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Review

From Smart Irrigation to Nature-Positive Water Management in Australian Sugarcane: Irrigation Technologies, Nature Frameworks, and Integration Pathways

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Abstract

This narrative and conceptual review examines how irrigation management in Australian sugarcane can progress from practice-based efficiency improvement towards an integrated evidence system supporting productivity, water-quality improvement and nature-positive reporting. It reviews regional irrigation conditions, standard and best management practices, crop and water modelling, grower-facing scheduling, Internet of Things (IoT) monitoring and automation, remote sensing, forecast-informed irrigation and artificial intelligence. It then considers natural-capital, nature-positive and environmental-reporting frameworks relevant to reef-connected sugarcane landscapes. The review identifies a persistent gap between information generated by irrigation technologies and the credible, transparent and auditable indicators required for broader environmental reporting. A five-part integration pathway connects established components from farm monitoring and modelling, environmental-pressure estimation, supporting evidence, documented methods and defined reporting applications. Existing studies support individual components and several adjacent linkages; this review maps how they could operate as a whole system. Farm-scale technology outputs are treated as evidence of management actions or modelled pressure pathways rather than direct measurements of ecosystem condition. Smart irrigation is thereby positioned as an enabling component linking farm profitability, reduced pressure on soil and water assets, and more credible nature-positive water management in Australian sugarcane.

Keywords: precision irrigation; nature-positive agriculture; sugarcane production; water-quality management; Great Barrier Reef

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1. Introduction

Situated adjacent to the UNESCO World Heritage–listed Great Barrier Reef, the Australian sugar industry is a major agricultural sector extending across approximately 2100 km of coastline from Mossman in Far North Queensland to Grafton in northern New South Wales. Queensland is the centre of the national industry, producing approximately 95% of Australia's sugar [1]. In 2023–24, Queensland sold 28.6 million tonnes of sugarcane, accounting for 96% of Australia's sugarcane production and 86% of sugarcane-producing businesses, including 3140 Queensland businesses selling sugarcane [2]. Industry figures

indicate that Queensland's sugar industry crushes around 30 million tonnes of cane annually from approximately 366,470 ha of sugarcane, producing about 4.5 million tonnes of raw sugar [3]. This scale and its proximity to waterways that feed into the Great Barrier Reef make irrigation and water-quality management central issues for both industry productivity and environmental stewardship. The spatial distribution of Australia's main sugarcane-growing areas in relation to mean annual rainfall is shown in Figure 1.

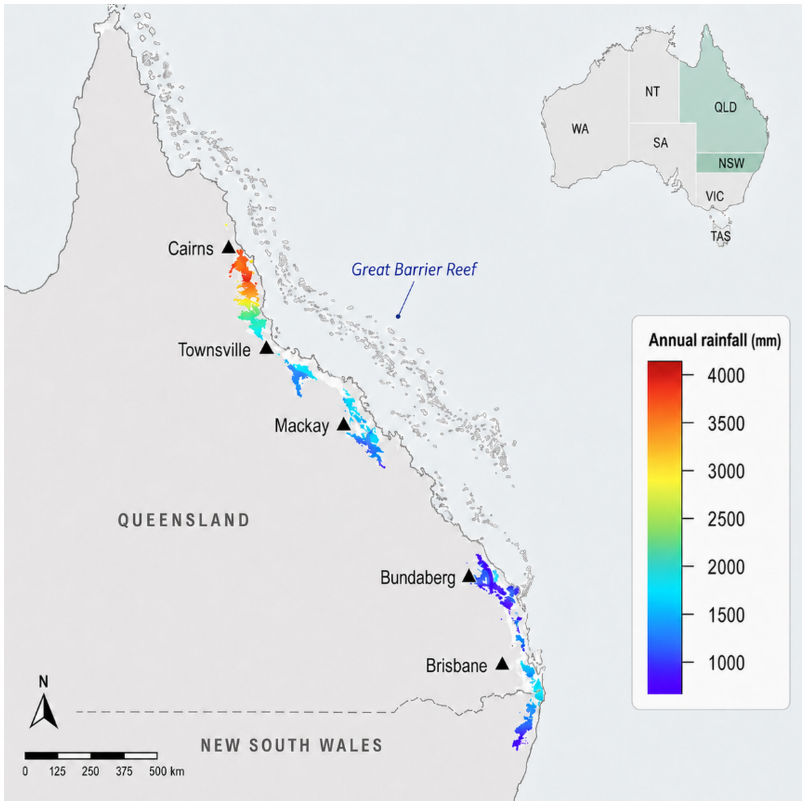


Figure 1. Mapped sugarcane-growing areas along eastern Australia, coloured by mean annual rainfall for 1991–2020. Sources: ABARES commodity-scale land-use mapping, Bureau of Meteorology rainfall climatology, GBRMPA reef features and ABS state boundaries. Map prepared by the authors [4–7].

Sugarcane production in Queensland is concentrated in coastal and near-coastal districts, including Far North Queensland and the Wet Tropics, the Herbert, Burdekin, Mackay–Whitsunday, Bundaberg–Wide Bay Burnett and more southern cane-growing areas [1]. These regions differ substantially in rainfall, soil type, irrigation infrastructure, water security and hydrological connectivity [8]. The Burdekin provides the clearest example of a highly irrigation-dependent sugarcane system, with approximately 80,000 ha of land under sugarcane, around 95% of which is furrow irrigated, and annual production of about 8.3 million tonnes of cane from approximately 530 growers and 927 farms [9,10]. Irrigation is central to productivity in the Burdekin, but the dominance of furrow irrigation also creates challenges associated with irrigation duration, tailwater, excess water runoff, deep drainage, labour, pumping cost and nutrient-loss risk. In contrast, high-rainfall districts such as the Wet Tropics face major water-management issues associated with drainage, waterlogging, runoff and wet-season nutrient movement [11]. Mackay and Bundaberg have different irrigation contexts. In Mackay, rainfall contributes to crop water supply, but irrigation remains important for managing dry periods and seasonal rainfall variability. Bundaberg is generally drier and more dependent on reliable irrigation water, making irrigation efficiency and water availability particularly important for maintaining yield

and farm profitability. This regional diversity means that sugarcane water management in Australia cannot be treated as a single uniform problem.

Irrigation systems used in Australian sugarcane include furrow, overhead, drip and targeted subsurface drip approaches. Effective irrigation is agronomically important because sugarcane has high seasonal water demand and is sensitive to water stress during key growth stages [12,13]. At the same time, poorly timed or excessive irrigation can increase pumping costs, labour requirements, tailwater, runoff and deep drainage, while insufficient irrigation can reduce yield and sugar production potential. This creates a management challenge in which growers must balance crop demand, water availability, energy cost, labour constraints and variable rainfall.

The environmental significance of this challenge is heightened by the connection between many Queensland sugarcane landscapes and the Great Barrier Reef lagoon. Reef water-quality assessments and agricultural water-quality reviews identify dissolved inorganic nitrogen, sediments and pesticides from land-based runoff as major pressures on inshore ecosystems, with sugarcane areas contributing substantially to anthropogenic nutrient and pesticide loads [11,14,15]. Within sugarcane systems, nitrogen losses through runoff, deep drainage and leaching are strongly influenced by the interaction between fertiliser inputs, crop uptake, soil water balance and irrigation management [16–18]. Irrigation therefore matters not only as a production input, but also as a driver of water movement through the soil–plant–drainage system and, consequently, as a potential influence on pollutant-loss risk. Excess water leaving the farm can carry excess nitrogen, pesticides and sediment, which can reduce ecosystem health in the Great Barrier Reef. For example, algal blooms caused by excessive nitrogen provide nutrition for crown-of-thorns starfish, which can destroy coral and compromise coral reef health.

This connection provides the basis for considering irrigation within a nature-positive water management agenda. Nature positive is increasingly framed as a measurable improvement in the state of nature, reflected in gains in health, abundance, diversity, integrity and resilience of species, ecosystems and natural processes [19,20]. Accordingly, in this review, improved irrigation efficiency, reduced environmental pressure and demonstrated improvement in ecological condition are treated as related but distinct levels of evidence. Improved efficiency and reduced pressure can contribute to a nature-positive direction, but neither alone demonstrates ecosystem recovery. At the paddock scale, improved irrigation can reduce avoidable movement of water and nutrients beyond the crop root zone, while at the landscape scale it interacts with drainage systems, wetlands, riparian areas and receiving waters. Farm records, monitoring and modelling can provide evidence of management and pressure changes, whereas claims of improved ecological condition require observations at the relevant spatial and temporal scale.

