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Artificial Intelligence for Improving Agricultural Water-Use Efficiency: A Comparative Descriptive Analysis of Spain and South Korea

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Abstract

Agricultural water-use efficiency has become an increasingly important policy and research priority as water scarcity, climate variability, and pressure on agricultural production intensify. Artificial intelligence (AI) may support more responsive irrigation management through crop-water requirement estimation, soil-moisture monitoring, predictive modelling, and data informed irrigation scheduling. However, the adoption of digital technologies does not necessarily demonstrate that AI has been used, nor does improved irrigation performance automatically establish a reduction in water consumption at the wider hydrological scale. This study examines AI-enabled and data-driven irrigation management in Spain and South Korea through a comparative descriptive analysis based on official statistics, institutional publications, documented initiatives, and relevant scientific literature. Spain's 2023 Farm Structure Survey recorded 2,739,252 hectares of irrigated land, of which 49.0% was irrigated using localised methods. In South Korea, institutional reporting on selected smart-irrigation applications for apple and peach cultivation indicates irrigation-water savings of 10–31% under the reported conditions. These figures describe different types and levels of evidence and are not directly comparable measures of national AI performance. The analysis therefore distinguishes technological development from demonstrated outcomes and examines the implications of differences in measurement, implementation context, and evidence quality. Finally, the study derives policy-relevant lessons for Algeria, emphasising reliable agricultural data, farmer training, technical support, and monitored pilot projects before wider implementation.

Keywords: Artificial intelligence; agricultural water-use efficiency; smart irrigation; precision agriculture; Spain; South Korea.

1. Introduction

Agricultural water management is a central concern for sustainable food production as water scarcity, climate variability, and competition among economic sectors increase pressure on freshwater resources. Irrigated agriculture supports crop production in many regions, but its long-term sustainability depends not only on the availability of water but also on how irrigation is planned, managed, and evaluated. Under conditions of water stress, irrigation decisions must account for variations in soil moisture, weather, crop water requirements, and the timing of agricultural operations. These requirements have strengthened interest in technologies that can improve the precision, responsiveness, and informational basis of agricultural water management.

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Artificial intelligence (AI) offers several potential applications in this context. When combined with soil-moisture sensors, meteorological data, remote sensing, crop monitoring, and irrigation infrastructure, AI based methods can help estimate crop water requirements, predict irrigation needs, identify patterns associated with water stress, and support irrigation scheduling. Machine learning models can analyse relationships among environmental and agronomic variables and generate recommendations that respond to changing field conditions. Nevertheless, their practical contribution depends on data quality, model validation, sensor calibration, local agronomic conditions, and the ability of farmers and institutions to operate and maintain the systems. AI should therefore be regarded as one component of an integrated irrigation management approach rather than as a stand-alone solution to agricultural water scarcity.

A fundamental distinction must also be made between technological adoption and measurable water use outcomes. The presence of sensors, automated valves, drip irrigation, or digital monitoring does not, by itself, establish that an irrigation system uses AI. Likewise, a reduction in the volume of water applied to a field does not necessarily produce an equivalent reduction in water consumption at farm, irrigation district, or river basin level. The interpretation of water savings depends on the indicator used, the baseline against which performance is assessed, and the hydrological conditions in which irrigation takes place. Improvements in field level irrigation performance may increase agricultural output per unit of water, but their wider effects depend on such factors as changes in irrigated area, cropping patterns, return flows, and farmers' responses to lower irrigation costs. Research on irrigation efficiency consequently cautions against treating technical improvements as automatic evidence of basin level water conservation (Lankford et al., 2020).

Spain and South Korea provide two useful, although not directly equivalent, contexts for examining these issues. Spain is relevant because irrigation is an important component of agricultural production and water management is shaped by regional and seasonal constraints. According to the Spanish National Statistics Institute's 2023 Farm Structure Survey, the irrigated area amounted to 2,739,252 hectares. Localised irrigation accounted for 49.0% of this area, while sprinkler and gravity irrigation accounted for 31.6% and 19.4%, respectively (Instituto Nacional de Estadística [INE], 2025). These figures establish the structural context in which digital and precision irrigation technologies may be deployed. They do not, however, measure the adoption of AI or establish its contribution to water savings.

Spain's research and innovation initiatives provide additional evidence of interest in combining digital technologies with irrigation management. The HOPE project, for example, illustrates efforts to integrate AI related approaches with connected technologies and renewable energy in the development of sustainable irrigation solutions. Such initiatives are relevant to understanding technological development and institutional priorities. However, the existence of a research project or demonstration system should not be interpreted as evidence of a measurable reduction in national agricultural water consumption unless outcome data substantiate that conclusion.

South Korea offers a complementary perspective through institutional reporting on smart agricultural technologies and selected irrigation applications. The National Institute of Agricultural Sciences describes a smart irrigation system that uses soil moisture measurements and crop related information to detect water stress and determine irrigation timing and volume using AI. In applications involving apple and peach trees, the institute reports irrigation water savings of 10–31%, alongside increases in crop yield of 19–40% and a reduction in water management effort of 95% (National Institute of Agricultural Sciences [NIAS], n.d.). These figures indicate potential application level benefits under the conditions reported by the institution. They should not be interpreted as national averages, nor should they be compared directly with Spain's national statistics on irrigated land. The available institutional summary also needs to be distinguished from a fully documented independent evaluation, particularly where details of the baseline, experimental design, measurement period, and uncertainty are not available.

The central challenge is therefore not simply to determine whether Spain or South Korea has adopted more advanced agricultural technologies. It is to assess what the available evidence can establish about AI enabled irrigation, how the evidence differs between the two countries, and which lessons can reasonably be transferred to other contexts. A meaningful comparison must distinguish between national irrigation

characteristics, documented technological applications, reported performance outcomes, and the strength of the evidence supporting each claim.

Against this background, the study addresses the following research question: What does the available evidence from Spain and South Korea reveal about the potential contribution of AI enabled irrigation to agricultural water use efficiency, and what lessons can be drawn for the development of water efficient agricultural practices in Algeria?

To answer this question, the study pursues four objectives. First, it clarifies the conceptual relationship between AI, smart irrigation, irrigation efficiency, water productivity, and water savings. Second, it describes the principal characteristics of the Spanish and South Korean cases using official and institutional evidence. Third, it compares the two cases in terms of technological applications, reported outcomes, and the comparability and limitations of the available evidence. Fourth, it identifies policy implications for Algeria, with particular attention to data availability, farmer capabilities, technical support, and the evaluation of pilot interventions.

The study contributes to the discussion by applying a consistent analytical framework to evidence that differs in geographical scale, methodological detail, and type of outcome. Rather than estimating a causal effect or ranking the two countries according to a single performance indicator, it distinguishes documented developments from reported application-level results and from outcomes that remain insufficiently verified. This approach is particularly important when national structural statistics in one case are compared with technical results from selected applications in another.

The remainder of the paper is organised as follows. Section 2 develops the conceptual framework and reviews the literature on AI enabled irrigation, irrigation efficiency, water productivity, and the interpretation of water savings. Section 3 explains the research design, source selection, analytical dimensions, and methodological limitations. Section 4 examines the Spanish case, while Section 5 analyses the South Korean case. Section 6 presents the comparative analysis, and Section 7 discusses the implications for Algeria. The final section summarises the main conclusions, policy recommendations, and priorities for future research.

