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MAKHMUD DINARA MARLENKYZY

Development of a model of increasing the efficiency of natural resources using in agriculture in the Turkestan region, preventing climate change

Dissertation for the degree of Doctor of Philosophy (PhD) in the educational programme 8D04110 – Economy

Domestic scientific consultant:
Doctor of Economic Sciences, Professor,
A.M. Yessirkepova

Foreign scientific consultant:
Doctor of Economic Sciences, Professor, Katowice Business University,
Poland
S. Dyrka

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TERMS AND DEFINITIONS

In this dissertation, the following terms with the corresponding definitions are applied:

Natural-resource efficiency – the ratio between the production result and the configuration of limited land, water, energy, pasture and other resources required to achieve it under given climatic conditions

Resource architecture – the system of interrelated natural resources of agricultural production (land and soil, water, climatic conditions, pasture and feed resources, energy-related inputs) analysed through the relationship «resource endowment – production configuration – resource pressure»

Resource pressure – the degree to which the resource requirement of a production configuration approaches or exceeds the available resource capacity of a territory or farm

Effective scarcity – a shortage of a resource that depends not only on its physical quantity but also on when it is available, on its quality and accessibility and on whether it can be combined with the other resources required for production

Evidence concordance – how many of the four independent evidence streams – statistical indicators, climate relationships, the stakeholder survey and implementation cases – confirm a given strategic direction

Evidence hierarchy – the ordering of input data according to their origin – direct observation, official statistics, a measurement entered by the user, a normative or reference coefficient, or an estimate obtained from the model

Feasible production set – the set of production structures that satisfy the land, water and structural constraints of a territory or farm

QŪNAR score (resource-climate utility) – a comparative indicator of the suitability of an agricultural alternative that combines climatic suitability and water pressure

Forecast guard – a rule of the model that withholds or downgrades a numerical forecast when its validation evidence is insufficient

Resource productivity – the output or margin obtained per unit of a resource (per hectare of land, per cubic metre of water, per kilowatt-hour of energy)

Climate resilience – the ability of a production system to keep its results under climatic deviations and to recover after them

Environmental stability – the ability of a territory to keep the condition of land, water and other natural resources under agricultural use

DESIGNATIONS AND ABBREVIATIONS

In this dissertation, the following abbreviations and designations are applied:

%	–	Percent
°C	–	Degrees Celsius
AI	–	Artificial Intelligence
APE	–	Absolute Percentage Error
APSIM	–	Agricultural Production Systems sIMulator
AquaCrop	–	Crop water productivity model of the Food and Agriculture Organization of the United Nations
BNS	–	Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan
c/ha	–	Centners per hectare
CMIP6	–	Coupled Model Intercomparison Project, Phase 6
CO_2	–	Carbon dioxide
CO_2e	–	Carbon dioxide equivalent
CSC	–	Crop Specialization/Concentration Coefficient
DSSAT	–	Decision Support System for Agrotechnology Transfer
EF	–	Emission factor
EPIC	–	Environmental Policy Integrated Climate model
ET0	–	Reference evapotranspiration
GHG	–	Greenhouse gas
GIS	–	Geographic Information System
ha	–	Hectare
HHI	–	Herfindahl-Hirschman Index
kg CO_2/kWh	–	Kilograms of carbon dioxide per kilowatt-hour
kg/ha	–	Kilograms per hectare
kWh	–	Kilowatt-hour
KZT	–	Kazakhstani tenge
LLP	–	Limited liability partnership
LU	–	Livestock unit
m^3	–	Cubic metre
MAE	–	Mean Absolute Error
MJ	–	Megajoule
ML	–	Machine Learning
mln KZT	–	Million Kazakhstani tenge
mln m^3	–	Million cubic metres
mm	–	Millimetres
MPW	–	Margin per cubic metre of water
N	–	Number of observations
n	–	Sample size or number of observations in a subsample
NASA POWER	–	National Aeronautics and Space Administration Prediction of Worldwide Energy Resources
N_2O	–	Nitrous oxide

OAT	–	One-at-a-Time sensitivity analysis
p	–	Statistical significance probability, p-value
QŪNAR	–	Quantified Utilization of Natural Agricultural Resources
r	–	Pearson correlation coefficient
R^2	–	Coefficient of determination
REAP	–	Resource-Efficient Agricultural Production framework
RF	–	Random Forest
RH	–	Relative Humidity
RMSE	–	Root Mean Squared Error
RSE	–	Republican state enterprise
SSP	–	Shared Socioeconomic Pathway
th. ha	–	Thousand hectares
th. KZT/ha	–	Thousand Kazakhstani tenge per hectare
th. t	–	Thousand tonnes
TOPSIS	–	Technique for Order of Preference by Similarity to Ideal Solution
VAT	–	Value added tax
VIF	–	Variance Inflation Factor

NORMATIVE REFERENCES

In this dissertation, references are made to the following normative documents:

1 Law of the Republic of Kazakhstan. On State Regulation of the Development of the Agro-Industrial Complex and Rural Territories: approved 8 July 2005, № 66-III (as amended on 26 July 2026).

2 Resolution of the Government of the Republic of Kazakhstan. Concept for the Development of the Water Resources Management System of the Republic of Kazakhstan for 2024-2030: approved 5 February 2024, № 66 (as amended by Resolution № 695 of 28 August 2024).

3 Order of the Minister of Water Resources and Irrigation of the Republic of Kazakhstan. On approval of the aggregated norms of water consumption and water disposal: approved 4 June 2025, № 108-NQ (registered in the Register of State Registration of Normative Legal Acts under № 36253).

4 Decree of the President of the Republic of Kazakhstan. Strategy for Achieving Carbon Neutrality of the Republic of Kazakhstan until 2060: approved 2 February 2023, № 121.

5 Water Code of the Republic of Kazakhstan: approved 9 April 2025, № 178-VIII LRK.

6 Order of the Minister of Water Resources and Irrigation of the Republic of Kazakhstan. On approval of the aggregated norms of water consumption and water disposal: approved 9 September 2026, № 288-NQ (in force since 16 September 2026).

7 Environmental Code of the Republic of Kazakhstan: approved 2 January 2021, № 400-VI LRK.

8 Land Code of the Republic of Kazakhstan: approved 20 June 2003, № 442-II (as amended on 26 July 2026).

9 Decree of the President of the Republic of Kazakhstan. Concept for the Transition of the Republic of Kazakhstan to a Green Economy: approved 30 May 2013, № 577 (as amended by Decree № 568 of 10 June 2024).

10 Resolution of the Government of the Republic of Kazakhstan. Concept for the Development of the Agro-Industrial Complex of the Republic of Kazakhstan for 2021-2030: approved 30 December 2021, № 960 (as amended by Resolution № 671 of 29 July 2026).

INTRODUCTION

Relevance of the research topic. Unlike other sectors, agriculture depends directly on the condition, availability and interaction of natural resources [1]. Output is created from a physical resource base of land, soil, water, pasture and climate, and the extent to which this base can be used depends on energy, infrastructure and technology. With climate change these links shift, since temperature, precipitation, soil moisture and solar radiation act on the development of crops, the demand for irrigation and the growth of pastures, as well as on the water needs of animals and the economic value of the resource base [2].

This challenge is especially relevant for agricultural systems with water limitations and high territorial variability [3]. Agricultural output can grow through expansion of the cultivated area, higher yields, changes in the crop mix, more intensive irrigation or a combination of these processes, and each of them places different demands on land, water, energy and the environment. Therefore, growth of agricultural output alone does not indicate natural resource efficiency [4].

The Republic of Kazakhstan has a large agricultural land area and a high geographic variability of climate, water resources, soils, irrigation dependence and agricultural specialization, which is particularly pronounced in the south. Intensive specialization, the importance of irrigated agriculture, the concentration of several high-value crops and combined crop-livestock systems give Turkestan region a special place in the national agricultural system [5].

The empirical analysis of this dissertation shows significant differences in production scale, cultivated area, crop-livestock specialization and climatic exposure among the 17 territorial units of Turkestan region. Therefore, similar production practices and similar climatic exposures have different resource and economic effects in different districts, depending on the crop, irrigation dependence, pasture conditions and production infrastructure.

Stakeholder evidence also supports the relevance of the research. In the 2026 survey of 208 respondents, water was one of the most frequently named scarce resources, and climatic risks and irrigation development were among the main barriers and adaptation priorities. The respondents also showed considerable acceptance of mathematical modelling as a decision-support instrument. In the same survey, 85.6% of respondents noted a significant or moderate impact of climate change on agriculture in the region. These results confirm the practical need to link agricultural production decisions with explicit resource and climatic constraints.

At the same time, the methodology of agricultural modelling has changed significantly. The systematic review and bibliometric analysis of 860 Scopus publications conducted in the research [6] showed a shift from process-based simulation to spatial, data-driven, machine-learning and AI-supported decision systems. Modern modelling increasingly combines climate information and remote sensing [7] with yield prediction, irrigation analysis and decision support.

This methodological development opens new possibilities for agricultural economics. However, a prediction is not yet a production decision, especially when

water, land and other resources are limited. Resource accounting does not capture the nonlinear climate-production relationship, and an optimization can give a mathematically consistent solution that has only weak empirical support. Approaches of climate-smart agriculture also stress that agricultural resilience requires both evaluation and practical pathways [8]. This creates the need for an integrated economic-mathematical solution in which prediction, resource assessment, climate conditions, uncertainty and explicit constraints are complementary elements of one decision process.

The research problem is, therefore, to develop a scientifically sound model of agricultural decision-making that takes into account both the physical resource capacity of a territory and production system and the expected production performance.

Degree of scientific development of the problem. International agricultural modelling has developed along several complementary lines. Process-based models formalized the connection between weather, soil, water and crop growth [9]; spatial modelling and remote sensing added territorial heterogeneity; data-driven and machine-learning methods improved the detection of nonlinear relationships and interactions; optimization methods allocated limited resources among competing production options. Recent studies increasingly combine these methods in digital decision-support frameworks.

Despite these advances, several methodological problems of regional agricultural resource management remain. Many ratios and composite indicators of natural resource efficiency are used, and some of them mix physical resources with economic functions. Regional averages can hide district-level production structures and resource constraints [10]. Climate-yield relationships may differ between sites and crops. Normative values and model-derived estimates are sometimes treated as observed data. Finally, a good prediction does not mean that a production structure is feasible under limited land and water.

The dissertation fills these gaps by connecting the resource architecture, territorial heterogeneity, empirical prediction, evidence quality and limited resource allocation in a single economic-mathematical decision framework.

Research hypothesis. Natural resource efficiency in agriculture can be improved if decisions take into account the differences between territories and crops, the likely production performance and explicit resource constraints, and keep information on uncertainty and evidence throughout the decision-making process. Accordingly, an economically sound decision matches the production potential with the resource capacity of the chosen agricultural system.

The purpose of the research. The purpose of the dissertation is the development of a model of increasing the efficiency of natural resources using in agriculture in the Turkestan region, preventing climate change.

Research object. The research object is agriculture as a territorially differentiated system of crop and livestock production of Turkestan region.

Research subject. The subject of the research is the economic relations, resource limitations and decision-making aspects of the use and allocation of natural resources in agriculture in the context of climatic variability and climate change.

Research objectives:

– to reveal the natural resource architecture of agricultural systems and the transformation of natural resource efficiency in agriculture under climate change;

– to summarize international experience of economic-mathematical approaches to resource-efficient agricultural decision-making;

– to analyse the current state and to assess the efficiency of natural resource use in agriculture of Kazakhstan and Turkestan region;

– to assess the relationships among natural resource use, agricultural production and climate change;

– to substantiate strategic directions and an organizational-economic mechanism for improving natural resource efficiency in agriculture;

– to develop an economic-mathematical model for resource-efficient and climate-resilient agricultural decision-making and to implement it as a digital decision-support tool.

Theoretical and methodological basis of the research. The theoretical basis includes natural resource economics, agricultural economics, concepts of resource efficiency and climate-resilient agricultural development, and economic-mathematical decision theory. Methodologically, agricultural resource efficiency is treated as a multidimensional and state-dependent property determined by the interaction of the resource base, climatic conditions, production specialization and adaptive decision-making.

The research uses theoretical synthesis and comparative analysis, systematic literature review and science mapping, descriptive and structural statistical analysis, territorial comparison, decomposition of production changes into area and yield effects, Pearson and Spearman correlation analysis, within-territory transformation, multicollinearity diagnostics, stakeholder survey analysis, machine-learning prediction, out-of-sample and chronological validation, robustness and sensitivity analysis, scenario analysis, livestock resource assessment, Herfindahl-Hirschman concentration analysis and constrained mathematical optimization.

The machine-learning component represents the nonlinear relationships between territorial characteristics, production history and growing-season climatic conditions by Random Forest regression. The optimization component selects the allocation that maximizes the objective function subject to the available cultivated land, the irrigation-water budget and structural constraints. Prediction and optimization are separated so that the expected productivity is not automatically treated as the optimal production decision.

A key methodological principle is that each variable keeps its status as evidence: direct observations, official statistics, user-supplied measurements, normative or reference coefficients and model-based estimates are distinguished. Missing environmental information is not treated as zero

pressure, and a numerical forecast is withheld when the available validation data do not support it.

Information base of the research. The empirical base includes official agricultural and resource statistics, climatic data, stakeholder evidence and model input parameters. National climatic indicators are taken from Kazhydromet, district-level climatic variables from NASA POWER. The crop machine-learning panel consists of 1,362 district-crop observations across 17 territorial units and six crops observed over 2004-2025; the panel is unbalanced (1,362 of 2,244 possible district-crop-year combinations), because not every crop is grown in every territory and year. The climatic variables include temperature, precipitation, root-zone soil wetness and solar radiation. The empirical base is complemented by a survey of 208 agricultural producers and specialists of the region conducted in 2026.

Patent research and metrological support. Patent research was not required for the dissertation; the developed software (the QŪNAR web application) is protected as an object of copyright. Metrological support of the research is not required, because the empirical analysis is based on official statistical data, open climate databases and survey data and does not use measuring instruments. The scientific and technical level of the developed model corresponds to current international agricultural decision-support systems, as the comparison with existing tools in Section 3.3 shows.

Use of artificial intelligence technologies. Artificial intelligence tools were not used in the preparation of the dissertation. The research design, data collection and processing, model specification, calculations, interpretation of the results, scientific provisions and conclusions were formulated by the author independently; all code fragments and edited text were checked by the author**.**

Scientific novelty of the research.

1) The theoretical understanding of natural resource efficiency in agriculture has been developed through the concept of resource architecture, which connects resource endowment, production configuration and resource pressure under changing climatic conditions.

2) An empirical differentiated framework has been substantiated for Turkestan region, in which territorial heterogeneity is retained instead of being reduced to one efficiency coefficient, and the production response of crops and the form of resource pressure are taken into account.

3) An approach to strategic prioritization has been developed on the basis of independent statistical, climate-relationship, stakeholder and implementation evidence, in which the completeness of evidence is kept separate from the economic effectiveness of an intervention.

4) An adaptive organizational-economic approach for resource efficient and climate-resilient agricultural development has been created, linking monitoring, prediction, resource-feasibility assessment, decision selection, decision implementation and verification at farm, district and regional levels.

5) An integrated economic-mathematical model has been created that integrates machine-learning prediction, resource-climate assessment, evidence

hierarchy and constrained optimization of agricultural alternatives under explicit resource constraints, including land and water.

6) The model has been implemented as a computational environment, the QŪNAR digital decision environment, to allow for territorially differentiated crop and livestock assessment, resource accounting, scenario analysis, confidence diagnostics and resource-constrained allocation.

Main scientific provisions submitted for defense.

1) Natural resource efficiency in climate-sensitive agriculture is a state-dependent property of the whole resource-production configuration, determined by the compatibility of agricultural production with the availability, condition and interaction of land, water, soil, pasture, climatic and supporting resources.

2) Agriculture of Turkestan region needs to be assessed on a territorial and crop basis because of heterogeneous production specialization, climatic exposure, irrigation dependence and crop-livestock resource structure.

3) Evidence concordance clarifies the strategic prioritization of resource-efficient development: it separates the empirical evidence for a strategic direction from the assumed policy effect and avoids unsupported quantification of data-deficient resource dimensions.

4) The organizational-economic mechanism of resource-efficient agricultural development can be organized as a continuous feedback cycle of monitoring, prediction, resource-feasibility assessment, decision selection, implementation and verification.

5) The developed economic-mathematical model supports agricultural decision-making by combining nonlinear production prediction with a separate resource-climate layer and constrained optimization of production configurations, while the recommended configurations remain conditional on the actual or explicitly specified resource limitations of the production unit.

6) QŪNAR operationalizes the proposed model as a publicly reproducible digital decision environment in which each result carries information on its origin, certainty and feasibility, and insufficient evidence is a legitimate reason to withhold a numerical prediction or to give it only as a conditional result.

Theoretical and practical significance of the results. The theoretical significance is that the conceptual framework of Chapter 1 distinguishes four complementary analytical dimensions of a single approach: productivity, natural-resource efficiency, environmental stability and climate resilience. The practical significance is that the empirical diagnostics of Chapter 2, combined with the QŪNAR decision support of Chapter 3, provide district- and farm-level decision-makers, water-management organizations and agricultural producers with a resource-feasible, evidence-based production planning tool, which is confirmed by the act of implementation.

Relation of the research to state programmes. The research corresponds to the priorities of the Concept for the Development of the Agro-Industrial Complex of the Republic of Kazakhstan for 2021-2030, the Concept for the Development of the Water Resources Management System of the Republic of Kazakhstan for 2024-2030

and the Strategy for Achieving Carbon Neutrality of the Republic of Kazakhstan until 2060. The research was carried out within the grant project AP23487689 funded by the Ministry of Science and Higher Education of the Republic of Kazakhstan under the priority «Intellectual potential of the country» (fundamental and applied research in the field of social sciences).

Approbation and implementation of research results. The main results of the dissertation were obtained within the state-funded research grant AP23487689 [11] and were reported in the grant analytical reports for 2024-2026. The QŪNAR model is registered as an object of copyright (certificate of state registration № 77839 of 28 August 2026) [12] and is available as a web application (https://qunar-turkestan.streamlit.app) [13]. The theoretical and empirical results were also presented in the monographs [4; 14] and the textbook [15] prepared with the participation of the author. Intermediate results of the model validation were discussed during the research internship at the Department of Economics of Arizona State University (January–March 2026). The method of assessing natural resource efficiency, the organizational-economic mechanism and the QŪNAR digital decision environment were implemented in the production and economic practice of the agricultural production cooperative «BIO-AGRO» LLP for the analysis of the resource base, production planning and scenario planning of crop allocation (act of implementation, Appendix A). The act confirms the implementation of the results; the expected effect of QŪNAR is shown by calculation in Section 3.3, and the realized effect can be assessed during further monitoring.

Publications. The main results of the dissertation are published in 20 scientific works, including: 1 article in an international peer-reviewed journal indexed in Scopus (Qubahan Academic Journal) [6]; 10 articles in journals recommended by the Committee for Quality Assurance in the Sphere of Science and Higher Education of the Ministry of Science and Higher Education of the Republic of Kazakhstan [16-25]; 2 monographs [4; 14]; 1 textbook [15]; 6 certificates of state registration of rights to objects of copyright, including the certificate for the QŪNAR web application [12].

Structure and content of the work. The dissertation contains an introduction, three chapters, conclusion, list of references and appendices. Chapter 1 presents the theoretical and methodological foundations of natural-resource efficiency in climate-sensitive agricultural systems and a systematic and bibliometric analysis of the international development of agricultural modelling. Chapter 2 examines the use of natural resources, agricultural output and its links with resources and climate in Kazakhstan and Turkestan region over 2004-2025, comparing the 17 administrative units, individual crops and the results of the stakeholder survey. In Chapter 3, the strategic directions and the organizational-economic mechanism for resource-efficient and climate-resilient agriculture are justified, and the QŪNAR economic-mathematical decision-support system is described from its development and implementation to its validation and robustness testing. The dissertation is presented on 179 pages of the main text and contains 31 tables, 43 figures, 117 titles of references and 5 appendices.

1 Theoretical and methodological foundations of natural resource efficiency in climate-sensitive agricultural systems

1.1 Natural resource architecture of agricultural systems and its role in production development

Agricultural production takes place in a system of interdependent natural resources whose economic value depends on their joint ability to support biological production [26]. Cultivation and grazing take place on land as their spatial basis [27]; much of the productive capacity of this land comes from soil [28]; water sets the potential that can be realized in operation, and climate shapes how crops, pastures and animals respond biologically [29]. What agriculture can produce depends on how these resources are combined, not on the amount of any one of them.

This gives agriculture a special place among economic activities. Production is directly linked to natural cycles [15], seasonal variation and spatially fixed resources. Agricultural land cannot be separated from its soil and climatic properties, irrigation demand depends on temperature and precipitation, pasture capacity depends on climate and vegetation, and livestock production depends on feed, water and environmental conditions. The productivity of each resource therefore depends on the state of the others [30].

The natural-resource structure used in this research has five components: land and soil, water, climatic resources and conditions, pasture and feed resources, and energy-related inputs (Table 1.1). They are included because they create and limit the physical form of agricultural production and provide common resource conditions for the two main subsystems, crop and livestock production [31], although the nature and degree of dependence differ between them.

Land has several functions. It determines the physical scale of cultivation, the availability of pasture and feed for livestock and the territorial organization of agricultural specialization. Its productive value varies with soil characteristics, irrigation access, climatic vulnerability and the production option selected for a site. Agricultural area is thus both a production resource and an allocation space in which competing uses interact.

Soil is the qualitative component of this spatial resource [32]. Fertility, salinity, erosion, moisture-retention capacity and degradation processes change land productivity without changing the area, so two territories with the same agricultural area can differ significantly in effective productive capacity. The difference between land quantity and soil quality is especially important when intensive use strains fertility, moisture balance or salinity.

Water plays a more dynamic role, since its availability varies between seasons, territories and production systems. Crop production uses water from precipitation, soil moisture and irrigation [33]; livestock production needs drinking water and water for pasture and feed. Water shortage can therefore change both the scale and the structure of agriculture: different water limits may lead to different crops on the same irrigated area, and the same number of animals may create different resource pressure under different climate, pasture and water conditions.

Pasture resources are a separate element of the architecture, because livestock production is a biological process that depends on vegetation rather than on cultivated land [34]. The livestock load that a landscape can sustain without excessive pressure depends on the scale of pasture use, vegetation condition, carrying capacity and seasonality of feed. This creates a direct relationship between herd structure and the resource capacity of the territory.

Climatic conditions have an integrating role in the system. Temperature, precipitation and solar radiation affect irrigation needs, crop-growing and soil-moisture conditions, pasture productivity, feed availability and livestock heat exposure, mainly through the productive capacity of other resources. Hence, the same pasture area or the same volume of irrigation water can have different economic value under different climatic conditions.

The resulting classification is summarized in Table 1.1.

Table 1.1 – Natural-resource structure of agricultural production and its analytical role

Resource block	Economic role in agriculture	Main production link	Relevance
Land and soil	Spatial and qualitative basis of production	Availability and condition of cropland and pasture: fertility, salinity, degradation	Scale of production, allocation, territorial differences
Water	Renewable production resource limited in space and season	Irrigation, livestock water supply and fodder production	Availability, demand, losses, reuse and water pressure
Climatic conditions	Determines the productive state of land and water resources.	Environmental factors: temperature, precipitation, soil wetness, solar radiation.	Yield formation, climate exposure and seasonal variability
Pasture and feed resources	Capacity of livestock systems to use resources	Capacity of land to support animals through grazing and feeding	Livestock sustainability
Energy-related inputs	Ensures access to natural resources and their delivery and productive use	Pumping, irrigation, machinery	Energy intensity and resource support costs

Note – Compiled by the author based on the theoretical synthesis of natural-resource functions in agricultural production.

Energy, irrigation infrastructure and agrotechnologies shape the capacity to convert the natural-resource base into agricultural output [35]. Their contribution is greatest in irrigation-dependent systems, where available water is not yet productive capacity: water has to be supplied, conveyed and applied through a technological system whose efficiency affects both resource use and production costs. Energy is therefore included in the resource architecture as a production input for pumping, irrigation, mechanization, storage and other operations [16].

These relationships are summarized in accordance with Figure 1.1.

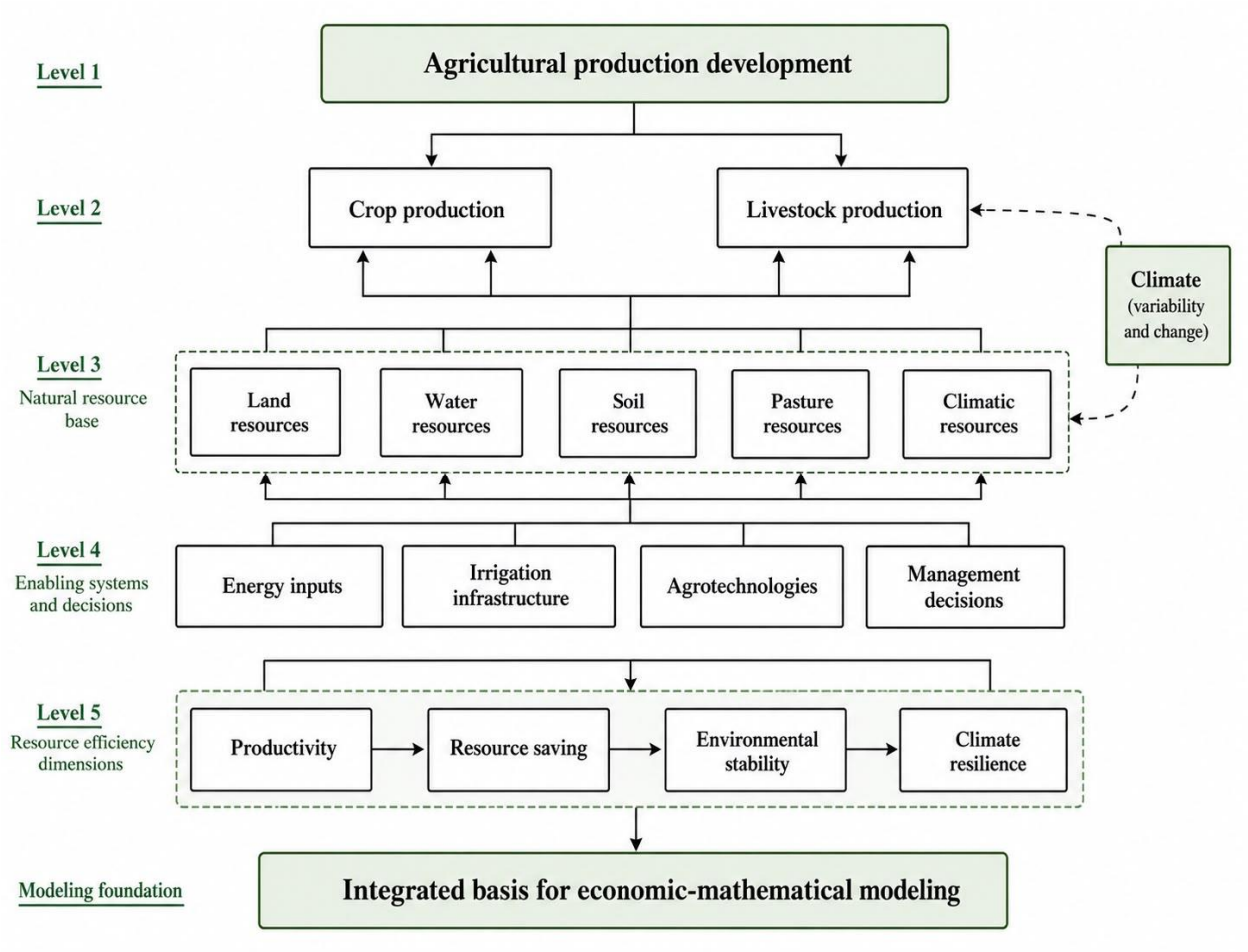


Figure 1.1 – Natural resource architecture of agricultural systems

Note – Compiled by the author based on the theoretical framework of natural-resource interactions in agricultural systems.

Operational energy must be clearly distinguished from naturally available climatic energy [36]. Solar radiation is an environmental factor of crop development and photosynthesis, whereas electricity and fuels are operational inputs used to move water and run machinery and infrastructure. Both have an economic function, but their nature is different. This separation allows the energy intensity of production to be evaluated without mixing it with the climatic variables of the natural production environment.

A management dimension is added because limited land, water, pasture and other resources must be allocated among competing crop and livestock activities, and the more binding a resource becomes, the more important its allocation is. Crop and livestock production compete for land [37], irrigation water, pasture and feed, but also complement each other through crop residues and livestock by-products. In accordance with Figure 1.1, the natural-resource architecture is a hierarchy that connects agricultural production with its resource base and with the systems that manage resource use. Crop and livestock production are based on land, water, soil, pasture and climatic resources; energy inputs, irrigation infrastructure, agrotechnologies and management decisions influence the transformation of these

resources into output, while climate influences both the condition of the resource base and the biological response of the production subsystems.

The productive capacity of agriculture depends on both the quantity and the state of resources [38]. Production can expand through a larger cultivated area or more irrigation water and can contract through degradation of soil quality, water reliability, pasture condition or climatic conditions. Agricultural growth thus depends on both resource availability and resource productivity.

The hierarchy of resource constraints links land with the productive quality of soil, water with the intensity of use and crop composition, and pasture and feed with livestock capacity. Climate affects these constraints in multiple ways, and energy and infrastructure determine their practical availability. Therefore, the resource architecture is assessed through the relationship of three elements: resource endowment – production configuration – resource pressure [17].

The productive capacity of resources and the demand placed on them change with climatic variability, so the efficiency of the same production configuration may differ under different climatic conditions. Resource scarcity, climate and production structure thus form the theoretical framework for analysing changes in natural resource efficiency under explicit resource constraints.

1.2 Transformation of natural resource efficiency in agriculture under climate change and resource constraints

Natural-resource efficiency in agriculture changes together with the environmental and production conditions in which resources are used. The productive value of land, water, soil and pasture changes over time, because their contribution to output depends on temperature, precipitation, moisture availability, production specialization and technology. Climate change therefore affects resource efficiency both indirectly, through the state of the resource system, and directly, through the production response to this change [39].

This connection is most evident in irrigated farming. Higher temperature increases evapotranspiration and can raise crop water demand, while lower or less frequent precipitation reduces the natural moisture contribution to crop production. In such cases, more water is needed to obtain the same yield from the same area: the land area remains constant, but the resource input required to maintain its productivity increases.

Crop-specific studies for Turkestan region also showed that the relationship between climatic conditions, irrigation practices and productivity is particularly important for climate-sensitive crops such as cotton [18].

A similar change occurs when soil moisture decreases. Lower root-zone wetness directly affects crop development and increases the reliance on irrigation, which strengthens the link between climatic exposure and water scarcity. Where water supply is already constrained, climate change affects not only biological stress but also water allocation, because additional demand in one use reduces the supply for others. Climatic pressure also changes the productivity of pastures and livestock systems: drought and prolonged heat reduce available vegetation, increase feed

requirements, aggravate heat stress and raise the demand for drinking water. The resource requirement of a herd of a given size therefore varies with climatic conditions. These processes illustrate the state-dependency of agricultural resource efficiency: the same resource bundle may give different results in different environments, and the same production objective may require different amounts of land, water, energy or feed. Resource efficiency is thus defined as the ratio between the production result and the resource configuration needed to achieve it. Resource productivity is also used as an economic indicator in the Concept for the Transition of the Republic of Kazakhstan to a Green Economy, which links it with value creation on the basis of water, land and energy resources and with environmental pressure [40].

The main conceptual dimensions used to describe this transformation are summarized in Table 1.2.

Table 1.2 – Conceptual dimensions of natural-resource efficiency under climate change and resource constraints

Productivity	Natural-resource efficiency	Environmental stability	Climate resilience
• Output from a given production base • Typical indicators: yield, output per hectare, output per head	• Output per unit of scarce resource • Typical indicators: water productivity, land productivity, energy intensity	• Condition of the resource base over time • Typical indicators: soil quality, salinity, degradation, pasture condition, water quality	capacity to maintain functions under climatic variability • Typical indicators: yield stability, drought response, recovery capacity
These dimensions jointly define the transformation of resource efficiency under climate change and resource constraints.			

Note – Compiled by the author based on the theoretical synthesis of natural-resource efficiency, environmental stability and climate resilience.

Table 1.2 distinguishes productivity, natural-resource efficiency, environmental stability and climate resilience. Productivity is the physical output obtained with a given set of production factors. Natural-resource efficiency refers to the combination of limited resources needed for production. Environmental stability characterizes the state of the resource base over time, and climate resilience is the ability of the production system to maintain or adjust its functions under climatic variability.

How climate change transforms natural-resource efficiency is summarized in accordance with Figure 1.2.

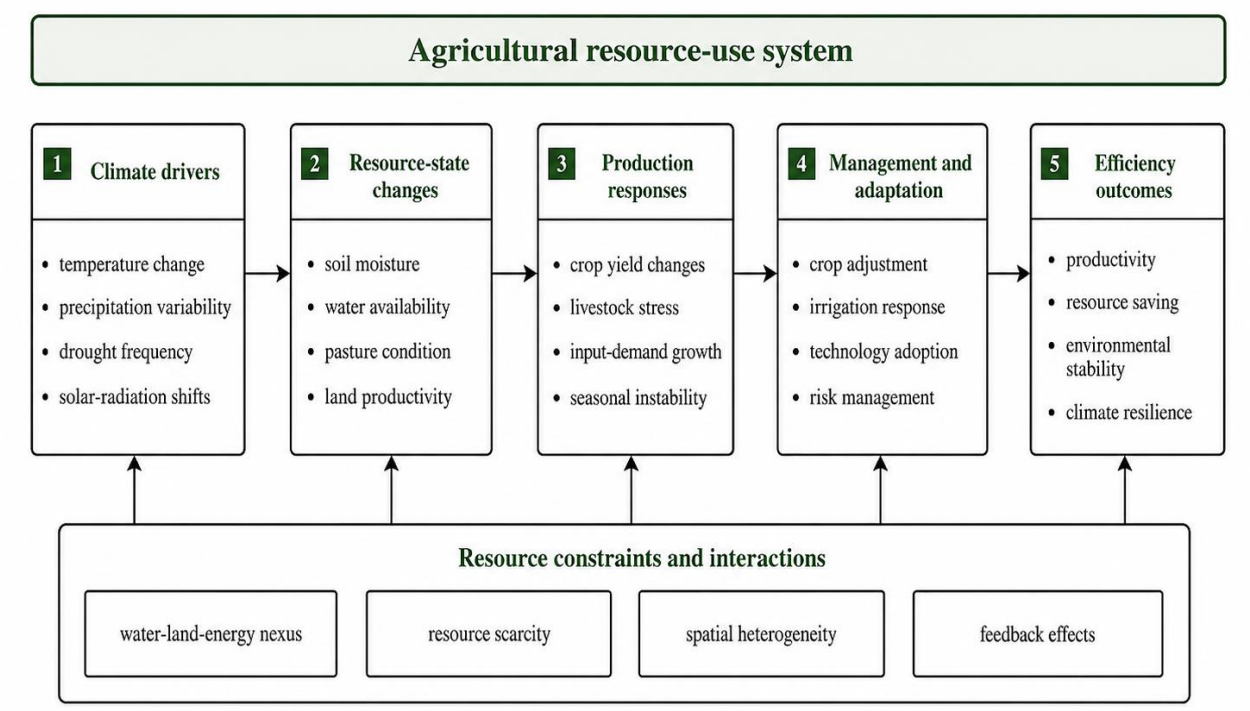


Figure 1.2 – Mechanism of climate-driven transformation of natural resource efficiency in agriculture

Note – Compiled by the author based on the theoretical relationships between climate drivers.

In accordance with Figure 1.2, climatic pressure changes resource conditions [41], which in turn change production responses and adaptation decisions. The efficiency result depends on the combination of climatic exposure, resource limitations and reallocation of resources among agricultural activities.

The notion of effective scarcity plays a key role here. Production possibilities are not fully explained by the physical volume of resources: the timing, quality and complementarity of a resource also determine how much of it can be used. Water may exist in the system but be unavailable in a critical production period; a large land area may be limited by soil quality or irrigation access; degraded pasture or seasonal feed shortages may support only a reduced stocking rate over a large area.

Climate change alters effective scarcity because it changes the amount of complementary resources needed to maintain production. A warmer season may increase irrigation demand, prolonged moisture deficits may reduce pasture productivity and increase feed requirements, and changes in radiation and moisture may change crop suitability [42]. The relative value of resources therefore changes with the climatic state of the system.

Natural resource efficiency is thus a variable characteristic of the agricultural system. It reflects the ability to produce within the limits of a changing environment and to keep resource demand compatible with resource availability. The appropriate unit of analysis is, therefore, the configuration of land, water, climate, pasture and energy-related inputs together with the activities to which they are allocated.

This interpretation directly implies a methodological requirement for economic-mathematical modelling. Agricultural resource efficiency must be quantified in a way that reflects the different production response to different resources, the interactions between resource dimensions and the effect of climatic variability and explicit constraints on feasible production options. Such models are being developed in many countries, which provides a methodological basis for choosing an appropriate analytical framework for resource-use decisions in agriculture.

Resource-saving technologies can produce rebound effects. Higher irrigation efficiency may reduce water use per hectare but increase the irrigated area [43], so that total water use remains the same or grows. Similarly, a more efficient pump lowers energy costs and may encourage more irrigation. Resource efficiency should therefore be assessed at both the unit and the system level.

Climate-sensitive resource efficiency is a multi-objective problem, because higher productivity, diversification, water saving and resilience may involve trade-offs between resource dimensions. The value of land, water, pasture and energy is therefore relative and depends on the production system and environment in which they are used. The marginal contribution of irrigation water in a water-intensive crop system differs from that in a diversified system with a lower total irrigation requirement, and pasture quality depends on stocking density, feed availability and climatic conditions.

The interaction between resources can produce threshold effects [44]. At first, higher temperature can be absorbed by existing irrigation capacity, soil moisture and soil management. Once water demand comes close to the available supply, however, even a modest climatic shift can affect production feasibility out of proportion to its size, and climatic pressure turns from a tolerable condition into a factor that limits resources [45]. Similar thresholds may occur when stocking rates are high or when drought reduces forage production below the level needed for the current herd.

Threshold behaviour limits the usefulness of a linear interpretation of resource pressure. A change of temperature or precipitation by one unit does not have the same marginal effect under all resource conditions; the effect depends on the gap between the current resource requirement and the relevant constraint. Agricultural systems close to their water, land or pasture limits are therefore more vulnerable to climatic deterioration than systems with larger resource buffers.

Resilience is closely related to the resource buffer, that is, slack or flexibility that allows a production system to withstand adverse conditions without structural change. Buffers can be increased through additional water storage, crop diversity, reserve pasture, alternative feed sources or flexible irrigation technologies. Their economic benefit is most visible under unfavourable conditions, when they prevent a temporary shock from becoming a permanent loss of production.

Climate change can also modify the regenerative capacity of resources. Higher temperatures and changes in precipitation may slow the natural recovery of soil moisture [46], increase evaporation from reservoirs and irrigation systems, extend the recovery time of pastures or change vegetation composition. Resource

pressure can therefore build up even when annual production seems stable, and stable yields may hide a growing dependence on irrigation, energy and supplementary feed.

Separating observed output from the underlying resource pressure is key to the economic interpretation of climate adaptation [47]. A system can compensate for adverse climatic conditions by using more resources and thus maintain production. From the output point of view, such adaptation is successful; from the resource-efficiency point of view, the same result may indicate declining efficiency if more and more limited water, energy or feed is needed to maintain production.

Therefore, the cost of maintaining stability should be included in the assessment of adaptation. Outcomes such as yield preservation, herd maintenance or expansion of cultivated area should be assessed together with the additional resources required to achieve them. Adaptation is more resource-efficient when it reduces sensitivity to climatic pressure without a disproportionate dependence on other limiting resources [19]. These trade-offs can be represented by the concept of the feasible production set. At any moment, the land, water, pasture, climate and infrastructure of an agricultural system allow a range of technically feasible production structures; resource scarcity narrows this range, technological development extends it, and climatic change may reduce it. Adaptation decisions move the system within this feasible set.

Highly productive production structures may be close to one or more resource limits and therefore fragile under shocks, whereas a more diversified structure may operate less intensively but with more room for adjustment. The economic assessment of resource-use efficiency should therefore consider both the efficiency of the current configuration and the flexibility that remains for future adaptation.

This interpretation is particularly relevant under climate uncertainty, when future resource conditions are not well known. Crop allocation, livestock intensity, irrigation technology and resource investments must be decided before the climatic outcome of the season is known. Past weather patterns indicate possible future conditions and their variability, but recent changes may make past averages unreliable.

Uncertainty creates a gap between expected and robust efficiency. Expected efficiency is the performance under a particular or average state [48], whereas robust efficiency is the ability of a production configuration to maintain satisfactory resource and production performance over a range of plausible states. A highly specialized system may perform very well under the expected climate but poorly under drought, while a more flexible allocation may give a slightly lower average result with smaller losses in unfavourable conditions.

This distinction makes scenario analysis a practical planning tool. Climate and resource scenarios allow the effects of different states to be compared before decisions are made. Scenarios can be defined by water availability, temperature, precipitation, crop structure, irrigation technology or livestock pressure, and their analytical value lies in showing how the ranking of production alternatives changes with the resource environment [20].

Scenario analysis also reveals trade-offs. Under a reduced water budget, the crop portfolio that maximizes output under normal water supply may cease to be optimal, just as trade-offs between land-use functions change with resource conditions [49]. A technology that is economical at low energy prices may lose its advantage when pumping needs increase, and a livestock structure that is sustainable under normal pasture productivity may create excessive pressure during prolonged drought. The best choice therefore depends on the resource conditions of the scenario, and analytical decision tools are increasingly used to structure such strategic choices [50].

This dependence creates the need for sensitivity analysis. A decision is vulnerable if small changes in assumptions or resource parameters lead to large changes in the preferred production structure, and robust if it remains stable over a reasonable range of conditions.

The same applies to empirical relationships. Observed climate-yield responses [51; 52], water requirements and production coefficients are uncertain [53], and data quality, temporal coverage and model stability must be taken into account when they are used in decision analysis. In a resource-efficiency framework, observed values, reference parameters and model-based estimates should be kept separate; otherwise, uncertainty is hidden in one indicator.

This is particularly relevant when several data sources are integrated. Production and land-use data may come from agricultural statistics, climatic data from climate and land-management databases [54], and inputs from farm-level descriptions of available resources and technology. These sources differ in spatial scale, temporal resolution and measurement certainty, so their integration requires a hierarchy in which each variable enters the analysis according to its evidential status [55].

The concept of evidence quality extends resource-efficiency analysis beyond physical measurement [56]. A model can give an exact number from uncertain and incomplete inputs, so the quality of a decision depends both on the estimate and on the reliability of the underlying information. This is especially important in district- or farm-level resource analysis, where some variables are observed and others are assumed or taken from reference values.

This theoretical development creates specific methodological requirements for measuring natural-resource efficiency under climate change [57]. The analytical framework must reflect several resources simultaneously, retain territorial and production diversity, include nonlinear responses, distinguish observed and model-generated information, include explicit constraints, compare scenarios and assess the stability of decisions.

These requirements explain the growing role of data-driven approaches in agricultural research. Machine-learning methods capture the relationship between climatic, production and resource variables more flexibly, while optimization methods convert the predicted results into an implementable allocation decision.

In this structure, prediction and optimization are two different analytical functions [58]. Prediction estimates the expected production response under given

historical, climatic and production conditions; optimization allocates scarce resources among activities subject to explicit constraints. Scenario analysis connects them by changing the conditions under which predicted responses and allocation decisions are assessed [59].

Combined, these functions allow agricultural resource efficiency to be interpreted as a decision problem under constraints and uncertainty. The relevant question is which production configuration gives adequate productivity without exceeding the available resource limits and without losing adaptability to climatic variation [21]. This formulation reflects the shift from descriptive resource characterization to an integrated decision-support framework based on economic-mathematical models. A previous empirical assessment of Turkestan region showed substantial territorial differentiation of climatic exposure and agricultural performance, which requires moving from general climate-resource relationships to spatial analysis [60].

Under climate change, natural-resource efficiency can therefore be explained as a dynamic interaction between the characteristics of natural resources, the environmental state, the production structure and the adaptive capacity and flexibility of decision-making. Methods based on individual indicators and fixed coefficients cannot capture it, and a more integrated analysis of resource interactions is needed [61]. The international evolution of agricultural modelling provides the methodological basis for this transition and for decision systems that integrate empirical evidence, prediction, scenario evaluation and constrained allocation.

1.3 Evolution of economic-mathematical approaches to resource-efficient agricultural decision-making: international experience and methodological framework

The international development of economic-mathematical models in agriculture has gradually broadened their analytical functions from representation to spatial analysis, forecasting, optimization and decision support. This evolution reflects the complexity of agricultural systems, in which natural resources [62], climate, crop and livestock production interact at different spatial and temporal scales.

Process-based modelling was one of the earliest and most influential directions. Systems such as DSSAT [63], APSIM [64], AquaCrop [65] and EPIC [66] simulate the biophysical processes that link weather, soil, water and crop development. Their analytical strength is the explicit description of causal mechanisms: crop growth is simulated through phenological stages, soil-water balance, temperature response, irrigation schedules and other agronomic parameters. This makes process-based models especially useful for the analysis of climate impacts, irrigation demand and adaptation.

Over the last three decades, these systems have been widely used to study conditions that cannot be tested directly at the territorial scale: alternative temperature trajectories, precipitation changes, irrigation regimes and crop management strategies can be analysed in a controlled environment [67]. Process-

based modelling thus laid the foundation for climate-sensitive agricultural analysis by connecting environmental factors with observable production results.

Such models also relate water use, soil conditions and management practices to crop performance within a single biophysical framework, which linked water management with resource-efficiency analysis; today artificial intelligence is applied for the same purpose of maximizing resource efficiency along the whole food chain [68]. Irrigation methods, sowing dates and crop varieties can be compared by their effects on yield and resource use, which gives a detailed physical representation of how natural resources affect production.

As agricultural research increased in scale, territorial heterogeneity became more important. Field-level simulation gives detailed information on production processes, whereas regional resource management requires an understanding of spatial differences in climate, irrigation access, land condition, water availability and infrastructure. This led to the use of geographic information systems, remote sensing and spatially explicit environmental data in agricultural modelling.

Spatial and data-driven approaches extended the analysis from production units to larger territorial systems. Satellite observations, land-cover databases, evapotranspiration estimates, vegetation indices and climate grids revealed patterns that individual ground measurements could not show. Water stress, drought exposure, irrigation performance, land degradation and land-use change can now be assessed at the level of districts, basins and agricultural regions.

Spatial monitoring also changed the nature of agricultural information. Traditional agricultural data were based mainly on periodic statistical observations [69], whereas modern systems integrate remote sensing, meteorological databases, administrative and farm-level data and sensor networks. The analytical problem thus became the integration of heterogeneous data sources with different spatial coverage, temporal resolution and measurement structure.

The international methodological trajectory is summarized in accordance with Figure 1.3.

In accordance with Figure 1.3, agricultural modelling has moved from process-based representation to spatial observation, AI-driven prediction and hybrid decision-support systems, that is, towards the growing integration of biophysical, territorial, predictive and economic functions in agricultural modelling.

The systematic review and bibliometric science mapping of agricultural modelling under climate change confirm this trajectory. The analysed corpus of 860 Scopus publications showed a gradual shift from process-oriented crop and resource models to spatial, data-driven and AI-based models.

The thematic structure of the field is centred on four broad concepts – climate change, agriculture, crops and learning systems – which shows the growing connection between environmental analysis, production modelling and predictive technologies [6]; automation and digital technologies are also changing agricultural work itself under climate change [70]. The evolution is also visible over time. Climate effects, drought, food security, crop production and yield dominated the first period; vulnerability, sustainable farming, soil, adaptation and forecasting gained

weight in the second; and in 2021-2025 the thematic structure was organized around machine learning, artificial intelligence, learning systems, remote sensing, prediction and Random Forest.

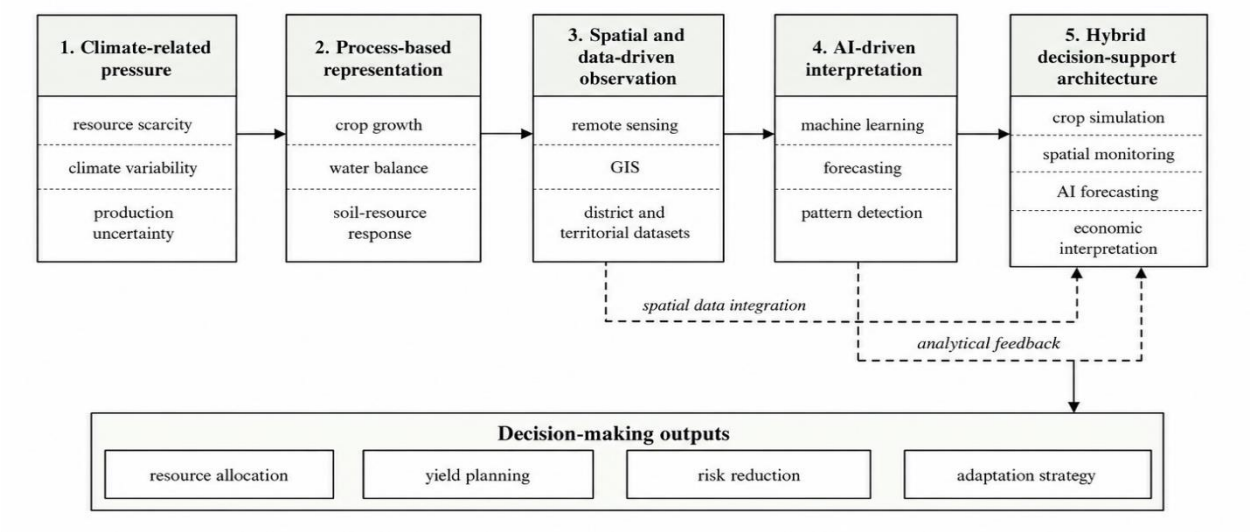


Figure 1.3 – Methodological evolution of agricultural modelling under climate change

Note – Compiled by the author based on the synthesis of international approaches to agricultural modelling under climate change.

This development is presented in accordance with Figure 1.4.

The growth in the number of publications confirms this: of the 860 publications in the systematic review, 715 were published in 2021-2025, a significant increase compared with previous periods [6, p.102].

This acceleration shows the rapid development of agricultural modelling as an interdisciplinary field that combines climate science, environmental monitoring, agricultural production and digital technologies.

The international trend also shows the convergence of different modelling traditions. Process-based models provide agronomic and biophysical explanation, spatial approaches provide territorial visibility, machine-learning methods strengthen prediction and pattern recognition, and optimization formalizes the allocation of scarce resources. Integrated, they form a methodological architecture in which different models perform complementary functions within a shared decision context.

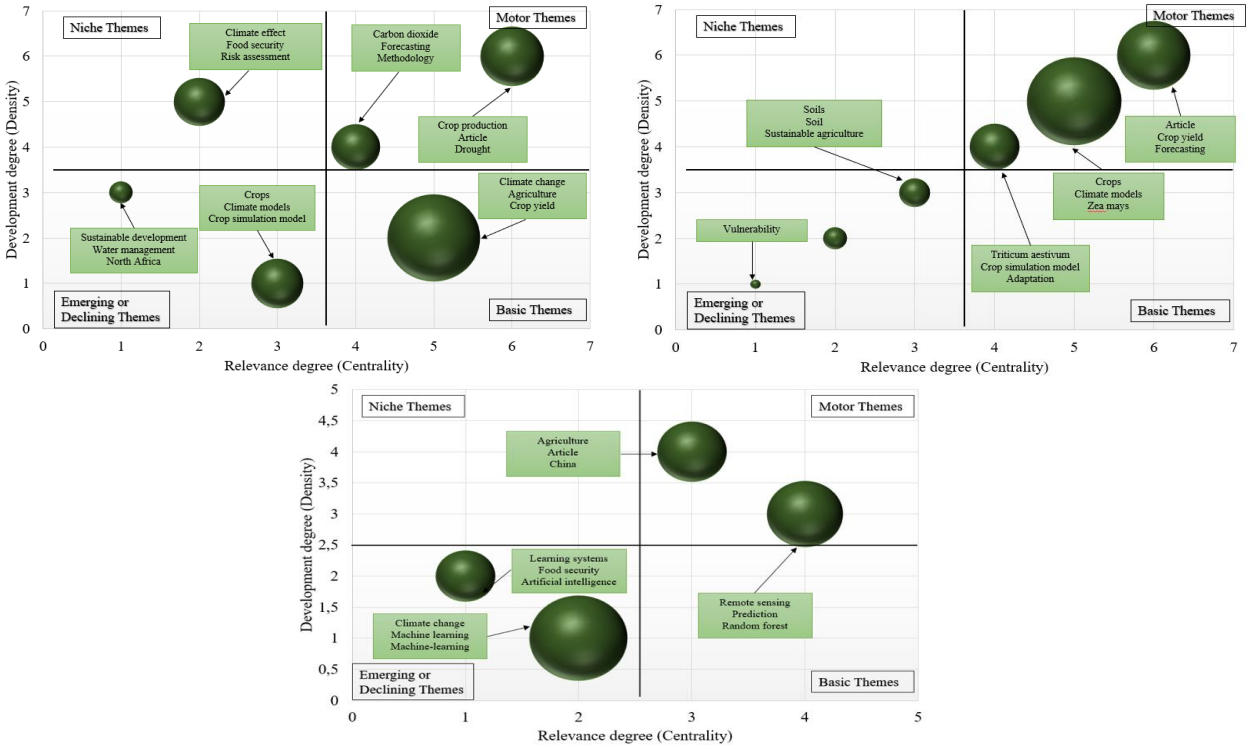


Figure 1.4 – Thematic evolution of agricultural modelling under climate change, 1992-2025

Note – Centrality measures the links of a theme with the rest of the research field, and density measures the development and coherence of the theme. Motor themes are well developed and highly connected; basic themes are central to the field but less internally developed; niche themes are internally well developed but less central; emerging or declining themes are less central and less developed and may reflect new or diminishing research directions. Thematic maps: centrality and density of Callon [6, p.101]. The panels show the first period (top left), the second period (top right) and 2021-2025 (bottom).

