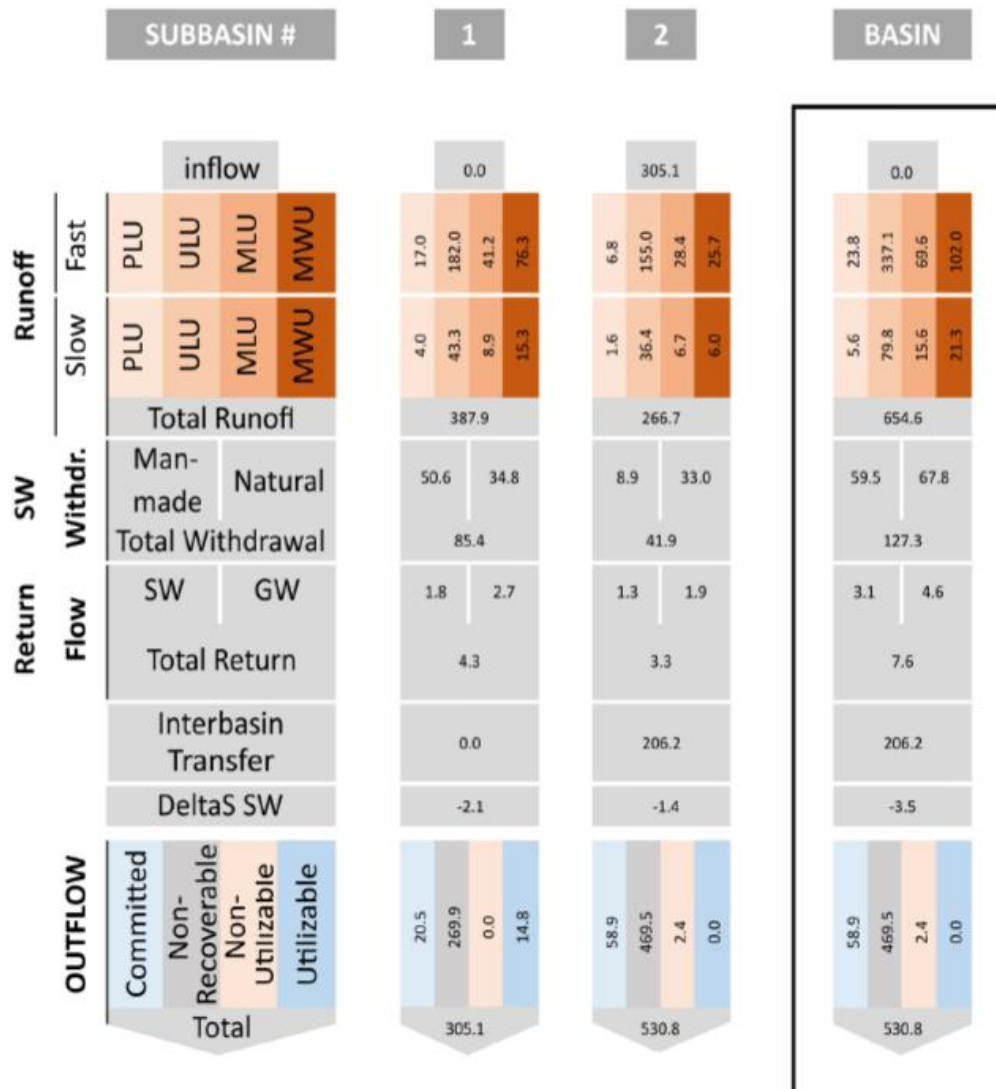


FIGURE 5.13 SHEET 5: SURFACE WATER FOR THE LITANI BASIN (SOURCE: FAO AND IHE DELFT, 2019)

SHEET 6 : GROUNDWATER

The groundwater sheet like the surface water sheet has been added to the Water Accounting Plus framework and relies on an internal 100 m pixel water balance model. The model estimates recharge to groundwater as well as natural and human withdrawals. The sheet provides the change in storage and groundwater baseflow (FAO and IHE Delft, 2019; Mul et al., 2020). The purpose of the sheet is help in management of groundwater, particularly as a buffer during dry seasons and droughts as well as in developing groundwater withdrawal plans (Mul et al., 2020). An example of a Groundwater sheet for the Litani Basin is shown in Figure 5.14 (FAO and IHE Delft, 2019).

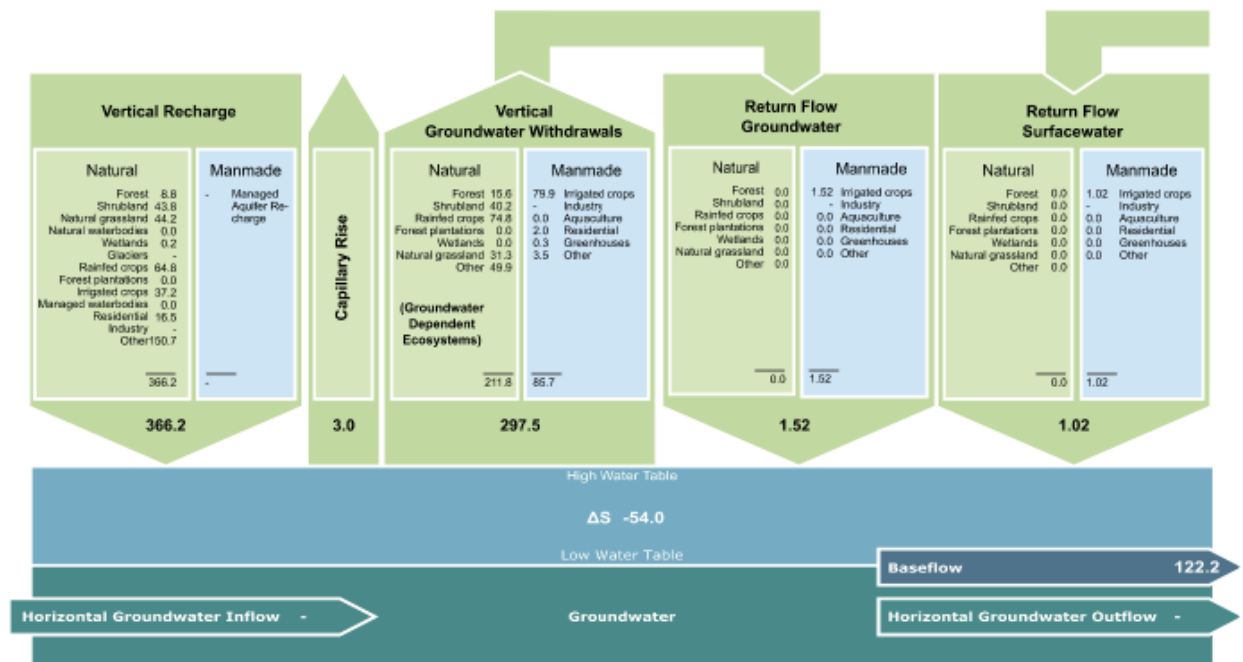


FIGURE 5.14 SHEET 6: GROUNDWATER FOR THE LITANI BASIN (SOURCE: FAO AND IHE DELFT, 2019)

WATER ACCOUNTING PLUS FLOW ESTIMATIONS

The original Water Accounting Plus framework being a depletion-based accounting system tracks where water is being depleted and has a high degree of uncertainty when determining outflows (Karimi et al., 2015). When looking at a global scale, basin water balances (equations (iv) and (v)) calculated from RS derived evapotranspiration, rainfall and change in storage were poor predictors of discharge (Michailovsky et al., 2023).

To overcome these limitations hydrologic models have been added to Water Accounting Plus such as the mesoscale hydrologic model (mHM) (Dembélé et al., 2023) and SWAT (Delavar et al., 2022; Delavar et al., 2020). To address the limitations of the original framework, Water Accounting Plus now includes a pixel based water balance model, known as WaterPix, used to calculate withdrawals and flows (Mul et al., 2020). The included model is also used to calculate flows for the two new sheets for surface (Sheet 5) and groundwater (Sheet 6).

The Waterpix model uses a 100m grid and the version used by IHE Delft uses a soil moisture water balance methodology to derive flows (IHE Delft, 2020). A more detailed description of the model is found in Appendix B. The model was used in Rapid Water Accounting studies, that utilised WaPOR data, for the Awash River Basin - Ethiopia (FAO and IHE Delft, 2020b), Jordan River Basin (FAO and IHE Delft, 2020a), Litani River Basin- Lebanon (FAO and IHE Delft, 2019), Niger River Basin (FAO and IHE Delft, 2020c) and the Nile River Basin (FAO and IHE Delft, 2020d). Other iterations of Water Accounting Plus, (e.g. Chatterjee et al., 2025; Dembélé et al., 2023; Salvatore et al., 2020; Singh et al., 2022) use a version of the WaterPix model where the Budyko Hypothesis is used to calculate ET_{green} and ET_{incr} (Espinoza-Dávalos and Bastiaanssen, 2017) with the rest of the model remaining similar to IHE Delft version.

The Waterpix model requires flow data for calibration making it unsuitable for ungauged or data poor sub-basins. The Budyko Hypothesis methodology is also unsuitable for smaller sub-basins -see Appendix A for

a more detailed explanation. Consequently, there are limited methodologies to generate flow data for small data scarce sub-basins using WA+ and RS data. However, RS data has been successfully used to estimate withdrawals, water balances and productivity at basin scales. Remote sensing will be covered in more detail in the next chapter.

6 REMOTE SENSING IN AGRICULTURAL WATER MANAGEMENT

6.1 INTRODUCTION TO REMOTE SENSING

REMOTE SENSING AND RELATED PRINCIPLES

Understanding water availability across diverse agricultural landscapes would require data obtained from remote sensing missions. While in-situ monitoring of river flows, groundwater levels, and irrigation withdrawals remains limited and uneven across river basins, satellite observations provide efficient, consistent, cost-effective, and repetitive means of assessing hydrological changes (Balsamo et al., 2018; van Dijk and Renzullo, 2011). Remote sensing involves acquiring information about an object/phenomenon or process from a distance (Weiss et al., 2020). As a result, it provides a non-destructive means of collecting agricultural water management (AWM)-related information, often with near-real time availability. For instance, the use of remote sensing to quantify irrigation water use at regional and farm scales, supporting improved irrigation efficiency and water use, is now well established (Muturi et al., 2025), offering a clear advantage over destructive data collection methods. The fundamental principle of remote sensing is the detection and measurement of electromagnetic radiation associated with targets of interest (e.g., vegetation, water), either reflected or emitted energy, and in some cases backscattered energy from active sensors such as radar. These measurements are then processed and analysed to derive information products (e.g., vegetation indices, soil moisture, etc.) used across applications such as agriculture, hydrology, etc. Remote sensing systems and platforms, including satellites, aircrafts, drones, ground-based sensors, are increasingly being used to support agricultural water management. Compared with traditional methods that are often inefficient, costly, laborious-intensive (as mentioned above) and spatially limited, Remote sensing provides spatially explicit information across vast agricultural landscapes.

In remote sensing, a platform (e.g., satellite) carries an instrument or sensor. Sensors (e.g., camera, scanner, etc) are devices that measure electromagnetic radiation. The target (e.g., soil moisture, vegetation) either reflects, absorbs, or emits the electromagnetic radiation, which is measured by the sensors onboard the platforms. These sensors have different capabilities and can either be active or passive. Active sensors can generate their own energy and can operate day and night, whereas passive sensors rely on sunlight, cannot collect data at night, and are more affected by cloud cover and poor weather conditions. However, satellite gravimetry (geodetic methods) such as NASA's Gravity Recovery and Climate Experiment (GRACE) are neither passive nor active in the conventional remote sensing sense as they infer changes in terrestrial water storage from time-varying measurements of Earth's gravity field. This section reviews satellite data, including GRACE and their potential applications in agriculture water management.

PARAMETERS, SPATIAL AND TEMPORAL RESOLUTIONS

At the global scale, NASA's Gravity Recovery and Climate Experiment (GRACE) and its follow-on (GRACE-FO) have improved the monitoring of terrestrial water storage (Yuen et al., 2021). These missions detect changes in terrestrial water storage (i.e., sum of groundwater, soil moisture, surface water etc.) by tracking minute variations in the Earth's gravity field. The GRACE mission has helped address hydrological data-knowledge gaps by enabling assessment of changes in terrestrial water storage, improving water budget evaluations and understanding of groundwater processes such as recharge (Kalu et al., 2025; Ndehedehe et al., 2023, 2025). GRACE and GRACE-FO provide observations at a coarse spatial resolution of about 300-400 km and a temporal resolution of one month. These data have the potential of providing useful information about basin-wide depletion or groundwater recharge that cannot be captured by infrequent measurements from in-situ monitoring bores. However, the coarse spatial resolution of GRACE data limits

its suitability for assessing the status of groundwater at catchment or small scales, although downscaling approaches have been developed to enhance its effective resolution.

Soil moisture missions such as NASA's Soil Moisture Active Passive (SMAP) and ESA's Soil Moisture and Ocean Salinity (SMOS) provide high-frequency observations of surface soil water content. SMAP delivers global coverage at ~9 km resolution (with a 3-day revisit time) and SMOS at ~25-50 km resolution with a 3-day temporal frequency (Blank et al., 2025; Reichle et al., 2025). These measurements are valuable for linking rainfall to short-term water availability for crops and for assessing drought onset across different agro-ecological zones, including the Mekong Delta and upland rice systems (Chowdhury et al., 2024). On the other hand, dedicated precipitation missions are also important for water accounting. For example, the Tropical Rainfall Measuring Mission (TRMM), which has been operational from 1997 to 2015, offered rainfall estimates at ~0.25° (~25 km) resolution every 3 hours. Its successor, the Global Precipitation Measurement (GPM) mission, continues this service with improved resolution at ~0.1° (~10 km) and half-hourly updates. Observations from these products can complement the uneven rain gauge distribution over data-poor areas, as well as support water balance assessments, estimation of irrigation water supply, and drought monitoring in the region e.g. (Zhang et al., 2020).

At finer spatial scales, optical and radar missions such as Landsat, Sentinel-1 and Sentinel-2 extend their monitoring capacity by providing imagery of rivers, reservoirs, canals, and rice paddies. Landsat offers a spatial resolution of 30 m with a 16-day revisit period, making it suitable for long-term mapping of irrigated areas and cropping intensity. Sentinel-2 provides a 10 to 20 m resolution with a 5-day revisit time, enabling detailed monitoring of field-level water use and crop growth. Sentinel-1, through synthetic aperture radar (SAR), supplies all-weather, day-and-night coverage at 10 m resolution with a 6-12 day repeat cycle, making it effective in measuring inundation extent regardless of the persistent cloud cover over a given region.

REMOTE SENSING CATEGORIES

Remote sensing can be divided into many categories; however, the scope of this report is limited to two major types, Optical Remote Sensing and Microwave Remote Sensing, as well as some specific and unique missions (e.g., GRACE).

OPTICAL REMOTE SENSING

In Optical Remote Sensing (ORS hereafter), electromagnetic radiation is detected and recorded in the visible, near-infrared (NIR), and short-wave infrared (SWIR) regions of the spectrum. The process begins with an energy source, typically the Sun, whose radiation travels through the atmosphere. During this process, the radiation interacts with atmospheric components such as large molecules like water vapor, carbon dioxide, and ozone, leading to absorption and scattering that can attenuate the signal. However, specific "atmospheric windows" exist where absorption is minimal, making these regions of the EM spectrum particularly useful for remote sensing. As the incident energy reaches the Earth's surface, it can be absorbed, transmitted, or reflected. A key term in this regard is albedo (proportion of reflected energy), which is different for different land covers, such as vegetation, water, or soil, and the specific wavelength of the energy. Sensors onboard satellites then capture this reflected energy to create images. Different land covers exhibit unique spectral signatures. For example, water absorbs most visible and near-infrared radiation, particularly longer wavelengths, causing it to appear blue. Various spectral indices are developed on these distinct interactions.

MICROWAVE REMOTE SENSING

Microwave Remote Sensing (MRS hereafter) operates in the microwave portion of the spectrum, with wavelengths ranging from approximately 1 cm to 100 cm. This technology can be either active, i.e., it

provides its own illumination (e.g., radar), or passive, where naturally emitted microwave energy is detected (Figure 6. 1).

A significant advantage of microwaves is their ability to collect data under nearly all-weather conditions. Moisture content has a profound influence on microwave emission, i.e., drier soil emits more microwave energy, whereas wetter soil emits less. This property makes microwave remote sensing particularly effective for measuring soil moisture, a critical parameter in agricultural water management. Passive (Active) microwave sensors typically have lower (higher) spatial resolution.

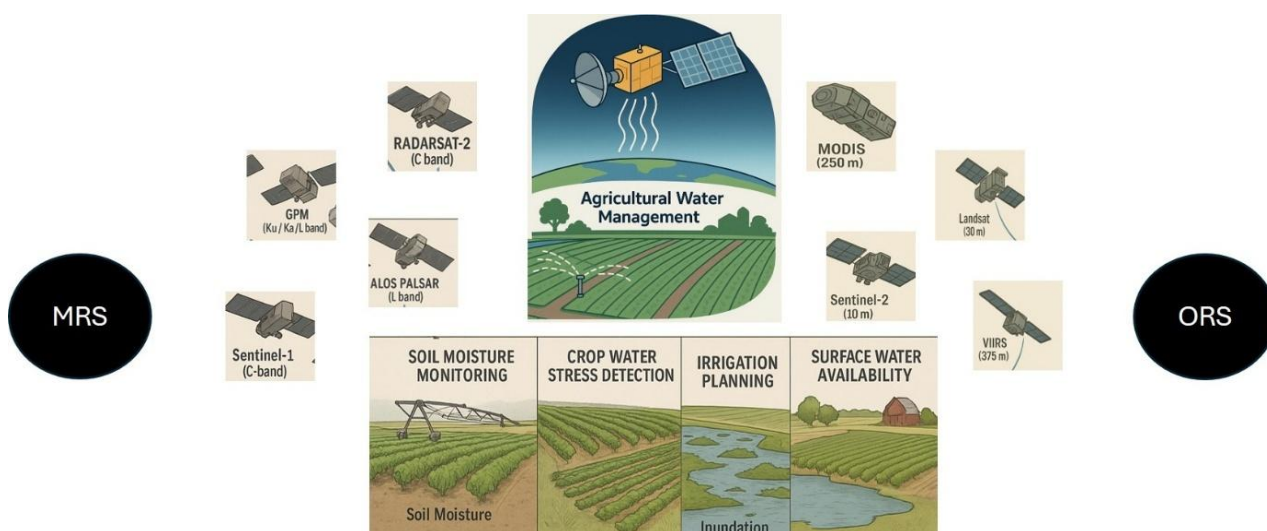


FIGURE 6.1 OVERVIEW OF REMOTE SENSING IN AGRICULTURAL WATER MANAGEMENT

GRAVITY RECOVERY AND CLIMATE EXPERIMENT (GRACE)

GRACE/GRACE FO missions measure changes in Earth’s gravity field to track large-scale mass movements – most notably, changes in terrestrial water storage. Unlike the radar satellites that observe the surface, GRACE/GRACE-FO provides capability to quantify changes in terrestrial water storage, including groundwater depletion (Ndehedehe et al., 2021). This makes them uniquely valuable for agricultural water management at regional to continental scales, especially in areas where direct groundwater monitoring is limited or unavailable.

Some of the key characteristics of ORS and MRS, along with their capabilities and limitations in the context of AWM, are provided in Table 6.1

TABLE 6.1 CHARACTERISTICS OF ORS, MRS, AND GRACE, ALONG WITH THEIR GENERAL USAGE/LIMITATIONS IN AWM.