2. Conceptual Framework and Literature Review

2.1. Artificial Intelligence and the Development of Smart Irrigation

Artificial intelligence has attracted increasing research interest in agriculture because it can process diverse data and support decisions under changing environmental conditions. In irrigation management, AI applications may be used to estimate crop water requirements, predict soil moisture conditions, analyse meteorological information, detect crop water stress, and recommend the timing or volume of irrigation. Their potential value lies in combining information from different sources and identifying patterns that may not be adequately captured by fixed irrigation schedules or simple threshold-based rules.

AI enabled irrigation must nevertheless be distinguished from agricultural digitalisation more broadly. Digital agriculture includes technologies such as soil moisture sensors, automated valves, satellite imagery, weather stations, remote monitoring systems, and Internet of Things (IoT) networks. These technologies can collect, transmit, and process information without necessarily incorporating AI. A digitally connected or automated irrigation system should therefore not automatically be classified as an AI based system. Conversely, an AI model may generate irrigation recommendations without directly controlling irrigation equipment. Identifying the specific technological component is essential when assessing whether an intervention genuinely uses AI.

Machine learning is one of the approaches examined in the smart irrigation literature. Models can be trained on historical and real time observations to estimate crop water requirements or predict irrigation needs under different environmental conditions. Abiadi et al. (2024), in a systematic literature review published in Smart Agricultural Technology, analysed 55 studies published between 2017 and 2023. The review examined machine learning techniques, estimation accuracy, model comparisons, and the contexts in which the models were applied. Although the findings indicate the potential of machine learning for smart irrigation, the authors also identified the need for more robust and generalisable results. Model performance in a particular dataset or experimental setting does not, therefore, establish reliability across different crops, climates, soils, or farming systems.

The operational value of AI also depends on factors that extend beyond predictive accuracy. An irrigation recommendation must be sufficiently reliable, understandable, and feasible for the farmer or operator expected to implement it. Data availability, sensor calibration, system maintenance, digital skills, connectivity, user confidence, and compatibility with existing agricultural practices may all influence adoption. These considerations become particularly important when moving from controlled experiments and demonstration projects to routine farm operations.

AI should consequently be evaluated as part of a wider irrigation management system rather than as an isolated technological input. Its contribution depends on the quality of the underlying data, the suitability of the model, the availability of appropriate irrigation infrastructure, and the extent to which recommendations influence actual water management decisions. This perspective provides a basis for comparing Spain and South Korea without assuming that all smart irrigation initiatives use AI or that greater technological sophistication necessarily leads to measurable water savings.

2.2. Irrigation Efficiency, Water Productivity, and the Meaning of Water Savings

A rigorous assessment of AI enabled irrigation requires clear distinctions among irrigation efficiency, water productivity, and water savings. Although these concepts are closely related, they describe different aspects of agricultural water management and should not be used interchangeably.

Irrigation efficiency generally refers to the relationship between the water supplied to an irrigation system and the portion that is beneficially used, according to a specified definition and measurement boundary. At field level, an assessment may examine how much of the water delivered contributes to crop water requirements. The precise interpretation depends on the calculation method, measurement conditions, and water flows included in the analysis. An increase in a reported efficiency ratio is therefore not, by itself, sufficient evidence of an equivalent reduction in water consumption.

Water productivity relates agricultural output to a specified quantity of water used or consumed. Depending on the study, the numerator may represent crop yield, biomass, or economic value, while the denominator may refer to irrigation water applied, water withdrawn, or crop water consumption. These measures answer different questions. For example, an increase in crop output per cubic metre of irrigation water applied does not necessarily mean that total water consumption has declined. Meaningful comparisons consequently require a clearly defined indicator, unit of measurement, and system boundary.

Water savings must be interpreted with similar care. A reduction in the volume of water applied to a field may indicate improved irrigation scheduling or reduced application losses. However, some water that is not retained in the crop root zone may return to groundwater or surface water systems and remain available for downstream use. Whether a reduction in field level application constitutes a genuine saving at a wider hydrological scale depends on the fate of these flows and the way water is allocated and consumed.

Behavioural and production responses can further complicate the relationship between irrigation efficiency and water conservation. If improved irrigation performance encourages farmers to expand irrigated areas, introduce more water intensive crops, or increase cropping intensity, total water consumption may remain unchanged or increase. These possibilities do not negate the potential benefits of improved irrigation management; rather, they demonstrate why the scale and definition of evaluation matter.

Lankford et al. (2020) provide a scale based framework for understanding the promises, limitations, and paradoxes associated with irrigation efficiency. Their analysis emphasises that efficiency should not be treated as a universal solution to water challenges without considering hydrological processes, institutional arrangements, and the responses of water users. An intervention that reduces water application per hectare may improve farm management without producing an equivalent reduction in water depletion at the river basin level.

These distinctions have direct implications for the present study. Reported reductions in irrigation water application are interpreted according to the definitions and measurement boundaries provided by the original sources. Claims concerning water productivity are considered separately from claims concerning water savings. Neither type of improvement is treated as proof of basin level water conservation unless the supporting evidence explicitly establishes that outcome. This approach helps prevent the

environmental benefits of AI enabled irrigation from being overstated.

2.3. Evidence from Literature: Potential Benefits and Persistent Limitations

Research on smart irrigation identifies several potential benefits of integrating digital monitoring with AI based analysis. These include improved estimation of crop water requirements, more responsive irrigation scheduling, earlier identification of crop stress, and better coordination between water availability and agricultural demand. Such applications may be particularly relevant where rainfall is irregular, water resources are constrained, or crop water requirements vary substantially throughout the growing season.

Bounajra et al. (2024), in a systematic literature review, examined the use of emerging technologies to monitor and predict field characteristics relevant to irrigation management. Their review considered the roles of climatic, physical, chemical, hydrological, and biological conditions in irrigation processes. The analysis reinforces the importance of understanding field specific characteristics when developing irrigation strategies. Soil moisture or weather information alone may not be sufficient to produce an appropriate recommendation because crop characteristics, soil properties, and local growing conditions also influence irrigation requirements.

Despite these potential benefits, the evidence base remains heterogeneous. Studies differ in their objectives, crops, geographical settings, model architectures, data sources, evaluation periods, and performance indicators. Some assess predictive accuracy, others evaluate automated irrigation systems, and still others report changes in water application, crop yield, or water productivity. These outcomes cannot be combined into a single measure of effectiveness without considering their definitions and measurement conditions. In particular, a model that predicts irrigation demand accurately has demonstrated predictive performance, not necessarily a reduction in water consumption. Establishing the latter requires observed water use data and a clearly specified comparison baseline.

The distinction between model validation and agricultural impact is therefore central to evaluating AI enabled irrigation. A model may perform well on the dataset used during development but prove less reliable when applied to a different crop, soil type, climate, or irrigation system. Operational performance may also be affected by sensor calibration, missing observations, communication failures, maintenance requirements, and practical constraints that prevent farmers from following recommendations. Results from a limited number of trials should consequently be interpreted within the conditions under which they were obtained.

Economic and institutional considerations also influence implementation. AI based systems may require initial investment in equipment, recurring maintenance expenditure, reliable connectivity, technical assistance, and farmer training. These requirements can create barriers for smaller farms or areas with limited digital infrastructure. Data ownership, transparency, and the interpretability of recommendations may also affect users' confidence in the technology. The practical feasibility of an irrigation system is therefore as important as its technical performance when assessing its potential for wider adoption.