The methodological change is international in scope, as the geographical distribution of research activity shows [6], which is consistent with the global character of climate change impacts on economic outcomes [71]. The main centres of publication activity are India, China and the United States, followed by Germany, Australia, Italy and a wider group of countries involved in climate-sensitive agricultural modelling, in accordance with Figure 1.5.

This geography is methodologically significant. The field has developed within the research traditions of large agricultural economies, technologically advanced farming systems and climatically and water-stressed regions. Foreign experience therefore offers a diversified methodological basis that includes crop simulation, modelling of water resources and irrigation water use, remote sensing, machine learning and digital decision-support systems.

Although agricultural problems differ by country, international modelling addresses a set of recurring issues: climatic uncertainty, territorial heterogeneity,

resource scarcity, production forecasting and production allocation under constraints. This convergence has gradually linked prediction with optimization and scenario analysis and created the methodological foundations of integrated resource-efficient agricultural decision-making.

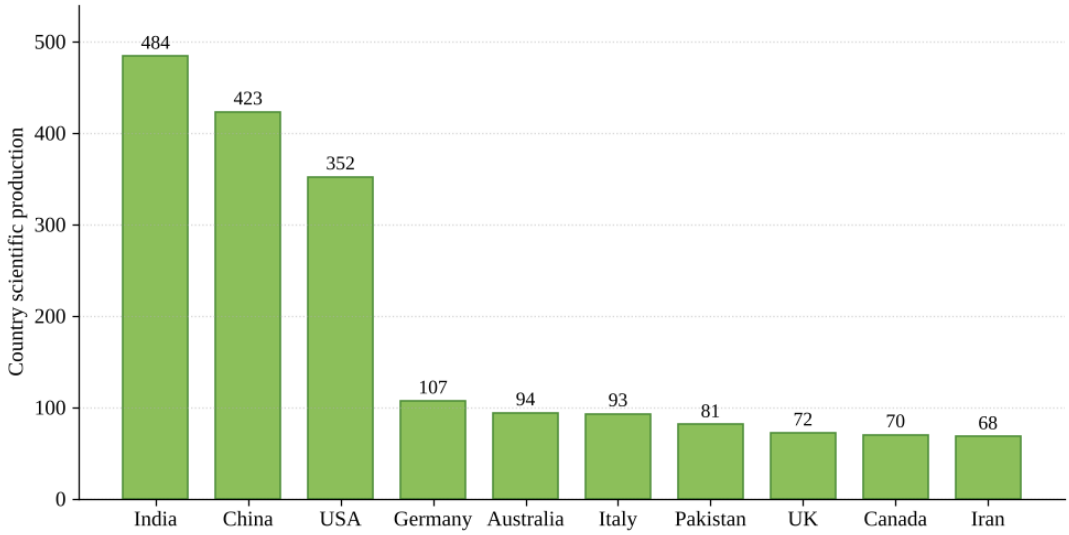


Figure 1.5 – International distribution of scientific activity in agricultural modelling under climate change

Note – Compiled by the author based on bibliometric analysis [6, p.102].

International experience thus shows a gradual convergence of explanation, observation, prediction and allocation, and modern resource-efficient agricultural decision-making requires modelling that links these functions in an integrated framework. This provides the basis for identifying the properties required of an integrated economic-mathematical system for managing agricultural resources under climate change.

As a result, agricultural research increasingly focuses on integrated decision environments that combine observation, prediction, resource constraints and resource allocation as analytical functions [72]. Modern crop models provide information on crop response, climatic exposure, water stress, soil conditions and production risk, but their practical value for efficient resource management depends on the ability to convert these outputs into categories of scarcity, feasibility, adaptation and allocation.

Agricultural decisions are made under several simultaneous constraints. Crop and livestock production share the same land, water and pasture base, and climatic conditions and energy inputs belong to the same production system. A higher yield projection may increase irrigation demand, livestock expansion may increase the demand for pasture, feed and drinking water, and irrigation modernization may reduce water losses but increase energy requirements. The economic effect of a production choice can therefore be seen only in the resource setting in which it is made.

International methodological development structures this complexity through a sequence of analytical functions. Resource and climate observations describe the current or past state of the agricultural system; predictive analysis estimates the production response under specific production and environmental conditions; feasibility assessment establishes the boundary set by available land, water, pasture and infrastructure; allocation and scenario analysis compare production structures within these limits.

Remote sensing, GIS and environmental monitoring have greatly strengthened the observation function [73]. These technologies provide territorial information on vegetation, soil moisture, land use, irrigation performance and climatic exposure and reveal regional heterogeneity that conventional field observations could not capture efficiently. For this reason, spatial data now matter for agricultural decisions, above all where producers share resources and where production conditions differ strongly within a territory.

The predictive function has been reinforced by machine-learning methods [74]. These methods are most useful where production responds nonlinearly to the joint action of climate, crop properties, location and resources – for example, where the temperature effect changes with soil moisture, where the crop response varies with the season and precipitation, or where identical inputs lead to unequal results in different territories. Predictive models derive such relationships from past data and translate them into estimates for planning.

The next analytical step is feasibility, since agricultural production always takes place within a limited resource space [75]. Land availability limits spatial expansion, seasonal water supply determines the scale of irrigated production, pasture capacity determines livestock intensity, and infrastructure and energy access determine how far natural resources can be mobilized. These restrictions set the boundaries of possible production options.

Water allocation is an example. Competing crops have different expected yields, water needs and climatic sensitivities but use the same irrigation water in a given season, so a larger area of one crop reduces the water available for others. A production structure that is feasible under normal water supply may reach the water boundary and become infeasible when availability decreases.

Land creates a similar interaction, since the space for crops, feed production and pasture-based activities is limited [76]. Crop and livestock activities are also interdependent, because the number of animals determines feed and pasture pressure and the demand for drinking water. Resource-efficient agricultural planning therefore requires crop and livestock activities to be evaluated within a common system of resource limitations.

Optimization captures these interactions mathematically by turning scarcity into explicit constraints on the decision space. Scenario analysis adds a dynamic dimension by making climatic and resource conditions variable: limited irrigation water may represent a drought scenario, temperature or precipitation scenarios change predicted productivity, new irrigation technologies change water demand, and changes in the crop-livestock structure shift resource pressure.

The integration of these functions is summarized in accordance with Figure 1.6, which shows the relation between resource and climate observation, predictive analysis, feasibility assessment, allocation and scenario evaluation. The framework translates land, water, climate, soil and pasture information into production responses and resource constraints; alternative production configurations are then compared by production, resource saving, resilience and environmental stability, and the outcomes are used as feedback for subsequent decisions. This is consistent with the global shift towards hybrid decision-support systems that combine process-based simulation, spatial observation, artificial intelligence forecasting and economic interpretation for climate adaptation.

The rapid development of machine learning, remote sensing, prediction and learning systems in recent years confirms the growth of this integrated approach. At the same time, international experience reveals an important methodological imbalance: environmental, crop-oriented and digital modelling has grown very quickly, while the economic interpretation of their outputs remains comparatively weak. The systematic review of 860 Scopus publications identified this as one of the main gaps in the current research field.

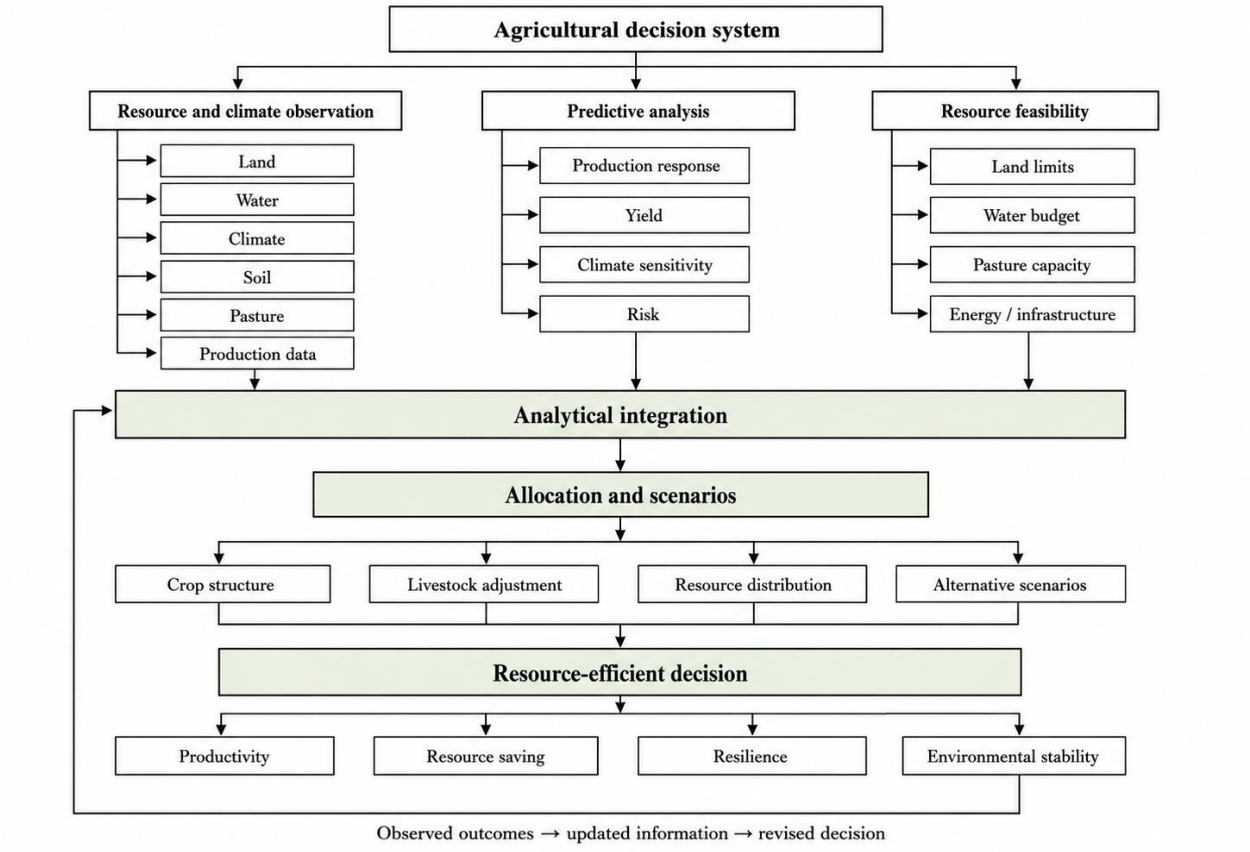


Figure 1.6 – Integration of analytical functions in resource-efficient agricultural decision-making

Note – Compiled by the author based on the methodological synthesis of predictive, feasibility, allocation and scenario-analysis functions.

This is particularly significant for agricultural economics, because prediction alone is not sufficient to decide on the optimal use of scarce resources. A forecast can approximate the yield under given climatic conditions [77], but resource-efficient decisions also require information on the water, land and other inputs needed to produce this yield and on the opportunity cost for other activities. The same applies to climate adaptation: additional irrigation can maintain crop productivity during drought but increases the pressure on water and energy; additional feeding can stabilize livestock production but increases the demand for purchased feed [78]; changes in crop structure can reduce exposure to water scarcity but alter land allocation and production composition. An economic evaluation of adaptation therefore depends on how each response redistributes resource pressure.

The methodological synthesis of these relationships is presented in accordance with Figure 1.7.

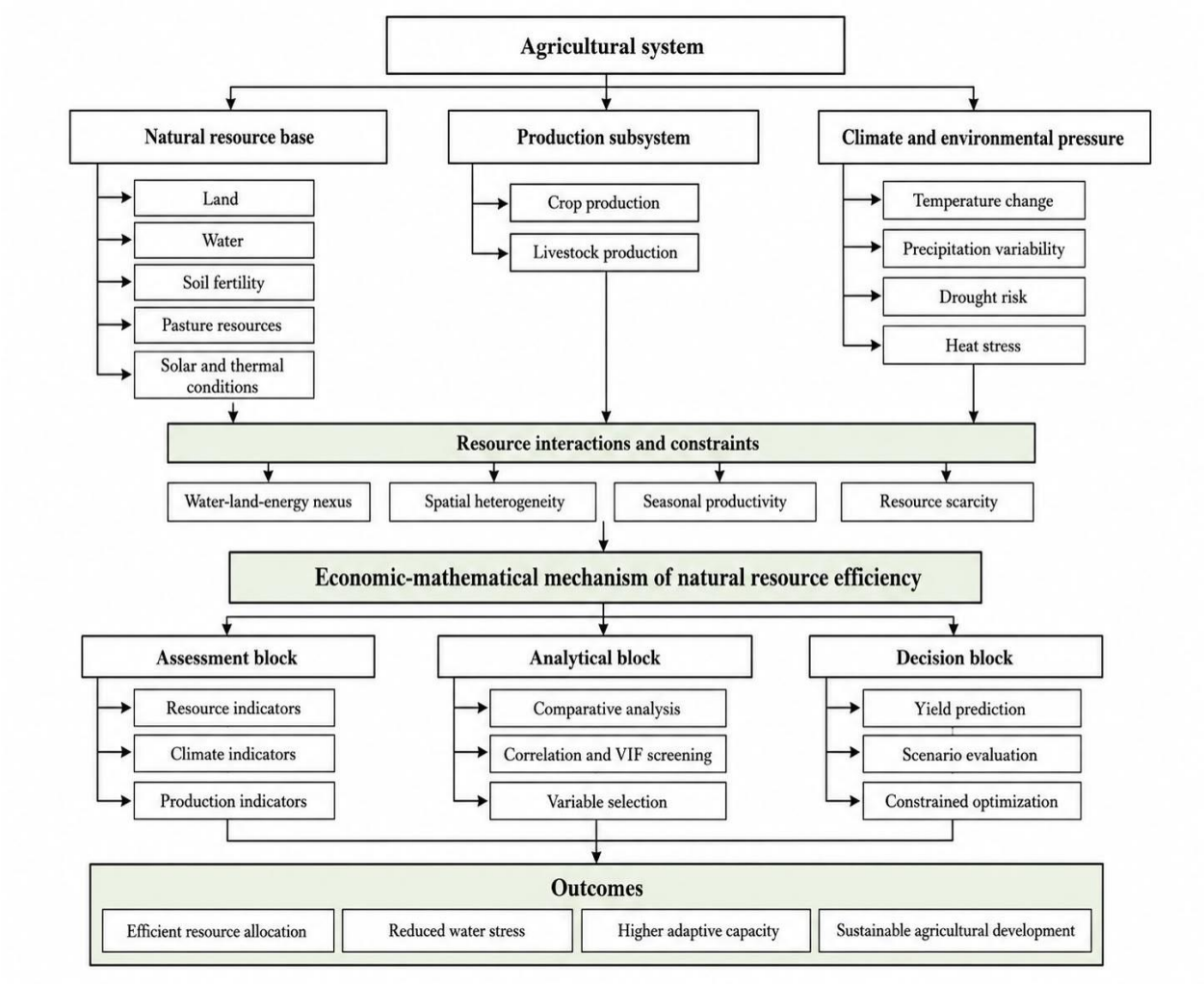


Figure 1.7 – Integrated framework for economic-mathematical assessment and resource-efficient agricultural decision-making

Note – Compiled by the author based on the theoretical and methodological synthesis presented in Chapter 1.

In accordance with Figure 1.7, the main theoretical and methodological elements of resource-efficient agricultural decision-making are combined in one framework. Its lower level consists of three interconnected domains of the agricultural system: the natural-resource base, the production subsystems and climatic and environmental pressure, whose interaction creates spatial heterogeneity, temporal variation, resource scarcity and interdependence of land, water, climate and energy inputs. The natural-resource base includes land, water, soil and pasture and their productive state, which depends on climatic conditions [79]. Crop and livestock production are separated into subsystems because they use the common resource base in biologically and technologically different ways. Climatic pressure affects both the productivity of these resources and the quantity needed to maintain production.

The intermediate level of the framework captures resource interactions and constraints. Water-land-energy relationships, territorial heterogeneity, seasonal productivity and scarcity define the effective production potential of the agricultural system [80]. These relationships are dynamic: higher temperature can increase irrigation needs, lower pasture productivity can increase feed stress, and changes in crop specialization can shift land and water pressure across the territory.

The economic-mathematical framework converts this resource structure into three analytical functions. The assessment block describes production, climatic and resource conditions; the analytical and predictive block identifies key relationships and predicts production responses; the decision block evaluates scenarios and determines feasible production options under specified conditions. This architecture links empirical evidence with agricultural allocation: statistical and environmental observations describe the state of the system, analytical screening selects independent and informative variables, predictive methods estimate likely outcomes, resource constraints define the feasible set, and alternatives within this set are evaluated and optimized for each scenario.

The resulting framework is based on the methodological complementarity identified in international experience. Process-based approaches add knowledge of biological mechanisms, spatial systems describe territorial heterogeneity, data-driven methods improve nonlinear prediction, optimization formalizes competition for limited resources, and scenario and sensitivity analysis improves the stability of decisions under uncertainty, so that each method performs a specific function in the integrated system. This structure is especially suitable for regional agricultural systems with large differences in specialization, climatic conditions, irrigation needs and livestock composition: these differences are retained within a common decision architecture and assessed by consistent principles of resource efficiency, and territorial heterogeneity is included explicitly in the model instead of being treated as noise around a regional mean. Transparency is another requirement. Official statistics, reference parameters and operational observations are increasingly combined with environmental databases and model-derived estimates, which differ in measurement scale and certainty; this information should be retained throughout

the decision-making process so that a recommendation can be interpreted together with the quality of its supporting evidence.

Thus, the international development of agricultural modelling leads to an integrated methodology in which the assessment of natural resources, the prediction of their climatic sensitivity, explicit resource constraints and allocation decisions are parts of a shared analytical framework. Resource-efficient decisions depend on the condition of the resource base, the production response, the resource limits and the available adaptive management options. This is the theoretical basis for the empirical assessment of resources and production relationships and for their formalization in an economic-mathematical model.

2 Analysis and assessment of natural resource use in agriculture of Kazakhstan and the Turkestan region

2.1 Current state and regional characteristics of natural resource use in agriculture of the Republic of Kazakhstan

The development of agriculture in Kazakhstan is shaped by the spatial distribution and economic scarcity of natural resources [81]. Despite the huge territory, the productive potential of land is unevenly distributed and is not determined by the size of the territory. Production may be limited by the simultaneous availability of arable land, precipitation, surface and groundwater, thermal conditions, energy, soil quality and infrastructure. The main resource problem of Kazakh agriculture is therefore the spatial mismatch between the physical availability of resources and the technologies, locations and production systems that can convert them into output.

This distinction is crucial for the empirical measurement of natural-resource efficiency. The national agricultural land area may be large, while water availability, soil quality, climatic exposure or infrastructure losses constrain production locally [82]. National abundance of agricultural resources can therefore coexist with local scarcity of production resources. In Kazakhstan, this coexistence is a real problem, because traditional indicators such as total agricultural land or total output do not adequately describe either resource availability or agricultural efficiency, and the analysis should focus on the configuration of resources. The legal basis of land use and land protection is the Land Code of the Republic of Kazakhstan of 20 June 2003 № 442, which regulates land relations [83].

This configuration is reflected in the structure of sown areas. As can be seen in Table 2.1, crop production in Kazakhstan in 2025 was concentrated in a few crop groups. Cereals and legumes, including rice, covered about 16.05 million ha, or 67.9% of the sown area; oilseeds accounted for 16.88% (3.99 million ha) and fodder crops for 13.02% (3.08 million ha). Cotton, potatoes, open-field vegetables, melons and sugar beet occupied only a small part of the national cultivated area.

Table 2.1 – Sown area by crop group in Kazakhstan, thousand ha and %, 2025

Crop group	Sown area, thousand ha	Share of total sown area, %
Cereals and legumes, incl. rice	16046.99	67.90
Oilseeds	3990.52	16.88
Potatoes	131.20	0.56
Open-field vegetables	129.32	0.55
Melon crops	93.78	0.40
Sugar beet	19.13	0.08
Cotton	144.51	0.61
Fodder crops	3077.34	13.02

Note – Compiled by the author using preliminary data of the Bureau of National Statistics on the sown areas of agricultural crops for the 2025 harvest [84].

The concentration shown in Table 2.1 means more than the dominance of cereals in the crop portfolio. It shows that the agricultural land system of Kazakhstan is based on crops whose production logic differs from that of high-value irrigated horticulture, so a national average hectare exists only in a statistical sense. A system of predominantly rainfed cereal production cannot be equated economically or ecologically with the irrigated food and fibre production of the south.

This results in a scale-composition asymmetry. The most widespread crops are not necessarily the most intensive in labour, output or value per hectare, nor the most irrigation-demanding. A crop with a small national area may, if concentrated in a few irrigated districts, place a heavy burden on regional water resources that is invisible in national land statistics. Conversely, a crop grown on millions of hectares may have a low national irrigation dependence because it is mostly rainfed, even if it depends on irrigation in some regions.

In accordance with Figure 2.1, the national sown area is dominated by cereals, fodder crops and oilseeds; national indicators therefore follow the resource logic of extensive and semi-extensive field farming and miss the resource limits of the irrigated south.

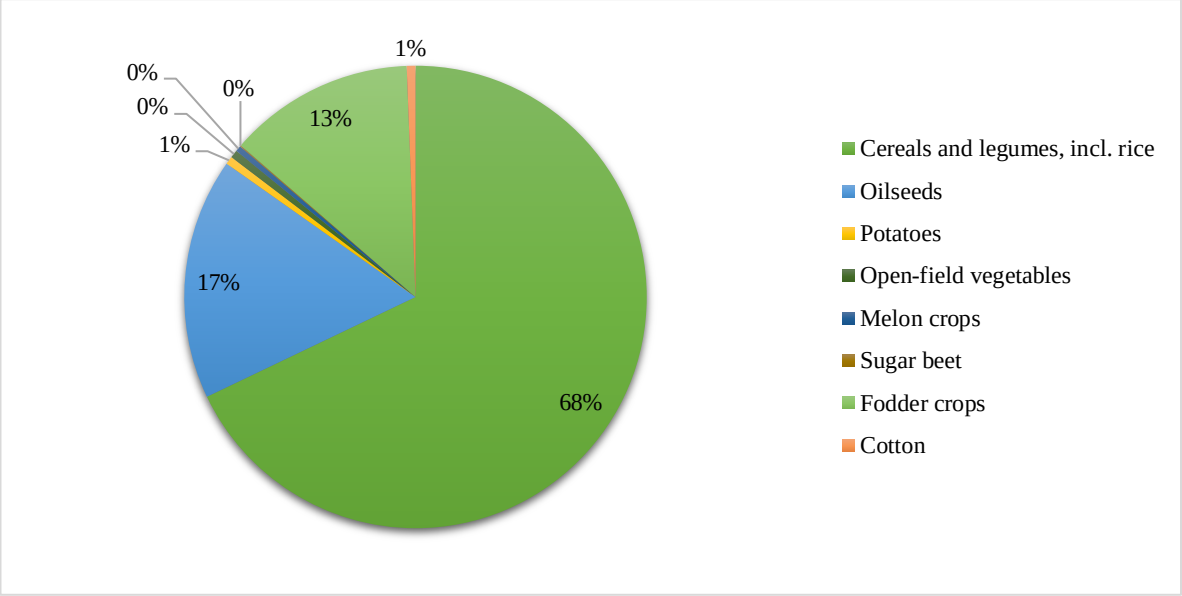


Figure 2.1 – Structure of sown area by crop group in Kazakhstan, %, 2025

Note – Compiled by the author using official statistics of the Republic of Kazakhstan [84].

An important implication for the regional comparison is that Turkestan region should not be assessed as a miniature Kazakhstan. Its contribution to individual crops, irrigation dependence and climatic conditions may differ significantly from the national production structure. The transition from Kazakhstan to Turkestan region is therefore a change in the resource structure rather than only in territorial scale.

The national resource environment confirms this. Selected climatic, water and agrochemical indicators for 2004-2024 are shown in Table 2.2. The indicators are grouped together because agricultural resources are interdependent: temperature and precipitation change affect evapotranspiration, soil-moisture demand and the marginal value of irrigation; water losses determine how much abstracted water becomes economically available; reuse shows whether the water system operates linearly or circularly; and the intensity of pesticide application indicates the technological pressure on agricultural land.

Table 2.2 – Climate, water and agrochemical indicators in Kazakhstan, selected years of 2004-2024

Year	Mean annual temp., ℃	Temp. anomaly, ℃	Annual precip., mm	Precip. vs norm, %	Freshwater abstraction, mln m³	Water loss, %	Freshwater reuse, %	Pesticide use, kg/ha
2004	7.10	1.70	332.20	105.00	23,640.00	14.53	1.94	0.15
2008	6.90	1.50	259.30	82.00	20,474.00	11.92	1.65	0.20
2010	6.30	0.90	318.70	100.00	23,811.70	12.41	3.99	0.18
2012	5.90	0.50	278.10	88.00	21,389.00	13.96	3.71	0.40
2015	7.10	1.60	366.20	115.00	21,661.00	7.01	0.96	0.50
2018	5.50	0.10	323.20	102.00	23,542.00	15.80	3.84	0.59
2020	7.30	1.90	270.70	85.20	24,585.00	15.33	4.15	0.64
2022	7.20	1.80	311.20	98.00	24,966.00	13.70	5.30	0.40
2024	7.20	1.70	391.80	123.30	25,558.00	14.70	2.74	0.50

Note – Compiled by the author using official statistics of the Republic of Kazakhstan [84] and Kazhydromet data [85].

Several analytical points follow from Table 2.2. First, the mean annual temperature of the country remains above the long-term average (1961-1990) in all selected years: the anomaly is approximately +1.7°C in 2004, +0.9°C in 2010, +1.6°C in 2015, +1.9°C in 2020 and +1.7°C in 2024. These values should not be read as a simple annual sequence because of significant interannual variability; their importance lies in the persistence of positive thermal anomalies. The climatic baseline of agricultural production decisions is therefore not stationary.

The full annual Kazhydromet series shows this more clearly. In accordance with Figure 2.2, the series contains thermal oscillations that are mostly above the historical average. The point matters because climate does not change monotonically and adaptation cannot follow a strictly linear trend: producers face a long-term shift in one direction and year-to-year fluctuations at once, and both add to the economic cost of adaptation.

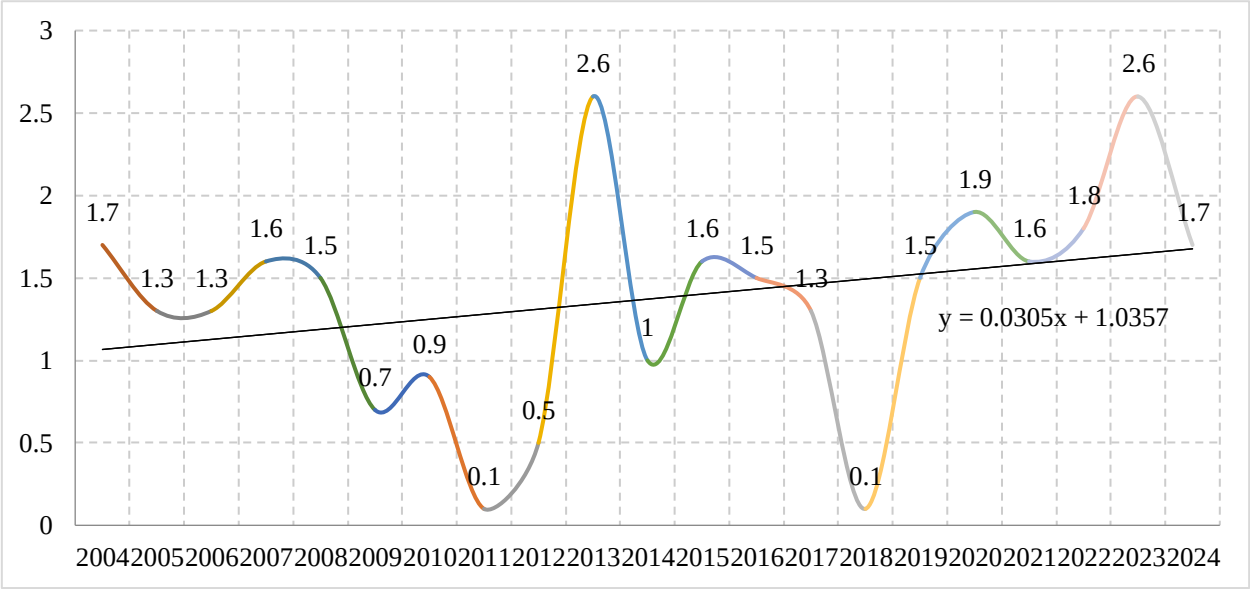


Figure 2.2 – Annual temperature anomaly in Kazakhstan, °C, 2004-2024
Note – Compiled by the author using Kazhydromet data [85].

In accordance with Figure 2.2, the climatic challenge is therefore not simply higher temperature but a change in the probability distribution within which production decisions are made. Persistent positive deviations shift the normal climate, and short-term variations cause short-term changes in realized yields and resource needs. Economically, this increases the option value of adaptive production systems – crop structures, irrigation systems and management methods that remain resilient under different climatic scenarios – compared with systems optimized for average historical conditions.

This also changes the meaning of natural-resource efficiency. Under a stationary climate, efficiency can be estimated by comparing output with a more or less constant amount of inputs. Under climatic non-stationarity, the same land and water may give different results under different thermal and moisture conditions, and resource efficiency becomes state-dependent:

$$RE_t = f(R_t, C_t, T_t), \tag{2.1}$$

where RE_t denotes realized resource efficiency;
R_t represents the quantity and composition of productive resources;
C_t represents climatic conditions;
T_t denotes the technological and organisational system in which productive resources are converted into output.

Thus, an increase or decrease in output per hectare or per cubic metre is not necessarily caused by better or worse management; part of the change may be caused by a climatic shift. Conversely, stable output under increasingly adverse conditions may hide additional inputs of irrigation, energy or chemicals. In such a case,

production stability may be achieved while the underlying resource efficiency declines.

Water statistics illustrate this difference. National freshwater abstraction varied considerably in 2004-2024 instead of growing in proportion to agricultural production, while water losses remained large. The official series records transportation losses of approximately 14.5% of freshwater abstraction in 2004, 12.4% in 2010, 7.0% in 2015, 15.3% in 2020 and 14.7% in 2024. These values refer to the national water system as a whole, not only to agriculture, and show that the gap between abstracted and delivered water is economically significant.

The difference between gross and usable water is key: abstracted water is not equal to water used in the production process. When part of the water is lost during transportation, an increase in abstraction does not lead to a proportionate increase in the effective supply. The economic resource constraint can therefore be expressed as:

$$W_t^{eff} = W_t^{abs}(1 - L_t), \tag{2.2}$$

where W_t^{eff} is effective delivered water;
W_t^{abs} is abstracted water;
L_t proportional loss prior to productive use.

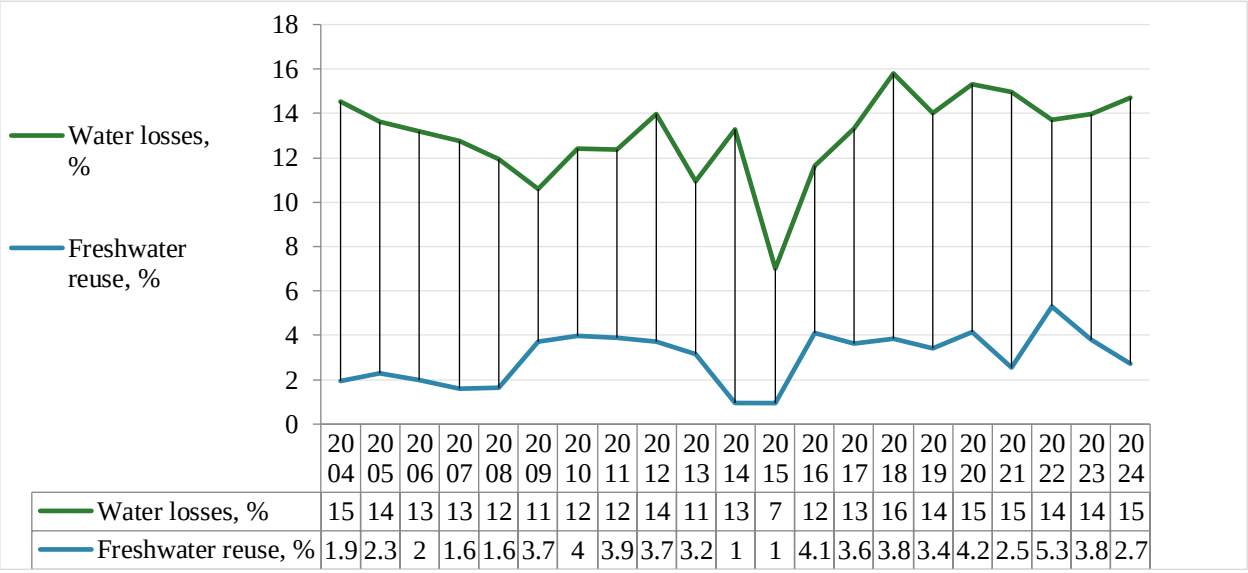
This approach agrees with the Water Code of the Republic of Kazakhstan of 9 April 2025 № 178-VIII LRK, the law that governs how water is used, protected and managed.

The Concept for the Development of the Water Resources Management System of the Republic of Kazakhstan for 2024-2030 follows the same line, giving priority to economical water use, integrated and adaptive management of water resources and water-saving irrigation technologies.

This simple distinction has a significant policy implication. When a water system has continuing losses, saving a cubic metre through infrastructure improvement differs economically from obtaining the same cubic metre through additional abstraction: the former increases effective availability without proportionately increasing the pressure on the source, while the latter increases the effective supply at the cost of greater withdrawal from the hydrological system.

This can be described as the distinction between supply growth and resource recovery. Supply expansion brings more water into the system, whereas resource recovery increases the productive share of water that has already been abstracted. In water-scarce areas, the marginal economic benefit of resource recovery may therefore exceed the value of the physical volume itself, because it avoids the environmental and infrastructure costs of additional abstraction.

In accordance with Figure 2.3, a second dimension is added by comparing water losses with the share of reused freshwater.



	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Water losses, %	15	14	13	13	12	11	12	12	14	11	13	7	12	13	16	14	15	15	14	14	15
Freshwater reuse, %	1.9	2.3	2	1.6	1.6	3.7	4	3.9	3.7	3.2	1	1	4.1	3.6	3.8	3.4	4.2	2.5	5.3	3.8	2.7

Figure 2.3 – Water losses and freshwater reuse in Kazakhstan, %, 2004-2024

Note – Compiled by the author using official water statistics of the Republic of Kazakhstan [84].

In accordance with Figure 2.3, there is an imbalance between linear and circular water management: water losses remain at a double-digit level, while freshwater reuse is a minor component of total freshwater use. The two indicators measure different processes and should not be subtracted from each other, but their comparison is economically informative: losses show the resource value lost during water transmission, while reuse shows how many productive or service cycles can be obtained from a unit of water.

This leads to a broader concept of water-system productivity. Conventional water productivity refers to output per unit of water used, whereas a system perspective also includes losses and recirculation. Two economies with the same gross freshwater use may have different effective resource burdens depending on the shares of water lost in transmission and reused.

Although national water indicators include non-agricultural activities, they are important for agricultural economics, because they describe the infrastructure and the management of competition for water. In water-limited areas, agricultural efficiency is partly determined beyond the farm boundary: a technically efficient producer may still depend on an inefficient water-delivery system. Farm-level and system-level efficiency should therefore be treated as different but interdependent dimensions.

The same caution applies to the pesticide series in Table 2.2. The official series of the Bureau of National Statistics [84] describes pesticide use in the Republic of Kazakhstan as a whole and is not evidence of pesticide use in Turkestan region. Nationally, it shows that agrochemical use is part of a dynamic resource-technological environment of agriculture. The indicator is retained here only as a contextual sign of intensification and is not mechanically transferred to the regional analysis. This methodological distinction between the national context and regional

measurement is significant: national indicators represent the external resource context but do not explain variation at the district level.

Repeating the same national value for each region would add no empirical information. The empirical architecture of Chapter 2 therefore keeps the scale at which each variable is actually measured. The national picture thus shows multiple constraints.

Aggregate land resources are abundant but highly differentiated in productive value and use. Thermal conditions show a persistent deviation from the historical climatic norm. Significant system losses reduce water availability, and reuse is limited. The production pattern is structurally concentrated, and the resource needs of minor crops differ considerably from those implied by the national land structure. The efficiency of natural resource use therefore cannot be expressed as the ratio of agricultural production to a single natural resource.

The share of Turkestan region in the national sown area by crop group is given in Table 2.3.

Table 2.3 – Turkestan region share of Kazakhstan's sown area by crop group, %, 2021-2025

Crop group	2021	2022	2023	2024	2025
Cereals and legumes, incl. rice	1.90	1.90	1.80	1.99	2.13
Sunflower seed	0.23	0.17	0.16	0.14	0.09
Potatoes	7.81	7.97	7.67	11.60	9.54
Cotton	100.00	100.00	100.00	100.00	100.00
Open-field vegetables	25.40	25.40	27.80	34.94	33.54
Fodder crops	6.90	7.44	7.45	7.13	7.47

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84]; for 2024-2025 – preliminary data of the Bureau of National Statistics on sown areas; therefore the regional sown areas may differ slightly from the updated data of the long-term regional series analysed below.

This provides the analytical basis for moving from Kazakhstan as a whole to Turkestan region. The next question is whether Turkestan has a typical position in the national agricultural system or whether its crop specialization and relative productivity create a different resource-economic profile. This question is answered below by comparison with the national cropping system rather than by an isolated analysis.

The agricultural economy should be understood as a resource portfolio in which the shadow prices of inputs vary in space. The value of an additional hectare depends on water supply and crop suitability; the value of an additional cubic metre of water depends on temperature, infrastructure losses and the crop for which it is used; the value of additional energy depends partly on whether it is used for

irrigation, mechanization or inefficient resource substitution. In such a system, scarcity is relative rather than absolute.

The national-to-regional comparison shows that the position of Turkestan region in the agricultural system is asymmetric. Its importance is determined not only by the cultivated area but also by its concentration of certain crops and by the deviation of its land-use pattern from the national production structure. This matters because the resource pressure in the region depends more on the composition of agriculture than on its total size.

Table 2.3 shows the share of Turkestan region in the national sown area of selected crop groups in 2021-2025. The comparison shows highly uneven specialization: the region has a relatively small share of the national cereal area and a significant share of open-field vegetables. The extreme case is cotton, whose national area was located entirely in Turkestan region in all years considered.

The analytical interest of Table 2.3 is that the territorial and crop-specific levels of concentration differ. If the region's share were the same for all crop groups, the shares would be similar; instead, they vary considerably, which shows that the region has a specific role in the national agricultural division of labour.

Because of this specialization, resource scarcity has different economic consequences. A small territory can supply a large part of the country's irrigation-dependent output while holding a much smaller part of its cereal area. The resource pressure generated by agriculture therefore depends less on the area under production than on what is produced and which resource bundle is used.

This can be quantified by the crop concentration coefficient:

$$CSC_{jt} = \frac{A_{jt}^{TR}}{A_{jt}^{KZ}} \times 100, \tag{2.3}$$

where A_{jt}^{TR} is the area of crop j in Turkestan region at time t;
A_{jt}^{KZ} is the corresponding national area.

In the available series, CSC approaches 100% for cotton. This means that the irrigation, heat-exposure, land-suitability and technological risks of national cotton production are concentrated in a single regional agricultural system, so cotton is far more important for the region than its share in the national sown area suggests. A similar but less pronounced pattern is observed for vegetables: the share of Turkestan region in the national open-field vegetable area increased from about 25% in 2021-2022 to about 35% in 2024 and about 34% in 2025.

Vegetables thus occupy only a small part of the national sown area, yet the role of the region in their production has grown.

Here the national-area paradox of specialized agriculture becomes visible: a crop that barely registers in national statistics can carry great economic and resource weight in one region, so national averages consistently understate its natural-resource constraint. This imbalance in 2025 is shown in accordance with Figure 2.4.

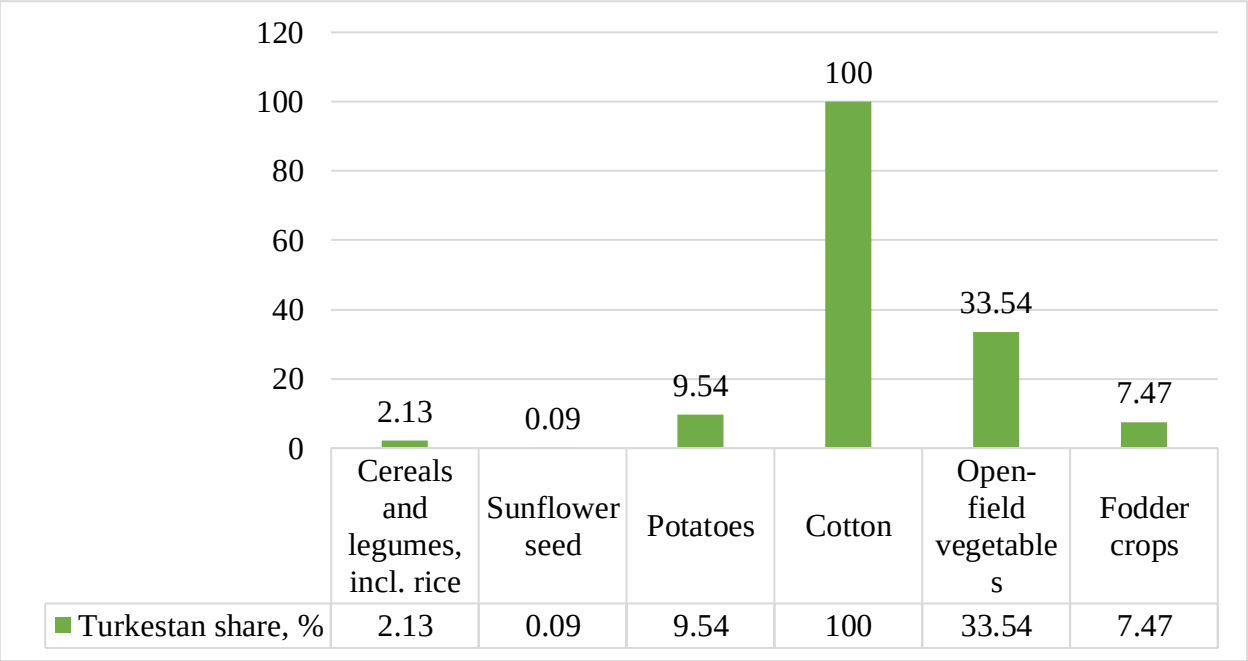


Figure 2.4 – Turkestan region share of Kazakhstan's sown area by crop group, %, 2025

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

In accordance with Figure 2.4, the agricultural profile of Turkestan region is highly concentrated, and the concentration is not proportional to its overall participation in the national crop system. Cotton has a unique position, followed by open-field vegetables and several groups with considerably lower national shares.

The economic interpretation of the concentration shown in accordance with Figure 2.4 should not therefore rely on the traditional assumption that a higher regional share means comparative efficiency. Concentration may reflect comparative advantage, agroclimatic suitability, historical specialization, infrastructure, market access or institutional persistence. It may also reflect path dependence, when investments in irrigation and processing make further production economically rational even at high resource costs.

The difference between comparative advantage and path-dependent specialization is significant for natural-resource analysis. A crop can stay dominant in a region because the local production system is built around it, so that a change would carry costs in processing, labour skills, input supply, transport networks and irrigation infrastructure. Observed specialization may therefore not respond to relative water scarcity or climatic exposure.

The analytical task is therefore not to assume that the current crop concentration is optimal, but to assess whether historical specialization is resource-efficient under current and future constraints.

This question becomes clearer when the cultivated area is combined with yield. Yields of selected crops in Kazakhstan and Turkestan region in 2021 and 2025

are shown in Table 2.4; the comparison tests whether the region has a systematic productivity advantage.

Table 2.4 – Crop yields in Kazakhstan and Turkestan region, c/ha and %, 2021 and 2025

Crop group	Kazakhstan 2021, c/ha	Turkestan 2021, c/ha	Relative yield 2021, %	Kazakhstan 2025, c/ha	Turkestan 2025, c/ha	Relative yield 2025, %
Cereals and legumes, incl. rice	10.4	19.6	188.5	16.3	18.6	114.1
Sunflower seed	11.0	18.1	164.5	13.9	16.0	115.1
Potatoes	207.4	194.6	93.8	222.5	206.6	92.9
Cotton	26.4	26.4	100.0	32.0	32.0	100.0
Open-field vegetables	252.7	302.3	119.6	286.9	245.5	85.6

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

As can be seen in Table 2.4, the regional advantage is crop-specific rather than general. In 2021, the cereal yield in Turkestan region was considerably higher than the national yield, and the sunflower yield was above the national average, whereas the potato yield was below it. The cotton yield is the same in the national and regional series, because national cotton production is statistically concentrated in Turkestan region. Open-field vegetables show another pattern: their yield was above the national average in 2021 but below it in 2025.

This variation does not support a simple interpretation of Turkestan region as more productive because of its warmer climate or longer growing season. Climatic suitability provides a considerable biological potential, but realized yield is still limited by water availability, production technology, soil quality, crop structure and annual weather conditions.

The cereal comparison is of particular interest. In 2021, the regional yield was nearly 1.9 times higher than the national yield, but by 2025 the advantage decreased to about 14%. Productivity gains in one year should therefore not be interpreted as a structural advantage.

This is important for model building, because cross-sectional superiority and dynamic resilience are different phenomena: high average yields may be accompanied by high interannual sensitivity. To identify resource-efficient production, the model must separate the realized level of productivity from its stability under changing climatic and resource conditions.

The vegetable series shows this best. In 2021, the open-field vegetable yield in Turkestan region was above the national average, but in 2025 it was below the national level, while the region's share in the national vegetable area increased.

This combination is a potential signal for resource-efficiency analysis. If a territory keeps or increases its share of the national crop area while its relative productivity declines, the relative burden of maintaining its production role may

increase, and more land or other inputs may be needed to maintain the output previously achieved with a higher productivity advantage.

This situation can be described as specialization-productivity divergence. Let

$$SPD_{jt} = \Delta CSC_{jt} - \Delta RY_{jt}, \quad (2.4)$$

where CSC_{jt} represents the regional share of national crop area;
RY_{jt} represents the relative regional yield to the national yield.

A positive value does not necessarily indicate inefficiency; it shows that the territorial importance of a crop grows faster than its relative productivity advantage. The indicator identifies crop-territory combinations for the subsequent resource-efficiency analysis.

The concept is important because it combines specialization and productivity, which are usually analysed separately. Specialization indices show what a region produces, and yield indicators show production per unit of land; their divergence shows whether the regional production structure becomes more or less demanding relative to its productivity.

Under resource constraints, this divergence may say more than either indicator alone. If a crop yields well but is spread across many regions, its weight at the system level may be small; if, by contrast, a crop with a low relative yield is highly concentrated in a region that supplies much of the national output, the regional resource problem may become more acute.

Cotton is a special case. National production and the yield of Turkestan region coincide in the available series, because the region is the main cotton producer of the country, so there is no national benchmark for cotton in Turkestan. For cotton, analysis over time within the region is therefore more relevant than a national cross-sectional comparison.

The absence of a benchmark is itself informative: the efficiency of cotton production cannot be judged by comparing Turkestan with other parts of Kazakhstan and should be assessed against its own historical productivity, water use, climatic adaptability, profitability and viable alternative crops.

This difference in benchmarking logic is relevant for the design of the optimization model. For widely distributed crops, regional performance can be compared with national benchmarks; for geographically concentrated crops, efficiency must be determined by temporal, technological or counterfactual comparison.

The regional structure therefore includes several analytical cases:

– crops with low national concentration and moderate regional productivity;
– crops with increasing concentration but decreasing relative productivity;
– crops with high concentration and a productivity advantage;
– crops for which Turkestan region is the main national producer, so that their efficiency can be judged only by temporal or technological comparison.

Each case should be assessed on its own terms rather than by a single standard.

The overall conclusion is that the assessment of natural resource use must depend on the crop structure. A nationally strategic crop concentrated in certain areas may require different resource-management priorities than a crop that can be grown in many areas; for spatially diversified crops, the opportunity cost of reducing their water allocation may not include national supply effects.

At the same time, high concentration may increase vulnerability. When a significant part of national production is located in a resource-constrained region, regional climatic shocks become national agricultural shocks. This forms a spatial transmission mechanism: regional resource shock → crop production shock → national supply effect.

The intensity of this transmission depends on the concentration of the crop in the region.

The economic importance of the region is therefore determined not by its share in the total agricultural area of Kazakhstan, but by its contribution to the national agricultural portfolio through specific crops. The region becomes a focal point for activities whose resource needs differ significantly from the prevailing extensive crop structure of the country.

Another important difference between the national and regional resource regimes is the greater significance of water in the south. Nationally, cereals, fodder crops and oilseeds dominate the crop area, while in Turkestan the crop groups typical of southern agricultural conditions are more important in relative national terms. The regional resource problem is therefore more irrigation-sensitive than the national crop-area structure suggests.

This does not mean that all agriculture of Turkestan region depends on irrigation to the same extent: the region is internally diverse, and resource limitations vary among districts, crops and production systems. At this stage, however, the comparison shows that national average relationships are not sufficient for the region.

Another implication concerns the definition of productivity. A higher regional yield does not necessarily mean higher resource efficiency, because yield measures output per unit of land rather than per unit of water, energy or environmental pressure. A crop with a high irrigation requirement may have high land productivity, while a lower-yielding crop may offer a better combination of resource use, climatic suitability and economic return.

This can be expressed by separating land productivity from multidimensional resource efficiency:

$$LP_{ij} = \frac{Q_{ij}}{A_{ij}}, \tag{2.5}$$

while a broader resource-efficiency concept requires:

$$RE_{ij} = f\left(\frac{Q_{ij}}{A_{ij}}, \frac{Q_{ij}}{WU_{ij}}, \frac{Q_{ij}}{EU_{ij}}, V_{ij}, C_{ij}\right), \quad (2.6)$$

where LP_{ij} represents land productivity;
WU_{ij} water requirement;
EU_{ij} energy requirement;
V_{ij} economic value;
C_{ij} climatic suitability.

This separation avoids an important analytical mistake – treating agricultural intensification as synonymous with resource efficiency. Intensification can increase yield but may also require more water, energy or agrochemicals. Only a multidimensional assessment shows whether a productivity increase is a real efficiency gain or a shift in the use of limited resources.

The comparison of Kazakhstan and Turkestan region therefore serves two purposes: it identifies the specialization of the region, and it shows that relative yield advantages are neither uniform nor stable over time. It is therefore appropriate to move from the national comparison to a long-term regional analysis.

The long-term dynamics of sown area and crop yields in Turkestan region are given in Table 2.5.

Table 2.5 – Sown area and crop yields in Turkestan region, thousand ha and c/ha, 2004-2025

Year	Total sown area, th. ha	Cereal area, th. ha	Vegetable area, th. ha	Melon area, th. ha	Cereal yield, c/ha	Potato yield, c/ha	Vegetable yield, c/ha	Melon yield, c/ha
2004	762.7	226.4	24.2	16.9	21.3	136.4	182.0	158.2
2010	697.2	213.2	29.8	36.2	17.6	152.3	213.1	181.3
2015	775.8	255.6	36.5	62.5	23.7	172.2	210.3	221.8
2020	847.9	304.6	43.1	62.0	24.5	186.0	231.0	230.3
2023	863.4	321.7	43.3	67.7	23.5	194.8	243.3	255.5
2025	911.1	344.4	43.2	62.0	18.6	206.6	245.5	256.4

Note – Compiled by the author using official statistics of the Republic of Kazakhstan [84]; crop yields are calculated by the Bureau of National Statistics per harvested area.

The next analytical step is temporal rather than spatial. Since Turkestan region has a specialized resource-economic function, it is necessary to explain how this position developed. The 2004-2025 series allows the contributions of cultivated area, physical output and yield to be separated and shows whether long-term growth was driven by land expansion, by productivity growth or by both.

The empirical data presented below turn the question of how Turkestan differs from Kazakhstan into the more demanding question of how the resource

organization of the regional agricultural economy has developed over time. Current specialization is not fixed; it is the result of more than 20 years of land reallocation, output restructuring and adjustment to the changing climate and resource base.

The long-term evolution of agriculture in Turkestan region in 2004-2025 shows that the current production system passed through different stages rather than a linear and uniform expansion. The total sown area grew by about 19.5%, from 762.7 thousand ha in 2004 to 911.1 thousand ha in 2025, but this growth was accompanied by significant reallocations between crop groups and changes in land use and physical output. Table 2.5 places these changes in the context of the climatic conditions in which they occurred.

The first important feature of Table 2.5 is the difference between short-term instability and long-term expansion. The total sown area did not grow steadily: it decreased by 16.0%, from 762.7 thousand ha in 2004 to 641.0 thousand ha in 2009, then recovered to 826.3 thousand ha by 2017, 29% above the 2009 level, and grew more slowly in 2018-2025 to 911.1 thousand ha.

The observed trajectory can therefore be divided into several regimes: contraction of the sown area (approximately 2004-2009), rapid recovery and spatial growth (2009-2017), and, after the administrative reorganization of 2018, slower but continued growth of the production base. In recent years, land use has expanded again, while the physical performance of individual crop groups has become more variable.