Platform/Sensor Type	Principle of Measurement	Key Wavelength/Band	Primary AWM Applications	Advantages for AWM	Limitations for AWM
Optical	Reflected solar radiation	Visible, NIR, SWIR	Vegetation, water bodies, crop stress	High spatial/spectral resolution, detailed vegetation info	Cloud/haze interference, atmospheric absorption
Microwave (Passive)	Emitted microwave radiation	L-band, C-band	Soil moisture, water bodies	Cloud/rain penetration, direct moisture sensitivity	Lower spatial resolution

Platform/Sensor Type	Principle of Measurement	Key Wavelength/Band	Primary AWM Applications	Advantages AWM	Limitations for AWM
Microwave (Active/SAR)	Reflected active microwave signal	L-band, C-band, X-band	Soil moisture	High resolution, weather capability	Data spatial complexity, all-speckle, orientation sensitivity
GRACE	Measuring Earth's Gravity Field	Gravimetric system	Subsurface water	All-weather capabilities	Coarse spatial resolution

6.2 USES OF REMOTE SENSING IN AGRICULTURAL WATER MANAGEMENT

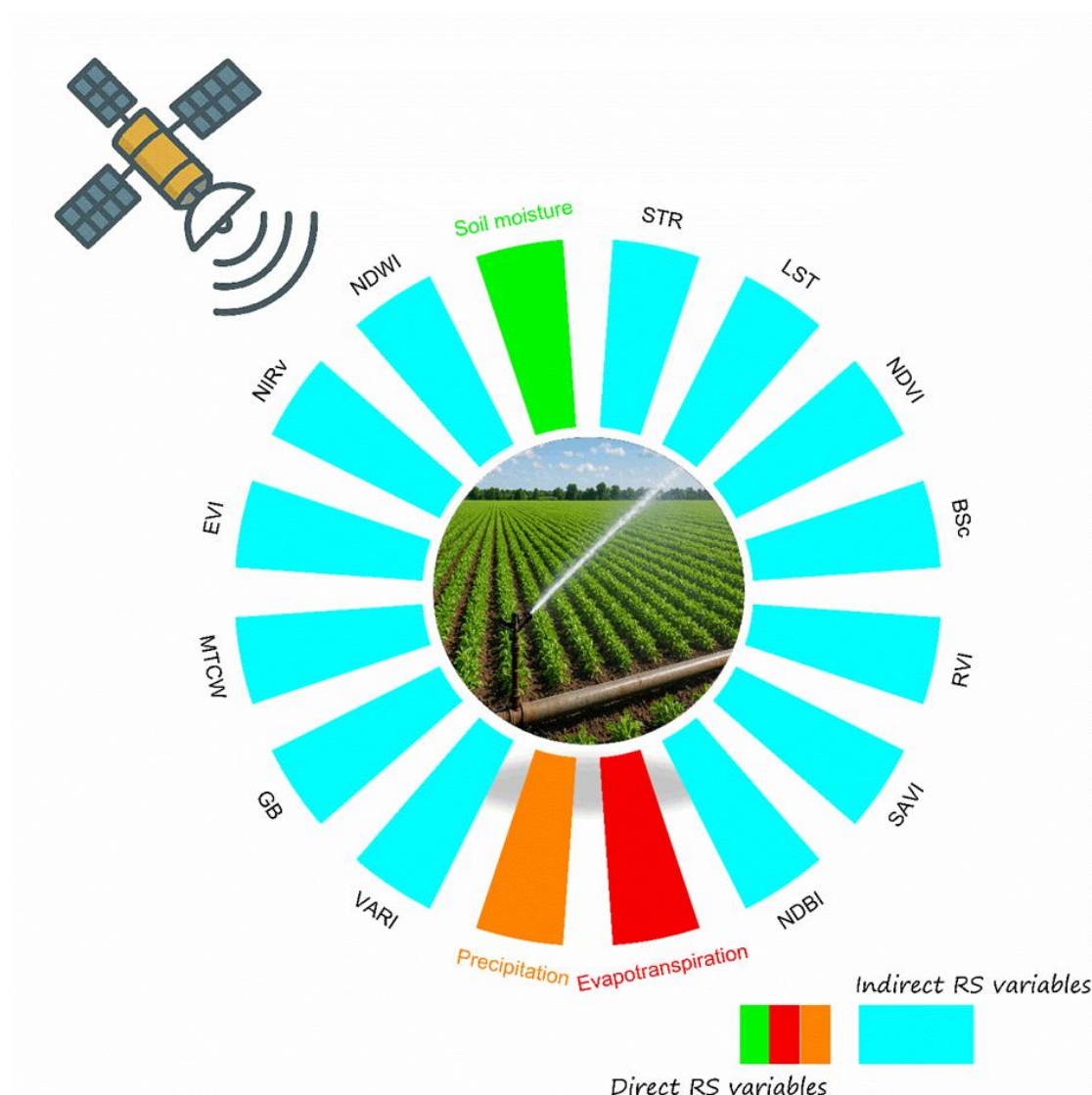
BASIN AND IRRIGATION SCALE AGRICULTURAL WATER MANAGEMENT

Remote sensing data includes different levels of complexity associated with their processing. An overview of common satellite data sources and their application in agricultural water management (AWM) is shown in Table 6.2, while more detailed discussion of different missions is shown in Appendix B.

TABLE 6.2 OVERVIEW OF KEY SATELLITE MISSIONS AND THEIR PRODUCTS FOR AWM

Mission/Program	Sensor Type	Key Products for AWM	Spatial Resolution (Typical)	Temporal Resolution (Revisit)	Primary AWM Applications
Landsat Program	Optical (Multispectral)	Level-1, Level-2 Reflectance, Surface Spectral Indices), Level-3 (ETa)	ARD, (Surface Temp, Indices), 10-30m	Every 16 days	Crop mapping, ET estimation, groundwater use, historical trends
ESA Sentinel-1	SAR (C-band)	Surface Moisture, Crop Type Mapping	Soil (SSM), (crop mapping) 500-1000m, 10m	Every 6-12 days (global)	Soil moisture monitoring, crop identification, drought
ESA Sentinel-2	Optical (Multispectral)	Vegetation (NDVI), Cover, ETa	Indices Land Water 10-60m	Every 5 days	Broad-scale vegetation health, ET, land cover
MODIS	Optical/Thermal (Multispectral, Thermal Infrared)	Surface Moisture, Soil Root-zone Moisture, ET	Soil Root-zone Moisture, 250m-1km	Daily (L3), 3-hourly (L4)	Broad-scale vegetation health, ET, land cover

Mission/Program	Sensor Type	Key Products for AWM	Spatial Resolution (Typical)	Temporal Resolution (Revisit)	Primary AWM Applications
VIIRS	Optical/Thermal (Multispectral, Thermal Infrared)	Surface Moisture, Root-zone Soil Moisture, ET	375m-1km	Daily	Broad-scale vegetation health, ET, land cover
SPOT	Optical (Multispectral,)	Vegetation (NDVI), Cover, Cover,	Indices Land Water 2.5-10m	1-3 days	Broad-scale vegetation health, land cover
SMAP	Passive Microwave (L-band)	Surface Moisture, zone Soil Moisture, ET	Soil 3km-36km Root- (surface), 9km (root-zone)	Daily (L3), 3-hourly (L4)	Surface/root-zone soil moisture, freeze/thaw



RS data/variables abbreviations	RS data/variables
BSc	Backscatter coefficient
NDVI	Normalized Difference Vegetation Index
LST	Land Surface Temperature
STR	Shortwave infrared transformed reflectance
NDWI	Normalized Difference Water Index
NIRv	Near infrared vegetation
EVI	Enhanced Vegetation Index
MTCW	Modified tasselled cap wetness
GB	Green-Blue (GB)
VARI	Visible Atmospherically Resistant Index
NDBI	Normalized Difference Built-up Index
SAVI	Soil adjusted vegetation index
RVI (from backscatter coefficient values)	Radar vegetation index

FIGURE 6.2 SOME OF THE IMPORTANT DIRECT AND INDIRECT RS VARIABLES IN AWM

The water balance is dynamic therefore understanding of water balance requires some dynamic data monitoring for basin and irrigation areas as well, which can be assessed and analysed, paving the way for efficient water management within basins and irrigation areas. RS can assist with rapid acquisition of data.

Precipitation, evapotranspiration, soil moisture (surface, subsurface), groundwater, and land use and land cover are among the broader-level components of water management within basins and irrigation areas. While they are crucial for agricultural water management, there are often constraints in their data availability owing to a multitude of reasons, from financial to labour. In an ideal scenario, these variables can be directly accessed from RS data sources, e.g., precipitation can be directly accessed by some of the RS data providers (data providers do all the processing and analysis of raw data and users can directly use the final product). While in many other cases, RS data providers provide the indirect data that needs to be acquired, processed, and analysed by the user to make it usable in AWM applications, for instance, surface reflectance data. In some instances, data can be directly available as a single variables (e.g., Land Surface Temperature (LST)) but it's use in AWM is not direct, i.e., unlike precipitation which can be directly used as a key component of AWM, LST can be used to calculate evapotranspiration (which is a direct component of AWM). Therefore, we consider LST (and similar datasets) to be indirect in this report. Figure 5.2 illustrates some of the key direct and indirect variables that can be accessed from RS.

The RS data summarised in Figure 6.2 are particularly important because they can either directly be obtained from ORS and MRS sensors or indirectly using relatively simple indices or equations derived from relevant spectral channels and wavelength. Precipitation, evapotranspiration, and soil moisture are key AWM variables that can be directly obtained from the satellite sources, while indirect variables (Figure 5.2) require some kind of processing to make them useful for AWM applications. For the direct variables, precipitation has the largest share in terms of data availability, followed by soil moisture, while evapotranspiration was the least available dataset.

A detailed database of RS data sources, covering both direct products and indirectly derived information has been compiled (Table 6.2). The spreadsheet database (called DB-RS) has multiple sheets in it with different names. These sheet names include "Precipitation", "Evapotranspiration", "Soil moisture", "LST", "Surface reflectance", "Brightness temperature", "Spectral indices" and "LULC Biomass Vegetation" data. For each sheet, there are 19 columns provided in the database; the description of the columns is shown in Table 6.3. The different database sheets are discussed in more detail below.

Precipitation serves as the primary natural input of water into agricultural systems at basin and irrigation area scales, directly replenishing soil moisture and surface water sources like streams and reservoirs. Its variability, such as intensity, duration, and seasonal patterns, can lead to either water surpluses (risking erosion or flooding) or deficits (causing droughts), making accurate forecasting essential for planning irrigation and crop planting cycles. At basin levels, precipitation data helps in modelling runoff and infiltration, which informs decisions on water storage infrastructure and sustainable withdrawal rates to prevent overexploitation of groundwater. For instance, in arid or semi-arid basins, low precipitation necessitates supplemental irrigation, while in humid areas, excess can be harvested for later use, enhancing overall water resilience.

Evapotranspiration encompasses the combined loss of water through soil evaporation and plant transpiration, representing the largest consumptive use of water in agricultural systems, often accounting for 60-90% of total water inputs in irrigated fields. At basin scales, ET is crucial for calculating crop water requirements and closing the water balance (inputs like precipitation minus outputs like ET and runoff). High ET rates in warm, dry sub-basins can exacerbate water scarcity, while accurate estimation helps in designing efficient irrigation systems that minimize waste and mitigate overuse. It interacts dynamically with soil moisture and precipitation; for example, adequate soil moisture increases ET potential, but

deficits reduce it, signalling the need for supplemental water. In AWM, ET data informs sustainable practices like deficit irrigation or crop selection, and when integrated with remote sensing, it supports basin-wide assessments of ecosystem productivity and human impacts on water cycles.

TABLE 6.3. DETAILED DESCRIPTION OF COLUMNS PROVIDED IN THE DATABASE DB-RS

No.	Column names	Description
1	RS product	This is the name (short) of the RS product that provides the data about a certain variable, e.g., precipitation
2	Full name	Some RS products have both short and long names; long (full) names for products in col. 1 are given here.
3	Version/division/sub-type	This represents the version or type, or division of the RS product (col. 1). This is provided in the database as it is given in the RS product reference documentation, e.g., version 7 as V7 or V07.
4	Spatial extent	This is the spatial extent covered by the product, e.g., how much area globally is covered by a given product. For some products, spatial extent is given by terms like “Global”, for others is shown as a bounding box of latitudes and longitudes, information in the database is provide accordingly.
5	Bands	These are spectral bands that different RS products have. For many direct variables, spectral band info is not provided, so it is shown with a “-“.
6	Wavelength/Bandwidth	This is the wavelength or bandwidth of a given RS product, which may or may not be available depending on the specific RS product.
7	Launch-end dates/continuity	These represent the dates when a given RS product was launched, discontinued, is available now, or is planned for the future.
8	Data format	RS products come in different formats from different data providers. This column gives the information about the data format of a given RS product (e.g., netCDF, HDF)
9	Spatial resolution (degree, m, or km)	This refers to the smallest area on the ground that a sensor can distinguish, typically measured as the pixel size in meters or the ground sample distance (GSD). It determines the level of detail captured in imagery by a given RS product, e.g., 30 meters. Values are provided in the database as degrees or metres (based on the original documentation of a given RS product).
10	Frequency/temporal resolution	This indicates how often the data from a given RS product is available: 1 hour, 1 month.
11	Platforms	This refers to the vehicle or structure that carries the sensor or instrument used to collect data about the Earth’s surface, atmosphere, or oceans. Platforms provide the physical and operational framework for sensors, determining their vantage point, orbit, or trajectory, which affects data coverage, revisit time, and spatial resolution. Examples include Landsat, MODIS, and SPOT.

No.	Column names	Description
12	Instrument/ <i>Sensor</i>	This refers to the device or system on a platform that detects and records electromagnetic radiation (e.g., visible, infrared) reflected or emitted from the Earth's surface, converting it into measurable data. Sensors are categorised as passive (detecting natural radiation, like sunlight reflection) or active (emitting and receiving signals, like radar).
13	Download links	These are the download links for a given RS product. All the links given in the databases were working at the time of database creation. Their work in future is not guaranteed.
14	Variables	This shows the actual variable provided by a given RS product, e.g., Precipitation, Soil moisture, surface reflectance.
15	Cost to access	This is the cost to access data. This does not include the costs related to computing resources or training or technical skills to access the data. It only refers to the cost associated with having access to the data, e.g., freely available, subscription required, or ordering data by payment.
16	Software tools to process	This includes the costs related to computing resources (processing software for example, R, Panoply, ArcGIS) or training or technical skills to access the data.
17	Notes	In some instances, extra information is pertinent for a specific RS product (in accessing or processing), which is not a business-as-usual scenario.
18	DOI/website links	These are the related links of Digital Object Identifiers (DOI) for a given RS product (inclusion subject to availability).
19	References/links	These are the citations or complete references for a given RS product (inclusion subject to availability).

Soil moisture represents the water stored in the soil profile that is accessible to plant roots, acting as a critical buffer between precipitation inputs and crop water demands. Monitoring soil moisture is vital for agricultural drought assessment, for instance, as it directly indicates plant stress and yield potential, enabling timely interventions like precision irrigation to avoid under- or over-watering. It influences infiltration rates, runoff, and groundwater recharge, which are key for maintaining sub-basin hydrological balance and preventing soil degradation. In management practices, soil moisture data, often derived from remote sensing or in-situ sensors, supports deficit irrigation strategies, optimizes fertilizer application (as moisture affects nutrient uptake), and aids in flood forecasting by revealing saturation levels. This is particularly important in heterogeneous basins where soil types vary, allowing for zone-specific management to improve water use efficiency and crop resilience.

Land Surface Temperature plays a pivotal role in understanding energy and water fluxes, complementing precipitation, soil moisture, and evapotranspiration (ET) in optimizing water use, enhancing crop productivity, and ensuring sustainable resource management within basins. LST is crucial to the evapotranspiration budget (Anderson et al., 2012), as it controls the exchange of fluxes between the Earth's surface (e.g., basin) and atmosphere, hence important for agricultural water resources management. LST can also be used as an indicator of crop water stress and irrigation needs, as it is closely linked to soil moisture and ET, as cooler surfaces often indicate higher moisture content and active transpiration, while higher LST signals water stress or dry conditions. At basin scales, LST data helps identify spatial variations in crop health, enabling precision irrigation to target water-deficient areas, thus optimizing water use and preventing yield losses. For example, increased LST in a sub-basin's agricultural fields can prompt timely irrigation to mitigate heat stress, especially in arid or semi-arid regions. Additionally, LST is important for climate change adaptation. This is because it helps to track long-term trends in surface warming, which can affect crop suitability and water availability in basins. By analysing LST alongside precipitation and ET, managers can adapt agricultural practices—such as selecting heat-tolerant crop varieties or adjusting planting schedules, to mitigate the impacts of climate variability and ensure sustainable production.

Surface reflectance data from remote sensing refers to the fraction of incoming solar radiation reflected by the Earth's surface, measured in specific spectral bands (e.g., visible, near-infrared (NIR), shortwave infrared (SWIR)) and corrected for atmospheric effects to represent ground-level reflectance. This data, derived from optical remote sensing platforms like Landsat, Sentinel-2, MODIS, VIIRS, and SPOT (Table 6.2), is critical for water management, as it provides insights into land surface characteristics, vegetation health, soil moisture, and water body dynamics. While many RS products (e.g., Normalized Difference Vegetation Index - NDVI) are derived from surface reflectance bands, individual surface reflectance bands provide oneself the flexibility of creating as many products as possible (e.g., different versions of NDVI and more).

Brightness temperature in remote sensing is a measure of the radiance of microwave or infrared radiation emitted or reflected from a surface, expressed as the temperature of a blackbody that would emit the same amount of radiation at a given wavelength. It is commonly used in optical (e.g., Landsat, ASTER) and microwave (e.g., SMAP, AMSR-E) remote sensing to infer surface properties like soil moisture and water body characteristics, which is important for agricultural water management.

Spectral indices are mathematical combinations of surface reflectance data from different spectral bands (e.g., visible, near-infrared (NIR), shortwave infrared (SWIR)) derived from optical remote sensing platforms like Landsat, Sentinel-2, MODIS, VIIRS, and SPOT (Table 6.2). These indices capture changes in land surface and biophysical conditions, including vegetation health, crop stress, soil moisture, water content, and land cover, making them critical for water management. Indices like NDVI and Normalized Difference Water Index (NDWI) are used for evapotranspiration, soil moisture and to detect different land cover units, crucial in basin and irrigation area water management.

Spectral indices like NDVI and NDWI are provided directly by some RS data providers, but some application (basin scale) specific challenges can arise where these indices may not be the most useful. However, other spectral indices, specifically vegetation indices, could be more helpful in providing information needed. These can be calculated by oneself given the reflectance data is available. Nine different spectral indices widely recognized by the scientific community to be used for AWM in basin are summarised in Figure 6.3 along with their names, formulas (surface reflectance band combinations) and reference. The paragraphs below describe each of the nine indices in detail.

The NDVI is one of the most widely used spectral indices for assessing vegetation vigour and health in basin and irrigation areas where NIR (near-infrared) and red bands exploit the high reflectance of healthy vegetation in NIR due to cell structure and low reflectance in red due to chlorophyll absorption. NDVI values range from -1 to 1, with 0.2–0.8 indicating healthy crops or wetlands. This makes it essential for agricultural water management by monitoring crop growth stages, water stress, and ET.

The Green-Red Vegetation Index (GRVI) is a spectral index designed to detect early-stage vegetation growth and chlorophyll content, leveraging the difference in reflectance between green (high for vegetation) and red (low due to chlorophyll absorption) bands. GRVI values range from -1 to 1, with positive values indicating green vegetation, making it particularly useful for agricultural water management by identifying early water stress in crops before visible symptoms appear, thus enabling timely irrigation or agronomic interventions.

The Green Normalized Difference Vegetation Index (GNDVI) is a modified version of NDVI. It uses the green band instead of red to better estimate chlorophyll content and vegetation health with values ranging from -1 to 1. Higher values (e.g., >0.5) indicate dense, healthy vegetation. The GNDVI is more sensitive to chlorophyll variations than NDVI, making it valuable for agricultural water management by detecting water stress that affect photosynthesis and water use efficiency.