A further challenge concerns the transferability of results. A technology that performs effectively in a particular orchard, experimental field, or protected cultivation system may not deliver the same outcomes in open field crops or under different climatic and institutional conditions. Differences in irrigation infrastructure, crop water requirements, farm size, access to finance, and water allocation rules may influence both adoption and results. Consequently, evidence of success in one setting should be treated as a basis for further evaluation rather than as a guarantee of equivalent performance elsewhere.

These limitations do not imply that AI enabled irrigation lacks value. They indicate that its contribution should be evaluated through a framework that considers technical performance, agricultural outcomes, resource use, and practical feasibility. A credible assessment should identify the intervention being evaluated, define the baseline and indicators, explain the measurement period and system boundary, and provide sufficient methodological detail to judge the reliability and transferability of the findings. Where such information is unavailable, conclusions should remain proportionate to the evidence.

2.4. Implications for the Comparative Analysis of Spain and South Korea

The preceding literature indicates that a comparison of AI enabled irrigation should not rely solely on the

number of digital initiatives, the sophistication of a technology, or the magnitude of a reported percentage improvement. It should instead examine the nature of each intervention, the geographical and operational scale of the evidence, the outcomes measured, and the limitations affecting interpretation.

For Spain, national statistics on irrigated land and irrigation methods provide a structural description of the agricultural irrigation context. These statistics are important for understanding the scale and characteristics of irrigation, but they do not independently measure AI adoption or establish the impact of AI on water use. Documented research initiatives may provide evidence of technological development and institutional priorities, but their results must be distinguished from demonstrated outcomes at farm or national level.

For South Korea, institutional reports on selected smart irrigation applications provide evidence of how AI supported systems may operate in particular agricultural settings. Reported outcomes can illustrate potential benefits, but their interpretation depends on the details available concerning the crops, comparison baseline, measurement methods, duration of evaluation, and operating conditions. Application level results cannot be treated as national estimates unless evidence supports that generalisation.

The comparison therefore applies four analytical dimensions:

1. Irrigation context: the characteristics of each country's agricultural irrigation system, as described by available official statistics and institutional evidence.
2. Nature of the technological intervention: whether the documented application explicitly incorporates AI, how AI is integrated with sensors and monitoring technologies, and whether the system provides recommendations, automates irrigation decisions, or performs both functions.
3. Reported outcomes: the indicators documented by each source, including irrigation water applied, reported water savings, crop yield, water productivity, and operational requirements, where such information is available.
4. Strength and comparability of evidence: the credibility and transparency of the source, the scale of analysis, the availability of baseline information, the clarity of the measurement boundary, and the extent to which findings can be generalised.

These dimensions provide a consistent analytical structure without assuming that the two countries have equivalent data or that all reported indicators permit direct comparison. Where one country is represented by national structural statistics and the other by results from selected field applications, the difference in evidence scale must remain explicit. The analysis will therefore distinguish between descriptive context, documented technological applications, reported outcomes, and independently verifiable effects.

This framework serves the study's central purpose: to assess the potential contribution of AI enabled irrigation to agricultural water use efficiency while maintaining a clear distinction between established evidence, plausible benefits, and outcomes that require further empirical verification. It also provides the basis for identifying lessons for Algeria without assuming that technologies or reported results can be transferred directly across different agricultural, hydrological, and institutional settings.

3. Methodology and Data Sources

3.1. Research Design and Analytical Approach

This study adopts a comparative descriptive analytical approach to examine the potential contribution of artificial intelligence (AI) and related digital technologies to agricultural water use efficiency in Spain and South Korea. The two countries provide contrasting contexts for examining digital agricultural development, although differences in climate, agricultural structure, irrigation practices, and institutional arrangements limit direct comparisons.

Spain is characterised by substantial irrigated agricultural areas and significant regional pressures on water resources, particularly in areas exposed to recurrent droughts. South Korea provides a complementary case, given its investment in agricultural digitalisation and the development of AI assisted crop management technologies. Comparing these experiences helps identify the technological, institutional, and economic conditions under which digital tools may support more efficient irrigation.

The descriptive component documents agricultural water management challenges, relevant policy initiatives, and reported technological applications. The analytical component examines how digital

technologies can support irrigation decisions through soil moisture monitoring, crop water requirement estimation, meteorological forecasting, and the early detection of water stress.

A central distinction is maintained between AI and the wider digital systems with which it may be combined. Sensors, remote sensing, geographic information systems, and Internet of Things (IoT) devices collect, transmit, or organise information. AI algorithms may subsequently analyse these data to generate predictions or recommendations. Automated irrigation equipment, in turn, translates operational instructions into water application. These functions are complementary but should not be treated as interchangeable.

The study does not assume that the introduction of digital technologies necessarily produces measurable water savings. Instead, it examines whether published evidence documents improvements in irrigation management, agricultural performance, or water productivity. It also distinguishes farm level efficiency gains from reductions in total water consumption, which depend on water allocation, crop selection, irrigated area, and the governance of water resources.

3.2. Data Sources and Documentary Evidence

The analysis draws on secondary evidence from international organisations, national statistical authorities, public agricultural institutions, and published scientific research. Priority is given to sources that identify the geographical and agricultural setting, the technology examined, the reference period, and the outcomes reported.

Four categories of evidence inform the analysis.

First, the Food and Agriculture Organization of the United Nations (FAO), particularly its AQUASTAT information system, provides contextual indicators on water resources, agricultural water use, and irrigation. Because the reference years and availability of individual indicators vary, observations are interpreted according to their original reporting periods rather than treated as contemporaneous national measurements.

Second, publications from the Organisation for Economic Co operation and Development (OECD) provide information on agricultural innovation, water governance, and the institutional conditions affecting technology adoption. The OECD's country assessment of Korea reports that agriculture accounted for 53% of total water abstractions in 2018 and that irrigated land represented approximately 44% of agricultural area in the same year (OECD, 2021). These historical indicators establish the context for examining agricultural water management but do not measure the effects of AI.

Third, national government publications and official statistics are used to document agricultural structures, policy priorities, and technological initiatives. For Spain, the National Statistics Institute (Instituto Nacional de Estadística [INE]) provides the principal statistics on irrigable and irrigated agricultural land. For South Korea, publications from the Rural Development Administration (RDA) provide evidence on AI assisted crop water management and the development of agricultural data infrastructure. Government announcements are treated as evidence of policy direction or reported project performance, not as independent proof of national environmental outcomes.

Fourth, peer reviewed research and documented agricultural projects are used to examine applications of digital irrigation and their reported performance. Particular attention is given to studies reporting measurable indicators, including irrigation volumes, crop yields, water productivity, and the accuracy of irrigation recommendations. Where a project documents technological deployment without providing a sufficiently clear quantitative assessment, it is treated as evidence of implementation rather than proof of improved water use efficiency.

3.3. Comparative Framework and Analytical Indicators

The comparison is organised around five dimensions: water resource pressures, technological applications, institutional support, agricultural outcomes, and implementation constraints.

The first dimension considers the context in which digital technologies are introduced, including irrigation dependence, drought exposure, agricultural water withdrawals, and the characteristics of agricultural production.

The second identifies the technologies deployed, distinguishing AI based prediction and decision support from sensor monitoring, remote sensing, conventional irrigation equipment, and automation.

The third examines institutional and economic conditions, including public programmes, research capacity, digital infrastructure, farmer training, and

access to investment. These conditions influence whether technological applications can be adopted, maintained, and used effectively.