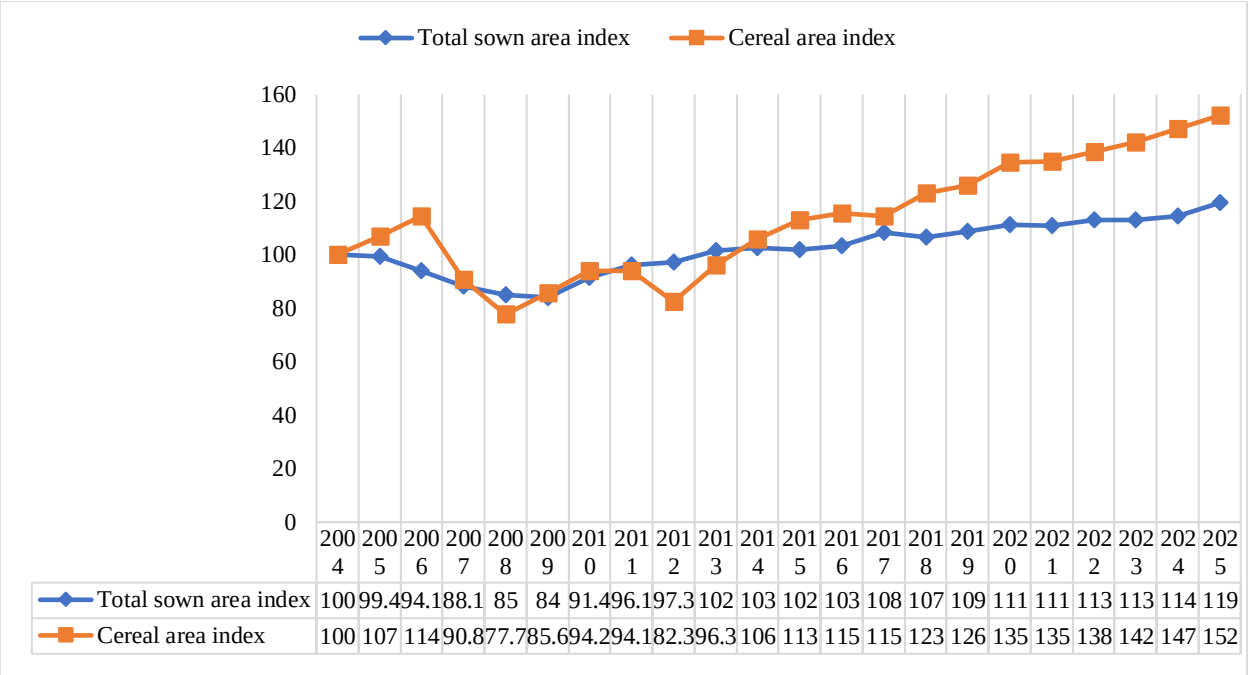
These regimes are descriptive periods based on the observed series rather than formally estimated structural breaks. They identify the periods in which the economic mechanism of growth appears to have changed and serve as a reference for the subsequent analysis.

A further qualification concerns territorial comparability. Statistical continuity is interrupted by the administrative reform of 2018, when Shymkent became a city of republican significance and the present Turkestan region was formed. For 2004-2017, the regional series refer to the former South Kazakhstan region as published by the Bureau of National Statistics. The agricultural area of Shymkent city is small (9.9 thousand ha of sown area in 2025, about 1% of the sown area of Turkestan region [84]), so the change of the regional boundary has little effect on the comparability of the long-term series, but it is taken into account when the 2004-2025 dynamics are interpreted.

The same principle is applied to the 2023 observations. The official crop statistics for that year were later revised on the basis of updated farm accounting data, and the revised values are used precisely because they are the official statistical correction. A sudden movement in a revised series is not smoothed because it disturbs the trend: removing such movements would replace official information with a trajectory imposed by the analyst and hide real changes in the statistical base.

The composition of cultivated land is more informative than its total expansion. Total sown area and cereal area are therefore shown as indices relative to 2004.

In accordance with Figure 2.5, the cereal area grew faster than the total sown area from 2017: in 2025, the total sown area was about 119.5% of the 2004 level, and the cereal area about 152.1%. The cereal area therefore increased not only through land expansion but also, to some extent, through a reconfiguration of the crop portfolio.



	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Total sown area index	100	99.4	94.1	88.1	85	84	91.4	96.1	97.3	102	103	102	103	108	107	109	111	111	113	113	114	119
Cereal area index	100	107	114	90.8	77.7	85.6	94.2	94.1	82.3	96.3	106	113	115	115	123	126	135	135	138	142	147	152

Figure 2.5 – Sown area and cereal area indices in Turkestan region, 2004 = 100, 2004-2025

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

This difference is interpreted as an internal land-allocation effect: when the area of a crop group grows faster than the total agricultural area, its relative importance in the land portfolio increases. The opportunity cost of such expansion includes not only the cost of new land but also the other crops displaced by the change in the cropping pattern.

This is especially relevant because crops differ in the water, labour, energy and climatic exposure involved in converting land into output. Shifting land from one crop group to another is therefore not neutral, even if the number of hectares is unchanged: it alters the intensity and the risk profile of the regional agricultural system.

The cereal trajectory shows the limitation of area expansion as a measure of agricultural progress. The area of cereals and legumes (including rice) rose from 226.4 thousand ha in 2004 to 344.4 thousand ha in 2025, an increase of 52.1%. Physical output also rose, by about 33.4%, to 632.4 thousand tonnes, while the yield fell from 21.3 to 18.6 c/ha between the two end points.

This asymmetry is economically important: the cereal area grew faster than production, and the physical output increased much less than proportionally. This is not in itself evidence of economic inefficiency, since prices, the composition of cereals and year-specific climatic shocks may affect the result, but it suggests that long-term cereal growth was not productivity-led.

The difference is especially clear in the last year. The cereal area expanded from about 333.3 thousand ha in 2024 to 344.4 thousand ha in 2025, whereas the gross harvest declined from 862.9 to 632.4 thousand tonnes and the yield from 25.9 to 18.6 c/ha. The sharp decline of cereal production in 2025 therefore occurred during an expansion of the area and cannot be explained by a reduction of the cultivated land.

This is an empirical warning against relying on land expansion to reduce production risk: additional hectares can offset weak productivity only partly, and when the yield decline is significant, total production does not stabilize even after a large expansion.

At this stage, it cannot be concluded that the 2025 cereal decline was caused solely by temperature or precipitation. The climatic panel provides plausible variables for later testing, but causality requires formal analysis. The conclusion here is more limited: 2024-2025 saw a productivity shock rather than an area shock.

The difference between area-based and productivity-based change becomes clearer when crops are compared over the same period. The end-point changes in cultivated area, physical output and yield of the main crop groups are summarized in Table 2.6.

Table 2.6 shows several distinct growth mechanisms in the regional agricultural system.

For cereals and legumes, the main long-term process was expansion of the area: the area grew by about 52.1% and physical output by 33.4%, while the end-point yield decreased by 12.7%. The production gain was therefore achieved mainly through cultivated area rather than land productivity.

Oilseeds followed a different trend: their area fell by about 11.2%, but output fell by only about 1.7% because the yield rose by about 9.3%. Productivity thus partly offset the smaller area: output per hectare rose while the cultivated area declined.

The contraction of sunflower is far deeper: from 2004 to 2025 its area decreased by about 84.2% and its output by about 85.4%, while the yield became slightly lower. The similar decline of area and output means that the fall in production was caused mainly by the shrinking role of the crop in the regional land portfolio rather than by lower productivity.

Table 2.6 – Changes in crop area, output and yield in Turkestan region, 2004-2025

Crop group	Area 2004, th. ha	Area 2025, th. ha	Area Δ, %	Output 2004, th. t	Output 2025, th. t	Output Δ, %	Yield 2004, c/ha	Yield 2025, c/ha	Yield Δ, %
Cereals and legumes, incl. rice	226.4	344.4	52.1	474.1	632.4	33.4	21.3	18.6	–12.7
Oilseeds	82.2	73.0	–11.2	59.2	58.2	–1.7	7.5	8.2	9.3
Sunflower seed	10.6	1.7	–84.2	18.5	2.7	–85.4	17.6	16.0	–9.1
Potatoes	10.0	12.5	25.0	138.2	258.6	87.1	136.4	206.6	51.5
Vegetables	24.2	43.2	78.5	434.6	1 173.9	170.1	182.0	245.5	34.9
Melon crops	16.9	62.0	267.0	263.9	1 588.2	501.8	158.2	256.4	62.1

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

This is analytically important, as it indicates a significant change in the attractiveness of the crop. The contraction may be related to market incentives, competition for irrigated land, agronomic conditions, processing capacity or the profitability of alternative crops. The analysis does not attribute it to a single cause but records the structural displacement of sunflower from its previous place in the regional crop system.

Potatoes show almost the opposite situation: the area grew by 25%, physical output by about 87.1% and yield by about 51.5%, so long-term production growth was driven mainly by higher yields.

This indicates a stronger intensive margin: output increased much more than the moderately larger land base, because each hectare became more productive. The resource interpretation, however, must still consider water, energy and other inputs, since higher land productivity may reflect technical progress or higher input intensity. The appropriate term is therefore productivity growth, not necessarily resource-efficient growth.

The differences are even more pronounced for vegetables: the area increased by about 78.5%, output by about 170.1% and yield by about 34.9%, so both the extensive and the intensive margins contributed positively.

This mixed trend has different economic implications than for cereals. In vegetables, output per hectare increased while the land base expanded, so higher productivity magnified the returns from the additional cultivated land. Whether this is sustainable intensification depends on the change in irrigation and other resources needed for the output, which is considered later within the resource-efficiency framework.

Melon crops show the largest structural expansion: their area grew from about 16.9 thousand ha in 2004 to nearly 62.0 thousand ha in 2025, by about 267%, the gross harvest increased by more than 500%, and the yield by about 62%.

This trajectory combines strong extensive and intensive effects: the crop became much more significant spatially and much more productive per hectare, and it shows the largest physical growth of all crop groups.

This strength, however, raises a new analytical concern. Even with fairly favourable unit resource requirements, a rapidly growing crop can become increasingly important for the regional resource balance: when the cultivated area grows several times, even a moderate water intensity produces a large aggregate water burden. It is therefore necessary to distinguish intensity per hectare from system pressure.

This can be expressed as:

$$TRP_j = A_j r_j, \tag{2.7}$$

where TRP_j is total resource pressure associated with crop j;
A_j is cultivated area;
r_j is the resource requirement per hectare.

A decline in r_j does not guarantee a decline in TRP_j if A_j expands sufficiently rapidly. The situation is similar to the resource economics rebound effect, whereby increased activity can reduce the overall gains from the efficiency gains of a single unit.

The long-term expansion of melons therefore shows why static coefficients are an incomplete measure of crop-level resource efficiency. Scale matters: a crop with balanced unit resource use may become systemically important if its production grows too quickly.

As Table 2.6 shows, the comparison reveals three analytically distinct margins of agricultural development:

$$Scale\ margin = \Delta A, \tag{2.8}$$

$$Productivity\ margin = \Delta Y, \tag{2.9}$$

$$Structural\ margin = \Delta s_j, \tag{2.10}$$

where ΔA represents change in cultivated area;
ΔY change in yield;
Δs_j change in the share of crop j within the total land portfolio.

The first two margins describe changes in output within a crop, and the third reflects the reallocation of resources between crops. The structural margin is important because changes in crop shares alter aggregate water demand, energy demand and climatic exposure even when the technical coefficients of individual crops remain unchanged.

To compare the trends in physical production, crop output is shown as indices with 2004 = 100 in accordance with Figure 2.6.

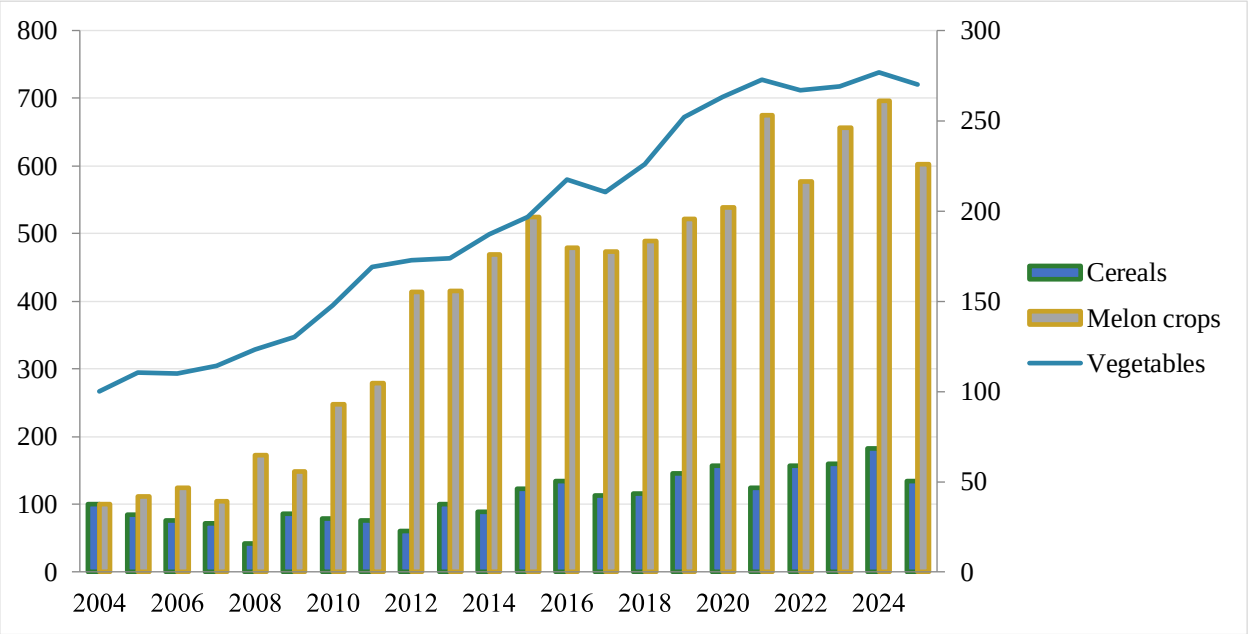


Figure 2.6 – Crop output indices in Turkestan region, 2004 = 100, 2004-2025

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

The figure shows that the structure of the regional agricultural system became increasingly differentiated over time. While vegetable and especially melon output grew strongly, cereal production remained within a narrow band: in 2025, vegetable output was about 2.7 times and melon output more than 6 times the 2004 level, while cereal output was only slightly more than one third higher.

The divergence of these indices is more than a difference in growth rates: it reflects a restructuring of the sources of regional agricultural growth, which is increasingly concentrated in crop groups whose output trends differ greatly from the traditional cereal pattern.

Consequently, a single aggregate crop-production variable would lose important structural information in a model. Growth of vegetables and melons may offset lower cereal productivity and increase aggregate output, so that the total hides the fact that crop groups move in different directions.

Such aggregation may create a compensation illusion: growth in one crop group offsets decline in another and gives the false impression of a stable or improving regional system, although the shift may change irrigation demand, land allocation and climatic risk.

The evidence therefore supports a more precise interpretation of the long-term transformation of agriculture in Turkestan region. The regional system did not simply grow; it underwent a structural reallocation in which some crops increased both area and productivity, others increased mainly in area, and some contracted significantly, reflecting the long-standing specific position of southern Kazakhstan in the agricultural space of Central Asia [86].

The area and yield effects on crop production are given in Table 2.7.

Table 2.7 – Area and yield effects on crop production in Turkestan region, 2004-2025

Crop group	Area change, %	Yield change, %	Output change, %	Growth trajectory	Resource-economic interpretation
Cereals and legumes, incl. rice	52.1	-12.7	33.4	Predominantly extensive	Output growth depends mainly on land expansion; resource pressure may outpace land productivity
Oilseeds	-11.2	9.3	-1.7	Contraction with productivity compensation	Cultivated area decreases, but yield at least partly compensates for the loss of scale
Sunflower seed	-84.2	-9.1	-85.4	Structural contraction	The crop lost area without sufficient productivity improvement
Potatoes	25.0	51.5	87.1	Mixed expansion and intensification	Growth combines area expansion with significant yield gains
Vegetables	78.5	34.9	170.1	Mixed expansion and intensification	Growth combines area expansion with significant yield gains
Melon crops	267.0	62.1	501.8	Mixed expansion and intensification	Growth combines large area expansion with large yield gains

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

This is the basis for the next analytical step – the formal decomposition of the observed changes into area and yield contributions, which shows which part of the growth or contraction of physical production is due to the extensive margin and which to the intensive margin. In Table 2.7 and in accordance with Figure 2.7, these trajectories are converted into a resource-economic typology that links the descriptive structural analysis with the assessment of the hidden resource cost of agricultural growth.

The structural comparison has shown that agricultural growth in Turkestan region cannot be assessed by output alone. Production can grow through more land, higher yields or both, and these paths have different implications for land and water pressure.

For crop j, physical output is represented as:

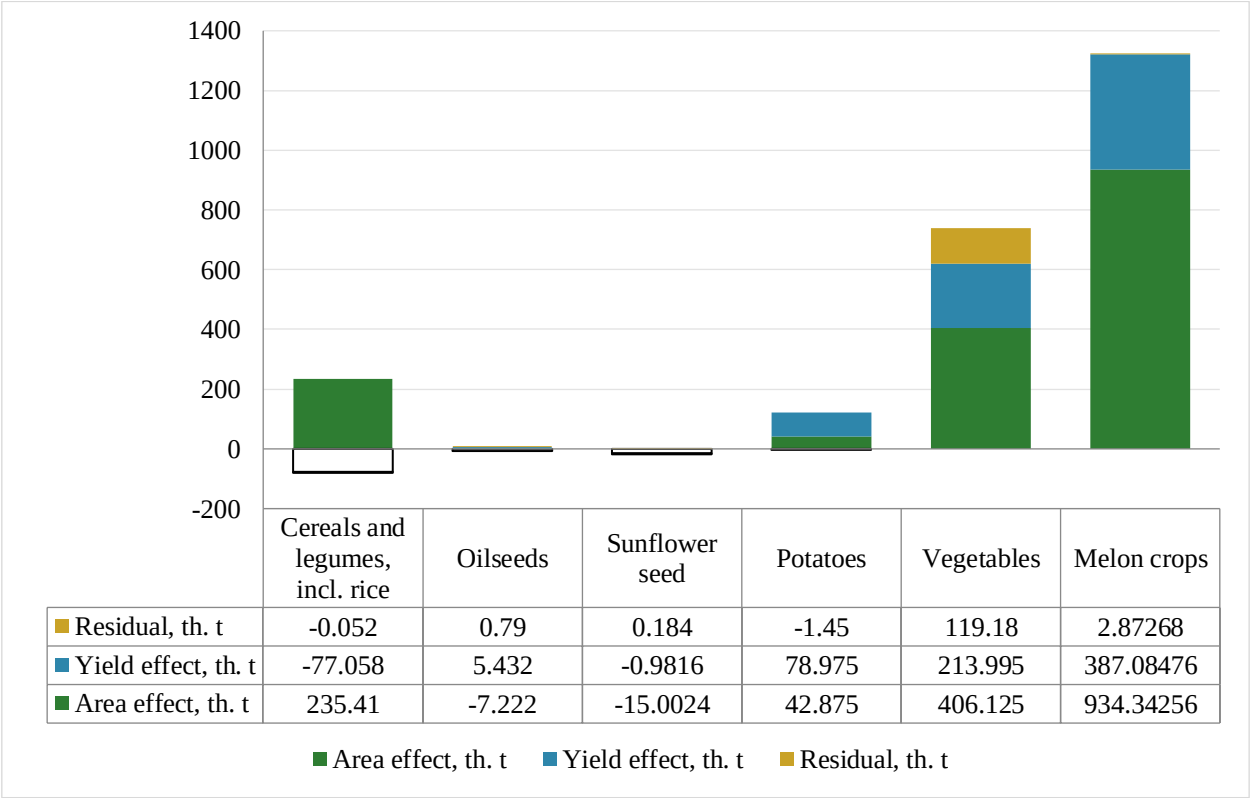
$$Q_j = \frac{A_j Y_j}{10}, \tag{2.11}$$

where A_j is cultivated area;

Y_j is yield. To separate the extensive and intensive contributions, the change in output is decomposed symmetrically:

$$\Delta Q_j = \frac{(A_{j1} - A_{j0})(Y_{j0} + Y_{j1})}{20} + \frac{(Y_{j1} - Y_{j0})(A_{j0} + A_{j1})}{20}. \quad (2.12)$$

The first one is the area effect and the second the yield effect.



	Cereals and legumes, incl. rice	Oilseeds	Sunflower seed	Potatoes	Vegetables	Melon crops
Residual, th. t	-0.052	0.79	0.184	-1.45	119.18	2.87268
Yield effect, th. t	-77.058	5.432	-0.9816	78.975	213.995	387.08476
Area effect, th. t	235.41	-7.222	-15.0024	42.875	406.125	934.34256

Figure 2.7 – Area and yield effects on crop production in Turkestan region, thousand tonnes, 2004-2025

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

The resulting growth trajectories are summarized in Table 2.7.

The typology shows different mechanisms of crop development in Turkestan region. Cereals grew mostly extensively, through a larger area and with a lower yield in the final year; in potato, vegetable and melon crops, structural growth was accompanied by higher productivity; and sunflower contracted structurally. These differences are quantified in accordance with Figure 2.7.

In accordance with Figure 2.7, production growth from additional land differs considerably from growth through higher yield. However, productivity-based growth is not automatically resource-saving, because higher yields may require more irrigation, energy and other inputs. The analysis therefore distinguishes production growth from resource-adjusted growth.

In conceptual terms:

$$G^{RA} = G^{Q} - G^{RB}, \quad (2.13)$$

where G^{RA} denotes resource-adjusted growth;
G^{Q} output growth;
G^{RB} growth of the associated resource burden. True resource efficiency gains would occur if output increases were not matched by an increase in pressure on the scarce resources. This distinction will become even more relevant in the context of the variability in climate. The productivity of land and water is influenced by temperature, precipitation, soil moisture, and this can lead to different outcomes in agriculture for the same amount of resources in different years.

Annual and April-September temperatures at the 17 territorial NASA POWER points are shown in accordance with Figure 2.8.

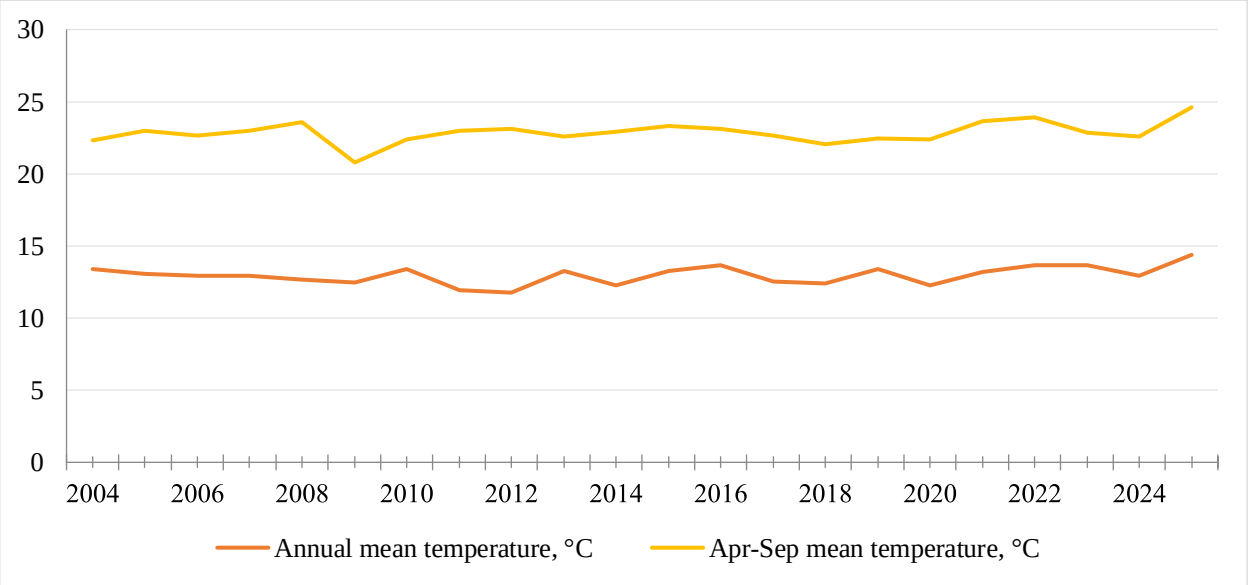


Figure 2.8 – Annual and growing-season temperature in Turkestan region, °C, 2004-2025

Note – Compiled by the author using NASA POWER data for 17 territorial observation points [87].

Annual and growing-season temperatures are separated because the April-September temperature is more directly related to crop development, evapotranspiration and irrigation demand.

The dynamics of annual and growing-season precipitation are shown in accordance with Figure 2.9.

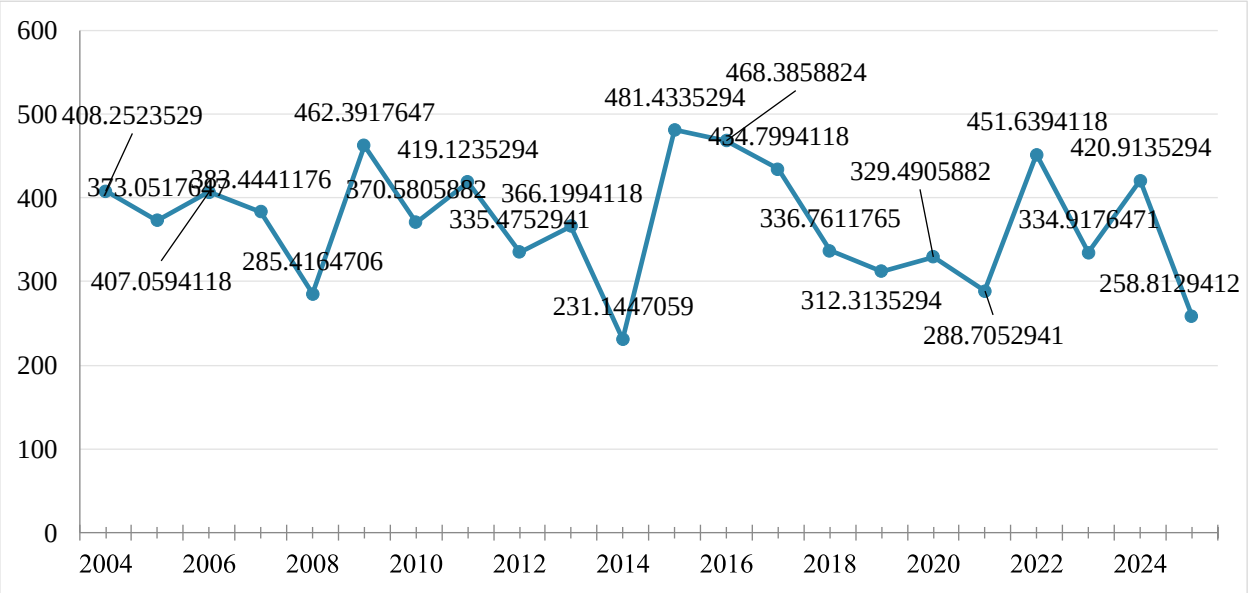


Figure 2.9 – Annual and growing-season precipitation in Turkestan region, mm, 2004-2025

Note – Compiled by the author using NASA POWER data for 17 territorial observation points [87].

The temperature series shows significant year-to-year fluctuations and provides a climatic perspective for the later evaluation of resource efficiency.

In accordance with Figure 2.9, the precipitation dynamics are considered together with temperature.

The precipitation series also shows large interannual variation and no mechanical relationship with temperature. Climatic pressure therefore cannot be described adequately by a single indicator, and the link between climate and agricultural resource use should be analysed by considering temperature, precipitation and soil moisture together.

This is especially important for water, because the efficiency of irrigation water depends on climate and crop characteristics:

$$MP_W = f(T, P, SM, C), \tag{2.14}$$

where MP_W is the marginal productivity of water;
T temperature;
P precipitation;
SM soil moisture;
C crop characteristics.

Therefore, official water statistics and the modelled crop water requirement are presented separately: official data describe the aggregate resource envelope, while the resource-specific requirement is estimated later from cultivated areas and resource coefficients. Regional water totals are not split and distributed among districts.

Overall, Section 2.1 shows that agricultural development in Turkestan region combined expansion with structural reallocation. Land expansion was the main driver for cereals, vegetables and melons combined land expansion with productivity growth, and climatic variability is becoming an increasingly important factor of land and water productivity.

The main analytical finding is that the regional agricultural problem has gradually shifted from production to resource allocation. Regional averages hide differences between territories and crop combinations that are central to this shift. Section 2.2 therefore turns to the spatial level and examines the variation of agricultural activity, resource use and climatic conditions among the districts of Turkestan region.

2.2 Assessment of the efficiency of natural resource use in agriculture of Kazakhstan and the Turkestan region

The regional averages of Section 2.1 show the general direction of agricultural transformation in Turkestan region but hide significant variation among territories. Regional output gains may come from districts with different crop mixes, land intensities, climatic vulnerability and livestock specialization. For natural resources, this requires moving from regional indicators to the spatial pattern of agricultural production.

The analysis covers 17 territorial units of Turkestan region: Baydibek District, Zhetysay District, Kazygurt District, Keles District, Maktaaral District, Ordabasy District, Otyrar District, Sairam District, Saryagash District, Sauran District, Suzak District, Tolebi District, Tulkibas District, Shardara District, Arys City, Kentau City and Turkestan City.

The current territorial structure is relevant for policy, because agricultural decisions are made within these administrative units, but it also creates a problem of statistical comparability, since it did not exist throughout the whole period. Zhetysay and Keles districts have been separate statistical units since 2018, and Sauran District was established later. The cleaned district panel is therefore unbalanced rather than mechanically balanced, and newly established districts have shorter historical coverage than older ones.

A structural missing value reflects the absence of an administrative unit that did not yet exist and therefore could not be observed; it differs from a true zero, when the unit existed but did not produce the crop.

Formally:

$$X_{it} = NA, \tag{2.15}$$

for periods in which territorial unit i had not yet been formed independently, rather than

$$X_{it} = 0. \tag{2.16}$$

Replacing such observations with zeros would create false drops before the formation of districts and jumps afterwards and would distort averages, growth rates, correlations and any subsequent panel model.

Thus, independent observations are used for Zhetysay and Keles districts from 2018, and for Sauran District the data are considered fully reliable for the comparative analysis of 17 territories from 2021. Earlier observations are not reconstructed by proportional allocation from neighbouring districts, because there is no empirical basis for such allocation.

This is especially important for resource-efficiency analysis. A reconstruction of historical values would create apparent precision while hiding its assumptions in the model and give a false impression of statistical accuracy. The appropriate solution is an explicitly unbalanced panel whose information set reflects the actual administrative history of the region.

The empirical architecture of Section 2.2 therefore has two temporal dimensions: long-established districts keep their full observation period when a dynamic interpretation is required, while cross-sectional comparisons of all 17 units are based mainly on periods with a complete administrative structure.

Table 2.8 makes this explicit by separating true zeros from structural missingness. The distinction is important: a zero observation means that an existing territorial unit had no activity for the indicator.

Table 2.8 – Coverage of territorial units in the district panel, 2004-2023

Territorial unit	First non-missing year in cleaned panel	Latest year	Number of observed years	Recommended comparable period
Arys City	2004	2023	20	2004-2023
Baydibek	2004	2023	20	2004-2023
Zhetysay	2018	2023	6	2018-2023
Kazygurt	2004	2023	20	2004-2023
Keles	2018	2023	6	2018-2023
Kentau City	2004	2023	20	2004-2023
Maktaaral	2004	2023	20	2004-2023
Ordabasy	2004	2023	20	2004-2023
Otyrar	2004	2023	20	2004-2023
Sairam	2004	2023	20	2004-2023
Saryagash	2004	2023	20	2004-2023
Sauran	2020	2023	4	2021-2023
Suzak	2004	2023	19	2004-2023
Tolebi	2004	2023	19	2004-2023
Turkestan City	2004	2023	20	2004-2023
Tulkibas	2004	2023	19	2004-2023
Shardara	2004	2023	20	2004-2023

Note – Compiled by the author using the district-level analytical dataset [84; 87]. Data for 2024-2025 are used only in the machine-learning panel (Section 3.3).

The first complete spatial snapshot analysed here is agricultural production in 2025. Observed values are available for all 17 current territorial units for this year, which allows the spatial distribution of production to be compared without artificial adjustment of former territorial units.

The distribution of gross agricultural output by districts and cities is shown in accordance with Figure 2.10.

In accordance with Figure 2.10, agricultural production is very unevenly distributed across the region. Sairam, Saryagash and Zhetysay districts have the highest output in 2025, while units with small agricultural bases, such as Turkestan City and Kentau City, have much lower output.

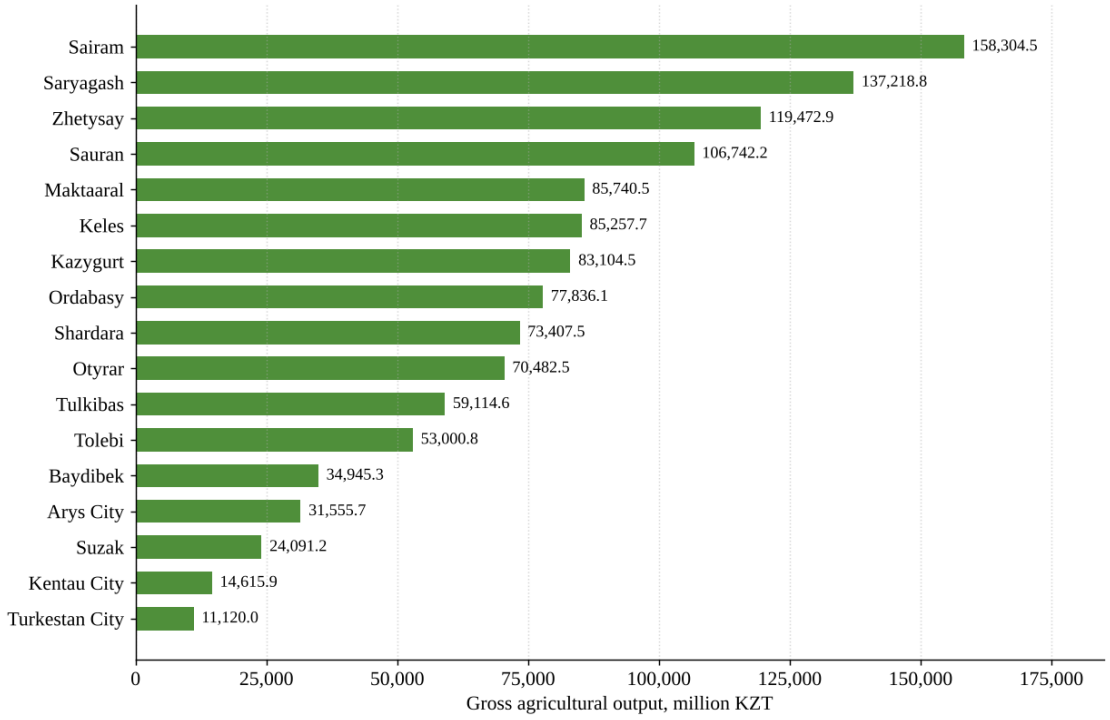


Figure 2.10 – Gross agricultural output by territorial unit in Turkestan region, million KZT, 2025

Note – Compiled by the author using official statistics of the Republic of Kazakhstan [84].

The difference is large enough to reject the assumption that Turkestan region consists of economically comparable agricultural units.

In 2025, gross agricultural output amounted to KZT 158.3 billion in Sairam District, KZT 137.2 billion in Saryagash District and KZT 119.5 billion in Zhetysay District, compared with about KZT 11.1 billion in Turkestan City and about KZT 14.6 billion in Kentau City at the other end of the distribution.

These disparities should not be interpreted directly as differences in efficiency. Gross output measures the scale of production, not output per hectare, per cubic metre of water or per unit of another resource. A district may have high

total output because of a large agricultural base, specialization in high-value crops, a large livestock sector or high output per unit of resource.

Scale and efficiency must therefore be distinguished.

Let total agricultural output of district i be denoted by G_i. A high value of G_i does not imply:

$$RE_i \uparrow, \tag{2.17}$$

because resource efficiency RE_i depends on the resource base used to generate that output.

A more appropriate conceptual representation is:

$$G_i = f(A_i, W_i, E_i, L_i, C_i, S_i), \tag{2.18}$$

where A_i represents land;
W_i water;
E_i energy;
L_i labour and other productive capacities;
C_i climatic conditions;
S_i production structure.

Thus, two districts can achieve the same total agricultural output with different combinations of resources.

This is especially important when cities are compared with large rural districts. In the consolidated data for 2025, the sown area of Turkestan City is very small compared with the main agricultural districts, so its output per hectare can be very high. This does not mean that Turkestan City is the most resource-efficient agricultural area: its agricultural structure, level of urbanization, crop mix and the role of activities that do not depend on land differ considerably from those of large rural districts.

The same applies to Kentau City.

Including cities of regional significance in a system dominated by rural districts creates valuable but methodologically challenging heterogeneity. These observations are not removed from the analysis, because they are part of the existing administrative and agricultural system, but scale-adjusted indicators must be interpreted together with the composition of production rather than as isolated measures of efficiency.

In accordance with Figure 2.10, there is also a concentration risk: if a small number of districts produce a large share of output, a local water shortage, climatic shock or production disruption in one of them can have an effect disproportionate to its area.

This can be expressed by a simple spatial contribution ratio:

$$SC_i = \frac{G_i}{\sum_{i=1}^{N} G_i}, \quad (2.19)$$

where SC_i represents the contribution of territorial unit i to regional agricultural output.

The spatial pattern of gross output also shows that agricultural specialization is not uniform across the region. In 2025, Maktaaral, Zhetysay, Shardara, Otyrar and Saryagash districts are strongly crop-oriented, Tulkibas District has a relatively balanced crop-livestock mix, and Suzak, Kazygurt, Sairam, Tolebi and Baydibek districts are mainly livestock-oriented.

This matters because crop and livestock systems use natural resources differently.

Crop-oriented territories convert cultivated land, irrigation water and climate directly into crop output, whereas pasture-based livestock territories depend more on pasture, fodder production, drinking water and the balance between herd size and the feed base. Natural-resource efficiency should therefore be assessed relative to the production system rather than by a single district indicator.

The spatial problem is therefore multidimensional and includes at least three questions:

1) What is the size of the agricultural production base of each territory?
2) What shares of production come from crop and livestock activities?
3) What is the observed output per unit of cultivated land?

The first question is answered in accordance with Figure 2.10; the second and third require the structural and land-intensity indicators presented below.

This sequence avoids an important analytical mistake. A ranking by gross agricultural output would place Sairam and Saryagash districts among the strongest and smaller agricultural units among the weakest, while a ranking by output per hectare might place very small urban units at the top.

Neither ranking measures resource efficiency by itself.

The key information is the relationship between scale, structure and resource intensity.

This leads to a distinction between absolute agricultural capacity and relative land-output intensity:

$$AC_i = G_i, \quad (2.20)$$

$$LOI_i = \frac{G_i}{A_i}, \quad (2.21)$$

where AC_i represents the absolute agricultural capacity of district i, while LOI_i represents observed agricultural output per unit of sown area.

Neither indicator is a final measure of resource efficiency, because water, energy, climate, crop structure and livestock composition are not included in the ratio. Their purpose is diagnostic: they reveal contrasts that must be explained by

the multidimensional assessment, in line with the overall strategy of Section 2.1, and show differences between districts and crop combinations that regional averages hide.

The next stage is therefore an analysis of the agricultural structure and land-output intensity of the territorial units.

Below, the comparison separates the total scale of production, crop-output intensity and the crop-livestock mix of agricultural output, so that spatial differences are interpreted as differences between agricultural systems rather than as a simple best-worst ranking.

Table 2.9 divides the spatial comparison into two components: agricultural scale and the relationship between the agricultural land base and recorded crop output.

Table 2.9 – Agricultural output, sown area and crop-output intensity by territorial unit, 2025

District	Gross output, mln KZT	Crop output, mln KZT	Livestock output, mln KZT	Sown area, th. ha	Gross output intensity, th. KZT/ha	Crop output intensity, th. KZT/ha	Crop share of gross output, %
1	2	3	4	5	6	7	8
Turkestan city	11,120.00	7,450.20	2,761.80	0.80	13,900.00	9,312.75	67.00
Kentau city	14,615.90	8,902.40	5,692.10	2.50	5,846.36	3,560.96	60.91
Keles	85,257.70	56,271.00	28,875.60	22.50	3,789.23	2,500.93	66.00
Sauran	106,742.20	81,754.70	24,839.30	47.40	2,251.95	1,724.78	76.59
Saryagash	137,218.80	106,636.70	30,393.80	78.00	1,759.22	1,367.14	77.71
Sairam	158,304.50	57,700.30	99,727.00	51.60	3,067.92	1,118.22	36.45
Zhetysay	119,472.90	97,638.00	21,418.00	79.00	1,512.32	1,235.92	81.72
Maktaaral	85,740.50	72,145.50	13,272.70	60.90	1,407.89	1,184.66	84.14
Shardara	73,407.50	59,715.70	11,983.80	58.30	1,259.13	1,024.28	81.35
Otyrar	70,482.50	54,815.70	15,382.20	55.90	1,260.87	980.60	77.77
Ordabasy	77,836.10	46,299.70	31,445.70	71.20	1,093.20	650.28	59.48
Arys city	31,555.70	20,445.30	10,838.40	34.20	922.68	597.82	64.79
Tulkibas	59,114.60	28,294.10	30,701.80	63.60	929.47	444.88	47.86
Tolebi	53,000.80	21,647.10	31,303.10	61.30	864.61	353.13	40.84
Suzak	24,091.20	4,754.70	18,756.50	14.70	1,638.86	323.45	19.74
Kazygurt	83,104.50	25,833.50	57,016.00	94.60	878.48	273.08	31.09
Baydibek	34,945.30	14,925.00	19,913.50	114.40	305.47	130.46	42.71

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84]. Gross agricultural output includes agricultural services; therefore, the sum of crop and livestock output may be lower than the total.

The results show that adjusting gross agricultural output for sown area changes the ranking of territories significantly, which means that spatial concentration of production and land-output intensity are two different aspects of the regional agricultural system.

In 2025, Sairam District had the highest gross agricultural output, followed by Saryagash District, but neither ranks first by crop output per hectare of sown area. Conversely, Turkestan City and Kentau City have extremely high output per hectare because of their very small recorded sown area.

This result must be interpreted with care. The ratios for the two cities do not indicate that urban agricultural systems are superior to rural districts: the denominator is the recorded sown area, while gross agricultural output includes a wider range of activities. The indicator is therefore best interpreted as land-output intensity rather than technical land efficiency.

This is particularly evident for Turkestan City: according to the consolidated data for 2025, its total agricultural output is KZT 11.1 billion with a sown area of less than 1 thousand ha, which gives an extremely high output-to-area ratio. Traditional area-based efficiency measures are therefore unreliable where agricultural production depends only loosely on the land base.

Crop output is therefore a more meaningful intermediate measure:

$$COI_i = \frac{CO_i}{A_i}, \tag{2.22}$$

where COI_i is crop-output intensity;
CO_i is crop-production value;
A_i is sown area.

This measure is also monetary and therefore includes crop-composition and price effects, but it removes part of the distortion caused by livestock and other activities when the question concerns the productive use of cultivated land. The resulting spatial distribution is shown in accordance with Figure 2.11.

In accordance with Figure 2.11, crop-output intensity varies significantly between territories. The distribution is not simple, because it is affected by the cultivated area: several districts with large sown areas have moderate values, while some districts with more compact agriculture have relatively high values.

Keles, Sauran and Saryagash districts form an important group in this respect: they are much more intensive than many larger agricultural districts. Zhetysay and Maktaaral districts also have relatively high values, consistent with their strong crop orientation.

In contrast, crop-output intensity is much lower in Baydibek, Kazygurt, Suzak and Tolebi districts. This does not mean that agriculture there performs poorly in general: in some of these territories, crop production is only part of a broader crop-livestock system.

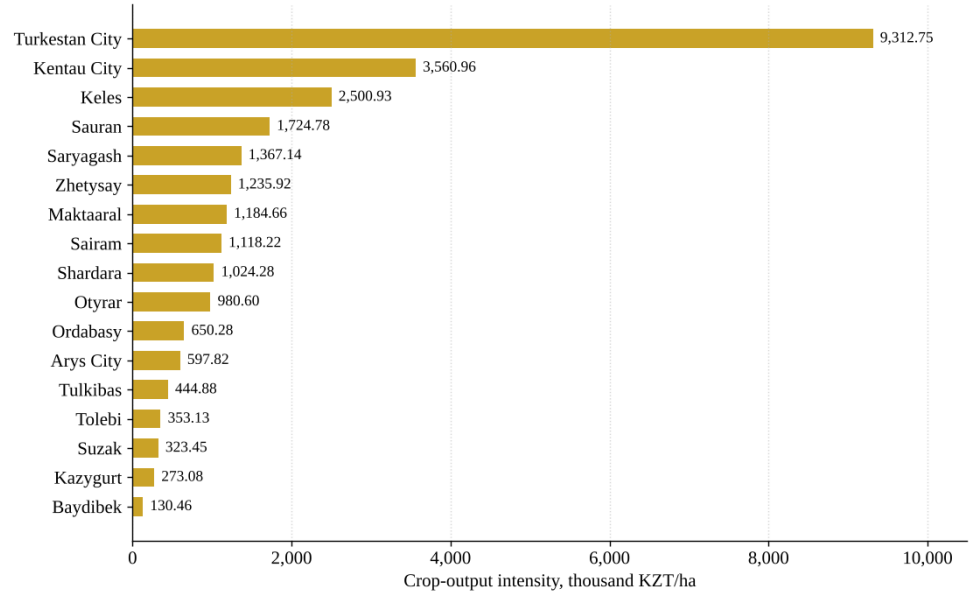


Figure 2.11 – Crop-output intensity by territorial unit in Turkestan region, thousand KZT/ha, 2025

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84].

This difference is shown in accordance with Figure 2.12.

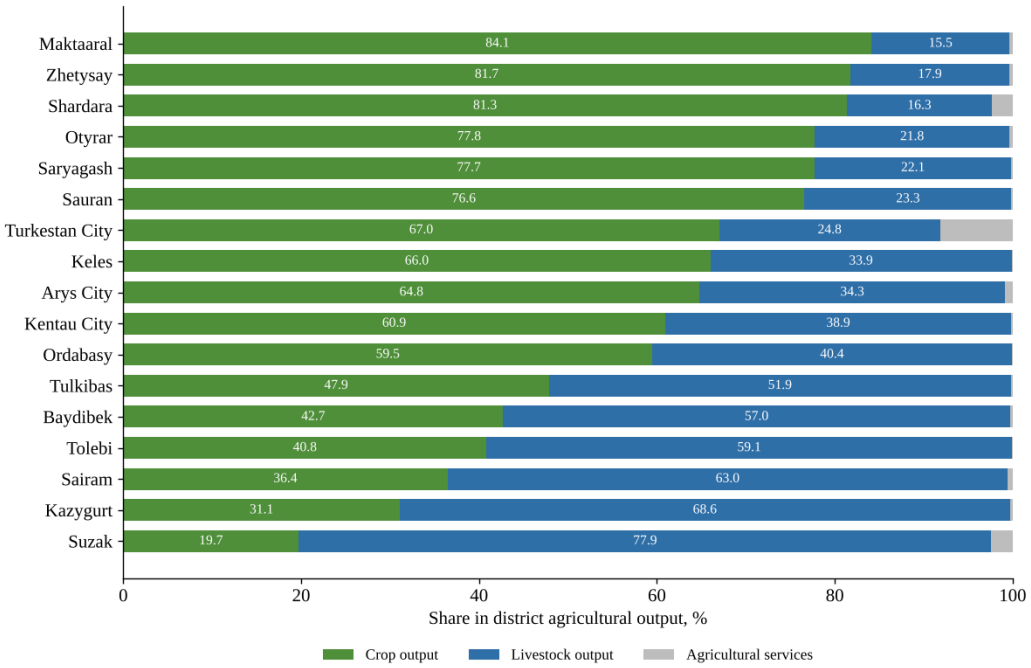


Figure 2.12 – Crop and livestock share in agricultural output by territorial unit, %, 2025

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84]. The remainder to 100% is agricultural services.

In accordance with Figure 2.12, crop and livestock activities are unevenly distributed among the 17 territorial units. Maktaaral, Zhetysay, Shardara, Otyrar and Saryagash districts have strongly crop-oriented structures, while the livestock component is much higher in Suzak, Kazygurt, Sairam and Tolebi districts.

Conceptually, at least three types of agricultural production can be distinguished in the spatial system of Turkestan region.

The first type relates to strongly crop-oriented areas where crop production and cultivated land are the main economic drivers.

The second consists of mixed crop-livestock areas where neither the crop nor the livestock sector dominates agricultural production.

The third consists of livestock-based territories, where pasture land, feed stocks and livestock production matter more than the intensity of direct crop output suggests. This distinction has important consequences for natural-resource efficiency. In crop-based districts, the main resource relationship is reasonably represented by area, water requirement, climate and crop productivity; in livestock-based districts, this representation is only partial, because pasture availability, fodder production and livestock water demand also matter.

Crop-output intensity therefore has different meanings in different production systems. In Suzak District, for instance, the relatively low crop-output intensity should not be assessed without livestock production, which accounts for a large share of agricultural output. Likewise, the low crop share in Kazygurt and Tolebi districts reflects a different type of specialization rather than poor use of cultivated land.

This is consistent with the results of research project AP23487689 [11; 14], which characterize the region as territorially specialized rather than structurally homogeneous. The project materials distinguish, in particular, livestock and poultry districts and emphasize the efficiency gains from the spatial organization of primary production, processing and logistics.

These project findings are used only as context for the quantitative district comparison, which is based on the consolidated agricultural panel. The spatial structure can be represented by a simple production-composition coefficient:

$$CS_i = \frac{CO_i}{G_i}, \tag{2.23}$$

where CS_i is the crop share of agricultural output;
CO_i is crop output;
G_i is total agricultural output.

Similarly:

$$LS_i = \frac{LO_i}{G_i}, \tag{2.24}$$

where LS_i represents the livestock share.

These coefficients identify the production regime within which an efficiency indicator should be interpreted. This is important because the value of natural resources depends on the production system: in a crop-dominated district, an additional hectare of irrigated land is used directly for crops, whereas in a livestock-dominated district the economic value of land may come from pasture or feed production. An efficiency framework that treats all agricultural hectares as homogeneous would therefore lead to false comparisons.

The results also show why one-dimensional measures of agricultural resource efficiency, such as land productivity, should be avoided. A district may record:

$$COI_i < COI_k. \tag{2.25}$$

Such a district may still achieve a good agricultural result, because livestock production compensates for the lower cropping intensity.

Conversely, a district with very high crop-output intensity may have a more resource-intensive structure if its high yields depend critically on irrigation.

This shows the difference between economic intensity and resource intensity.

The observed crop-output intensity is:

$$COI_i = \frac{CO_i}{A_i}. \tag{2.26}$$

A resource-adjusted concept would include the effective resource bundle in the denominator:

$$RAI_i = \frac{CO_i}{f(A_i, W_i, E_i, C_i)}, \tag{2.27}$$

where W_i denotes water pressure;
E_i energy requirements;
C_i climatic conditions.

The second expression is deliberately conceptual at this stage. Observed district-level data on water and energy flows are not available, so the indicator cannot be calculated without model-based assumptions; such assumptions are excluded from the descriptive assessment and are used in the economic-mathematical model. Even so, the spatial results allow several clear conclusions.

First, production is spatially concentrated: a few territories produce a large share of the agricultural value of the region. Second, high absolute production can be achieved without the highest output per unit of cultivated land. Third, the crop-livestock composition varies greatly between districts, so regional resource use takes place in different production regimes rather than in one uniform technological structure. Finally, monetary productivity is a diagnostic parameter rather than a measure of ultimate efficiency. These findings have a direct implication for the

climatic analysis: if agricultural structures vary spatially, the effect of climatic conditions should also vary with the type of agriculture in each territory.

Irrigated crop-oriented districts are likely to be more constrained by high temperatures through crop water demand, while in livestock-oriented districts high temperatures affect mainly pasture and fodder availability and heat stress of animals.

The climate indicators of the territorial units are given in Table 2.10.

Table 2.10 – Climate indicators by territorial unit in Turkestan region, 2021-2025 average

Territorial unit	Annual temp., ℃	Annual precip., mm	Apr-Sep temp., ℃	Apr-Sep precip., mm	Apr-Sep humidity, %	Root-zone wetness
1	2	3	4	5	6	7
Maktaaral District	16.57	321.25	26.31	68.73	33.98	0.48
Shardara District	15.42	207.57	25.86	39.93	29.97	0.17
Zhetysay District	15.88	316.00	25.84	56.02	36.82	0.42
Otyrar District	14.68	175.18	25.55	35.53	30.50	0.49
Arys City	15.08	245.02	25.49	47.21	32.45	0.34
Keles District	15.51	306.88	25.20	53.88	33.33	0.39
Saryagash District	15.51	306.88	25.20	53.88	33.33	0.39
Ordabasy District	14.55	462.07	24.22	89.73	37.04	0.53
Baydibek District	13.45	388.35	23.60	76.74	35.78	0.52
Sauran District	12.74	260.22	23.36	57.88	33.16	0.45
Turkestan City	12.74	260.22	23.36	57.88	33.16	0.45
Suzak District	11.64	165.18	23.35	50.12	32.98	0.43
Kentau City	11.42	261.95	21.95	58.24	35.70	0.50
Sairam District	11.92	563.73	20.79	126.42	41.19	0.58
Tolebi District	11.92	563.73	20.79	126.42	41.19	0.58
Tulkibas District	11.92	563.73	20.79	126.42	41.19	0.58
Kazygurt District	9.50	599.01	18.03	134.05	44.04	0.64

Note – Calculated by the author using NASA POWER data [87]. Identical values for adjacent units (Keles and Saryagash districts; Sauran District and Turkestan City; Sairam, Tolebi and Tulkibas districts) reflect shared NASA POWER grid points of the district series.