Existing industry frameworks such as Smartcane BMP and irrigation manuals provide an important foundation for improved practice by helping growers identify and document appropriate irrigation and drainage management. However, practice records alone do not quantify how changes in irrigation affect runoff, deep drainage or nutrient-loss risk. Crop models and water-balance tools are therefore important because they can estimate these consequences across different soils, seasons and management conditions. Field observations, irrigation records, sensors and other monitoring technologies can then complement the modelling by improving input data, documenting what was implemented and strengthening confidence in the estimated outcomes [21–23].

This paper presents a narrative and conceptual review of conventional and advanced sugarcane irrigation management and extends towards integrated, evidence-based and nature-positive water management. It first examines regional irrigation conditions, standard practices and best management practice frameworks in the Australian sugarcane

industry. It then reviews crop and water modelling, grower-facing scheduling tools, automation, monitoring, remote sensing, weather forecasting and artificial intelligence, with emphasis on how these approaches support irrigation decisions and the estimation of productivity and environmental outcomes. The review subsequently considers natural-capital, nature-positive and environmental-reporting frameworks relevant to reef-connected sugarcane landscapes in Australia. Finally, it proposes an integration pathway linking farm management, modelled environmental pressures, supporting observations and reporting mechanisms. The central contribution is conceptual: to show how existing irrigation management, modelling and monitoring systems can be connected to support farm profitability, water-quality improvement and more credible nature-related reporting, while identifying where validation and assurance are still required.

This is a narrative and conceptual rather than systematic review. The topic brings together several established but largely separate bodies of literature: Australian sugarcane irrigation and Reef water quality; crop modelling and digital irrigation technologies; and natural-capital and nature-related reporting. Given the newness of this integration, a conventional systematic search would return limited literature addressing the complete pathway, so the review draws across these separate bodies of work. The literature was updated to July 2026. Formal systematic inclusion and exclusion criteria were not applied. The five-part pathway was developed through conceptual synthesis of recurring functions and gaps across these bodies of work.

2. Standard Sugarcane Irrigation Practices and Best Management Practice Frameworks

2.1. Standard Irrigation Practice and Industry Guidance

Irrigation management in Australian sugarcane is shaped by regional rainfall, soil type, water availability, allocation reliability, farm layout, labour, electricity tariffs and existing irrigation infrastructure. These factors vary substantially between districts and influence both the irrigation systems used and the value of precision irrigation. The Burdekin is one of Australia's most irrigation-secure sugarcane regions, supported by extensive irrigation infrastructure, regulated surface-water supplies and groundwater resources. Furrow irrigation therefore remains dominant because it is compatible with existing field layouts and can deliver large volumes of water across broadacre cane systems. In this context, the main management challenge is often to apply available water efficiently while reducing labour, pumping costs, tailwater, deep drainage and nutrient-loss risk. In Bundaberg, irrigation is also essential, but tighter or more variable water availability can make efficient scheduling particularly important for maintaining yield, improving the return from each megalitre applied and reducing production risk. In higher-rainfall districts such as the Wet Tropics and parts of Mackay, irrigation may be used more intermittently, while drainage, waterlogging, rainfall variability and the timing of irrigation around rainfall events become more important. Irrigation systems across these regions may include furrow, overhead, drip and subsurface drip approaches. Standard practice is therefore not a single method, but a set of regionally adapted irrigation routines. More generally, irrigation performance depends on matching water application to crop demand, soil-water storage, system capacity and operational constraints, as emphasised in the broader irrigation-scheduling and water-productivity literature [24,25].

Grower decisions commonly combine fixed rotations, experience, soil inspection, crop appearance, recent rainfall, pump or channel access and labour availability. In furrow systems, irrigation timing and cut-off are influenced by furrow length, inflow rate, advance time, the number of sets to be watered and the ability to change sets at the right time. In overhead and drip systems, decisions are more strongly affected by application rate,

system uniformity, pressure, fertigation, maintenance and energy cost. These approaches are practical and familiar, but they can be imprecise when rainfall is variable, soils differ between blocks, crop demand changes quickly, or operational constraints prevent irrigation at the technically preferred time.

The Sugar Research Australia (SRA) *Irrigation of Sugarcane Manual* provides an authoritative technical reference for improving these decisions. It explains irrigation-system types, crop water requirements, soil-water storage, irrigation scheduling, system performance and drainage considerations [8]. SRA scheduling resources also describe practical tools such as mini-pans, evaporation-based scheduling, soil moisture monitoring and water-balance approaches [26]. The technical basis is consistent with sugarcane physiology research showing that water deficit during key growth stages can reduce growth and productivity [12,13]. The practical challenge is that recommendations still need to be implemented under real farm constraints such as pump capacity, irrigation priorities, electricity tariffs, labour shortages and costs, and rainfall uncertainty.

2.2. Best Management Practice Frameworks in the Sugarcane Industry

Best management practice frameworks provide a structured pathway for improving irrigation and drainage management while supporting productivity, profitability and environmental stewardship. Smartcane BMP is the main voluntary industry BMP and accreditation program for Queensland canegrowers. It allows growers to benchmark practices, identify improvement areas and document whether management is below, at or above industry standard [27]. The program includes modules covering soil health and nutrients, irrigation and drainage, weeds, pests and diseases, planting and harvesting, farm business, natural systems, workplace health and safety, and sustainable sugar pathways [27].

The Irrigation and Drainage Management module is particularly relevant because it links efficient water use with productivity, profitability, electricity savings, water savings and reduced loss of chemicals and nutrients through runoff and deep drainage [27]. This provides the industry with an accepted framework for identifying and documenting improved irrigation and drainage practices. However, BMP accreditation is primarily practice-based: it records whether recommended management actions have been considered or adopted, rather than quantitatively estimating their consequences under every combination of soil, weather and irrigation management. Crop models and water-balance tools are therefore important complementary approaches because they can estimate how changes in irrigation practice are likely to affect runoff, deep drainage, nutrient-loss risk, water use and productivity across different conditions. Operational records and field observations can further strengthen this assessment by improving model inputs and confirming how the recommended practice was implemented.

A further challenge is that BMP documentation is often separated from the operational information needed to represent actual irrigation management. Irrigation timing, pump run time, applied volume, rainfall, soil-water observations, nutrient applications and field conditions may be stored in different systems or may not be recorded consistently. This separation makes it difficult to determine whether the management represented in a model or assessment reflects what occurred in the paddock. Better integration of BMP records with irrigation and farm-management data would improve model inputs, provide clearer evidence of implementation and reduce the effort required to support water-quality and sustainability reporting.

2.3. Strengths and Limitations of Standard Irrigation Approaches

The current standard irrigation-management pathway has an important practical strength: growers already understand their soils, irrigation infrastructure, crop response

and local seasonal conditions, and BMP guidance is familiar to growers, advisors and industry organisations. These frameworks also recognise that irrigation is both an economic and environmental issue, because inefficient irrigation can increase water use, pumping costs, tailwater, runoff and drainage risk.

The main limitation is not the absence of irrigation guidance, but the additional modelling, data preparation and technical interpretation required to translate practice change into quantitative estimates of environmental and production outcomes. Existing BMP and industry systems can document whether irrigation and drainage practices have been considered or adopted, while crop models and water-balance tools can estimate how those practices may affect water use, runoff, deep drainage, nutrient-loss risk and productivity under different soils and seasonal conditions. The reliability of these estimates depends on how well the model inputs and management assumptions represent actual paddock conditions. Irrigation timing, applied volume, rainfall, soil-water observations, pump operation and nutrient records can therefore add value by improving model inputs and confirming how management was implemented.

The opportunity is therefore to build on existing BMP and industry guidance rather than replace them. The following section considers how modelling, monitoring and digital technologies can add operational and evidential detail to these established practices.