The fourth assesses documented outcomes using the following indicators, where sufficiently reliable observations are available:

- **Irrigation water applied:** the volume of water delivered to fields over a specified period.
- **Water productivity:** agricultural output or economic value generated per unit of water, with the denominator explicitly defined.
- **Irrigation performance:** the timing, adequacy, and precision of water application.
- **Agricultural productivity:** crop yield or other relevant production outcomes.
- **Environmental performance:** changes in water abstraction or consumption and related pressures on water resources.

The fifth dimension examines barriers such as installation and maintenance costs, fragmented farm structures, data limitations, interoperability problems, digital skills, and the difficulty of translating farm level efficiency gains into basin level conservation.

Table 1. Comparative analytical framework

Dimension	Main indicators or evidence	Analytical purpose
Water resource context	Irrigated area, water withdrawals, drought exposure	Establish the context for irrigation improvement
Digital and AI applications	Sensors, predictive models, decision support tools, automated irrigation	Identify technological functions and their actual degree of AI integration
Institutional environment	Public programmes, research support, infrastructure, training	Assess the conditions supporting adoption
Agricultural outcomes	Irrigation volumes, yields, water productivity, scheduling performance	Examine documented results
Implementation constraints	Costs, data quality, skills, farm structure, governance	Identify barriers to effectiveness and wider adoption

Source: Author's analytical framework, informed by FAO AQUASTAT, OECD publications, national statistics, and documented agricultural applications.

3.4. Data Comparability and Methodological Limitations

Comparability is a central methodological concern. Spain and South Korea differ in climatic conditions, crop composition, agricultural organisation, irrigation infrastructure, and institutional arrangements. The available studies also examine different crops, geographical areas, technologies, and observation periods. Accordingly, a percentage reduction reported for an individual orchard cannot be generalised to a national agricultural sector or directly compared with a result obtained under different experimental conditions.

The analysis therefore distinguishes national level contextual indicators from project level performance evidence. It also recognises differences between water withdrawal, irrigation application, consumptive water use, and water productivity. These indicators describe different aspects of agricultural water management and should not be used interchangeably.

Causal attribution presents a further limitation. Improvements observed after a digital technology is introduced may also reflect changes in irrigation infrastructure, agronomic practices, crop varieties, weather conditions, or complementary investment. Causal claims are therefore avoided unless the original study provides a research design capable of supporting them.

Finally, publicly accessible and standardised measurements of water savings attributable specifically to AI remain limited in the evidence reviewed. Policy announcements, adoption targets, and the expansion of digital infrastructure demonstrate institutional commitment but do not establish environmental effectiveness. The subsequent country analyses consequently assess the evidence according to its scope and quality rather than assuming that technological sophistication necessarily leads to better water outcomes.

4. Spain: Artificial Intelligence and Agricultural Water Use Efficiency

4.1. Agricultural Irrigation and Pressure on Water Resources

Spain provides a relevant setting for examining digital approaches to agricultural water management. Its agricultural sector includes extensive irrigated areas, diverse irrigation systems, and substantial regional variation in water availability. These characteristics make irrigation management particularly important in areas exposed to drought and seasonal water scarcity.

According to the INE's 2023 Farm Structure Survey, Spain had 3,513,097 hectares of irrigable agricultural land, of which 2,739,252 hectares were irrigated at least once during the reference period (INE, 2025). The difference reflects the distinction between land equipped for irrigation and land actually irrigated during the year.

Table 2. Irrigable and irrigated agricultural land in Spain, 2023

Indicator	Area (hectares)
Irrigable agricultural area	3,513,097
Agricultural area actually irrigated	2,739,252
Difference	773,845
Irrigated area as a share of irrigable area	78.0%

Source: INE (2025). The percentage is calculated from the reported figures.

The calculation indicates that approximately 78.0% of the irrigable area was irrigated during the reference period. This provides a structural indicator of the scale of irrigation management, but it does not measure water application per hectare or the efficiency with which crops use water.

Digital tools may help farmers estimate crop water requirements, monitor spatial variations in soil moisture, and adjust irrigation schedules to weather conditions. Their effectiveness, however, must be assessed using water volumes, crop performance, and environmental indicators rather than irrigated areas alone.

4.2. Irrigation Structure and Opportunities for Digital Optimisation

The distribution of irrigation methods provides further insight into Spain's agricultural water management system. The INE reports that localised irrigation accounted for 49.0% of irrigated area in 2023, compared with 31.6% for sprinkler irrigation and 19.4% for gravity irrigation (INE, 2025).

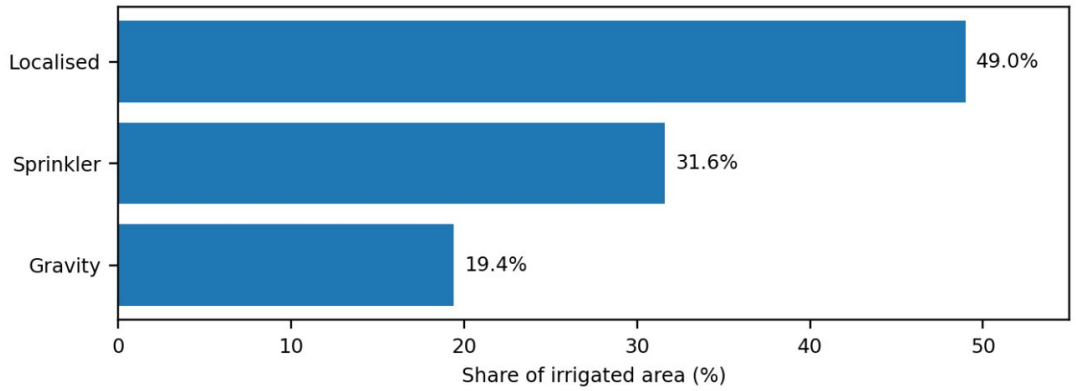


Figure 1. Distribution of irrigated agricultural area by irrigation method in Spain, 2023

Source: Author's visualisation based on INE (2025). Localised irrigation includes drip and other localised methods.

The relatively large share of localised irrigation indicates that a substantial part of Spain's irrigated agricultural area already uses systems capable of delivering water close to plant roots. This infrastructure may provide a foundation for further improvements through digital monitoring and decision support. Nevertheless, irrigation equipment and AI perform different functions: the former delivers water, whereas AI based systems may help determine when and how much water should be applied.

The remaining irrigated area using sprinkler and gravity methods should not automatically be classified as inefficient. Performance depends on system design, maintenance, operating conditions, crop characteristics, and local agronomic requirements. Digital interventions should therefore target demonstrated opportunities for improvement rather than assume that one irrigation method is universally superior.

Crop composition also matters. The INE reports that grain cereals represented 30.7% of Spain's irrigated outdoor agricultural area in 2023, while olive groves accounted for 16.1%. These figures suggest that improvements in irrigation management for cereals and olives may be relevant to substantial parts of the irrigated system. However, the potential benefits will vary according to crop water requirements, production practices, and local water constraints.

4.3. Evidence from Digital Agriculture and Irrigation Decision Support

Spain's documented experience includes projects combining agricultural monitoring, sensor networks, and digital decision support tools. The strength of the evidence depends on the functions actually deployed and the outcomes measured.

An illustrative example is the MARIPOSA operational group in Andalusia, documented by the EU CAP Network. The project, implemented during 2023–2025, aims to improve the measurement and management of agricultural water and carbon footprints through distributed monitoring and analytical tools. Its practice abstract reports that the installed LoRaWAN sensor network achieved real time data transmission in 95% of cases. It also reports a 15% reduction in water consumption in pilot areas compared with traditional practices, while noting that smart irrigation had not yet been implemented at the stage described (EU CAP Network, n.d.-b).