Therefore, two districts with similar climatic exposure may face different economic impacts of climate change, because their agricultural systems convert exposure into production risk differently.

The economic effect of climatic exposure is thus mediated by the agricultural structure.

This can be represented as:

$$CE_i = f(CL_i, S_i), \tag{2.28}$$

where CE_i is economic climate exposure;
CL_i represents physical climatic conditions;
S_i represents agricultural specialization.

The distinction between physical and economic climate exposure is especially useful for Turkestan region. According to NASA POWER data, growing-season temperature, precipitation and root-zone soil moisture vary significantly among the 17 territorial points, but the economic significance of these physical differences depends on the agricultural structures identified in Table 2.9 and in accordance with Figure 2.12.

The next step of Section 2.2 is therefore a climate-resource profile of the 17 territorial units. Growing-season temperature, precipitation, relative humidity and soil moisture for 2021-2025 are compared in Table 2.10 and in accordance with Figure 2.13. The purpose is not to rank the climate of territories, but to determine whether territories with different agricultural structures operate in systematically different climatic-resource environments.

The differences in agricultural structure described above become more meaningful when combined with the climatic conditions of production. Agroclimatic conditions vary across Turkestan region: each of the 17 units differs in growing-season temperature, precipitation, relative humidity and root-zone moisture, and these differences alter how land and other natural resources are turned into agricultural output.

Table 2.10 summarizes the climate-resource profile of the territorial units on the basis of NASA POWER data averaged over 2021-2025.

A recent five-year average is used for two reasons: it reduces the effect of outlier years on the comparison, and it corresponds to the current administrative structure of the region, which makes it a more suitable climatic context for the 17-unit analysis than a long-term average.

The comparison shows significant spatial variation of thermal conditions. The southern and south-western parts of the region generally have higher growing-season temperatures, while some northern and foothill areas are more moderate. Precipitation and soil moisture do not mechanically follow the temperature ranking: a relatively warm territory is not necessarily a relatively dry one, and vice versa.

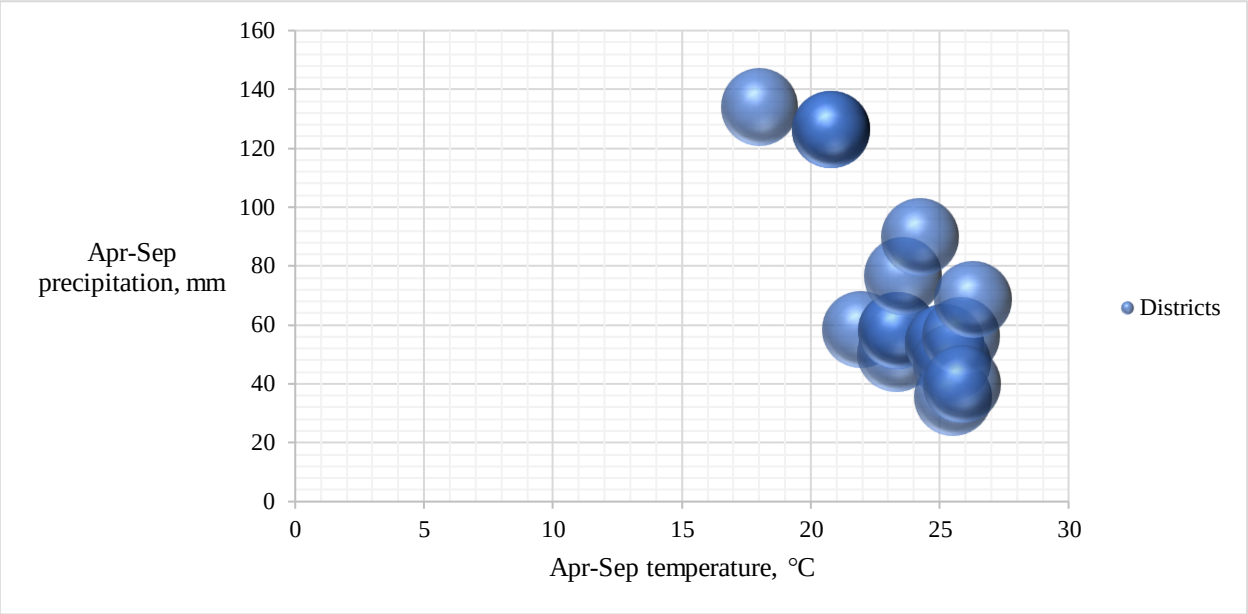


Figure 2.13 – Growing-season temperature and precipitation by territorial unit, °C and mm, 2021-2025 average

Note – Calculated by the author using NASA POWER data [87].

This lack of one-to-one correspondence is important because agricultural climatic pressure is multidimensional: temperature is related to evaporative demand, precipitation contributes to the natural replenishment of soil moisture, and root-zone wetness measures moisture supply in the layer most critical for plant growth. Assessing the natural resource environment by temperature alone would therefore be a simplification. The spatial profile of average April-September temperature and precipitation is shown in accordance with Figure 2.13.

In accordance with Figure 2.13, the climatic environment of Turkestan region is not uniform but includes different combinations of heat and moisture: some territories combine relatively high growing-season temperatures with low precipitation, while others have more favourable moisture conditions.

For agricultural resource use, the hardest case is not just the hottest territory but one where strong heat, little natural moisture and a production system relying on cultivated crops occur together. This is why physical and economic climate exposure must be distinguished.

Physical climate exposure is the actual climate of a territory, whereas economic climate exposure reflects how strongly the local agricultural system depends on climate-sensitive resources.

A hot district with extensive irrigated crop production is likely to suffer much larger economic impacts of water scarcity than a district with the same temperature and a larger livestock sector. Conversely, a cooler district may be at risk if its crop production is very moisture-sensitive or its pastures are in poor condition.

In several crop-based territories, agricultural structure and climate reinforce each other: Zhetysay, Maktaaral, Saryagash, Shardara and Otyrar districts combine relatively high crop orientation with relatively warm climates. Their agricultural

performance should therefore be considered in relation to irrigation dependence, not only land productivity.

This does not mean that these districts are inefficient. Their specialization may reflect accumulated experience, infrastructure, crop suitability and market access; however, their production advantage is sustainable only if water is supplied reliably and used efficiently.

The monograph [14] reaches a similar conclusion: water is one of the main constraints on the development of Turkestan region, and agriculture accounts for a large part of regional water demand.

This project conclusion is used only as context; the district-level climatic comparison is based independently on NASA POWER data.

Livestock-based districts show a different configuration. Suzak, Kazygurt, Sairam and Tolebi districts have lower crop shares in agricultural output, so their climate-resource relationship is not limited to irrigated crops: precipitation and soil moisture affect the pasture and fodder base, and heat stress affects animal productivity and livestock water needs.

It follows that one efficiency frontier for all 17 territorial units cannot be drawn without considering their production structure, because the same climatic variable has unequal economic effects in crop-dominated, livestock-dominated and mixed systems. For this reason, Table 2.11 brings together crop-output intensity and growing-season climatic exposure. The classification in the table is simple and descriptive: each territory is placed above or below the sample median of crop-output intensity and of growing-season temperature (only values above the median count as high), which results in four combinations:

– high land-output intensity and high thermal exposure;
– high land-output intensity and lower thermal exposure;
– lower land-output intensity and high thermal exposure;
– lower land-output intensity and lower thermal exposure.

The classification is not an efficiency indicator and assigns no normative weights; it identifies combinations that require different interpretation.

The second group is of special significance: a territory may have high observed output per hectare and low thermal exposure. This may indicate efficient specialization and high-value production on a small area rather than a climatic advantage, whereas dependence on compensating inputs such as irrigation is more typical of the first group with high thermal exposure. High observed land productivity does not remove the resource question and in some cases makes it even more important.

The opposite combination – lower land-output intensity and high thermal exposure – represents another type of vulnerability: the territory faces relatively high climatic stress with a comparatively low monetary return per hectare. Such combinations are of particular interest for the subsequent relationship analysis, because climatic constraints may interact with crop composition, production technology or other structural factors.

Table 2.11 – Crop-output intensity (2025) and growing-season climate indicators (2021-2025 average) by territorial unit

District	Crop output intensity, th. KZT/ha (2025)	Apr-Sep temperature, °C (2021-2025 mean)	Apr-Sep precipitation, mm (2021-2025 mean)	Relative position vs median
Turkestan City	9,312.75	23.36	57.88	High land-output intensity / lower thermal exposure
Kentau City	3,560.96	21.95	58.24	High land-output intensity / lower thermal exposure
Keles	2,500.93	25.20	53.88	High land-output intensity / high thermal exposure
Sauran	1,724.78	23.36	57.88	High land-output intensity / lower thermal exposure
Saryagash	1,367.14	25.20	53.88	High land-output intensity / high thermal exposure
Zhetysay	1,235.92	25.84	56.02	High land-output intensity / high thermal exposure
Maktaaral	1,184.66	26.31	68.73	High land-output intensity / high thermal exposure
Sairam	1,118.22	20.79	126.42	High land-output intensity / lower thermal exposure
Shardara	1,024.28	25.86	39.93	Lower land-output intensity / high thermal exposure
Otyrar	980.60	25.55	35.53	Lower land-output intensity / high thermal exposure
Ordabasy	650.28	24.22	89.73	Lower land-output intensity / high thermal exposure
Arys City	597.82	25.49	47.21	Lower land-output intensity / high thermal exposure
Tulkibas	444.88	20.79	126.42	Lower land-output intensity / lower thermal exposure
Tolebi	353.13	20.79	126.42	Lower land-output intensity / lower thermal exposure
Suzak	323.45	23.35	50.12	Lower land-output intensity / lower thermal exposure
Kazygurt	273.08	18.03	134.05	Lower land-output intensity / lower thermal exposure
Baydibek	130.46	23.60	76.74	Lower land-output intensity / lower thermal exposure

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84] and NASA POWER data [87]. Crop-output intensity is given for 2025 (Table 2.9); identical climate values of adjacent units reflect shared NASA POWER grid points (see the note to Table 2.10).

Lower thermal exposure does not automatically lead to higher performance: low crop-output intensity is also found in several territories with relatively moderate

climatic conditions, so the spatial variation of agricultural performance cannot be explained by temperature alone.

The comparison is visualized in accordance with Figure 2.14.

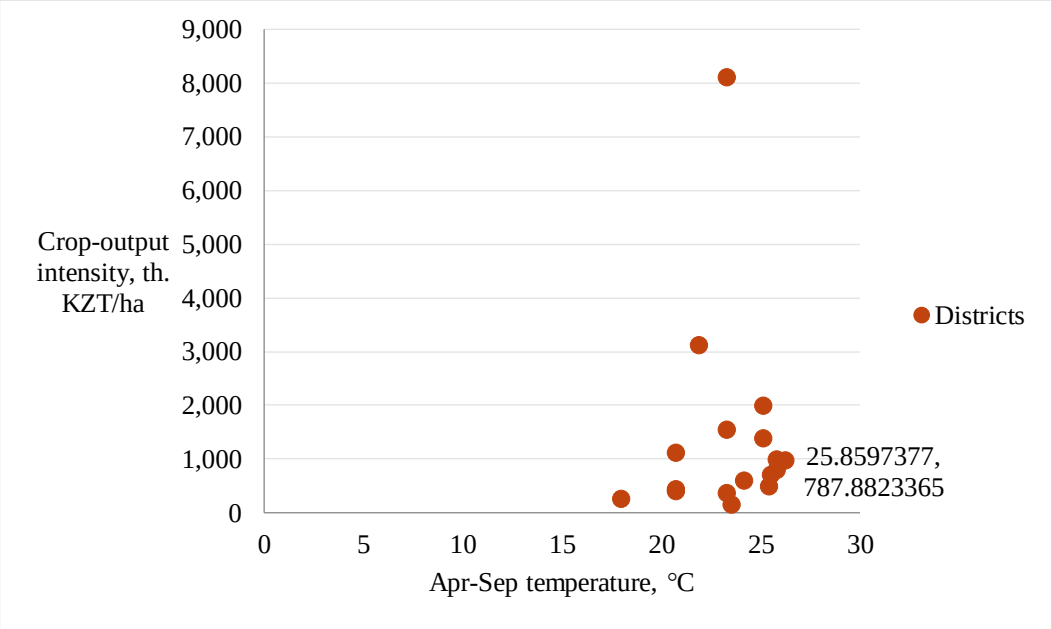


Figure 2.14 – Crop-output intensity and growing-season temperature by territorial unit, 2021-2025 average

Note – Calculated by the author using official statistics of the Republic of Kazakhstan [84] and NASA POWER data [87].

In accordance with Figure 2.14, observed crop-output intensity is plotted against the average growing-season temperature. The dispersion of territorial points is more informative than a simple ranking: crop output per hectare varies significantly between districts with similar thermal conditions, and high-output areas occur under different thermal conditions.

The absence of a visible relationship has an important methodological implication: temperature should not be treated as a single factor of agricultural efficiency, since its effect is likely to operate through interactions with precipitation, soil moisture, crop structure and irrigation availability.

This leads directly to Section 2.3. Instead of assuming a known climate-output relationship, the next subsection tests whether empirical relationships exist, how strong they are and whether several explanatory variables contain redundant information.

One limitation of the climate data should be stated clearly. NASA POWER is based on gridded meteorological and reanalysis data rather than dense station observations in each district, so the climatic series may be identical or very similar for adjacent areas that fall into the same or neighbouring grid cells.

Such coincidence does not mean that the physical environments of these districts are identical; it reflects the spatial resolution of the climate product.

This creates a climatic resolution ceiling: agricultural statistics cover 17 administrative units, but the climate data cannot reproduce all microclimatic differences within them.

Therefore, NASA POWER values are treated as indicators of the climatic exposure of a district rather than as exact district-level values. They show general spatial and temporal differences, while finer-scale conclusions would require station-based or higher-resolution climatic information.

This limitation does not invalidate the analysis but defines the appropriate scope of climatic conclusions.

The same applies to precipitation. The NASA POWER point assigned to a district represents conditions at the selected location rather than an area-weighted district average, which is particularly relevant for large or topographically varied districts. The climatic variables are therefore used as explanatory exposure measures, not as a complete hydrological balance.

These limitations are stated explicitly rather than hidden by interpolation, so that observed agricultural statistics remain empirically separate from climatic indicators derived from NASA POWER.

The results of Tables 2.10 and 2.11 and the data in accordance with Figures 2.13 and 2.14 lead to three conclusions.

First, the 17 territorial units operate in materially different climate-resource situations.

Second, temperature alone does not explain the spatial distribution of crop-output intensity: similar heat exposure is associated with very different agricultural outcomes.

Third, the importance of climatic exposure depends on local agricultural specialization: it is greater for a territory whose crop production depends on irrigation than for a territory with a mixed crop-livestock structure.

The spatial assessment therefore moves from descriptive comparison to the analysis of interactions. The question is no longer whether one district is hotter, wetter or more productive than another, but which combination of resource, production and climatic variables is systematically related to differences in agricultural performance.

Before the statistical relationships are explored in Section 2.3, Section 2.2 concludes with an independent source of evidence – the 2026 survey of agricultural stakeholders. The survey shows whether the constraints identified in the statistical and climatic data, in particular water scarcity, climatic risk and infrastructure, are also perceived as significant by the participants of the regional agricultural system.

The survey results are given in Table 2.12.

The statistical and climatic assessment of Turkestan region identified several structural factors, but these are external quantitative indicators of the agricultural system. The analysis is therefore supplemented by the 2026 survey, which shows whether the participants of the sector identify the same problems.

Table 2.12 – Survey results on resource constraints, adaptation priorities and mathematical modelling, %, 2026 (N = 208)

Panel A. Resource considered scarce		
Category	Responses	Share, %
1	2	3
Water resources	120	57.7
Financing	95	45.7
Qualified personnel	69	33.2
Energy resources	62	29.8
Land resources	44	21.2
Panel B. Barrier to sustainable development		
Category	Responses	Share, %
Insufficient financing	124	59.6
Climatic risks	93	44.7
Weak infrastructure	82	39.4
Lack of information and knowledge	56	26.9
Imperfect legislation	24	11.5
Panel C. Priority adaptation measure		
Category	Responses	Share, %
Development of irrigation systems	105	50.5
Introduction of drought-resistant varieties	81	38.9
Agricultural risk insurance	73	35.1
Staff training and qualification improvement	48	23.1
Production diversification	44	21.2
Panel D. Usefulness of mathematical modelling		
Category	Responses	Share, %
Will help greatly	109	52.4
Will partially help	55	26.4
Hard to assess	38	18.3
Will not help	6	2.9

Note – Compiled by the author based on the 2026 stakeholder survey (N = 208).

The questionnaire, with 208 responses, complements official statistics rather than replacing them. It provides stakeholder validation of the constraints identified from agricultural and climate datasets and allows the measured resource pressure to be compared with perceived resource scarcity, adaptation priorities and attitudes to analytical decision-support tools.

The survey results are summarized in Table 2.12 and are used throughout the dissertation.

The complete questionnaire used for the 2026 stakeholder survey is presented in Appendix B.

The most frequent finding concerns water: 120 respondents, or 57.7%, named water resources as one of the scarcest resources for sustainable agriculture, which puts water first among the resource constraints included in the questionnaire.

This is analytically important because it matches the statistical structure identified earlier: the water problem is not only shown by hydrological indicators and climatic interpretation but is also experienced directly by the participants of the agricultural system.

Together, these two types of evidence strengthen the case for focusing on water efficiency in the model: official and climate data show that agricultural production takes place in a moisture-limited environment, and most respondents consider water availability a practical constraint.

At the same time, the survey shows that water is not the only constraint: 95 respondents named financing, 69 qualified personnel, 62 energy resources and 44 land resources.

Financing was the second most frequently named scarce resource and the most frequently cited barrier. This does not turn the work into a study of financial efficiency, but suggests that physical resource efficiency depends partly on the capacity of agricultural organizations and farms to acquire resource-saving technologies.

For example, switching from conventional to drip or precision irrigation requires purchasing, installing, monitoring and maintaining equipment, so a technically feasible water-saving solution may be economically unfeasible when investment capacity is low.

This distinguishes technical resource potential from achieved resource efficiency: technologies can save water or energy in principle, but the efficiency actually captured depends on producers' ability to introduce them. The project materials also highlight this mechanism in relation to natural resources, infrastructure, technological modernization and organizational capacity. This project conclusion complements, but does not replace, the evidence of the 2026 survey.

The barrier block supports this: lack of funding was named by 124 respondents (about 59.6% of the sample), climatic risks by 93, weak infrastructure by 82 and lack of information or knowledge by 56.

The results indicate that agricultural resource inefficiency may result from several layers of constraints. The first layer is physical: water, land, climatic conditions and energy availability. The second is technological and infrastructural: irrigation systems, equipment, storage, logistics and monitoring technologies required for efficient resource use.

The third is institutional and informational: resource-saving technologies spread only where producers can obtain knowledge, advice and decision-support instruments. This layered interpretation of the survey responses is more useful than a simple ranking by frequency, because it connects stakeholder perceptions with the structure of the agricultural system described earlier.

Climatic risk occupies a particularly important place: about 44.7% of respondents named it as a constraint on sustainable agricultural development, which shows that climatic variability is perceived not only as an external environmental characteristic but also as an economic production risk. The result also supports the explicit use of climatic variables in the statistical analysis rather than as descriptive background: if climate affects agricultural decisions, yields or production costs, excluding it from the relationship analysis could cause an omitted-variable problem.

The adaptation responses are also informative. The most common adaptation priority was the development of irrigation systems, named by about 50.5% of

respondents; 81 respondents chose drought-resistant varieties, 73 agricultural risk insurance, 48 training and professional development, and 44 diversification of production.

Taken together, the answers show that respondents do not see climate adaptation as a single technological solution: their preferences cover physical infrastructure, biological adaptation, risk management, human capital and structural diversification. The empirical results of Section 2.2 support this multidimensional view: the territorial units differ in crop-livestock structure, land-use intensity and climatic vulnerability, so one adaptation policy would hardly work equally well in all districts.

Better irrigation infrastructure is likely to give the clearest resource effect in irrigated, strongly crop-oriented territories; where livestock matters more, adaptation must address pasture management, stable feed supply and heat risk; and in less equipped areas, a lack of advisory and training mechanisms may slow the spread of resource-saving practices.

The survey therefore supports a differentiated regional approach rather than a one-size-fits-all policy package. Another result concerns mathematical modelling. The respondents' views on the usefulness of mathematical modelling for sustainable agricultural development are presented in accordance with Figure 2.15.

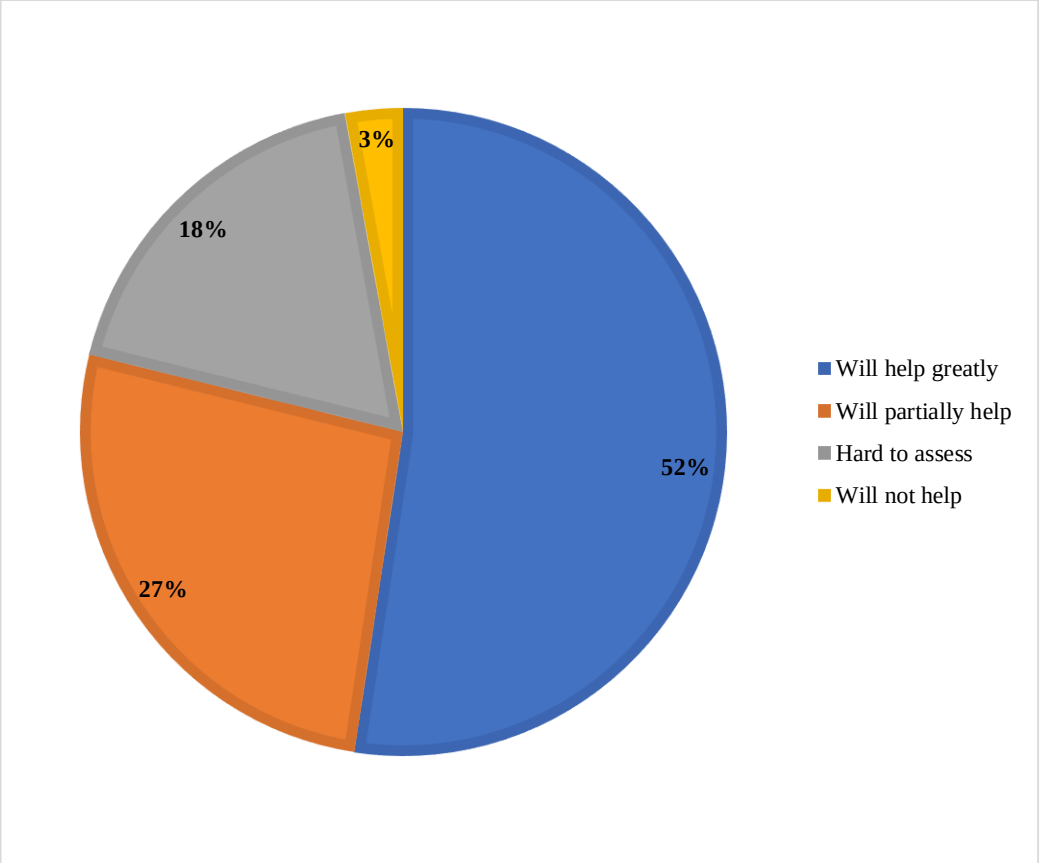


Figure 2.15 – Perceived usefulness of mathematical modelling for sustainable agricultural development, %, 2026 (N = 208)

Note – Compiled by the author based on the 2026 stakeholder survey (N = 208).

A large proportion of respondents, 109 of 208 (about 52.4%), believed that mathematical modelling could help significantly, and another 55 (26.4%) that it could help to some extent. Only 6 respondents (about 2.9%) answered that modelling would not help, and 38 found it difficult to assess.

This is not evidence of the effectiveness of any specific model: respondents assessed the perceived usefulness of mathematical modelling as a decision-support tool, not the model developed in this work.

The distribution is nevertheless important in two respects.

First, it shows a relatively high acceptance of data-driven and analytical decision support, which lowers the barrier between quantitative modelling and its practical application.

Second, the large share of respondents who found it difficult to assess shows that developing a model is not enough: a technically advanced tool that users cannot easily understand will have little practical value.

Model transparency is therefore an economic requirement rather than only a methodological preference, and modelling frameworks should be both predictive and optimizing while remaining easy to interpret.

The survey evidence is also useful for methodological triangulation.

Official agricultural statistics show spatial concentration and differences in production structure.

NASA POWER data characterize climatic exposure across territories.

The questionnaire shows participants' perceptions of scarce resources, barriers and adaptation priorities.

These three evidence streams are methodologically independent, and their common focus on water, climatic risk and irrigation confirms that these elements should be central to the resource-efficiency agenda.

The limitations of the survey must, however, be stated explicitly.

First, questionnaire responses reflect perceptions rather than measured quantities: naming water as scarce is not a direct measure of water deficit.

Second, several questions allow multiple answers, so the percentages in these blocks do not add up to 100% and show only the share of respondents who chose each option.

Third, the survey was conducted from 24 June to 3 July 2026 using purposive and snowball sampling. The sample took into account the territorial features of the 17 administrative-territorial units of Turkestan region and differences in population and concentration of agricultural producers; the survey aimed at wide territorial coverage and avoided excessive concentration of answers in individual districts. Participation was voluntary and anonymous, which allowed respondents to express their opinions freely. In total, 208 representatives of the agricultural sector took part; because the sample is purposive and partly formed by the snowball method, the results are not statistically representative of all producers of the region, reflect the views of the surveyed stakeholders and are used to triangulate the statistical findings.

Because of these limitations, the survey results are not merged with official statistical variables but are used for separate validation.

The evidence of Section 2.2 leads to several important conclusions.

Agricultural production in Turkestan region is spatially heterogeneous: it is concentrated in relatively few territories, and the crop-livestock mix varies significantly between districts.

Observed crop-output intensity also differs considerably, which shows that agricultural scale and land-output intensity are not equivalent.

Climatic exposure varies among the 17 territorial units, but differences in temperature do not fully explain the spatial variation of agricultural performance.

The economic impact of climate depends on the production specialization and resource structure of a district.

Finally, apart from insufficient financing, the most frequent barrier (59.6%), the respondents named water scarcity, climatic risks and irrigation development as the most important constraints and adaptation priorities.

Together, these results show that natural-resource efficiency cannot be explained by a single variable; it results from the combination of agricultural structure, resource availability, climatic conditions and territory.

This conclusion leads to the analysis of Section 2.3, which moves from spatial description to the statistical analysis of relationships. Correlation patterns, multicollinearity and the joint behaviour of agricultural, resource and climatic variables are examined to determine which variables contain independent explanatory information and should be included in the subsequent economic-mathematical modelling.

2.3 Assessment of the relationships among natural resource use, agricultural production and climate change

The previous analysis showed considerable spatial variation of agricultural production in Turkestan region: territorial units differ in the scale and composition of production, crop-production intensity and climatic exposure. However, spatial variation alone does not show whether the variables are systematically related. The next analytical step therefore moves from descriptive comparison to the evaluation of statistical relationships between agricultural production, land use and climatic conditions.

This subsection does not aim to identify a single climatic or resource factor that explains agricultural performance. Agricultural production results from the joint action of several factors, some of which are statistically correlated with each other. The empirical task is more specific and methodologically important: to identify the information content of the variables, the relationships revealed by different correlation measures and the variables that can be retained for modelling.

Before the correlations were calculated, the analytical sample was checked for territorial comparability, missing observations and inconsistencies in the source data, since statistical relationships are meaningful only when the observations refer to comparable territorial and production units.

The number of observations by crop is given in Table 2.13.

It should be noted that the correlation analysis shows statistical relationships and does not prove a causal effect of climate on yield. The within-district coefficients remove stable differences between districts, but other factors, such as technology, varieties and water supply, can also change over the years. Therefore, the results of this section are used for the selection of variables and for the interpretation of the model, and not as an estimate of causal effects.

Table 2.13 – Number of observations by crop in the analytical sample

Crop	Number of yield observations	Number of area observations	Decision
Wheat	275	277	Use
Barley	275	222	Exclude pending verification
Corn	279	279	Use
Rice	46	46	Use
Cotton	189	183	Use
Sunflower	253	253	Use
Potato	295	277	Use

Note – Compiled by the author using the district-level crop and climate analytical dataset [84; 87].

As Table 2.13 shows, the number of usable observations varies greatly between crops. This reflects the actual structure of the official district-level series rather than a balanced panel. Wheat, corn, sunflower and potato have wide geographic and temporal coverage, while rice has fewer district-year combinations because of its geographic concentration.

The different sample sizes have direct implications for interpretation: a coefficient based on several hundred district-year observations has a different evidential basis than one based on several dozen. The results are therefore considered for each crop separately rather than as a combined agricultural relationship.

Territorial missingness is also treated structurally: Zhetysay and Keles districts are treated as independently observed from 2018, and Sauran District as independently comparable from 2021. Observations before the formation of these units are not altered and are not replaced by zeros.

This treatment is essential for correlation analysis. Artificial zeros would create mechanical relationships between administrative history and agricultural variables: a new district would appear to have zero production before its formation and a jump afterwards, although its production was not zero but recorded within another district. Such coding would create artificial variation and distort the relationship between agriculture and climate.

The analytical dataset therefore retains an unbalanced panel structure, which is methodologically preferable to creating continuity where independent statistical observations do not exist.

The second screening issue is the difference between total production and the physical productivity of crops. The monetary value of agricultural production characterizes the economic size of a territory but is less suitable as the main dependent variable of the correlation analysis, because it includes price effects and differences in production structure.

Production performance is therefore measured here by crop yield. Yield relates production to the cultivated area and allows the same crop to be compared without aggregating products with different biology, prices or production technologies.

This does not mean that yield equals natural-resource efficiency: higher yields may result from technological improvement but also from more energy, agrochemicals or irrigation. The relationship of yield with climatic and land-use variables is therefore examined as a production-performance relationship before a broader efficiency interpretation is given.

Both annual and growing-season climatic indicators were initially included in the candidate list: annual temperature and precipitation and April-September temperature, precipitation, relative humidity, solar radiation and root-zone soil wetness.

The choice between annual and growing-season variables matters economically: annual values describe the overall environmental regime of a territory, while April-September indicators follow the period of the main crop-production processes.

At this stage, both groups remain candidate variables, and neither is assumed to be better; their redundancy is tested later by correlation and multicollinearity diagnostics.

During data screening, a significant problem was found in the crop-yield statistics: district-level barley and wheat yields were exactly the same in all 275 overlapping district-year observations.

Such complete correspondence between two crops with different biological and technological characteristics is extremely unlikely and indicates that the barley series needs to be checked against the original statistical source.

For this reason, a separate correlation analysis for barley is not included in this section.

This exclusion is not intended to improve the results; it is a data-quality decision that prevents an apparently accurate but possibly duplicated series from affecting variable selection and subsequent modelling.

The remaining crop-specific analysis therefore focuses on wheat, corn, rice, cotton, sunflower and potato.

The screening procedure reflects the broader methodological approach of the work: a large dataset is not necessarily a good one, and including unreliable observations only to increase the sample size can reduce confidence in the model.

Only observations with a clear statistical meaning of the variable are therefore retained.

The same applies to the climate data. NASA POWER provides complete annual climatic series for all territorial points, while agricultural coverage is less complete, so the effective sample size is determined by the intersection of agricultural and climatic data rather than by the climate series alone.

After removal of the duplicated barley series, the working dataset for 2004-2023 contains 1,337 crop-district-year yield observations (Table 2.13); the correlation analysis below uses fewer pairs (1,246 climate-yield and 1,223 area-yield pairs), because only observations with complete climatic and area data are included. The observations are unevenly distributed between crops because of differences in cultivation geography and statistical coverage.

The structure of the data also affects the meaning of ordinary correlations. A pooled correlation across all districts combines two types of variation.

The first is variation between districts, since some territories are systematically warmer, wetter or more productive than others.

The second is variation within districts, since temperature, precipitation and yield change over time in the same area.

These two types of variation may produce different statistical relationships.

For example, a crop may be concentrated in warmer areas that also have better irrigation, more experience with the crop or more favourable soils. Then a pooled correlation between temperature and yield may be positive even if unusually hot years reduce productivity within individual districts.

The opposite is also possible: yields may be structurally higher in cooler areas for reasons unrelated to temperature, even though the temporal response within districts is positive.

For this reason, the analysis is not based on a single pooled Pearson coefficient.

Three complementary measures are therefore used.

Pearson correlation measures the linear association of variables in the pooled crop-district-year sample.

Spearman rank correlation is used as a robustness measure, because it is less sensitive to the scale and distribution of observations and detects monotonic relationships that are not strictly linear.

Finally, a within-district correlation is calculated after subtracting the district mean from both variables. It is based on co-movement over time within the same territorial unit and removes time-invariant differences between units.

The within-district coefficient is not a causal estimate, because it does not account for all time-varying factors that affect yield. It is a diagnostic tool that tests whether a pooled relationship persists after permanent differences between territories are removed.

This distinction is key to the interpretation of the data.

For the within-district relationship, the district-specific means are subtracted from both the production variable and the explanatory variable:

$$\tilde{Y}_{it} = Y_{it} - \overline{Y}_i, \tag{2.29}$$

$$\tilde{X}_{it} = X_{it} - \overline{X}_i, \quad (2.30)$$

where Y_{it} denotes crop yield in district i and year t;
X_{it} denotes the corresponding climatic or resource variable;
$\overline{Y}_i$ denotes the district-specific mean of crop yield over the available observation period;
$\overline{X}_i$ denotes the district-specific mean of the explanatory variable over the available observation period.

The correlation is then calculated between $\tilde{Y}_{it}$ and $\tilde{X}_{it}$. This transformation eliminates all the constant spatial variation in the cross-district data, allowing for the identification of spatial variation over time that is consistent across districts as well as the variation which is not consistent with time across the districts.

The transformation cannot remove time-varying omitted factors and is not a causal estimator. Here it is used only for diagnosis, to determine whether the direction and strength of a pooled relationship remain after permanent district-level differences are removed.

When the pooled Pearson, Spearman and within-district correlations have the same direction, the observed relationship is reasonably robust to the method of calculation.

When the pooled coefficient is high but the within-district coefficient is low, a substantial part of the pooled association is probably due to persistent structural differences between territories.

When the sign changes, the spatial and temporal relationships differ even more, and the variable cannot be interpreted by a simple cross-sectional narrative.

This structure of analysis avoids a common pitfall of regional climate-agriculture research – interpreting a geographical correlation as a temporal production response.

A warm district may have high yields because it specializes in crops suited to a warm climate or has appropriate irrigation facilities and production practices [88]; this does not mean that further warming would increase its yields.

The statistical analysis must therefore distinguish differences in production levels between territories from production responses to changing conditions.

This distinction is particularly important for Turkestan region, because its spatial agricultural structure, as shown in Section 2.2, is already highly differentiated: crop-based and livestock-based districts, irrigated areas and foothill farming systems are not interchangeable production areas.

The relationship analysis therefore starts from crop-specific climate-yield associations rather than from one aggregate coefficient for regional agriculture.

Table 2.14 presents the Pearson, Spearman and within-district correlations of crop yields with the growing-season climate indicators.

The coefficients show that climate affects productivity differently across crops and with unstable statistical strength; explaining this heterogeneity is the main empirical task of the next stage of the analysis.

The results in Table 2.14 show significant variation in crop-climate relationships and, in some cases, a change of direction depending on whether pooled observations or within-district variation are analysed.

For wheat, the pooled correlation between yield and growing-season temperature is extremely low: the Pearson coefficient (about 0.055) is not statistically significant, and the Spearman coefficient is very close to zero. Taken alone, these results would suggest no strong relationship between wheat yield and growing-season temperature in the district-year sample.

The within-district estimate reverses this reading: without the persistent differences between districts, wheat yield and April-September temperature are negatively and significantly correlated (about -0.288).

Table 2.14 – Correlations between crop yield and growing-season climate indicators (temperature, precipitation, root-zone wetness)

Crop	N	Pearson r	Pearson p	Spearman rho	Spearman p	Within-district r	Within-district p
Wheat – Apr-Sep temperature	265	0.055	0.375	-0.007	0.914	-0.288	<0.001
Wheat – Apr-Sep precipitation	265	0.133	0.030	0.186	0.002	0.361	<0.001
Wheat – root-zone wetness	265	-0.031	0.612	0.118	0.055	0.221	<0.001
Corn – Apr-Sep temperature	259	0.410	<0.001	0.411	<0.001	0.215	0.001
Corn – Apr-Sep precipitation	259	-0.235	<0.001	-0.193	0.002	-0.162	0.009
Corn – root-zone wetness	259	-0.210	0.001	-0.288	<0.001	-0.087	0.161
Rice – Apr-Sep temperature	45	0.092	0.548	0.053	0.729	0.165	0.279
Rice – Apr-Sep precipitation	45	-0.004	0.981	-0.032	0.833	-0.021	0.890
Rice – root-zone wetness	45	0.007	0.965	-0.001	0.997	0.058	0.706
Cotton – Apr-Sep temperature	169	0.358	<0.001	0.347	<0.001	0.150	0.052
Cotton – Apr-Sep precipitation	169	-0.293	<0.001	-0.310	<0.001	-0.133	0.085
Cotton – root-zone wetness	169	-0.311	<0.001	-0.334	<0.001	0.011	0.884
Sunflower – Apr-Sep temperature	233	0.248	<0.001	0.291	<0.001	0.104	0.113
Sunflower – Apr-Sep precipitation	233	-0.135	0.039	-0.155	0.018	-0.083	0.210
Sunflower – root-zone wetness	233	-0.124	0.059	-0.209	0.001	-0.043	0.514
Potato – Apr-Sep temperature	275	0.142	0.019	0.146	0.015	0.205	0.001
Potato – Apr-Sep precipitation	275	-0.028	0.646	0.021	0.734	-0.126	0.037
Potato – root-zone wetness	275	-0.076	0.211	-0.076	0.210	-0.099	0.101

Note – Calculated by the author using the district-level crop and climate analytical dataset [84; 87].

This divergence is analytically important. It means that the pooled association is weak, while a different temporal pattern exists within individual territories. Some structurally warm districts may have conditions favouring relatively high wheat yields, such as irrigation systems, soils, crop-management practices or other

persistent attributes, and these between-district differences may mask the negative temporal relationship between temperature and yield within districts.

This is not a causal estimate of the temperature effect, but it shows that comparisons between territories and over time do not coincide: for wheat, the climatic relationship becomes more evident after persistent territorial heterogeneity is removed.

A similar pattern is observed for precipitation. The pooled Pearson correlation between wheat yield and April-September precipitation is positive but weak (about 0.133), the Spearman coefficient is slightly higher (about 0.186), and the within-district coefficient rises to about 0.361.

The direction of the relationship is therefore the same for all measures, while its strength increases considerably in the within-district comparison.

This means that, within the same district, year-to-year growing-season precipitation is more strongly related to wheat yield than the regional comparison suggests, and between-district variability masks part of the temporal association.

Root-zone soil wetness gives a more complex picture: for wheat, the pooled Pearson coefficient is near zero and the rank coefficient slightly positive, while the within-district coefficient rises to about 0.221 and is statistically significant.

This difference shows that precipitation and soil moisture are not synonyms. Precipitation is the atmospheric water supply, whereas root-zone wetness is the moisture content of the soil profile resulting from precipitation, temperature, evaporation, the previous moisture regime and other hydrological processes.

The statistical pattern is different for corn.

Its pooled associations with growing-season temperature are among the strongest positive associations in Table 2.14: the Pearson coefficient is about 0.410 and the Spearman coefficient about 0.411. The similarity of the two measures suggests that the result is not driven by extreme values or by the linearity assumption.

The within-district coefficient remains positive (about 0.215) and significant.

The decrease in magnitude is important: part of the high pooled association is due to persistent differences between territories, but the positive association does not disappear when these differences are controlled for.

This does not mean that corn productivity would keep rising with higher temperatures. The coefficient describes the relationship within the historical climatic range of the sample; outside this range, agronomic responses may differ, and excessive heat will eventually be harmful.

The precipitation results for corn reinforce this caution. In the pooled sample, growing-season precipitation is negatively related to corn yield (Pearson $r \approx -0.235$, Spearman ≈ -0.193), and within districts the relationship remains negative but weaker (about -0.162).

This negative correlation does not mean that water reduces corn productivity. In an irrigated system, rainfall is only part of the total water supply; a wetter season may also coincide with lower solar radiation, cooler temperatures, disease pressure or specific weather patterns, and irrigation can compensate for low precipitation.

The coefficient therefore measures observed co-movement rather than an agronomic effect.

This is very important in Turkestan region, where the effective water supply of many crops combines natural precipitation and irrigation, so a rainfall-yield coefficient cannot replace the measurement of irrigation.

The pooled association of corn yield with root-zone wetness is also negative (about -0.210), while the within-district association is much weaker and statistically insignificant.

Here, too, the pooled result contains a strong spatial element: districts with systematically different moisture regimes may also differ in crop technology, irrigation and production structure, and once these persistent differences are reduced, the independent relationship is far less visible.

Rice provides a useful contrast with the larger crop samples. The available observations show no strong statistical link between rice yield and any of the three main climate indicators: for temperature, precipitation and root-zone wetness the pooled coefficients are close to zero and the within-district ones are weak.

The absence of a significant relationship does not mean that rice production is insensitive to climate.

The rice sample is much smaller than those for wheat, corn, sunflower or potato. Rice is also geographically concentrated and highly dependent on managed water supply; when irrigation compensates for natural moisture limitations, natural climatic variation explains relatively little of the actual yield variation.

The small sample size further limits statistical power.

Thus, for rice, the lack of a significant correlation is not proof of no relationship; it shows that the variation in the present dataset is insufficient to support a simple bivariate relationship.

Cotton shows a stronger pooled climatic pattern.

Cotton yield is positively correlated with growing-season temperature (Pearson $r = 0.358$, Spearman $r = 0.347$), and both coefficients are significant at the 0.05 level.

After district-specific means are subtracted, however, the coefficient falls considerably, to about 0.150, and is only marginally significant.

This difference implies that the strong pooled temperature-cotton relationship partly reflects spatial factors: cotton production is highly localized in relatively warm areas with a long production history, so the pooled coefficient combines long-term territorial specialization with climatic exposure.

Within districts, the relationship between cotton yield and year-to-year temperature change is weak.

The difference has economic weight: cotton is tied to the particular agricultural system of Turkestan region, and its apparent climatic advantage is difficult to separate from the inherited irrigation infrastructure, accumulated knowledge of the crop, processing capacity and long-standing territorial specialization.

In the pooled analysis, growing-season precipitation is negatively correlated with cotton yield (about -0.293 by Pearson and -0.310 by Spearman); the within-district coefficient is smaller (about -0.133) and not quite statistically significant.

Root-zone wetness shows a similar pattern: the pooled coefficients are about -0.311 (Pearson) and -0.334 (Spearman), while the within-district association is close to zero.

That the relationship disappears after district de-meaning is itself informative: much of the pooled association between soil moisture and cotton yield comes from differences between cotton-growing areas, not from a stable relationship over time inside each of them.

For sunflower, pooled associations with growing-season temperature are moderately positive (Pearson about 0.248, Spearman about 0.291), while the within-district relationship is very weak (0.104) and not significant.

The pooled correlation between precipitation and sunflower yield is weakly negative and becomes even weaker within districts.

The sunflower pattern thus resembles the cotton pattern in one important respect: the pooled relationship is stronger than the temporal association within individual districts.

This is important because Section 2.1 showed a significant long-term contraction of sunflower production in Turkestan region. Pooled relationships may therefore be affected by changes in the geographical distribution of the crop: increasing concentration of sunflower in a subset of territories may strengthen or weaken regional climate-crop relationships independently of year-to-year relationships.

Potato yields show weaker but more consistent temperature relationships: the pooled Pearson coefficient is 0.142, the pooled Spearman coefficient 0.146 and the within-district coefficient 0.205.

The sign is positive in all three calculations, but the magnitude is modest.

Growing-season precipitation has practically no pooled relationship with potato yield and a marginally negative relationship within districts, and the relationship with root-zone wetness remains weak under all three measures.

The potato results again show that no single climatic variable dominates crop production in the regional agricultural system.

The key methodological difference is illustrated in accordance with Figure 2.16, which compares pooled and within-district temperature-yield correlations.

In accordance with Figure 2.16, the magnitude of the temperature relationship may change after permanent differences among districts are removed, and for wheat even the sign changes.

For corn, the relationship is positive under both approaches but less pronounced within districts.

For cotton and sunflower, the relationship is positive but becomes weaker after the within-district transformation.

For wheat, the almost negligible pooled coefficient becomes negative within districts.

Rice shows weak relationships under both approaches, and potato is only modestly positively related to temperature.

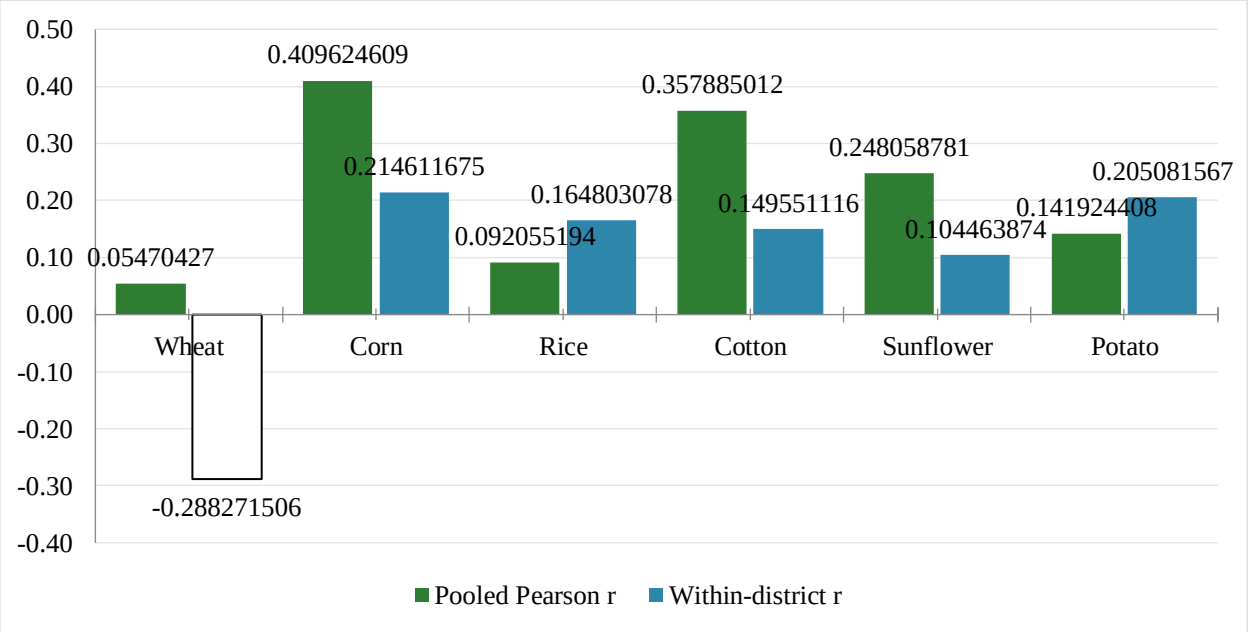


Figure 2.16 – Pooled and within-district temperature-yield correlations by crop

Note – Calculated by the author using the district-level crop and climate analytical dataset [84; 87].

The figure thus provides empirical evidence that the climatic relationships in the agriculture of Turkestan region have both spatial and temporal components.

This is directly relevant for the next step of modelling: the apparent effects of climatic variables on a crop may be due to soil conditions, infrastructure, specialization, irrigation systems or other relatively persistent district characteristics that a pooled specification would overlook.

The findings therefore support modelling methods that control for territorial heterogeneity instead of relying only on pooled cross-sectional relationships.

At the same time, the within-district coefficients should not be treated as causal parameters, since time-varying omitted factors may remain: irrigation intensity, seed quality, technology, fertilization, pest pressure and other management changes may coincide with climatic variation and yield changes.

The present analysis is therefore diagnostic rather than causal.

Its main contribution is to show that the climate-productivity relationship is crop-specific, scale-sensitive and dependent on the source of variation analysed.

This result is significant for natural-resource efficiency: if different crops respond differently to the same climatic variables, a regional strategy based on one aggregate climate coefficient would hide economically relevant heterogeneity.

The next analytical step extends the analysis from climate to land use: Table 2.15 examines the relationship between changes in cultivated area and crop yield and whether it differs between and within districts.

Table 2.15 thus extends the relationship analysis to the land component of agricultural production by examining the correlation between crop sown area and yield.

Table 2.15 – Correlations between sown area and crop yield by crop

Crop	N	Pearson r	Pearson p	Spearman rho	Spearman p	Within-district r	Within-district p
Wheat	265	-0.243	<0.001	-0.213	<0.001	0.069	0.262
Corn	259	0.362	<0.001	0.387	<0.001	0.319	<0.001
Rice	45	0.224	0.139	0.178	0.242	0.453	0.002
Cotton	163	0.096	0.224	0.359	<0.001	-0.126	0.108
Sunflower	233	0.004	0.953	-0.049	0.456	-0.097	0.140
Potato	258	0.353	<0.001	0.343	<0.001	0.081	0.193

Note – Calculated by the author using the district-level crop analytical dataset [84].

This comparison does not assume that a larger cultivated area should automatically be more productive. Sown area measures the extent of crop production, and yield measures physical output per hectare; their relationship may show that expansion is associated with higher productivity, lower productivity or no systematic change.

This is directly related to the extensive and intensive development patterns identified in Section 2.1: area expansion represents the extensive margin of growth, and higher yield the intensive margin. The two processes are not mutually exclusive – a crop may expand and become more productive, or expand onto less suitable land and become less productive.

The results in Table 2.15 show that there is no fixed area-yield relationship for the main crops of Turkestan region.

For wheat, the pooled Pearson correlation between sown area and yield is negative (-0.243), and so is the Spearman coefficient (-0.213), which at first glance suggests a negative relationship between wheat area and productivity.

However, after persistent district differences are removed, the correlation is about 0.069 and not significantly different from zero.

This contrast is important: the negative pooled relationship appears to reflect structural differences between territories rather than a decline in wheat yield when the wheat area increases within a district.

In other words, districts with larger wheat areas tend to have lower average wheat yields, but within individual districts there is no consistent relationship between wheat area expansion and yield.

A spatial specialization effect is visible here: large wheat areas often include land under less intensive production systems, so the pooled coefficient captures where wheat is grown as well as the effect of expanding its area.

Corn shows a different picture.

The pooled Pearson correlation between corn area and yield is about 0.362, and the Spearman correlation about 0.387; more importantly, the within-district correlation is positive ($r = 0.319$) and statistically significant.

Of all the area-yield relationships examined, this is one of the most consistent.

The result suggests that expansion of corn area within a district during the study period was more likely to be associated with higher yields than with diluted productivity.

This does not mean that a larger area causes higher yields: expansion may occur in periods when producers simultaneously introduce improved seed, irrigation, technology or crop-management practices. The coefficient therefore reflects joint development rather than a direct land effect.

However, the positive correlation that remains after district de-meaning shows that the corn pattern is not fully explained by differences between districts.

Rice also shows a positive area-yield relationship, but with fewer observations it should be interpreted more cautiously; the within-district coefficient is higher, about 0.453, and statistically significant.

This indicates that, in the limited rice-growing areas, a larger planted area was associated with higher yields over the years.

This is probably connected with the specific production system of rice, which is highly localized and fully dependent on irrigation: expansion is more likely in years or areas with sufficient water and favourable production conditions for both larger area and higher output.

The rice sample is small, and the result cannot be generalized to the broader regional agricultural system.

The pattern for cotton is ambiguous.

Its pooled Pearson coefficient is low (about 0.096), while the Spearman coefficient is higher (about 0.359); this difference suggests that a simple linear relationship does not describe the data well.

After district-specific means are subtracted, the coefficient becomes slightly negative (-0.126) and is not statistically significant.

The positive pooled rank association therefore appears to reflect structural differences between cotton-growing areas rather than a stable effect of area expansion within districts.

This result is especially significant because cotton plays a highly specialized role in the agricultural economy of Turkestan region, and cotton area expansion depended on irrigation availability, crop rotation, soil conditions and the opportunity cost of land for alternative crops.

For sunflower, the pooled area-yield association is negligible: the Pearson coefficient is near zero, the Spearman coefficient is slightly negative, and the within-district relationship is weak and statistically insignificant.

As with cotton, there is no stable area-yield relationship: the overall reduction of the cultivated area does not correspond to a consistent productivity response within districts over time.

This suggests that the sunflower area depends on crop substitution and relative economic attractiveness rather than on a simple area-productivity relationship.

For potato, the pooled area-yield relationship is positive (Pearson about 0.353, Spearman about 0.343), but after district de-meaning the coefficient drops to about 0.081 and is no longer statistically significant.

The pooled and within-district area-yield coefficients of the six crops are compared in accordance with Figure 2.17.

