



REGIONAL PRIORITIZATION OF DIGITAL IRRIGATION MANAGEMENT IN SOUTHERN KAZAKHSTAN: A MULTI-LEVEL DECISION-SUPPORT FRAMEWORK

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Abstract. *The purpose:* Irrigated agriculture in Southern Kazakhstan faces water scarcity, climatic stress, and uneven adoption of water-saving irrigation technologies, creating a need for transparent regional prioritization of digital irrigation management. *Methods:* This study develops a multi-level, non-causal decision-support framework for Turkestan, Kyzylorda, and Zhambyl. The framework combines three analytically separate evidence blocks: a descriptive field-level water-balance comparison, contextual treatment-level economic evidence, and regional indicators of technology adoption, relative climate stress, land suitability, and observable implementation readiness. *Results:* The first two blocks provide contextual evidence and do not measure digitalization or enter the composite index. Only regional indicators are integrated through the Digital Irrigation Management Priority Index (DIMPI). In the source-reported grain-maize trial, seasonal total water consumption was 3,282 m³/ha under drip irrigation versus 3,996 m³/ha under discrete irrigation, a descriptive difference of 17.87%. *Conclusions:* Under all prespecified DIMPI weighting scenarios, Turkestan ranked first, while Kyzylorda and Zhambyl exhibited contrasting need-readiness profiles. The results support the use of DIMPI as a preliminary screening tool for identifying where more detailed digital-irrigation feasibility assessment may be warranted, rather than as an estimate of digitalization effects or project-level investment returns.

Keywords: digital irrigation management, regional prioritization, decision-support framework, water-saving irrigation technologies, implementation readiness, composite index, Southern Kazakhstan.

Introduction

In irrigated farming, water is a scarce economic good, the distribution of which has significant opportunity cost; its improvement involves more than just physical efficiency gains (Molden et al., 2010). Decreased use of water on a field basis does not necessarily mean decreased use on a basin basis because decreased return flows and behavior can counterbalance reductions (Grafton et al., 2018). For this reason, economic analysis stresses that

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the benefits of investments in water-saving technologies will be contingent upon the quality of water allocation and available information to irrigation managers (Pérez-Blanco et al., 2020). Therefore, irrigation policy should be based on information about the economic efficiency of operations alongside technological efficiency.

These problems manifest themselves particularly acutely in Southern Kazakhstan, specifically in Turkestan, Kyzylorda, and Zhambyl, which experience water scarcity and use of transboundary flows in some parts of the southern irrigation system. According to national estimates, inadequate conveyance infrastructure and water consumption inefficiency represent the major restrictions to the development of Kazakhstan's water economy (Karatayev et al., 2017); however, recent field research conducted in the Turkestan area shows significant variations in water availability and salinity limits to the utilization of drainage waters (Ayana et al., 2024). The implementation of water-saving irrigation systems is rather patchy and incomplete (World Bank, 2024), and agriculture is one of the sectors that are the least developed in terms of digitalization (Shalbolova et al., 2025). Under these circumstances, the determination of regional priorities in the modernization of irrigation practices represents a meaningful problem.

In this research, digital irrigation management is understood in its broadest sense as irrigation decision-making informed through the use of monitoring data, geospatial technology, remote sensing data, hydrologic databases, and computerized water allocation, with possible future inclusion of control sensors and automatic water delivery. The economic importance of the phenomenon under investigation relates mostly to informational and management aspects: better monitoring, improved irrigation scheduling, more accurate water accounting, spatial coordination, and reduction of decision uncertainty (Abioye et al., 2020; Bwambale et al., 2022). The above-mentioned potential benefits, however, are not guaranteed automatically but depend on a number of factors: infrastructure, funding, skill set, institutions, data management, and organizational capacity, among others (Klerkx et al., 2019; Pronti et al., 2024). In other words, the above-mentioned technologies cannot be assumed to deliver water savings or profitability automatically.

Existing research offers important but fragmented evidence on these questions. Separate strands examine water productivity, field-level irrigation efficiency and its basin-level consequences, digital monitoring and control, technology adoption, climate stress, land suitability, and agricultural digitalization, while persistent regional data constraints complicate integrated assessment across Central Asia (Xenarios et al., 2019). Few studies bring together complementary evidence on field-level water-saving performance and treatment-level economic efficiency while separately integrating regional adoption, climate stress, land suitability, and observable readiness within a transparent need-readiness prioritization framework for Southern Kazakhstan. The existing literature therefore provides limited integrated guidance for assessing where digital irrigation management is comparatively more needed and where implementation conditions appear more favorable.

The study aims to develop a transparent, multi-level decision-support framework for the preliminary regional prioritization of digital irrigation management in Southern Kazakhstan under incomplete and heterogeneous data. It pursues five analytical objectives: to compare reported field-level water use under discrete and drip irrigation; to use selected treatment-level economic observations as contextual evidence on the relationship between agronomic and economic performance; to examine exploratory associations between yield, production costs, profit, and profitability; to evaluate regional adoption of water-saving irrigation technologies, relative climate stress, suitable-land potential, and observable readiness; and to construct and sensitivity-test a Digital Irrigation Management Priority Index (DIMPI). The analysis addresses four questions: how reported field-level water use differs between discrete and drip irrigation; what the selected treatment-level observations reveal about the relationship between agronomic and economic performance; how Turkestan, Kyzylorda, and Zhambyl differ in relative need and observable readiness for digital irrigation management; and how sensitive the resulting regional prioritization is to alternative weighting assumptions.

Accordingly, the principal contribution of this study is methodological rather than causal: it develops a transparent, sample-relative framework for the preliminary regional prioritization of digital irrigation management under incomplete and heterogeneous data. The framework distinguishes relative need from observable implementation readiness and identifies where more detailed digital-irrigation feasibility assessment may be warranted. Field-level water-balance evidence and treatment-level economic observations are retained as analytically separate contextual evidence on irrigation-system performance and the distinction between agronomic and economic outcomes; neither block is interpreted as a measure of digitalization, and neither enters DIMPI. Regional prioritization is determined

only by the regional indicator block comprising technology adoption, relative climate stress, land-suitability potential, Existing WST Scale, and Drip-Irrigation Readiness. This separation avoids attributing observed field or treatment outcomes to digital technologies in the absence of direct digital-adoption data.

Literature review

Contemporary agricultural economics treats irrigation water not merely as a physical input but as a scarce resource whose use involves substantial opportunity costs. Within this approach, water productivity (physical or economic output per unit of water) has become the main principle guiding all the discussion, though the leading advocates of this idea call for some care. According to Molden et al. (2010), the highest increase in water productivity comes when water is used inefficiently and becomes lower as yields come closer to their maximum, implying that water productivity could be seen as an indicator of areas where changes are possible rather than the ultimate policy goal. A systematic review of crop water productivity in wheat, maize, and rice covering three decades shows large variations in it within the irrigated regions and proves that water productivity could be calculated using remote sensing data (Foley et al., 2020). As for Kazakhstan, the economic relevance of these terms increases because of poor infrastructure, growing pollution risks, and water-saving opportunities remaining unused, reducing the value of each cubic meter of water (Karatayev et al., 2017). The literature thus converges on the importance of water productivity while warning that physical and economic productivity can diverge.