The reported results suggest that more detailed information may support changes in farm management. However, the 15% reduction cannot be attributed specifically to an operational AI irrigation system. The evidence concerns the combined effects of monitoring and changes in agricultural practices, and the source does not establish an isolated causal contribution from AI.

A second example is a sensor based decision support tool evaluated in a commercial olive orchard in eastern Spain during 2022 and 2023. The study, published in *Agricultural Water Management*, reports that the Soil Atmosphere Adjusted Model (SAAM) reduced irrigation volume by 11%, equivalent to 11.9 mm, compared with a conventional technician guided strategy. Reported irrigation volumes were 99.4 mm under the decision support approach and 111.3 mm under the conventional strategy. No statistically significant differences were observed in olive or oil yields between treatments (Bonet, 2026).

This study provides field level evidence that sensor based scheduling can reduce irrigation application without a detected yield penalty under the tested conditions. Nevertheless, the system is described as a simplified sensor based model using evapotranspiration and soil water information. It should therefore be classified as digital decision support rather than presented as direct proof of an AI specific effect.

Table 3. Selected evidence on digital monitoring and irrigation optimisation in Spain

Application	Setting	Reported result	Interpretation
MARIPOSA monitoring network	Andalusia; 2023–2025 project	95% real time data transmission; 15% reported reduction in water consumption in pilot areas	Evidence of monitoring deployment and reported management improvements, not an isolated AI irrigation effect
Sensor based irrigation decision support	Commercial olive orchard, eastern Spain; 2022–2023 trials	11% reduction in irrigation volume (11.9 mm), with no significant difference in olive or oil yield	Field level evidence of improved irrigation management under the tested conditions

Sources: EU CAP Network (n.d.); (Bonet, 2026). These results arise from distinct projects and should not be interpreted as directly comparable national water saving rates.

Taken together, the cases indicate that monitoring and decision support technologies can improve the alignment between irrigation supply and crop requirements. However, the available evidence does not establish that comparable savings can be achieved throughout Spain's irrigated agricultural sector.

4.4. Assessment of the Spanish Experience

Three conclusions emerge from the Spanish case.

First, the scale of irrigated agriculture makes improvements in water management potentially important for agricultural and regional water policy. Even modest improvements could matter if achieved across large areas without reducing agricultural output. The magnitude of any aggregate benefit, however, cannot be inferred from irrigated area alone.

Second, digital irrigation depends on complementary technologies and practices. Sensors collect information on soil and crop conditions, meteorological services provide information about weather, and decision support systems combine these inputs into operational recommendations. AI may add value where predictive or learning based methods improve decision quality, but such added value must be demonstrated rather than assumed.

Third, farm level efficiency does not necessarily translate into lower water consumption at basin level. Water savings may be used to expand irrigated areas, change crop choices, or increase production. Consequently, the environmental contribution of digital irrigation depends on water allocation, abstraction monitoring, and the management of surface water and groundwater resources.

For Spain, the principal policy implication is that digital irrigation should be evaluated through transparent indicators, including irrigation volume per hectare, crop output per unit of water consumed, changes in groundwater abstraction, and production stability under drought conditions. These measures would help distinguish improvements in operational performance from genuine reductions in pressure on water resources.

Overall, Spain offers evidence of the potential of digital monitoring and decision support, but the additional contribution of AI and the durability of water savings require further independent, standardised field evaluation.

5. South Korea: Artificial Intelligence and Agricultural Water Use Efficiency

5.1. Water Resource Constraints and the Development of Smart Agriculture

South Korea provides a complementary case for examining the potential contribution of AI to agricultural water management. Its experience includes institutional investment in digital agriculture and the development of technologies intended to improve crop monitoring, irrigation decisions, and agricultural productivity.

According to the OECD's assessment of agriculture and water policies, agriculture accounted for 53% of total water abstractions in South Korea in 2018, while irrigated land represented approximately 44% of the country's agricultural area (OECD, 2021). Although these figures are historical, they illustrate the importance of agricultural water management in the national context.

Table 4. Selected indicators of agricultural water management in South Korea

Indicator	Reported value	Reference year
Agriculture's share of total water abstractions	53%	2018
Irrigated land as a share of agricultural area	Approximately 44%	2018

Source: OECD (2021), country note on agriculture and water policies in Korea.

These indicators establish the relevance of agricultural water management but do not measure the impact of AI. The share of national water abstractions allocated to agriculture is different from irrigation efficiency, which concerns the relationship between water inputs and agricultural outputs.

The Korean experience is therefore assessed at two levels: the institutional and technological conditions supporting innovation, and the reported outcomes of specific applications of AI assisted crop water management.

5.2. Evidence from AI Based Crop Water Management

A relevant example is the AI based crop water management technology developed by South Korea's Rural Development Administration (RDA). The system combines information on crop physiological conditions with data used to diagnose water stress and predict the water supply required by plants.

The RDA's 2020 research achievements report states that the system achieved 98% accuracy in predicting crop water supply requirements. In applications involving apple and peach production, the RDA also reported a 25–31% reduction in agricultural water use, a 27–34% reduction in crop water stress during heatwaves and droughts, a 14–26% increase in fruit weight, and an approximately 8% increase in sweetness (RDA, 2020).

These results are relevant because they link a specific technological application to several reported performance indicators. Nevertheless, the indicators measure different outcomes. Prediction accuracy concerns the technical performance of the system, water use reduction concerns irrigation related inputs, and fruit weight and sweetness concern agricultural production and quality.

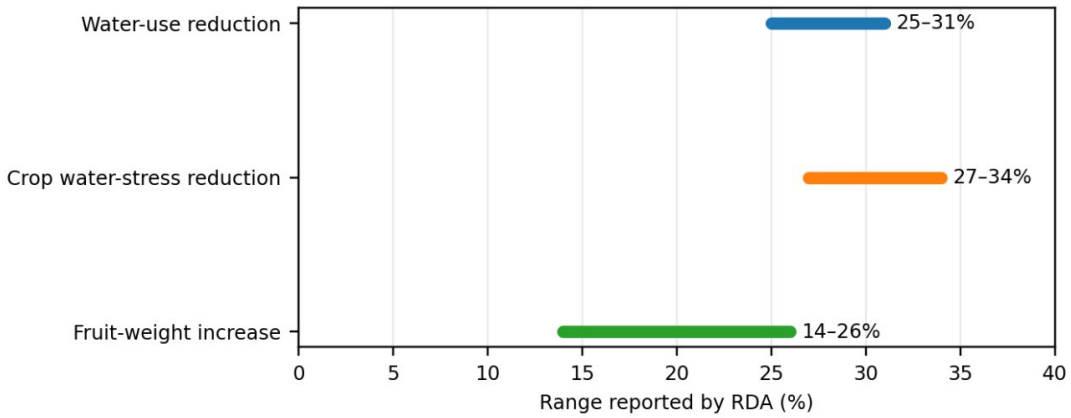


Figure 2. Selected outcomes reported for AI based crop water management in South Korea

Source: Author's visualisation based on RDA (2020). Outcomes are reported separately and should not be interpreted as a common performance index.

The reported findings suggest that AI assisted crop water management may improve irrigation decisions while supporting selected crop characteristics. However, the official summary does not provide all the information needed for an independent assessment of the experimental design, sample size, baseline irrigation volumes, and statistical uncertainty. The results should therefore be treated as institutionally reported application level evidence, not as nationally representative estimates.