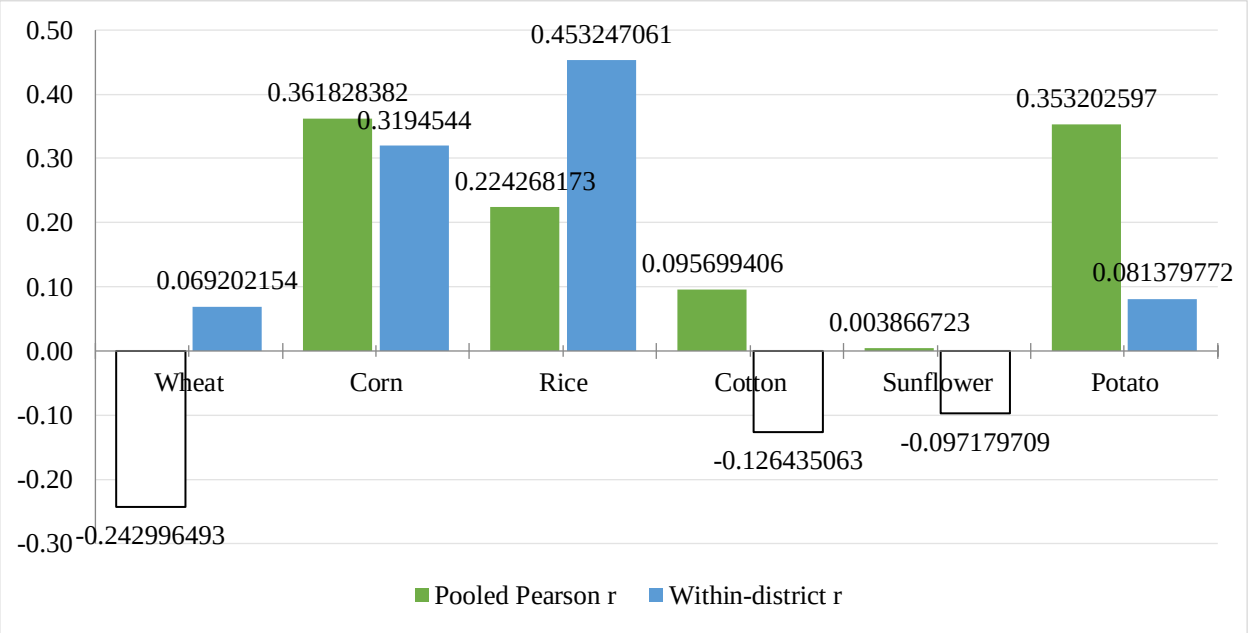


Figure 2.17 – Pooled and within-district area-yield correlations by crop

Note – Calculated by the author using the district-level crop analytical dataset [84].

The potato case again shows the importance of separating spatial and temporal components: districts with larger potato areas tend to have higher average yields, but within a district a larger potato area is not systematically associated with a higher yield.

Territorial specialization explains this: in some districts, favourable soils, access to markets, irrigation conditions or production experience make it possible to combine larger potato areas with higher yields, so the pooled correlation is positive although short-run changes in area are only weakly related to productivity.

In accordance with Figure 2.17, the difference between the two measures is significant for several crops: the negative pooled relationship for wheat practically disappears when persistent district differences are taken into account, while the positive correlation for corn remains relatively high.

The within-district association strengthens for rice, although the small sample limits this result, and for cotton, sunflower and potato the relationships weaken considerably or disappear after district de-meaning.

This comparison is an important empirical test of the extensive-intensive contrast.

Area growth cannot be described mechanically as inefficient: whether expansion is accompanied by declining, stable or improving productivity depends on the crop and the territorial production system. The findings thus support a crop-specific concept of land-use efficiency.

In some cases, expansion coincides with productivity improvement when both result from the same investment, irrigation or technological change; in others, extensive cultivation simply continues a traditional specialization in extensive production systems.

In some cases, area variation is only loosely related to yield. This is especially important for the subsequent economic-mathematical model: a single land-expansion coefficient for all crops would ignore the empirical evidence.

The land variable should therefore enter the next stage of modelling with a crop-specific interpretation rather than as an undifferentiated regional input.

The relationship analysis has thus identified two kinds of empirical heterogeneity.

The first is crop heterogeneity: the relationship of yield with climatic and area variables differs between crops.

The second is spatial-temporal heterogeneity: pooled relationships may differ considerably from within-district relationships.

Before the candidate variables are taken to the modelling stage, a third condition must be considered – multicollinearity among the explanatory variables.

Several climatic indicators measure related aspects of the same agroclimatic environment. Annual and growing-season temperature are not two distinct concepts, and precipitation, relative humidity and root-zone soil wetness may contain overlapping information on moisture conditions.

If correlated explanatory variables enter a model together, its overall predictive performance may be acceptable while individual coefficients are unstable and difficult to interpret. Therefore, the variance inflation factor (VIF) is used to assess the candidate climate variables.

For each explanatory variable X_j, the diagnostic is calculated as:

$$VIF_j = \frac{1}{1-R_j^2}, \tag{2.31}$$

where R_j^2 is obtained from an auxiliary regression of X_j on all remaining candidate explanatory variables.

The corresponding tolerance statistic is:

$$Tolerance_j = 1 - R_j^2 = \frac{1}{VIF_j}. \tag{2.32}$$

A high R_j^2 in the auxiliary regression means that a large proportion of the variation in X_j can already be reproduced by the remaining variables. In this situation, X_j is less informative and might be sensitive to specification changes.

VIF values around 5 are considered a possible sign of multicollinearity, and values around 10 or more a strong warning of substantial redundant information.

The variance inflation factors for the candidate climate variables are given in Table 2.16.

Table 2.16 – Variance inflation factors for candidate climate variables

Climate variable	VIF - full candidate set	Tolerance - full set	VIF - final baseline set
Annual temperature	7.43	0.13	excluded
Annual precipitation	3.56	0.28	excluded
Growing-season temperature	11.10	0.09	2.39
Growing-season precipitation	5.16	0.19	2.78
Growing-season humidity	5.43	0.18	excluded
Root-zone wetness	3.45	0.29	2.64
Solar radiation	1.98	0.51	1.84

Note – Calculated by the author using the candidate climate-variable set based on NASA POWER data [87].

These thresholds are diagnostic rather than exclusion criteria, because a variable also has substantive meaning: a variable is not removed only because its VIF exceeds a threshold if it represents a theoretically distinct mechanism not sufficiently captured by another indicator.

The results of the multicollinearity diagnostics are presented in Table 2.16.

They clearly show the overlap between annual and growing-season temperature in the full candidate set.

The VIF is about 7.43 for annual temperature and about 11.10 for growing-season temperature.

This means that the two variables should not be included in the baseline specification together: they represent similar aspects of thermal exposure, and once one of them is included, the other adds little independent information.

For crop production, the April-September indicator matches the analysed production season more closely. Growing-season (April-September) temperature is therefore retained as the main thermal variable, while annual temperature serves for alternative specifications and robustness checks.

Growing-season precipitation also has a relatively high VIF in the full candidate set (about 5.16). For growing-season relative humidity the VIF reaches about 5.43. This overlap reflects the climatic correlations behind the variables: precipitation and relative humidity for April-September show a strong positive correlation (about 0.85). Both variables thus describe closely related aspects of atmospheric moisture conditions.

Their individual effects would be difficult to identify if both were included in the baseline model.

Relative humidity is therefore not discarded but moved from the baseline specification to sensitivity analysis. Root-zone soil wetness has a lower VIF in the full candidate set (about 3.45). It is correlated with precipitation and humidity but reflects a different stage of the moisture process – moisture in the soil rather than moisture supply from the atmosphere.

This justifies keeping soil moisture as a separate candidate variable.

Solar radiation has the lowest multicollinearity of all climate indicators, with a VIF of about 1.98 in the full specification. It therefore provides comparatively unique information on the climatic energy environment and is retained.

Removing annual temperature, annual precipitation and growing-season relative humidity (RH) from the baseline candidate set markedly reduces the multicollinearity among the remaining variables. After this reduction, the VIF is about 2.39 for growing-season temperature, about 2.78 for growing-season precipitation, about 2.64 for root-zone wetness and about 1.84 for solar radiation, and none of these values points to severe multicollinearity. The change in VIF before and after variable reduction is shown in accordance with Figure 2.18.

The decrease is especially large for growing-season temperature: its initial VIF above 11 was caused mainly by its joint inclusion with annual temperature and other overlapping variables rather than by the variable itself.

After the redundant measures are removed, growing-season temperature is statistically suitable for the baseline candidate set.

This is relevant because multicollinearity diagnostics do not make a variable bad in itself: a high VIF is a problem of the combination of variables rather than a flaw of an individual variable.

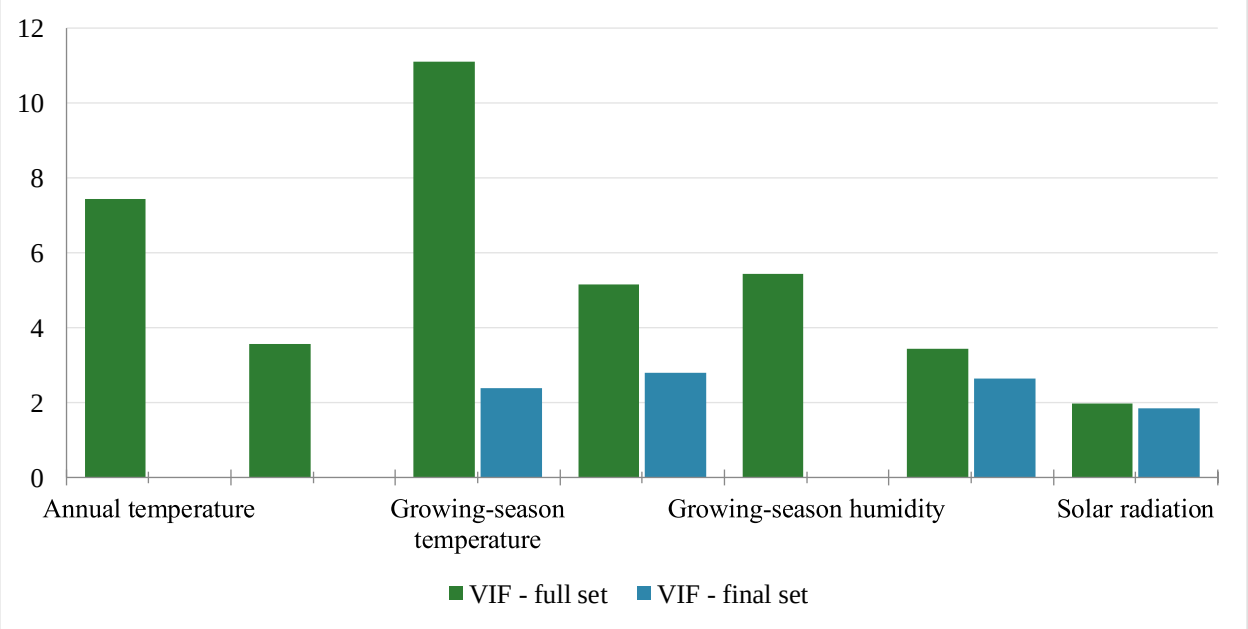


Figure 2.18 – Variance inflation factors before and after climate-variable selection

Note – Calculated by the author using multicollinearity diagnostics of the candidate climate-variable set based on NASA POWER data [87].

The purpose of the diagnostics is therefore to find a more parsimonious specification in which each retained variable carries distinct information.

The correlation matrix of the candidate climate variables is shown in accordance with Figure 2.19.

In accordance with Figure 2.19, the climate variables form several related clusters.

Annual and growing-season temperature share much of their information.

Growing-season precipitation is strongly correlated with relative humidity.

The moisture variables are also associated with root-zone wetness, but do not fully replicate it.

Solar radiation is negatively correlated with several moisture indicators and represents a clearly distinct dimension.

This structure supports a baseline climate block of four variables: growing-season temperature, growing-season precipitation, root-zone soil wetness and solar radiation.

Variable	Annual temp.	Annual precip.	Apr-Sep temp.	Apr-Sep precip.	Apr-Sep humidity	Root-zone wetness	Solar radiation
Annual temp.	1.00	-0.29	0.88	-0.29	-0.37	-0.59	0.18
Annual precip.	-0.29	1.00	-0.56	0.77	0.79	0.72	-0.45
Apr-Sep temp.	0.88	-0.56	1.00	-0.60	-0.65	-0.75	0.38
Apr-Sep precip.	-0.29	0.77	-0.60	1.00	0.85	0.64	-0.67
Apr-Sep humidity	-0.37	0.79	-0.65	0.85	1.00	0.73	-0.62
Root-zone wetness	-0.59	0.72	-0.75	0.64	0.73	1.00	-0.35
Solar radiation	0.18	-0.45	0.38	-0.67	-0.62	-0.35	1.00
Pearson r	-1.0		-0.5		0.0	+0.5	+1.0

Figure 2.19 – Correlation matrix of candidate climate variables

Note – Calculated by the author using the candidate climate-variable set based on NASA POWER data [87].

Conceptually, the four indicators represent heat, atmospheric water input, soil-moisture status and incoming solar energy.

The aim of this reduction is not to maximize statistical significance but to build an interpretable and parsimonious climate block for further modelling.

The results of the screening, correlation and multicollinearity analysis are summarized in Table 2.17 as a variable selection framework for the next modelling step.

The table identifies variables suitable for the baseline specification, variables better used in robustness analysis, and variables that should be excluded until the quality of their source is confirmed.

Growing-season temperature remains the main thermal indicator for three reasons: it is more closely related to the biological production period than annual temperature; annual and growing-season temperature overlap considerably in the full candidate set; and after the annual measure is removed, the VIF of growing-season temperature falls to about 2.39, so it can be retained without high multicollinearity.

Growing-season precipitation is also retained. It partly overlaps with relative humidity but has a clear interpretation as the atmospheric water input during crop development, and its VIF in the reduced specification is about 2.78, which indicates reasonable independence from the other retained variables.

Table 2.17 – Selection of variables for the final model

Candidate variable	Decision	Empirical reason	Planned role
Annual temperature	Exclude from baseline	VIF 7.43 in the full climate set; strong overlap with April-September temperature, which is more directly related to crop development	Use only for descriptive/robustness analysis
Annual precipitation	Exclude from baseline	Conceptually overlaps with April-September precipitation, which is more closely related to the crop-development window; moderate VIF	Retain as robustness alternative
Apr-Sep temperature	Retain	Thermal exposure during the main growing season; direct measure; final-set VIF 2.39	Baseline explanatory variable
Apr-Sep precipitation	Retain	Natural moisture input during crop development; final-set VIF 2.78	Baseline explanatory variable
Apr-Sep relative humidity	Sensitivity only	High correlation with April-September precipitation ($r \approx 0.85$) and VIF 5.43 in the full candidate set.	Use in sensitivity checks rather than in the baseline
Apr-Sep root-zone wetness	Retain	Moisture condition of the soil beyond precipitation; final-set VIF 2.64	Baseline explanatory variable
Apr-Sep solar radiation	Retain	Distinct climatic-energy dimension with low multicollinearity; final-set VIF 1.84	Baseline explanatory variable
Crop sown area	Retain with crop-specific interpretation	Direct land-use measure; area-productivity relationships differ by crop and between pooled and within-district comparisons	Resource-use variable
Crop yield	Retain as production performance	Physical output per hectare is less affected by inflation than monetary output and is available for a range of crops	Primary production-performance outcome
Barley yield series	Exclude pending source verification	District barley yields are identical to wheat yields in all 275 overlapping observations of the source data	Do not use for inference until the source is corrected

Note – Compiled by the author based on correlation analysis and multicollinearity diagnostics.

Root-zone soil wetness is retained because it contains information not provided by precipitation. The two variables are related but represent different stages of the water process: precipitation measures the atmospheric water supply, and root-

zone wetness the moisture condition of the soil layer that matters for plant growth. Its final-set VIF of about 2.64 shows no excessive duplication of information.

The fourth baseline climatic variable is solar radiation, which adds a distinct production dimension and has the lowest VIF among the retained variables (about 1.84).

The resulting climate block therefore consists of four complementary indicators rather than several partly redundant indicators of one climatic process.

Annual temperature is excluded from the baseline specification but kept as a robustness alternative. This does not mean that annual temperature is unimportant; it means that its independent information content is low when growing-season temperature is included.

The same approach is applied to annual precipitation: it remains useful for descriptive and robustness analysis, while growing-season precipitation is a more direct indicator of moisture availability during the main crop-production season.

Growing-season relative humidity is moved to sensitivity analysis. It is strongly correlated with growing-season precipitation and has a high VIF in the full candidate set, so in the baseline specification it would add little independent information but could make the interpretation of coefficients more difficult.

This shows the difference between baseline variables and robustness alternatives. Variable selection is not an elimination process: the baseline specification gives the simplest description of the main mechanisms, and alternative specifications test whether the conclusions change when related indicators are substituted.

The land component is represented by the sown area of crops. It is retained not because the preceding analysis showed a direct area-yield effect, but because it is the observable land-use input for each crop.

The empirical results show that the influence of area is conditional: corn and rice have positive within-district area-yield associations, while for wheat, cotton, sunflower and potato the within-district associations are weak and statistically insignificant, and the pooled associations weaken or reverse after district means are subtracted.

This heterogeneity means that land cannot be given a universal productivity interpretation for all crops.

Yield is retained as the main physical production-performance variable. It is less affected than current-price output by inflation, crop prices and the monetary composition of production and is therefore more suitable for measuring the relationships of land use and climatic conditions with physical agricultural productivity.

At the same time, yield is not treated as the only indicator of natural-resource efficiency, since a high yield may require intensive water or energy use. The subsequent model therefore considers productivity together with resource requirements instead of focusing on yield maximization.

Inferential analysis of the barley series is postponed until the data are verified. The reason is methodological rather than theoretical: the district-level barley yields

provided for the study coincide exactly with wheat yields in the overlapping observations, so including barley would double-count information already represented by wheat.

This data-quality finding also illustrates the difference between statistical completeness and empirical reliability: a dataset with more variables, some of which are duplicated or misplaced, may be worse than a smaller but reliable dataset.

The findings of Section 2.3 divide the candidate variables into three analytical groups.

The first group consists of baseline variables with relatively distinct and economically interpretable information: growing-season temperature, growing-season precipitation, root-zone soil wetness, solar radiation, sown area and crop-specific yield.

The second group consists of alternative or sensitivity variables – annual temperature, annual precipitation and growing-season relative humidity – which are informative but should not enter the baseline specification together with closely related variables.

The third group includes variables that require further source verification; in the screening process, barley yield is the main variable of this group.

This classification creates a direct empirical link between the descriptive assessment of Chapter 2 and the modelling framework of Chapter 3.

Each selected variable has a clear place in the resource-production system: land sets the spatial base of production, temperature governs biological development and evaporative demand, precipitation supplies natural moisture, root-zone wetness characterizes the water conditions in the soil, solar radiation sets the energy available for photosynthesis, and yield is the physical result of all these factors combined with management practices.

The statistical evidence, however, shows that these relationships are not uniform.

Different crops respond differently to the same temperature change.

Increases in cultivated area are associated with different productivity patterns for different crops.

Relationships may weaken, disappear or even reverse when persistent territorial differences are removed.

The results therefore indicate that the subsequent economic-mathematical model should not be based on a single undifferentiated regional production equation.

Instead, the empirical structure supports a model that recognizes crop-specific production characteristics and territorial heterogeneity.

This is particularly important for the central aim of the work. Improving natural resource efficiency does not mean maximizing agricultural production without regard to resource limitations; it means identifying production configurations in which an economically adequate level of production can be maintained or increased with a lower use of constrained resources.

The results of Section 2.3 set several requirements for such a model.

First, territorial heterogeneity must be controlled rather than ignored, since the differences between pooled and within-district correlations show that district characteristics can strongly affect the observed relationships.

Second, crop heterogeneity must be retained: combining all crops into one response function would hide the different relationships found for wheat, corn, rice, cotton, sunflower and potato.

Third, the baseline climate specification should be as simple as possible: closely related variables should not be included together without theoretical and empirical justification.

Fourth, alternative specifications should be retained for robustness analysis, for example, annual instead of growing-season indicators or relative humidity instead of other moisture indicators, to determine whether the main conclusions are sensitive to the representation of climate.

Finally, statistical association is not causation. The correlation analysis identifies patterns that help to select and structure the variables, while explaining observed and unobserved heterogeneity and allowing causal interpretation would require a more extensive modelling framework.

This distinction also defines the role of Section 2.3 in the dissertation.

Section 2.1 discussed the national and regional dynamics of agricultural resource use and production; Section 2.2 showed that the agricultural space of Turkestan region is heterogeneous in production structure, land-use intensity and climatic vulnerability; Section 2.3 demonstrated that the relationships of productivity with land use and climate are also heterogeneous and that several explanatory variables are correlated.

Together, these three levels provide a consistent empirical basis for Chapter 3: the first defines the problem of natural-resource efficiency at the regional level, the second its territorial organization, and the third the statistical relationships and constraints of variable selection.

The next chapter therefore moves from diagnosis to solution design.

The strategic directions of Section 3.1 should reflect the resource limitations and territorial differences identified in Chapter 2 rather than generic agricultural policies; the organizational-economic mechanism of Section 3.2 should specify how these differentiated strategies are implemented; and the economic-mathematical model of Section 3.3 should represent the relationships between land, water, energy, climate and crop production decisions with explicit constraints.

The results of Section 2.3 therefore provide the empirical basis for model specification rather than a substitute for the model.

The main conclusion of Chapter 2 is that the natural-resource efficiency of agriculture in Turkestan region is not determined by one resource, one climatic factor or one general production relationship, but by the combination of territorial conditions, crop structure, land-use intensity, moisture availability and climatic exposure.

A modelling framework for resource-efficient agricultural development should therefore retain this multidimensional nature without duplicating explanatory variables.

This requirement is the methodological starting point for the strategic and model development presented in Chapter 3.

3 Strategic and model foundations for resource-efficient and climate-resilient development of agriculture in the Turkestan region

3.1 Strategic directions for improving natural resource efficiency in agriculture under climate change

The empirical results for Turkestan region show that agricultural development increasingly depends on the compatibility of production growth with the physical capacity of the resource base. The long-term dynamics discussed in Chapter 2 show significant growth of agricultural production, while the territorial analysis reveals large differences in production specialization, cultivated land, crop-livestock balance and climatic characteristics among the 17 territorial units. These differences become strategic because the same measures have different effects in territories with different irrigation dependence, land availability, climatic vulnerability, livestock density and infrastructure capacity.

The analytical understanding of resource efficiency therefore requires a move from a sectoral approach to a differentiated system of territorial decisions. The unit of strategic analysis is the territorial production configuration formed by the interaction of natural resources, agricultural specialization and adaptive capacity. In such a configuration, water shortage limits possible cropping patterns, temperature and precipitation affect crop production and livestock needs, cultivated land is contested by alternative production options, pasture quality limits livestock expansion, energy for pumping, irrigation and storage forms part of operating costs, and environmental pressure affects the long-term reproduction of the agricultural resource base.

This interpretation is consistent with the author's previous publications. The author's earlier work on climate-smart cotton cultivation found that cotton yields respond to temperature, precipitation and irrigation conditions and stressed the economic importance of optimizing irrigation and conserving resources [18, p.36].

The subsequent territorial study of agriculture in Turkestan region related climatic fluctuations to agricultural productivity and land use at the district level and confirmed the need for spatially differentiated adaptation measures [21]. Research on natural-resource use extended the concept to the interaction of land, water and degradation processes in agricultural production [17, p.392].

Another methodological premise is related to the development of agricultural modelling. The Scopus search conducted by the author identified 860 publications for 1992-2025 and revealed a clear shift from process-based crop and resource simulation to spatial, data-driven and AI-supported decision systems. The themes of the field are more and more connected with climate change [89], with machine learning and prediction, irrigation and soil moisture, crop productivity, adaptation and decision support, whereas the economic interpretation of these digital and environmental modelling directions is still less developed.

The international development of methods is a further reason to treat the strategic development of agriculture in Turkestan region as one continuous

analytical framework in which data-based diagnostics of resources, prediction and economic decision-making are linked [14].

The transition from empirical results to strategy is formalized by the evidence-concordance principle. Each strategic direction is assessed against four independent evidence streams: statistical, climate-relationship, stakeholder-survey and project-implementation evidence. The procedure separates directions supported by several independent analyses from those whose support is currently based on more limited empirical data.

For strategic direction j, the Evidence-Concordance Score is defined as:

$$ECS_j = \sum_{k=1}^{4} I_{jk}, \tag{3.1}$$

where ECS_j – evidence-concordance score for strategic direction j;
I_{jk} – binary indicator equal to 1 when strategic direction j is independently supported by evidence stream k, and 0 otherwise;
k – statistical evidence, climate/relationship evidence, stakeholder-survey evidence and project-implementation evidence.

Accordingly,

$$0 \leq ECS_j \leq 4.$$

Equation (3.1) is used only for classification. The score is not a weight in the economic-mathematical model, a cost-benefit coefficient or an estimate of policy effectiveness; it makes strategic prioritization transparent: a score of four means that all four evidence streams support the direction, while a lower score identifies areas with less empirical evidence.

The binary indicators in (3.1) are assigned according to explicit rules. Statistical evidence is recorded when the direction relates to indicators of official statistics analysed in Chapter 2 at the national, regional or district level. Climate-relationship evidence is recorded when the direction addresses a constraint identified in the climate and climate-yield analysis of Sections 2.2-2.3. Stakeholder-survey evidence is recorded when the 2026 questionnaire (Appendix B) contains a question or an answer option that directly refers to the direction. Project-implementation evidence is recorded when the direction is already being implemented in the region through state programmes and normative documents (see Normative references); documented practical cases, such as the drip-irrigation project of LLP «Taimas-2024» (Section 3.3), are used only as illustrations. The indicators assigned to each direction and their basis are given in Table C.1.

Water has the most direct position in this structure. In the 2026 stakeholder survey, 57.7% of respondents named water as a scarce resource, 50.5% included irrigation development among priority adaptation measures, and 44.7% identified climatic risk. These perceptions are consistent with the climate-resource relationships identified in Chapter 2 and with the importance of irrigated production in the region. The convergence of statistical, climatic and stakeholder evidence

makes water management a strategic direction rather than a narrowly technical irrigation issue.

The directions agree with the Concept for the Development of the Agro-Industrial Complex of the Republic of Kazakhstan for 2021-2030, in which the development of agriculture is tied to the rational use of resources, technological renewal, innovation and the adjustment of the sector to new production and climatic conditions [90].

Since crops respond to climate in different ways, climate adaptation becomes even more important strategically. Growing-season conditions are formed by temperature, precipitation, root-zone soil wetness and solar radiation acting together, and because crops respond differently and territories are exposed to different degrees, their impact cannot be expressed by one regional coefficient. The author had earlier shown that the adaptation of cotton, as a climate-sensitive crop, requires coordinated changes in irrigation, crop management and technology [20, p.71]. The district-level analysis of agriculture in Turkestan region confirmed the need for territorial adaptation and the interaction of climatic conditions with land and production indicators.

Digital monitoring and model-based decision support also received the maximum concordance score. This is particularly significant, because information is a coordinating resource throughout the strategic system: one district may have an adequate land base but a water constraint, another may have less water pressure but higher climatic exposure, and a livestock district may need to focus on pasture and fodder conditions rather than on irrigated crops. The economic value of information lies in identifying the binding constraint under a specific territorial-production situation, in line with the territorial approach to economic development [91].

The degree of convergence of the four evidence streams is illustrated in accordance with Figure 3.1.

Its analytical value is the distinction between strategic centrality and completeness of evidence. The evidence-concordance score is not the only criterion of a direction's relevance: directions with lower scores are also relevant, and their lower scores are mainly due to less complete district-level observations. This applies particularly to energy use and environmental indicators, which have no harmonized territorial data and therefore are not quantified artificially.

Energy is therefore recognized as a strategic resource, although its evidence-concordance score is lower because electricity use lacks the territorial continuity of land, production and climatic indicators. The energy component of the strategic framework is therefore based on technology-specific and farm-level measurements rather than on artificially created district values [92].

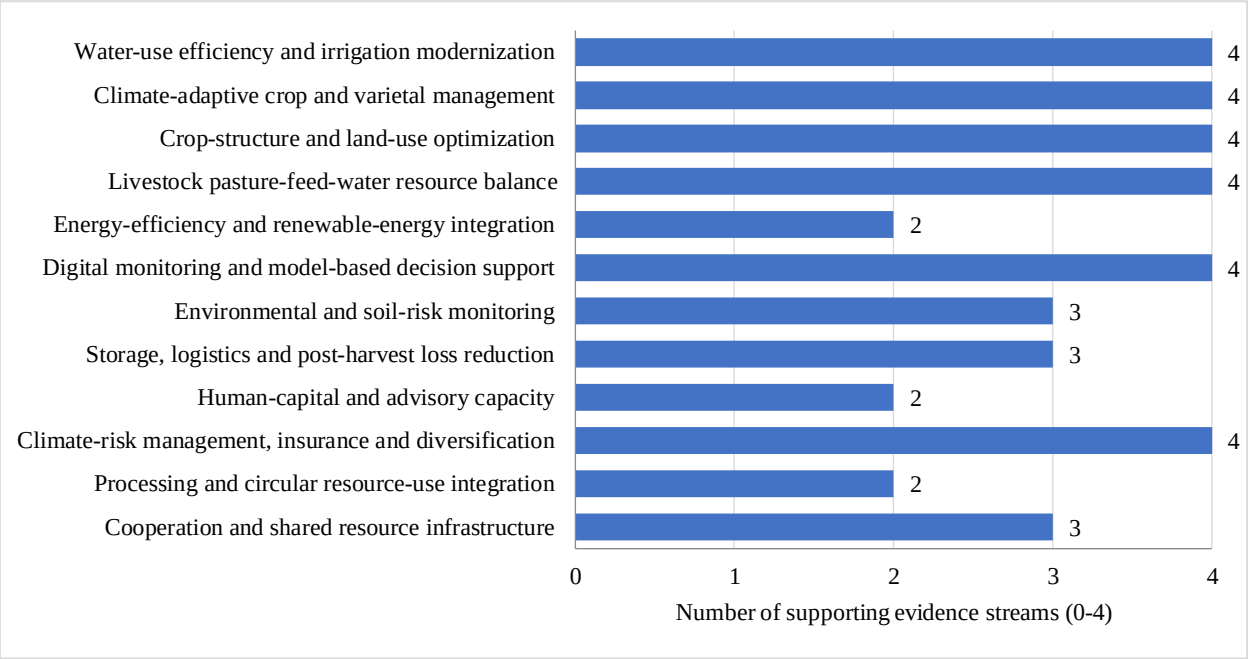


Figure 3.1 – Evidence-concordance of strategic directions in agriculture of Turkestan region

Note – Compiled by the author based on the empirical results of Chapter 2, the 2026 stakeholder survey (N = 208), official statistical evidence and project implementation evidence. Score – number of the four evidence streams (Table C.1) that support the direction.

A similar evidence rule applies to environmental pressure. The author's previous research on natural-resource use [17] showed the importance of land degradation, grazing patterns and climatic pressure on agricultural resources.

Research on agricultural waste management [25] extended the resource-efficiency concept to circular resource use, biomass energy, digital monitoring and reduction of environmental pressure.

These results support environmental diagnostics as a strategic direction, while pesticide load, salinity and pasture degradation can be added quantitatively only when comparable or directly measured spatial data are available.

The territorial-production typology of Turkestan region is given in Table 3.1.

The resource system becomes meaningful when it is expressed through the territorial differentiation of agricultural production. The 17 territorial units of Turkestan region differ widely in the weight of crop and livestock production, and this changes the resource structure of agricultural choices: territories with irrigated crops are limited by other binding constraints than mixed crop-livestock or livestock-based territories.

Table 3.1 – Territorial-production typology of Turkestan region (production structure, 2025)

Territorial unit	Crop share, %	Livestock share, %	Sown area, th. ha	Type
1	2	3	4	5
Turkestan City	67.0	24.8	0.8	A
Arys City	64.8	34.3	34.2	C
Kentau City	60.9	38.9	2.5	A
Baydibek District	42.7	57.0	114.4	D
Zhetysay District	81.7	17.9	79.0	C
Keles District	66.0	33.9	22.5	C
Kazygurt District	31.1	68.6	94.6	D
Maktaaral District	84.1	15.5	60.9	C
Ordabasy District	59.5	40.4	71.2	B
Otyrar District	77.8	21.8	55.9	C
Sairam District	36.4	63.0	51.6	D
Saryagash District	77.7	22.1	78.0	C
Sauran District	76.6	23.3	47.4	C
Suzak District	19.7	77.9	14.7	D
Tolebi District	40.8	59.1	61.3	D
Tulkibas District	47.9	51.9	63.6	B
Shardara District	81.3	16.3	58.3	C

Note – Compiled by the author using official agricultural statistics [84]. Type A – units with sown area below 5 thousand ha; type C – crop share of 60% and more; type B – 45-60%; type D – below 45%. The shares are calculated from gross agricultural output of 2025 (Table 2.9); the remainder to 100% is agricultural services.

The territorial-production types and their dominant strategic responses are as follows:

Type A – Urban / small-area agricultural system: Compact high-value production + controlled systems + logistics; avoid crude per-hectare ranking.

Type B – Mixed crop-livestock system: Coordinate crop land, feed base, livestock water, shared infrastructure and digital monitoring.

Type C – Crop-intensive irrigated rural system: Water accounting + irrigation efficiency + crop-specific allocation + heat/drought adaptation.

Type D – Livestock-oriented system: Pasture/fodder balance + livestock water access + heat-risk management + diversification.

Table 3.1 shows the territorial-production typology, which classifies agricultural systems by production structure, resource dependence and strategic exposure. Type A includes units with a sown area below 5 thousand ha, type C –

units with a crop share of 60% and more, type B – 45-60%, and type D – below 45%. Crop-intensive territories depend more on cultivated land and irrigation and therefore need higher water productivity, appropriate crop allocation and irrigation technology. Livestock-based territories depend more on pasture, fodder, livestock water supply and the climatic stress on pastures. Mixed systems need to coordinate cropland, feed production and livestock resource demand simultaneously.

The strength of the typology is that it translates spatial heterogeneity into differentiated strategic responses. In an intensively irrigated territory, expansion of the cultivated area may initially increase gross crop output but intensify pressure on available resources [93]. In livestock-oriented territories, herd growth without corresponding growth of pasture, fodder and water resources creates a similar imbalance. Mixed systems combine both mechanisms: for example, land used for commercial crops may compete with feed production, and irrigation may indirectly affect livestock resilience through feed availability.

This distinction reflects the broader climate adaptation logic developed in the author's previous research. The study of climate change and the agricultural economy of Kazakhstan [19] identified the key elements of long-term resilience – innovation, insurance, monitoring, strategic planning and territorial adaptation – and climate risk insurance in Kazakh agriculture was considered separately [22].

These general directions are translated into the territorial typology based on the actual production structure of Turkestan region.

The adaptation priorities identified by stakeholders are compared with the degree of their support by independent evidence (in accordance with Figure 3.1). Irrigation development has the strongest position: it was chosen by about 50% of respondents and is supported by all four evidence streams. The second group includes drought-resistant varieties and agricultural risk insurance, which have somewhat weaker direct stakeholder support but high analytical relevance, because they reduce concentration and distribute production risk across crops and activities. The resulting priority levels of the water, climate and crop directions by territorial unit are shown in accordance with Figure 3.2: they are generally higher in the crop-intensive irrigated units of type C and lower in the livestock-oriented units of type D (Table 3.1).

The link between stakeholder preferences and empirical evidence is crucial for agricultural strategy. Stakeholders may overestimate problems that are easily visible in the field and underestimate technically complex ones, while model evidence alone may suggest a theoretically effective intervention with low implementation feasibility that stakeholders do not support. Combining the two dimensions prevents either source from dominating strategic choice.

The identified strategic directions were then organized by the resource through which they affect agricultural production. This structure links each empirical constraint with a transmission mechanism, a measurable indicator and a corresponding decision instrument.

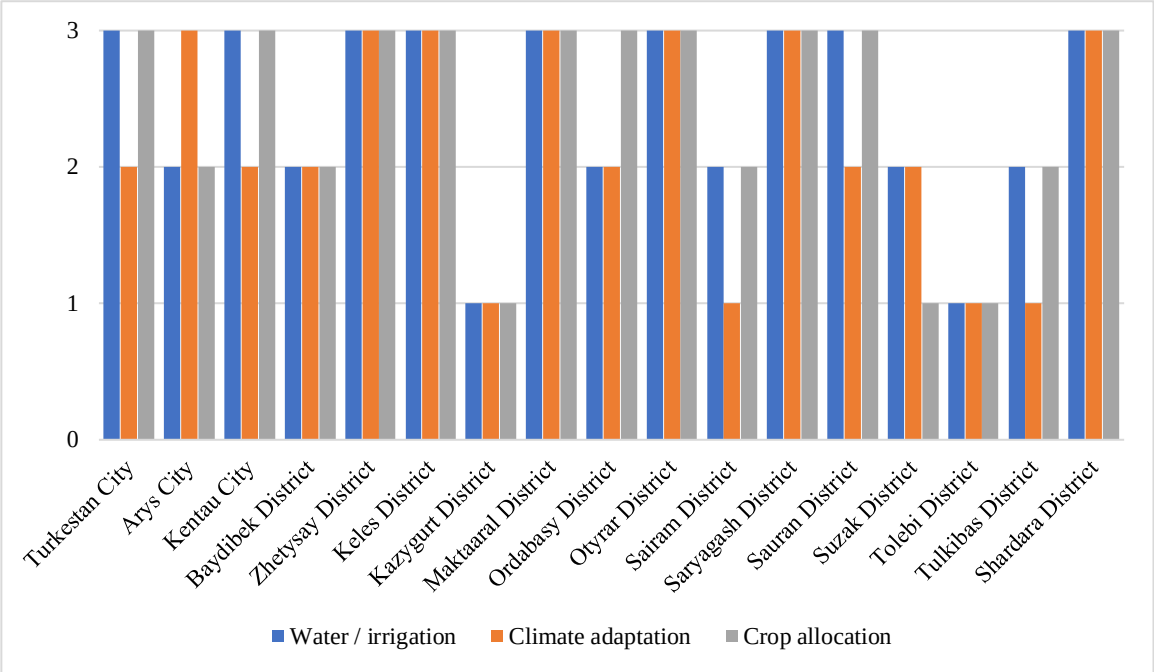


Figure 3.2 – Strategic priorities by territorial unit in Turkestan region

Note – Compiled by the author based on the territorial-production typology and strategic assessment. Priority level: 1 – low, 2 – medium, 3 – high.

This resource-to-decision architecture provides a common decision-making vocabulary for diverse agricultural constraints. In this architecture, water scarcity appears as irrigation needs, water productivity and limits of available water; land scarcity as cultivated area, crop shares and feasible allocation [94]; climate as growing-season temperature, precipitation, root-zone wetness and solar radiation; energy as electricity consumption, pumping requirements and operational emissions; livestock resources as herd size, the availability of pasture and feed, water per head and pressure in livestock units; and information quality as how timely, credible and accessible the information used for decisions is.

The author's research on energy efficiency in peasant farms [16] linked agricultural production with renewable energy, costs and CO_2 emissions, and the natural-resource study [17] showed that degradation of soil, water, climatic and land-use conditions should be considered within the same production system.

Overall, these findings show that resource efficiency can be treated as a multidimensional allocation problem.

How the main resource blocks depend on each other is illustrated in accordance with Figure 3.3. Climate acts on crop development, evapotranspiration, natural moisture and the heat load on animals; water links climate with production, with soil moisture serving as a short-term signal of these effects; land and pasture set the spatial capacity of crop and livestock systems; and energy is spent on irrigation, pumping, machinery and storage. Production generates economic returns and environmental consequences, and environmental degradation in turn affects the productive capacity of land, pasture and water.

This feedback structure is critical for resource-efficient development. Agricultural resources are not independent inputs whose effects are additive: water-saving irrigation may change energy demand, crop substitution may reduce irrigation pressure but also profitability, diversification may increase resilience but require other markets and storage facilities, and livestock expansion may increase output but also pressure on pasture and feed. Efficiency is therefore strategic, because it depends on the compatibility of resource blocks.

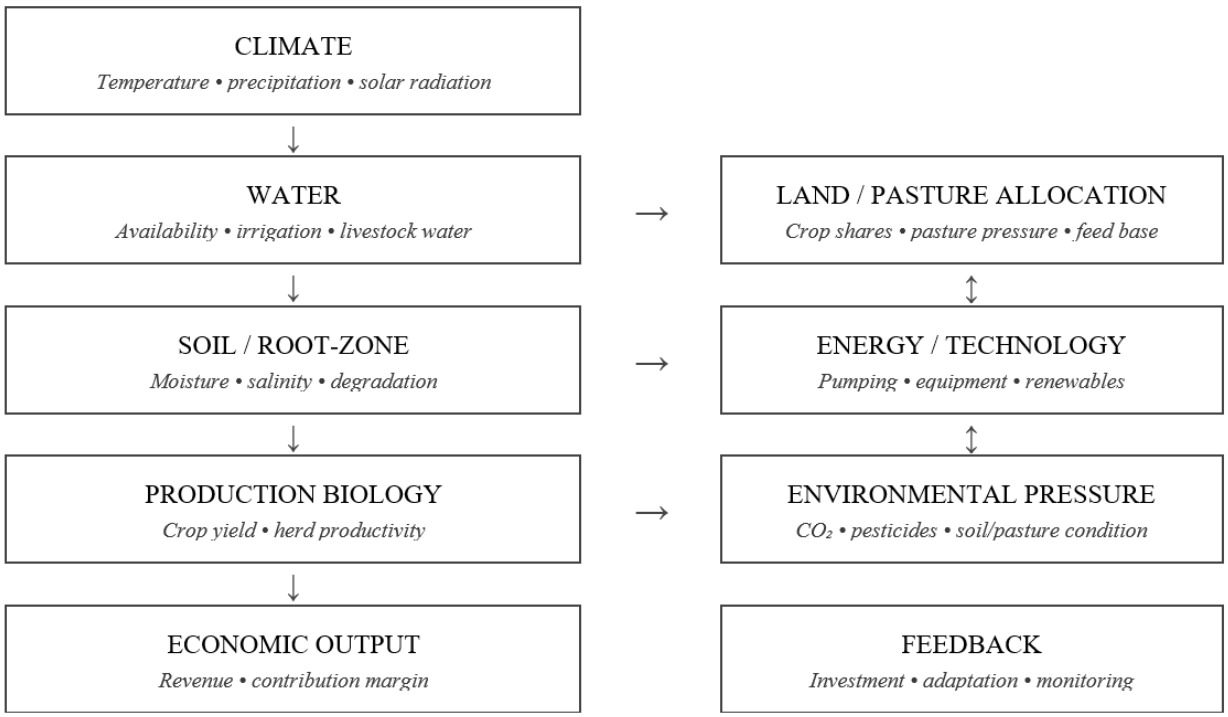


Figure 3.3 – Interdependence of agricultural resource blocks

Note – Compiled by the author based on the empirical results of Chapter 2.

The strategic architecture must also clearly distinguish production growth from resource-efficient development: growth of agricultural production is economically meaningful only when it can be achieved with the available land, water, energy, feed and environmental capacity of the territory.

This distinction is crucial for the irrigated areas of Turkestan region, where high climatic risk, considerable crop-livestock specialization and irrigation dependence create several forms of resource stress. A production alternative that is favourable by one indicator may become less favourable when its resource demand is taken into account.

The interaction between production and resource constraints can be expressed through a generalized strategic feasibility condition:

$$R_{id} \leq \bar{R}_d, \tag{3.2}$$

where R_{id} represents the resource requirement associated with agricultural activity i in territory d;
$\bar{R}_d$ denotes the corresponding available resource capacity of that territory.

Strategically, this condition is most evident for crop production in irrigated areas. The economic interpretation of a potential yield depends on the water, land and energy needed to achieve it: a crop that grows well in a favourable climate may place excessive demands on limited irrigation supplies, while a crop with a slightly lower predicted yield may stabilize the production structure if it needs much less water or improves diversification. The strategic goal is therefore to find combinations that maintain productive performance under explicit resource limits.

Livestock production faces the same issue in a different form. The feasible scale of livestock activity depends on the resources required to maintain a herd of a given size: pasture area, feed and drinking water, energy and climatic risk. Livestock units provide a common pressure framework for heterogeneous animal categories and allow the intensity of pasture use to be compared.

Pasture pressure for livestock category s may be defined as:

$$LP_{sd} = \frac{LU_{sd}}{P_d}, \tag{3.3}$$

where LP_{sd} is livestock pressure in territory d;
LU_{sd} is the number of livestock units for category s;
P_d is the available pasture area.

Livestock water requirements follow the same resource-accounting logic. The biological needs of cattle, dairy cows, sheep, goats, horses, camels and poultry differ significantly, and temperature further changes drinking-water demand, which links livestock resource needs directly with climatic exposure. Consequently, in territories where livestock is a key activity, water planning and feed and pasture management become part of climate adaptation alongside traditional animal husbandry measures.

Table 3.2 presents the differentiated strategic responses for crop and livestock production systems and the variables of their decision space.

As shown in Table 3.2, crop and livestock systems share some resource dimensions but differ in how these dimensions affect production. Water is used in both systems, but in crop production its demand is determined mainly by the requirement per hectare, and in livestock production by the biological demand per animal and herd size. Land is represented in crop production by cultivated area and crop allocation, and in livestock systems also by its pasture and feed-support function. Climatic conditions affect crop yields directly and livestock production indirectly through heat stress, water demand and feed quality. Both systems require energy for irrigation, pumping, machinery, housing, storage and other operations.

The integration of crop and livestock systems also creates intersectoral resource linkages: land and water used for feed crops could be used for market crops, crop residues can serve as feed or biomass, and livestock waste offers opportunities for nutrient recycling and bioenergy. These interactions justify including circular

resource-use principles in the strategic architecture, which reduce the need for external inputs and environmental pressure.

Table 3.2 – Differentiated strategic responses for crop and livestock production

Panel A. Crop production components			
Component	*Validation / empirical signal*	*Resource focus*	*Strategic response*
Wheat	$R^2 = 0.516$; n = 294	Climate + water + land	Protect yield stability; prioritize moisture management
Corn	$R^2 = 0.458$; n = 289	Water + land + feed linkage	Controlled expansion where resource fit supports it
Rice	$R^2 = 0.219$; n = 53	Water intensity + climate	Restrict to water-feasible territories[1]
Cotton	$R^2 = 0.287$; n = 181	Water + heat + infrastructure	Evaluate historical specialization against water constraint
Sunflower	$R^2 = 0.354$; n = 255	Land reallocation + climate	Targeted recovery/pilot only where resource fit allows
Potato	$R^2 = 0.412$; n = 290	Water + storage + land productivity	Prioritize intensification and post-harvest logistics
Panel B. Livestock production components			
Component	*Validation / empirical signal*	*Resource focus*	*Strategic response*
Cattle	$R^2(\log) = 0.739$; APE = 10.8%	Water + feed + pasture	Balance herd scale with annual water/feed reference
Cows	$R^2(\log) = 0.666$; APE = 14.0%	Water + feed + productivity	Link dairy herd scale to water/feed requirement
Sheep/goats	$R^2(\log) = 0.883$; APE = 8.3%	Pasture + feed + water	Manage pasture carrying pressure and drought/heat risk
Horses	$R^2(\log) = 0.863$; APE = 5.8%	Pasture + water	Maintain low pasture pressure and adequate seasonal access
Camels	$R^2(\log) = 0.893$; APE = 21.6%	Water + rangeland	Use species-specific water requirement and arid tolerance
Poultry	$R^2(\log) = 0.824$; APE = 12.3%	Water + energy + productivity	Separate layer/broiler production logic; monitor closely
Pigs	$R^2(\log) = -0.077$; APE = 103%[2]	Feed + water + forecast uncertainty	Resource diagnosis retained; numerical forecast suppressed[2]

Notes

1 Rice: small validation sample (n = 53); interpret coefficients with caution.

2 Pigs: negative out-of-sample R^2 and high APE indicate that the current model does not add predictive value for this species; the resource diagnosis is retained, but the numerical forecast is suppressed pending model revision.

3 All rows share the following: analytical role – crop ML yield forecast + resource-climate suitability score (Panel A) or livestock resource profile + one-step forecast (Panel B); decision safeguard – component-specific metrics are shown with their confidence status rather than as a single pooled figure; status – modelled output plus observed history (Panel A) or official herd panel plus reference coefficients (Panel B); primary indicator – R^2 / MAE / water $m^3 \cdot ha^{-1}$ (Panel A) or $LU \cdot ha^{-1}$, $water \cdot head^{-1}$, $feed \cdot head^{-1}$, forecast error (Panel B). Compiled by the author using QŪNAR crop and livestock validation results and the empirical results of Chapter 2.

Kazakhstan research has already shown the relevance of technologies for agricultural waste reuse, biomass energy, digital monitoring and closed production cycles for the sustainability of the agricultural sector [25].

The strategic system therefore includes both competitive and complementary relationships between resources. Competition occurs when several agricultural uses compete for a limited resource such as irrigated land or water; complementarity arises when one activity produces a resource for another, for example, livestock by-products in a circular production system or crop residues as livestock feed. These relationships are economically important, because the optimization problem concerns the structure of the whole agricultural system rather than individual activities.

The strategic portfolio by the functional role of each direction in the resource-efficiency system is shown in accordance with Figure 3.4.

In accordance with Figure 3.4, the portfolio classifies measures by their role in the system.

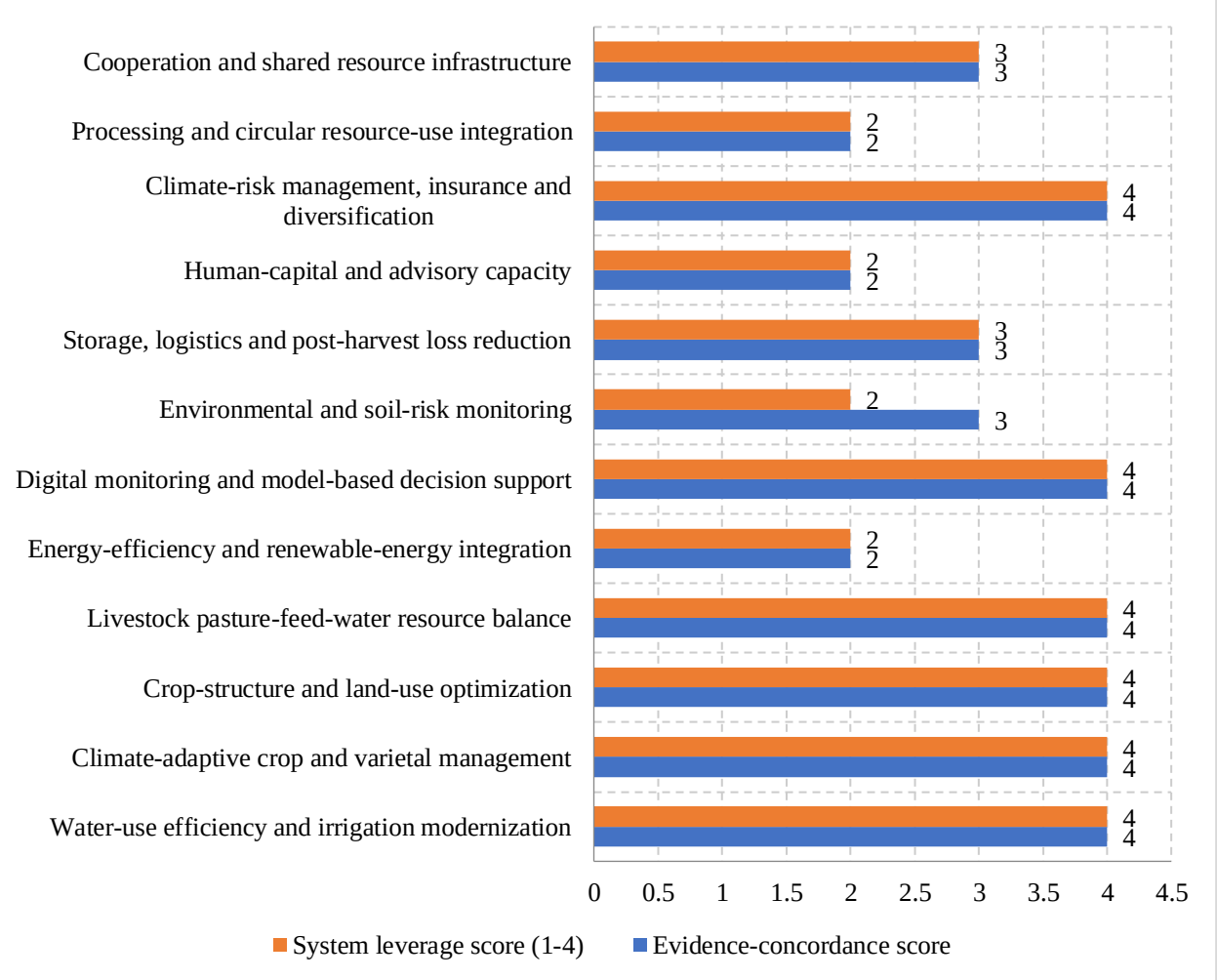


Figure 3.4 – Strategic priority portfolio for resource-efficient agriculture

Note – Compiled by the author based on evidence-concordance and system-leverage scores.

Core resource priorities affect the immediate physical feasibility of agricultural production: water efficiency, land allocation and climate adaptation belong here, because their failure can directly limit the production set of a territory. Resilience priorities reduce vulnerability to climatic and production shocks through diversification, insurance and adaptive management. Enabling priorities strengthen the decision-making capacity of producers and institutions through digital monitoring, infrastructure, cooperation and professional competence. Environmental priorities manage the long-term impact of agriculture on the resource base through energy use, emission monitoring, soil condition, pasture health and circular resource use.

This also sets the order of strategic intervention. Measures that address binding constraints have priority, because without them other measures may be economically unfeasible: investment in better production technology cannot offset an unsolved water constraint in an irrigation-dependent system, and livestock productivity indicators are of little strategic use when pasture or feed is insufficient for the existing herd. Enabling and environmental measures then determine the durability, information quality and long-term sustainability of the production configuration.

Digitalization occupies an intermediate position: it does not change the physical resource itself but improves the quality of its allocation. Digital monitoring, forecasting and data-driven analysis reduce informational uncertainty and can identify resource constraints before irreversible production decisions are made. As the international development of agricultural modelling shows, predictive systems, machine learning and digital decision-support environments are gaining importance as climate-agriculture relationships become more complex.