3. Advanced Irrigation Technologies and Decision-Support Systems

Advanced irrigation systems combine several different functions. Crop and water-balance models estimate crop demand, soil-water status and the likely consequences of alternative irrigation practices. Grower-facing scheduling tools translate this information into practical irrigation advice. Sensors, telemetry and farm records provide information about field conditions and actual irrigation events, while automation helps implement irrigation decisions more consistently. Remote sensing, weather forecasts and analytical methods can further improve spatial diagnosis and forward planning. These approaches are most useful when their roles are clearly distinguished and their outputs are connected, rather than when each technology is treated as a standalone solution.

3.1. Crop and Water Modelling Foundations

Crop and water models provide the analytical foundation for estimating processes that are difficult or impractical to observe continuously across every paddock, soil type and season. In irrigation management, these processes include soil-water balance, crop water use, water stress, crop growth, yield response, runoff, deep drainage and nutrient-loss risk. Models are therefore used not only to support irrigation decisions, but also to compare management options and estimate their likely productivity, water-use and environmental consequences under different weather, soil and crop conditions. Their value lies in representing the interactions between climate, soil, crop growth and management in a consistent framework.

A range of modelling approaches has been developed internationally to represent crop water use, soil-water balance and yield response under different irrigation conditions. These range from relatively simple crop-coefficient and water-balance methods to process-based crop and farming-systems models. Within sugarcane research, Agricultural Production Systems sIMulator (APSIM) and Decision Support System for Agrotechnology Transfer (DSSAT)/CANEGRO are among the most widely used modelling frameworks. APSIM has been extensively applied in Australian farming systems and includes sugarcane modules capable of representing crop growth, water stress and management responses [28–30]. DSSAT is an international crop-modelling framework, while CANEGRO is its sugarcane model and has been used to simulate sugarcane growth and yield under different irrigation and man-

agement conditions [31,32]. AquaCrop provides a more general crop-water-productivity modelling approach and has also been applied to irrigated sugarcane scenarios [33,34].

Crop models can support several types of irrigation decisions, depending on how they are configured and presented to users. Grower-facing scheduling tools use current paddock, crop, soil and weather information to estimate soil-water deficit and guide near-term decisions about when irrigation may be required. IrrigWeb is an example of this type of application, translating crop and soil-water calculations into paddock-level irrigation advice. APSIM, DSSAT/CANEGRO and AquaCrop can also provide paddock-level irrigation advice and can be used as modelling engines to compare alternative irrigation rules, soil types, planting dates, crop cycles, water constraints and climate sequences over multiple seasons to answer 'what-if' questions [35]. These models can also support scheduling, but they are often applied through research or decision-support platforms rather than directly by growers. The distinction is therefore based mainly on the purpose, time horizon and user interface, rather than on completely different underlying modelling principles.

i-RAT illustrates how a sophisticated crop model such as APSIM can be incorporated into an easy-to-use scenario-assessment platform for sugarcane irrigation. The platform uses APSIM-based simulations to compare alternative irrigation practices and to estimate their implications for productivity, water use, economics and environmental pressures [36]. Rather than providing day-to-day irrigation instructions, i-RAT supports discussion between growers, advisors and industry by showing how different irrigation strategies may perform across multiple seasons and conditions. Related scenario analyses have compared different levels of irrigation-technology adoption, with modelled results indicating improvements in water-use efficiency and energy use while maintaining yield under more advanced scheduling and automation scenarios [37]. These outputs should be interpreted as modelled evidence of likely outcomes under the assumptions used, and their value increases when the model inputs and management assumptions reflect actual farm conditions. The relationship between model inputs, modelling frameworks, modelled outputs and decision-support applications is summarised in Figure 2.

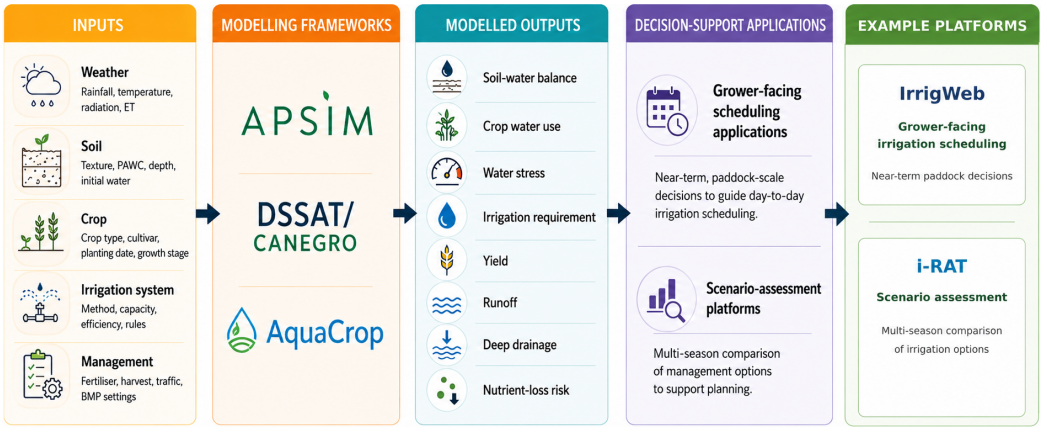


Figure 2. Relationship between crop-modelling engines and irrigation decision-support applications. Weather, soil, crop and management information is processed through modelling frameworks such as APSIM, DSSAT/CANEGRO and AquaCrop. Outputs can support grower-facing scheduling, scenario assessment and the estimation of productivity and environmental-pressure indicators.

The strength of crop modelling is that it can estimate long-term trade-offs across multiple seasons for multiple soils, climate and management scenarios. The limitation is that model outputs depend on input quality, calibration, assumptions about soil and irrigation efficiency, and correct representation of actual management. For reporting use, modelled indicators such as drainage or leaching risk should be transparent, reproducible and checked against monitoring data where possible.

3.2. Irrigation Scheduling Products and Grower-Facing Decision Support

Irrigation scheduling tools translate crop and soil-water information into practical advice about when irrigation is likely to be required and, in some cases, how much water to apply. In sugarcane, most approaches follow the same general principle: irrigation is considered when depletion in the effective root zone approaches a threshold at which crop stress or yield loss may occur. The approaches differ mainly in how this depletion is estimated. The WaterCheck program promoted practical scheduling and irrigation-efficiency methods, including evaporation mini-pans, tensiometers, soil-water assessment and grower-led evaluation of irrigation performance [38,39]. Related Burdekin research showed that furrow design and management, including furrow length and inflow conditions, can substantially influence the amount of water applied and irrigation efficiency [40]. WaterSense subsequently used a daily crop and soil-water-balance model to predict crop water use and root-zone water status from weather, soil, crop and irrigation information rather than directly measuring soil water [41]. IrrigWeb extended this model-based approach through a grower-facing digital platform that uses CANEGRO with weather data, soil characteristics, crop-cycle inputs and irrigation-system constraints to estimate soil-water deficit, crop water use and future irrigation requirements [42]. These approaches therefore range from simple field-based methods to model-based applications, but all translate an estimated water deficit into practical irrigation decisions.

3.3. Internet of Things (IoT) Monitoring, Telemetry and Field Automation

IoT monitoring and automation systems support irrigation management by recording field conditions, documenting irrigation events and helping implement scheduling decisions. Their role is different from that of crop and water models: models estimate crop demand and the likely consequences of management, while IoT systems provide operational information about what occurred in the paddock. Typical components include soil-water sensors, flow meters, pressure transducers, pump- and valve-status sensors, weather stations and end-of-row sensors. These devices may be connected through radio to farm software and control equipment such as pumps, valves, actuators and gates [43–45]. In this way, IoT systems can reduce the gap between an irrigation recommendation and its actual implementation, while also creating digital records that can improve model inputs and support later assessment.

Irrigation automation can support several operational functions, including remote pump and valve control, timed irrigation, automated set changing, sensor-triggered cut-off and digital recording of irrigation events. In furrow and surface-irrigation systems, end-of-row sensing and automated control can help determine when water has reached the end of the field and when an irrigation set should be changed or stopped, reducing the need for manual checking and potentially limiting excessive irrigation duration [46]. In pressurised systems, automation may be used to coordinate pumps, valves, centre-pivot or lateral-move equipment, drip irrigation and fertigation. The specific technology varies between irrigation systems, but the common purpose is to implement irrigation decisions more consistently and to record how the irrigation event was carried out.