The Normalized Difference Red Edge Index (NDRE) is a spectral index that utilizes the red-edge band to assess vegetation content with values ranging from -1 to 1, and relatively higher values (e.g., >0.3) indicate healthy, nitrogen-sufficient crops. The NDRE is less saturated than NDVI in dense canopies, making it essential for agricultural water management by detecting mid- to late-season water stress for precision irrigation.

The Enhanced Vegetation Index (EVI) corrects NDVI for atmospheric and soil influences with values ranging from -1 to 1, and values within 0.4–0.8 indicates healthy vegetation. The EVI is vital for agricultural water management by accurately assessing crop water use in canopy-dense areas, reducing saturation errors in ET models.

The Two-Band Enhanced Vegetation Index (EVI2) is a simplified version of EVI that uses only red and NIR bands to assess vegetation vigour, with values ranging from -1 to 1. As with EVI, values ranging from 0.4–0.8 in EVI 2 indicate healthy vegetation, and it corrects for atmospheric and soil background effects better than NDVI, making it valuable for agricultural water management by monitoring crop water use and stress in variable environments.

The Soil Adjusted Vegetation Index (SAVI) adjusts NDVI for soil background effects, with values ranging from -1 to 1, with higher values indicating dense vegetation. It is crucial for agricultural water management as it accurately assesses vegetation in sparse or soil-exposed areas, reducing errors in ET estimates.

The Optimized Soil Adjusted Vegetation Index (OSAVI) improves SAVI by dynamically adjusting for soil background, producing values ranging from -1 to 1 (typically 0.3–0.7 for healthy crops). It supports agricultural water management by providing more reliable vegetation assessment across varying soil conditions, enhancing ET estimation and water stress detection.

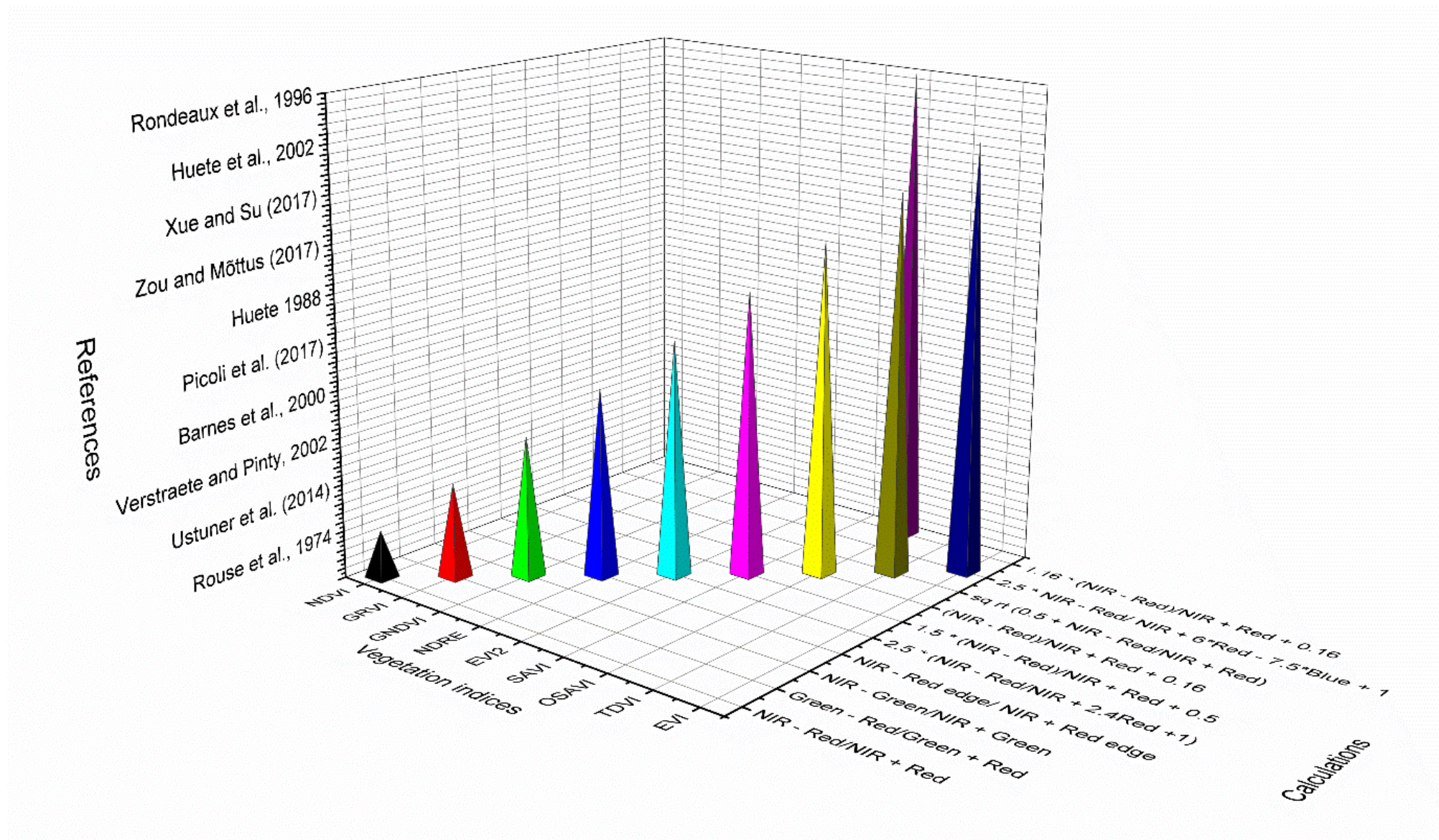


FIGURE 6.3 . WIDELY RECOGNISED SPECTRAL INDICES, USED IN AWM APPLICATIONS

The Transformed Difference Vegetation Index (TDVI) is a variation of NDVI that uses a transformation to reduce saturation in high-biomass areas. Values typically range from -1 to 1, with higher values indicating denser vegetation. TDVI can support agricultural water management by improving vegetation characterisation in mature crops, which can strengthen ET estimation and assessment of water use efficiency.

While Figure 6.3 and the above description provide the basis and practical understanding of how surface reflectance data can be used, users are recommended to look for more combinations of surface reflectance bands in previous research (if the provided indices in this report do not suffice). The principle for obtaining a different spectral index will be the same.

The next key thing is to find out where this data can be accessed. Some of the data providers, along with their associated details, are given in Table 6.4. While Table 6.4 gives the glimpse of data sources for providing the variables given in Figure 6.3, the RS-DB spreadsheet provides a detailed database of products that can be used in AWM covering the product name, version/division/sub-type, spatial extent, bands, wavelength/bandwidth, launch-end dates/continuity, data format, spatial resolution (m), frequency/temporal resolution, platforms, instrument/sensor information, download links, available variables (that can directly or indirectly be used in AWM), cost to access, software tools to process, as well as digital object identifiers (DOI) and websites/references links.

TABLE 6.4 KEY VARIABLES USED IN APPLICATIONS OF RS IN AWM AND THEIR ACCESSIBILITY

Data provider (Satellite)	Key variables	Agency/Organisation	Mission / Instrument(s)	Data access
ALOS-2 PALSAR-2 25m & 50m ScanSAR NRB	*SAR-NRB	JAXA	ALOS-2 PALSAR-2	PALSAR-2 ScanSAR Level 2.2 Earth Engine Data Catalog Google for Developers
ALOS-2 PALSAR-2 Global Mosaics (RTC)	SAR-NRB	JAXA	ALOS-2 PALSAR-2	Dataset ALOS@EORC
Catalyst Sentinel-1 RTC	SAR-NRB	Catalyst/PCI	Sentinel-1A, 1B	Analysis Ready Data - CATALYST
Catalyst SPOT 5 HRG 2.5m	**SR	Catalyst/PCI	SPOT-5	Analysis Ready Data - CATALYST
DESI L2A	SR	DLR	DESI-on-ISS	EOC Geoservice DESI – Level 2A Hyperspectral Images – Global
EnMAP	SR	DLR	EnMAP	Data & Access - EnMAP
L8 SR (Aerospace Information Institute)	SR	AIR-CAS	Landsat-8	Landsat 8 Land Surface Reflectance Product -- Landsat 8 surface reflectivity products and

						surface temperature products
L8 Information Institute)	ST (Aerospace Research	***ST	AIR-CAS	Landsat-8		Landsat 8 Land Surface Temperature product -- Landsat 8 surface reflectivity products and surface temperature products
Landsat Collection 2		SR	USGS	Landsat 4, 5, 7, 8, 9		USGS EROS Archive - Landsat Archives - Landsat 4-5 TM Collection 2 Level-2 Science Products U.S. Geological Survey USGS EROS Archive - Landsat Archives - Landsat 7 ETM Plus Collection 2 Level-2 Science Products U.S. Geological Survey USGS EROS Archive - Landsat Archives - Landsat 8-9 OLI/TIRS Collection 2 Level-2 Science Products U.S. Geological Survey
Landsat Collection 2		ST	USGS	Landsat 4, 5, 7, 8, 9		USGS EROS Archive - Landsat Archives - Landsat 4-5 TM Collection 2 Level-2 Science Products U.S. Geological Survey USGS EROS Archive - Landsat Archives - Landsat 7 ETM Plus Collection 2 Level-2 Science Products

				U.S. Geological Survey
				USGS EROS Archive - Landsat Archives - Landsat 8-9 OLI/TIRS Collection 2 Level-2 Science Products U.S. Geological Survey
NovaSAR-1 RTC	NRB	CSIRO	NovaSAR-1	data.novasar.csiro.au/#/home
NRCan RCM NRB	SAR-NRB	NRCan	RCM-1/2/3	EODMS
NRCan RCM POL	****SAR-POL	NRCan	RCM-1/2/3	RCM CEOS Analysis Ready Data Données prêtes à l'analyse du CEOS pour le MCR - Registry of Open Data on AWS
				EODMS
Opera RTC Sentinel-1	NRB	NASA/JPL	Sentinel-1 (A, B)	OPERA Sentinel-1 RTC NASA Earthdata
PROBA-V L3 (0.1/0.333/1 km) TOC	SR	VITO / ESA	PROBA-V	PROBA-V Level-3 TOC Data PROBA-V
RISAT-1A (EOS-04) NRB	SAR-NRB	ISRO	RISAT-1A (EOS-04)	E04 SAR MRS ST UC00ZTD
				E04 SAR CRS STU C00ZTD
Sentinel-1 RTC	NRB	Sinergise Digital Africa & Earth	Sentinel-1A, 1B	S1_CARD4L
Sentinel-2 Level-2A	SR	ESA	Sentinel-2A, 2B	Copernicus Data Space Ecosystem Europe's eyes on Earth

*Synthetic Aperture Radar-Normalised Radar Backscatter

** Surface reflectance

*** Surface temperature

****Polarimetric Radar-Normalised Radar Backscatter

SPECIFIC APPLICATIONS OF RS FOR AWM POTENTIALLY RELEVANT TO BASINS

Several studies have applied remote sensing indicators and data to specific agricultural water management applications. Such applications include crop water stress detection, evapotranspiration estimation, soil moisture content monitoring, surface water mapping, irrigation scheduling and optimization, and agricultural drought monitoring. The use of variables such as precipitation and evapotranspiration is relatively straightforward in basin scale AWM applications. However, applying indirect remote sensing products in AWM typically requires additional efforts. Therefore, this section describes studies that have used indirectly derived variables, primarily indexed based products in AWM. These studies (Fig 6.4), include the applications of indirect RS vegetation indices such as NDVI and EVI in fields, farms, parks, croplands, etc. emphasizing the fact that even smaller areas can be studied using the datasets provided in DB-RS database. This makes them a feasible choice to be used at all scales in agricultural water management. Figure 6.4 shows that ORS and MRS systems support different aspects of AWM. However, it does not clearly indicate how resulting products are used in the listed applications. Therefore, it is necessary to investigate, which remote sensing products have been used in the studies shown in Figure 6.4, to identify where they have been successfully applied in AWM. Further details about how these (Figure 6.4) studies were conducted and what was involved are provided in the attached spreadsheet database (DB-INDS). This database is provided as a guide, and we suggest that readers refer to other studies of their interest as well. In the attached database (DB-INDS), there are twelve different columns, for which the details are given in Table 6.5.

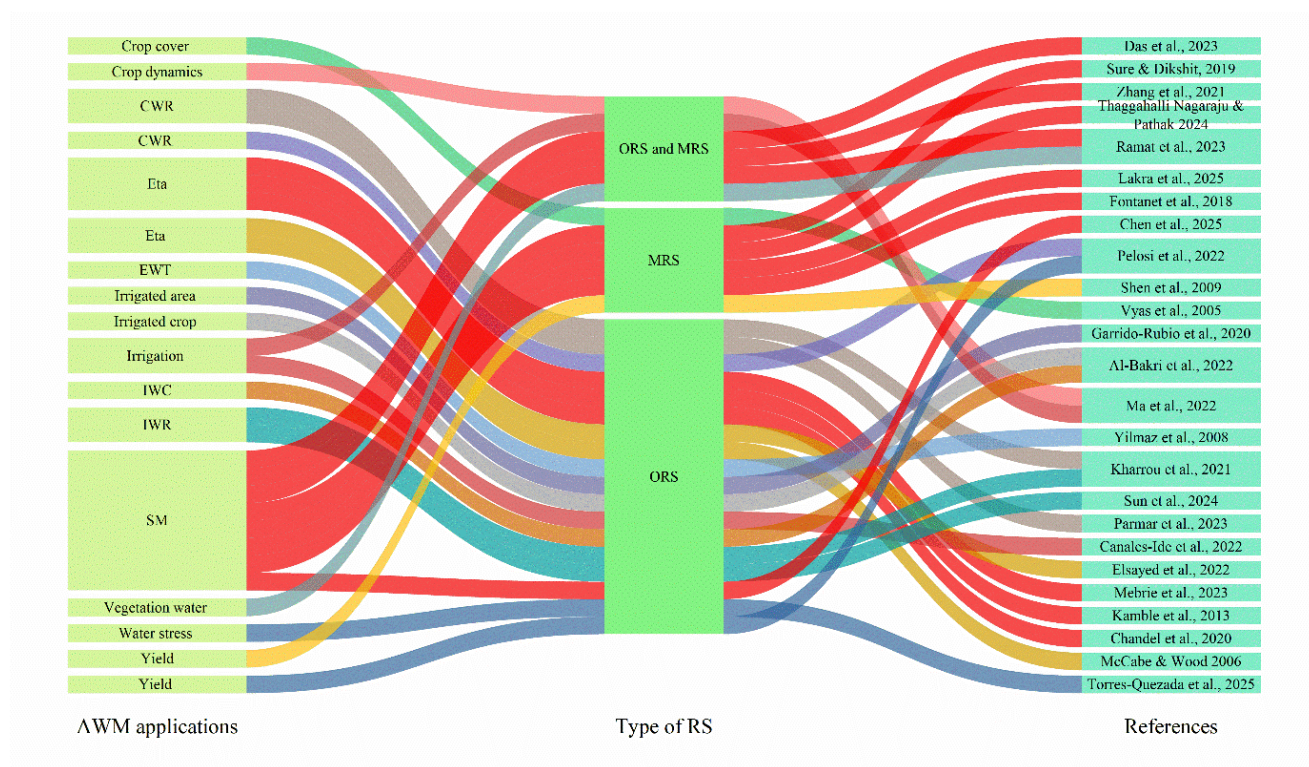


FIGURE 6.4 SPECIFIC APPLICATIONS OF ORS AND MRS IN AWM

TABLE 6.5 DETAILED DESCRIPTION OF COLUMNS PROVIDED IN THE DATABASE DB-INDS

No.	Column names	Description
1	No.	Serial number of reference studies

No.	Column names	Description
2	Type of RS	Indicates type of RS, e.g., ORS or MRS
3	Data sources	RS data provided
4	Products/variables used (if available)	Specific variable used from a given RS product, e.g., NDVI, LST
5	Application land type	Where the studies were conducted, e.g., farms, agricultural areas with varying size
6	Area	Indicated the area of land where reference studies were conducted
7	Crops	The types of crops that were available in the study region
8	Time period	Period of analysis used in the reference studies
9	City/Country/region	In which geographic location were the studies conducted.
10	Study purpose	Indicates the goal of the study in terms of AWM
11	Citation	Citation for a given reference study
12	References	Complete reference for a given reference study

REMOTE SENSING IN WATER QUALITY MONITORING

As water strongly absorbs in the near infrared range the remote sensing of water quality occurs mainly in the visible to very near infrared region (400-850 nm). In optically deep inland water, where there is no light reflection from the bottom, optically active water constituents alter radiation by absorption and scattering giving the water body its inherent optical properties. The inherent optical property will vary depending on the concentrations of the different optically active constituents giving water bodies their colour and spectral reflectance (Dörnhöfer and Oppelt, 2016; Malthus and Zamyadi, 2024).

‘Optical water quality parameters’, shown in Figure 6.5, include coloured dissolved organic matter (CDOM) which absorbs light in the blue and yellow wavelengths (~440-500nm), phytoplankton containing Chlorophyll-A absorbs light in the blue and red wavelengths with the main wavelengths being around 680 nm plus also scatters light, cyanobacteria containing phycocyanin absorbs light around 620 nm plus scatters light, suspended particulate matter scatters light and usually detected in the 500 and 750 nm wavelength ranges (Dörnhöfer and Oppelt, 2016; Giardino et al., 2019; Malthus and Zamyadi, 2024). Temperature and salinity effect the emissivity of microwaves from water due to altering the dielectric constant of water (Lang et al., 2016; Vine et al., 2022). These properties are independent of the illuminating light and are known as ‘inherent optical properties’ (IOPs)(Giardino et al., 2019; Malthus and Zamyadi, 2024).

In optically shallow waters, Figure 6.5, where radiation reflects off the bottom of the water body then different benthic substrates and aquatic vegetation communities can be identified as well as bathymetry (Dekker and Pinnel, 2018; Giardino et al., 2019). Inland waters are considered ‘optically complex’ as there are multiple optically active parameters contributing to the spectral reflectance and colour. Reflectance is an ‘apparent optical property’ (AOP) because its optical properties not only depend on the IOPs of the water constituents but also the ambient conditions at the time of measurement (Figure 5.5). Turbidity,

transparency and light attenuation are AOPs (Dörnhöfer and Oppelt, 2016; Giardino et al., 2019; Malthus and Zamyadi, 2024).