The identified shift to AI-assisted and data-driven systems provides a methodological justification for embedding computational decision support in the economic-mathematical model of resource-efficient agricultural development.

Digital modelling is especially important for economic decisions under several interacting constraints [95]. A farmer or regional decision-maker often has to compare options that differ in expected yield, water use, climatic suitability, energy inputs and economic and environmental performance. When a second resource becomes limiting, a simple ranking by one criterion may lead to a wrong decision. A data-based model assesses these dimensions together and compares feasible alternatives rather than hypothetical production potential.

The strategic framework requires indicators that track resource availability and the efficiency of converting resources into agricultural output. The monitoring system is given in Table 3.3.

The indicators in Table 3.3 are organized by their analytical status. Observed indicators are measured or officially reported; model-derived indicators include production outcomes, relative resource pressure and optimization results; conditional indicators are used only when reliable observations are available at an appropriate spatial scale. This distinction prevents missing environmental information from being implicitly interpreted as favourable performance.

Table 3.3 – Strategic monitoring system for natural resource efficiency

Indicator	Unit	Status	Source	Frequency
1	2	3	4	5
Sown area by crop	th. ha	Observed	Official statistics [84]	Annual
Crop yield	c/ha	Observed	Official statistics [84]	Annual
Crop and livestock output	mln KZT	Observed	Official statistics [84]	Annual
Livestock numbers by species	head	Observed	Official statistics [84]	Annual
Water abstraction and losses in transportation	mln m^3	Observed	Official water statistics	Annual
Growing-season temperature and precipitation	°C, mm	Observed	NASA POWER [87], Kazhydromet	Monthly, seasonal
Water delivered to the farm	m^3	Observed where metered	Farm and water-management records	Seasonal
Electricity use for pumping	kWh	Observed where metered	Farm records	Seasonal
Forecast crop yield with prediction interval	c/ha	Model-derived	QŪNAR (Random Forest)	Before each season
Water requirement and water balance of the crop structure	m^3/ha, m^3	Model-derived	QŪNAR, Order № 108-NQ	Seasonal
Optimal crop structure and contribution margin	ha, KZT	Model-derived	QŪNAR optimizer	Seasonal
Operational CO_2 emissions from pumping	t CO_2	Model-derived	QŪNAR, emission factor	Seasonal
Livestock feed and water requirement	t, m^3	Model-derived	Reference coefficients	Annual
Pasture pressure	LU/ha	Model-derived	QŪNAR, herd and pasture area	Annual
Pasture degradation	index	Conditional	Field observations, remote sensing	When available
Soil salinity	dS/m	Conditional	Soil surveys	When available
Actual feed availability	t	Conditional	Farm records	When available

Note – Compiled by the author. Observed – measured or officially reported; model-derived – calculated in QŪNAR; conditional – used only when reliable observations are available at an appropriate spatial scale.

Water monitoring uses the available volume, the normative or observed requirement and water productivity [96]. Land monitoring includes cultivated area, structural allocation and crop concentration. Climate monitoring uses growing-season temperature, precipitation, root-zone wetness and solar radiation. Energy monitoring covers electricity use and operational carbon emissions when energy data are available. The livestock block includes herd size, livestock units, pasture pressure, feed coverage, water requirements and productivity. Salinity, pesticide load and pasture degradation are included in environmental monitoring when they are supported by direct observations.

Crop concentration is additionally measured by the Herfindahl-Hirschman Index [97]:

$$HHI = \sum_{i=1}^{n} s_i^2, \tag{3.4}$$

where s_i represents the share of crop i in the total allocated area;
n is the number of crops included in the production structure.

The effective number of crops can additionally be expressed as:

$$N_{eff} = \frac{1}{HHI}. \tag{3.5}$$

This transformation gives an intuitive interpretation of structural concentration: the number of equally represented crops that would give the same concentration. The indicator is useful in scenario analysis, because the effects of optimized land allocation can be summarized together with production and resource indicators.

The inclusion of environmental indicators is also consistent with the Environmental Code of the Republic of Kazakhstan of 2 January 2021 № 400-VI LRK, which provides the national legal framework for environmental protection and prevention of adverse impacts on natural resources [98].

The monitoring architecture creates a feedback loop between observed conditions and strategic decisions. New climatic observations change the environmental profile of a territory, new production outcomes update the empirical basis for prediction, new water availability changes the feasible crop structure, changes in herd size change pasture, feed and water requirements, and new observations of salinity or degradation change the environmental interpretation. The strategic system is thus an adaptive information structure whose decision parameters are adjusted to changes in the resource environment.

These elements are combined into a comprehensive decision architecture in accordance with Figure 3.5.

In accordance with Figure 3.5, the architecture covers the entire sequence from observation to agricultural decision. The information layer consists of statistical, climatic and farm-level information, and territorial and production diagnostics reveal the structure of resource constraints.

Predictive algorithms estimate production responses and expected dynamics; resource assessment determines the compatibility of agricultural alternatives with water, land, pasture, feed and energy; economic and environmental diagnostics provide further criteria of comparison. Optimization then identifies production configurations under explicit constraints, and new observations are returned to the information layer for subsequent optimization [99].

The result is a formalization of resource-efficient agricultural production (REAP) as a repeated decision problem under changing climatic and resource contexts. Its economic content is the allocation of scarce resources among alternative production activities; its environmental content is the preservation of the productive capacity of the resource base; its predictive content is the ability to anticipate the

agricultural response before resources are allocated; and its territorial content is the ability of one analytical structure to give different recommendations for different combinations of production specialization and resource availability.

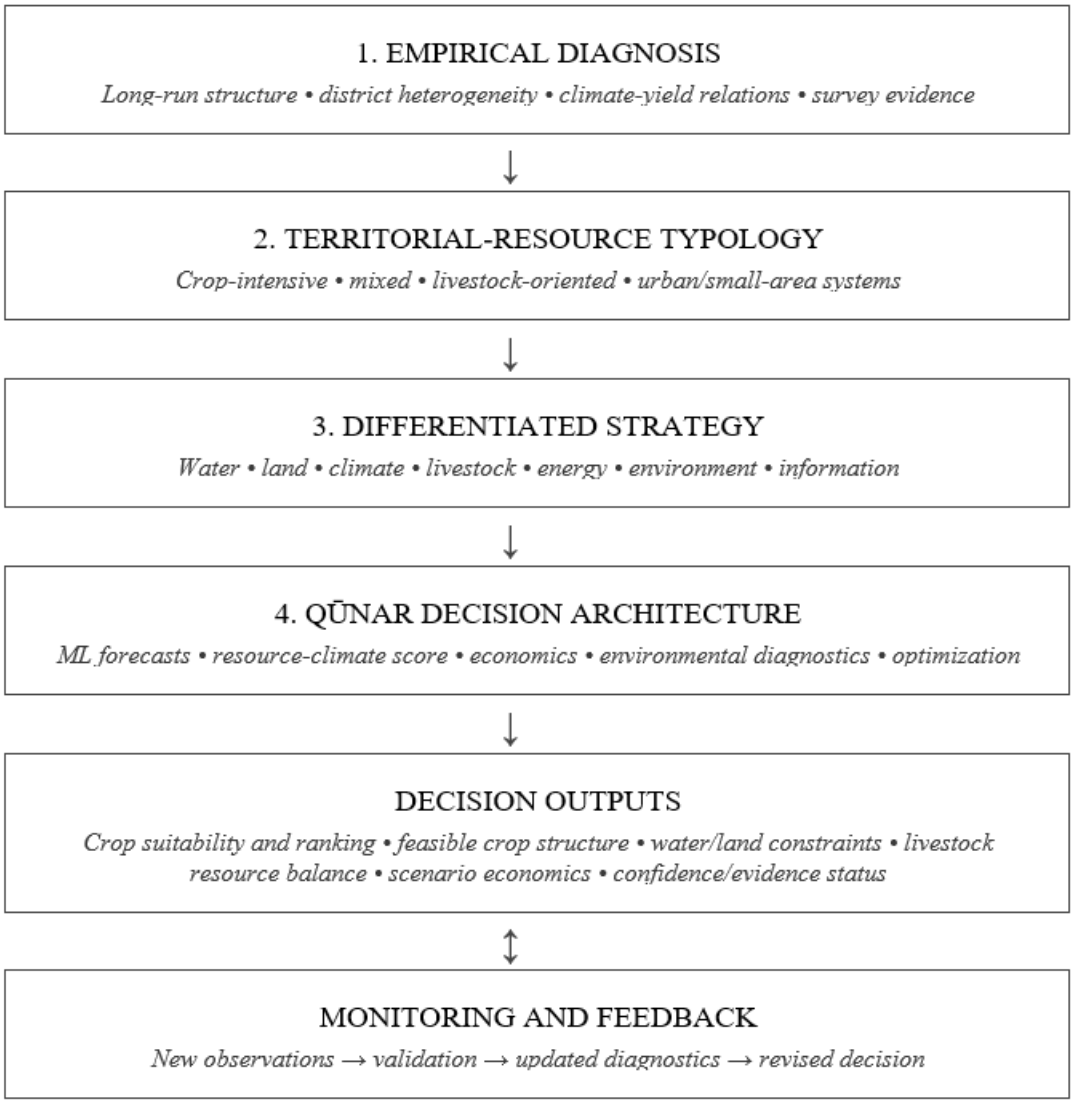


Figure 3.5 – Integrated architecture for resource-efficient agricultural decision-making

Note – Compiled by the author based on the empirical framework and QŪNAR decision architecture.

Additional support for this architecture comes from the international methodological shift towards data-driven agricultural decisions. The large-scale analysis of scientific literature showed an increasing coupling of climate modelling, machine learning, prediction, irrigation, soil moisture, crop management and adaptive decision-making.

The economic-mathematical model developed for Turkestan region extends this methodological line by explicitly incorporating resource constraints, regional differences and economic interpretation into the decision-making process.

The model architecture is therefore based on three mutually reinforcing principles: empirical evidence, resource feasibility and adaptive computation. Empirical evidence describes the condition of the agricultural system and the reliability of the information used; resource constraints define the set of physically admissible production alternatives; adaptive computation converts diverse observations into predictions, comparisons and optimized decisions. Together, they provide a stable methodological framework for assessing resource efficiency under climatic uncertainty.

The digital implementation of this economic-mathematical model is QŪNAR – Quantified Utilization of Natural Agricultural Resources. QŪNAR implements the defined resource logic through territorial selection, crop and livestock assessment, climate-based predictive components, water and land constraints, energy and environmental diagnostics, confidence assessment and constrained optimization. It is the computational part of the economic-mathematical model, which turns the relationships formulated in the research into repeatable calculations and decision outputs for practice.

The resulting strategic system defines resource-efficient agricultural development as the search for a production configuration in which the expected agricultural performance remains consistent with the water, land, climatic, energy and biological capacity of a specific territory. This provides a basis for differentiated agricultural policy and farm-level decision-making under climate change and pressure on natural resources.

3.2 Organizational-economic mechanism for resource-efficient and climate-resilient agricultural development

The organizational-economic mechanism of resource-efficient agricultural development is based on the need to organize information on natural resources, production conditions and climatic exposure in a coordinated way and to use it at the farm, district and regional levels. Its economic premise is that agricultural production in Turkestan region takes place in a system of limited and spatially differentiated resources whose availability, productivity and interrelations change over time. Land, irrigation water, pasture, feed, energy, climatic conditions and environmental quality are therefore parts of one resource system and enter management decisions together.

The proposed mechanism is consistent with the Law of the Republic of Kazakhstan of 8 July 2005 № 66 «On State Regulation of the Development of the Agro-Industrial Complex and Rural Territories», which establishes the legal, organizational and economic basis of state regulation of agriculture and defines sustainable development and the use of scientifically sound agricultural technologies as key goals of this regulation [100].

The practical difficulty is the multi-level nature of resource constraints. Farmers decide on crop areas, livestock numbers, irrigation methods, production inputs and operational energy use; water organizations determine the amount and timing of available irrigation water; district authorities plan territorial infrastructure,

advisory measures and local agricultural priorities; development programmes and investment priorities are decided at the regional level; research and analytical organizations provide forecasts and updated model parameters and assess the reliability of quantitative results. These actors must coordinate closely, because the effects of production decisions extend beyond the farm to water demand, infrastructure capacity, environmental pressure and competition for shared resources.

The mechanism therefore treats agricultural management as a chain of interrelated analytical and institutional processes [101]. Resource monitoring identifies the actual condition of the production environment; predictive assessment estimates likely changes in crop and livestock productivity; resource-feasibility analysis checks whether a production configuration fits the available land, water, pasture, feed and other resources; economic evaluation compares the results of feasible options; optimization identifies optimal configurations under explicit restrictions; implementation assigns responsibility for the selected measures; environmental safeguards prevent short-term production gains at the cost of resource deterioration; feedback and recalibration update the analytical system when new observations become available.

This functional logic corresponds to the structure of modern climate-oriented agricultural management. Empirical studies within the research programme showed the need to combine economic, technological and institutional instruments of environmental and climate management [23], and digital monitoring is increasingly becoming the coordination infrastructure for these instruments [24].

Research on agricultural adaptation in Kazakhstan has also identified monitoring, strategic planning, territorial differentiation and technological innovation as conditions of long-term resilience [19, p.219].

These results justify an organizational-economic mechanism that integrates information and resource limits into a single decision cycle together with institutional responsibility and technological implementation.

The functional structure of the mechanism is given in Table 3.4. Its first block is resource monitoring, which converts raw observations into a verified resource profile. This is economically important, because agricultural decisions often use information of different reliability: official statistics may provide the cultivated area, water organizations or farm records the current water availability, meters the energy consumption, while soil salinity may be available only for selected territories or farms. Treating these data as equally complete would be misleading, so the mechanism records the source, relevance and evidential status of each variable before it is used in further calculations.

This is particularly important for variables that would otherwise be treated as zero pressure when missing. Missing pesticide data do not mean that pesticides were not applied, missing salinity observations do not mean that salinity is unchanged, and missing farm-level electricity data do not mean that no electricity is used. The resource-monitoring block keeps unknown values unknown and distinguishes observed, normative, model-derived and contextual indicators. This improves

analytical transparency and reduces the risk of a favourable recommendation resulting from a missing environmental variable.

Table 3.4 – Functional structure of the organizational-economic mechanism

Mechanism block	Key function	Connection with QŪNAR
Resource monitoring	Assess current resource availability, pressures and data gaps	Enter and provide evidence layer
Predictive assessment	Predict the likely production response and short-term dynamics	Crop and livestock forecast modules.
Resource feasibility	Determine whether production alternatives are compatible with physical resource limits	Provides data on constraints and resource balance
Economic evaluation	Compare the consequences of feasible alternatives	Economics and energy overlay.
Decision optimization	Select the production structure subject to explicit constraints	Optimization layer
Implementation coordination	Provide actions and responsibilities	Decision-output interface
Environmental safeguards	Prevent resource-efficiency gains from increasing ecological pressure	Environmental diagnostics
Feedback and recalibration	Revise decisions when circumstances or evidence change	Monitoring and loop for model updating.

Note – Compiled by the author based on the strategic framework developed for resource-efficient agriculture.

The second functional block is predictive assessment. Under climatic variability, agricultural decisions require forward-looking information, because current production conditions are only a partial basis for seasonal and structural decisions [102]. A crop may have performed well in the past while facing increasing heat or moisture stress, and livestock numbers may have grown while feed and pasture conditions deteriorated. Predictive assessment therefore uses past data, climatic conditions and geographic setting to forecast production parameters.

Predictive information is validated continuously, and the quality of the model and the evidential status of each output are reported. High aggregate accuracy does not mean equal accuracy for all crops, livestock types or territories, and weaker validation requires a more conservative interpretation. This rule prevents probabilistic outputs from acquiring undue authority in management practice.

The third block is resource feasibility. Its economic role is central, because an agricultural alternative is acceptable only if it fits the available resource bundle. Land and water are the main hard constraints for crop production [103], while the feasibility of livestock production depends on the relationship between herd size, water, feed, pasture and climatic conditions. The mechanism therefore distinguishes what an alternative is likely to produce from what is physically possible.

Let the set of agricultural activities be represented by $i = 1, \dots, n$, territories by $d = 1, \dots, D$, and resources by $r = 1, \dots, R$. A generalized feasibility condition can be written as:

$$\sum_{i=1}^{n} a_{ird}\, x_{id} \leq B_{rd}, \tag{3.6}$$

where x_{id} – scale of agricultural activity i in territory d;
a_{ird} – requirement of resource r per unit of activity i;
B_{rd} – available quantity of resource r in territory d.

The economic boundary of the feasible production set is given by equation (3.6). It is interpreted according to the resource in question. For land, a_{ird} is equal to 1 ha for every 1 ha of crop area allocated. For irrigation water it is the water requirement of the crop under the irrigation technology and territorial conditions. For livestock feed, the coefficient is the amount of feed required per head or livestock unit. Different kinds of resource constraints can therefore be described by the same general structure without changing their physical meaning.

The resource-feasibility block has two management implications. First, it excludes options that do not meet physical requirements, however attractive their expected output. Second, it identifies the limiting resource, which is important because managerial intervention should focus on the limiting factor: when water is binding, irrigating more land increases water scarcity; when feed is binding, livestock expansion increases vulnerability; when land is fully allocated, structural reallocation becomes more relevant than area expansion. The mechanism therefore links each recommended action with the resource state that caused it.

The fourth functional block combines economic evaluation and optimization. Feasible alternatives may have very different economic and resource implications: crop A may have a higher predicted yield but a greater irrigation demand, while crop B may yield less but use less water and improve diversification; a livestock scenario may increase herd size but reduce feed coverage; an energy-saving technology may require capital investment but reduce electricity costs and operational CO_2 emissions. Economic evaluation makes these trade-offs explicit.

In irrigated agriculture, the energy dimension is particularly significant, because water use is directly linked with the energy spent on pumping and delivering water and with the operating costs of machinery and storage [104]. Previous studies on energy efficiency in Kazakh agriculture showed that renewable-energy technologies and better energy management can reduce production costs and environmental impact.

The mechanism therefore treats energy as a production factor with economic and environmental implications.

These trade-offs are then formalized as a structured allocation problem. Optimization seeks a feasible configuration that gives the best performance according to the model objective while satisfying explicit constraints, and thus provides decision support within the organizational-economic mechanism. The solution is passed to the institutional or farm level together with information on resource use, remaining constraints, diversification and evidence quality [12].

The separation of analytical results from institutional control is essential. A model can identify a less resource-intensive crop structure, estimate a water deficit or reveal a heavy pasture burden, but implementation requires actors with legal and economic competence. Farmers control most production decisions, water organizations manage water delivery within their scope, and public authorities decide on support programmes and infrastructure priorities. The analytical system improves the decision environment by providing regular quantitative information, while responsibility for action always remains traceable to the institution or producer authorized to act.

The fifth block is implementation coordination. Resource-efficient development may require several actors to act simultaneously: shifting crops to lower water allocations has little effect if irrigation infrastructure still has large conveyance losses; livestock planning may be insufficient without pasture monitoring and adequate feed infrastructure; digital recommendations have limited uptake if users cannot understand them or advisory services are not available. Implementation therefore links the selected decision with the institutions, technologies and support measures it requires.

The survey data confirm this: 52.4% of respondents believe that mathematical modelling can help greatly and 26.4% partially, while 18.3% found it difficult to assess and 2.9% saw no benefit (N = 208, Table 2.12). This indicates analytical acceptance together with a gap in interpretation and implementation.

The mechanism closes this gap by linking model calculations with communication, advisory support, institutional coordination and monitoring.

Environmental safeguards form a cross-cutting block. An improvement in one indicator is not a real gain if it causes deterioration elsewhere, so resource efficiency cannot be reduced to a single indicator. Higher agrochemical inputs, higher stocking rates or more frequent irrigation causing salinization may increase short-term efficiency but reduce production potential. Environmental diagnostics are therefore embedded in the mechanism as conditions and risk signals when reliable observations exist.

This component is supported by the author's previous research on natural-resource degradation and agricultural waste management [17; 25], which identified land degradation, grazing practices and climatic pressure as threats to the productive potential of agricultural resources.

Research on agricultural waste management showed that circular resource use, biomass energy, digital monitoring and technological modernization can reduce environmental pressure while creating additional economic value [25].

The mechanism incorporates these conclusions through environmental monitoring, circular resource-use opportunities and corrective actions based on observed risks.

Feedback and recalibration form the last functional block. Agricultural systems change, and a recommendation based on certain conditions may no longer hold when rainfall, water availability, crop prices, herd size, infrastructure or technology change. The mechanism therefore closes the decision cycle by

comparing expected and observed results: forecast errors are recorded, resource assumptions are adjusted, implementation deviations are documented and new data are added to the analytical base.

In accordance with Figure 3.6, the mechanism is a cycle rather than a linear sequence. Resource inputs are verified; predictive assessment estimates expected production dynamics; resource-feasibility analysis defines the admissible set of alternatives; economic evaluation and optimization select the preferred decision; implementation coordination turns the analytical recommendation into operational and institutional measures; and feedback returns the observed results to the monitoring block.

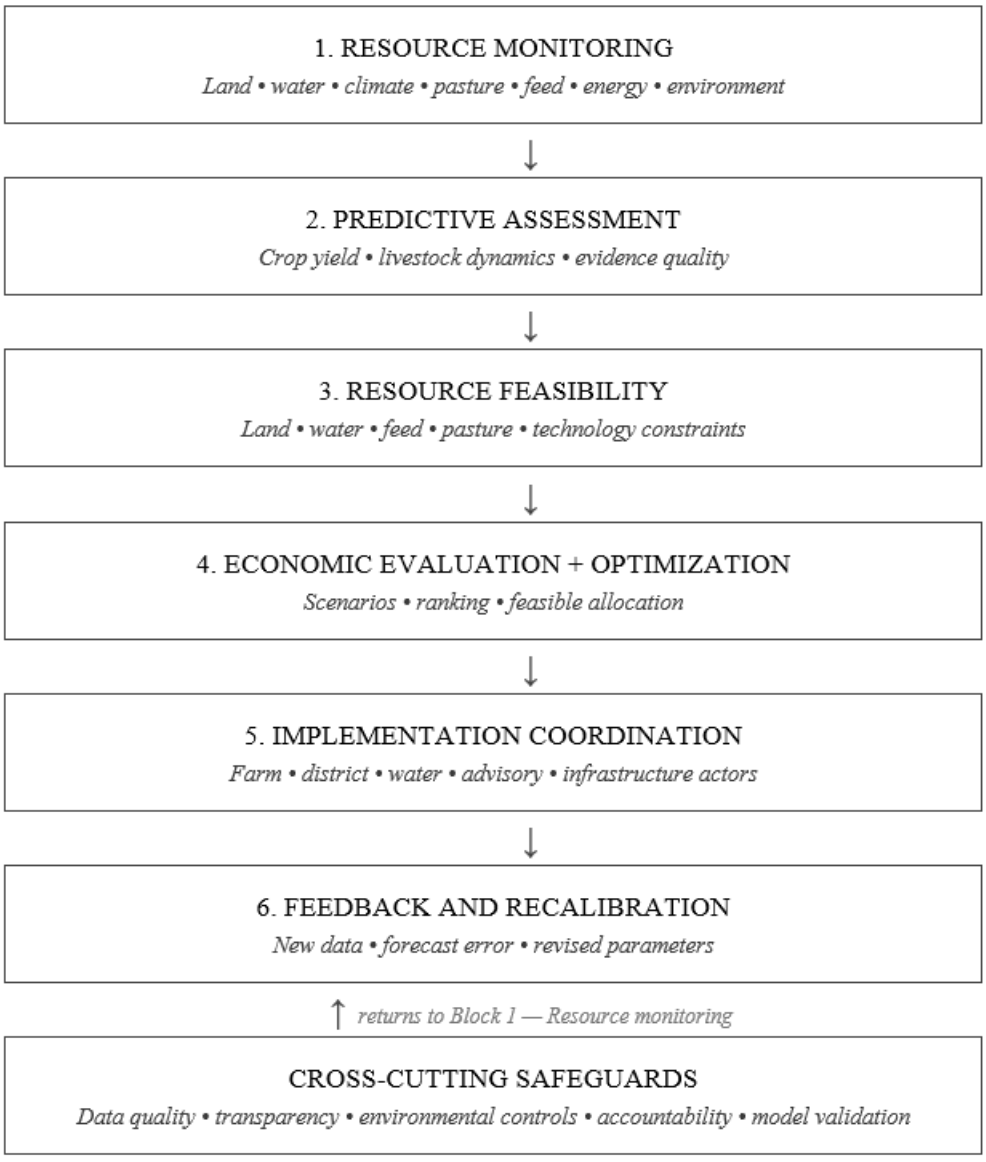


Figure 3.6 – Organizational-economic mechanism for resource-efficient agriculture

Note – Compiled by the author.

The cyclical structure is economically significant, because resource efficiency is a state that must be re-evaluated continuously under changing constraints. An

efficient crop allocation may become infeasible in a drier season, and a livestock structure that matches current pasture conditions may lead to overgrazing when the herd grows or during drought.

An energy-saving investment may become more attractive after changes in electricity tariffs or pumping requirements. The feedback loop allows such changes to be analysed instead of producing a static list of policy measures.

In accordance with Figure 3.6, the integrity of the cycle is supported by cross-cutting safeguards. Data quality ensures that the model uses credible inputs; transparency allows users to distinguish observed values from reference values and forecasts; environmental controls prevent resource optimization at the cost of degradation; accountability identifies who provided the data, who prepared the recommendation and who made the decision; model validation assesses whether model outputs are reliable enough for operational use.

The resulting organizational-economic mechanism is therefore a coordinated system that links information on resources with accountable management decisions in agriculture. Its economic basis is the allocation of limited resources among alternative production options; its organizational basis is the division of responsibilities between producers, public authorities, water-management organizations and analytical and support infrastructure; its technological basis is digital monitoring, predictive modelling and optimization; and its adaptive basis is the systematic use of observed results in the next calculation.

The system links each type of resource scarcity with a managerial response. Water scarcity requires decisions on water allocation and crop choice; excessive crop concentration triggers diversification analysis; climatic deterioration affects expected yields and risk interpretation; changes in feed or pasture pressure change the feasible livestock configuration; high energy intensity triggers efficiency scenarios; environmental pressure activates additional safeguards; and weak evidence reduces confidence and requires more evidence. Each signal therefore has a clear analytical path from observation to decision.

This institutional structure is important because it allows the economic-mathematical model to be used as a decision-support instrument. QŪNAR is the analytical core of the system: it processes verified observations, makes forecasts, assesses resource pressure, compares alternatives and produces optimized outputs, while the mechanism determines how these outputs are interpreted, communicated, implemented and verified. Computational intelligence is thus integrated into an accountable resource-management system in which decisions and actions remain based on measurable conditions in the farming sector.

The distribution of tasks in the organizational-economic mechanism is presented in accordance with Figure 3.7. Functions are allocated according to data ownership, analytical competence, decision authority and implementation responsibility, which usually belong to different actors. Agricultural producers hold the most detailed information on actual cultivated area, irrigation technology, herd size, feed availability, energy consumption and production practices; water-management organizations control information on delivered volumes, seasonal

limitations and infrastructure operation; district and regional authorities hold information on territorial structure, priority areas of public support and infrastructure; research and analytical institutions ensure the methodological quality of forecasts, validation and model recalibration; advisory organizations translate analytical outputs into production guidance.

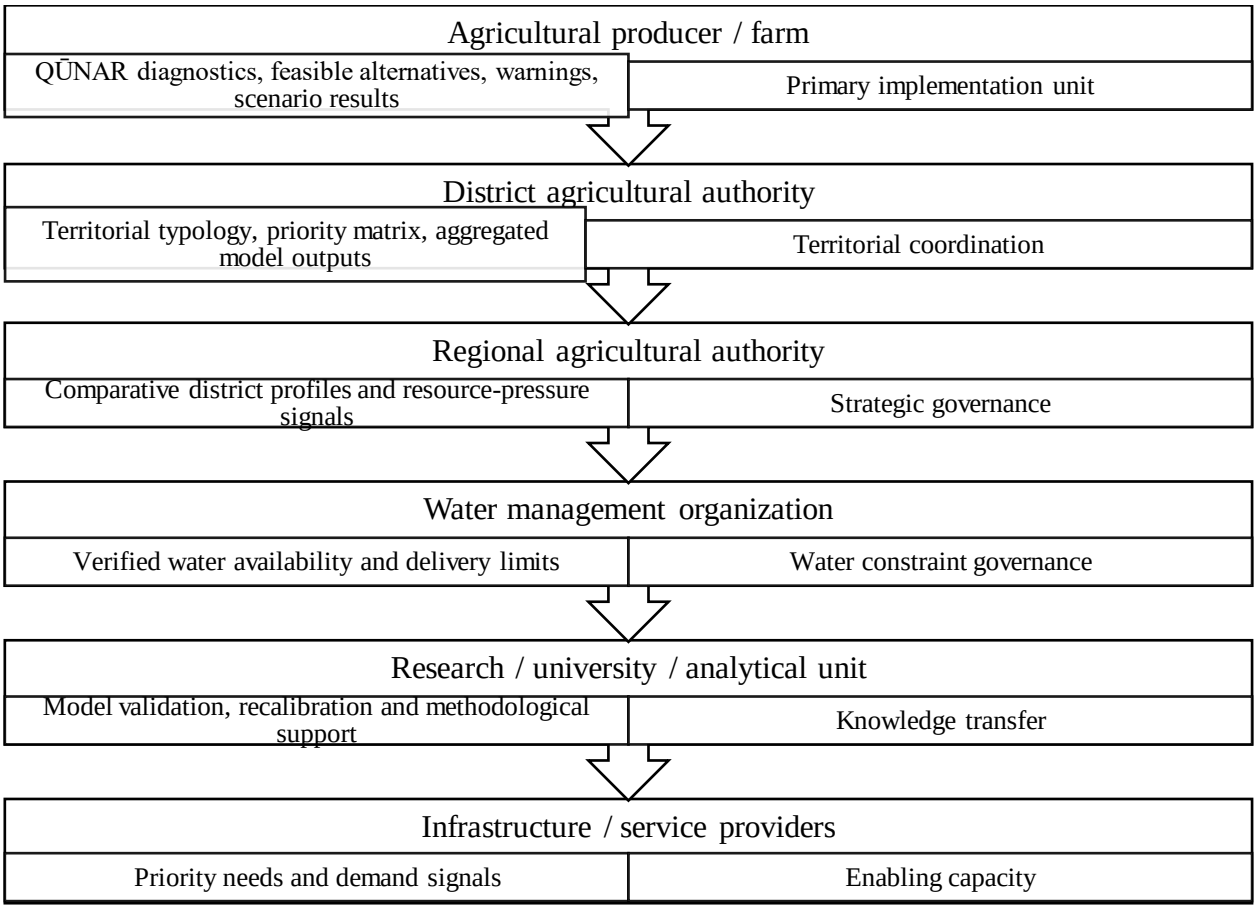


Figure 3.7 – Stakeholder responsibilities in agricultural resource management

Note – Compiled by the author based on the institutional structure of agricultural resource management.

This functional separation reduces one of the main institutional risks of digital decision-support systems – confusing data interpretation with managerial control. When the origin of each input, the calculation method, the responsible actor and the output can be distinguished, quantitative recommendations acquire practical validity, and an audit trail of decisions is created that can be reviewed without delegating institutional authority to the model.

Farm-level decision rights concern the production structure and operational resource use. Crop selection, cropped area, livestock type, irrigation method, feed management and energy use determine the short-term structure of agricultural resource demand, so model recommendations can produce real efficiency gains mainly at the farm level. Their effectiveness, however, depends on factors beyond the producer's control: even when the technically preferred configuration is

determined, the feasible set may change with water delivery, infrastructure access, advisory capacity, market services and public support.

The proposed distribution of functions in the mechanism is shown in accordance with Figure 3.7. The farm provides production parameters and makes the final decision on the crop structure; district and regional agricultural authorities use aggregated results for territorial coordination; the water-management organization provides information on available water within its powers; the university provides scientific and methodological support of QŪNAR. Input data are updated before each production season.

The district level has a coordinating role, because many agricultural constraints are territorial: irrigation facilities serve several producers, storage and processing facilities have spatial effects beyond individual farms, pastures may be common or administratively regulated, and climatic exposure affects groups of producers simultaneously. District-level coordination is therefore essential when the actions of one producer depend on those of other producers or resource-management organizations.

The regional level addresses structural imbalances that cannot be solved locally: persistent irrigation losses, concentration of irrigation in water-intensive crops, inadequate storage, uneven extension services and low energy modernization of farms. The mechanism therefore transmits aggregated resource signals upwards while keeping them territorially traceable, since a regional indicator has managerial meaning only if it can be traced to the districts and production systems it refers to.

Water-management organizations have a special place, because water is both a production factor and a limited shared resource: irrigation choices of one farm affect other farms served by the same water supply system. Agricultural demand must therefore be compared with the physically available supply before production plans are finalized. In the mechanism, water information is a constraint variable, and its verification is the responsibility of the organization able to confirm actual water availability and delivery.

Research and analytical units have another special function: data harmonization, model validation, algorithmic transparency, sensitivity analysis and maintenance of reproducible calculations. This function becomes more important when machine learning is introduced into the decision architecture, because prediction accuracy may change when climatic conditions, production technologies or territorial structures differ from historical ones. Good performance in a validation period does not justify permanent acceptance of a model; continuous diagnostic control is required.

In this respect, it is particularly important to distinguish methodological authority from managerial authority. Validation results determine the level of confidence in a forecast, but they do not limit a farmer's choices or the interventions that a public authority decides to fund. The organizational-economic mechanism turns statistical reliability into a decision condition without changing institutional responsibility for the decision.

Advisory and extension services provide the interpretive link between quantitative outputs and production practice. Their role grows with the multidimensional output of the model, which includes yield prediction, water requirement, resource pressure, environmental diagnostics and alternative scenarios: a technically correct recommendation may be ignored if the producer cannot see which variable caused the result or what action should follow. The 2026 survey confirms this, showing good acceptance of mathematical modelling as a decision-support tool together with considerable uncertainty about its usefulness.

This combination shows that interpretability and communication are operational requirements for implementing the model.

Infrastructure and service providers complete the institutional configuration. Irrigation equipment, pumps, energy systems, storage, processing facilities and digital services determine the range of resource-efficient alternatives, and their contribution is especially important when adjustment requires technological change rather than reallocation of existing resources. For example, solving the water efficiency problem of a crop may require not only a change in crop structure but also better irrigation technology, so the mechanism is linked with the infrastructure needed to change the underlying production function.

This creates four interrelated chains of responsibility: data, analytical results, management decisions and feedback. Data come from farms, official statistics, climate databases, water-management bodies and other validated sources; they are processed into analytical outputs such as forecasts, feasibility assessments, resource balances and comparative scenarios; decisions are made at the level that has decision-making authority; and implementation results provide new observations that are fed back into the information system.

The vertical and horizontal flows of information in the mechanism are shown in accordance with Figure 3.8. The vertical dimension links the farm, district and regional levels: farm observations on production practices and resource use move upwards, territorial signals are aggregated for district and regional planning, and programmes, coordination measures and operational guidance move downwards from strategic priorities and institutional decisions. The analytical core crosses these flows and converts verified data into understandable outputs for decision-making.

The horizontal dimension concerns interaction between actors at the same territorial level. A farm-level water decision may need coordination with a water organization, a livestock adjustment may require advisory support and feed-market information, and a district infrastructure decision may depend on producer demand and regional financing. The mechanism therefore treats governance levels not as separate administrative layers but as interacting levels whose interaction depends on the resource concerned.

In this system, information quality becomes a governing variable, because recommendations are useful only if their input data correspond to the actual decision context. A district average can serve as a reference but cannot replace farm observations; a normative water requirement allows crops to be compared but cannot be presented as water consumption; a historical herd estimate gives a territorial

baseline but should not be confused with the current livestock numbers of a farm. These distinctions preserve the economic meaning of variables and reduce errors caused by inappropriate data sources.

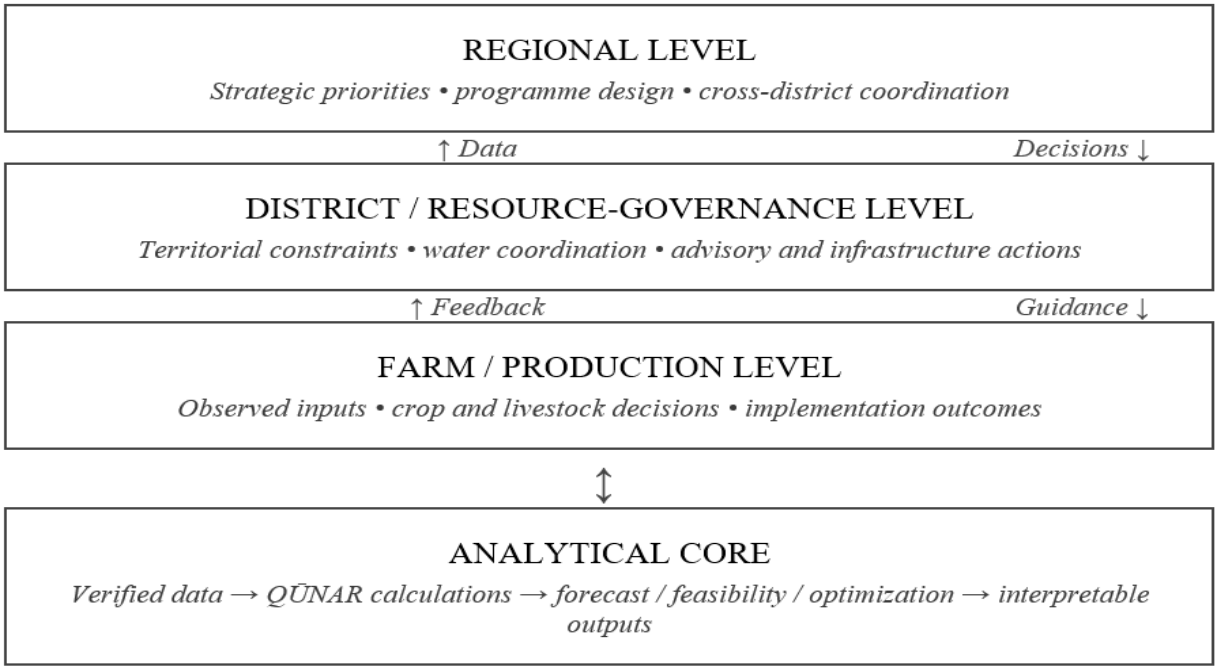


Figure 3.8 – Information and decision flows across governance levels

Note – Compiled by the author based on the proposed organizational-economic mechanism.

Let z_m represent an analytical output generated from a set of inputs $x_1, \dots, x_p$. Each input is associated with a source s_j, observation time t_j and evidence status e_j. The output is therefore represented as:

$$z_m = f\left(x_1, x_2, \dots, x_p \mid s_j, t_j, e_j\right), \tag{3.7}$$

where $f(\cdot)$ denotes the corresponding analytical transformation.

Equation (3.7) shows that the same numerical value can have different analytical reliability depending on its source and period: a water value for the current production season and a generic regional reference value may be numerically similar but have different evidential meaning. The mechanism therefore keeps information on the source and status of data throughout the decision-making process.

This is particularly important under high resource stress and limited information. A recommendation based on weak evidence under low resource pressure can reasonably be treated as provisional, but the same standard of evidence is inadequate for decisions on severe water scarcity, high pasture pressure or significant reallocation of production. The mechanism therefore links the strength of

the managerial response both to the estimated severity of the problem and to the credibility of the evidence.

This principle is translated into specific resource-management rules in accordance with Figure 3.9.

In accordance with Figure 3.9, each resource problem is associated with an observable trigger, required evidence, a management instrument, a decision rule and a responsible level. The matrix converts resource diagnosis into operational logic, because a diagnosis without an action rule is of little use to managers. Water scarcity becomes economically relevant when it changes the feasible crop structure, irrigation schedule or choice of water technology, and pasture pressure becomes actionable when it affects herd, feed or grazing decisions.

Water scarcity is the most obvious case: if available water is less than the requirement of the planned crop structure, the mechanism treats it as a binding feasibility problem.

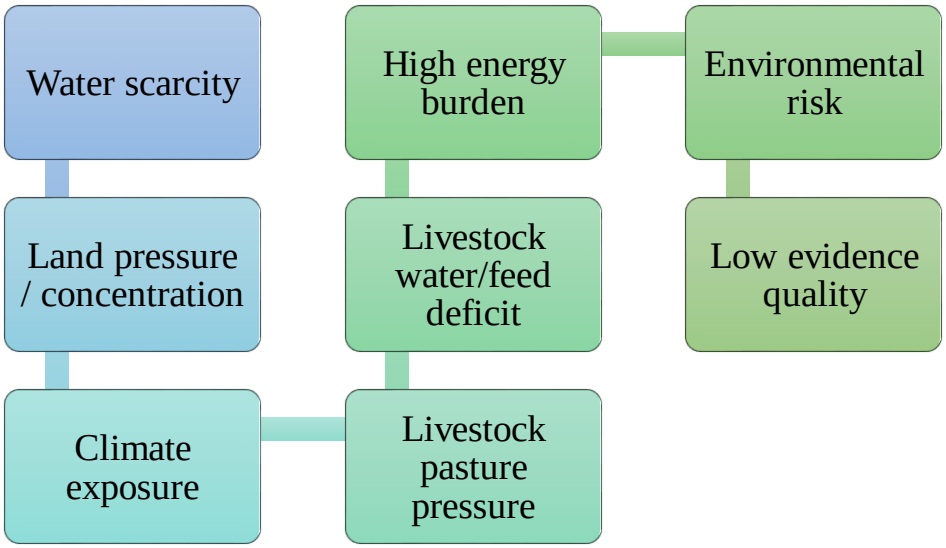


Figure 3.9 – Resource constraints, management triggers and responses

Note – Compiled by the author based on the strategic monitoring system and QŪNAR decision logic.

The first analytical response is to quantify the resource imbalance. The management response may include reducing the area of water-intensive crops, shifting to water-saving crops, modernizing irrigation or changing irrigation scheduling; the appropriate combination depends on the source of the shortage and the decision level that can influence it.

The corresponding balance condition is:

$$WB_d = W_d^{avail} - \sum_{i=1}^{n} w_{id}\, x_{id}, \tag{3.8}$$

where WB_d – water balance in territory or farm d;
W_d^{avail} – verified available irrigation water;
w_{id} – water requirement of agricultural activity i;
x_{id} – scale of activity i.

The coefficient W_{id} requires careful interpretation. Direct assessment of observed water-use intensity is facilitated where actual measurements of the use of water on farms are available. If these measurements are not available, then normative crop-specific requirements can be used as reference coefficients. The two quantities are not of the same empirical status. Normative requirement is used as a guide for planning and comparison and does not reflect actual consumption of a particular producer.

A similar feasibility concept applies to land pressure: the total crop allocation must not exceed the cultivated area:

$$\sum_{i=1}^{n} x_{id} \leq L_d, \tag{3.9}$$

where L_d represents available agricultural land allocated to the relevant production system.

The crop-structure problem also has a concentration dimension. A production system focused on one or two crops may show high short-term specialization while being exposed to climatic, water or market shocks. The HHI and the effective number of crops are used as structural indicators of this concentration; their management function is to reveal whether an optimized allocation becomes too concentrated and therefore vulnerable.

Climatic exposure has different dynamics, because climatic variables are generally not controlled by agricultural actors, so the management response is adaptation rather than removal of the constraint. Seasons that are hotter, wetter or drier than normal affect crop development and production and may require a different crop, variety, planting date, irrigation schedule or risk-management plan. Predictive modelling is especially valuable here, because it estimates the production response before the final allocation decision.

Livestock pressure creates a different set of triggers. Increasing livestock units per hectare, decreasing feed coverage or insufficient water relative to reference requirements indicate growing pressure on the biological resource base. The mechanism responds by assessing the balance between herd size and feed, water and pasture resources; a deficit can be addressed by developing the feed base, adjusting herds, managing pastures, improving water supply or a combination of these measures.

Feed coverage can be expressed as:

$$FC_{sd} = \frac{F_{sd}^{avail}}{F_{sd}^{req}} \times 100, \tag{3.10}$$

where FC_{sd} – feed coverage for livestock category s in territory d;
F_{sd}^{avail} – observed available feed;
F_{sd}^{req} – reference feed requirement for the corresponding herd.

Values below 100% mean that available feed does not meet the reference requirement under the given assumptions. When the actual amount of available feed cannot be determined, the mechanism reports the reference requirement without creating an artificial coverage ratio, which keeps calculated biological demand separate from actual resource provision. Energy pressure is triggered when electricity use or pumping effort is high relative to output; the responses include improving pump efficiency, introducing renewable energy, adjusting operations and changing irrigation technology. When energy data are available, energy costs and the associated operational CO_2 emissions are included in the economic evaluation of these alternatives. Earlier research on energy efficiency in Kazakh agriculture has shown the economic significance of renewable energy and better resource use for reducing costs and environmental pressure [16].

Environmental triggers are treated conservatively because territorial data are limited. Salinity, pesticide load and pasture degradation are included when direct observations or authoritative measurements are available; when they are absent, this is treated as an information gap. This evidence rule prevents the analytical system from assigning a favourable environmental profile merely because a variable is missing.

The last trigger in accordance with Figure 3.9 concerns evidence quality. Missing, inaccurate or inconsistent inputs are a management issue, because they increase decision uncertainty, and weak validation for a crop or livestock category limits the permitted use of its forecast. In the mechanism, information deficiency is therefore a measurable constraint, and the response is further data collection, conservative interpretation, manual review or temporary suppression of an insufficiently validated numerical forecast.

As a result of this trigger architecture, the organizational-economic mechanism is rule-based: each resource signal has a corresponding evidence requirement, response instrument and responsible actor, and management is traceable from the observed condition to the action taken. This traceability is especially important for digital decision-support tools, because it allows recommendations to be challenged, recalculated and improved when new evidence appears.

The mechanism thus turns agricultural resource management into a series of conditional decisions: resource pressure determines which problem should be solved, evidence quality determines how strongly the analytical result can justify action, institutional responsibility determines who implements the response, and monitoring shows whether the intervention had the desired effect. These four elements form the basis of an adaptive management cycle that can cope with climatic uncertainty and changing resource availability.

The six stages of the adaptive management cycle – monitoring, prediction, resource-feasibility assessment, decision selection, implementation and verification – are shown in accordance with Figure 3.10. The sequence is circular, because resource-efficient agricultural management must continuously adapt to new information: climatic conditions, irrigation water availability and resource prices may change within one production cycle, while infrastructure, technology and institutions evolve over longer periods. A management mechanism without feedback quickly loses touch with the conditions it is meant to manage.

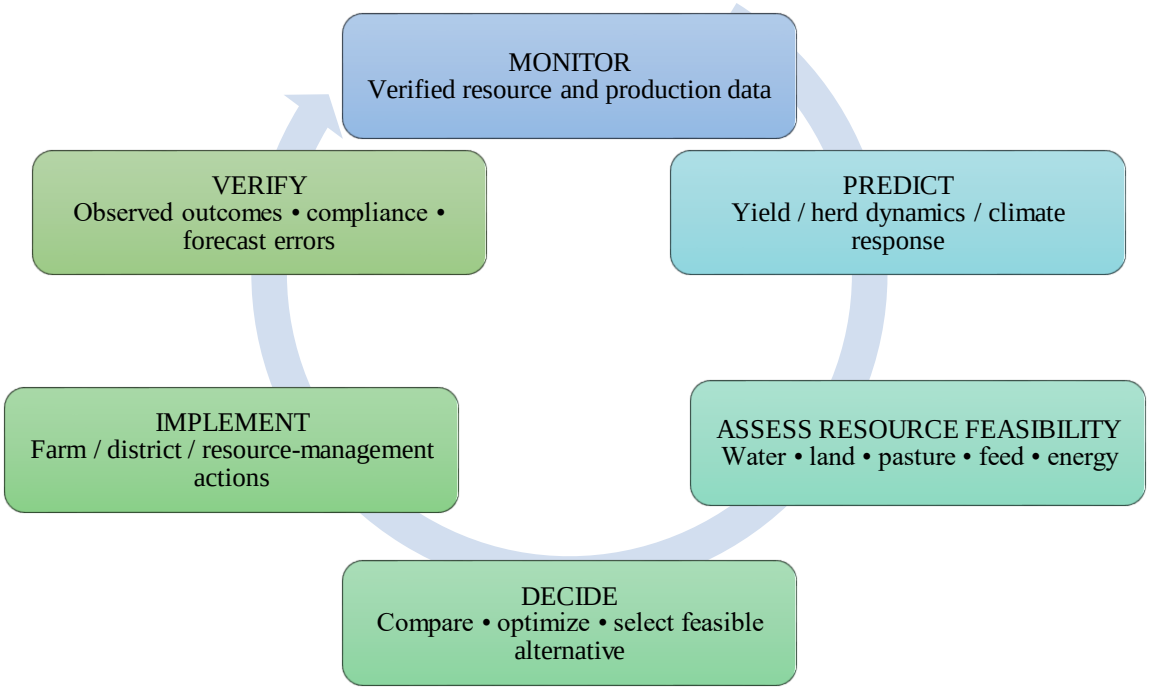


Figure 3.10 – Adaptive agricultural resource management cycle
Note – Compiled by the author.

The monitoring stage establishes the current state of the agricultural system through credible data on production, land, water, climate, livestock, feed, pasture, energy and environmental indicators. Its importance lies in identifying both resource pressure and information gaps, which require different responses: a resource shortage must be remedied, while an unknown resource status requires further evidence before a strong decision is made.

Prediction estimates future production conditions from current and past observations. In crop production, it gives the expected yield for the observed territorial and climatic situation; for livestock, it covers only parameters whose historical series provide sufficient predictability of herd dynamics. Forecasts become economically relevant when they allow resource allocation to be evaluated before irreversible production decisions are made.

Resource-feasibility assessment compares likely production with the physical capacity of the resource base, and the available land, water, pasture and feed define the admissible production set. When the resources needed exceed those available,

higher potential output does not make a development path feasible. The mechanism therefore treats feasibility as a condition that precedes optimization.

Decision selection compares feasible alternatives by their production, resource, economic and environmental consequences. The preferred alternative satisfies the constraints and gives the best result according to the objective and the diagnostic criteria; when several alternatives give similar results, resource intensity, diversification and evidence quality are used as additional criteria.

Implementation converts the selected alternative into operational and institutional action according to the type of problem. Some decisions, such as crop allocation, irrigation practice or feed planning, can be implemented at the farm level, while others require coordinated infrastructure, advisory, water-management or regional intervention. The mechanism therefore keeps the link between the type of resource problem and the actors who can influence it.

Verification closes the cycle by comparing expected and observed results. Deviations between planned and actual outcomes show the performance of forecasts, the quality of implementation and changes in underlying conditions; this information is fed back to monitoring and becomes part of the next decision cycle.

The adaptive structure can be expressed by a dynamic update relationship:

$$S_{t+1} = \Phi(S_t, D_t, Y_t, E_{t+1}), \tag{3.11}$$

where S_t – observed state of the agricultural-resource system at time t;
D_t – decision implemented at time t;
Y_t – observed production and resource-use outcomes resulting from that decision;
E_{t+1} – new external conditions, including climate, resource availability and institutional changes;
$\Phi(\cdot)$ – state-transition function describing the update of the decision environment.

Equation (3.11) captures the adaptive nature of the mechanism: the next resource state depends on the previous state and on the decisions made in it, and agricultural activities affect future system states through cropping patterns, stocking rates, technology, water use and resource pressure. This dynamic interpretation is especially relevant for natural resources whose productive capacity can decline with repeated use: over-irrigation may increase salinity or waterlogging under sensitive conditions, high pasture pressure may reduce future forage capacity, crop concentration may amplify climatic or biological shocks, and energy-intensive irrigation may increase operating costs and emissions. The mechanism therefore evaluates current decisions partly by their effect on the next decision context.

Let the prediction error for activity i at time t be:

$$\varepsilon_{it} = Y_{it} - \hat{Y}_{it}, \tag{3.12}$$

where Y_{it} is the observed outcome;
$\hat{Y}_{it}$ is the corresponding forecast.

Accumulated prediction errors can be evaluated with a rolling error measure:

$$MAE_{i,T} = \frac{1}{T}\sum_{t=1}^{T}\left|Y_{it} - \hat{Y}_{it}\right|, \quad (3.13)$$

where $MAE_{i,T}$ represents mean absolute prediction error over T validation observations.

This is particularly relevant in agricultural systems undergoing structural change. Relationships based on historical data may become unstable when new irrigation technologies or varieties are introduced, water policy changes or extreme climatic conditions occur. Adaptive validation identifies such changes instead of treating historical model performance as a permanent characteristic of the system.

The decision levels and time horizons are given in Table 3.5.

Table 3.5 – Decision levels and time horizons for agricultural resource management

Decision horizon	Typical frequency	Review condition
1	2	3
Operational	Daily-weekly / event-driven	Resource shortage, extreme weather, observed deviation
Seasonal	Pre-season / intra-season	Updated climate/water information or major forecast revision
Annual	Annual planning cycle	Annual monitoring results and cross-district comparison
Structural	Multi-year	Persistent constraint, technological change, policy revision

Note – Compiled by the author based on the proposed organizational-economic mechanism.

The cyclical form in accordance with Figure 3.10 also reconciles strategic planning with operational management. Many resource decisions are made seasonally or even daily, while strategic agricultural development has a multi-year horizon; the cycle can serve both horizons if monitoring, prediction and intervention are aligned with the type of decision.

Table 3.5 distinguishes operational, seasonal, annual and structural decision horizons. This distinction is important because the economic value of resource information depends on when it becomes available and how long it takes to change the decision based on it.

Operational decisions are made over days or weeks in response to rapidly changing conditions, for example irrigation timing, emergency water adjustments, feed supply and operational energy use. They require current, directly applicable information: current water availability and weather matter more than long-term averages, and delayed information can greatly reduce the value of a decision because the production opportunity may have passed.