A sharper tension emerges around water-saving irrigation technologies. Engineering studies typically evaluate drip and sprinkler systems by field-level application efficiency, whereas economic and hydrological analyses insist on basin-level water accounting — and the two perspectives can yield opposite conclusions. Grafton et al. (2018) formulate this as the paradox of irrigation efficiency: efficiency gains frequently fail to reduce basin-scale consumption because return flows to aquifers and downstream users shrink, lower per-hectare water costs encourage area expansion and the cultivation of more water-intensive crops. Basin-scale modeling had earlier shown that subsidized conservation investment can even increase total depletion (Ward & Pulido-Velázquez, 2008), and decomposition of the rebound effect in China's Hetao district confirms area expansion and reduced return flows as its main drivers (Xu & Song, 2022). The accounting foundations of this critique — the distinction between consumed and recoverable fractions of withdrawals — are set out by Perry and Steduto (2017). Synthesizing over two hundred studies, Pérez-Blanco et al. (2020) conclude that water-conservation technologies primarily stabilize agricultural productivity and farm income under scarcity, while genuine basin-level conservation requires accompanying allocation policies. This literature should be interpreted with care in this particular case study: high efficiency at the field level does not imply basin-level water conservation.

The economic rationale for digital irrigation revolves more around information provided by digital devices rather than water savings. Literature reviews show that there is a well-developed arsenal of technologies, including soil moisture and weather monitoring, open and closed loop control, and model predictive scheduling, which help align water application with crop water requirements and minimize the uncertainty of decision-making (Abioye et al., 2020). Closed-loop monitoring and control approaches show significant improvements in water use efficiency compared to traditional scheduling (Bwambale et al., 2022). Remote sensing adds informational capabilities of digitalization to the regional level, making it possible to consistently calculate water productivity in large irrigated territories (Foley et al., 2020). A limitation of this literature is that digital irrigation is often approached primarily as an engineering problem, with comparatively limited evidence on economic outcomes such as profitability or investment performance. Its economic value therefore lies primarily in improved monitoring, water accounting, scheduling, and allocation decisions, although the resulting benefits remain conditional on the surrounding implementation environment.

The question of whether adoption takes place rests upon several variables, and the existing body of work repeatedly emphasizes that adoption cannot be gauged purely by technological efficiency. A systematic review of econometric adoption literature reveals that water-conservation technology adoption determinants (farmers' farm size, education, financing, and information access) are highly heterogeneous across settings and lack a single unambiguously generalizable determinant (Pronti et al., 2024). From the point of view of systems thinking, the social science literature reaches an analogous conclusion: Agriculture 4.0 also raises unresolved challenges related

to digital divides, data governance, and distributional effects that are commonly overlooked by technology-driven assessment frameworks (Klerkx et al., 2019; Klerkx & Rose, 2020). For the case of Central Asia, these personal barriers are coupled with the problem of collective action due to the post-Soviet transformation of the irrigation sector, wherein informal water-users' groups emerge due to the underperformance of formal organizations (Abdullaev et al., 2010). Experimental findings demonstrate that institutional path dependence, along with transaction costs are jointly determines farmers' cooperation with regard to infrastructure (Amirova et al., 2019). This multi-faceted nature of readiness is what makes farm-level adoption studies insufficient for priority setting in the region.

Southern Kazakhstan is an especially relevant example for the analysis of the convergence of such research streams. For instance, according to the national assessments, infrastructure degradation and inefficiency are critical problems that bind Kazakhstan's water economy (Karatajev et al., 2017). At the same time, less than one-third of the irrigated area in the country uses modern water-saving technologies (World Bank, 2024). Thus, in Maktaaral district in Turkestan region, the supply of water for irrigation changes between 50% and 95% of needs, depending on transboundary inflow, whereas salinity limits the reuse of drainage water (Ayana et al., 2024). The climate projections complicate the situation further, as warming is expected to decrease the yields of spring wheat and barley but positively affect some winter crops (Islyami et al., 2020). In addition, institutional inheritance from the Soviet period continues to affect the choice of adaptation measures by the farmers (Barrett et al., 2017). Simultaneously, agriculture is the least digitized sector of the economy in Kazakhstan due to lack of network infrastructure, lack of competence, and high cost of innovations (Shalbolova et al., 2025). However, the studies discussed above remain fragmented across contextual, hydrological, and policy-oriented questions and, given the documented data constraints in Central Asia (Xenarios et al., 2019), provide limited integrated guidance for the economic evaluation and regional prioritization of digital irrigation management in Southern Kazakhstan.

A final strand concerns spatial prioritization. GIS and remote-sensing-based land-suitability evaluation is a standard methodology for identifying where irrigated agriculture is viable, including in arid settings methodologically comparable to Southern Kazakhstan (AL-Taani et al., 2021). Climate-related variables such as temperature, precipitation, and humidity provide relevant contextual indicators for comparing regional agricultural water stress, particularly in settings exposed to climatic variability and irrigation dependence (Islyami et al., 2020; World Bank, 2024). However, transforming such heterogeneous variables into comparable regional indicators requires a transparent normalization procedure. Composite indicators provide an established vehicle for such integration when built transparently — with an explicit conceptual framework, documented normalization such as the min-max transformation, justified weighting and aggregation, and sensitivity checking (OECD & Joint Research Centre of the European Commission, 2008). Yet these spatial and indicator-based approaches are seldom connected to the economic prioritization of irrigation digitalization, while persistent regional data gaps favor transparent indicator-based frameworks over data-intensive structural models (Xenarios et al., 2019).

Related irrigation-prioritization frameworks address decision problems adjacent to, but distinct from, that considered here. Luo et al. (2021) combine remote-sensing-derived agricultural indicators with AHP-TOPSIS to prioritize irrigation-water allocation within an irrigation district, whereas LaFevor et al. (2021) identify priority municipalities for irrigation expansion using farm typologies and development-oriented criteria. These approaches primarily prioritize water allocation or irrigation expansion. DIMPI addresses a different decision problem: the regional prioritization of digital irrigation management under incomplete data, explicitly separating relative need from observable implementation readiness rather than optimizing water allocation, selecting a specific irrigation technology, or identifying locations for irrigation expansion. This distinction defines the intended methodological contribution of the present framework.