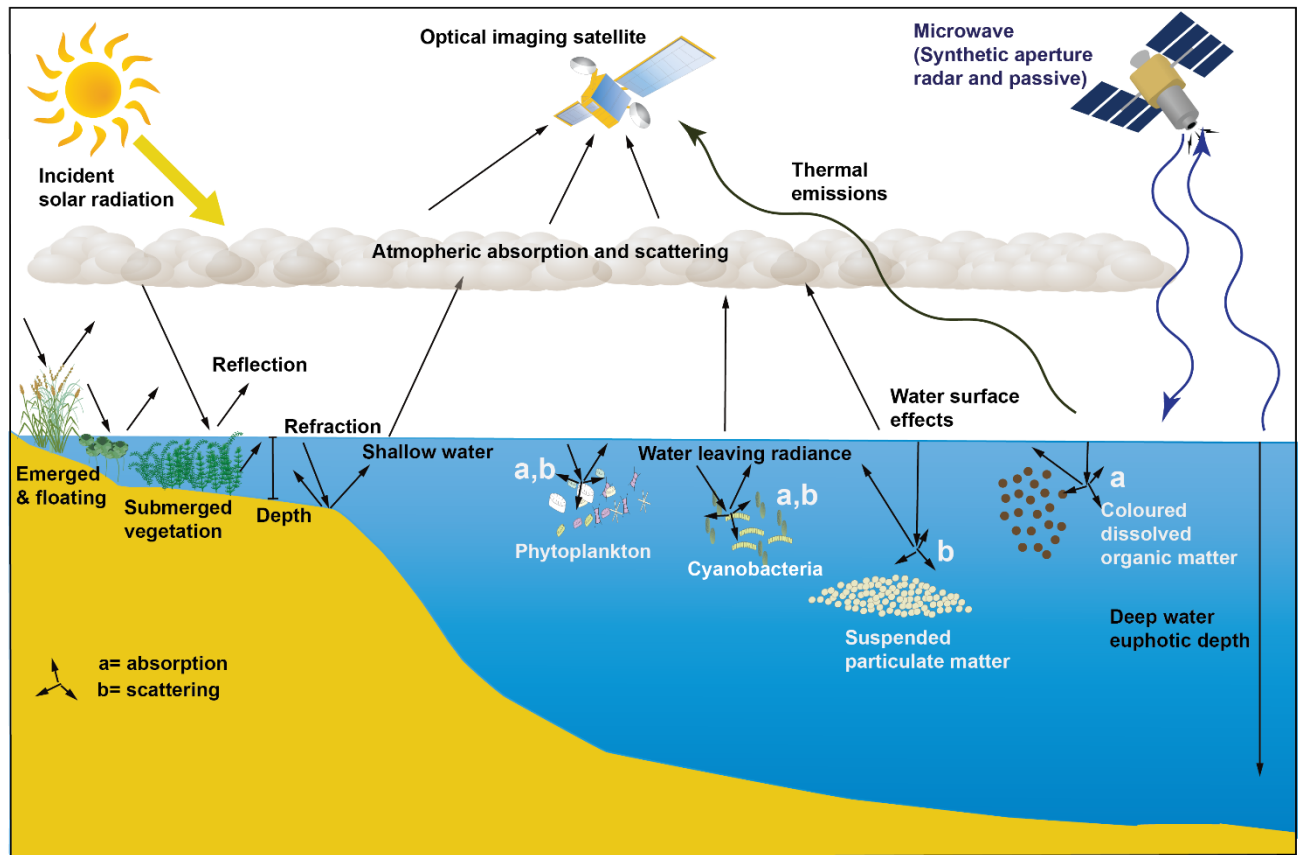


FIGURE 6.5 THE INTERACTIONS BETWEEN THE MAIN OPTICAL AND MICROWAVE ACTIVE SUBSTANCES IN WATER AND ATMOSPHERE AND SATELLITE SENSORS (AFTER CHEN ET AL. 2022, DÖRNHÖFER AND OPPELT, 2016) – FIGURE CONTAINS IMAGES FROM INTEGRATION AND APPLICATION NETWORK (IAN.UMCES.EDU/MEDIA-LIBRARY)

Only around 2-10 % of the signal received at the satellite sensor, water leaving radiance, is available to identify water quality parameters which is why accurate removal of water surface and atmospheric radiance is essential (Figure 6.5). There are numerous algorithms used to retrieve optical parameters from water body reflectance which can be broadly divided into empirical and semi-analytical methods (Dörnhöfer and Oppelt, 2016).

Empirical and semi-empirical methods develop statistical relationships between RS observed and field measured data. The statistical relationships are only applicable for the sensor used over the observed ranges of the parameter measured. There is also a greater uncertainty when applied retrospectively (Chen et al., 2022; Dörnhöfer and Oppelt, 2016; Malthus and Zamyadi, 2024). Semi-analytical models retrieve optical parameters through inversion of bio-optical models which benefit from using a physics-based approach. In the inversion approach curves are fitted to different spectral bands to identify which parameters give the closest fit to the observed signal which then determines the concentrations of the parameters (Chen et al., 2022; Dörnhöfer and Oppelt, 2016; Giardino et al., 2019; Malthus and Zamyadi, 2024). Remotely sensed water quality data can lack accuracy (Baltodano et al., 2024; Dekker and Pinnel, 2018). This is in part due to confounding or masking effects of different parameters having overlapping effects on the signal making it difficult to determine the optical parameters (Chen et al., 2020).

Satellite data cannot be used to directly estimate parameters that do not have direct optical expressions such as nutrients. These in some situations maybe empirically estimated by developing relationships with remotely sensed optical properties but the relationships may not be causal and have limited validity ranges. However, by combining information from different optical water properties it may be possible to derive information about trophic states and primary productivity which can then guide management action

((Malthus and Zamyadi, 2024). Remotely sensed derived water quality products for inland waters are available for download (Table 6.6) though only for optically active constituents. These when combined could help identify aquatic health of inland waters.

TABLE 6.6 DOWNLOAD LINKS FOR INLAND WATER QUALITY DATA (AFTER BALTODANO ET AL 2024)

Source	File format	Web link
NASA Ocean Color	NetCDF	https://oceancolor.gsfc.nasa.gov/l3/
Copernicus Global Land Service (GLS)	NetCDF	https://land.copernicus.eu/global/index.html water / lake water quality
Terrascope	TIFF	https://docs.terrascope.be/#/DataProducts/Sentinel-2/WaterQual/WaterQuality
ESA Climate Change Initiative (CCI)	NetCDF	https://github.com/ccilakes/lakes_cci_tools

6.3 REMOTE SENSING CONSTRAINTS

COST OF REMOTE SENSING PRODUCTS

While detailed information about costs is provided Appendix B, further details are provided in the attached spreadsheet DB-CF. Figure 6.6 summarises different RS data sources, their availability, application scale, related costs, and future availabilities. The optical data is mainly free while the microwave products, particularly at finer resolutions can cost.

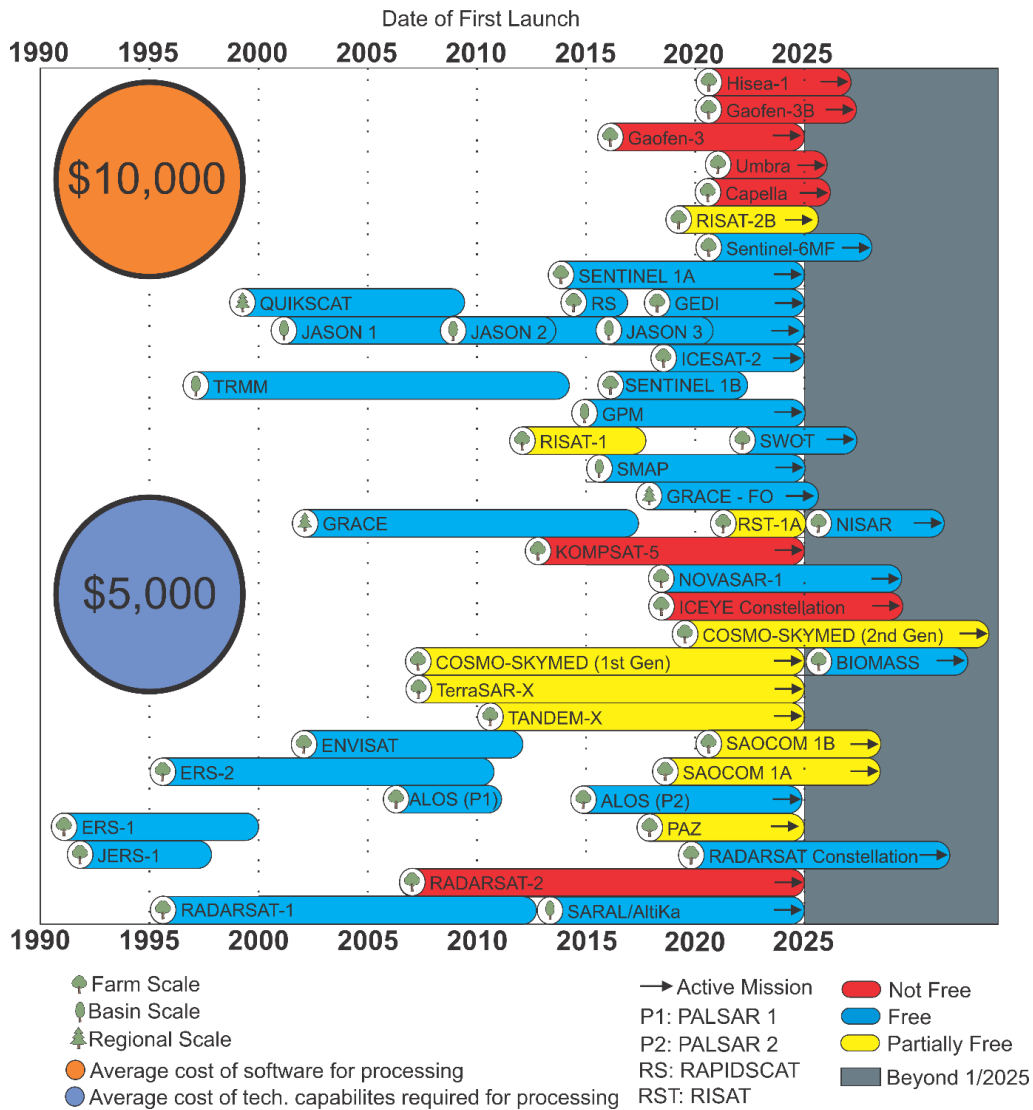


FIGURE 6.6 KEY CHARACTERISTICS ASSOCIATED WITH DIFFERENT RS DATA PROVIDERS

The attached database showing costings, DB-CF, one sheet (with data) and 10 columns, details for which are provided in Table 6.7.

TABLE 6.7 DETAILED DESCRIPTION OF COLUMNS PROVIDED IN THE DATABASE DB-CF

No.	Column names	Description
1	Data type	This is the type of the RS product.
2	Coverage	This is the spatial extent covered by the product, e.g., how much area globally is covered by a given product.
3	Satellite missions	Names of the RS product providers.
4	Bands/Wavelength/Bandwidth	These are spectral bands, wavelength, or bandwidth that different RS products have.
5	Launch-end dates/continuity	These represent the dates when a given RS product was launched, discontinued, is available now, or is planned for the future.
6	Frequency/temporal resolution	This indicates how often the data from a given RS product is available: 1 hour, 1 month.

7	Spatial resolution	This refers to the smallest area on the ground that a sensor can distinguish, typically measured as the pixel size in meters or the ground sample distance (GSD). It determines the level of detail captured in imagery by a given RS product.
8	Accessibility	1. Cost to access and generate data (in USD) 2. Cost to process (e.g., commercial software requirements, computing platforms, etc.) in USD 3. Technical capabilities required (e.g., cost to acquire). Cost in USD
9	AWM applications	This is the cost to access data. This does not include the costs related to computing resources or training or technical skills to access the data. It only refers to the cost associated with having access to the data, e.g., freely available, subscription required, or ordering data by payment.
10	Other comments	These include planned future missions, limitations and constraints, suitability for basin, sub-basin, farm scale, etc.

OTHER FACTORS LIMITING USE OF REMOTE SENSING DATA

In low- and middle-income countries, agricultural water management decisions are often made with limited or outdated information. While remote sensing has expanded the availability of hydrological and agricultural data, significant challenges remain in ensuring that this information is accessible, usable, and actionable for decision-makers operating at the farm and sub-basin scales. Addressing these needs requires attention to accessibility, technical capacity, scalability, and the cost of sustaining data-driven approaches (See details in the supplementary document DB-CF).

Accessibility and Usability

Although satellite-derived datasets are increasingly open-access, the technicalities required to translate them into practical tools for local water managers are limited and/or expensive. Many datasets are delivered in formats that require advanced processing, or at spatial and temporal resolutions that do not directly align with the decision cycles of farmers and irrigation authorities. Usability is further constrained by language gaps, a lack of user-friendly interfaces, and limited integration of remote sensing outputs into local planning frameworks. Ensuring accessibility means not only providing open data, but also packaging it in forms—such as maps, dashboards, and advisories—that can directly inform irrigation scheduling, reservoir releases, and crop planning.

Technical capacity and scalability

The capacity to process, interpret, and apply remote sensing data remains uneven across LMICs. While universities and research institutes often possess the skills to work with advanced datasets, many irrigation agencies and farmer cooperatives lack in-house expertise. This creates a gap between data availability and data use. Training programs, regional data hubs, and collaborations with international partners are essential to build local capacity. Scalability is another concern: pilot projects often demonstrate success in small areas but fail to expand to broader regions due to institutional and technical limitations. Building scalable systems requires not only technical training but also governance structures that support cross-basin data sharing and coordinated use.

Computer resourcing and costs

Effective use of remote sensing data for water management demands significant computing power, internet connectivity, and long-term financial investment. Many low- and middle-income countries still rely

on outdated hardware and lack access to cloud computing services, which are increasingly required for processing large datasets from missions such as Sentinel or Landsat. Costs associated with upgrading systems, licensing specialized software, and maintaining skilled personnel create further barriers (see supplementary document DB-CF). While open-source platforms like Google Earth Engine or cloud-based processing offered by space agencies have reduced some of these constraints, sustainable financing models remain necessary to ensure long-term operation and accessibility of water management tools.

Emerging remote sensing missions

The landscape of remote sensing is evolving rapidly, with a new generation of missions designed to improve spatial detail, revisit frequency, and the diversity of observable parameters (see supplementary document DB-CF). These missions promise to narrow key information gaps in agricultural water management by providing near-real-time insights into precipitation, evapotranspiration, groundwater storage, and land use. For Vietnam and other low- and middle-income countries, such missions represent both an opportunity and a challenge: they expand the evidence base for decision-making but also require careful attention to accessibility, technical usability, and long-term sustainability.

Appropriateness for lower- and middle-income country decision-making

Emerging missions such as Landsat Next, Sentinel-1 and -2 Next Generation, NASA's Mass Change mission, and ESA's ROSE-L radar mission are designed to provide higher resolution and more frequent coverage than their predecessors. These improvements align well with the operational needs of low- and middle-income countries, where water allocation decisions must be made at fine spatial and temporal scales. For instance, 10 m radar data from ROSE-L could allow irrigation managers to track soil moisture or flood extent at the field level (Iannini et al., 2024), while higher-frequency precipitation products from next-generation GPM satellites could better support early warning systems (Nardi et al., 2025). However, the appropriateness of these missions is not just about technical capacity, but on the suitability of the data to be integrated into existing datasets and decision models of irrigation agencies and farming communities. For low- and middle-income countries, the value of these missions lies in their ability to deliver timely, reliable, and context-relevant information that improves daily management decisions rather than remaining at the level of research outputs.

Usability and accessibility, and computer resourcing

Despite being open access, many of these new datasets are computationally intensive, requiring substantial processing power, cloud storage, and stable internet connectivity. Low- and middle-income countries often face constraints in these areas, which limit the practical application of emerging mission data. Platforms such as Google Earth Engine, NASA's AppEEARS, and ESA's Copernicus Open Access Hub partially offset these challenges by offering cloud-based data storage and processing, reducing the need for local high-performance computing. Usability also depends on the development of simplified interfaces, dashboards, and advisory systems that bridge the gap between raw data and decision-ready products. Ensuring accessibility therefore requires investment not only in infrastructure and connectivity but also in institutional partnerships that can transform complex data streams into actionable information at the sub-basin and farm scales

FUTURE AVAILABILITY AND MISSION COVERAGE FROM RS MISSIONS

Looking forward, the next generation of free and accessible remote sensing missions promises to provide more accurate, higher-resolution, and more frequent information on water availability, directly addressing some of the limitations of current satellite datasets. For changes in terrestrial water storage, the planned Mass Change mission under NASA's Earth System Observatory (ESO) will continue the legacy of GRACE and GRACE-FO. This mission is expected to improve both the spatial resolution (potentially finer than the current ~300 km footprint) and the robustness of monthly gravity-based water storage measurements

(Wiese et al., 2020; Wiese et al., 2022). For soil moisture, the continuation of SMAP and the planned development of enhanced passive-active systems will ensure higher-resolution coverage and shorter revisit times. ESA's upcoming Copernicus High Priority Candidate Missions (such as the L-band radar mission ROSE-L) will be particularly important for Southeast Asia (Torres et al., 2020). With spatial resolution below 10 m and revisit cycles of only a few days, these missions will significantly improve the monitoring of soil moisture variability at the basin and farm scale, offering a capability that current global missions cannot deliver (Khanal et al., 2020). Also, precipitation monitoring will benefit from continuity and refinement. The GPM constellation is expected to be maintained and expanded through additional partner satellites, ensuring high-frequency rainfall estimates at resolutions of ~5km or better (Kidd et al., 2021; Kummerow et al., 2020). Further, missions like the Meteostat Third Generation (MTG) and next-generation Japanese Himawari satellites (Bessho et al., 2016; Lee et al., 2017; Miura and Nagai, 2019) will provide rapid-refresh observations that can improve early warning for extreme rainfall events and floods across South-East Asia's monsoon-driven climate.

Optical and radar imaging capacity is also set to grow. The Landsat Next mission, scheduled for launch in the early 2030s, will triple the number of spectral bands while retaining 30 m spatial resolution and increasing revisit frequency to every 6-8 days. This will enhance the monitoring of crop water use, evapotranspiration, and vegetation stress. Meanwhile, the Sentinel Expansion missions, including Sentinel-1 Next Generation and Sentinel-2 Next Generation, will preserve continuity of existing programs while offering improved resolution and shorter revisit times. This will ensure an uninterrupted data stream for mapping agricultural and irrigation activities in regions like South-East Asia. Additional information on future availability and mission of these agro-related satellite missions is provided in Appendix C and spreadsheet DB-CF

BRIEF METHODOLOGY AND ADVICE ON REPEATING THIS ACTIVITY

The assessment of remote sensing missions for water management involves three key steps: identifying relevant missions, evaluating their technical specifications and requirements (spatial/temporal resolution, coverage, data latency), and mapping these to the decision-making requirements of local users. In this report, missions were reviewed based on their current and planned availability, their capacity to monitor key parameters such as precipitation, evapotranspiration, and groundwater, and their suitability for the proposed study areas agricultural water needs. The process can even be repeated in other low- and middle-income regions following a similar methodology:

Scoping – Define the agricultural and hydrological decision points where data are most needed (e.g., irrigation, drought response, flood management).

Mission Review – Compile a list of relevant past, present, and planned remote sensing missions, noting their data type, resolution, revisit frequency, and accessibility.

Contextual Assessment – Match mission capabilities with local needs, considering institutional capacity, infrastructure, and end-user requirements.

Integration with existing datasets – Identify tools and platforms (cloud-based services, decision-support dashboards, mobile applications) that can make the data usable for practitioners.

Repeating this activity successfully depends on collaboration between technical experts, local institutions, and decision-makers. This shows that global mission outputs can be translated into local management needs, and with this, low- and middle-income regions are able to get maximum value from emerging remote sensing investments and strengthen their agricultural water management systems.

6.4 LIMITATIONS OF REMOTE SENSING DATA IN AGRICULTURAL WATER MANAGEMENT

Remote sensing can provide data on precipitation, potential and actual evapotranspiration, soil moisture, snow and ice cover as well as vegetation and land use / land cover (Malthus and Zamyadi, 2024; Sheffield et al., 2018). Remote sensing can only estimate changes in total water storage from inferred changes in observed mass, changes in groundwater storage must be interpreted or modelled (Humphrey et al., 2023; Sheffield et al., 2018). The coarse resolution of changes to groundwater storage prevents direct use though its utility increases when coupled with models (Humphrey et al., 2023; Malthus and Zamyadi, 2024; Sheffield et al., 2018).

Sheffield et al. (2018) observed that while remotely sensed precipitation and evapotranspiration data, can be essential, particularly precipitation, in data poor areas they contain large uncertainties. Karimi and Bastiaanssen (2015) in their study found the following error rates; actual evapotranspiration ($95\% \pm 5$), precipitation ($82\% \pm 15$) and land use / land cover ($85\% \pm 7$). While Fuentes et al. (2024) found that RS derived evapotranspiration data to be more accurate at catchment / basin scales than upscaled field evapotranspiration data.

River discharge can be estimated from RS, though limited to larger rivers and contains large uncertainties. Newer satellite missions could improve the robustness of RS estimated discharges (Malthus and Zamyadi, 2024; Sheffield et al., 2018). Discharge is often estimated from RS data by closing out the water balance;

$$Q = P - ET_a - \Delta S \quad (xxii)$$

Where Q is discharge, P is precipitation, ET_a is actual evapotranspiration and ΔS is change in storage. This approach can lead to large uncertainties as errors in the individual RS datasets are combined (Karimi et al., 2015; Michailovsky et al., 2023). Therefore, needs to be supported by terrestrial monitoring data.