WiSA provides a sugarcane-specific example of how monitoring, scheduling and automation can be connected. The system uses radio communication between a base station and field units to collect information from devices such as soil-moisture probes, flow meters and pressure transducers, and to control pumps and valves [22]. Earlier work developed an uplink from WiSA to IrrigWeb so that irrigation and rainfall records could be transferred automatically into the scheduling platform [47]. A subsequent downlink allowed IrrigWeb scheduling outputs to be transferred back to WiSA and converted into implementable irrigation actions while accounting for practical constraints such as pump

capacity, electricity tariffs, block priorities and grower preferences [22,42]. Farm in ONE provides the associated cloud-based platform for managing irrigation data, control functions and farm records. Together, these components illustrate a closed-loop pathway in which model-based scheduling informs irrigation control, while field records are returned to the platform to document what was implemented. An example of this monitoring and automation architecture is shown in Figure 3.

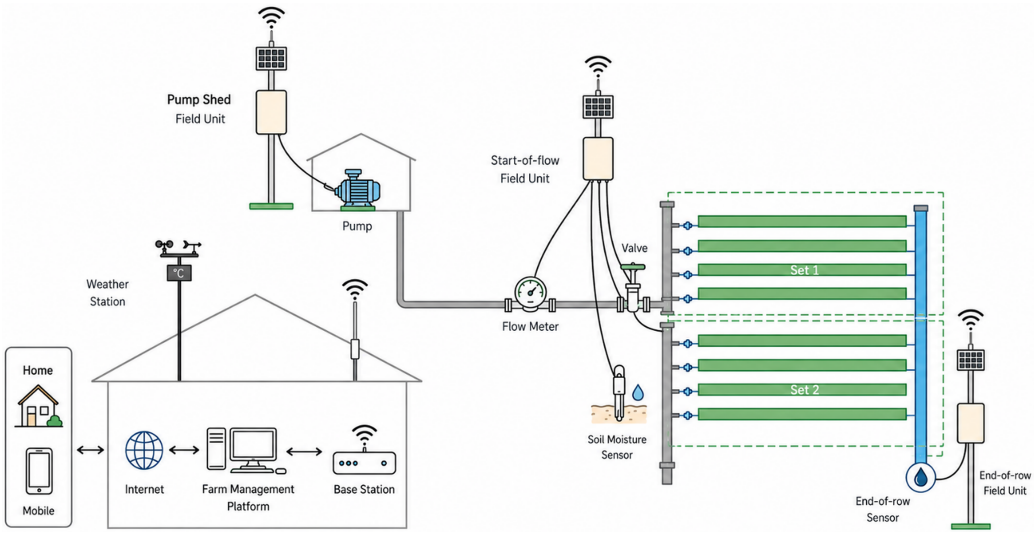


Figure 3. Example of an IoT-enabled monitoring and automation architecture for furrow-irrigated sugarcane. Weather observations, pump operation, flow measurement, soil-water sensing, pressure monitoring, valve control and end-of-row detection are connected through wireless telemetry and a farm-management platform.

The main contribution of IoT monitoring and automation is to reduce the gap between intended and implemented irrigation management. These systems can record whether pumps and valves operated, how long irrigation continued, whether water reached the end of the row and, where flow is measured, how much water was applied. This information improves the representation of actual management in crop and water-balance models and helps distinguish between the expected and observed performance of an irrigation strategy. Operational records do not, by themselves, quantify environmental outcomes such as runoff, deep drainage or nutrient loss. Their value lies in providing stronger evidence of implementation and more reliable inputs for models that estimate these consequences.

3.4. Remote Sensing, Light Detection and Ranging (LiDAR) and Spatial Crop Diagnosis

Remote sensing complements field observations and crop models by extending irrigation assessment from individual measurement points to spatial patterns across blocks, farms and districts. Multispectral imagery can indicate variation in canopy vigour, crop cover and crop development [48,49]. Thermal imagery can identify areas of elevated canopy temperature and possible water stress [50,51]. Satellite-based evapotranspiration products support spatial estimates of crop water use [52,53]. LiDAR and photogrammetry can describe crop height, structure and biomass-related variation [54–56]. These observations are valuable because a single soil-water sensor or field inspection may not represent variability in soil properties, infiltration, crop development or irrigation performance across an entire field.

IrriSAT is a grower-facing scheduling application that combines satellite-derived crop information with weather data to estimate crop water use and irrigation requirement over large areas [57]. Its value lies in using remotely sensed crop development to support paddock-scale scheduling where direct field measurements may be limited.

Other sugarcane studies demonstrate broader remote-sensing applications rather than direct scheduling. UAV LiDAR and multispectral imagery have been used to estimate fine-scale variation in biomass and leaf nitrogen [55]. Photogrammetry and LiDAR have been compared for monitoring crop-height responses to nitrogen management [54]. Multispectral imagery combined with machine learning has been used for plot-level yield estimation [56]. Thermal crop-water-stress indices have also been evaluated for sugarcane irrigation scheduling [58]. Together, these studies show that remote sensing can support both irrigation scheduling and broader spatial diagnosis, although the cause of observed crop variation still requires interpretation using field information and modelling. The main remote-sensing information pathway for spatial irrigation diagnosis is summarised in Figure 4.

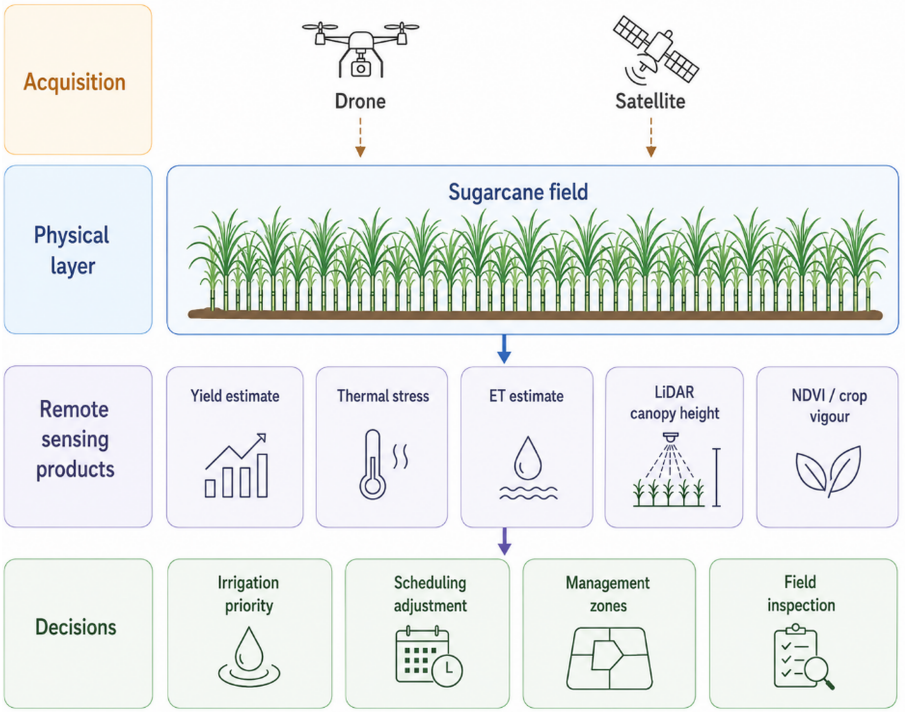


Figure 4. Remote-sensing pathway for spatial irrigation diagnosis in sugarcane. Satellite, uncrewed aerial vehicle (UAV) and airborne observations can identify spatial variation in canopy vigour, thermal response, evapotranspiration, crop structure and biomass, while field information and modelling are needed to diagnose the cause.

The main limitation of remote sensing is that similar spatial patterns can arise from different causes. Reduced canopy vigour, lower biomass or elevated canopy temperature may indicate water stress, but may also reflect nutrient deficiency, disease, pest damage, poor ratooning, soil constraints, waterlogging or differences in harvest history. Remote sensing is therefore most useful as a spatial screening and prioritisation tool. Its value increases when imagery is interpreted alongside irrigation records, soil-water information, crop models and targeted field inspection.