Taken together, the literature offers substantial but compartmentalized evidence on water productivity, the distinction between field-level saving and basin-level conservation, the informational economics of digital irrigation, the multidimensional determinants of technology adoption, and Kazakhstan's water-management and digitalization challenges. What remains insufficiently developed is a transparent framework that can use relevant irrigation-system evidence while keeping it analytically distinct from the regional indicators that determine digital-management priority. The present study addresses this gap through a multi-level, non-causal design. Field-level water-balance evidence is used descriptively to characterize irrigation-system performance, while treatment-level economic observations are used only to illustrate why agronomic improvement cannot automatically be equated

with economic efficiency. Neither block is treated as a measure of digitalization or enters DIMPI. Regional prioritization is based exclusively on climate stress, the adoption gap, suitable-land potential, Existing WST Scale, and Drip-Irrigation Readiness. This separation enables the framework to address a regional need-readiness decision problem without artificially pooling incompatible units of observation or attributing observed agronomic and economic outcomes to digital technologies.

Research methods

Research design and data

This study develops a data-driven economic assessment and decision-support framework for identifying regional priorities for digital irrigation management in Southern Kazakhstan. Digital irrigation management is defined as irrigation decision-making supported by monitoring information, geographic information systems, remote-sensing products, hydrological databases, and software-assisted water allocation. The study does not estimate causal effects of digital technologies on yield, profit, profitability, or water productivity because farm-level before-and-after observations on digital adoption, sensor deployment, IoT streams, and automated gate operation are unavailable. Direct region-level measures of sensor deployment, telemetry, digital connectivity, software use, data-system interoperability, and related institutional digital capacities are likewise unavailable. Accordingly, the regional analysis does not measure digitalization itself; it prioritizes relative need and observable enabling conditions for subsequent digital-irrigation assessment.

The non-causal, multi-level design comprises three analytically distinct evidence blocks: (i) a descriptive field-level water-balance comparison; (ii) a contextual region $\times$ site $\times$ crop $\times$ treatment assessment of economic performance supplemented by exploratory accounting diagnostics; and (iii) a regional analysis of WST adoption, relative climate stress, suitable-land potential, observable implementation readiness, and the Digital Irrigation Management Priority Index (DIMPI). Because these blocks have different units of observation and different analytical purposes, they are analyzed within their native units rather than mechanically pooled. The first two blocks provide contextual evidence only and do not measure digitalization or determine regional rankings. Only the regional adoption, climate-stress, land-suitability, Existing WST Scale, and Drip-Irrigation Readiness indicators enter DIMPI.

The empirical analysis uses aggregated secondary data reported in a 2023 final research report prepared under research programme 0.0970 and registered in the national scientific and technical information system under state registration No. 0121RK00747. Five data blocks are employed: water-balance observations comparing discrete and drip irrigation; ten region $\times$ site $\times$ crop $\times$ treatment observations; adoption indicators for all seventeen regions of Kazakhstan; 2,395 climate observations in region $\times$ station $\times$ year $\times$ metric format; and monitoring-based regional land-suitability estimates. The treatment sample contains five grain-maize observations from OPU-1 Besagash in Zhambyl and five cotton observations from OPU-2 Shugyla in Turkestan. OPU denotes the experimental production-site classification used in the source report.

The five treatments are control, phosphogypsum, sulfuric acid, aqueous ammonia, and combined phosphogypsum and aqueous ammonia. Phosphogypsum was applied at 5 t/ha, sulfuric acid at 2.5%, and aqueous ammonia at 50 kg/ha with a concentration of 25%; the combined treatment used the same respective application rates. Water-balance and treatment-level economic data refer to the 2023 growing season. Adoption indicators represent cumulative sprinkler- and drip-irrigated areas as of 2023. Climate observations cover 2000–2021, while land-suitability estimates derive from the 2021–2023 integrated ground and satellite monitoring programme, supported by field validation at 84 test sites in 2023. Turkestan, Kyzylorda, and Zhambyl were selected because of their importance to irrigated agriculture, exposure to water scarcity, and policy relevance to irrigation modernization.

The field-level water-balance comparison refers specifically to a source-reported 2023 grain-maize trial at OPU-1 Besagash in the Zhambyl region. The source provides two irrigation-regime-level seasonal water-balance values—discrete and drip irrigation—rather than a replicated sample of independent farms. The reported values of 3,996 and 3,282 m³/ha represent seasonal total water consumption per hectare, while the corresponding irrigation norms are 3,550 and 2,910 m³/ha. Both regimes therefore refer to the same crop, experimental site, and growing season. The available source material does not report the values as cross-farm sample means and does not provide sufficient information on the number and area of experimental plots, replication structure, or whether measurement

instrumentation and all plot-level water-delivery conditions were identical between regimes. The comparison is consequently treated strictly as a descriptive comparison of source-reported aggregated values, without statistical inference or causal interpretation.

Strict treatment-level physical or economic water-productivity ratios cannot be calculated because the water-balance data are organized by irrigation technology, whereas the economic data are organized by crop, site, and treatment, and treatment-specific water use is unavailable. The study therefore evaluates field-level water-saving performance and treatment-level economic efficiency within their native units rather than constructing yield-per-cubic-meter or profit-per-cubic-meter measures.

Descriptive Water-Balance Comparison

The water-balance stage compares total field-level water consumption under drip irrigation with what the source report terms “discrete irrigation.” In this study, discrete irrigation refers operationally to a regime of seven separate, relatively high-volume irrigation applications of 450–600 m³/ha each during the 2023 growing season. The source term is retained for traceability and is not presented as a universally standardized international irrigation-system category. By comparison, drip irrigation involved fourteen smaller applications of 90–260 m³/ha. Absolute and relative water saving are calculated as:

$$WS = TW_{\text{discrete}} - TW_{\text{drip}}, WSR = 100 \times \frac{TW_{\text{discrete}} - TW_{\text{drip}}}{TW_{\text{discrete}}}. \quad (1)$$

Here, *WS* denotes absolute field-level water saving in m³/ha, *WSR* is the percentage reduction relative to discrete irrigation, and TW_{discrete} and TW_{drip} denote total field-level water consumption under the two regimes. Equation (1) describes field-level water-saving performance and does not imply an equivalent basin-level reduction in consumption or depletion.

Contextual Treatment-Level Economic Assessment

Treatment-level economic efficiency is assessed using yield, output price, gross output, production costs, profit, and profitability. Yield is measured in c/ha, where one centner equals 100 kg; output price is measured in KZT/c; monetary outcomes are measured in KZT/ha and reported in thousand KZT/ha where appropriate; and profitability is expressed as a percentage. Gross output equals yield multiplied by output price, profit equals gross output minus production costs, and profitability equals 100 times profit divided by production costs. Each treatment is compared with its crop- and site-specific control:

$$\Delta Y_i = 100 \times \frac{Y_i - Y_0}{Y_0}, \Delta P_i = 100 \times \frac{P_i - P_0}{P_0}, \Delta R_i = R_i - R_0 \quad (2)$$

In Equation (2), *Y*, *P*, and *R* denote yield, profit, and profitability; *i* identifies the treatment, and 0 denotes the corresponding control. Yield and profit changes are percentages, whereas profitability changes are percentage points. These treatments are soil-reclamation interventions rather than digital-irrigation technologies and are not used as proxies for digitalization. Their role in the present study is strictly contextual: they provide observed evidence that agronomic performance and economic performance can diverge within irrigated production systems, thereby demonstrating why yield improvement alone is insufficient for irrigation-management decision support. This block does not enter DIMPI, does not determine regional rankings, and is not interpreted as evidence of the economic effect of digitalization.