7 Conclusions

During the mid-20th century there was an emphasis on water resource development with large irrigation projects funded from public investment and in the later 20th Century massive private investment in bores and submersible pumps. The “Green Revolution” had succeeded in reducing poverty and malnutrition but was not uniform. The 21st century is now characterised by much of the world experiencing water scarcity with an estimated 1.2 billion people living in basins with water scarcity. It is projected that up to two-thirds of the world’s population could experience water scarcity due to population growth, changing diets, economic growth and changing climates

To improve water resource management particularly in the agricultural sector, the largest water consumer requires good data to inform decision making. Typically, in low/middle income countries, in situ monitoring of water resources such as river flows, groundwater levels, and water consumption by irrigated agriculture, is limited. The investment required for in situ monitoring infrastructure and capacity, particularly for groundwater, can be prohibitive. Consequently, there is often a paucity of detailed and robust data upon which to generate information to assist with decision making. At basin and larger scales, inroads are being made to address this gap through harnessing the latest in big data and applying remote sensing and earth observation data products. However, the potential for such data and associated products to assist with sub-basin scale water management is not known.

In many Asian countries the historic rapid expansion of irrigated agriculture has impacted on both surface and groundwater resources. There is now increasing competition for water between different economic sectors within basins. This has meant significant changes, over the last several decades, to agricultural water management in terms of its scope and direction. There are two prevailing approaches to agricultural water management, the first ‘classical’ approach is about irrigation development and improving irrigation efficiency. The pursuit of increased agricultural water use efficiency without supporting governance changes has resulted increased water usage not less as expected. The second ‘neoclassical’ agricultural water management approach is to manage water resources at the basin level, balancing water availability with needs. It also involves focusing on water consumption or depletion, tracking where the water being used. The ‘classical’ approach is often entrenched within government agencies and the ‘neoclassical’ approach is being pushed by agricultural development agencies such as FAO and IWMI. This can lead to tensions.

Consequently, due to these different approaches, agricultural water management is either occurring at the larger basin or irrigation area scales, often funded by external donors. There is little activity occurring at smaller sub-basin scales. Agricultural water management at smaller sub-basins is also hampered by complex governance arrangements, with different levels of government and agencies all having roles and often competing. Any hydrological data collected is often siloed and of limited duration.

Doner funded studies have shown remote sensing and water accounting frameworks can provide crucial hydrological data to help improve agricultural water management in data poor areas at larger basin scales and irrigation areas. It has not been used at smaller sub-basin scales. Part of the problem moving from larger basins to smaller basins are scaling issues, with many of the tools and approaches developed for larger basins not suitable for smaller basins. Water Accounting Plus (WA+) is designed for use with remote sensing data to calculate water balances for basins. However, it is a depletion-based water accounting system that tracks where water is being used, not where it flows. So, outflow data in WA+ can have a high degree of uncertainty. To overcome this a hydrologic model was built into the Water Accounting Plus framework to track surface and groundwater flows and to support water resource planning. Though the model needs to be calibrated with terrestrial discharge data often unavailable in smaller subbasins. The model is complex to set up, and lack of calibration data limits the model usage within smaller sub-basins.

Remote sensing data is available for most hydrological parameters needed to determine water balances, rainfall, evapotranspiration and changes in storage (GRACE). GRACE data though is coarse (~300 km) and only available for larger basins. There are multiple satellite-derived datasets that are increasingly open-access available for use smaller sub-basins. New missions are being developed that will increase data availability. Although, many datasets are now free, they are delivered in formats that lack user-friendly interfaces, require advanced processing, or are at unsuitable spatial and temporal resolutions. Advanced processing also requires significant computing power, internet connectivity, and licensing of specialized software that may not be available. This creates a gap between data availability and data use.

It has been shown that remote sensing and water accounting can help fill hydrological data gaps to lift water productivity and reduce poverty as seen in India. However, remote sensing cannot completely replace terrestrial data, though it has an important role in augmenting terrestrial data sources as in the case of China.

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APPENDIX A SOIL MOISTURE BALANCE WATERPIX MODEL

Since the initial inception of the Water Accounting Plus framework (Karimi, 2014; Karimi et al., 2013; Karimi et al., 2012) it has increased in complexity with the addition of two new sheets for surface and groundwater as well as a pixel based water balance model, known as WaterPix, used to calculate withdrawals and flows (Mul et al., 2020). The Waterpix model used a 100m grid and a soil moisture water balance methodology (IHE Delft, 2020). A conceptual model of the Waterpix model with the WA+ framework, as well as its variables, are shown in Figures A.1 and A.2 and Table A.1.

TABLE A.1 SOIL MOISTURE BALANCE WATERPIX MODEL VARIABLES OF USED IN WATERPIX MODEL

Variable	Class	Definition
P	Input	Precipitation
ET _a	Input	Actual Evapotranspiration
I	Input	Interception
lcc	Input	Land use land cover
θ _{SAT} (S _{sat})	Input	Saturated water content
Z _{root-zone}	Lookup table	Depth of root zone in different land use classes
f _{consumed}	Lookup table	The fraction of withdrawals consumed as ET
S _{SM}	Calculated	Soil moisture, S _{rain} or S _{green} natural, S _{incr} , water added through irrigation
Q _{sro, rain}	Calculated	Surface runoff, Q _{sro, incr} Surface runoff resulting from water supplied
Q _{perc}	Calculated	Recharge to groundwater, Q _{perc, rain} natural, Q _{perc, incr} recharge from supplied water
ET	Calculated	Evapotranspiration, ET _{rain} or ET _g natural, ET _{incr} ET from supplied water
Q _{supply}	Calculated	Additional water supplied
Q _{bf}	Calculated	Baseflow
Q _{tr}	Calculated	Total runoff

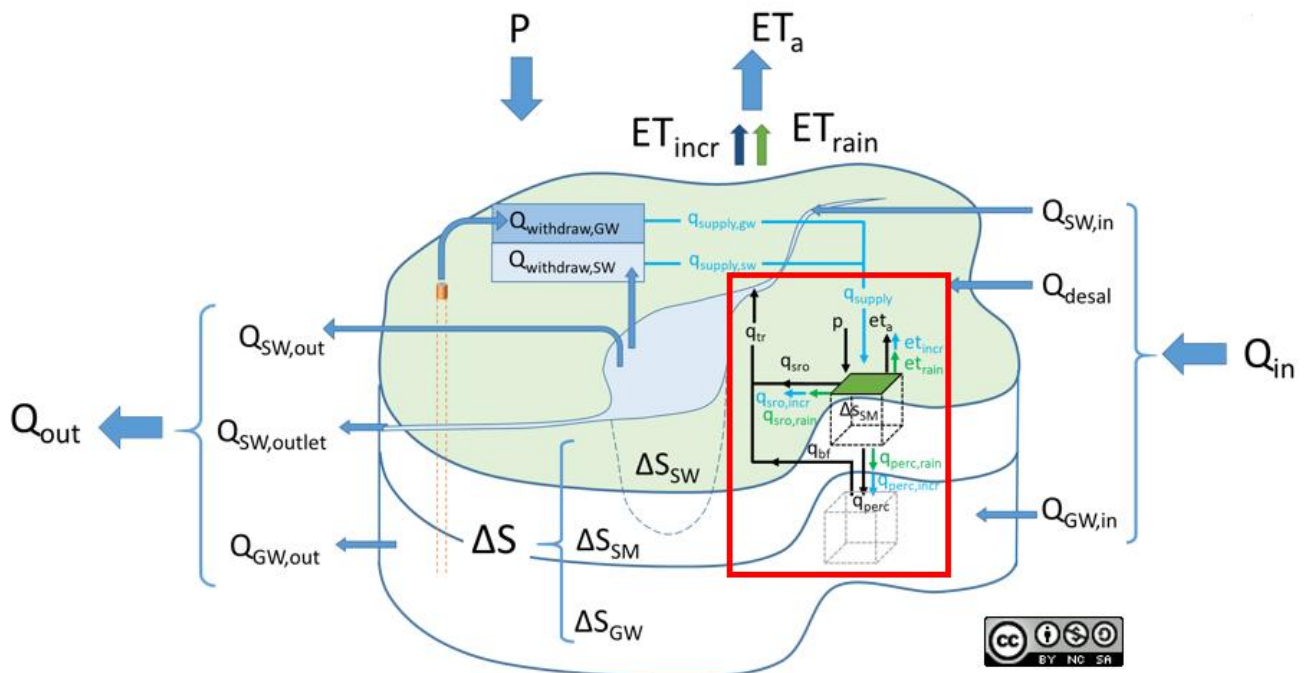


FIGURE A.1 WATERPIX FLUXES IN RELATION TO FLUXES IN SHEET 1 RESOURCE BASE (SOURCE: IHE DELFT 2020)

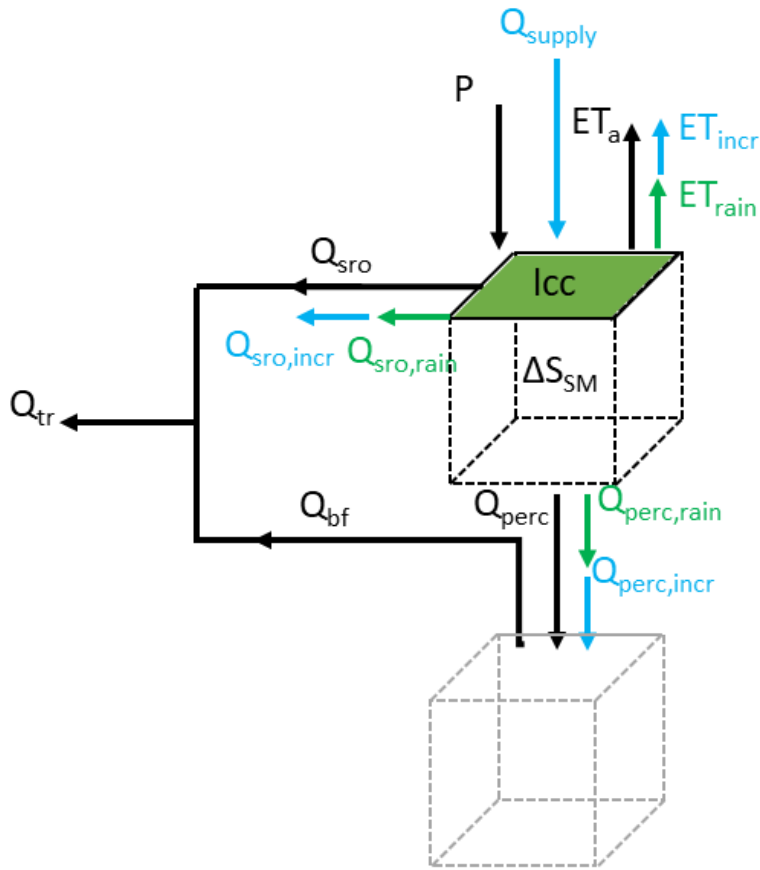


FIGURE A.2 FLUXES IN THE SOIL MOISTURE PIXEL WATER BALANCE MODEL (SOURCE: IHE DELFT 2020)

The variables for the soil moisture balance model for rainfall are shown in Figure A.3. The maximum soil water volume, S_{max} , varies by land use class with depth of the root zone, $z_{root-zone}$, provided in a lookup table that can be adjusted during the calibration process;

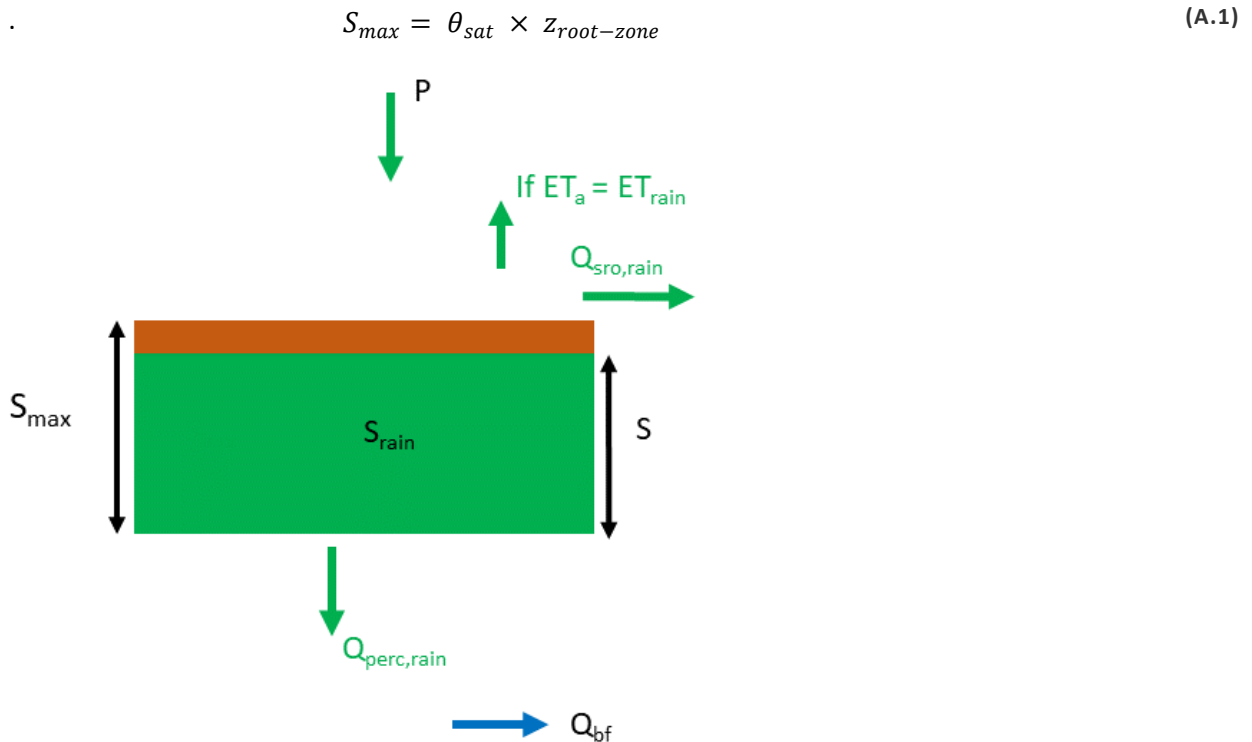


FIGURE A.3 VARIABLES FOR SOIL MOISTURE BALANCE MODEL FOR RAINFALL (SOURCE: IHE DELFT 2020)

The soil moisture for each timestep, S is;

$$S = S_{rain} + S_{incr} \quad (A.2)$$

The surface runoff component due to rainfall, $Q_{sro, rain}$, for the time step is calculated based on the NRCS-CN method;

$$Q_{sro,t} = \begin{cases} 0 & \text{if } P = 0 \\ n \times \left(\frac{\left(\frac{P_t - I_t}{n} \right)^2}{\left(\frac{P_t - I_t}{n} \right) + f \times (S_{max} - S_{t-1})} \right) & \text{if } P \neq 0 \end{cases} \quad (A.3)$$

Where f is a calibration constant and n is the number of rain days in the month.

The percolation or groundwater recharge, Q_{perc} , once S gets above a specified value is calculated by;

$$Q_{perc-rain,t} = S_{t-1} \times e^{-\frac{1}{S_{t-1}}} \quad (A.4)$$

The initial soil moisture balance for the time step becomes;

$$S_{temp} = (S_{t-1} + P_t - Q_{sro-rain,t} - Q_{perc-rain,t}) - ET_{a,t} \quad (A.5)$$

If $S_{temp} > 0$, there is sufficient water to meet $ET_{a,t}$ and if $S_{temp} > S_{max}$ then soil water in the timestep, S_t , becomes;

$$S_t = S_{max} \quad (A.6)$$

and excess water becomes surface runoff, $Q_{overflow}$;

$$Q_{overflow} = S_{temp} - S_t \quad (A.7)$$

with total surface runoff for the timestep, $Q_{sro,t}$, consisting of runoff from rainfall and overflow;

$$Q_{sro,t} = Q_{sro-rain,t} + Q_{overflow} \quad (A.8)$$

Otherwise, if $S_{temp} > 0$ and $S_{temp} < S_{max}$

$$S_t = S_{temp} \quad (A.9)$$

$$ET_{rain,t} = ET_{rain,t} \quad (A.10)$$

$$ET_{incr,t} = 0 \quad (A.11)$$

$$Q_{supply,t} = 0. \quad (A.12)$$

In the case that there is insufficient water stored in the soil to meet crop demand (ET_a) as shown in Figure A.4

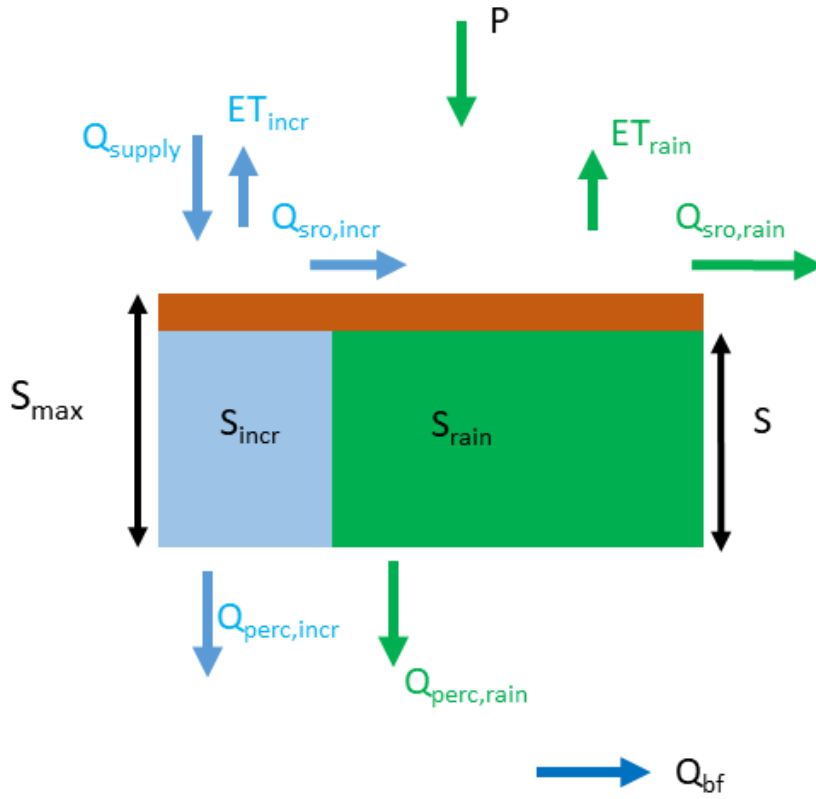


FIGURE A.4 VARIABLES IN THE SOIL MOISTURE BALANCE MODEL WHEN THERE IS INSUFFICIENT WATER STORED IN THE SOIL TO MEET EVAPOTRANSPIRATION (SOURCE: IHE DELFT 2020)

If $S_{temp} < 0$, i.e insufficient to meet ET_a then;

$$ET_{incr,t} = -S_{temp} \quad (A.13)$$

$$ET_{rain,t} = ET_{a,t} - ET_{incr,t} \quad (A.14)$$

$$S_{temp,updated} = (S_{t-1} + P_t - Q_{sro-rain,t} - Q_{perc-rain,t}) - ET_{incr,t} - ET_{rain,t} \quad (A.15)$$

$$Q_{supply,t} = \frac{ET_{incr,t}}{f_{consumed}} \quad (A.16)$$

If $(Q_{supply,t} - ET_{incr,t}) \leq S_{max}$

$$S_t = S_{temp} + Q_{supply,t} \quad (A.17)$$

$$Q_{sro-incr,t} = 0 \quad (A.18)$$

$$Q_{perc-incr,t} = 0 \quad (A.19)$$

If $(Q_{supply,t} - ET_{incr,t}) \geq S_{max}$

$$S_t = S_{max} \quad (A.20)$$

$$(Q_{sro-incr,t} + Q_{perc-incr,t}) = Q_{supply,t} - ET_{incr,t} - S_{max} \quad (A.21)$$

$$Q_{sro-incr,t} = (Q_{sro-incr,t} + Q_{perc-incr,t}) \times \frac{Q_{perc-rain,t}}{Q_{sro-rain,t} + Q_{perc-rain,t}} \quad (A.22)$$

$$Q_{perc-incr,t} = (Q_{sro-incr,t} + Q_{perc-incr,t}) \times \frac{Q_{sro-rain,t}}{Q_{sro-rain,t} + Q_{perc-rain,t}} \quad (A.23)$$

The algorithms described above were used in Rapid Water Accounting studies, that utilised WaPOR data, for the Awash River Basin - Ethiopia (FAO and IHE Delft, 2020b), Jordan River Basin (FAO and IHE Delft,

2020a), Litani River Basin- Lebanon (FAO and IHE Delft, 2019), Niger River Basin (FAO and IHE Delft, 2020c) and the Nile River Basin (FAO and IHE Delft, 2020d).