3.5. Forecast-Based Irrigation Indices and Climate-Informed Scheduling

Forecast-informed irrigation extends crop and water modelling into the near future by forcing a soil-water or crop model with predicted rather than observed weather. A rainfall forecast alone does not indicate whether the root zone will be sufficiently refilled, whether crop stress can be avoided or whether irrigation should be delayed. Its value increases when forecast rainfall, temperature and other weather variables are translated into irrigation-relevant indicators such as projected soil-water deficit, crop water use,

stress probability, irrigation requirement, runoff risk or deep-drainage risk [23,59]. This is particularly relevant in sugarcane because irrigation decisions may need to be made several days in advance, while irrigating shortly before substantial rainfall can increase unnecessary water application and the risk of water and nutrient movement beyond the root zone. Ensemble and calibrated forecasts can further support risk-based decisions by representing a range of plausible future conditions rather than presenting a single forecast as certain [60]. The main forecast approaches and their irrigation decision roles are summarised in Table 1.

Table 1. Forecast information and its irrigation decision role.

Forecast Approach	Methodological Role	Irrigation Use
Deterministic weather forecast	Uses a single predicted weather sequence, usually including rainfall and temperature	Helps identify near-term rainfall risk, but does not represent forecast uncertainty.
Ensemble forecast	Uses multiple plausible future weather sequences	Supports risk-based decisions, such as delaying irrigation when useful rainfall is sufficiently likely.
Downscaled and calibrated forecast	Adjusts numerical weather-prediction output for local conditions and systematic bias	Improves the relevance of forecast inputs for paddock-scale crop and soil-water calculations.
Forecast plus crop model	Uses forecast weather as input to a soil-water or crop model	Produces irrigation-relevant indices such as projected soil-water deficit, crop water use and crop-stress probability.

Seasonal and shorter-term climate information has been explored in Australian sugarcane for several related purposes. Southern Oscillation Index phases have been used to forecast sugarcane yield anomalies in northeastern Australia [61], while ensemble data-mining methods have supported regional production forecasting [62]. Climate and hydrological forecasts have also been examined in relation to irrigation-water availability and allocation decisions in water-constrained sugarcane regions such as Bundaberg [63]. More recently, Schepen et al. [23] coupled downscaled numerical weather prediction forecasts with APSIM to generate sugarcane irrigation indices. Their workflow post-processed ACCESS-G3 forecasts, produced locally relevant ensemble weather sequences and used APSIM to estimate future soil-water deficit, crop water use and crop stress. Together, these studies show the progression from seasonal production and water-allocation information towards more direct, paddock-relevant irrigation guidance.

In practice, forecast-informed irrigation indices can support decisions to irrigate immediately, delay irrigation, reduce the amount applied or prioritise particular blocks before forecast rainfall. Their usefulness depends on forecast skill, which varies with lead time, season, region and weather system, as well as on how uncertainty is communicated to growers. Forecast-based tools should therefore present a range of plausible outcomes or probabilities rather than a single recommendation treated as certain. When combined with crop and soil-water models, they can help growers balance the risk of crop stress against the risk of unnecessary irrigation before rainfall.

3.6. Artificial Intelligence, Machine Learning and Analytics

Artificial intelligence and machine-learning methods can support irrigation management by identifying patterns across large and diverse datasets. Relevant inputs may include soil-water observations, pump and valve records, flow data, weather information, remote sensing, crop-model outputs and farm-management records. These methods are particularly useful where relationships are nonlinear, where multiple data streams need

to be combined, or where large datasets must be screened for prediction, classification or anomaly detection. In irrigation applications, machine learning can support crop and soil-water prediction, spatial stress mapping, yield estimation, equipment-fault detection and prioritisation of irrigation decisions [64–66]. Representative AI and analytics methods and their potential irrigation roles are summarised in Table 2.

Table 2. AI and analytics methods relevant to sugarcane irrigation evidence.

Method Group	Typical Data Inputs	Potential Irrigation Role
Tree-based models, including random forest	Climate variables, crop-model outputs, yield records and seasonal indices	Yield or production forecasting and identification of factors associated with crop response [64,67].
Image-based machine learning	Multispectral, RGB, satellite or UAV imagery	Biomass and yield estimation, crop-vigour assessment, canopy-condition analysis and stress-zone mapping [49,56,68].
Time-series and transformer models	Soil moisture, weather, remote-sensing data and static soil and crop variables	Root-zone soil-moisture estimation and forward prediction of soil-water status [66].
Anomaly and rule-based analytics	Pump status, valve logs, flow, pressure and expected irrigation response	Detection of sensor faults, pump failures, unexpected flow behaviour or irrigation events that did not produce the expected soil-water response.

In sugarcane, machine learning has been applied mainly to yield prediction, production forecasting and interpretation of remotely sensed crop information. Everingham et al. [67] used a random forest algorithm to predict sugarcane yield, while earlier work combined ensemble data-mining methods with crop-model settings for regional production forecasting [62]. Remote-sensing studies have extended these applications to spatial crop assessment: UAV multispectral imagery has been used to predict sugarcane biometric parameters [49], plot-level yield has been estimated from multispectral imagery in Bundaberg [56], and multispectral and LiDAR data have been integrated for biomass estimation [68]. Although these studies are not all irrigation-specific, their outputs can help assess whether spatial patterns in crop growth and yield are consistent with irrigation records, modelled water stress or other management factors.

3.7. Synthesis: Evidence Pathways and Verification Needs

The technologies reviewed in this section perform different but complementary functions. Crop and water models estimate crop demand and the likely consequences of alternative irrigation practices. Grower-facing scheduling applications translate these estimates into practical advice. Monitoring and telemetry provide information about field conditions and actual irrigation events, while automation helps implement decisions more consistently. Remote sensing extends observation across space, forecasts extend decision-making into the future, and artificial intelligence helps interpret and combine multiple data streams. Their value, therefore, lies less in any single tool than in how effectively these components are connected.

Recent reviews identify clear trade-offs among these approaches. Ahmad and Sohel [69] found that process-based systems such as APSIM and DSSAT provide detailed representation of crop, soil and management interactions but require substantial input data, while simpler models such as AquaCrop have lower input requirements. Yang et al. [70] showed that crop-model validation should use appropriate error and agreement measures rather than relying on R^2 alone. Muturi et al. [71] identified spatial and temporal resolution, validation data and sensor choice as important limitations in remote-sensing

estimates of irrigation water use. Oğuztürk [72] identified variability in datasets, sensor calibration and limited region-specific training data as important constraints on the generalisability of AI-based irrigation models. These reviews indicate that no single approach is universally superior; suitability depends on the intended application, available data and validation requirements.

No single technology provides a complete account of irrigation performance or environmental consequence. A scheduling recommendation shows what should be done, automation and telemetry show what was implemented, field observations and remote sensing show how the crop or soil responded, and crop models estimate likely effects on runoff, deep drainage, nutrient loss and productivity. When these outputs are linked, they provide a more complete and traceable record of irrigation management. These combined records can then support BMP improvement, evaluation of irrigation strategies and, where suitable methods exist, broader water-quality and nature-related reporting. The resulting evidence types and remaining verification needs are summarised in Table 3.

Table 3. Evidence outputs from advanced irrigation technologies and remaining verification needs.

Evidence Type	Main Source	What It Shows	How It Should Be Interpreted
Irrigation recommendation	Scheduling tools and crop or water-balance models	When irrigation was recommended and what soil-water, crop or forecast information informed the recommendation	Evidence of the decision basis, but not evidence that the recommendation was implemented.
Implementation record	Automation systems, pump and valve logs, flow meters and telemetry	Whether irrigation occurred, when it occurred, how long it operated and, where measured, how much water was applied	Evidence of actual irrigation management.
Crop and soil-water response	Soil-water observations, field checks, remote sensing and crop models	Whether the crop and root zone responded as expected following irrigation or rainfall	Used to compare observed and modelled responses.
Spatial variability	Satellite, UAV, thermal, multispectral, LiDAR and yield data	Where crop condition, water stress or irrigation performance differs across a block or farm	Supports diagnosis and targeting, but does not independently identify the cause of the observed variation.
Modelled environmental-pressure indicator	Crop models, water-balance tools and integrated platforms	Estimated runoff, deep drainage, nutrient-loss risk, water use or other management-related pressures	Modelled evidence whose assumptions, uncertainty and confidence should be stated clearly.
Reporting-ready indicator	Agreed industry, water-quality, natural-capital or environmental-market method	A defined indicator calculated using documented inputs, assumptions and quality-control requirements	Suitable for reporting only where the calculation method and required evidence level are formally recognised.