Exploratory Accounting Diagnostics

Two ordinary least squares models assess whether the treatment-level observations are directionally consistent with their accounting relationships:

$$\text{Outcome}_i^{(m)} = \alpha_m + \beta_{1m} \text{Yield}_i + \beta_{2m} \text{Cost}_i + \varepsilon_i^{(m)}, \quad (3)$$

$$m \in \{\text{profit}, \text{profitability}\}.$$

Model 1 uses profit as the dependent variable, whereas Model 2 uses profitability; both models include yield and production costs as regressors. Inference uses HC3 heteroskedasticity-robust standard errors. The sample contains ten crop–site–treatment observations rather than independent farms and combines two crops, two sites, different prices, and different cost structures. Yield and production costs are highly collinear (; implied VIF = 43.6), while profit and profitability are partly constructed from the accounting quantities represented by the regressors. Leave-one-out diagnostics preserve positive yield and negative cost coefficients in both models, but magnitudes and precision remain sample-sensitive. The models are therefore exploratory accounting diagnostics and support no causal, structural, predictive, or digital-technology-related interpretation. Coefficients and inferential statistics are reported in the Results.

Regional Adoption and Observable Readiness Proxies

Regional adoption is examined for all seventeen regions. Total WST area equals sprinkler-irrigated plus drip-irrigated area, and drip share equals 100 times drip-irrigated area divided by total WST area. These indicators describe the existing technological base. Drip share proxies the scale of pressurized and closely controlled irrigation compatible with monitoring and software-supported scheduling; it is not a direct measure of digitalization, and sprinkler systems may also be digitalized.

Climate stress indicator

Relative climate stress is constructed from average annual mean temperature (T), annual precipitation (PR), and annual relative humidity (H). Station-year observations were averaged by regional climate metric over 2000–2021 and then normalized across Turkestan, Kyzylorda, and Zhambyl:

$$N_r^+(x) = \frac{x_r - x_{\min}}{x_{\max} - x_{\min}}, N_r^-(x) = \frac{x_{\max} - x_r}{x_{\max} - x_{\min}} \quad (4)$$

N_r^+ assigns higher normalized values to larger raw values, N_r^- assigns higher normalized values to smaller raw values, denotes the region, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum across the three-region comparison set. N_r^+ is applied to temperature, suitable-land area, total existing WST area, and drip share; N_r^- is applied to precipitation, relative humidity, and total WST area when constructing the Adoption Gap.

Accordingly, $T_{\text{norm},r} = N_r^+(T)$, $PR_{\text{norm},r} = N_r^-(PR)$, $H_{\text{norm},r} = N_r^-(H)$, $\text{AdoptionGap}_r = N_r^-(WST)$, $\text{SuitableLand}_{\text{norm},r} = N_r^+(\text{SuitableLand})$, $\text{WSTScale}_r = N_r^+(WST)$, and $\text{DripReadiness}_r = N_r^+(\text{DripShare})$. Because Adoption Gap and Existing WST Scale are inverse transformations of the same WST-area measure, $\text{AdoptionGap}_r = 1 - \text{WSTScale}_r$.

$$\text{ClimateStress}_r = \frac{N_r^+(T) + N_r^-(PR) + N_r^-(H)}{3} \quad (5)$$

Higher temperature, lower precipitation, and lower humidity increase the indicator. Equation (5) is sample-relative and is not an absolute drought or climatological classification.

Digital Irrigation Management Priority Index (DIMPI)

DIMPI is a transparent, sample-relative decision-support tool that compares where digital irrigation management may warrant greater policy attention on the basis of relative need and observable implementation readiness. It is not a causal estimator, universal ranking, investment model, or complete measure of institutional or digital capacity. Accordingly, DIMPI is intended as a preliminary screening instrument for identifying where more detailed digital-irrigation appraisal may be warranted. It does not replace project-specific techno-economic feasibility analysis, which would require information on digital-infrastructure costs, connectivity, sensors and software, human capital, institutional arrangements, water tariffs, financing conditions, and expected economic returns.

The Need Index combines relative climate stress, the Adoption Gap, and suitable-land potential:

$$\text{NeedIndex}_r = \frac{\text{ClimateStress}_r + \text{AdoptionGap}_r + \text{SuitableLand}_{\text{norm},r}}{3} \quad (6)$$

These terms represent climatic pressure, unmet WST adoption, and the potential spatial scale of intervention. Suitable land therefore represents intervention scale rather than automatic technical or investment feasibility, and the Need Index is not a pure scarcity or vulnerability measure.

The Readiness Index combines Existing WST Scale and Drip-Irrigation Readiness:

$$\text{ReadinessIndex}_r = \frac{\text{WSTScale}_r + \text{DripReadiness}_r}{2} \quad (7)$$

Readiness is observable and proxy-based. It reflects existing WST scale and drip-irrigation share but does not directly measure broadband quality, digital skills, access to finance, sensor penetration, data interoperability, institutional quality, or complete implementation capacity.

The general DIMPI specification is:

$$\text{DIMPI}_r(w) = w\text{NeedIndex}_r + (1 - w)\text{ReadinessIndex}_r, \quad (8)$$

$$w \in \{0.50, 0.60, 0.70\}$$

The baseline value $w=0.60$ was not empirically estimated or derived from expert elicitation. It was selected as a component-neutral baseline because the Need dimension contains three equally weighted component terms, whereas the Readiness dimension contains two. Assigning 60% to Need and 40% to Readiness therefore gives each of the five component terms an equal effective weight of 0.20 in the composite index. The baseline should consequently be interpreted as a transparent analytical reference specification rather than as an externally validated policy preference. This treatment is consistent with composite-indicator practice emphasizing transparent specification of weights and sensitivity analysis rather than treating a single weighting structure as objectively determined (OECD & Joint Research Centre of the European Commission, 2008). To examine sensitivity to this researcher-specified choice, alternative values of $w=0.50$ and $w=0.70$ shift the relative emphasis toward Readiness and Need, respectively, while leaving the internal component definitions unchanged. Adoption Gap and Existing WST Scale are inverse transformations of the same WST-area measure, so their contributions offset under $w=0.60$. The baseline therefore treats the existing WST scale as a neutral trade-off between unmet adoption need and observable implementation readiness. Relative to the baseline, $w=0.50$ gives Existing WST Scale a positive net contribution, whereas $w=0.70$ gives the Adoption Gap a positive net contribution. Software, reproducibility, and methodological limitations

All calculations were conducted in StataNow/SE 18.5 using reproducible do-files. The data were standardized by analytical block, checked for consistency, and exported as article-ready tables and figures.