The reported 25–31% reduction cannot be assumed to apply to rice production, all fruit orchards, or the entire agricultural sector. Comparisons with other countries also require similar crop conditions, baselines, monitoring periods, and definitions of water use.

5.3. Agricultural Productivity and Economic Implications

The economic relevance of AI assisted irrigation extends beyond water savings. More precise irrigation may reduce unnecessary water application, support crop performance during heat and drought, and reduce the time required for manual monitoring and irrigation decisions.

However, these benefits must be evaluated separately. Higher yields do not necessarily imply improved water productivity, and shorter irrigation times do not necessarily indicate lower water consumption. Similarly, the economic value of a technology depends on its installation and maintenance costs, energy requirements, operational reliability, and effects on crop revenues.

Table 5. Performance dimensions of AI assisted irrigation in South Korea

Performance dimension	Officially reported result	Analytical significance
Water supply prediction	98% prediction accuracy	Reported technical performance
Agricultural water use	25–31% reduction	Potential savings in documented applications
Crop water stress	27–34% reduction	Reported improvement under heat and drought
Fruit characteristics	14–26% increase in fruit weight; approximately 8% increase in sweetness	Potential production and quality benefits

Source: RDA (2020). The figures refer to the applications documented in the original report and should not be interpreted as national averages.

The table summarises the reported results without combining them into a single performance index. A more complete economic evaluation would require information on installation costs, maintenance, energy use, changes in irrigation volumes, crop revenues, and the time needed to recover the investment.

5.4. Agricultural Data Infrastructure and Digital Capacity

AI based irrigation depends on reliable information systems. Crop and soil observations, weather data, communication networks, and compatible field equipment are necessary to generate useful recommendations and translate them into practical decisions.

The RDA's 2021 research achievements report documents the expansion of agricultural data collection infrastructure. The figures used in the original manuscript indicate an increase from 1,690 collection locations covering 10 data categories in 2020 to 1,882 locations covering 17 categories in 2021. These figures should be retained in the final paper only after their precise definitions and source table have been verified against the original report.

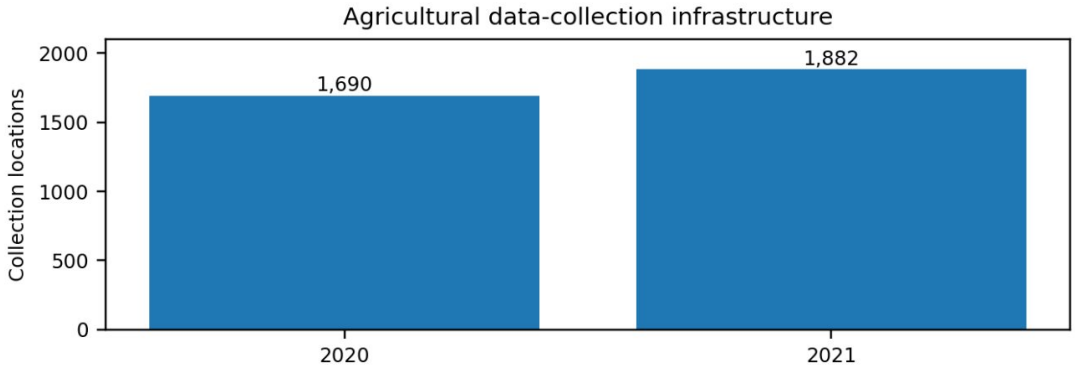


Figure 3. Expansion of agricultural data collection infrastructure in South Korea, 2020–2021

Source: Author's calculations based on RDA (2021). The RDA reports 1,690 collection locations across 10 data categories in 2020 and 1,882 locations across 17 categories in 2021.

The distinction matters because expanded data infrastructure can facilitate the development and validation of AI applications without automatically producing better water management outcomes. Data must be accurate, relevant, sufficiently frequent, and connected to operational decisions. Farmers and water managers must also be able to access and interpret the resulting recommendations.

The institutional implication is that investment in AI should be accompanied by support for data quality, interoperability, technical assistance, and farmer training.

5.6. Implementation Constraints and Conditions for Scaling Up

Despite technological progress, extending AI assisted water management

across agricultural holdings involves several challenges.

First, installation and maintenance costs may constrain adoption, particularly among farms with limited financial resources or restricted access to technical services. Second, model performance depends on the quality of the data and the suitability of the system for particular crops, soils, and climatic conditions. A model developed for fruit orchards cannot automatically be transferred to rice or vegetables without appropriate validation.

Third, farm level efficiency gains do not necessarily translate into reductions in total water consumption. If water saved through improved irrigation is used to expand irrigated areas or increase water intensive production, the net conservation effect may be limited. Water governance and allocation arrangements must therefore complement efficiency improvements.

A credible assessment of AI assisted irrigation should report water applied per hectare, crop output per unit of water consumed, changes in total abstraction, and agricultural performance under comparable climatic conditions. Where feasible, these indicators should be measured before and after adoption and compared with similar farms using conventional irrigation methods.

5.7. Overall Assessment

South Korea provides documented evidence of the potential contribution of AI based crop water management to more precise irrigation. The RDA's reported results demonstrate the feasibility of integrating crop water stress diagnosis and water supply prediction into agricultural decision making. The development of agricultural data infrastructure further indicates the institutional foundations supporting digital agriculture.

Three distinctions remain essential. Prediction accuracy is not equivalent to water savings; shorter watering times are not equivalent to lower water consumption; and results from selected applications cannot be generalised to the entire agricultural sector without broader validation.

The Korean experience therefore supports a qualified conclusion: AI may strengthen agricultural water management, but its contribution to sustainable water use depends on technological performance, implementation conditions, and governance arrangements.

6. Comparative Analysis of Spain and South Korea

6.1. Comparative Overview

Spain and South Korea provide complementary contexts for examining digital technologies in agricultural water management. Both countries have incentives to improve the efficiency of water use, but they differ in agricultural structure, irrigation practices, institutional arrangements, and the available evidence.

Spain's experience highlights the scale and structure of irrigated agriculture and selected applications of sensor-based monitoring and irrigation decision support. South Korea's experience highlights institutional investment in agricultural data infrastructure and reported applications of AI assisted crop water management.

Table 6. Comparative characteristics of agricultural water management in Spain and South Korea

Dimension	Spain	South Korea
Main analytical focus	Irrigated agriculture and digital irrigation management	Agricultural data infrastructure and AI assisted crop water management
Principal evidence	National statistics, project documentation, and field studies	Institutional reports and selected technology applications
Relevant technologies	Localised irrigation, sensors, and decision support tools	Crop water prediction, sensor-based monitoring, and data supported irrigation
Reported benefits	Reduced irrigation inputs in selected applications	Reported water savings and improvements in selected crop indicators
Main limitation	National irrigation statistics do not measure AI adoption or its independent impact	Selected application results are not national averages
Priority for further research	Link technology adoption to water withdrawals and basin conditions	Independently validate water savings and crop outcomes

Source: Author's synthesis based on INE (2025), OECD (2021), EU CAP Network documentation, and RDA (2020).

The comparison indicates that technological capacity alone is insufficient to establish environmental effectiveness. National indicators provide context, while project level results illustrate what particular technologies may achieve under specific conditions. These two types

of evidence should remain analytically distinct.

6.2. Interpreting Reported Water Savings

The evidence reviewed includes an 11% reduction in irrigation volume in a Spanish olive orchard study and a reported 25–31% reduction in agricultural water use in selected South Korean orchard applications. These results illustrate the potential benefits of improved irrigation management, but they do not establish that South Korean technologies are inherently more effective than Spanish approaches.