4. Natural Capital, Nature-Positive and Environmental Reporting Frameworks

4.1. From Irrigation Efficiency to Natural Capital and Ecosystem Services

The relationship between agriculture and nature is undergoing a fundamental transformation. Historically, agricultural sustainability has been evaluated primarily through production efficiency, economic performance and resource-use optimisation. Within irrigated systems, this perspective has driven considerable advances in irrigation engineering, irrigation scheduling, water-use efficiency and precision agriculture, improving agricultural productivity while reducing water consumption [73–77]. These advances remain essential for food security, particularly under increasing pressure on freshwater resources. However, they represent only one dimension of sustainability because they largely assess irrigation according to its capacity to optimise production rather than its contribution to maintaining, restoring or enhancing ecosystem health.

Within Reef-connected sugarcane systems, the pathway by which excess water movement can transport dissolved nutrients through runoff and leaching is well established. However, the 2022 Reef Scientific Consensus Statement notes that evidence for the effect of improved irrigation practices on dissolved nutrient losses and farm productivity remains limited and is derived mainly from mechanistic modelling; predicted reductions in DIN loss from lower irrigation application rates may also involve productivity trade-offs [78].

This shift is reflected in the broader evolution of ecosystem services and natural capital research. Foundational work has demonstrated that agriculture depends on natural assets such as soils, water, biodiversity, vegetation and climate regulation, which provide ecosystem services including water purification, nutrient cycling, carbon sequestration, habitat provision and soil formation [79–82]. In the irrigation literature, this perspective has been extended by studies showing that water management affects not only crop productivity but also ecosystem service provision, hydrological regulation and landscape resilience. Reconfiguring irrigation landscapes can improve ecosystem-service outcomes, and integrated water-resources management can incorporate ecosystem-service assessments when balancing agricultural and environmental water demands [83,84]. Work on ecosystem accounting further shows that changes in ecosystem assets and service flows can be quantified and incorporated into environmental decision-making, including financing and governance mechanisms that recognise restoration benefits not fully captured through conventional markets [85–87].

4.2. Water and Hydrological Pathways

Across the reviewed literature, water is the most visible pathway through which irrigation interacts with natural capital. For Australian sugarcane, the most directly relevant evidence concerns runoff, deep drainage, nutrient movement and Reef-connected water quality, which depend on interactions among irrigation, rainfall, soils and crop uptake [11,16–18]. International evidence can still inform mechanisms that are transferable to this context; for example, Zhang et al. [88] showed that irrigation can alter groundwater dynamics and salinity thresholds, although the magnitude and relevance of these effects depend on local hydrogeology. This distinction is important because evidence from unrelated arid or non-sugarcane systems should not be assumed to transfer directly to Queensland cane regions.

4.3. Soil Health as Natural Capital

Soil health represents a second major pathway linking irrigation to nature-positive outcomes. Rather than simply production media, soils are natural capital assets that regulate water, store carbon, cycle nutrients and support biological activity [82,89,90]. The reviewed studies show that irrigation practices affect soil structure, soil moisture, organic matter, salinity, erosion, nutrient availability and microbial functioning. Admas et al. [91] examined the impacts of irrigation practices on soil physico-chemical properties, while Abuzaid et al. [92], Abdou et al. [93], Regkouzas et al. [94] and Cammerino et al. [95] explored how irrigation, soil amendments, biochar, salinity management and alternative cropping strategies influence water productivity and soil condition. These studies suggest that irrigation contributes to nature-positive outcomes when it is combined with soil conservation, nutrient management, organic amendments and practices that maintain the biological and physical functions of soils.

4.4. Biodiversity, Habitat and Landscape Connectivity

Biodiversity and habitat provision form a third pathway. Several studies show that irrigation infrastructure can create or support multifunctional landscapes when designed and managed appropriately. Hansani et al. [96] identified farm dams as potentially nature-

positive assets that can support water security, biodiversity, water quality and climate resilience. Matsuzaki et al. [97] showed that abandoned rice paddies and irrigation ponds can support ecosystem multifunctionality and biodiversity, while Kuo and Wang [98] demonstrated the role of water management in enhancing ecosystem services in coastal wetlands. Sammonds et al. [99] examined the possibility of using irrigation water to conserve wetland ecosystems. However, the literature also highlights important risks. Kingsford and Thomas [100] showed how dams and irrigation can contribute to wetland degradation and waterbird decline when flow regimes are altered. Rideout et al. [101] similarly linked agricultural impacts on flow regimes with consequences for aquatic ecosystem functions. These findings reinforce that irrigation is not inherently nature positive; its outcomes depend on water allocation, infrastructure design, ecological connectivity and landscape context.

4.5. Climate Resilience and Nature-Positive–Net-Zero Synergies

A fourth pathway relates to climate resilience and system adaptation. Climate variability and water scarcity have increased interest in irrigation as a resilience strategy, particularly for smallholder and water-limited agricultural systems. Studies by Aguilar et al. [102], Fishman et al. [103], Koukouli et al. [104], Negera et al. [105], Lankford et al. [106], Amjath-Babu et al. [107] and Shrestha and Hales [108] show that irrigation, water harvesting, solar pumping, climate-smart agriculture and adaptive water management can strengthen livelihoods and agricultural resilience. At the same time, these studies indicate that resilience cannot be assessed only through yield stability or water productivity. A nature-positive lens requires attention to whether adaptation strategies also maintain ecosystem functions, reduce environmental pressures and protect natural assets over time. Importantly, many of these practices also contribute to climate mitigation. Improvements in irrigation efficiency can reduce the energy required for water extraction, distribution and pumping, thereby lowering greenhouse gas emissions, while simultaneously reducing water abstraction, nutrient losses and pressure on freshwater ecosystems [109,110]. This illustrates an important convergence between nature-positive and net-zero objectives, where the same management intervention can deliver both biodiversity and climate benefits when appropriately designed and monitored [111,112].

4.6. Technology, Monitoring and Governance

Technological innovation has fundamentally transformed the capacity to monitor, quantify and manage these ecological pathways across farm and landscape scales. The reviewed literature includes studies applying remote sensing, hyperspectral monitoring, hydrological modelling, crop models, sensors, geospatial analysis and decision-support tools to assess water quality, groundwater, irrigation demand, soil moisture, vegetation condition and ecosystem services. Benavides-Bolaños et al. [113] demonstrated the use of hyperspectral reflectance sensing for water quality monitoring in an agricultural irrigation district, while Masseroni et al. [114] examined opportunities to improve gravity-fed irrigation systems. Ha et al. [115], Cassiani et al. [116], Lin et al. [117] and Lankford et al. [106] further illustrate the increasing role of spatial modelling, monitoring and decision-support systems in water and irrigation management. However, these technologies often remain disconnected. They generate valuable data, but this information is rarely integrated into a coherent assessment of natural capital, ecosystem service delivery or nature-positive performance.

The social and governance dimensions of irrigation are equally important. Studies by Aida [118], Albizua et al. [119], Aoyagi et al. [120], Blackmore et al. [121] and Savari et al. [122] show that irrigation outcomes depend not only on technology, but also on farmer adoption, trust, collective action, institutions, knowledge exchange and governance arrangements. This is highly relevant to natural capital and nature-positive frameworks because

environmental improvement requires credible monitoring, adaptive management and transparent decision-making. A technically efficient irrigation system may fail to deliver broader ecosystem benefits if it is not supported by effective governance, farmer participation and long-term monitoring.

Adoption also depends on farm scale and digital capability, and on whether expected benefits justify hardware, connectivity, maintenance and data-management costs [123,124]. Data ownership, privacy, transparency and permission to reuse farm records for external reporting also require explicit governance; Australian smart-farming research shows that uncertainty over data control and benefit sharing can reduce willingness to participate in digital systems [124]. Because these costs and benefits vary among technologies, farms and regions, the reviewed evidence does not support a single cross-platform cost-benefit estimate.