Four limitations define the scope of inference. First, the absence of farm-level before-and-after digital-adoption observations and direct region-level measures of sensor deployment, telemetry, connectivity, software use, and data-system interoperability prevents causal estimation of digital-technology effects and direct measurement of regional digitalization. DIMPI should therefore be interpreted as a preliminary prioritization and decision-support tool based partly on observable readiness proxies. Second, HC3 does not overcome the ten-observation sample, extreme collinearity, cross-crop and cross-site heterogeneity, or the accounting construction of the regression outcomes. Leave-one-out diagnostics preserve coefficient directions, but magnitudes and precision remain sample-sensitive, precluding definitive, causal, structural, or predictive inference.

Third, DIMPI covers only three regions and uses comparison-set-dependent min-max normalization, researcher-specified weights, and proxy-based readiness measures. In particular, Kyzylorda's Readiness Index value of 0.000 is a mathematical consequence of being the minimum observed value within the three-region min-max normalization; it does not indicate an absolute absence of readiness and must not be extrapolated beyond this comparison set. Temperature, precipitation, and humidity receive equal internal weights; the alternative values of

in Equation (8) test the need–readiness balance but not alternative climate weights. Existing WST and suitable-land components are measured in absolute hectares and may partly capture regional scale; future applications should test area-normalized alternatives. Future applications may replace these analytical weights with stakeholder- or expert-elicited weights where sufficiently representative elicitation data are available. Fourth, only regional adoption, climate-stress, land-suitability, and readiness indicators are integrated through DIMPI; field-level water balance, treatment-level economic efficiency, and exploratory regression diagnostics remain analytically separate.

Results and Discussion

The results are presented as analytically separate evidence layers reflecting the multi-level design. The field-level water-balance block provides a descriptive comparison of irrigation regimes, and the treatment-level economic block provides contextual evidence on the distinction between agronomic and economic performance. Neither block measures digitalization, and neither enters the regional priority index. The regional adoption, climate-stress, land-suitability, and observable-readiness indicators form the only inputs to DIMPI and therefore constitute the empirical basis of the regional prioritization results. Exploratory regressions are reported solely as accounting diagnostics and do not inform the regional rankings or policy interpretation.

Descriptive Field-Level Water-Balance Comparison

For the source-reported 2023 grain-maize trial at OPU-1 Besagash, the seasonal water-balance values differed descriptively between the discrete- and drip-irrigation regimes (Table 1).

Table 1 – Descriptive Field-Level Water-Balance Comparison for Grain Maize at OPU-1 Besagash, 2023

Indicator	Discrete irrigation	Drip irrigation	Absolute difference	Difference relative to discrete irrigation, %
Irrigation norm, m ³ /ha	3,550	2,910	640	18.03
Soil-moisture contribution, m ³ /ha	446	372	74	16.59
Precipitation contribution, m ³ /ha	0	0	0	—
Total water consumption, m ³ /ha	3,996	3,282	714	17.87

Note. Differences are calculated as discrete irrigation minus drip irrigation and are expressed relative to the discrete-irrigation value. The table reports two source-reported seasonal irrigation-regime-level water-balance values for grain maize at OPU-1 Besagash in 2023. These values are descriptive and do not represent a replicated sample of independent farms or evidence of basin-level water conservation. Source: Authors' calculations based on the secondary data described in Research Methods.

Seasonal total water consumption was reported as 3,996 m³/ha under discrete irrigation and 3,282 m³/ha under drip irrigation, corresponding to a descriptive difference of 714 m³/ha, or 17.87% relative to the discrete regime. The corresponding irrigation norm was 3,550 versus 2,910 m³/ha, a difference of 640 m³/ha (18.03%). The remaining 74 m³/ha difference in the total water-balance values reflects the reported soil-moisture contribution (446 versus 372 m³/ha) and should not be interpreted as irrigation water that was not delivered to the field. Precipitation was reported as zero in both source rows. Because the comparison consists of two aggregated irrigation-regime-level values rather than replicated independent observations, no significance test is appropriate, and the result is interpreted strictly as a descriptive difference under the reported field conditions.

Operationally, the reported 640 m³/ha difference in irrigation norm may be relevant in water-scarce settings because it represents the difference in irrigation water applied per hectare between the two source-reported regimes. However, this is not without conditions, since the data set does not include prices for water, electricity, labor costs, or other farms. Equally important, the irrigation-efficiency literature cautions that field-level application reductions do not translate mechanically into basin-level conservation: lower field losses can shrink recoverable return flows, and cheaper water per hectare can encourage area expansion or crop intensification (Grafton et al., 2018; Pérez-Blanco et al., 2020; Perry & Steduto, 2017; Xu & Song, 2022). The observed 17.87% reduction therefore indicates

lower field-level water use under the reported conditions, but it does not establish an equivalent reduction in basin-level consumption or depletion. Physical water saving consequently needs to be evaluated alongside the economic outcomes of the associated field operations, to which the analysis now turns.

Contextual Economic Evidence from Soil-Reclamation Treatments

This block provides contextual economic evidence from soil-reclamation treatments rather than evidence of digital-irrigation effects. Within this limited treatment sample, the combined phosphogypsum and aqueous-ammonia treatment recorded the highest observed yield, profit, and profitability values in both crop-site groups, while yield gains did not uniformly translate into higher profit (Table 2).

Table 2 – Contextual Economic Performance of Selected Soil-Reclamation Treatments

Treatment	Yield, c/ha	Production costs, thousand KZT/ha	Profit, thousand KZT/ha	Profitability, %	Yield change, %	Profit change, %
Panel A. Grain maize, Zhambyl region — OPU-1 Besagash						
Control	105.3	915.9	412.1	45.0	—	—
Phosphogypsum	110.3	911.7	479.3	52.6	4.75	16.31
Sulfuric acid	114.5	1,065.5	378.4	35.5	8.74	-8.16
Aqueous ammonia	116.7	984.1	487.6	49.6	10.83	18.35
Combined treatment	126.2	999.9	591.6	59.2	19.85	43.57
Panel B. Cotton, Turkestan region — OPU-2 Shugyla						
Control	23.5	437.6	181.3	41.4	—	—
Phosphogypsum	26.7	436.9	266.2	60.9	13.62	46.85
Sulfuric acid	29.9	503.5	284.0	56.4	27.23	56.62
Aqueous ammonia	34.4	465.1	440.9	94.8	46.38	143.16
Combined treatment	35.6	460.1	477.5	103.8	51.49	163.36

Note. Treatment outcomes are compared with crop- and site-specific controls. Monetary values are reported in thousands of KZT/ha. The treatments are soil-reclamation interventions, not digital-irrigation technologies. Source: Authors' calculations from values reported in the 2023 final research report (state registration No. 0121RK00747).