Seasonal decisions concern crop choice, cropped area, livestock feed planning and technology set-up. They require forward-looking information on climate,

expected yields and resource availability and are economically important because they determine the production structure for the whole season; the cost of changing the crop allocation rises rapidly after sowing.

Annual decisions are taken at the interface between farms and territorial institutions and concern district priorities, infrastructure constraints, diversification, livestock-feed balance, advisory programmes and support measures. They use both farm-level information and aggregated territorial indicators, and annual monitoring allows persistent problems to be distinguished from seasonal disturbances.

Structural decisions take several years and include irrigation modernization, storage and processing infrastructure, renewable-energy systems, digital data architecture and institutional reform. Because of their capital intensity and persistence, they require evidence that the constraint is structural rather than temporary: a single water deficit may not be sufficient, while a longer series of deficits can justify a major decision.

This hierarchy leads to the economic principle of temporal proportionality: the duration and irreversibility of an intervention should be proportional to the persistence and evidential strength of the problem it addresses. Flexible operational responses are justified for short-term deviations, whereas structurally confirmed and repeated constraints justify long-term institutional change and investment.

The same principle helps to avoid overreaction. Agricultural systems are subject to random variation, and one poor yield may result from local weather, a management problem or statistical coincidence, so immediate structural reallocation based on one observation may cause unnecessary adjustment costs. However, repeated deterioration confirmed by several evidence sources should not be dismissed as noise. Such cases are distinguished by the extent and persistence of evidence and the frequency of monitoring.

The timing of a decision can be expressed through the expected value of an intervention under uncertainty:

$$V_h = E(B_h) - C_h - \Omega_h, \tag{3.14}$$

where V_h – expected net value of intervention at decision horizon h;
$E(B_h)$ – expected benefit associated with the intervention;
C_h – implementation and adjustment cost;
Ω_h – expected cost of decision uncertainty, including the risk of acting on insufficient evidence.

The expression is conceptual rather than an empirically estimated equation. It illustrates that stronger evidence is needed as the cost and irreversibility of an intervention increase: a daily irrigation adjustment can be reversed quickly and can tolerate more uncertainty than a multi-year infrastructure investment.

The organizational-economic mechanism applies this logic by linking evidence confidence with resource pressure: higher pressure increases the cost of inaction, while weaker evidence increases the risk of inappropriate intervention, so the intensity of a decision depends on the interaction of these two dimensions.

This relationship is presented as a decision escalation matrix in Table 3.6.

Table 3.6 – Resource-pressure and evidence-confidence decision matrix

Resource pressure / Evidence confidence	Low confidence	Moderate confidence	High confidence	Interpretation	Response principle
LOW pressure	Monitor and improve data	Routine monitoring	Routine management	No immediate binding constraint identified	Continue observation; avoid over-intervention
MODERATE pressure	Verify before intervention	Targeted advisory	Targeted corrective action	Constraint emerging or locally important	Proportional intervention and confirmation of response
HIGH pressure	Immediate verification	Strong corrective action	Binding-constraint response / reallocation	Resource feasibility or resilience materially threatened	Prioritize constraint relief; reconsider the production configuration

Note – Compiled by the author based on the proposed resource-management decision rules.

Low resource pressure with high evidence confidence usually requires routine monitoring and ordinary management; moderate pressure with high confidence justifies targeted corrective action; high pressure with strong evidence requires active constraint relief, which may involve reconfiguration of production.

Low-confidence situations are treated differently. With low estimated pressure and weak evidence, the main response is better observation, because neither the severity of the problem nor the data justify strong intervention. Under moderate pressure, verification and scenario analysis become more important. Under high pressure, the mechanism combines precautionary steps with verification of evidence, because the potential cost of inaction may exceed the risk of partial uncertainty.

The relationship can be formalized by a simple response function:

$$A_{rd} = g(P_{rd}, C_{rd}), \tag{3.15}$$

where A_{rd} – intensity of managerial action for resource r in territory d;
P_{rd} – estimated resource pressure;
C_{rd} – confidence in the evidence supporting that estimate;
$g(\cdot)$ – response rule linking pressure and evidence quality to intervention intensity.

The function is deliberately qualitative to avoid the false precision of a universal numerical mapping based on indicators that differ between resources: water pressure, crop concentration and pasture burden are measured in different units, and energy intensity and environmental risk have different normative bases. The mechanism therefore uses explicit decision classes, while quantitative indicators remain available for each resource behind these classes.

This treatment of confidence has an important implication for machine-learning outputs: predictive estimates are useful only to the extent that they are

validated for the specific decision context. A pooled model may perform well while some crops or livestock categories perform worse, and the mechanism does not hide this. If the reliability of a prediction does not reach an acceptable evidential level, the numerical output is given a lower confidence status or is not used as a direct recommendation.

This transparency is economically significant, because apparently precise numbers affect users differently from explicitly uncertain estimates. A forecast without sufficient evidence may create false confidence and lead to resource commitments that are difficult to reverse. A confidence-aware recommendation allows the decision-maker to distinguish a high-confidence quantitative result from an exploratory analytical signal.

The escalation matrix can also guide public intervention. Strong evidence of a persistent water constraint supports infrastructure investment and irrigation modernization; strong evidence of structural crop concentration supports diversification programmes; repeated livestock feed shortages justify feed-base development or pasture-management measures; high-risk indicators with weak evidence require targeted monitoring before significant investment.

The mechanism thus links analytical uncertainty with fiscal and organizational discipline. Resources for adaptation and modernization are limited, so public support should be directed where resource failure is reasonably certain and its impact significant, and the decision matrix makes this prioritization explicit.

The same principle applies to environmental management: an increase in salinity identified by direct observation or documented pasture degradation is more convincing than a general assumption of environmental stress and allows more targeted intervention. When only contextual information on environmental risk is available, monitoring and preventive measures are more appropriate than numerical statements about the extent of degradation.

The handling of missing information is therefore an essential component of the mechanism rather than a technical detail, because data completeness affects the reliability of forecasts, the feasibility analysis and the legitimacy of recommendations. The mechanism therefore assigns responsibility for maintaining and checking each major evidence block.

The monitoring, accountability and feedback protocol is set out in accordance with Figure 3.11. Each indicator is linked with its main data owner, update frequency, verification procedure, typical analytical use and required feedback action, so every recommendation can be traced back to the information that produced it.

Crop production and area indicators are updated from farm records, district reporting and official statistics. Their consistency is crucial, because the cultivated area is both a historical indicator and a physical limit for allocation, and significant differences between farm and official data must be reconciled before results are used for major reallocations.

Climate variables have a separate verification process, since their value depends on the spatial definition and the temporal completeness and consistency of

the selected climatic measure. Growing-season temperature, precipitation, root-zone wetness and solar radiation represent different environmental factors and are not interchangeable, so the protocol documents the source and period of each climate series.

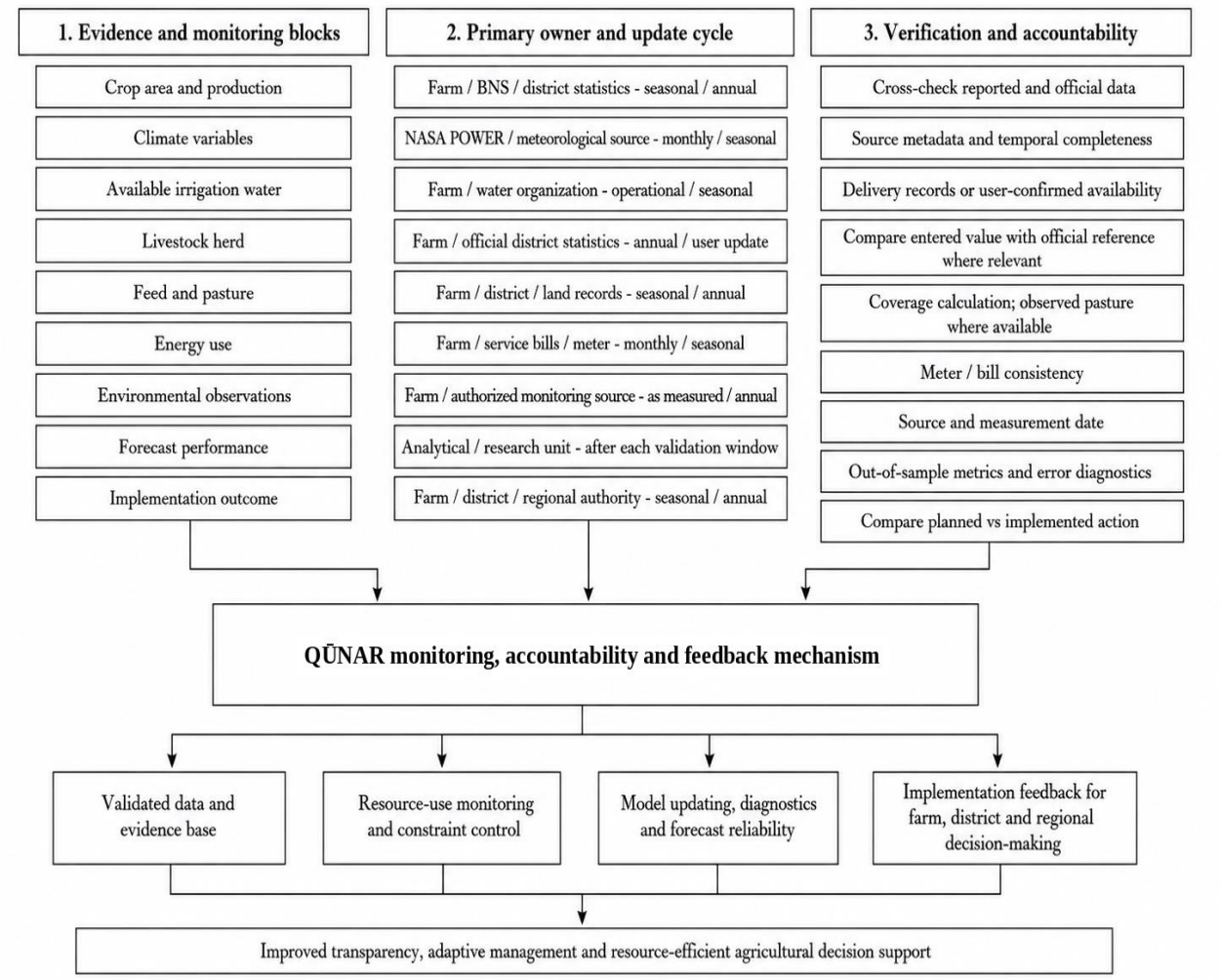


Figure 3.11 – Monitoring, accountability and feedback protocol

Note – Compiled by the author based on the proposed organizational-economic mechanism.

The update frequency of irrigation-water data is particularly important when availability changes during the season. An annual reference is sufficient for strategic planning but not for operational allocation, so the mechanism gives priority to current availability data when they are provided, while reference water requirements remain useful for comparing production alternatives and assessing resource pressure.

Livestock information is treated similarly. A district herd statistic can serve as a territorial benchmark and a basis for historical modelling, but a farm-level decision requires the actual or user-confirmed herd. The analytical output shows the

source of the herd value, and a district reference is never confused with the producer's actual livestock numbers.

Feed and pasture information is more difficult. Feed requirements can be determined from species-specific reference values, while actual feed availability depends on farm-specific conditions. Pasture pressure can be calculated when pasture area and livestock units are known, but pasture degradation can be assessed only from direct observations or authoritative data. The monitoring protocol therefore distinguishes biological requirements, observed resource supply and observed ecological condition.

Wherever possible, energy information is treated as an observed production input: energy-intensity and operational-emission calculations are based on meter readings, utility bills or user-entered values. Regional average electricity costs are poor proxies for farm electricity use because of differences in pumping depth, irrigation technology, equipment efficiency and production structure.

The evidence rule is applied most strictly to environmental indicators. Salinity, pesticide load and pasture degradation are included only when the source, date and context of measurement are known, and missing environmental information is explicitly reported as missing. This prevents the lack of data from implying good environmental performance.

The analytical unit tracks forecast performance through out-of-sample validation and error diagnostics. The validation report answers whether the predictive component can continue to be used in its current form, and deterioration of model performance triggers recalibration, restriction or revision.

Implementation outcomes complete the accountability structure: the scientific and economic value of a recommendation becomes clear only after it has been applied. The protocol therefore records whether the selected action was implemented, how resource use changed and what production response followed.

This creates a closed accountability chain:

$$\begin{aligned}\text{Observation} &\rightarrow \text{Verification} \rightarrow \text{Analysis} \rightarrow \text{Decision} \\ &\rightarrow \text{Implementation} \rightarrow \text{Outcome} \rightarrow \text{Reassessment}.\end{aligned} \tag{3.16}$$

The sequence in equation (3.16) reflects the main organization of the mechanism: every recommendation is based on explicit evidence and leads to an observable result that becomes new evidence.

The economic significance of this structure goes beyond model accuracy, because it reduces information asymmetry between agricultural actors. Producers can see the basis of a recommendation; authorities can judge whether a resource problem is structural or one-off; water organizations can compare agricultural demand with available resources; analytical institutions can determine whether poor model performance is due to data scarcity or structural change.

Accountability also creates incentives to improve data. When users see that stronger evidence gives more accurate and actionable recommendations, they value high-quality resource information more, which gradually improves the information

infrastructure of regional agriculture without requiring complete measurement of all variables from the beginning.

The organizational-economic mechanism therefore has a recursive relationship between decision quality and data quality: better observations improve predictions and feasibility analysis, better decisions create more structured implementation records, and these records improve subsequent validation and show which variables need further measurement. Information quality thus becomes an integral part of resource-management capacity.

This recursive approach is especially important for the digitalization of agriculture. Digital systems often fail to create sustainable economic value when they are introduced as stand-alone technological products without a governance system. A decision-support system requires data responsibilities, verification rules, institutional users, implementation channels and feedback procedures, and the mechanism developed here provides them around the analytical model.

Within the proposed mechanism, QŪNAR performs the analytical work without taking over the institutional functions around it. Verified data enter the model; predictive, resource, economic and environmental calculations transform them; the outputs are communicated to producers and institutions together with information on feasibility and evidence quality; implementation takes place outside the computational core and creates new observations that return to the system.

This positioning keeps algorithmic recommendation clearly separate from managerial responsibility while preserving the benefits of advanced quantitative analysis, and it creates the institutional framework that keeps the economic-mathematical model adaptive, auditable and practically applicable under changing climatic and resource conditions.

In accordance with Figure 3.12, QŪNAR is the analytical engine of the organizational-economic mechanism between observed resource conditions and interpretable production decisions. Agricultural management actors provide the verified inputs and receive the outputs of the system. The system logic moves from verified inputs to prediction, resource assessment, economic and environmental diagnostics and constrained optimization, and ends with outputs that management actors can interpret and act on; implementation results then return to the information base for subsequent calculations.

The advantage of this architecture is that it separates three analytical states that are often confused in agricultural planning: observed, predicted and recommended. Observed information describes the current or historical state of the resource-production system, predicted information anticipates what will happen next, and recommendations result from testing forecasts against resource limits and decision rules. Keeping these states separate prevents a predicted yield from being treated as an actual yield and an optimized production structure from being presented as an inevitable result.

QŪNAR processes these states in sequence. The first layer contains the territorial unit, agricultural activities and available observations on land, water, climate, production history, livestock, feed, pasture, energy and selected

environmental variables, and the evidential status of each parameter is preserved: direct observations have priority when available; contextual values are taken from official territorial statistics where appropriate; normative resource requirements are reference values based on regulations or scientifically supported sources; model-derived values are shown as estimates. Missing values are kept and remain distinguishable from measured zeros.

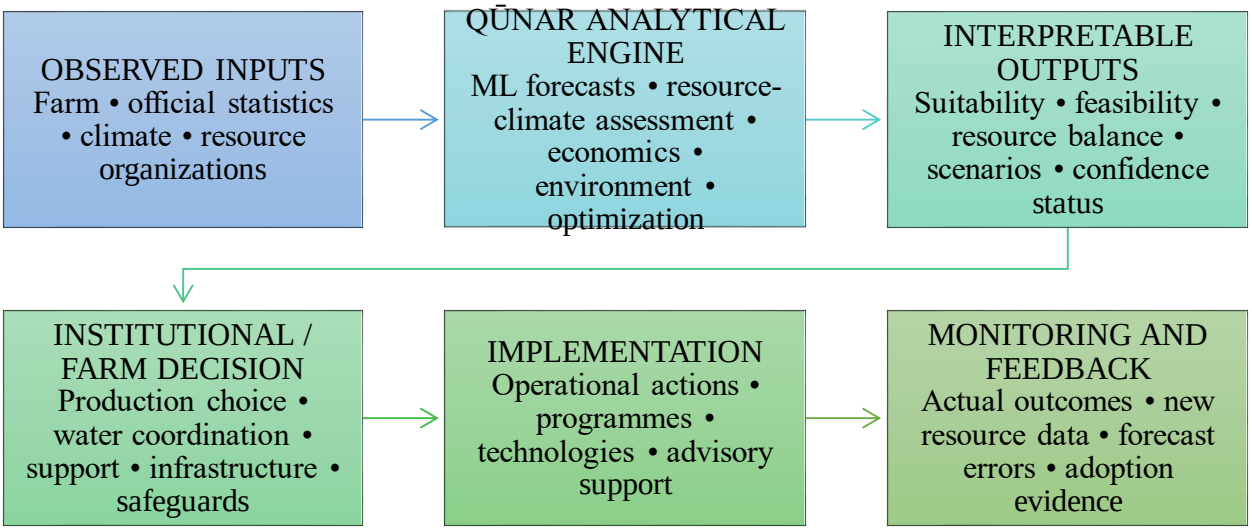


Figure 3.12 – Integration of QŪNAR into the organizational-economic mechanism
Note – Compiled by the author.

All subsequent outputs are interpreted in the light of this evidence hierarchy. A farm result based on thorough farm observations can support a more specific operational recommendation than a result based on territorial reference values, so users with different amounts of data can use the same analytical architecture without hiding differences in confidence.

The predictive layer links past and future production by converting historical and climatic data into predictions. In crop production, machine-learning algorithms predict yields from crop and district information, historical cultivated areas and growing-season climate data. The prediction provides one part of the decision problem – the expected physical response of the crop – but not the final decision, because expected productivity must still be compared with resource needs and feasibility.

This distinction is economically significant: a yield-maximizing recommendation may be infeasible when irrigation water is limited, a water-saving crop may be economically unviable when its productivity is very low, and a historically strong specialization may create concentration risk. The analytical mechanism therefore assesses production potential within the broader resource setting.

Water has two distinct roles. The first is comparative: crops have different water requirements, and their relative water pressure is included in the resource

assessment. The second is limiting: when the user specifies the water actually available, the water demand cannot exceed it. The comparative assessment shows the water use associated with an alternative, while the hard constraint shows whether the proposed production structure is physically possible with the available water supply.

For crop i in decision unit d, total irrigation requirement can be represented as:

$$W_{id} = w_{id}x_{id}, \tag{3.17}$$

where w_{id} is the crop-specific reference water requirement per hectare;
x_{id} is allocated area. The aggregate restriction is:

$$\sum_{i=1}^{n} W_{id} \leq W_d^{avail}. \tag{3.18}$$

The economic interpretation of equations (3.17) and (3.18) is straightforward: production can expand only as long as the irrigation requirement does not exceed the verified water budget. When this condition is violated, the mechanism treats the planned allocation as infeasible and shifts attention to crop substitution, area adjustment, water efficiency or additional water availability where this is institutionally and physically possible.

Land is an equally explicit constraint: the total allocated crop area may not exceed the available agricultural area. The combination of land and water constraints is particularly important, because either may be limiting in different situations: one farm may have unused land but not enough water to irrigate it profitably, while another has sufficient water but no unallocated land. The mechanism recognizes these situations and does not treat land expansion as the universal route to production growth.

Climate assessment is another dimension of differentiation. The climatic profile is based on growing-season temperature, precipitation, root-zone wetness and solar radiation, which represent separate factors of the production environment and enter prediction according to their empirical importance. Their role is not limited to prediction, since climate also affects resource stress: lower rainfall and soil moisture may increase dependence on irrigation, and higher temperatures may increase evapotranspiration and change crop and livestock water requirements. The climate block thus links natural climatic variability with the economic value of water and production adaptation.

The QŪNAR resource-climate assessment combines the dimensions relevant for comparative decision support without losing their content. The score is a comparative analytical measure within a given decision set; it does not replace physical constraints and does not imply economic interchangeability of

heterogeneous resources. A favourable climate component cannot offset a violated water constraint, and a high expected yield cannot offset a lack of land.

The separation of score and feasibility is one of the main methodological features of the mechanism. Composite indicators support comparison, ranking and communication, while physical restrictions determine whether an alternative belongs to the admissible solution set. Keeping these functions separate prevents a high composite score from giving false legitimacy to an impracticable option.

The livestock component follows a similar logic but uses resource relationships specific to biological production: herd size is linked with species-specific water and feed requirements, pasture area and climatic conditions. Predictive analysis of herd dynamics is used when sufficient historical information exists; where predictive performance is unstable, numerical forecasts are restricted and the analysis relies on observed and reference resource calculations.

The livestock water requirement can be expressed as:

$$LW_{sd} = N_{sd} \cdot q_{sd} \cdot 365, \tag{3.19}$$

where N_{sd} is the number of animals in category s within decision unit d;
q_{sd} is reference daily drinking-water requirement per head. Where a verified available livestock-water volume is supplied, the corresponding coverage ratio becomes:

$$LC_{sd}^{water} = \frac{LW_{sd}^{avail}}{LW_{sd}} \times 100. \tag{3.20}$$

Feed is treated in a similar way: when actual coverage is unknown, the mechanism reports biological resource requirements separately, which prevents a reference norm from being turned into an unproven claim of farm resource sufficiency.

Pasture pressure extends the livestock analysis from input demand to land capacity. Livestock units standardize data on heterogeneous species for structural comparison, and the ratio of livestock units to pasture area indicates the intensity of pasture use. The indicator is diagnostic: ecological carrying capacity depends on pasture productivity, seasonal changes and degradation and cannot be deduced from livestock density alone.

Energy calculations form an operational resource layer for crop and livestock production. Electricity used for pumping, mechanized operations, housing, cooling, storage and other production purposes has a direct cost and associated operational emissions, so energy efficiency can be assessed by both economic and environmental criteria.

For observed electricity use E_d, operational electricity-related carbon emissions are represented as:

$$CO_{2,d}^{op} = E_d \cdot EF, \tag{3.21}$$

where EF is the applicable electricity-emission factor (its value for Kazakhstan is given in Section 3.3).

This boundary is important because environmental indicators differ in scope: electricity emissions can be calculated when energy use is known, but pesticide pressure requires observations of pesticide use, salinity requires reliable information on affected land, and pasture degradation requires an observed degradation measure. An advantage of QŪNAR is that it does not synthesize an environmental score when data are missing: environmental information is recorded when its evidential basis is sufficient and otherwise reported as unavailable. The economic layer interprets feasible alternatives using scenario variables, prices, production quantities, costs and energy expenditure when data are available. It shows trade-offs between resource efficiency and economic results: some resource-saving alternatives may need technological or institutional support to become economically viable, while an economically attractive alternative may place too much pressure on a binding resource and be excluded from the feasible set.

Let x_i represent the scale of agricultural alternative i and v_i its expected contribution to the selected economic or integrated objective. The general optimization structure is:

$$\max Z = \sum_{i=1}^{n} v_i \, x_i, \tag{3.22}$$

subject to the constraints:

$$\sum_{i=1}^{n} a_{ri} \, x_i \leq B_r, \quad r = 1, \dots, R, \tag{3.23}$$

$$x_i \geq 0. \tag{3.24}$$

Here a_{ri} represents consumption of constrained resource r by alternative i, and B_r represents the corresponding available amount.

The economic meaning of this formulation is the allocation of limited resources among alternative agricultural uses. The solution is an achievable configuration that satisfies the specified objective and constraints, and its value lies not only in the solution itself but also in the information it provides on binding constraints, unused resources and structural concentration.

An optimal solution should therefore be interpreted together with information on the constraint structure. If water is binding while land is not fully used, the unused land cannot become productive without more water or a change in crop technology; if land is binding and water is plentiful, productivity growth or structural reallocation

becomes more relevant. The solution thus shows the marginal strategic value of different resources, even if they are not formally shadow-priced for each user.

Diversification diagnostics are used together with the optimization result, since a mathematically optimal solution may be overly concentrated when one alternative dominates the objective. The HHI and the effective number of crops describe the structure of the allocation and are interpreted as indicators of production resilience and concentration risk, not of biological diversity.

The confidence layer balances analysis with prudence. Each output is based on a combination of observed information, reference coefficients and model predictions, so the mechanism reports confidence and evidence status together with substantive results. This prevents users from assuming that every number is equally empirically certain.

The architecture in accordance with Figure 3.12 also clearly separates the analytical engine from implementation. QŪNAR can propose a water-limited crop structure, estimate its yields, calculate livestock resource needs and compare energy scenarios, but it cannot provide irrigation water, funding or environmental standards or force producers to change production. These actions belong to the organizations and producers of the wider mechanism.

This separation reflects a division of comparative advantage. The model performs calculations that would be difficult to do consistently by human judgement with many interacting variables; producers provide information on local conditions and make production decisions; water organizations verify resources and control water delivery; public authorities coordinate shared infrastructure and support; research institutions validate and update the analytical system; advisory services turn outputs into practical actions.

This distribution significantly changes the role of modelling in agricultural policy: the model becomes an information-processing tool within a resource-governance process rather than a stand-alone forecasting tool, and its usefulness depends on how well calculation and implementation are connected.

The mechanism can be assessed by four groups of outcomes: resource outcomes (water balance, land use, pasture pressure, feed coverage and energy intensity), production outcomes (expected production, herd composition and production structure), economic outcomes (scenario performance, costs, production value and efficiency effects where applicable) and governance outcomes (data completeness, implementation status, frequency of recalibration and traceability of decisions).

This multidimensional assessment measures the success of implementation more broadly than the growth of gross agricultural output. Output growth accompanied by a worsening water deficit, higher pasture pressure or lower information reliability would indicate a decline in resource quality despite nominal production gains, whereas a temporary slowdown of output growth may be economically justified if it significantly reduces sensitivity to a binding resource constraint.

The mechanism therefore defines efficiency as a relationship between output, resource pressure and adaptive capacity. The management goal can be expressed in general terms as:

$$\mathcal{E} = F(Y, W, L, P, F_d, En, C, Env, I), \tag{3.25}$$

where Y represents production performance;
W water conditions;
L land;
P pasture;
F_d feed resources;
En energy;
C climate;
Env environmental conditions;
I information quality.

This formulation has an important corollary: the value of an agricultural resource depends partly on the other resources. When water is scarce, additional land has little value; a better water supply system can increase the economic value of land; better climate information allows water to be allocated more effectively before production starts; feed availability changes the potential for livestock expansion; and digital information can raise the productivity of existing resources by eliminating allocation errors without any physical increase in these resources.

This interaction is the economic basis for treating information as an enabling resource. Information does not replace land, water or energy, but it affects how effectively they are used, so the economic value of forecasts, validation and resource diagnostics lies in reduced uncertainty and avoided infeasible decisions.

Feedback is important because the real effects of model use can be documented systematically and used for future recommendations. Each implementation cycle adds evidence for future predictions and diagnostic blocks, and the verified observations accumulated in the digital system gradually increase the information resolution of agricultural management.

In this chain, the computational consistency of QŪNAR is needed to process heterogeneous information, and the governance consistency of the organizational-economic mechanism is needed to use model results in practical decisions. Together, they provide a structure for repeatedly assessing, applying and adapting natural-resource efficiency under changing agricultural and climatic conditions.

The developed mechanism is thus a continuous process of evidence-based resource allocation with explicit physical constraints and institutional responsibility, that is, resource-efficient agricultural management. Its analytical framework integrates crop and livestock production with climatic variability, water scarcity, land allocation, energy use and selected environmental risks within a single decision system; its organizational structure allocates responsibilities according to the information, authority and implementation capacity of actors; and its feedback architecture allows data and model behaviour to be revised as new evidence appears.

This provides the organizational-economic basis for using the economic-mathematical model as a practical decision-making system for the agricultural sector of Turkestan region.

The organizational-economic mechanism can also be assessed by how much it reduces the mismatch between resource availability and production decisions. Such a mismatch arises when the water, land, feed, pasture or energy needed by an agricultural enterprise is checked only after production decisions have been made. The crop structure, herd use and some infrastructure decisions cannot always be reversed during the season and may lead to significant correction costs, so early identification of resource incompatibility has value even when it does not increase physical output.

The resource mismatch that can be avoided by analytical intervention for decision unit d can be generalized as:

$$ARM_d = \sum_{r=1}^{R} \max\left(0, D_{rd}^{base} - B_{rd}\right) - \sum_{r=1}^{R} \max\left(0, D_{rd}^{rec} - B_{rd}\right), \quad (3.26)$$

where D_{rd}^{base} – demand for resource r under the initial production configuration;
D_{rd}^{rec} – demand for resource r under the recommended feasible configuration;
B_{rd} – available quantity of resource r;
ARM_d – reduction in aggregate resource mismatch.

Equation (3.26) is applied separately to each resource, because hectares, cubic metres, kilograms of feed and kilowatt-hours are not equivalent. Its purpose is to express a common principle: a recommendation creates value in resource management if it closes an identified gap or prevents a production configuration from exceeding a resource limit. The actual evaluation is therefore made through resource balances rather than through artificial aggregation of heterogeneous physical quantities.

The same applies to unused capacity. A satisfactory solution may use much less of one resource than is available when another resource is limiting, which is important information for regional development policy. Unused land with a binding water constraint means that expansion of water-intensive production requires additional water, technological water savings or a change in the crop mix; unused water with suitable land points to productivity improvement, technological intensification or a change in the economic composition of production. The mechanism therefore distinguishes resource scarcity from underutilization and does not confuse either with the volume of production.

The resource utilization ratio can be calculated for each constraint:

$$UR_{rd} = \frac{D_{rd}}{B_{rd}}, \quad (3.27)$$

where UR_{rd} denotes the utilization ratio of resource r in decision unit d.

A generalized resilience margin can be expressed as:

$$RM_{rd} = 1 - UR_{rd}. \quad (3.28)$$

This distinction becomes more important under climatic uncertainty. An agricultural system that operates continuously at the edge of a critical resource may show high measured utilization but have low capacity to absorb shocks. The resilience margin RM therefore has economic value: a reserve of water, feed or storage reduces the probability that an adverse climatic event turns into a production loss.

3.3 Economic-mathematical model for resource-efficient and climate-resilient agricultural decision-making

The analytical results for Turkestan region were incorporated into an economic-mathematical decision system that links agricultural production potential, climatic conditions, water resources, land use, energy consumption, environmental characteristics and structural limitations. The model was implemented in the QŪNAR software environment (Quantified Utilization of Natural Agricultural Resources), which integrates machine-learning prediction, resource accounting, climate suitability assessment and constrained optimization in a single computational sequence.

The model is based on the idea that agricultural resource efficiency results from several quantitatively different processes. Crop yield is a biological and production result; water and energy measure resource intensity; cultivated area measures the spatial scale of production; climatic variables describe the environmental conditions of production; and optimization determines whether the resulting production structure fits the available resource budget. QŪNAR therefore analyses these elements at different stages, where they have different temporal and mathematical meanings.

A critical feature of the model is the separation of three computational layers. The predictive layer estimates yield from historical relationships between districts, crops and climate; the resource-climate layer assesses the climatic suitability and water pressure of agricultural alternatives and retains energy and environmental information; the optimization layer allocates available land and water among alternatives under explicitly formulated constraints. This separation prevents a single indicator, such as expected yield, from dominating the whole decision process.

To develop the empirical crop machine-learning core, the panel was harmonized by districts and crops for 2004-2025. The final analytical sample consists of 1,362 observations for 17 territorial units and the six crops with the most consistent series – wheat, corn, rice, cotton, sunflower and potato. The machine-learning panel (1,362 observations) consists of the 1,223 complete observations for 2004-2023 used in the correlation analysis (Tables 2.14-2.15) and 139 observations for 2024-2025 (68 and 71, respectively). Only observations with positive official

area and yield and complete climate data were included; Table 2.13 reports all available yield observations before this restriction. District-level climatic observations were taken from NASA POWER and matched with agricultural production variables in a common district-crop-year structure. For calibration each territorial unit is represented by its NASA POWER grid point; in application, when the user draws the field on the map, QŪNAR determines the NASA POWER grid cells that intersect the field and calculates the climate of the field as an average weighted by the area of intersection; for the next season the long-term climatic norm of the field for 2004-2025 is used. The summary of the input architecture in the model is presented in Table 3.7.

In addition, the current version contains monthly NASA POWER data for 1995-2025 for 65 grid cells covering the region. These data are used only in the application (field-level climate); the Random Forest model was trained on the district grid-point data described above, and its training features were not changed.

The variables in Table 3.7 have different roles in the model. District and crop identify the territorial and production context; historical district-crop sown area reflects the scale and continuity of local specialization; climatic predictors describe the environmental conditions of yield formation; water, energy and other direct inputs describe the resource needs of the production decision; the irrigation budget limits the solution space at the optimization stage. Assessment confidence characterizes the evidence and does not make a crop more attractive merely because more evidence is available.

The temporal architecture is particularly important because climatic predictors and resource accounting do not have a single time scale. The crop machine-learning specification uses the fixed period April-September, over which temperature, precipitation, root-zone soil moisture and solar radiation are aggregated. This boundary is an analytical period for the main open-field crops of the calibrated core, when thermal, moisture and radiation influences are greatest.

This definition does not mean that all crops begin their biological cycle in April and end it in September; it defines how the specification is treated in the software. QŪNAR operates in three time modes. The next-season mode is the main planning mode, in which the next agricultural season is assessed using the historical climatic profile and the resources and production conditions set by the user. The current-season mode uses observed climatic information of the current season for a preliminary assessment, and the completed-season mode gives a retrospective assessment after the climatic period has ended. The year, the type of evaluation and the climatic period are therefore explicitly defined in the system rather than implied by the date on which the application is opened.

In addition to April-September, an alternative climate window (March-October) was tested to assess the sensitivity of model performance to the seasonal boundaries of climate aggregation, especially given the relatively long warm season of Turkestan region. The alternative specification was calculated from the same monthly NASA POWER district data and evaluated on the same 1,362 district-crop observations. Since the timing of winter wheat establishment and of early and late

production may differ from the typical system, the model separates the climate-feature window from the resource-accounting boundary. Water, electricity and other direct inputs entered for a crop cover its full production cycle, including soil preparation, sowing, input application, crop maintenance and harvesting; resources used outside April-September are thus included in the resource-efficiency assessment, while the baseline climatic predictors are aggregated over the standardized active season.

Table 3.7 – QŪNAR architecture, data coverage and input variables, 2004-2025

Layer / item	Value / unit	Time basis	Mathematical role
1	2	3	4
Dataset – district-crop observations, total	1362	2004-2025	Training and validation base
Dataset – observations added for 2024-2025	139 (2024=68; 2025=71)	2024-2025	Sample expansion for updated RF
Dataset – crops modelled	6	2004-2025	Individual RF yield prediction
Identification – district	categorical	current decision	Territorial selector / categorical predictor
Identification – crop	categorical	current decision	Alternative / categorical predictor
Production history – historical sown area	thousand ha	2004-2025	RF predictor
Climate – Apr-Sep temperature	℃	growing season	RF predictor + climate envelope
Climate – Apr-Sep precipitation	mm	growing season	RF predictor + climate envelope
Climate – root-zone wetness	index	growing season	RF predictor + climate envelope
Climate – solar radiation	MJ/m²/day	growing season	RF predictor + climate envelope
Production outcome – crop yield	c/ha	2004-2025	RF target
Water – reference requirement	m³/ha	scenario/reference	Comparative water pressure
Water – available budget	m³	current/seasonal	Hard optimization constraint
Land – available area	ha	current	Optimization scale
Evidence – evidence score	0-100	current	Separate evidence layer; outside attractiveness objective
Livestock – herd panel	mixed	2015-2023 + current	Separate RF + resource balance
Environment – environmental indicators	mixed	current/observed	Conditional diagnostics

Note – Compiled by the author using the QŪNAR analytical dataset and model architecture.

This distinction can be represented by two temporal domains:

$$\mathcal{T}^{clim} = [Apr, Sep], \qquad \mathcal{T}_c^{res} = \left[t_c^{prep}, t_c^{harv}\right], \tag{3.29}$$

where $\mathcal{T}^{clim}$ denotes the standardized climate-feature window;
$\mathcal{T}_c^{res}$ denotes the complete resource-accounting interval for crop c, beginning with production preparation t_c^{prep} and ending with harvesting t_c^{harv}.

The result also clarifies the limitations of this temporal simplification. The current crop machine-learning core does not explicitly represent autumn establishment, winter dormancy or crop-specific sowing-to-harvest calendars, which may affect yields, especially of winter crops. This does not exclude autumn or winter resource inputs from the resource-accounting layer; it only restricts the climatic predictor block to a standard active-season representation. A future version could include antecedent soil moisture, accumulated pre-season rainfall and winter-temperature predictors for crop groups where they significantly improve out-of-sample accuracy.

The predictive part of QŪNAR is a nonlinear model of crop yield as a function of territorial identity, crop identity, historical production scale and seasonal climatic conditions:

$$\hat{Y}_{dct} = \mathcal{F}_{RF}\left(D_d, C_c, A_{dct}, T_{dt}^{AS}, P_{dt}^{AS}, W_{dt}^{AS}, S_{dt}^{AS}\right), \tag{3.30}$$

where $\hat{Y}_{dct}$ is the predicted yield of crop c in district d for agricultural year t;
D_d identifies the district;
C_c identifies the crop;
A_{dct} is historical district-crop sown area;
T_{dt}^{AS} is April–September mean air temperature;
P_{dt}^{AS} is accumulated April–September precipitation;
W_{dt}^{AS} is mean root-zone soil wetness;
S_{dt}^{AS} is mean surface solar radiation;
$\mathcal{F}_{RF}$ denotes the fitted Random Forest regression operator.

Random Forest was chosen because the empirical relationship between climatic conditions and agricultural production involves nonlinearity, thresholds and interactions: the same temperature may have different consequences under different precipitation or root-zone moisture conditions, the effect of rainfall differs between crops and districts, and historical specialization may modify the observed response through accumulated infrastructure, production practices and local adaptation. A single constant-coefficient regression would considerably restrict the form of these relationships.

The computational architecture of QŪNAR is shown in accordance with Figure 3.13.

For an ensemble containing B regression trees, the crop-yield prediction is obtained from:

$$\hat{Y}_{dct} = \frac{1}{B}\sum_{b=1}^{B} f_b\,(\mathbf{x}_{dct}), \tag{3.31}$$

where $f_b(\mathbf{x}_{dct})$ denotes the prediction generated by tree b for the corresponding observation vector.

After all independent validation stages are completed, the final production estimator is fitted on the complete validated historical crop panel. Future observations are excluded only within the validation procedure, where they are needed to obtain genuine out-of-sample evidence; the deployed estimator uses the full 2004-2025 series so that the most recent agricultural observations are not lost in operation.

The QŪNAR economic-mathematical model is implemented as a web-based decision-support system [13]; its main interface elements and computational modules are presented in Appendix C in accordance with Figures C.1-C.5. An example of a complete QŪNAR decision-support report generated for an illustrative agricultural scenario is presented in Appendix D (Tables D.1-D.9).

In accordance with Figure 3.13, the analytical sequence starts with validated information on agriculture, climate and user-provided resources. The next-season, current-season and completed-season modes require different interpretations of climatic availability, so the temporal definition is set before prediction. Data quality control includes missing-value screening, duplicate detection, consistency checks and multicollinearity diagnostics, after which the validated variables are passed to the machine-learning core. The predicted yield then enters a broader decision framework in which climatic compatibility, water pressure, land availability, resource demand and assessment confidence are considered separately. This order prevents predictive accuracy from being mistaken for decision optimality: a crop may have a relatively high expected yield but be unsuitable for the given irrigation budget, while another crop with a lower potential yield may be more compatible with the same land and water conditions. Agricultural alternatives are therefore evaluated under a resource-limited production regime.

This is most evident in the water component. Actual water use can be entered when the producer knows the water use of an individual crop; when direct measurement is unavailable, a reference (normative) estimate is used, and QŪNAR does not present it as actual farm consumption. In the optimization mode, the producer specifies the total irrigation water available for the season, and the model allocates this limited budget among the candidate crops, so the user does not need to allocate water to particular crops in advance.

The same evidence hierarchy applies to energy. Energy consumption can be entered for the whole production cycle, and estimates are explicitly identified where measured values are not provided. Electricity-related carbon emissions are calculated only when energy use is entered or a scenario is specified. This evidence-preserving structure is necessary because a value derived from an assumed energy parameter has a different epistemic status than a farm measurement.

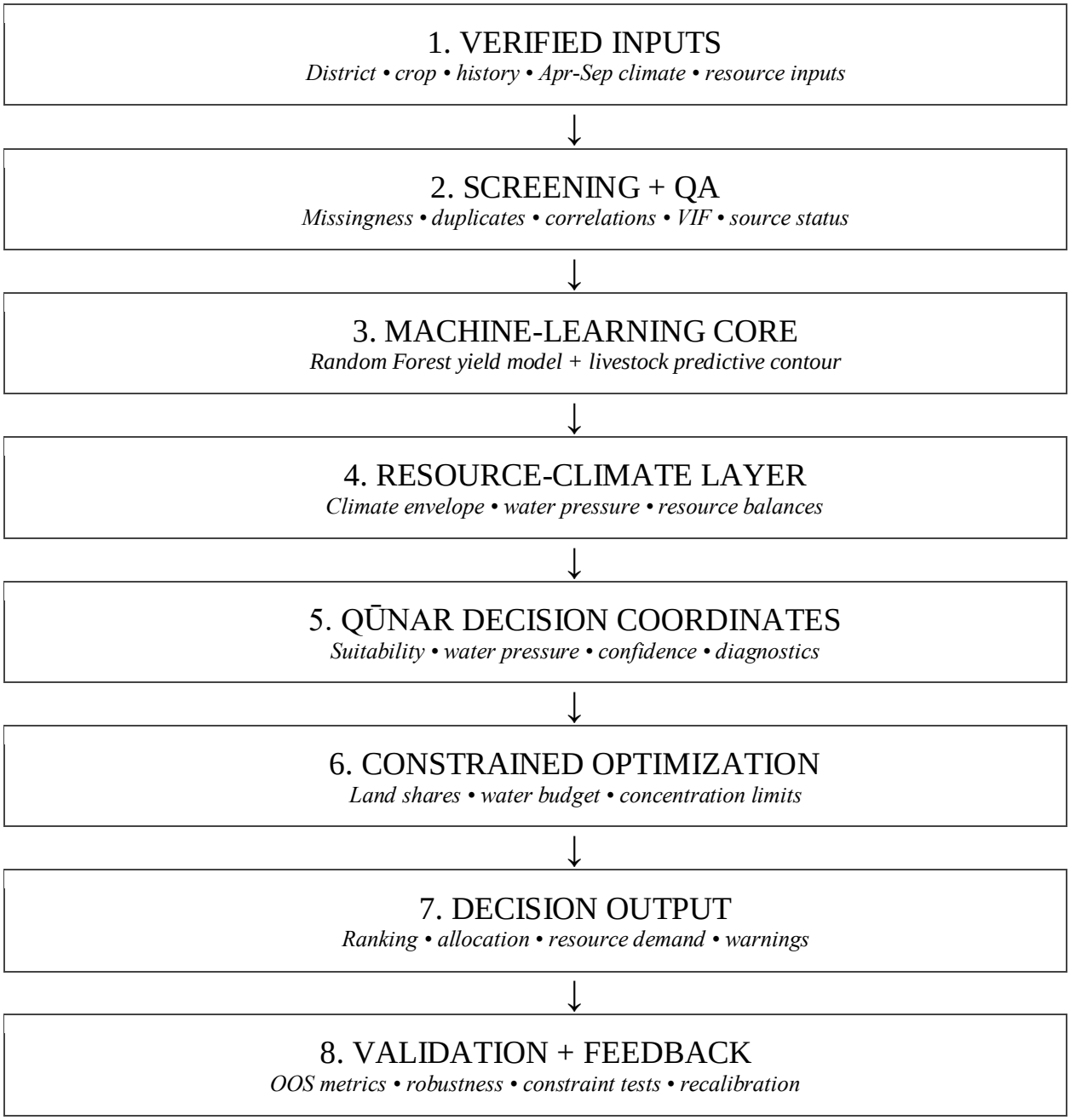


Figure 3.13 – Computational architecture of QŪNAR

Note – Compiled by the author. Every final output is traceable to explicit inputs, a machine-learning layer, validation status and resource constraints.

Environmental diagnostics follow the same principle: climatic exposure is assessed from the modelled climatic environment, while pesticide load, salinity or land degradation are reported only when information is available. Missing environmental information is reported as missing, and QŪNAR does not treat missing observations as zero environmental pressure. The current crop machine-learning calibration is deliberately limited to the six crops with a reasonably complete district-year panel. Additional crops can be included in the broader

resource-climate decision layer when sufficient water and climate information exists, but they do not receive an artificial machine-learning yield forecast. Barley is a clear example: its historical yield series was excluded from the crop-yield core because the source data duplicate the wheat series in the overlapping period. Since QŪNAR partly relies on external official statistical series, it cannot provide a barley history when the source does not contain a reliable one; the unsupported ML yield estimate is therefore withheld, while the crop remains available for resource-climate comparison. Protected (greenhouse) cultivation is excluded from the calibrated crop core for a different reason. Greenhouse production takes place in a controlled environment where heating, artificial lighting, ventilation, humidity control, protected irrigation and possibly several production cycles per year change the relationship between outdoor climate and production. Transferring an open-field climate-yield function to greenhouses would create inappropriate precision, so greenhouse cultivation is treated as a separate extension requiring its own controlled-environment specification. This architecture creates a single computational structure and makes explicit the boundaries between observed data, predicted outputs, normative resource parameters, scenario assumptions and unavailable information. These distinctions are essential scientifically, because the model is intended for agricultural decision-making with incomplete and uncertain information, and uncertainty must not be turned into computational false precision. The diagnostics in Table 3.8 check the statistical validity of the predictors retained in the final model and the degree to which the final specification controls multicollinearity. The variable selection step was designed to keep agronomically interpretable and statistically distinct information in the machine-learning core and to avoid a specification in which several climatic indicators capture the same signal and create an illusion of additional dimensions. This is especially important for regional agricultural panels, where temperature and precipitation, humidity and soil moisture, and different soil-moisture indices are often linked in time and space.

The multicollinearity diagnosis is given in Table 3.8.

Table 3.8 – Variable selection and multicollinearity diagnostics

Candidate variable	Full-set VIF	Tolerance	Final-set VIF
Annual temperature	7.43	0.13	excluded
Annual precipitation	3.56	0.28	excluded
Apr-Sep temperature	11.10	0.09	2.30
Apr-Sep precipitation	5.16	0.19	2.85
Apr-Sep relative humidity	5.43	0.18	excluded
Apr-Sep root-zone wetness	3.45	0.29	2.49
Apr-Sep solar radiation	1.98	0.51	1.87
Historical sown area	–	–	1.03

Note – Compiled by the author using the QŪNAR predictor set and variance inflation factor diagnostics. Historical sown area was not included in the full climatic set; excluded – variable removed from the final specification. Final-set VIF differ from Table 2.16, because here they are calculated together with historical sown area.

The initial candidate variables were annual temperature, annual precipitation, April-September temperature, April-September precipitation, April-September relative humidity and root-zone soil wetness. The strongest similarity was found between annual and seasonal climatic variables and between precipitation and relative humidity, so the full candidate specification included indicators that were individually meaningful but statistically redundant when entered together.

No automatic variable selection algorithm was used; instead, variance inflation factors were applied as a diagnostic, and the procedure was repeated to check whether the remaining predictors provided sufficient unique information after theoretical screening. In the wider candidate specification, the VIF was 7.43 for annual temperature, 11.10 for April-September temperature and 5.43 for April-September relative humidity. These values reflected climatic interdependence rather than measurement error, but all these overlapping indicators together would have made interpretation difficult without adding an independent information signal.

The final climatic block therefore consists of four variables: April-September air temperature, accumulated precipitation, root-zone soil wetness and solar radiation, and historical district-crop sown area is retained as a production-scale variable. After reduction, the maximum VIF in the final specification was 2.85: April-September precipitation, root-zone wetness and temperature have moderate VIF values, and historical sown area shows very little multicollinearity.

The reduction of VIF values after refinement of the specification is shown in accordance with Figure 3.14.

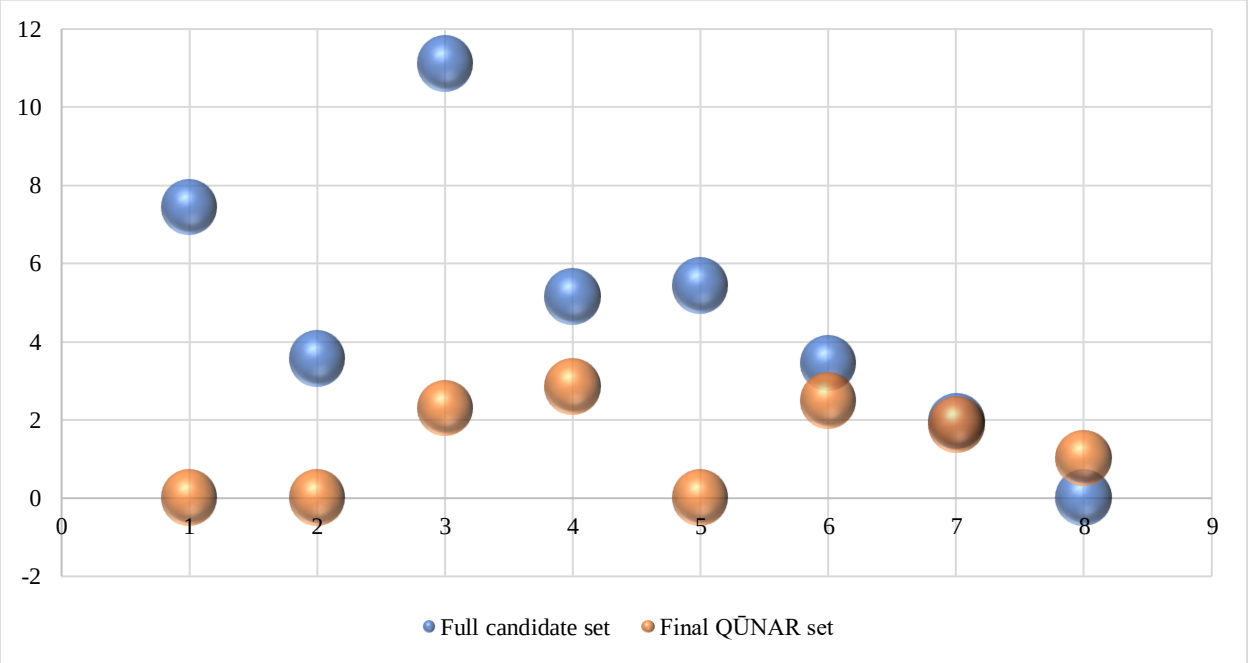


Figure 3.14 – Variance inflation factors before and after variable selection

Note – Compiled by the author using QŪNAR multicollinearity diagnostics.

The final combination is analytically coherent and has a clear meaning: temperature describes the thermal conditions of crop development, precipitation the atmospheric water supply, root-zone wetness the soil moisture in the root zone rather than simply the amount of rainfall, solar radiation the energy available for photosynthesis, and historical sown area the production scale related to local crop specialization and persistence of the cultivated structure.

The distinction between precipitation and root-zone wetness is key: the same precipitation may produce different crop conditions because of soil properties, evaporation, antecedent moisture and infiltration. Root-zone wetness is therefore a state variable, and precipitation an external climatic input, and keeping both allows the model to distinguish water entering the system from moisture in the root environment.

Solar radiation had the lowest VIF and was retained because it represents a physical process different from thermal and moisture processes. Its inclusion prevents the climatic specification from being reduced to a purely temperature-water form and allows the yield response to vary with incoming surface energy.

Relative humidity was not included in the baseline predictive set. This does not mean that air humidity is agronomically unimportant: the variable was highly correlated with precipitation and soil wetness and provided little unique information once the final moisture block was defined. It remains suitable for sensitivity analysis and for crop-specific extensions where physiological humidity effects justify its explicit inclusion.

The same principle applies to annual climatic indicators. Their exclusion from the final machine-learning core does not mean that annual climate is unimportant; it reflects the seasonal focus of the model, whose crop-yield specification represents the climatic conditions most directly linked with active production. Annual averages include winter months, when thermal and radiation conditions are only weakly related to yield formation for most of the calibrated open-field crops.

However, the model does not assume that pre-April climate has no effect. Such effects may operate through accumulated soil moisture, overwintering or production preparation and are recognized as potential antecedent predictors rather than combined in the same seasonal aggregate. This separation gives a transparent baseline specification and a clear path for future crop-specific extensions.

The predictive validation and robustness results of the crop model are given in Table 3.9.

The pooled GroupKFold result, using the April-September baseline, was found to be R^2=0.9263 and for March-October the result was R^2=0.9264. The results are almost identical, and similar stability was observed in the chronological forward-validation blocks: for the 2011-2015 test period, R^2 increased from 0.9494 to 0.9557 under the broader window, for 2016-2020 from 0.8912 to 0.8946, and for 2021-2025 from 0.8079 to 0.8099.