The studies differ in crop characteristics, baseline practices, experimental conditions, monitoring periods, and technology design. Furthermore, the Spanish decision support tool is described as a sensor-based model, whereas the Korean application explicitly incorporates AI. Their results should therefore be compared as examples of different approaches rather than as equivalent tests of AI performance.

A rigorous comparison would require consistent definitions of irrigation water applied, comparable baseline conditions, information on crop yield and quality, and clear reporting of evaluation periods. Where possible, studies should also report uncertainty estimates and distinguish reductions in irrigation application from reductions in total abstraction or consumptive water use.

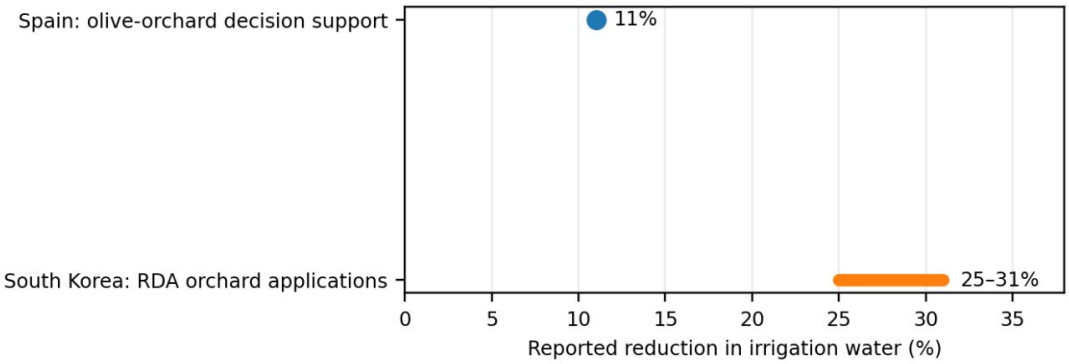


Figure 4. Reported irrigation water reductions in selected orchard applications

Source: Author's synthesis based on (Bonet, 2026) *and RDA (2020). The approximately 11% Spanish result and the 25–31% Korean result should be displayed as separate case study findings, not as national performance indicators or directly equivalent estimates.*

6.3. Farm Level Efficiency and Basin Level Conservation

A central issue in evaluating digital irrigation is the distinction between improving farm level water use efficiency and reducing pressure on water resources at basin level.

A farmer may use sensors, predictive models, or automated controls to apply less water while maintaining crop yields. This may represent an improvement in irrigation management. The wider hydrological outcome, however, depends on how saved water is used and how allocation is governed. Farmers may expand irrigated areas or shift towards more water intensive crops, limiting the net reduction in water consumption.

Assessment should therefore cover three levels:

- **Farm level:** irrigation volume, crop yield, water productivity, energy consumption, and operating costs.
- **Irrigation scheme level:** aggregate water deliveries, distribution performance, supply reliability, and compliance with allocation rules.
- **Basin level:** total abstraction, groundwater trends, environmental flows, and changes in consumptive water use.

These distinctions are necessary to avoid overstating the environmental benefits of technologies that reduce water application per hectare without reducing overall pressure on water resources.

6.4. Institutional and Technical Conditions for Successful Adoption

The experiences of Spain and South Korea indicate that digital irrigation depends on more than algorithms and sensors. Reliable data, suitable infrastructure, farmer capacity, institutional

coordination, and economic viability also matter.

First, recommendations are only as reliable as the data used to generate them. Soil moisture observations, weather information, crop characteristics, irrigation system performance, and water availability must be sufficiently accurate and timely.

Second, the value added by AI should be assessed against simpler alternatives. Soil moisture sensors, weather based scheduling, and established agronomic decision rules may deliver substantial benefits at lower cost. AI should be prioritised where it demonstrably improves decision quality or operational performance beyond what simpler methods can achieve.

Third, adoption requires technical support and training. Farmers must be able to interpret recommendations, identify equipment problems, and respond when model outputs conflict with field observations. Systems that are expensive or difficult to maintain may remain confined to demonstration projects even when their technical performance is promising.

Finally, public authorities, research institutions, agricultural organisations, and technology providers have complementary roles. Public institutions can establish measurement standards and support water accounting; researchers can independently evaluate agronomic and technical performance; and technology providers can supply equipment and maintenance. Claims about performance should be assessed against independently measured outcomes.

6.5. A Framework for Evaluating AI Enabled Irrigation

Future studies would benefit from a common evaluation framework covering the indicators below.

Table 7. Recommended indicators for evaluating digital and AI enabled irrigation

Indicator	Measurement purpose	Reporting requirement
Irrigation water applied	Measures water delivered to fields	Volume per hectare and evaluation period
Crop yield	Identifies production effects	Yield per hectare, crop, and season
Water productivity	Relates output to water use	Clearly defined output per cubic metre
Irrigation energy use	Measures energy implications	Energy per hectare or unit of output
Economic performance	Assesses financial viability	Installation, maintenance, operating costs, and net benefits
Soil moisture and crop stress	Evaluates agronomic relevance	Measurement method, calibration, and monitoring frequency
Total abstraction and consumptive use	Assesses wider water resource implications	System boundary and consistent water accounting method
Model performance	Evaluates prediction or recommendation quality	Validation method, error metrics, and baseline comparison

Source: Author's proposed framework, informed by the methodological limitations identified in the reviewed evidence.

Evaluations should report both absolute and relative changes. Percentage savings alone can be misleading when baseline irrigation volumes differ substantially. Studies should also document crop yield and quality, weather conditions, irrigation system characteristics, and whether results were compared with conventional scheduling, a control group, or a previous production season.

Where feasible, independent field evaluations should be complemented by multi-season monitoring. This would help distinguish genuine technological improvements from differences arising from rainfall, temperature, crop development, or other changes in farm management.

6.6. Policy Implications

The comparison yields five policy implications.

First, investment should focus on clearly defined water management problems rather than technology adoption as an end in itself. Programmes should establish measurable objectives and specify how performance will be evaluated.

Second, pilot projects should establish credible baselines and, where feasible, use comparison groups or other appropriate evaluation methods. Decisions to scale up should depend on demonstrated agronomic, economic, and water management benefits rather than equipment installation or model accuracy alone.

Third, public support should encourage data quality, interoperability, and transparent reporting. Common measurement standards would improve comparability across projects and reduce dependence on individual technology providers.

Fourth, farm level efficiency programmes should be coordinated with water allocation, groundwater monitoring, and basin level planning. Without such coordination, improvements in irrigation efficiency may not produce equivalent reductions in total water consumption.

Finally, implementation should account for differences in farm size, crop type, digital connectivity, technical skills, and financial capacity. Training and appropriately designed support programmes can improve access while recognising that no single technology is suitable for every agricultural setting.

7. Conclusions and Policy Recommendations

7.1. Main Conclusions

This study examined the potential contribution of artificial intelligence (AI) and data driven technologies to agricultural water use efficiency through a comparative descriptive analytical assessment of Spain and South Korea. Drawing on official statistics, institutional reports, project documentation, and selected scientific studies, the analysis considered the potential benefits of digital irrigation management and the limitations of the available evidence.

The findings indicate that digital technologies can support more precise irrigation decisions by integrating information on soil moisture, weather conditions, crop water requirements, and irrigation system performance. Selected applications have reported reductions in irrigation inputs or improvements in crop related indicators. However, the magnitude and reliability of these benefits depend on the technology employed, crop characteristics, data quality, evaluation methods, and implementation conditions.