In the Zhambyl grain-maize experiment (OPU-1 Besagash), the combined treatment raised yield from 105.3 to 126.2 c/ha (+19.85%) and profit from 412.1 to 591.6 thousand KZT/ha (+43.57%), lifting profitability from 45.0% to 59.2%. Aqueous ammonia alone also recorded gains in both yield and profit (+10.83% and +18.35%, respectively), with profitability of 49.6%, and phosphogypsum improved both yield (+4.75%) and profit (+16.31%) at nearly unchanged cost. By contrast, sulfuric acid increased yield by 8.74% yet reduced profit by 8.16% and profitability by 9.5 percentage points, because production costs rose from 915.9 to 1,065.5 thousand KZT/ha. In the Turkestan cotton experiment (OPU-2 Shugyla), responses were proportionally larger throughout: the combined treatment raised yield by 51.49% and profit by 163.36%, with profitability reaching 103.8% against a control value of 41.4%, while aqueous ammonia alone raised profit by 143.16% (profitability of 94.8%).

Three interpretive points follow. First, the divergence between agronomic and economic outcomes under the sulfuric-acid treatment in Zhambyl illustrates that an observed yield improvement need not imply higher economic efficiency once production costs are considered. Second, absolute monetary values should not be compared directly across the two crop-site panels because crops, output prices, sites, and cost structures differ; comparisons are therefore made relative to the corresponding crop- and site-specific controls. Third, and most importantly for the scope of this study, these treatments are soil-reclamation interventions on irrigated land rather than digital-irriga-

tion technologies. They are not used as digitalization proxies, do not enter DIMPI, and do not determine regional rankings. Their relevance is limited to demonstrating why future digital-irrigation appraisal should incorporate economic outcomes such as costs, profit, and profitability rather than relying on agronomic performance alone. Because treatment-specific water-use observations are unavailable, no treatment-level physical or economic water-productivity ratios are calculated. Whether the observed yield–cost–profit relationships are directionally coherent is examined next.

Exploratory Accounting Diagnostics

The exploratory regressions assess whether the treatment-level observations are directionally consistent with their accounting structure. In both models, yield has a positive coefficient and production costs have a negative coefficient, and these directions remain unchanged across all ten leave-one-out replications. However, yield and production costs are highly collinear, and HC3 correction materially increases the standard errors. The estimates are therefore interpreted as diagnostics of directional consistency rather than as evidence of reliably separable economic effects (Table 3). Given the sample size and accounting structure of the variables, these regressions are reported for diagnostic transparency only and are not used to support the regional prioritization or the policy conclusions of the study.

Table 3 – Exploratory OLS Accounting Diagnostics with HC3 Standard Errors

Explanatory variable / model statistic	Model 1: Profit, thousand KZT/ha	Model 2: Profitability, %
Yield, c/ha	11.365	1.605
HC3 standard error	(6.401)	(1.846)
p-value	[0.119]	[0.413]
Production costs, thousand KZT/ha	–1.571	–0.304
HC3 standard error	(1.119)	(0.326)
p-value	[0.203]	[0.382]
Constant	706.405	162.036
HC3 standard error	(335.095)	(97.507)
p-value	[0.073]	[0.141]
Observations	10	10
R ²	0.739	0.541
Robust F-statistic, F(2, 7)	9.70	0.83
Prob > F	0.010	0.473
Root MSE	71.787	17.143

Note. HC3 standard errors are reported in parentheses and exact p-values in square brackets. Profit and production costs are measured in thousands of KZT/ha, while profitability is expressed as a percentage. The estimates are exploratory, non-causal diagnostics based on ten observations. Source: Authors’ estimates using the secondary data described in Research methods.

In Model 1, the yield coefficient is 11.365 thousand KZT/ha per additional centner per hectare, while the production-cost coefficient is –1.571. Neither coefficient is individually statistically distinguishable from zero under HC3 inference ($p = 0.119$ and $p = 0.203$, respectively). The regressors are jointly significant, $F(2, 7) = 9.70$, $p = 0.010$, and the model accounts for 73.9% of the observed variation in profit. This joint result does not identify the independent contribution of either regressor because yield and production costs are nearly collinear.

Model 2 produces the same coefficient directions but substantially weaker statistical performance. The yield and production-cost coefficients are 1.605 and –0.304, respectively, with HC3 p-values of 0.413 and 0.382. The model is not jointly significant, $F(2, 7) = 0.83$, $p = 0.473$, despite an R^2 of 0.541. Leave-one-out diagnostics preserve both coefficient directions, although the estimated magnitudes remain sample-sensitive. The maize sulfuric-acid treatment is particularly influential because it combines relatively high yield with high production costs and comparatively

weak economic performance; it is retained as a substantively valid treatment observation rather than treated as a data error. These models provide no causal, structural, predictive, or digital-technology-related evidence.

Regional Adoption, Climate Stress, and Digital-Irrigation Readiness

The adoption of water-saving irrigation technologies is spatially uneven across Kazakhstan and among the three study regions. At the national level, Pavlodar ranks first in terms of the area equipped with irrigation technologies – 77.383 thousand hectares, then Zhambyl (57.233 thousand ha) and Turkestan (36.700 thousand ha). Kyzylorda has the smallest area of equipped lands – 1.219 thousand ha. Regarding the technological composition, 79.56% of the area of equipped lands in Turkestan is under drip irrigation (29.200 out of 36.700 thousand ha), 68.31% in Zhambyl (39.096 out of 57.233 thousand ha), and 61.28% in Kyzylorda (0.747 out of 1.219 thousand ha). As specified in Research Methods, the area equipped with drip and sprinkler irrigation cannot be interpreted as direct evidence of digitalization. Instead, it is used as an observable readiness proxy because pressurized and more closely controlled irrigation systems may be comparatively compatible with sensor-based monitoring and software-supported scheduling. Conversely, very low observed adoption, as in Kyzylorda, may reflect limited implementation capacity, historical adoption patterns, or other infrastructure, financial, and institutional constraints rather than low technological need. This situation is consistent with the empirical literature on the heterogeneity of adoption determinants in different situations (Pronti et al., 2024) and social science literature on digital divides and governance constraints as factors conditioning the adoption process (Klerkx et al., 2019; Klerkx & Rose, 2020). In general, agriculture is one of the sectors least digitized in Kazakhstan (Shalbolova et al., 2025).

Climate stress is multidimensional and cannot be represented by temperature alone. The aggregated station-year data show that Turkestan recorded the highest mean temperature (12.57°C) and the highest annual precipitation (398.90 mm), with a mean relative humidity of 55.11%. Kyzylorda recorded the lowest precipitation (114.63 mm) and relative humidity (53.96%), with a mean temperature of 10.80°C. Zhambyl occupied an intermediate position in precipitation (269.26 mm) and temperature (10.93°C), while recording the highest relative humidity (56.32%). No single climate variable therefore ranks the three regions consistently, providing the rationale for combining temperature, precipitation, and relative humidity in the composite relative climate-stress indicator.