BUDYKO BASED METHODS

The other iterations of Water Accounting Plus, (e.g. (Chatterjee et al., 2025; Dembélé et al., 2023; Salvatore et al., 2020; Singh et al., 2022) use a WaterPix model based on the Budyko Hypothesis to calculate ET_{green} and ET_{incr} (Espinoza-Dávalos and Bastiaanssen, 2017) with the rest of the model remaining similar to the algorithms described above.

The basis of the Budyko Hypothesis are the assumptions that over large spatial scales the long-term average annual water and energy balances for natural catchments or basins can be expressed for water as⁵;

$$P = ET + Q, \Delta S = 0 \quad (A.24)$$

and energy as;

$$R_n = L \cdot ET + H \quad (A.25)$$

Where, in the energy balance equation, R_n is average annual net radiative heat flux from the atmosphere to the land surface, L is the latent heat of evaporation, the product $L \cdot ET$ is the latent heat flux and H is the average flow from the land surface to the atmosphere, the sensible heat flux (Budyko, 1974; Sposito, 2017). Dividing Equation (A.25) by the latent heat of evaporation (L) provides an energy balance constraint on ET;

$$\frac{R_n}{L} = ET + \frac{H}{L} \quad (A.26)$$

From Equation (A.26) the maximum possible ET occurs when all incoming radiation energy is consumed by evapotranspiration of green water and there is negligible sensible heat flux. The maximum possible ET is equivalent to R_n/L and is designated as the potential evapotranspiration (ET_0 or PET). Therefore, there are both water and energy limits on ET. When P is not limiting, $ET \rightarrow ET_0$ and when there is low water availability and relatively high sensible heat flux, $ET \rightarrow P$. So under wet conditions, ET is energy-limited by ET_0 and under dry conditions ET is limited by P (Budyko, 1974; Sposito, 2017).

If ET_0 is divided by P it becomes the Aridity Index and given the symbol ϕ . If $\phi < 1$ it indicates a humid climate and if $\phi > 1$ it indicates an arid climate. When ET is divided by P it is known as the evaporative index. Using the above reasoning, when energy limited, as $ET_0/P (\phi) \rightarrow 0$, $ET/P \rightarrow \phi$, and when water limited, as $\phi \rightarrow \infty$, $ET/P \rightarrow 1$. Therefore the graph of the Budyko equation is tangential to the 1:1 line, Energy limit (Figure A.5), and asymptotically approaches the horizontal line defined by $ET/P = 1$, the Water limit, Figure A.5 (Budyko, 1974; Sposito, 2017).

⁵ Equation (B.24) is simply a variation of Equation (vi)

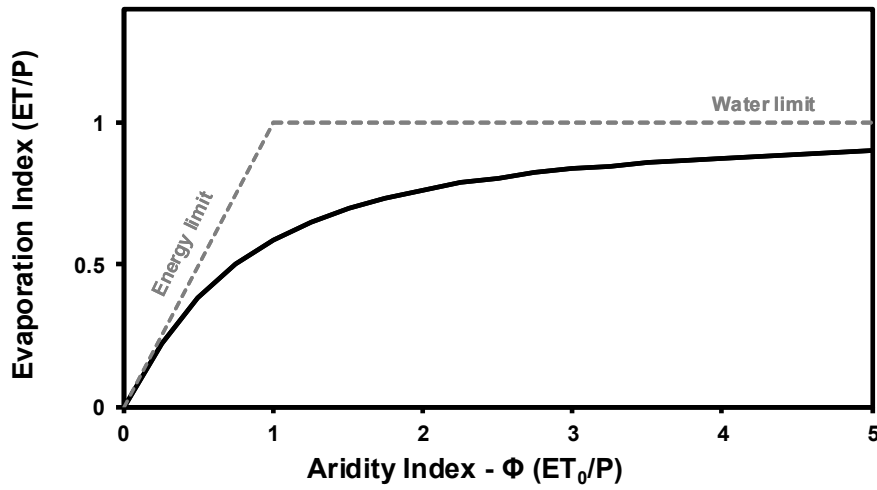


FIGURE A.5 A GRAPH OF THE BUDYKO EQUATION

The Budyko equation expressed in terms of the aridity and evaporation indexes is (Chatterjee et al., 2024; Reaver et al., 2022);

$$F(\Phi) = \frac{ET}{P} = \left[\frac{ET_0}{P} \tanh\left(\frac{P}{ET_0}\right) \left(1 - \exp\left(-\frac{ET_0}{P}\right)\right) \right]^{0.5} \quad (\text{A.27})$$

The iterations of the WaterPix model within the Water Accounting Plus framework uses Equation (A.27) to estimate ET_{green} and ET_{incr} (Espinoza-Dávalos and Bastiaanssen, 2017). Satellite derived ET_0 and P is used in Equation (A.27) to derive the evaporation index (ET/P). The evaporation index and satellite derived P is then used to calculate ET_{green} ;

$$ET_{green} = F(\Phi) * P = \frac{ET}{P} * P \quad (\text{A.28})$$

ET_{green} , and satellite derived actual ET (ET_a) used then be used to derive ET_{incr} also called ET_{blue} ;

$$ET_{blue} = ET_{act} - ET_{green} \quad (\text{A.29})$$

Empirical relationships such as the Budyko equation removes most of the hydrological information making it difficult to understand the physical basis, or its validity, in calculating components of the water balance (Berghuijs et al., 2020; Berghuijs and Woods, 2016; Reaver et al., 2022). Berghuijs et al. (2020) using *Model Parameter Estimation Project* (MOPEX) data for 410 small basins, located across the contiguous United States, found though the data fell around the Budyko curve when P was removed from the evaporative index and ET alone was compared with the aridity index there was no correlation. For this study hydro-climatic data from the United States - CAMELS (Newman et al., 2022) and Great Britain – CAMELS-GB (Coxon et al., 2020) were combined giving a total of 1322 basins. The Aridity and Evaporation indexes for the combined CAMELS basins (Figure A.6a) fell around the Budyko Curve though there was a poor correlation (Pearson, 0.07) between evaporation and the aridity index (Figure A.6b) for these basins. The CAMELS data, an independent dataset to Berghuijs et al. (2020), gave similar results to Berghuijs et al. (2020). Using the Waterpix procedures, equations (A.27) and (A.28), the Budyko evaporation for the CAMELS basins was estimated and compared with average annual evaporation (Figure A.6c).

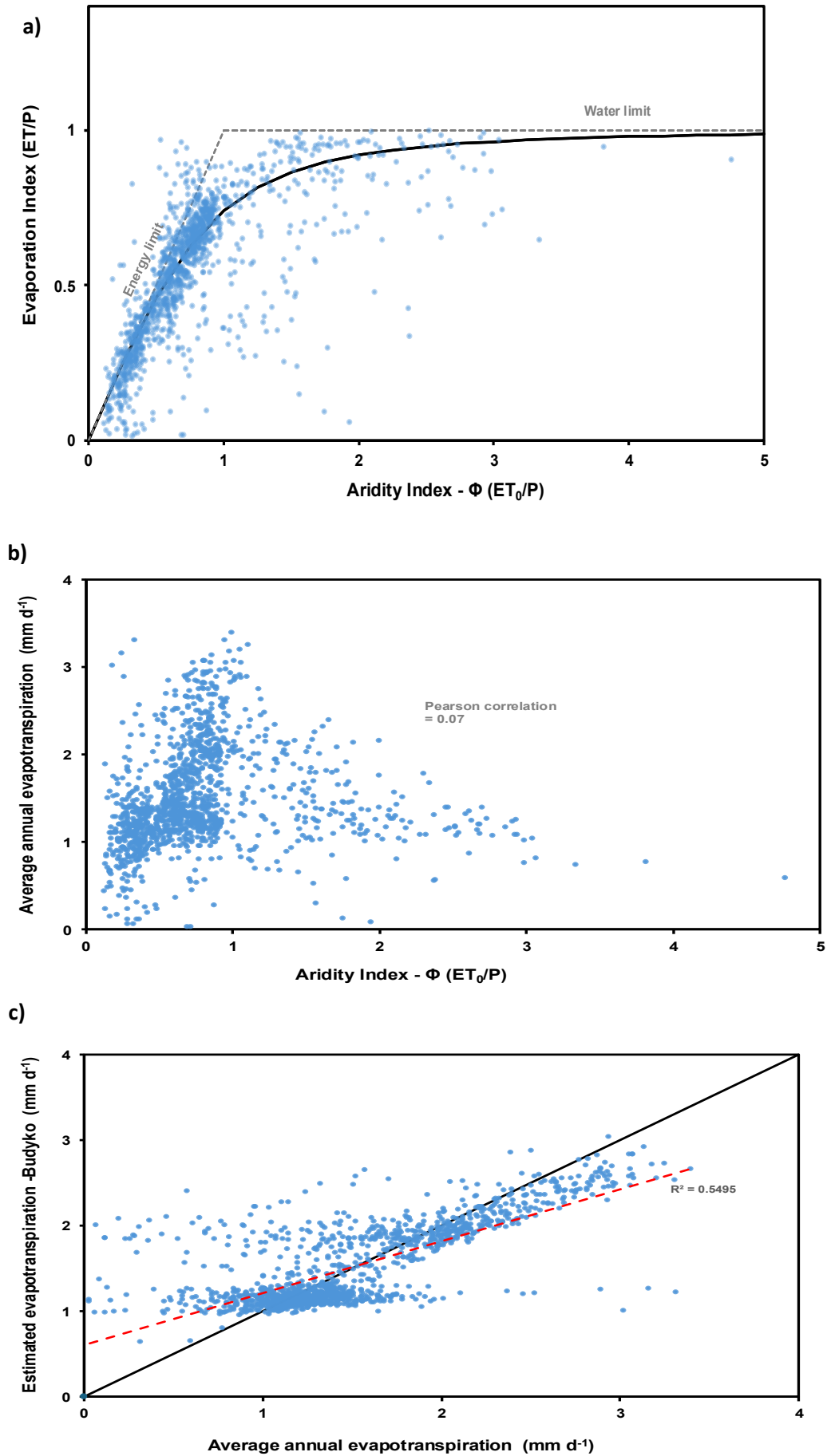


FIGURE A.6 HYDRO-CLIMATIC DATA FOR CAMELS BASINS IN THE UNITED STATES AND GREAT BRITAIN COMPARING EVAPORATIVE INDEX WITH ARIDITY INDEX IN A) EVAPORATION WITH ARIDITY INDEX B) AND ANNUAL EVAPORATION CALCULATED USING THE BUDYKO EQUATION (XLVI) WITH AVERAGE ANNUAL EVAPORATION IN B)

There was no correlation between the Budyko derived evaporation and average annual evaporation. There was also a large group of datapoints parallel to the independent axis indicating no relationship between Budyko E and actual E. These results demonstrate that deriving evapotranspiration from the aridity index is undeterminable and lacking predictive ability as also highlighted by (Reaver et al., 2022). It also calls into question the accuracy and the robustness of the Budyko Waterpix model procedures to calculate ET_{green} from the aridity index i.e. equations (A.27) to (A.28) especially for smaller basins. Additionally, measured data were observed to deviate from the curve of the Budyko equation (A.27) so new equations were developed to account for these variations (Reaver et al., 2022; Xu et al., 2013). One of the most commonly used equations is a one-parameter equation developed by Fu (1981) as cited in Zhang et al. (2004);

$$\frac{ET}{P} = 1 + \frac{ET_0}{P} - \left[1 + \left(\frac{ET_0}{P} \right)^\omega \right]^{1/\omega} \quad (A.30)$$

The dimensionless parameter ω is meant to represent both climate forcings and catchment characteristics (Chen et al., 2020). The Fu equation has been used to calculate ET_{green} and ET_{incr} (e.g. (Hessels et al., 2022; Simons et al., 2020). Chatterjee et al. (2025) found that the estimations of ET_{green} and ET_{blue} (ET_{incr}) were very sensitive to value of ω chosen. Xu et al. (2013) derived equations to calculate values of ω for basins globally, though the predictive capacity of ω was weak particularly for high ω values. Xu et al. (2013) found that estimating ω values for large basins $> 100,000 \text{ km}^2$ was easier than for small basins with equations for small basins having lower explanatory power (r^2) and greater variability. They hypothesised that this was because large basins were more heterogenous and smaller basins were more homogeneous and distinct from each other. Xu et al. (2013) also found the common independent variables in all equations were latitude and NVDI, a surrogate for vegetation type. These variables, however, are not independent of each other as vegetation type is related to latitude (Budyko, 1974). Zhang et al. (2004) also found that ω changes with vegetation type, globally forested basins had an average ω of 2.84 and grassed basins had an average ω of 2.55 though ranged between 1.7 and 5.

Even within basins, ω varied by subbasin as well as on monthly, seasonal and annual timescales (Chen et al., 2020; Du et al., 2016; Huang et al., 2022). Basins have been modified by anthropogenic activities, so the original assumptions underpinning the Budyko Hypothesis had become violated. Therefore, variations of the Fu equations were developed to correct for this. Some equations adding extra parameters to the original Fu equation (e.g. (Du et al., 2016; Greve et al., 2016) while others adjusted the water balance to account for additional water sources creating a new variable effective precipitation which was substituted for precipitation in the Fu equation (e.g. (Chen et al., 2020; Han et al., 2023).

However as Reaver et al. (2022) observed “Empirical relationships, such as the Budyko curve, emerge from the underlying physics within a given context, but those relationships are susceptible to losing their physical foundations outside of that context”. The Budyko Framework originally applied globally over large spatial scales, using long term averages, to natural basins. It is now being used over shorter time periods for perturbed basins. To better understand the applicability of the Budyko Framework, particularly to smaller basins it is necessary understand the physical foundations of a natural basin being deforested for agriculture, in terms of changes to the water and energy balances (Figure A.7).

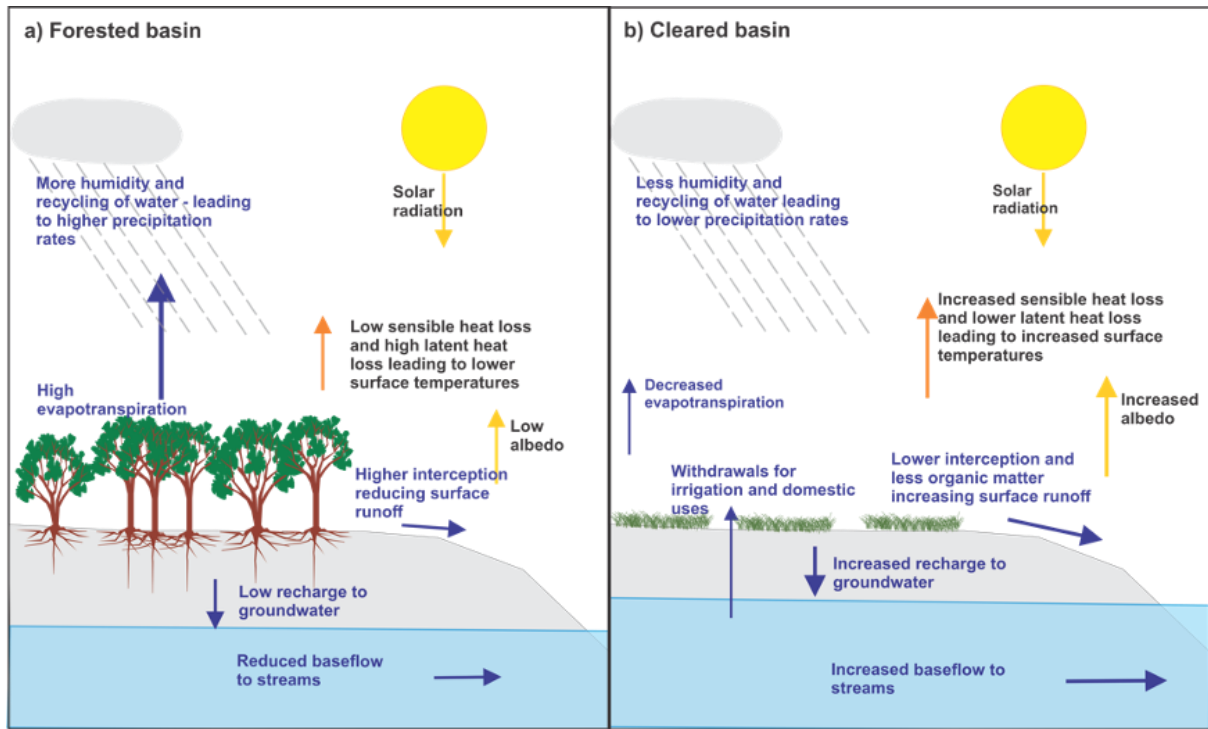


FIGURE A. 7 CHANGES IN THE WATER AND ENERGY BALANCES ONCE BASINS ARE CLEARED FOR AGRICULTURE (AFTER FOLEY ET AL 2003B AND LILICRAP, 2015)

When a basin is cleared or deforested for agriculture, there is the removal of deep rooted vegetation with large Leaf Area Indexes and replacement by shallow rooted crops which result in a reduction in evapotranspiration (Foley et al., 2003b; Lillicrap, 2015; Zhang et al., 2001). Deforestation also changes the soil properties where soil organic matter, infiltration rates, total porosity and saturated hydraulic conductivity are all reduced (Recha et al., 2012; Zimmermann et al., 2010). The loss of the original vegetation canopy results in lower rainfall interception and higher rainfall intensities reaching the ground during storm events and when combined with altered soil properties, leads to increased surface runoff (Lillicrap, 2015; Recha et al., 2012; Zimmermann et al., 2010). The reduction in rooting depth also leads to an increase in recharge to groundwater and the consequent increase in groundwater storage (Lillicrap et al., 2014; Lillicrap et al., 2018), which may be offset by irrigation usage. In some instances for large basins or large areas of deforestation there is a feedback loop where the reduction in ET through deforestation results in a reduction in precipitation (Smith et al., 2023). The decrease in ET also results in changes to the energy budget with increased sensible heat fluxes and consequent higher temperatures as well as a higher albedo leading to increased reflection of incoming solar radiation (Foley et al., 2003b). Looking back at equations (A.24) and (A.25) forming the basis of the Budyko equation, the water and energy balances have been fundamentally altered by clearing or deforestation;

$$P = ET \downarrow + Q \uparrow + \Delta S \uparrow$$

$$R_n = L \cdot ET \downarrow + H \uparrow + \alpha \cdot R_n \uparrow, \text{ where } \alpha \text{ is albedo}$$

The basins, particularly smaller subbasins, under a cleared regime may reach a new equilibrium water and energy balance, but it will be in a different equilibrium state to a natural catchment (Foley et al., 2003a; Scheffer et al., 2001).