4.7. Reporting Frameworks, Indicators and the Integration Gap

4.7.1. Reporting and Accountability Frameworks

Natural capital and nature-positive frameworks provide a way to connect these ecological and governance dimensions to broader reporting and accountability requirements. Frameworks such as the Taskforce on Nature-related Financial Disclosures (TNFD), Environmental, Social and Governance (ESG) reporting, the Natural Capital Protocol, ENCORE [125], the Science Based Targets Network (SBTN) and Reef Credits increasingly require evidence of nature-related impacts, dependencies, risks, opportunities and environmental outcomes. At the same time, governments, investors, financial institutions and agricultural supply chains are seeking more consistent, transparent and scientifically credible information to demonstrate environmental performance, support natural capital accounting, access environmental markets and meet emerging sustainability expectations [112,126–128]. Recent studies also argue that irrigation should be evaluated beyond water-use efficiency, recognising its influence on ecosystem services, natural capital and landscape resilience [110].

However, the reviewed irrigation literature rarely links irrigation-generated data directly to these frameworks. Most studies measure individual outcomes such as water productivity, groundwater quality, salinity, soil condition, biodiversity or yield. Unfortunately, few translate these outcomes into indicators suitable for disclosure, environmental markets or natural capital accounting. This represents a critical gap: although modern irrigation technologies are increasingly capable of generating high-quality environmental and production data, these data are rarely integrated into standardised evidence pathways that support natural capital accounting, sustainability reporting and decision-making across farm, catchment and investment scales [129–131]. Bridging this gap requires a whole-of-system approach that connects irrigation monitoring, ecosystem processes, natural capital assessment and reporting within a common evidence-generation pathway. Such integration would enable irrigation technologies to evolve from operational management tools into integrated evidence-generation systems that support farm management, landscape planning and consistent reporting across multiple natural capital and nature-related frameworks [110,112,127].

4.7.2. Indicators for Nature-Positive Assessment

Indicators are the bridge between irrigation technologies and nature-positive frameworks. The reviewed literature suggests a wide range of possible indicators, including water-use efficiency, groundwater recharge, salinity, runoff, nutrient losses, sediment loads, water quality, soil organic carbon, erosion risk, soil moisture, vegetation condition, habitat quality, biodiversity proxies, carbon storage, climate resilience, farmer adoption, monitoring frequency and governance quality. However, not all indicators are equally useful. To sup-

port nature-positive claims, indicators must be scientifically credible, practical for farmers to obtain, repeatable over time, sensitive to management change, scalable across farms and landscapes, and compatible with reporting or market frameworks [80,112,132,133]. Without this translation step, irrigation technologies may continue to produce data that are valuable for farm management but insufficient for demonstrating natural capital enhancement or ecosystem health.

Moreover, the reviewed literature demonstrates that irrigation can influence nature-positive outcomes through multiple interconnected pathways, including water regulation, soil health, biodiversity, carbon storage, climate resilience, landscape connectivity, governance and adaptive management. Collectively, these studies show that irrigation has evolved beyond its traditional role as a production technology to become a strategic environmental management tool capable of influencing ecosystem condition and the provision of ecosystem services across agricultural landscapes.

4.7.3. Integration Limitations and Pathway Forward

The review identifies three persistent limitations:

- Environmental outcomes are often assessed in isolation, with water, soil, biodiversity and climate treated as separate domains rather than interacting components of agricultural systems.
- Irrigation technologies and environmental monitoring systems generate increasingly sophisticated information, but these data remain fragmented across platforms and are rarely integrated into coherent assessments of ecosystem condition or natural capital.
- Nature-related reporting and environmental-market frameworks define the evidence required to demonstrate impacts, dependencies, risks and outcomes, but provide limited practical guidance for translating farm- and landscape-level irrigation data into scientifically credible, standardised evidence.

Collectively, these limitations reveal a gap between the information generated through irrigation management and the evidence required for natural-capital assessment, environmental markets and nature-related reporting. The challenge is not simply to generate more data, but to connect farm-management records, environmental modelling, indicator development and reporting requirements within a coherent evidence pathway. The following section examines how existing connections between these components could be extended into a whole-of-system approach for sugarcane irrigation.

5. Conceptual Integration Pathway

5.1. Existing Integrations and the Remaining System Gap

Several existing approaches already demonstrate the value of connecting parts of this pathway. Irrigation scheduling and automation systems link model-based recommendations with farm implementation records, while platforms such as i-RAT connect irrigation scenarios with productivity, economic and environmental indicators [22,36]. These applications show how operational farm data and biophysical modelling can be combined to improve decisions and compare management alternatives.

Great Barrier Reef water-quality programs connect other parts of the system. The Paddock to Reef framework links management-practice information with paddock and catchment monitoring, modelling and reporting across scales [134], while subsequent modelling connects agricultural paddock models with catchment models and uses monitoring data to evaluate dissolved inorganic nitrogen loads [135]. Water-quality accounting and Reef Credit approaches extend this connection by linking quantified environmental improvements with defined baselines, calculation procedures, uncertainty and assurance requirements [136,137].

Natural-capital accounting and nature-related reporting provide further connections. Farm-scale natural-capital accounting combines operational and spatial data, models and selected field observations to produce practical environmental accounts [131]. The Natural Capital Protocol and System of Environmental-Economic Accounting—Ecosystem Accounting (SEEA EA) connect the identification of natural-capital impacts and dependencies with measurement, modelling, indicators and decision-making [127,132], while TNFD and SBTN connect nature-related pressures with metrics, targets and progress tracking [112,133].

Together, these examples show that many of the required connections have already been demonstrated: farm data have been linked with models, models with environmental indicators, indicators with accounting methods, and accounting methods with reporting or market applications. However, these connections are generally applied to individual parts of the system. A continuous pathway linking irrigation decisions, actual implementation, modelled environmental pressures, supporting evidence, standardised methods and recognised reporting applications remains underdeveloped. Figure 5 therefore organises these established partial linkages into a proposed end-to-end pathway; it should not be interpreted as a fully validated management system.

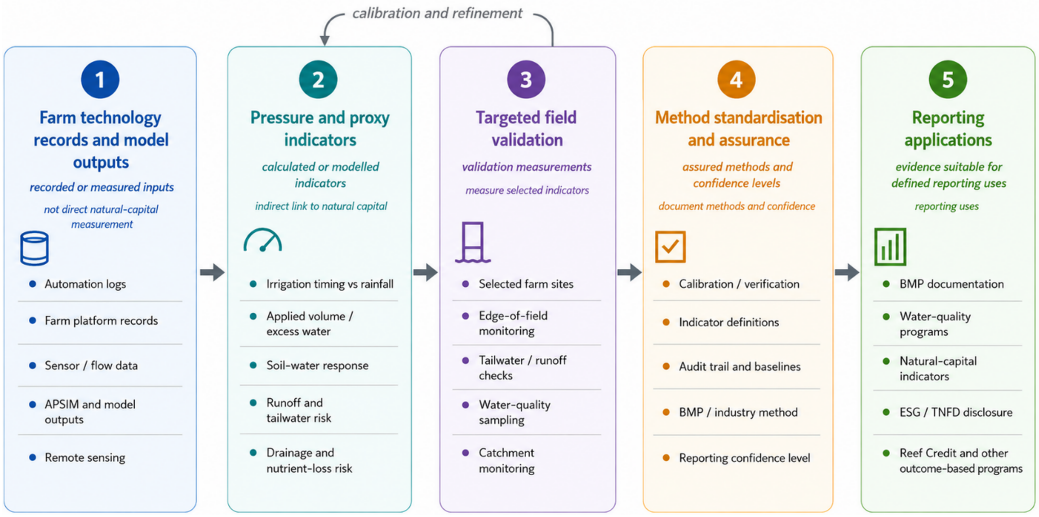


Figure 5. Five-part integration pathway for smart irrigation in sugarcane. Existing agricultural monitoring, modelling, water-quality, natural-capital accounting and nature-related reporting approaches support the individual components and many adjacent linkages. The pathway connects these elements into a continuous chain from farm-management information and model outputs through environmental-pressure indicators, supporting evidence and documented methods to defined reporting applications.