Monitoring-based land-suitability estimates add a further dimension to regional prioritization. Turkestan contains approximately 112,094.5 ha of suitable land, compared with 23,564.2 ha in Zhambyl and 17,877.5 ha in Kyzylorda. These estimates indicate the potential spatial scale over which irrigation-management interventions could be relevant rather than automatic technical or investment feasibility. Considered jointly, the adoption, climate, and land-suitability evidence shows that no single indicator is sufficient to determine digital-irrigation priority: the regions differ simultaneously in relative pressure, technological gaps, observable implementation readiness, and potential intervention scale. This provides the empirical rationale for the joint need–readiness framework applied below.

DIMPI Results, Sensitivity, and Screening Implications

The central composite result is that Turkestan ranks first under all three prespecified weighting specifications reported in Table 4.

Table 4 – Regional Components, Scores, and Sensitivity Results of the Digital Irrigation Management Priority Index

Panel A. Normalized need and readiness components

Region	Climate stress	Adoption gap	Suit-able-land potential	Need Index	Existing WST scale	Drip-irrigation readiness	Readiness Index
Turkestan	0.504	0.367	1.000	0.624	0.633	1.000	0.817
Kyzylorda	0.667	1.000	0.000	0.556	0.000	0.000	0.000
Zhambyl	0.177	0.000	0.060	0.079	1.000	0.385	0.692

Panel B. DIMPI scores and sensitivity rankings

Region	DIMPI 60/40	Rank	DIMPI 50/50	Rank	DIMPI 70/30	Rank
Turkestan	0.701	1	0.720	1	0.682	1
Kyzylorda	0.333	2	0.278	3	0.389	2
Zhambyl	0.324	3	0.386	2	0.263	3

Note. Components are min-max normalized to [0,1] within the three-region sample. The baseline DIMPI combines Need and Readiness at 60/40; 50/50 and 70/30 are sensitivity specifications. Because Adoption Gap = 1 – WST Scale, the two terms offset in the baseline. Rankings are relative rather than universal. WST denotes water-saving irrigation technologies. Source: Authors' calculations using the regional secondary data described in Research methods; climate observations cover 2000–2021.

Under the baseline 60/40 formulation, Turkestan scores 0.701, followed by Kyzylorda (0.333) and Zhambyl (0.324). Because the adoption-gap and existing-WST-scale components are inverse transformations with equal effective weights, they offset in the baseline; rank variation therefore reflects climate stress, suitable-land potential, and drip-irrigation readiness. Turkestan remains first under both alternative specifications. Kyzylorda and Zhambyl exchange second and third place because the 50/50 specification gives a positive net contribution to existing WST scale and therefore favors Zhambyl, whereas the 70/30 specification gives a positive net contribution to the adoption gap and therefore favors Kyzylorda.

Figure 1 visualizes the underlying configurations in need–readiness space, with the Readiness Index on the horizontal axis and the Need Index on the vertical axis.

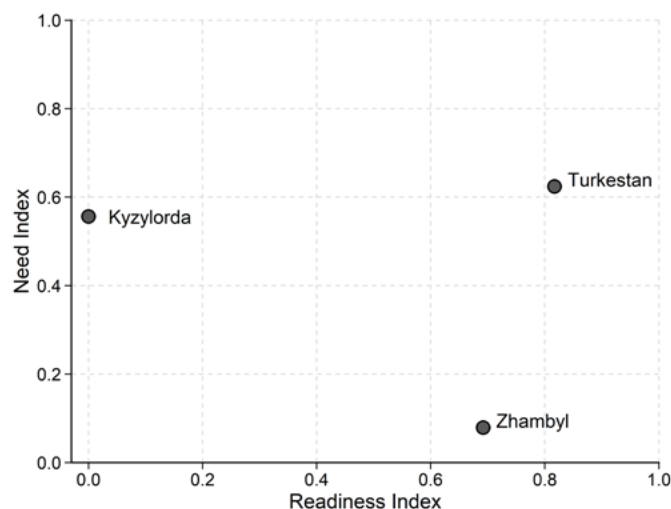


Figure 1– Need–Readiness Positioning of the Study Regions

Note: Axes represent sample-relative Need and Readiness indices normalized to [0,1]; the positions are not formal high/low classifications. Source: Authors' visualization based on Table 4.

Within the three-region comparison set, Turkestan records the highest Need and Readiness scores; Kyzylorda combines the second-highest Need score with the lowest Readiness score; and Zhambyl combines the second-highest Readiness score with the lowest Need score. As there are no established theoretical boundaries in this case, these patterns have been interpreted as relative positioning rather than as quadrants. Figure 1 illustrates why similar composite scores can imply substantially different next-stage appraisal priorities: Kyzylorda (0.333) and Zhambyl (0.324) have similar baseline DIMPI scores but occupy contrasting positions in need–readiness space.

Accordingly, these regional profiles are interpreted as screening implications rather than direct implementation recommendations. Within the three-region comparison set, Turkestan emerges as the strongest candidate for

detailed digital-irrigation feasibility appraisal and, subject to project-level engineering, financial, institutional, and stakeholder assessment, potential pilot design. Kyzylorda's profile points first to a need for more detailed readiness diagnostics because its normalized readiness value reflects its relative position within the three-region sample rather than an absolute absence of implementation capacity. Zhambyl's comparatively stronger observable readiness and lower relative need suggest that incremental demonstration, interoperability testing, or scaling from the existing technological base may warrant assessment. These interpretations identify different next-stage appraisal pathways; they do not establish that any specific digital-irrigation investment should be implemented.

DIMPI therefore functions as a preliminary screening tool rather than a substitute for a project-level techno-economic feasibility study. Any investment or implementation decision would require additional evidence on digital-infrastructure costs, connectivity, sensors and software, human capital, institutional arrangements, water tariffs, financing conditions, expected economic returns, and site-specific engineering feasibility.

Several limitations bound these conclusions. DIMPI covers only three regions, and min-max normalized values depend on the comparison set, so the index is relative rather than absolute. Readiness is measured through proxy indicators, while broadband connectivity, digital skills, financing access, sensor penetration, data interoperability, and institutional quality are not measured directly. The index does not estimate causal effects and does not predict project-specific rates of return. The rankings are therefore decision-support results, consistent with transparent composite-indicator practice (OECD & Joint Research Centre of the European Commission, 2008), rather than universal administrative classifications.

Conclusion

This study developed a transparent, multi-level decision-support framework for the preliminary regional prioritization of digital irrigation management in Southern Kazakhstan. The framework deliberately separates contextual field- and treatment-level evidence from the regional indicators that determine DIMPI, thereby avoiding causal attribution of agronomic, economic, or water-use outcomes to digital technologies in the absence of direct digital-adoption data.