As the physical assumptions on which Budyko equation (A.27) were founded, principally the relationships between ET/P and ET_0/P , have changed due deforestation it is difficult to justify its usage in determining dynamic changes in basin water balance properties. Especially when downscaling to smaller basins where specific localised landscape characteristics may dominate over regional climatic influences in hydrological processes such as elevation, slope, soil type, geology, orientation (e.g. north or east facing) etc (Blöschl and

Sivapalan, 1995; Han et al., 2023; Huang et al., 2022; Sidle, 2006; Sivapalan, 2003; Wood et al., 1988). This would also explain the lack of correlation between evapotranspiration and the aridity index in the CAMELS data (Figure A.6b). However, an argument could still possibly be mounted to justify use of the Budyko Hypothesis for much larger basins and subbasins with annual or greater timesteps, where regional climatic controls dominate the hydrological processes and $\Delta S \approx 0$ especially when using modified Budyko equations such as the Fu equation, as Xu et al. (2013) found that estimating ω values for large basins to be more robust.

In conclusion, the general global Budyko curve behaviour observed at large spatial scales, in natural catchments averaged over long periods is a well-documented and physically driven phenomenon (Reaver et al., 2022). Budyko (1974) observed that at regional scales, biomes, vegetation adapted to climatic forcings to maximise water availability for photosynthesis. Though within these broad regional climatic controls, there is considerable vegetation diversity driven by localised factors such as water availability, geology and soil type (Beadle, 1981). Similarly with hydrological processes, within broad climatic controls, localised landscape scale forcing can dominate hydrological processes. Therefore, as Reaver et al. (2022), based on their research findings, concluded *“the attribution of physical meaning to the specific functional forms of curves [Budyko], as well as explicitly interpreting them as trajectories... is an unsupported conjecture”*. They furthermore concluded that *“as an alternative to using explicit Budyko curves to understand catchment trajectories, we reiterate the long-standing suggestion that process-based evapotranspiration models should be used”*.

Hydrological models like MIKE SHE (Abbott et al., 1986) and SWAT (Arnold et al., 2012) used different methodologies to calculate evaporation but are physically based. SWAT uses Hydrological Response Units, which link areas of similar land use, soil type and slope to estimate runoff and evaporation (Arnold et al., 2012). SWAT has also been used with Water Accounting Plus for smaller basins to calculate values for the different sheets (e.g. (Delavar et al., 2022; Delavar et al., 2020).

Out of the iterations of the Water Accounting Plus pixel water balance models, the Soil Moisture Balance model is the most suitable for smaller basins, where calibration data such as discharge is available, as it is more physically based and closer to the algorithms used in MIKE SHE and SWAT. Additionally, Msigwa et al. (2021) found that the soil water balance model was more accurate than the Budyko methods in deriving ET_{green} and ET_{blue} . Therefore, at the smaller subbasin scale it recommend that physically based models be used to determine flows for sheets within the Water Accounting Plus framework. Data to calibrate models may not be available which limits the calculation of flow data for smaller sub-basins. However, for larger basins and subbasins, over longer timesteps such as annual, the Budyko methodology may be appropriate especially if using parametrised equations that allow for different basin characteristics such as the Fu equation.

APPENDIX B DETAILED REVIEW OF REMOTE SENSING MISSIONS APPLICABLE TO AGRICULTURAL WATER RESOURCE MANAGEMENT

In the following sections, broader details are provided for Optical Remote Sensing and Microwave Remote Sensing based remote sensing products and GRACE products. In a broader picture, RS based datasets are provided in this report, being divided into two main categories in terms of the costs related to their accessibility. First category is “Free” category which has most (if not all) the products that are freely available to public, a database (DB-RS) related to these products is explained in section (5.1), while an overview is provided in B1. While Section B2 has dataset details of the second category which mostly “paid” and have RS products that have related cost of access (although some of them are free).

B.1 OPTICAL REMOTE SENSING IN AGRICULTURAL RESOURCE MANAGEMENT

All the products in this section are available free of cost from the data providers.

LANDSAT SERIES

The Landsat program, a joint initiative between NASA and the U.S. Geological Survey (USGS), represents the longest-running enterprise for acquiring satellite imagery of Earth, beginning with the launch of Landsat 1 in the early 1970s. This series of Earth-observing satellites is designed primarily for monitoring land surface changes, providing multispectral data that supports applications in agriculture, forestry, urban planning, and environmental management. Landsat satellites carry optical sensors that capture images in visible, near-infrared (NIR), shortwave infrared (SWIR), and thermal infrared bands, with spatial resolutions ranging from 15 meters (panchromatic) to 100 meters (thermal). Key missions include Landsat 8, launched in 2013, which features the Operational Land Imager (OLI) for high-radiometric quality data in nine spectral bands and the Thermal Infrared Sensor (TIRS) for two thermal bands, enabling detailed land cover classification and surface temperature mapping. Landsat 9, launched in 2021, mirrors Landsat 8's capabilities to ensure data continuity. The program's global coverage, with a 16-day revisit time for most areas, has produced over 10 million scenes, freely available through the USGS EarthExplorer portal and other sources. Landsat data is calibrated across missions using simultaneous nadir overpasses, ensuring consistency for time-series analysis, such as detecting deforestation or urban expansion. Its moderate resolution (30 meters for multispectral bands) makes it ideal for regional studies, though it is limited by cloud cover, as with all optical sensors.

SENTINEL-2

Sentinel-2, part of the European Union's Copernicus Programme and operated by the European Space Agency (ESA), is a constellation of two polar-orbiting satellites (Sentinel-2A and Sentinel-2B, launched in the mid-2010s) designed for high-resolution optical imaging of Earth's land and coastal areas. The mission acquires multispectral data in 13 spectral bands, spanning visible, NIR, SWIR, and red-edge wavelengths, with spatial resolutions from 10 meters (for four visible/NIR bands) to 60 meters (for atmospheric correction bands). This enables detailed monitoring of vegetation health, land use changes, water quality, and disaster response, with a swath width of 290 km and a revisit time of 5 days at the equator when both satellites are operational. The Multi-Spectral Instrument (MSI) on board is a push-broom sensor that provides Level-1C (top-of-atmosphere reflectance) and Level-2A (bottom-of-atmosphere reflectance with atmospheric correction) products, freely available through the Copernicus Open Access Hub or others. Sentinel-2's data supports global applications, such as crop mapping via vegetation indices (e.g., NDVI) or

ocean surface current retrieval in coastal zones. Its high resolution and frequent coverage make it superior for local-scale studies compared to coarser sensors, though optical limitations like cloud interference persist. As of 2025, the mission continues to deliver near-real-time data, with extensions planned for Sentinel-2C and -2D to maintain continuity.

THE MODERATE RESOLUTION IMAGING SPECTRORADIOMETER (MODIS)

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a key satellite-based sensor aboard NASA's Terra and Aqua satellites launched at the turn of the 21st century, providing continuous global observations in 36 spectral bands, covering visible, NIR, SWIR, and thermal infrared wavelengths. MODIS collects data with spatial resolutions ranging from 250 meters (for two visible/NIR bands) to 1 km (for thermal bands), achieving full Earth coverage every 1–2 days. This makes it invaluable for monitoring large-scale phenomena such as land surface temperature, vegetation dynamics, aerosol optical thickness, cloud properties, and ocean colour, supporting applications in climate research, disaster management, and environmental monitoring. Data products include Level-1B (calibrated radiances), Level-2 (geophysical parameters like aerosol and cloud optical properties), and higher-level composites (e.g., MOD16 for evapotranspiration). Freely available through NASA's Earthdata portal, MODIS data has been used for over two decades to track global changes, such as deforestation or sea surface temperatures, with calibration propagated across missions for consistency. Its moderate resolution suits synoptic views rather than detailed local analysis, and while optical limitations like cloud cover apply, its frequent revisit and broad spectral range enable robust time-series studies. As of 2025, MODIS continues to operate, with data integrated into continuity products like VIIRS for future missions

THE ADVANCED SPACEBORNE THERMAL EMISSION AND REFLECTION RADIOMETER (ASTER)

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is aboard NASA's Terra satellite 9, offering 14 spectral bands in visible, NIR, SWIR, and thermal infrared, with resolutions from 15 meters (visible/NIR) to 90 meters (thermal), ideal for geology, volcanology, and land cover mapping; its data is freely available through Earthdata, though on-demand acquisition limits its temporal coverage.

THE VISIBLE INFRARED IMAGING RADIOMETER SUITE (VIIRS)

The Visible Infrared Imaging Radiometer Suite (VIIRS) is a sophisticated optical sensor developed by NASA and operated on multiple satellites, including the Suomi National Polar-orbiting Partnership (Suomi NPP) and the Joint Polar Satellite System (JPSS) series (JPSS-1/NOAA-20 in 2017, JPSS-2/NOAA-21 in 2022, and planned JPSS-3/4). VIIRS is a whiskbroom scanner radiometer that collects visible and infrared imagery across 22 spectral bands, with moderate spatial resolutions and a wide swath width, enabling full global coverage every 12 hours. This design extends the capabilities of predecessor instruments like MODIS and AVHRR, providing low-noise data for applications in land surface monitoring, atmospheric aerosols, ocean colour, fire detection, and cryospheric studies, with particular strengths in night-time imaging via its Day/Night Band (DNB) for low-light conditions. VIIRS data products include Level-1B calibrated radiances, Level-2 geophysical parameters (e.g., sea surface temperature, vegetation indices), and higher-level composites like aerosol optical thickness or land cover, freely available through NASA's Earthdata portal and calibrated for cross-mission consistency using techniques like simultaneous nadir overpasses. Its broad spectral range and frequent revisit time make VIIRS ideal for large-scale environmental monitoring, such as tracking wildfires or algal blooms, though it faces limitations from cloud cover and coarser resolution compared to high-resolution sensors like Sentinel-2. As of October 2025, VIIRS continues to support operational weather forecasting and climate research, with ongoing enhancements in response to scan angle characterization for improved data accuracy.

THE SATELLITE POUR L'OBSERVATION DE LA TERRE (SPOT)

The Satellite Pour l'Observation de la Terre (SPOT) series is a commercial high-resolution optical Earth observation satellite system developed by the French space agency CNES (Centre National d'Études Spatiales) in collaboration with international partners, with the first satellite (SPOT-1) launched in 1986 to improve knowledge and management of Earth's resources through multispectral and panchromatic imaging. Operating in Sun-synchronous polar orbits at approximately 832 km altitude, SPOT satellites provide imagery in visible and near-infrared bands, with resolutions ranging from 10 meters (multispectral) to 2.5–5 meters (panchromatic) for early models like SPOT-1 to SPOT-5 (launched 2002), and improved to 1.5 meters panchromatic and 6 meters multispectral for SPOT-6 and SPOT-7 (launched 2012 and 2014, respectively). The High Resolution Geometric (HRG) instruments on SPOT-5 and the NAOMI (New AstroSat Optical Modular Instrument) on SPOT-6/7 enable a 60 km swath width and off-nadir pointing for stereo imaging and rapid tasking, with revisit times of 1–3 days depending on latitude and sensor agility. SPOT data products include Level-1A (raw radiance), Level-1B (radiometrically corrected), and orthorectified imagery, distributed commercially by Airbus Defence and Space (formerly Spot Image), supporting applications in agriculture (e.g., crop monitoring via NDVI), urban planning, forestry, and disaster management. The series has evolved from SPOT-1's basic multispectral capabilities to SPOT-6/7's enhanced spectral bands (blue, green, red, NIR) and panchromatic mode, providing global coverage with a focus on Europe and Africa, though limited by cloud cover as an optical system.

B.2 MICROWAVE REMOTE SENSING IN AGRICULTURAL WATER MANAGEMENT

While most of the products provided in this section have associated costs, a minority of them are free (this information is explicitly provided at the end of each products description).

RADARSAT-1, 2, AND RADARSAT CONSTELLATION

The RADARSAT-1's radar backscatter response is sensitive to surface roughness and moisture, enabling the detection of surface soil moisture levels across agricultural areas (Álvarez-Mozos et al., 2005). This proved helpful for monitoring irrigation effectiveness, evaluating drought stress, and supporting water allocation decisions (Makkeasorn et al., 2006). The mission was also effective in flood monitoring (Bonn and Dixon, 2005), as it could rapidly identify inundated fields, particularly in flat terrains such as rice paddies, thereby aiding in flood response and planning of agricultural drainage systems. Aside from the capability of the mission to detect moisture, it also supports various indirect agricultural applications related to water use. It facilitates the mapping of irrigated versus non-irrigated areas, helps track crop development stages by observing changes in backscatter linked to canopy structure, and contributes to land use classification when combined with optical data (Huang et al., 2007; Sanli et al., 2017). Its ability to map wetlands and seasonal water bodies further enhanced irrigation planning and sustainable water resource management. This data is freely available.

RADARSAT2 provides consistent high-resolution radar imagery capable of capturing critical surface and moisture dynamics across farmlands. Unlike its predecessor, RADARSAT-1, which offered only single-polarization data and lower spatial resolution, RADARSAT-2 introduced significant advancements – most notably in its ability to capture dual and quad polarization imagery, finer spatial detail, and more flexible beam modes (Fox et al., 2004). These enhancements allow for more accurate soil moisture estimation, detection of irrigation patterns, and monitoring of crop water stress under varying weather conditions (Sharma et al., 2019; Yang et al., 2016). This means that the mission is able to deliver reliable data regardless of cloud cover or sunlight, making it particularly well-suited for real-time monitoring in regions prone to weather variability. This dataset is not freely available, commercial users are directed to the

MacDonald, Dettwiler and Associates customer services in partnership with the Canadian Space Agency via info@mdacorporation.com.

The RADARSAT Constellation Mission plays a vital role in agricultural water management by providing frequent, high-resolution radar imagery that helps monitor soil moisture, crop conditions, and irrigation practices (Dingle Robertson et al., 2022). Its ability to capture data regardless of weather or daylight conditions ensures consistent tracking of water usage and field variability. This allows farmers and water managers to detect over- or under-irrigated areas, improve irrigation efficiency, and respond quickly to drought or flooding, ultimately supporting smarter, more sustainable water use in agriculture. This dataset is free for students and Academic researchers. Its commercial use requires agreement with the Canadian Space Agency to explain its intended use, required data, area, frequency, and resolution. The email is rcm-cmr@asc-csa.gc.ca.

ALOS PALSAR-1/2

The ALOS PALSAR-1 and PALSAR-2 missions are advanced L-band Synthetic Aperture Radar (SAR) systems, particularly valuable for agricultural water management. Unlike C-band radar (like RADARSAT), L-band can penetrate deeper into vegetation and soil, making it highly effective for monitoring soil moisture under crop canopies and tracking long-term land surface changes. PALSAR data support accurate mapping of irrigated and non-irrigated fields, detecting water stress, and assessing crop conditions across large agricultural regions (Yang et al., 2018; Yusoff et al., 2017). Its ability to monitor subtle surface deformation and subsidence also helps identify areas affected by over-extraction of groundwater. The high-spatial resolution (up to 10 m for PALSAR 2) combined with the deep penetration of L-band makes it ideal for tracking soil moisture dynamics and evaluating the effectiveness of irrigation systems – especially in areas with dense vegetation or seasonal cloud cover. Overall, ALOS PALSAR provides reliable, repeatable insights that help optimise water use, reduce waste, and build resilience to drought in agricultural systems. This dataset is freely available; however, the ALOS PALSAR 2 might require a separate licensing agreement with the Japanese Aerospace Exploration Agency (JAXA) or its distributors, especially for commercial users.

SAOCOM-1A/1B

SAOCOM-1A and 1B are L-band SAR satellite systems designed with a strong focus on soil moisture monitoring. Their L-band radar penetrates vegetation and the upper soil layers, allowing for direct, high-accuracy soil moisture measurements even under crop cover or in cloudy conditions. These satellites provide near-real-time data that help farmers and land managers assess field-level moisture variability, detect water stress early, and optimise irrigation schedules (Roa et al., 2021). The data also support flood risk assessment, drought monitoring, and crop yield prediction (Agost et al., 2025). With frequent revisit times and high spatial resolution (~10-100 m), SAOCOM enables precision agriculture practices by identifying areas of over- or under-irrigation, improving water efficiency, and minimising environmental impact. This dataset is free for Academic Research, Educational & Public Use, and NGOs. For commercial users:

STRIPMAP Single Polarization: ~\$1,700/scene

STRIPMAP Dual Polarization: ~\$1,480/scene

STRIPMAP Quad Polarization: ~1,540/scene

More detailed pricing can be found in: <https://satellite-information.veng.com.ar/wp-content/uploads/2025/03/VENG-Price-List-SAOCOM.pdf>.

TANDEM-X

TanDEM-X uses twin satellites flying in close formation to generate high-resolution interferometric SAR data (Krieger et al., 2013). Its usefulness in agricultural water management is offered through its ability to monitor terrain changes and surface roughness at fine scales. By using InSAR techniques, TanDEM-X can detect subtle land surface movements caused by groundwater depletion or soil subsidence, which is common in over-irrigated or water-stressed agricultural areas. Its coherent SAR imaging also helps to characterise soil surface conditions, including compaction and moisture-related variations, which affect water infiltration and retention (Rossi and Erten, 2015). This mission also provides the necessary elevation and surface change data that support efficient irrigation planning, drainage design, and long-term land suitability assessments. When combined with other optical or radar datasets, it enhances our understanding of how water interacts with land in farming systems. This dataset is freely available for Academic Research and Scientific use.

For commercial users:

Minimum Order Size: 100 sq. km (per area); Product Type: 12-meter WorldDEM DSM; Price Per Sq Km: \$6.25

More detailed pricing can be found in <https://apollomapping.com/digital-elevation-models>.

TERRASAR-X

TerraSAR-X is a high-resolution X-band SAR satellite mission designed primarily for precision mapping and monitoring applications. In agricultural water management, its strength lies in delivering detailed surface information with spatial resolution as fine as 1 m, enabling field-level analysis of soil and crop conditions (Baghdadi et al., 2012). Although X-band radar is less effective at penetrating vegetation and soil compared to L-band, TerraSAR-X is capable of detecting surface features such as field boundaries, crop patterns, surface roughness, and water pooling (Baghdadi et al., 2008; Bargiel and Herrmann, 2011). This makes it very useful for tracking irrigation extent, mapping flooded fields, and monitoring surface runoff or drainage efficiency. For Scientific users based on the Cost of Fulfilling User Request (COFUR) pricing model:

1 - 30 products: \$231.10

31 - 100 products: \$202.21

over 100 products: \$184.88

For commercial users, pricing varies by resolution and product type:

Base cost: \$1,093.75 per sq km (<https://apollomapping.com/terrasax-satellite>).

COSMO-SKYMED (1ST & 2ND GEN)

Cosmo-SkyMed is a constellation of X-band SAR satellites designed for both civilian and military applications. This system has a very high revisit time which allows accurate and frequent tracking of field structures, water pooling, and irrigation patterns, thereby enabling near-real-time detection of changes in surface moisture, flood extent, and crop development (Lapini et al., 2021). The system's high spatial resolution also plays a critical role in supporting precision irrigation, water stress detection, and post-rainfall drainage assessment (Paloscia et al., 2014). "Free access may be available for approved academic and institutional research centres. For commercial users:

Product Type: SAR imagery (various modes: Spotlight, Stripmap, ScanSAR)

Minimum Order Size: Typically, 1 scene (size varies by mode, e.g., 10 × 10 km)

Price Range:

Spotlight Mode: ~\$4,280 (new) and ~\$695 (archive)

Stripmap Mode: ~\$2,140 (new) and ~\$320 (archive)

ScanSAR Mode: ~\$2,140 (new) and ~\$320 (archive).

More detailed pricing can be found in <https://www.e-geos.it/assets/images/test-img/cosmo-document/gd-com-20-001-e-geos-official-pricelist-june-22nd-2020.pdf>.

ICEYE CONSTELLATION

The ICEYE is a rapidly growing network of small X-band SAR satellites designed for high-frequency, all-weather Earth observations. Though relatively new, ICEYE has quickly become a valuable agricultural water management tool due to its high revisit rates (multiple times a day) and flexible imaging capabilities. The mission uses the X-band radar and can detect surface-level changes, flood extent, irrigation boundaries, and drainage issues. Its rapid response time makes it ideal for monitoring flash floods, tracking field moisture after rainfall, and supporting precision irrigation planning (Ardila et al., 2022). The constellation's ability to deliver near-real-time imagery with resolutions as fine as 1 meter helps farmers, water managers, and insurers detect anomalies quickly, minimize water waste, and assess damage following extreme weather events. This dataset is free for Academic Research and Scientific use: Access to ICEYE SAR data may be available through the European Space Agency's (ESA) Third Party Missions (TPM) program. Researchers can submit project proposals to ESA, and upon approval, receive a defined quota of scenes for their studies.