5.2. Connecting the Five Components

Figure 5 brings these partial integrations together and maps the information handovers required across the complete system. The pathway is intentionally defined at a functional rather than platform-specific level. For example, the handover from farm-technology records to the indicator stage may include irrigation start and stop times, applied water or flow-meter volume, pump or valve status, rainfall, soil-water observations and crop-model inputs; the indicator stage may return estimates of runoff, deep drainage, nutrient-loss risk, water-use efficiency or pumping energy. Targeted validation may add soil-water, flow, water-quality, crop, yield or remote-sensing observations, while standardisation and reporting require indicator definitions, baselines, model/version metadata, calculation rules and uncertainty records. These functional handovers are independent of the particular tools used in practice: exact file formats, APIs, database structures and communication protocols will depend on the sensors, telemetry systems, models, farm platforms and reporting

applications used in each implementation. What must remain consistent is traceability of inputs and outputs, reproducibility of calculations, and validation or assurance appropriate to the intended indicator and reporting use. The five components below therefore describe these functional information handovers without prescribing a single technical architecture. The first component consists of information generated through irrigation and farm management, including scheduling recommendations, irrigation timing and duration, pump and valve operation, applied water, rainfall, soil-water observations, crop stage, remote sensing and crop-model outputs. These data establish what was recommended, what was implemented and the conditions under which the irrigation event occurred [22,23].

The second component translates these inputs into environmental-pressure and resource-use indicators. Biophysical models can estimate excess irrigation relative to refill requirement, runoff, deep drainage and nitrogen-loss risk, while integrated decision-support platforms can also calculate water-use efficiency and pumping energy [16,17,36]. This step converts operational information into indicators that are more directly relevant to soil, water and natural-capital pressures while retaining the assumptions and uncertainty associated with modelled evidence.

The third component provides supporting evidence appropriate to the intended use. Selected field, farm or catchment observations can improve local inputs, test whether the direction and approximate magnitude of modelled responses are credible, and define the conditions under which an indicator can be transferred. Existing water-quality programs demonstrate how monitoring and modelling can provide complementary lines of evidence, with observations used strategically and models extending information across locations and seasons that cannot all be measured directly [134,135].

The fourth component converts the evidence into a reproducible method. Indicator definitions, required inputs, baselines, model configuration, calculation rules, spatial and temporal scale, uncertainty, quality control and assurance requirements need to be documented for the intended application. This creates consistency across farms and seasons and provides the basis for comparison, audit and recognition through industry, accounting, reporting or market systems [127,132,136].

The fifth component connects the method and evidence to a defined use. Potential applications include Smartcane BMP documentation, water-quality improvement programs, farm-scale natural-capital accounts, TNFD- or SBTN-aligned metrics and, where an applicable approved method exists, nature-market participation. The intended use determines the required indicator and level of evidence: an operational record may be sufficient to demonstrate implementation of improved practice, whereas a quantified environmental outcome or market unit requires stronger baseline, uncertainty and assurance provisions.

Viewed as a whole, the pathway creates a feedback structure rather than a one-way reporting exercise. Reporting and market requirements help define which indicators and evidence are needed; these requirements inform data collection and model configuration; and the resulting information can support both farm decision-making and broader environmental assessment. The opportunity is therefore created by the connection between the five components, rather than by any single technology, model or reporting framework.

5.3. Applications and Limitations

The pathway can support several applications, but the strength of each claim must match the supporting evidence. Practice records can demonstrate adoption of an irrigation method, pump and flow records can demonstrate implementation, and modelled runoff, drainage or nitrogen-loss indicators can support qualified claims about changes in environmental pressure. Claims about ecosystem condition require evidence at the relevant farm, landscape, catchment or receiving-water scale; farm-level operational and

modelled information is most defensible when used to demonstrate management change and reduced pressure pathways [14,15].

Nature-market applications impose additional requirements. The Reef Credit nutrient methodology cited in this review is based on managed fertiliser application, so irrigation records or modelled drainage indicators would contribute only where an applicable method explicitly recognised those inputs and specified the baseline, additionality, quantification, uncertainty, monitoring and assurance requirements [136]. Its relevance to the pathway lies in demonstrating how farm information, modelling, standardised calculation and assurance can be connected to a recognised environmental unit.

Practical implementation also depends on interoperability, governance and grower value. Farm platforms and modelling systems need compatible data structures; indicator definitions and model assumptions need transparent governance; and evidence requirements need to remain proportionate to the reporting or market benefit. Reusing information already generated through scheduling, automation and farm management can reduce the additional reporting burden and make sustainability information a by-product of improved irrigation management [138].

Regional implementation will also differ. In the Burdekin, irrigation volume, runoff, deep drainage and nutrient-loss risk are prominent evidence needs; in the Wet Tropics, separating rainfall- and irrigation-driven drainage or runoff is more important. Mackay–Whitsunday places greater emphasis on irrigation timing around variable rainfall, whereas Bundaberg places greater emphasis on water-use efficiency and water availability. The five components can therefore remain consistent while indicator selection and validation effort are adapted to regional hydrology and data availability.

The pathway therefore provides a system map and a research and method-development agenda. Future work should identify priority indicators, minimum data requirements, appropriate baselines, model applicability, evidence checks and assurance arrangements in collaboration with growers, industry organisations, scientists, reporting bodies and potential market administrators. Testing these interfaces will determine where the five-part system can provide credible and practical evidence for nature-positive water management in Australian sugarcane.

6. Conclusions

This review examined how irrigation management in Australian sugarcane can progress from practice-based efficiency improvement towards a connected evidence system supporting productivity, water-quality improvement and nature-positive water management. Standard irrigation guidance and BMP frameworks provide the management foundation, while scheduling tools, automation, sensors, remote sensing, forecasts and crop models improve decisions, document implementation and estimate productivity and environmental-pressure responses. Natural-capital, water-quality and nature-related reporting frameworks provide complementary approaches for organising indicators, setting evidence requirements and linking environmental information with decisions, disclosures and potential market mechanisms.

The literature demonstrates that many parts of this system already work well when connected. Scheduling recommendations have been linked with irrigation automation and operational records; farm-management scenarios have been linked with biophysical, economic and environmental modelling; paddock models have been linked with catchment water-quality assessment; and environmental indicators have been linked with accounting, assurance and reporting approaches. These integrations have improved irrigation implementation, scenario assessment, pollutant-load estimation, natural-capital accounting and the credibility of environmental reporting.

The remaining gap is the absence of a continuous pathway across the whole system. The five-part pathway developed in this review connects farm-management information, modelled environmental-pressure indicators, supporting evidence, documented methods and defined reporting applications. Mapping the interfaces between these components shows how information generated for irrigation management could also support BMP assessment, water-quality programs, farm-scale natural-capital accounting, nature-related disclosure and, where approved methods are available, nature-market applications. The value of the pathway lies in coordinating the existing components and allowing evidence requirements at the reporting end to inform data collection, modelling and management at the farm end.

Several limitations shape its application. Operational records and modelled indicators provide evidence of management and environmental pressures rather than direct attribution of ecosystem or Great Barrier Reef condition. Different applications require different baselines, levels of validation, uncertainty treatment and assurance, and current Reef Credit nutrient methods do not establish irrigation-only eligibility. Practical implementation will also require interoperable farm and modelling systems, transparent indicator definitions, clear governance and evidence requirements that remain proportionate to the benefits for growers.

The five-part pathway should therefore be treated as a proposed integration framework rather than a validated management system. Further work is required to test whether the linkages, indicators and assurance processes remain reliable across regions, data environments and reporting applications.

Overall, the proposed pathway primarily supports more credible estimation and reporting of environmental pressures, while evidence of direct ecological improvement remains more limited and dependent on local landscape and catchment conditions.

Priority next steps are to test the five-part pathway in representative sugarcane systems and verify the proposed linkages between farm records, modelled indicators, supporting observations, assurance and reporting applications. This testing should identify priority indicators, minimum data requirements, model applicability, baselines and validation needs before a broader implementation timetable is defined. If these interfaces can be established, smart irrigation can support both operational farm management and more credible reporting of environmental pressures, while claims of improved ecological condition remain dependent on appropriate landscape or catchment evidence.

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Abbreviations

The following abbreviations are used in this manuscript:

APSIM	Agricultural Production Systems sIMulator
BMP	Best management practice
DIN	Dissolved inorganic nitrogen
DSSAT	Decision Support System for Agrotechnology Transfer
ESG	Environmental, social and governance
IoT	Internet of Things
SBTN	Science Based Targets Network
SEEA EA	System of Environmental-Economic Accounting—Ecosystem Accounting
SRA	Sugar Research Australia
TNFD	Taskforce on Nature-related Financial Disclosures
UAV	Uncrewed aerial vehicle

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