In the source-reported 2023 grain-maize trial at OPU-1 Besagash, seasonal total water consumption differed descriptively by 714 m³/ha between discrete and drip irrigation, while the corresponding difference in irrigation norm was 640 m³/ha. These values represent a descriptive field-level comparison rather than a statistically estimated treatment effect or evidence of equivalent basin-level conservation. The separate soil-reclamation treatment block showed that higher agronomic performance does not necessarily imply higher economic efficiency; it is therefore interpreted only as contextual economic evidence and does not enter regional prioritization.

Under the baseline DIMPI specification, Turkestan ranked first (0.701), followed by Kyzylorda (0.333) and Zhambyl (0.324). Turkestan remained first across all prespecified weighting scenarios, whereas the ordering of Kyzylorda and Zhambyl changed with the relative emphasis placed on need and readiness. DIMPI should therefore be interpreted as a sample-relative screening instrument for identifying where more detailed digital-irrigation appraisal may be warranted, not as a causal model, universal ranking, or substitute for project-level techno-economic feasibility analysis. Future research should incorporate direct digital-readiness measures, farm-level panel evidence, treatment-specific water-use data, broader regional coverage, and project-level investment appraisal.

Gratitude, Conflict of interest

The authors declare that there are no conflicts of interest. The authors have no additional acknowledgments to declare.

Authors' contribution

B. Kair contributed to the conceptualization of the study, methodology development, secondary-data extraction and curation, formal analysis, visualization, and preparation of the original manuscript. Ye. Oskembayev contributed to the supervision of the study, validation and interpretation of the results, and critical review and editing of the manuscript. Both authors discussed the results and approved the final version of the manuscript.

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**Оңтүстік Қазақстандағы цифрлық суаруды басқарудың
өңірлік басымдықтарын айқындау: шешім қабылдауды қолдаудың көпдеңгейлі жүйесі**

Аңдатпа. Мақсаты: Қазақстанның оңтүстігіндегі суармалы егіншілік су ресурстарының тапшылығы, климаттық тәуекелдер және су үнемдеу суару технологияларының біркелкі енгізілмеуі жағдайында дамуда. Бұл цифрлық ирригациялық басқарудың өңірлік басымдықтарын айқын әрі негізді белгілеу қажеттілігін туындатады.

Зерттеу әдістері: Зерттеуде Түркістан, Қызылорда және Жамбыл облыстарына арналған көпдеңгейлі, себеп-салдарлық байланыстарды бағалауға бағытталмаған шешім қабылдауды қолдау жүйесі әзірленді. Ұсынылған жүйе бір-бірінен аналитикалық тұрғыдан ажыратылған үш дәлелдемелік блокты біріктіреді: егістік учаскелері деңгейіндегі су балансының сипаттамалық салыстырмасы; суару технологиялары деңгейіндегі контекстік экономикалық деректер; технологияларды енгізу, салыстырмалы климаттық жүктеме, жердің жарамдылығы және іске асыруға байқалатын дайындық бойынша өңірлік көрсеткіштер.

Нәтижелер: Алғашқы екі блок контекстік дәлелдемелік база ретінде пайдаланылып, цифрландыру деңгейін өлшемейді және композиттік индекстің құрамына енгізілмейді. Цифрлық ирригациялық басқарудың басымдық индексіне (DIMPI) тек өңірлік көрсеткіштер біріктірілді. Бастапқы дереккөзде келтірілген дәндік жүгері өсіру тәжірибесінің нәтижелері бойынша маусымдық жиынтық су тұтыну тамшылатып суару кезінде 3 282 м³/га, ал дискретті суару кезінде 3 996 м³/га болды. Көрсеткіштер арасындағы сипаттамалық айырмашылық 17,87%-ды құрады.

Қорытындылар: DIMPI көрсеткіштерін өлшеудің алдын ала белгіленген барлық сценарийлерінде Түркістан облысы бірінші орынға ие болды, ал Қызылорда және Жамбыл облыстары технологияларды енгізу қажеттілігі мен оларды іске асыруға дайындықтың әртүрлі арақатынасын көрсетті. Алынған нәтижелер DIMPI-ді цифрлық ирригацияны енгізудің орындылығына неғұрлым егжей-тегжейлі бағалау жүргізу қажет болуы мүмкін аумақтарды анықтайтын алдын ала іріктеу құралы ретінде қолдануға мүмкіндік береді. Алайда бұл индексті цифрландыру әсерінің немесе жекелеген жобалар деңгейіндегі инвестициялық кірістіліктің бағасы ретінде қарастыруға болмайды.

Түйін сөздер: цифрлық суаруды басқару, өңірлік басымдықтарды айқындау, шешім қабылдауды қолдау жүйесі, су үнемдейтін суару технологиялары, енгізуге дайындық, композиттік индекс, Оңтүстік Қазақстан

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Региональное определение приоритетов цифрового управления орошением в Южном Казахстане: многоуровневая система поддержки принятия решений

Аннотация. *Цель:* Орошаемое земледелие Южного Казахстана сталкивается с дефицитом водных ресурсов, климатическими рисками и неравномерным внедрением водосберегающих технологий орошения, что обуславливает необходимость прозрачного определения региональных приоритетов цифрового управления ирригацией.

Методы: В исследовании разработана многоуровневая некаузальная система поддержки принятия решений для Туркестанской, Кызылординской и Жамбылской областей. Предлагаемая система объединяет три аналитически обособленных блока доказательной базы: описательное сравнение водного баланса на уровне полевых участков; контекстные экономические данные на уровне отдельных технологий орошения; региональные показатели внедрения технологий, относительной климатической нагрузки, пригодности земель и наблюдаемой готовности к реализации соответствующих мероприятий.

Результаты: Первые два блока используются в качестве контекстной доказательной базы, не характеризуют уровень цифровизации и не включаются в состав сводного индекса. В Индекс приоритетности цифрового управления ирригацией (DIMPI) интегрированы только региональные показатели. Согласно исходным данным полевого опыта по выращиванию зерновой кукурузы, суммарное сезонное водопотребление составило 3 282 м³/га при капельном орошении и 3 996 м³/га при дискретном орошении. Описательная разница между показателями составила 17,87%.

Выводы: Во всех предварительно установленных сценариях взвешивания DIMPI Туркестанская область заняла первое место, тогда как Кызылординская и Жамбылская области продемонстрировали различные соотношения между потребностью во внедрении технологий и готовностью к их реализации. Результаты подтверждают возможность использования DIMPI в качестве инструмента предварительного отбора территорий, для которых целесообразно проведение более детальной оценки реализуемости цифровой ирригации. При этом индекс не следует рассматривать как оценку эффектов цифровизации или доходности инвестиций на уровне отдельных проектов.

Ключевые слова: цифровое управление орошением, региональное определение приоритетов, система поддержки принятия решений, водосберегающие технологии орошения, готовность к внедрению, сводный индекс, Южный Казахстан

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