The Spanish case demonstrates the importance of distinguishing the structure of irrigated agriculture from the actual adoption and effectiveness of AI. National statistics provide a valuable account of irrigated land and irrigation methods, while project documentation and field studies offer more specific evidence of technological performance. Nevertheless, the findings from individual applications cannot be generalised to the national agricultural sector without further validation.

The South Korean case highlights the role of institutional support, agricultural data infrastructure, and technology-assisted crop management. Selected applications have reported promising results, but their indicators differ in scope and meaning. Reductions in irrigation volume, watering time, and crop water stress are not interchangeable measures. In particular, a reduction in watering time does not necessarily imply an equivalent reduction in water consumption.

The comparative assessment therefore leads to a central conclusion: **the contribution of AI to agricultural water use efficiency must be demonstrated through transparent measurement and independent evaluation, rather than inferred from technology adoption or model performance alone.** Farm level improvements must also be distinguished from reductions in total water abstraction and consumptive water use at irrigation scheme and basin levels.

The findings further suggest that AI should be considered part of a broader irrigation management system rather than a stand-alone solution. Its effectiveness depends on reliable data, appropriate agronomic practices, economically viable equipment, farmer capacity, and effective water governance.

7.2. Policy Recommendations

The comparative findings support eight policy recommendations.

1. Establish measurable objectives before introducing technology.

Projects should identify the specific water management problem they intend to address, such as excessive irrigation, poorly timed water applications, high pumping costs, or inadequate information on crop water requirements. Baseline conditions and performance indicators should be established before implementation.

2. Begin with controlled pilot applications.

Initial implementation should focus on selected crops and production systems where irrigation is important and reliable monitoring is feasible. Pilot projects should compare the proposed technology with existing practices and, where appropriate, simpler decision support methods. Wider deployment should depend on verified results rather

than the number of devices installed.

3. Strengthen agricultural data quality and interoperability.

Effective decision support requires reliable and sufficiently frequent observations of weather, soil moisture, crop development, irrigation volumes, and system performance. Data should be collected using consistent protocols, maintained over time, and made compatible across systems wherever feasible. Sensor calibration errors, missing observations, and uncertainty in model outputs should be documented.

4. Evaluate AI against simpler alternatives.

AI should not automatically be preferred over established irrigation scheduling methods. Evaluations should determine whether advanced models provide additional benefits in water savings, crop performance, reliability, or economic returns compared with simpler approaches. The additional costs and technical requirements of AI should be assessed alongside its potential benefits.

5. Measure water savings directly.

Where feasible, programmes should use metered irrigation volumes and report water applied per hectare alongside crop yield, water productivity, energy consumption, and operating costs. Where resource conservation is the primary objective, monitoring should also consider total abstraction, groundwater conditions, and consumptive water use at an appropriate spatial scale.

6. Strengthen farmer capacity and technical support.

Training should cover the interpretation of irrigation recommendations, equipment operation and maintenance, the limitations of predictive systems, and the role of field observations in decision making. Accessible technical support is essential for maintaining systems beyond the initial project period.

7. Integrate irrigation efficiency with water governance.

Farm level efficiency programmes should be coordinated with water allocation, groundwater management, drought planning, and environmental requirements. Without such coordination, efficiency gains may be offset by expanded irrigated areas or changes in production patterns that increase total water demand.

8. Ensure transparent and independent performance evaluation.

Evaluation reports should disclose the study design, crop and location, baseline irrigation practices, monitoring period, weather conditions, data limitations, and statistical uncertainty where available. Independent evaluation can strengthen confidence in reported outcomes and distinguish robust benefits from results specific to a single project or season.

7.3. Proposed Implementation Roadmap

A phased implementation framework can translate the comparative findings into practical programmes while controlling technical and financial risks.

Table 8. Proposed roadmap for implementing AI enabled agricultural water management

Phase	Main activities	Key performance indicators	Decision criterion
Phase 1: Diagnosis and baseline	Identify water management problems, crops, sites, and existing irrigation practices	Baseline irrigation volume, yield, energy use, and operating costs	Sufficient data and a clearly defined management problem
Phase 2: Pilot design	Select the technology, establish comparison conditions, and define monitoring protocols	Data completeness, sensor reliability, and evaluation readiness	Credible design for measuring additional benefits
Phase 3: Field testing	Test the technology under operational conditions and compare it with existing practices	Water applied per hectare, yield, water productivity, and costs	Demonstrated performance without unacceptable agronomic or financial trade offs
Phase 4: Independent assessment	Evaluate results across relevant seasons and assess uncertainty	Consistency of results, cost-effectiveness, and reliability	Evidence that benefits are sufficiently robust to justify expansion
Phase 5: Targeted scaling	Expand to suitable production systems and strengthen training and maintenance	Adoption, system reliability, verified water savings, and economic performance	Continued monitoring and evidence of sustained benefits

Source: Author's proposal, based on the comparative analysis and the need for measurable, independently evaluated outcomes.

The roadmap is a general decision framework rather than a fixed timetable. Progress between phases should depend on data quality, technical feasibility, costs, and demonstrated performance. A technology that performs well for one crop or location may require adaptation before being introduced elsewhere.

7.4. Limitations of the Study

Several limitations should be acknowledged.

First, the study relies on published statistics, institutional reports, project documentation, and existing scientific literature rather than a harmonised primary dataset collected under a common experimental protocol. The evidence consequently differs in geographical coverage, measurement methods, reference periods, and methodological transparency.

Second, national statistics describe the structure of agricultural water use but do not necessarily identify the independent contribution of AI. Project level studies may provide more detailed performance information, but their findings are not automatically representative of national conditions.

Third, reported water savings may be influenced by crop type, baseline irrigation practices, weather, soil conditions, equipment, and monitoring duration. The comparison does not establish that the reported percentages are directly comparable across Spain and South Korea, nor does it demonstrate the causal superiority of one country's approach.

Fourth, the study does not independently reproduce the results of every documented project. Quantitative claims are therefore interpreted according to the original sources and the methodological limitations of the reported evidence. In particular, institutional announcements and project summaries should not be treated as equivalent to independently replicated field studies.

Finally, the available evidence does not consistently distinguish irrigation application, water withdrawal, and consumptive water use. These measures describe different aspects of agricultural water management, and differences in their definitions limit the scope for direct comparison.

7.5. Directions for Future Research

Future research should examine the long term performance of AI enabled irrigation under different climatic, agronomic, and institutional conditions. Multi season field studies could establish whether reported water savings persist across changing weather conditions and whether they can be achieved without compromising crop yield or quality.

Further work should compare AI based systems with lower cost alternatives, including soil moisture sensors and conventional weather based irrigation scheduling. Such comparisons would help determine when advanced models provide sufficient additional value to justify their cost and technical complexity.

A further priority is the development of consistent evaluation protocols. Studies should report baseline water use, irrigation volumes, crop outcomes, model performance, economic costs, and relevant environmental indicators. Where water resource protection is the objective, evaluations should extend beyond individual farms to examine aggregate abstraction, groundwater trends, and potential rebound effects.

Future research should also investigate technology adoption and distributional effects, including affordability, training requirements, technical support, and the capacity of farms of different sizes to maintain digital systems. These dimensions are essential for determining whether technological improvements can be sustained beyond demonstration projects.

Finally, comparative studies should distinguish the contribution of AI from that of sensors, automation, improved irrigation infrastructure, and changes in agronomic practices. This would provide a stronger basis for identifying the conditions under which AI generates measurable additional benefits.

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