For Commercial users:

Minimum Order Size: Typically, one scene, with sizes varying by imaging mode (e.g., 5 × 5 km for Spot Mode).

Product Type: SAR imagery (various modes: Spot Fine, Spot, Strip, Scan etc).

Pricing per scene starts from ~\$1,000 depending on imaging mode, resolution and delivery priority.

Imagery can be available within 8 hours of acquisition. For faster priority options, charges may apply.

More detailed pricing can be found in <https://www.iceye.com/partnerships/esa-tpm>.

NOVASAR-1

This mission is a cost-effective, medium-resolution SAR satellite operating in the S-band. The S-band balances the deeper penetration capabilities of the L-band and the surface sensitivity of the X-band and can detect soil moisture variations, particularly in sparsely vegetated or moderately covered fields, making it useful for mapping wet and dry zones within farmlands. NovaSAR-1's wide-area imaging modes allow efficient monitoring of large agricultural regions, supporting applications like irrigation mapping, flood detection, and seasonal water availability assessment (Rossberg and Schmitt, 2025). Additionally, NovaSAR-1 features a maritime surveillance mode and has been used for flood response and crop monitoring in data-scarce regions, especially in developing countries. While it doesn't offer the fine resolution of X-band missions, its affordability, flexible tasking, and complementary S-band frequency are very valuable in agricultural water management, especially when integrated with other radar or optical data sources. Access to NovaSAR-1 data is primarily facilitated through national agencies and research institutions, with pricing & availability potentially varying based on the user's location and the intended use of the data. (See DB-CF for more).

KOMPSAT-5

Kompat-5 is a high-resolution X-band SAR satellite designed for Earth observation with a strong capability in precision mapping and surface monitoring. Through its ability to detect fine-scale surface changes, including irrigation patterns and soil moisture conditions, this mission contributes strongly to agricultural

water management. The Kompsat-5 has a flexible range of imaging modes that allow it to monitor crop development, identify over- or under-irrigated zones, and support post-rainfall drainage assessment (Lee, 2024). Access to KOMPSAT-5 data is primarily facilitated through SI Imaging Services (SIIS), the exclusive worldwide marketing and sales representative for the KOMPSAT series. They provide high-resolution SAR images through a global network of over 160 sales partners. Order can be placed by emailing sales@si-imaging.com.

Access to Kompsat-5 data is not free for Academic Research and Students unless in special situations.

NISAR

3.2. NISAR is a new dual-frequency SAR satellite that operates using both L-band and S-band radar. The L-band radar will penetrate vegetation and upper soil layers to track soil moisture, root zone conditions, and subtle land deformation caused by groundwater withdrawals, while the S-band radar will enhance surface structure detection. This dual-band capability enables a critical view of water availability, crop water stress, irrigation effectiveness, and land subsidence. This is freely available data.

SMAP

SMAP measures global soil moisture and detects freeze-thaw states of the land surface by combining the L-band passive radiometry with active radar. Its near-daily revisit time makes it ideal for tracking root zone moisture variability, irrigation needs, and early signs of agricultural droughts. Its L-band frequency penetrates vegetation and the upper few centimetres of soil, delivering accurate, weather-independent soil moisture estimates, even under moderate crop cover (Rahman et al., 2017). This is freely available data.

SWOT

The SWOT measures the elevation extent, and storage of surface water bodies. It uses a Ka-band radar interferometry to map rivers, lakes, reservoirs, and wetlands at high spatial resolution, providing 2D water surface profiles. It is useful in agriculture by precisely monitoring water availability in reservoirs, measuring seasonal changes in river flow, and observing the expansion/shrinkage of surface water bodies that supply irrigation systems (Yao et al., 2025). This helps in forecasting and allocation of water resources, especially in regions dependent on managed surface water for farming. This is freely available data.

GPM AND TRMM PRECIPITATION

The GPM is designed to provide near-real-time, global precipitation data, including both rain and snow. It is essential for tracking rainfall patterns, estimating water input to the soil, and identifying drought or flood conditions. Its data support irrigation scheduling, crop water budgeting, and monitoring of rain-fed farming systems, particularly in regions lacking ground-based rain gauges (Li et al., 2019). GPM's ability to differentiate between light rain, heavy downpours, and even snowfall allows for more accurate modelling of soil moisture dynamics and runoff, which are critical for both short-term farm decisions and long-term water resource planning. This is freely available data.

The TRMM combines radar and passive microwave sensors to provide detailed, high-frequency data on rainfall intensity, distribution, and vertical structure. It laid the foundation for modern precipitation monitoring from space by enabling accurate estimates of rainfall accumulation, storm tracking, and seasonal variability. These factors are crucial for managing irrigation, forecasting droughts, and planning planting schedules in rain-fed agricultural systems (Ndehedehe et al., 2016). This is freely available data.

ICESAT-2

ICESat-2 is a laser altimetry mission designed to measure Earth's surface elevation with centimetre-level precision. Using its Advanced Topographic Laser Altimeter Systems (ATLAS), ICESat-2 provides highly accurate elevation profiles of rivers, lakes, reservoirs, and surrounding agricultural lands. It is valuable for the detection of changes in surface water levels in irrigation canals, reservoirs, and wetlands (Mulverhill et al., 2022; Narine et al., 2020). It can also aid in the monitoring of land subsidence, which can result from groundwater overuse in agricultural regions (Khorrami et al., 2021). This is freely available data.

JASON 1/2/3

The Jason 1/2/3 satellite altimetry missions track sea level and ocean heat content and help scientists monitor changes in ocean circulation patterns and climate phenomena such as El Nino and La Nina. These patterns strongly influence regional rainfall variability, monsoon intensity, and the timing of wet or dry seasons – factors that are critical to agriculture, especially in rain-fed farming systems. Moreover, the data feeds into hydrological and climate models that support long-term planning and drought forecasting. This is freely available data.

QUIKSCAT/RAPIDSCAT

QuikSCAT and RapidScat enhanced global weather models by capturing near-real-time data on wind patterns over oceans, which in turn improved the forecasting of rainfall and storm systems that impact agricultural regions. Their data can help hydrologists predict the movement and intensity of tropical cyclones, monsoons, and other weather events that directly affect water availability, flood risk, and planting schedules. This is freely available data.

PAZ

PAZ mission can monitor surface water, soil moisture conditions, and flooded areas with high spatial resolution and weather-independent imaging. It is capable of detecting subtle surface changes related to irrigation patterns, field wetness, and water pooling. Data from this mission supports mapping of agricultural land conditions even in cloud-prone regions and is particularly helpful for monitoring flood-prone farming areas and tracking how water is distributed across large agricultural landscapes (Busquier et al., 2021). PAZ data archive is Free for Academic & Scientific Research through the ESA's Third-Party Missions Program. However, access to the full archive and tasking data requires a project proposal that is evaluated and accepted by ESA and the data owner. Commercial users can obtain detailed pricing and data access information by contacting Hidesat through hidesat@hidesat.es.

RISAT-1, RISAT-1A, RISAT-1/RISAT-2B

RISAT-1 mission provided valuable data for monitoring crop conditions, detecting soil moisture changes, and mapping inundated fields (Kumara et al., 2017), even during the monsoon season when optical satellites are hindered by cloud cover. Its multi-resolution imaging modes allow users to observe large agricultural regions as well as focus on specific zones of interest, making it suitable for both broad regional assessments and localised monitoring. Free for Indian Academic Research, Central and State Government departments.

Private organizations and international users are required to purchase RISAT data through the Bhoonidhi portal. For the non-government users, below is the pricing list:

Geometrically Terrain Corrected products (ground sample distance of 3m) = \$56.83

Single Look Complex products (ground sample distance of 3m) = \$56.83

Multi Look Ground Range (ground sample distance of 3m) = \$56.83

Based on a recent release from the Bhoonidhi portal, satellite data of 5m and coarser is now free and open for all users.

RISAT-1A C-band mission succeeded *RISAT-1* and provides high-resolution data that is especially valuable during cloudy or rainy seasons, when optical satellites are less effective. It can monitor surface wetness, flooded fields, and irrigation patterns, making it highly suitable for tracking soil moisture changes and assessing water stress in crops (Kumara et al., 2017). These observations support better irrigation scheduling and early detection of drought or excess water conditions. Free for Indian Academic Research, Central and State Government departments. Private organizations and international users are required to purchase *RISAT* data through the Bhoonidhi portal. For the non-government users, below is the pricing list:

Geometrically Terrain Corrected products (ground sample distance of 3m) = \$56.83

Single Look Complex products (ground sample distance of 3m) = \$56.83

Multi Look Ground Range (ground sample distance of 3m) = \$56.83

Covariance (ground sample distance of 3m) = \$56.83

Polarimetric Decomposed (ground sample distance of 3m) = \$56.83

Based on a recent release from the Bhoonidhi portal, satellite data of 5m and coarser is now free and open for all users.

RISAT-1/RISAT-2B missions complement each other in agricultural water management. *RISAT 1*, with its C-band radar, is more suitable for soil moisture monitoring flood mapping, and tracking irrigated field conditions across wide agricultural landscapes (Sahadevan et al., 2019), while *RISAT-2B*, with its X-band imaging, is particularly useful for detecting small-scale changes in field conditions, including precise mapping of flooded zones, canal seepage, and localized irrigation patterns. Free for Indian Academic Research, Central and State Government departments. Private organisations and international users are required to purchase *RISAT* data through the Bhoonidhi portal. For the non-government users, below is the pricing list:

Geometrically Terrain Corrected products (ground sample distance of 3m) = \$56.83

Single Look Complex products (ground sample distance of 3m) = \$56.83

Multi Look Ground Range (ground sample distance of 3m) = \$56.83

Covariance (ground sample distance of 3m) = \$56.83

Polarimetric Decomposed (ground sample distance of 3m) = \$56.83

Based on a recent release from the Bhoonidhi portal, satellite data of 5m and coarser is now free and open for all users.

ENVISAT (ASAR)

ENVISAT supported early detection of flood or drought impacts on crops by detecting subtle surface changes (Shen et al., 2009). It also played a critical role in enabling consistent monitoring of surface soil moisture, flooded agricultural fields, and irrigated lands, especially in cloudy or rainy conditions (Zribi et al., 2011). This is freely available data.

SENTINEL 1A/B

Sentinel 1 data is widely used to monitor soil moisture, flooded fields, and irrigated lands with high spatial detail and temporal consistency (El-Shirbeny and Abutaleb, 2017). This Synthetic Aperture Radar (SAR) data can detect surface wetness and changes in crop structure, enabling the identification of over- or under-irrigated zones and supporting optimised water use in precision farming (Modanesi et al., 2022). It is particularly useful during cloudy or rainy seasons, when optical satellites fail to provide consistent imagery. This is a freely available data.

JERS-1

The L-band radar onboard JERS-1 could penetrate vegetation canopies and detect surface soil moisture and small land surface changes, which makes it ideal for the measurement of flooded fields, mapping wetlands, land cover changes and assessing the water status of large agricultural areas (Xiang-zheng et al., 2002). It is capable of operating independently of weather and lighting conditions and is able to provide consistent observations during rainy seasons. This is freely available data.

SEASAT

SeaSAT's SAR data offered early insights into the use of radar for monitoring surface water, soil moisture, and flooded areas. It showed how radar backscatter could be used to detect wet soils, inundated fields, and changes in surface roughness, paving the way for future SAR missions to support irrigation planning, crop condition assessment, and flood monitoring (Blanchard and Chang, 1983). This is freely available data.

ERS-1 AND ERS-2

This (ERS-1) pioneering mission was particularly valuable for monitoring soil moisture, surface roughness, and flooded areas, especially during periods when optical sensors were hindered by cloud cover by darkness (Esch et al., 2018). It's SAR imagery helped identify irrigated fields, map waterlogged zones, and assess the timing and extent of seasonal floods (Altese et al., 1996). This is freely available data.

ERS-2 succeeded ERS-1 and was useful in monitoring soil moisture conditions, flood extent, and irrigated agricultural areas under all weather and lighting conditions. The radar imagery helped detect waterlogged fields, identify areas at risk of water stress, and track the seasonal movement of surface water across large-scale farming regions (Shoshany et al., 2000; Wang et al., 2004). This is freely available data.

GEDI

This mission uses full-waveform LiDAR to map the three-dimensional structure of Earth's forests and vegetation. By capturing detailed vertical profiles of vegetation canopy height, density, and structure, GEDI can help improve our understanding of evapotranspiration, land-atmosphere water exchange, and ecosystem water demand. This could be useful in areas where agroforestry, watershed management, or forested catchments influence downstream water availability for agriculture. This is freely available data.

SARAL/ALTIKA

AltiKa uses a Ka-band altimeter to improve understanding of inland water dynamics, including lake and reservoir levels that are crucial for irrigation planning, especially in water-scarce regions (Fattras et al., 2018). By monitoring temporal changes in water storage, the satellite supports assessments of water availability for farming during dry seasons or drought conditions. It also assists in tracking the impact of seasonal rainfall on surface water supply, which directly influences planting decisions and irrigation scheduling. This is freely available data.

SENTINEL-6MF

By tracking long-term changes in global sea levels and ocean heat content, Sentinel-6MF supports improved climate forecasting and hydrological modelling, both of which are essential for anticipating rainfall variability, drought risks, and seasonal water supply. These forecasts directly impact agricultural planning, especially in regions dependent on seasonal rainfall or vulnerable to shifting climate patterns driven by ocean-atmosphere interactions like El Nino or La Nina. This is freely available data.

CAPELLA SPACE

These satellites are able to capture sub-meter resolution images in all weather conditions, day or night, with rapid revisit times. Capella's SAR imagery enables near real-time monitoring of surface soil moisture, flooded fields, and irrigation infrastructure, even during cloudy or rainy seasons. This capability is critical for regions that rely on continuous water input for crops but face challenges with cloud cover, such as in tropical or monsoon climates. The fine spatial resolution also allows for detailed assessments of field-scale water stress, water distribution uniformity, and changes in cropping patterns over time. Free for researchers and non-profit institutions to support research work across forestry, glaciology, volcanology, oil spill detection, disaster response and more.

For Commercial Users:

Interested users are encouraged to contact Capella Space directly to discuss specific requirements and obtain tailored pricing information for their various SAR products, including, Spotlight, Sliding Spotlight, and Stripmap modes.

UMBRA SPACE

Umbra Space satellites provide imagery with resolutions surpassing 25 cm, capable of capturing images through clouds, smoke, and darkness, making them invaluable for all-weather, day and night monitoring. Their high-resolution images allow for detailed monitoring of soil moisture levels, irrigation patterns, and detection of water stress in crops. This information is important for optimising irrigation schedules, improving water use efficiency, and ensuring crop health. Furthermore, Umbra's frequent revisit times enable timely assessments of changing conditions, such as the onset of drought or the impact of heavy rainfall. Umbra Space offers some free data available via Umbra's Open Data Program for various research works.

Spotlight Mode (5km by 5km Scene Size)

1.0m: \$675 (1 look), \$850 (2 look), \$1,000 (3-look), \$1,200 (4 look), \$1,350 (5-look), \$1,850 (8-look), \$2,200 (10-look)

0.5m: \$950 (1-look), \$1,200 (2-look), \$1,400 (3-look), \$1,650 (4-look), \$1,900 (5-look), \$2,600 (8-look).

0.35m: \$1,750 (1-look), \$2,200 (2-look), \$2,650 (3-look), \$3,050 (4-look), \$3,500 (5-look).

0.25m: \$3,250 (1-look), \$4,050 (2-look), \$4,900 (3-look)

Natural Footprint

1.0m: \$1,500 (1-look), \$1,900 (2-look), \$2,250 (3-look), \$2,650 (4-look), \$3,000 (5-look), \$4,150 (8-look), \$4,900 (10-look).

0.5m: \$1,900 (1-look), \$2,400 (2-look), \$2,850 (3-look), \$3,350 (4-look), \$3,800 (5-look), \$5,250 (8-look).

0.35m: \$2,650 (1-look), \$3,300 (2-look), \$4,000 (3-look), \$4,650 (4-look), \$5,300 (5-look).

0.25m: \$3,750 (1-look), \$4,700 (2-look), \$5,650 (3-look).

More detailed pricing information, including the Archival Data can be found in <https://help.umbra.space/product-guide/umbra-pricing>.

GAOFEN-3 / GAOFEN-3B

Gaofen-3 and its successor, Gaofen-3 B, are advanced C-band SAR satellites that have proved useful in monitoring soil moisture levels, assessing irrigation efficiency, and detecting water stress in crops (Luo et al., 2022). Their high-resolution SAR imagery allows for precise mapping of flooded areas, evaluation of water distribution in agricultural fields, and analysis of changes in land surface conditions over time. Data requests require submitting a proposal detailing the intended use to the China Center for Resources Satellite Data and Application (CRESDA). The pricing costs may vary based on factors including image resolution, area of interest and intended use.

HISEA-1 (MINISAT-SAR)

Hisea-1's high-resolution SAR imagery which enables detailed monitoring of soil moisture levels, irrigation patterns, and detection of water stress in crops. Its ability to penetrate cloud cover and operate regardless of lighting conditions ensures consistent data acquisition, which is crucial for timely assessments of changing field conditions (Xue et al., 2021). Data download request varies based on specific needs. Interested users are encouraged to contact cs@hisea.com for specific request application.

EOS SAR CONSTELLATION

This proposed mission will operate in X- and S-bands and will be beneficial for agricultural practices by providing high-resolution images, enabling precise monitoring of soil moisture levels. Not yet publicly available, but is unlikely to be free.

BIOMASS

This new mission represents a significant advancement in earth observation as it is the first ever spaceborne P-band SAR mission. Its data is important for agricultural water management, especially in areas where agriculture and forestry intersect. By providing insights into above-ground biomass, canopy height, and vegetation structure, the mission aids in understanding evapotranspiration rates and water cycling within the ecosystem. This is freely available data.

HRWS (DLR FUTURE MISSION)

This upcoming mission will include a wide swath coverage, which allows for extensive mapping of agricultural areas, supporting the assessment of water distribution and availability across large regions. Expected to be Free for Scientific and Academic Research, while commercial users may be subject to licensing fees.

SEASAR / CHEOS

Within the CHEOS framework, several satellites are dedicated to agricultural water management. For example, the Gaofen series, which is part of the CHEOS, includes satellites equipped with high-resolution optical and radar imaging capabilities. These satellites can monitor soil moisture levels, assess irrigation efficiency, and detect water stress in crops, thereby aiding in optimising water usage and improving crop yields. Expected to be Free for Scientific and Academic Research, while commercial users may be subject to licensing fees.

TERRASAR-L (PROPOSED)

This cancelled mission was intended to provide fully polarimetric L-band SAR data, enhancing capabilities in vegetation monitoring, soil moisture assessment, and land deformation studies.

NEXTAR

The high-resolution optical sensor on board NEXTAR can detect variations in crop health and soil moisture, while its SAR instruments provide consistent data regardless of weather conditions. It is essential for tracking irrigation patterns and assessing water stress in crops. Not publicly available.

WCOM

This future mission will provide comprehensive, high-accuracy measurements of key components of the global water cycle. This will be useful in agricultural water management practices by relating hydrological processes to climate change impacts. Not publicly available yet.

GRACE/GRACE FO

GRACE/GRACE FO missions measure changes in Earth's gravity field to track large-scale mass movements – most notably, changes in terrestrial water storage. Unlike the radar satellites that observe the surface, GRACE/GRACE-FO detects subsurface water dynamics, including groundwater depletion, soil moisture changes, and surface water fluctuations (Ndehedehe et al., 2021). This makes them uniquely valuable for agricultural water management at regional to continental scales, especially in areas where direct groundwater monitoring is limited or unavailable.