Table 3.9 – Predictive validation and robustness of the crop model

Evidence block	N	MAE, c/ha	RMSE, c/ha	R^2
Primary out-of-sample (GroupKFold by year, Random Forest)	1362	8.840	16.198	0.926
Median district-crop baseline (GroupKFold)	1362	8.664	17.473	0.914
Forward test 2011-2015 (Random Forest)	292	7.141	12.276	0.949
Forward test 2011-2015 (baseline)	292	7.746	13.161	0.942
Forward test 2016-2020 (Random Forest)	318	11.942	20.794	0.891
Forward test 2016-2020 (baseline)	318	13.314	24.108	0.854
Forward test 2021-2025 (Random Forest)	326	16.699	30.538	0.808
Forward test 2021-2025 (baseline)	326	16.880	32.112	0.788
Stress holdout 2014-2023 (Random Forest)	622	13.222	24.338	0.850
Stress holdout 2014-2023 (baseline)	622	14.589	26.548	0.821
Crop-specific: wheat	294	3.954	5.064	0.516
Crop-specific: corn	289	7.224	10.184	0.458
Crop-specific: potato	290	23.663	32.282	0.412
Crop-specific: sunflower	255	2.499	3.281	0.354
Crop-specific: cotton	181	3.918	5.839	0.287
Crop-specific: rice	53	10.965	12.821	0.219
Hyperparameter variant 1	1362	8.755	15.960	0.928
Hyperparameter variant 2 (baseline: 350 trees, min_samples_leaf=2)	1362	8.840	16.198	0.926
Hyperparameter variant 3	1362	9.209	17.325	0.916
Hyperparameter variant 4	1362	8.903	16.235	0.926
Hyperparameter variant 5	1362	9.389	17.087	0.918
Hyperparameter variant 6	1362	8.807	16.115	0.927
Hyperparameter variant 7	1362	8.850	16.210	0.926
Functional form: Random Forest	1362	8.442	15.454	0.928
Functional form: linear regression	1362	12.232	18.560	0.896

Note – Compiled by the author using QŪNAR crop-model validation results. The functional-form comparison uses one-hot encoding of district and crop and standardized numerical predictors; therefore its metrics differ slightly from the primary specification.

The high pooled R^2 mainly reflects differences in yield levels between crops: the median district-crop baseline already reaches $R^2 = 0.914$. The gain of the Random Forest over this baseline is assessed by the skill score (3.43), and the crop-specific R^2 values (0.219-0.516) are the relevant measure of forecasting quality for an individual crop.

Methodologically, these results show that the model does not depend on an arbitrarily narrow seasonal boundary: the main climatic signal does not change substantially when the seasonal window is extended by one month. April-September can therefore be used as a standard baseline, although March and October are not biologically negligible.

Predictive validation addressed two aspects: average performance and temporal transferability. The main validation used GroupKFold with the calendar year as the grouping variable, so that all observations of a given year were placed in

the same set rather than split between training and validation. This prevents temporal leakage, which could overestimate performance when district-crop observations of the same year share similar climatic conditions.

The main pooled result for the 2004-2025 crop panel was:

R^2=0.9263, MAE=8.84 c/ha, RMSE=16.20 c/ha.

The grouped median district-crop baseline gives R^2=0.9142. This non-machine-learning benchmark has a higher RMSE and a lower coefficient of determination than the Random Forest, but a marginally lower MAE. This mixed result is reported directly, because no single error metric fully measures prediction quality: the Random Forest explains overall variance better and makes fewer large errors (RMSE), while the baseline is competitive in mean absolute error.

Temporal transferability was then tested with three expanding out-of-sample five-year blocks: the first model was trained on 2004-2010 and tested on 2011-2015, the second trained on 2004-2015 and tested on 2016-2020, and the third trained on 2004-2020 and tested on 2021-2025. In all three blocks, the test period was not used in estimation.

The corresponding R^2 values were 0.9494, 0.8912 and 0.8079. The gradual decrease in later periods has an analytical explanation: the most recent years show the greatest deviation of production conditions, technology, climatic variability and agricultural structure from the historical relationships learned in earlier years. The decrease therefore indicates temporal non-stationarity rather than invalidating the model.

The crop-specific out-of-sample R^2 values are shown in accordance with Figure 3.15.

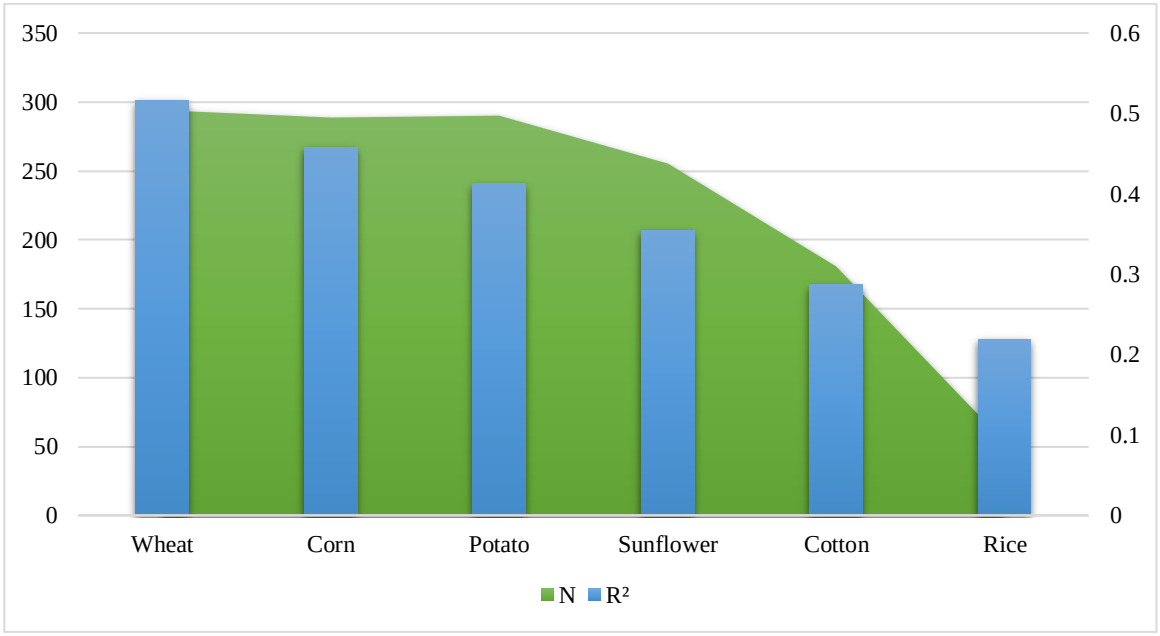


Figure 3.15 – Crop-specific out-of-sample R^2

Note – Compiled by the author using QŪNAR crop-specific out-of-sample validation results.

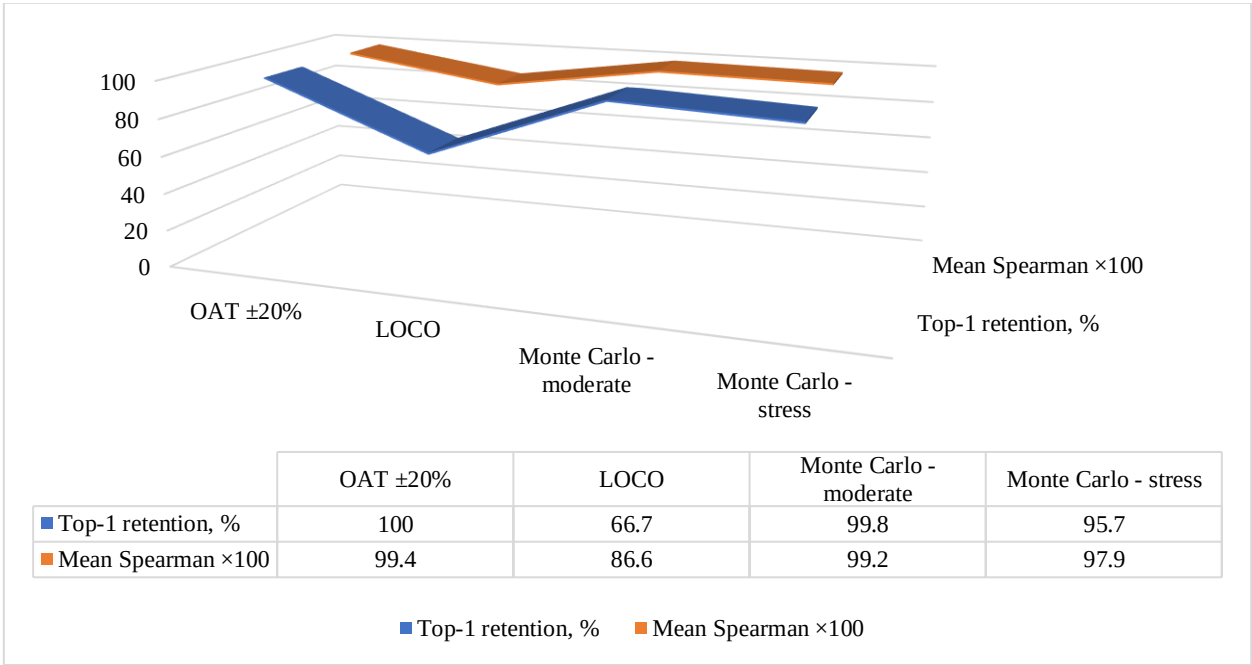
A separate ten-year stress holdout, trained on 2004-2013 and tested on 2014-2023, produced R^2=0.8499. The median baseline's corresponding R^2 was 0.8214. The result confirms that the Random Forest retains its explanatory capacity over a relatively long unseen period, but also shows that predictive uncertainty increases with the temporal distance between training and application.

The robustness to hyperparameters was tested with different Random Forest settings: varying the minimum leaf size, maximum tree depth, feature sampling and number of trees gave a relatively narrow range of grouped R^2 values (0.916-0.928). The baseline setting of 350 trees with at least two observations in terminal leaves therefore does not represent a single-point optimum. Similar performance across specifications suggests that the predictive result is driven by the data rather than by tuning to a single combination of parameters.

The overall performance should not be used to judge prediction accuracy for all crops; the crop-specific GroupKFold results in accordance with Figure 3.15 are therefore considered separately.

The highest R^2 for any crop occurred in wheat with an R^2 value of 0.516, compared to 0.458 in corn, 0.412 in potato, 0.354 in sunflower, 0.287 in cotton and 0.219 in rice. The pooled R^2 is much higher, because the model explains general differences in district-crop production levels, whereas variation within individual crops is far harder to explain.

The stability of the ranking under perturbations is shown in accordance with Figure 3.16.



	OAT ±20%	LOCO	Monte Carlo - moderate	Monte Carlo - stress
Top-1 retention, %	100	66.7	99.8	95.7
Mean Spearman ×100	99.4	86.6	99.2	97.9

Figure 3.16 – Ranking stability under perturbation regimes

Note – Compiled by the author using QŪNAR robustness analysis results.

The difference between pooled and crop-specific performance sets an important interpretive boundary. QŪNAR is best suited as a comparative decision-support tool for territories and crop alternatives, while numerical yield forecasts for individual crops, especially rice and cotton, should be treated with greater uncertainty. The model therefore reports confidence levels separately instead of one overall accuracy value presented as equal for all crops.

One reason is the relatively small number of rice observations: 53, compared with about 289-294 for wheat, corn and potato. A smaller sample covers a narrower range of climatic and territorial conditions for training and makes out-of-sample estimates less stable. The correct response is to report this limitation rather than enlarge the sample artificially by imputing or synthesizing yield values.

The validation results confirm that the predictive part of the integrated model can be based on Random Forest and also explain why the final decision cannot rely on yield prediction alone: prediction uncertainty differs between crops and years, and resource feasibility may conflict with the production potential estimated by the machine-learning component. The next step is therefore to test the stability of the decision layer under changes in assumptions, weights and constraints.

The decision layer of QŪNAR was assessed separately from the predictive layer, because more accurate predictions do not necessarily mean a more stable structure of recommendations: good statistical predictability does not guarantee stable rankings, and a small change in weighting assumptions can change the preferred crop structure. Sensitivity analysis, stochastic perturbation and optimizer verification of the decision layer were therefore performed.

The results are summarized in Table 3.10.

Table 3.10 – Decision-layer sensitivity and optimizer verification

Scenario / item	Mean Spearman	Top-1 retention	Mean Top-3 overlap	Max rank shift (OAT, LOCO) / mean of maximum shifts (Monte Carlo)	Numerical result
OAT ±20%	0.994	1	0.984	3	-
Leave-one-component-out	0.866	0.667	0.824	13	-
Monte Carlo - moderate	0.992	0.998	0.964	4.588	-
Monte Carlo - stress	0.979	0.957	0.929	6.529	-
Automated tests	-	-	-	-	68
Maximum share-sum error	-	-	-	-	$2.22 \cdot 10^{-16}$
Maximum area-sum error	-	-	-	-	$2.84 \cdot 10^{-14}$
Detected constrained infeasible cases	-	-	-	-	11

Note – Compiled by the author using QŪNAR sensitivity analysis, Monte Carlo simulation and optimizer verification results.

In the current specification of QŪNAR, climatic suitability and water pressure are the two key decision coordinates used to rank alternatives, with weights of 0.60

and 0.40, respectively. Assessment confidence is reported separately and is not part of the attractiveness component.

This separation is deliberate: confidence describes the strength of the evidence behind a recommendation, while the climate-water score describes the desirability of the alternative.

Including data completeness directly in the attractiveness objective would have an undesirable effect, making an alternative with complete data appear more desirable than one with incomplete data. QŪNAR therefore separates the question «How suitable is this option?» from the question «How certain is the system about this assessment?».

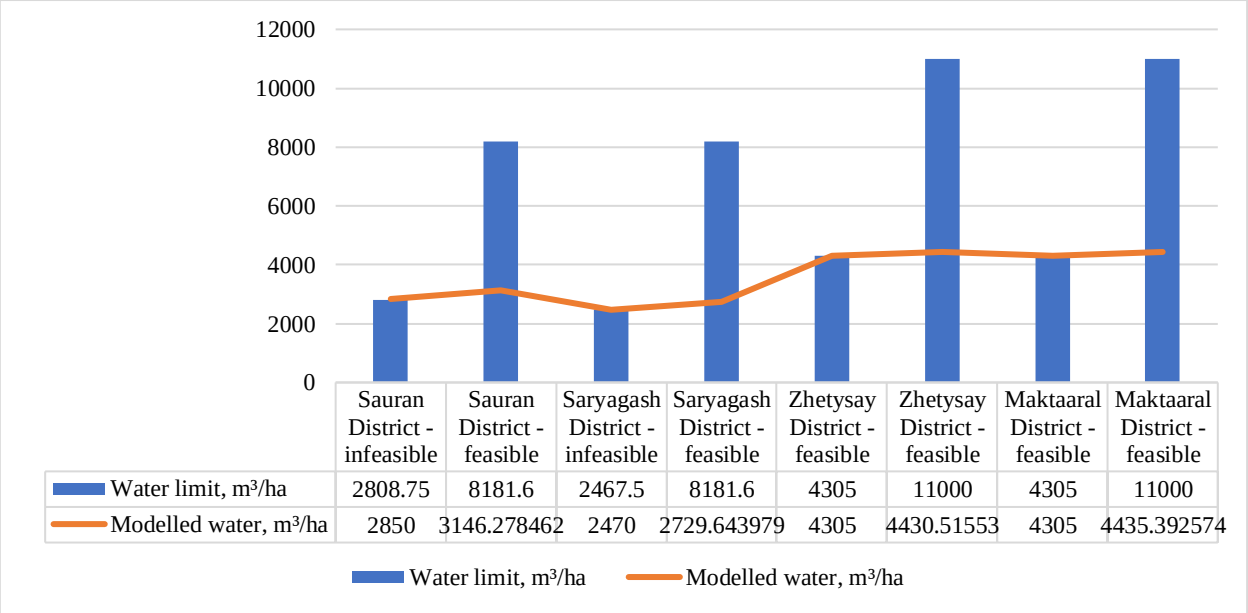
The normalized resource-climate utility for crop c in district d can be represented as:

$$U_{dc} = 0.60\, C_{dc} + 0.40\, (1 - WP_{dc}), \tag{3.32}$$

where C_{dc} is the normalized climatic-suitability component;
WP_{dc} is normalized water pressure.

Equation (3.32) represents the current operational decision baseline; the two weights are not universal agronomic constants. Their function is to balance climatic compatibility and irrigation pressure in a transparent and repeatable way, and robustness analysis therefore examines whether the ranking is sensitive to perturbations of these assumptions.

The comparative stability results are shown in accordance with Figure 3.16, and the optimizer performance under water constraints in accordance with Figure 3.17.



	Sauran District - infeasible	Sauran District - feasible	Saryagash District - infeasible	Saryagash District - feasible	Zhetysay District - feasible	Zhetysay District - feasible	Maktaaral District - feasible	Maktaaral District - feasible
Water limit, m³/ha	2808.75	8181.6	2467.5	8181.6	4305	11000	4305	11000
Modelled water, m³/ha	2850	3146.278462	2470	2729.643979	4305	4430.51553	4305	4435.392574

Figure 3.17 – Optimizer performance under water constraints

Note – Compiled by the author using QŪNAR water-constraint verification results.

In the first test, one-at-a-time perturbations of ±20% were applied to the main decision parameters. The mean Spearman rank correlation was 0.994, and the top-ranked alternative was retained in all tested cases; the mean overlap of the three highest-ranked alternatives was about 0.984, and the maximum rank shift was 3 positions. These values show that the overall ranking is little affected by moderate local changes.

The effect was larger in the more demanding leave-one-component-out test: the mean Spearman correlation fell to about 0.866, top-rank retention to 0.667, and the maximum rank change was 13. This is expected, because removing an entire decision component is a structural intervention rather than a small perturbation. The test therefore does not indicate numerical fragility; it shows that both climatic suitability and water pressure carry substantive information and that the recommendation naturally changes when either is deliberately omitted.

Stochastic robustness was also tested by Monte Carlo perturbations. In the moderate perturbation regime, top-rank retention was about 0.998 and the mean Spearman correlation 0.992; in the more severe stress regime, the same indicators remained high at about 0.957 and 0.979. The mean overlap of the three highest-ranked alternatives was about 0.964 under moderate perturbation and 0.929 under stress.

Overall, the results show that the recommendation structure is robust to reasonable local uncertainty in model parameters but responds correctly when a whole information block is removed. This is crucial: rankings that never changed under changing conditions would be uninformative, while rankings that changed considerably after very small perturbations would be unreliable. The QŪNAR decision layer lies between these extremes – it is protected against moderate parameter noise but sensitive to substantive changes in the decision environment.

The optimization problem can be expressed compactly as:

$$\max_{\mathbf{x}} \sum_{c=1}^{n} x_c \, [U_{dc}], \tag{3.33}$$

$$\text{s.t.} \quad \sum_{c=1}^{n} x_c = A,$$

$$\sum_{c=1}^{n} x_c \, w_c \le W^{avail},$$

$$0 \le x_c \le \bar{s}_c A,$$

$$\sum_{c=1}^{n} \mathbb{I}\,(x_c > 0) \ge K_{min},$$

where x_c is the land area allocated to crop c;
A is the total available cultivated area;

U_{dc} is the resource-climate utility;
w_c is the crop-specific water requirement;
W^{avail} is the aggregate irrigation-water budget available to the farm for the considered production season;
$\bar{s}_c$ is the maximum permitted share of crop c;
K_{min} represents the minimum diversification requirement where such a constraint is activated.

The core economic-mathematical principle of QŪNAR is that an agricultural option is not chosen merely because of a favourable climate score (equation 3.32); the expected yield enters the decision through the contribution margin (3.46), (3.47), and the option must also be feasible with the available land and water resources of the specific production system.

The water constraint is especially important in practice. The user does not need to decide in advance how much of the farm's irrigation water will be used for wheat, cotton, corn or another crop: the seasonal water budget is entered once in aggregate, and the water distribution among crops results endogenously from the optimized allocation.

This design considerably reduces the information burden on users. A farmer usually knows the available area and the irrigation water available for the season better than the optimal distribution of that water among several crops; requiring the user to provide this distribution would transfer part of the optimization problem to the user and reduce the advantage of the decision-support system.

The water requirement used in the constraint does not have to be measured historical consumption. If the producer provides reliable data on actual water use, these data are used in the resource-accounting layer; otherwise, QŪNAR uses an explicitly identified normative or reference requirement. The model therefore treats observed use, available water and normative demand as three different quantities.

This distinction can be written as:

$$W_c^{obs} \neq W_c^{norm} \neq W^{avail}, \tag{3.34}$$

where W_c^{obs} denotes actual crop-specific water use when known;
W_c^{norm} represents the normative or reference requirement;
W^{avail} is the total water volume available to the production system.

Deliberately restrictive water scenarios were also added for verification, and all 11 test cases were correctly identified as infeasible. This is methodologically important, because the optimizer should not always return a feasible allocation: if the specified crop structure, minimum diversification rule, land area and water budget cannot be satisfied together, the correct mathematical result is infeasibility.

An infeasibility signal is not a computational error but a result of the decision process: it shows the user that the stated production requirements and the resource constraint cannot be met simultaneously. The farmer can then change the candidate crop mix, reduce the land area, relax a structural limitation, adopt a less water-demanding irrigation technology or reconsider the water budget.

This logic makes scarcity prescriptive rather than descriptive by turning it into an active boundary of the solution space: water limitation is not merely expressed as a high or low index but can make some production structures impossible.

The same applies to maximum crop-share restrictions. Without upper bounds on shares, a purely numerical optimizer could allocate almost all land to a crop with a very high score, which may be optimal for the objective function but undesirable for production risk, crop rotation or strategic diversification. When diversification is required, QŪNAR allows a maximum crop share and a minimum number of crops to be specified.

The resulting allocation is therefore not a universal prescription to replace other crops; it is a conditional solution for a given district, season, land area, water availability, crop set and structural restrictions, and a change in any of these conditions may lead to a different recommended structure.

Energy is a resource dimension parallel to the hard irrigation constraint but treated differently mathematically. When actual energy consumption is known, it is entered for the full production cycle, including energy used for pumping, irrigation, mechanized cultivation, field operations and other processes directly attributable to production.

Purchased electricity is clearly separated from solar radiation: NASA POWER surface solar radiation is a climatic predictor of the crop-yield model, while kWh are an operational production input. The two variables have completely different meanings, although both relate to energy in a general sense.

When electricity consumption is available, operational carbon emissions are estimated as:

$$E^{CO_2} = E^{el} \cdot EF^{el}, \tag{3.35}$$

where E^{el} is electricity consumption;
EF^{el} is the applicable electricity emission factor.

The default emission factor is 0.813 kg CO_2/kWh, the carbon intensity of electricity generation in Kazakhstan in 2025 [105]. QŪNAR treats this coefficient as an externally set conversion value rather than a production or biological coefficient estimated by the machine-learning model, and it does not present the emission estimate as an observed farm value when energy use is unknown.

The same principle applies to the water reuse indicator, which shows the share of supplied water that is recovered and reused in the water supply system. It is included because gross water withdrawal differs from net freshwater pressure: a system with water recycling may use less external water than a system without recycling, even if their total process requirements are the same.

At the same time, QŪNAR does not assume water reuse by default: the indicator is used only when the user provides a meaningful value or the scenario specifies a reuse assumption.

Environmental indicators are deliberately not filled with synthetic placeholders. Pesticide intensity, degradation indicators and salinity are assessed

when supporting information exists; otherwise, the indicator is reported as unavailable. This rule avoids a common analytical error in which missing data in a multidimensional index are treated as zero and then interpreted as no environmental pressure.

Land concentration is additionally characterized through a diversification measure derived from the Herfindahl-Hirschman structure of allocated crop shares:

$$HHI = \sum_{c=1}^{n} s_c^2 , \qquad N_{eff} = \frac{1}{HHI}, \tag{3.36}$$

where s_c is the share of crop c in total allocated land;
N_{eff} represents the effective number of equally represented crop alternatives.

The measure must be distinguished from measures of biological diversity. A lower HHI indicates a more even distribution of land among alternatives, and a higher HHI a more concentrated one; the effective-number transformation gives a more intuitive interpretation of the same concentration pattern.

This distinction is scientifically essential. Crop diversification protects farmers against some risks, but an allocation-based HHI does not measure ecological biodiversity, genetic diversity or ecosystem quality and does not guarantee higher production resilience. In QŪNAR, the indicator is therefore used only in its structural sense.

The livestock component is a separate resource-prognostic contour because livestock production has a different temporal and biological structure than crop production. Transferring the crop-yield model to livestock categories would not adequately represent the persistence, breeding cycles and lagged adjustment of herd dynamics.

The livestock analytical base contains district herd histories, lagged herd indicators and climatic information, and rolling-origin validation ensures that each forecast uses only data preceding the test observation. The pooled log-scale fit of about 0.949 mainly reflects differences in herd size between species and is not used as a measure of forecast quality: the species-specific rolling-origin R^2(log) ranges from 0.666 (cows) to 0.893 (camels) with median APE from 5.8% to 21.6% (Table 3.2), and for pigs the model has no predictive value.

The model scope, evidence levels and methodological safeguards are summarized in Table 3.11.

The performance differs considerably between animal groups. QŪNAR therefore has a forecast guard that downgrades a numerical forecast when validation evidence is insufficient. The pig series is the clearest case: it is not reliable enough for prediction, and the system does not present a numerical forecast for pigs as if it had the same evidential strength as more successful livestock series.

This safeguard is conceptually important for the whole QŪNAR architecture. The model can give three types of results: a numerical result with adequate evidence; a conditional (low-confidence) result with an explicit warning; or no numerical

prediction because of inadequate evidence. A missing number can thus be a scientifically preferable outcome to false precision.

Table 3.11 – Model scope, evidence levels and methodological safeguards

Model element	Scientifically defensible claim	Prohibited overclaim
1	2	3
Crop yield ML	Conditional predictive performance	Causal climate effects or equal accuracy for all crops
Crop decision layer	Comparative resource-climate suitability	All decision-layer crops are ML-calibrated
Barley	Resource-climate comparison only	Independent ML yield forecast for barley
Water	Feasibility under the stated water budget	Normative values reported as historical farm water use
Energy	Operational energy/economic scenario	Measured farm energy where energy use was not entered
Environment	Evidence-supported environmental diagnostics	Complete ecosystem condition inferred from missing data
Livestock	Species forecast where validation permits	Numerical forecast for species with weak validation (pigs)
Optimization	Feasible allocation under stated assumptions	Universal optimum for all farms and future climates
QŪNAR score	Relative resource-climate suitability	Absolute measure of profitability

Note – Compiled by the author based on QŪNAR validation results and methodological limitations.

Table 3.11 defines these boundaries more precisely than a generic description of model limitations. The crop-yield machine-learning core is calibrated on the verified 2004-2025 panel for six crops and 17 territories. Other crops can be included in the resource-climate decision environment when sufficient reference information exists, but without an independently validated machine-learning yield forecast for each crop shown in the software.

Barley is not included in the crop-yield ML core because its yield series duplicates the wheat series in all overlapping observations, and retaining it as an independent target would artificially duplicate information and evidence of predictive performance. The exclusion therefore reflects data-quality protection, not the economic or agronomic unimportance of barley in Turkestan region.

The model is currently calibrated for open-field crop production. Greenhouse production would require a separate specification with controlled temperature, ventilation, heating, artificial lighting, protected irrigation, humidity control and, if necessary, several production cycles per year; adding a greenhouse component to the existing open-field function without separate calibration would be methodologically inconsistent.

Another limitation concerns antecedent climatic conditions. The robustness test shows that a wider climate window (March-October instead of April-September) does not significantly change predictive performance, but this does not mean that

autumn establishment or winter conditions are unimportant. Winter wheat, in particular, may respond to pre-winter soil moisture, winter temperature extremes and overwintering conditions, which are not currently represented as a separate antecedent block.

Their future inclusion is not assumed a priori: a more complex specification is scientifically better only if it adds stable information, and additional variables make the model more complex without necessarily improving its generalizability.

The temporal limitation is therefore explicit: the current crop ML core of QŪNAR uses a standardized representation of the active climatic season, while the resource-accounting layer covers the whole crop production cycle. The two time boundaries differ deliberately because they represent different phenomena.

The quality of external statistical and climatic data is also crucial. Official agricultural records, NASA POWER observations and normative resource parameters are not controlled by the model developer. QŪNAR can identify missing values, duplication, inconsistent coverage and implausible structure but cannot reconstruct a correct historical series when the original source does not contain sufficient information.

Data-quality control is therefore an integral component of the model rather than a preliminary technical procedure: depending on its analytical status, an observation is accepted, flagged, excluded from calibration or retained only for a lower-evidence decision layer.

The complete model can therefore be expressed as a sequence of transformations rather than a single prediction equation:

$$\mathcal{D}_t \overset{\mathcal{V}}{\rightarrow} \widetilde{\mathcal{D}}_t \overset{\mathcal{P}_{RF}}{\rightarrow} \widehat{\mathrm{Y}}_t \overset{\mathcal{R}}{\rightarrow} \mathrm{U}_t \overset{\mathcal{F}}{\rightarrow} \Omega_t \overset{\mathcal{O}}{\rightarrow} \mathrm{x}_t^* \overset{\mathcal{E}}{\rightarrow} (\mathrm{x}_t^*, \mathrm{R}_t, \mathrm{Q}_t, \mathrm{C}_t), \tag{3.37}$$

where $\mathcal{D}_t$ is the initial agricultural, climatic and resource information set;
$\mathcal{V}$ is the validation and preprocessing operator;
$\widetilde{\mathcal{D}}_t$ is the verified analytical information set;
$\mathcal{P}_{RF}$ is the machine-learning prediction operator;
$\widehat{\mathrm{Y}}_t$ is the vector of supported production forecasts;
$\mathcal{R}$ transforms the verified information into resource-climate utilities U_t;
$\mathcal{F}$ generates the feasible set Ω_t under land, water and structural restrictions;
$\mathcal{O}$ is the constrained optimization operator;
x_t^* is the resulting agricultural allocation;
$\mathcal{E}$ generates the final set of recommendations, resource balances R_t, evidence-quality indicators Q_t and environmental diagnostics C_t.

Equation (3.37) expresses the main methodological contribution of QŪNAR: the economic-mathematical model is not limited to prediction, and prediction is only an intermediate step in a sequence of feasibility tests, measurement of resource pressure, evidence analysis and constrained agricultural decision-making.

This also distinguishes QŪNAR from a traditional crop-yield forecasting application. Instead of a single predicted value in centners per hectare, it produces a

structured decision package that may include the predicted production potential, climate-water suitability, expected resource demand, land allocation, water feasibility, energy implications, environmental indicators, confidence information and explicit warnings when the evidence is inadequate.

The recommendation must therefore be interpreted conditionally: it is the best solution for the given land and water, the selected crops, the decision weights and constraints of the scenario and the calibrated predictive relationships, not a universal production optimum for all farms and all future climatic conditions.

The value of this conditional result lies in its ability to show trade-offs. Under resource scarcity, there is usually no single alternative that dominates on all criteria: one may be the most climatically suitable, another may use less water and yield less but remain viable, and a third may have high potential but increase structural concentration. The optimization shows these conflicts instead of hiding them in one descriptive indicator.

The model thus becomes an empirical-to-operational decision framework that links climate, water, land, energy and production capacity in a formally bounded system: machine learning provides the nonlinear predictive part, while resource accounting and mathematical optimization determine whether the predicted production possibilities can be realized within the available natural-resource base.

The result is an integrated economic-mathematical architecture that moves from past evidence to a conditional production decision with explicit information on uncertainty, resource scarcity and the limitations of input data.

The operational implementation of QŪNAR (3.38) combines four classes of information: farm-specific inputs, verified historical information, externally defined reference parameters and quantities generated endogenously by the model. They interact as follows:

$$\underbrace{x^{user}}_{\text{farm conditions}} + \underbrace{x^{hist}}_{\text{historical evidence}} + \underbrace{\theta^{ref}}_{\text{reference parameters}} \xrightarrow{Q} \underbrace{(\hat{y}, r, s, x^{*}, q)}_{\text{QŪNAR decision state}}, \tag{3.38}$$

where x^{user} contains current production and resource conditions;
x^{hist} represents the calibrated district-crop and climatic database;
θ^{ref} contains normative and conversion parameters;
$\hat{y}$ denotes supported production estimates;
r represents resource indicators;
s contains resource-climate characteristics;
x^{*} is the feasible optimized allocation;
q describes the evidential support of the result.

A basic feature of this architecture is the preservation of data provenance: observed farm consumption, normative resource requirements and machine-learning

predictions may be used in the same calculation but are not treated as identical measures, and missing information is not automatically replaced with zero.

A separation of scales is used to transfer the district-level calibration to farm-level application. The Random Forest predictor set still includes historical district-crop sown area, because the model was trained on district statistics, while the field area entered by the user is used to calculate resources and limits the area in the optimization problem. This prevents farm-level acreage from being substituted for the historical district production variable.

The temporal boundaries are also separated: the crop ML component uses the April-September climatic window, while water, energy and other direct production resources refer to the whole production cycle of the evaluated harvest. Resource use before April or after September is not included in the baseline climatic aggregation but remains in the resource assessment.

Future realized climate is not available for prospective calculations, so the historical climatic profile of the district is used as a planning baseline rather than as a forecast of future climate. Current-season calculations are preliminary, and completed-season calculations can use the full realized seasonal climatic conditions.

The distinction between observed, reference-derived and predicted quantities can be represented as:

$$\mathcal{Z}^{obs} \neq \mathcal{Z}^{ref} \neq \hat{\mathcal{Z}}, \tag{3.39}$$

where $\mathcal{Z}$ may represent water, energy, emissions or another model quantity.

For a set of candidate crops, the admissible solution space can be represented as:

$$\Omega(\mathbf{B}) = \left\{ \mathbf{x}: \sum_{c=1}^{n} x_c = A^{farm},\ \sum_{c=1}^{n} w_c\, x_c \leq W^{avail},\ 0 \leq x_c \leq \bar{s}_c A^{farm} \right\}, \tag{3.40}$$

where x_c is the land allocated to crop c;
A^{farm} is available cultivated area;
w_c is crop-specific water requirement;
W^{avail} is the seasonal farm water budget;
$\bar{s}_c$ is the maximum admissible crop share.

The allocation of the water budget among crops is endogenous to the optimizer and takes place at the farm level, which places the resource constraint inside the mathematical problem instead of shifting part of the resource allocation to the user.

The complete decision problem is then expressed as:

$$x^* = \arg\max_{x \in \Omega(B)} \Psi\left[\hat{Y}\left(X^{prod}, X^{clim}\right), W, E, L, Z^{env}; \theta\right], \quad (3.41)$$

where $\hat{Y}$ contains ML-supported production estimates;
W characterizes water conditions;
E characterizes energy conditions;
L characterizes land conditions;
Z^{env} contains available environmental information;
θ defines the decision configuration.

Equation (3.41) expresses the central economic-mathematical logic of QŪNAR: predicted productivity is evaluated in a limited resource environment. A crop with a substantially higher expected yield may receive a smaller allocation, and a lower-yielding crop a larger one, when their water requirements conflict with the available water budget.

The integrated computational sequence can finally be summarized as:

$$(D_t, B_t) \xrightarrow{\mathcal{V}} \tilde{D}_t \xrightarrow{\mathcal{P}} \hat{Y}_t \xrightarrow{\mathcal{R}} S_t \xrightarrow{\mathcal{F}(B_t)} \Omega_t \xrightarrow{\mathcal{O}} x_t^* \xrightarrow{\mathcal{E}} (x_t^*, R_t, Q_t), \quad (3.42)$$

where $\mathcal{V}$ denotes data verification;
$\mathcal{P}$ the predictive operator;
$\mathcal{R}$ formation of the resource-climate state;
$\mathcal{F}$ construction of the feasible set;
$\mathcal{O}$ constrained optimization;
$\mathcal{E}$ generation of the final resource and evidence characteristics.

The developed economic-mathematical model was implemented in the QŪNAR software environment, which performs the predictive, resource-assessment and optimization procedures in a single computational workflow and produces consistent analytical reports. The software layer is not a separate methodological element but the implementation of the model as a computer program.

The scientific contribution of QŪNAR is the shift from agricultural prediction to a resource-constrained decision state: climatic and production information determine plausible production outcomes, while land and water scarcity determine which of them are feasible. The recommended outcome is therefore conditional on the input resource environment, the calibrated functional relationships and the structural constraints.

This formulation allows productive potential to be assessed in a region such as Turkestan, where water scarcity and spatial climatic heterogeneity limit agricultural development. The model represents uncertainty, handles infeasibility, distinguishes observed from estimated information and does not give variables more precision than the evidence supports.

The validation results were additionally checked from three perspectives (3.43)-(3.45): the gain of the Random Forest over the non-ML benchmark, the spatial transferability of the forecast and the uncertainty of an individual forecast.

Since the median district-crop baseline already reproduces a large part of the pooled variance (R^2=0.914), the contribution of the Random Forest is measured by the skill score:

$$\mathrm{SS} = 1 - \frac{\mathrm{RMSE_{RF}}^2}{\mathrm{RMSE_{base}}^2}, \tag{3.43}$$

where $\mathrm{RMSE_{RF}}$ and $\mathrm{RMSE_{base}}$ are the root mean squared errors of the Random Forest and of the baseline in the same GroupKFold scheme. For the crop panel SS=1−16.198²/17.473²≈0.14, that is, the Random Forest reduces the mean squared error by about 14% compared with the baseline. The high pooled R^2 therefore mainly reflects persistent differences between crops and districts, and the crop-specific values of R^2 (0.219–0.516, Table 3.9) are the relevant measure of the forecasting quality for an individual crop.

Spatial transferability was tested by leave-one-district-out validation, in which the model is trained without territorial unit d and tested on the observations of this unit:

$$R_{-\mathrm{d}} = 1 - \frac{\sum_{\mathrm{i}\in\mathrm{d}}(Y_i - \hat{Y}_i^{(-\mathrm{d})})^2}{\sum_{\mathrm{i}\in\mathrm{d}}(Y_i - \overline{Y_d})^2}, \tag{3.44}$$

where Y_i is the observed yield and $\hat{Y}_i^{(-d)}$ is the yield predicted by the model trained without unit d. The median R^2 for the 17 territorial units is 0.863, and in 15 of 17 units it exceeds 0.70 (Table E.1, Appendix E). The weakest results were obtained for Otyrar District (R^2=−0.99; only 11 observations are available because the crop series of the district are short and contain gaps) and Sauran District (R^2=0.66 with 24 observations; the district was formed in 2021), where the historical sample is short. Therefore, for territories with fewer than 20 observations or with R^2 below 0.5 in this test, QŪNAR reports the forecast with a lower confidence status, and the recommendations are based mainly on the resource constraints.

The uncertainty of an individual forecast is represented by an empirical 90% interval based on the absolute grouped out-of-sample residuals e_c of crop c:

$$\mathrm{PI}_c = \hat{Y}_c \pm q_{0.90}(|e_c|), \tag{3.45}$$

The half-width of the interval is 7.9 c/ha for wheat, 14.8 c/ha for corn, 7.8 c/ha for cotton, 5.4 c/ha for sunflower, 20.9 c/ha for rice and 56.7 c/ha for potato, and the empirical coverage is 0.89–0.90 for all crops (Table E.2).

The out-of-fold permutation importance (decrease of R^2 in the test fold when one variable is randomly permuted) shows that the level of yield is determined mainly by crop identity (1.887), and then by district (0.041) and historical sown area (0.041), while root-zone wetness (0.008), solar radiation (0.008), temperature (0.005) and precipitation (0.001) have smaller importance (Table E.3). Therefore,

the climatic variables explain the year-to-year deviations within the crop-district profile rather than the yield level, which is consistent with the crop-specific R^2. For the same reason the VIF is used in the dissertation only as a diagnostic of interpretability of the climatic block and not as a condition of the Random Forest.

The relatively low crop-specific R^2 values, especially for rice and cotton, mean that the yield forecast is used in QŪNAR as a climate-dependent reference value with an uncertainty interval, and not as an exact forecast for a specific farm. The allocation is based mainly on the resource-climate utility and the hard land and water constraints (3.32), (3.33), while the yield enters the decision through the contribution margin. When the farm enters its own yield, this value is used in the economic calculation, and the model forecast is shown separately as a climatic reference. Therefore, forecast errors affect mainly the economic estimate, which is presented together with the 90% interval (3.45). The machine-learning yield component covers six crops with sufficient statistical series; other crops (vegetables, melons, fruits and forage crops) are assessed by water norms and climatic suitability with a lower confidence status. Thus QŪNAR is a tool for comparative planning of crop structures rather than for exact yield forecasting on a specific farm. The crop-specific accuracy is lower than in studies that use satellite indicators: for example, county-level machine-learning models of wheat yield in China reached R^2 of about 0.60 with solar-induced chlorophyll fluorescence [7]. The difference is explained by the absence of remote-sensing predictors and the smaller district panel of Turkestan region, which is why the forecast is used with an uncertainty interval.

In addition to the GroupKFold validation by years (MAE 8.84 c/ha), a sequential time validation was carried out, in which the models were trained on earlier years and tested on the next five-year period (2011-2015, 2016-2020 and 2021-2025); the results of the two schemes are not directly comparable. Random Forest was compared with six alternatives: Random Forest for separate crops, ExtraTrees, CatBoost, HistGradientBoosting, Ridge regression and the historical median of the district and crop (Table E.4). In all three periods, Random Forest has a lower error than the historical median (7.14 against 7.75; 11.94 against 13.31; 16.70 against 16.88 c/ha, Table 3.9), while ExtraTrees is slightly better only in the last period (15.90 c/ha). Therefore, Random Forest is kept as the main model. For rice, none of the methods gives a reliable forecast because of the small number of observations.

In the current version of QŪNAR the optimization objective also includes an economic component. When the user enters verified selling prices and variable costs, the contribution margin of crop c per hectare is calculated as:

$$M_c = p_c \cdot Y_c - v_c, \tag{3.46}$$

where p_c is the selling price, Y_c is the expected yield and v_c is the variable cost per hectare. The objective coefficient of the crop then combines the resource-climate utility (3.32) and the normalized margin:

$$O_c = (1-\lambda)\cdot U_c + \lambda \cdot E_c, E_c = \frac{M_c - M_{\min}}{M_{\max} - M_{\min}} \cdot 100, \quad (3.47)$$

where E_c is the contribution margin normalized within the candidate set and λ is the economic weight (λ=0 in the resource-climate mode, 0.35 by default in the balanced mode and 0.70 in the economic-priority mode). If economic data are entered for fewer than two crops, the model returns to the resource-climate objective and does not use proxy prices. The economic result of the recommended structure x_{rec} is compared with the current structure of the farm x_{base}:

$$\Delta M = \sum_c M_c x_{c,\text{rec}} - \sum_c M_c x_{c,\text{base}}, \quad \text{MPW} = \frac{\sum_c M_c x_c}{\sum_c w_c x_c}, \quad (3.48)$$

where ΔM is the change in contribution margin of the farm and MPW is the margin per cubic metre of irrigation water. The change in irrigation water demand is calculated in the same way with the coefficients w_c. An increase in natural resource efficiency is recorded when MPW increases and the water demand does not exceed the available water budget; an example of such a comparison is given in Appendix D. In the example of a demonstration farm in Sauran District (Tables D.2, D.3), switching 10 ha of wheat from furrow to drip irrigation reduces water delivery from 35,500 to 28,400 m³ per season, but with the extra technology costs of 10,000 KZT/ha the margin decreases by about 91,800 KZT (electricity use is kept unchanged, because drip irrigation requires additional pressure); under the stress test (price −10%, yield −10%, costs +10%) the decrease is about 100,900 KZT. Thus, the model shows the water saving and its cost separately and does not present a resource saving as a profit gain. If the water saving of 7,100 m³ is supplied by an own pump with a head of 25 m and an efficiency of 65%, the energy for pumping is 0.002725·25/0.65 = 0.105 kWh/m³ [106]; the saving then corresponds to about 744 kWh of electricity and 0.6 t of CO_2 per season at the emission factor of 0.813 kg CO_2/kWh [105] (3.35), which is the mitigation component of the model. In the partial greenhouse-gas inventory of the same plot, a 10% lower nitrogen rate and a lower diesel use reduce emissions from 6.38 to 6.04 t CO_2e per season (Table D.2). In the optimization of 100 ha with a water budget of 300,000 m³, QŪNAR allocates the area to sunflower, other oilseeds, wheat, potato and barley; when the budget is reduced by 20%, no feasible structure exists, because even the least water-intensive crops require about 267,500 m³ for the whole area (Table D.7).

The examples also show that the resource-efficient solution is not always the most profitable for the producer in the short term. In the Sauran example drip irrigation saves 20% of water but lowers the margin, and in the representative farm of Maktaaral District the economic optimum increases the margin but also increases water use and partial emissions (Table D.8). Therefore, QŪNAR shows this trade-off explicitly, and the economic choice of the producer is considered only within the resource-feasible set.

In addition to the resource-climate and economic modes, QŪNAR includes a sustainable compromise mode and a partial carbon footprint of the crop structure. The partial footprint covers direct N_2O emissions from nitrogen fertilizers, CO_2 emissions from diesel fuel and CO_2 emissions from electricity used for pumping irrigation water [107; 108]:

$$E = \sum_c x_c(0.01 \cdot 44/28 \cdot 273 \cdot N_c + 2.68 \cdot D_c + e_p \cdot w_c \cdot g) \quad (3.49)$$

where E is the partial carbon footprint of the structure, kg CO_2e; Nc is the nitrogen rate, kg N/ha; Dc is the diesel consumption, l/ha; ep is the energy for pumping, kWh/m³, calculated as $0.002725 \cdot H/\eta$, where H is the pumping head, m, and η is the efficiency of the pumping unit [106]; g is the emission factor of electricity, kg CO_2/kWh (0.813 for Kazakhstan in 2025 [105]); 0.01 is the default emission factor of N_2O-N from applied nitrogen, 44/28 converts N_2O-N to N_2O and 273 is the global warming potential of N_2O [109]. For flooded rice the factor 0.004 is used instead of 0.01 [107].

In the sustainable compromise mode the contribution margin is maximized under the condition that water use and partial emissions do not exceed the baseline structure and the margin does not decrease more than the allowed share δ:

$$\begin{aligned} &max\ M(x), \qquad W(x) \le W_0, \qquad E(x) \le E_0, \\ &M(x) \ge (1-\delta) \cdot M_0 \end{aligned} \quad (3.50)$$

where M(x), W(x) and E(x) are the margin, irrigation water and partial emissions of the structure x; W0, E0 and M0 are the same indicators of the baseline structure; δ is the allowed decline of the margin set by the user. If the constraints are not compatible, the model reports that there is no feasible solution.

The mode was tested on a representative farm of 100 ha in Maktaaral District with cotton, corn and wheat (Table D.8). The producer prices of 2025 for Turkestan region [84], the average district yields for 2023-2025 and the official water norms were used. The water tariff of 1.16 KZT/m³ for gravity supply of the Turkestan branch of RSE «Kazvodkhoz» (tariff estimate approved by Order of the Committee for Regulation of Natural Monopolies № 27-NN of 25.06.2024) [110] and the electricity tariff of 41.06 KZT/kWh [111] (both without VAT) were applied, and the farm supplies water with its own pump (head 25 m, efficiency 65%). The baseline structure (50%, 30% and 20%), variable costs, nitrogen and diesel rates are scenario assumptions for the demonstration of the model. The economic optimum increases the margin by 6.6%, but water use and partial emissions increase by 3.4%. The sustainable compromise increases the margin by 1.6% and reduces water use by 0.4% without an increase of partial emissions. Under the CMIP6 scenarios the irrigation requirement was increased in proportion to the reference evapotranspiration by the Hargreaves temperature relation $(T+\Delta T+17.8)/(T+17.8)$ [112]: by 4.6% under SSP2-4.5 and by 6.1% under SSP5-8.5. For the demonstration

plot in Sauran District, QŪNAR shows a similar increase of the reference evapotranspiration: by 5.2% under SSP2-4.5 and by 6.9% under SSP5-8.5 (Table D.4); the water indicators used in the reports are explained in Table D.5. If the margin is not allowed to decrease, there is no structure that keeps the water budget of 750 thousand m³ and the current level of partial emissions in both scenarios. When a decrease of the margin up to 5% is allowed, the feasible structures shift from corn to wheat, keep the emissions at the current level and use 735.6 and 739.9 thousand m³ of water, while the margin decreases by 2.7% and 4.2% compared with the current baseline. Under the combined stress (water −20%, yield −10%, costs +10%) the feasible structure shifts to wheat and the margin decreases by 56.8%. These results are scenario calculations under the stated assumptions and not measured effects of implementation.

The sensitivity of the final structure to the economic weight λ is shown in Table E.5. When λ increases from 0 to 0.35, the structure shifts from wheat and corn to cotton, and from λ = 0.50 it coincides with the economic optimum; the margin increases from 11.7 to 21.8 million KZT, but water use increases from 546.9 to 750.0 thousand m³ and partial emissions from 88.5 to 120.2 t CO_2e. The comparison with simple planning strategies (Table E.6) shows that the sustainable compromise keeps the margin close to the economic optimum (20.75 against 21.77 million KZT) with lower water use and emissions, while the water-minimizing structure uses 25% less water than the baseline structure but reduces the margin by 43%. Without re-optimization only the water-minimizing structure keeps the reduced water limit under the combined stress and SSP2-4.5; the compromise structure exceeds the SSP2-4.5 limit by 5.7 thousand m³. Therefore, the value of QŪNAR lies not in one structure being always the best, but in the fact that the model shows the economic, water and emission trade-offs and finds a new feasible structure when the constraints change, if such a structure exists (Table D.8); Table D.7 shows the cases where no feasible structure exists.

To test whether the recommendations survive the forecast error, the crop yields of the representative farm were perturbed 1,000 times within the empirical 90% prediction intervals (Table E.2). The economic optimum remained more profitable than the baseline structure in 86.5% of trials (median gain 1.34 million KZT), and the median loss compared with the ex-post optimal structure, estimated for the first 300 trials, was 0.5%. The exact crop shares, however, are sensitive to yield errors, and the margin advantage of the sustainable compromise lies within the forecast uncertainty; its value consists in keeping the margin close to the baseline without an increase of water use and partial emissions. Therefore, the recommended structures are conditional and should be interpreted together with the prediction intervals (Table E.7).

A scenario calculation was also performed in QŪNAR for the published case of LLP «Taimas-2024» in Otyrar District, where rice was grown on 400 ha with drip irrigation for the first time in Kazakhstan [113] (Table D.9). According to the published data, water use decreased from 26 to 15 thousand m³/ha. In QŪNAR this corresponds to a saving of 4.4 million m³ of water per season, about 461 thousand

kWh of electricity for pumping and about 375 t of CO_2, and the costs of water and electricity decrease by about 24 million KZT. At the same time, the published yield (50 c/ha) is lower than the district average of 2025 (60 c/ha), and at the regional price the revenue may decrease by about 73 million KZT. Thus, the real case shows that a large saving of water and emissions can be accompanied by an economic risk, and the decision on the technology requires data on the yield before the transition and on capital costs, which were not published. The calculation is performed outside the optimization layer, because rice is not included in the decision layer, and the yield forecast for Otyrar District has low reliability; the water figures are taken from the publication rather than measured, and the comparison with the district average yield is not a counterfactual comparison. Methane emissions from flooded rice, which are not included in the calculation, are usually much larger than pumping-related CO_2; therefore, the actual climate benefit of the transition to drip irrigation is likely to be higher than the estimate given here. The order of the water saving is consistent with the meta-analysis of drip irrigation in China, according to which drip irrigation saves water without yield losses compared with flood and furrow irrigation and, with sufficient water supply, increases yields by about 29% and 8%, respectively [96]; the lower published rice yield in this case therefore requires verification over several seasons.

The reference water requirements w_c are taken from the norms of water consumption for irrigation approved by Order № 108-NQ of the Minister of Water Resources and Irrigation of the Republic of Kazakhstan of 4 June 2025 (surface irrigation, automorphic soils, 50% probability) for the water-management zone of the district (Table E.8). The norms for the main crops of Maktaaral District (cotton 8,400, corn 7,450 and winter wheat 4,100 m³/ha) are the same in the new Order № 288-NQ of 9 September 2026, which has been in force since 16 September 2026. Where the order does not specify a crop or a zone, the regional benchmark of 8,181.6 m^3/ha is used and labelled as a fallback value. Rice is not included in the decision layer, because the order does not contain a directly comparable norm for the region.

The weights 0.60 and 0.40 in equation (3.32) are set as a normative baseline. A higher weight is given to climatic suitability because water availability is already included in the model as a hard constraint (3.18), (3.40), and a higher weight of water pressure in the utility would count the same resource twice. In addition to the balanced profile (0.60/0.40), QŪNAR offers the user a climate profile (0.78/0.22) and a resource profile (0.30/0.70); the resource profile gives priority to water pressure in water-deficit territories, which corresponds to the survey result where water was the most frequently named scarce resource (57.7%, Table 2.12). The weights 0.60 and 0.40 were obtained from the initial three-component scheme of QŪNAR (0.50 for climate, 0.35 for water and 0.15 for evidence reliability) after the reliability component was moved to a separate confidence indicator: 0.50/0.85 = 0.588 and 0.35/0.85 = 0.412, rounded to 0.60 and 0.40. The sensitivity tests in Table 3.10 show that the ranking is stable around the baseline. To check the weights against the opinions of the respondents, an experimental survey-based profile was calculated from the frequencies of answers on water scarcity (120 answers) and climatic risks

(93 answers): 0.437 for climatic suitability and 0.563 for water pressure. Under this profile the leading crop remained the same in all 17 territorial units, and the set of the three leading crops did not change in 15 of 17 units (in Zhetysay District and Arys City one of the three leading crops changed). Thus, the crop ranking is not sensitive to the replacement of the normative weights by the survey-based profile; the calibration of the weights by expert methods, for example the analytic hierarchy process, is a direction of further research. Water pressure is kept in the utility with a lower weight as a soft criterion that ranks crops within the feasible set, whereas the hard constraint only excludes infeasible structures.

The robustness of the ranking was also checked by another aggregation method and by random weights (Table E.9). With the TOPSIS method the set of the three leading crops is the same as with the weighted sum in all 17 territorial units, while the leading crop is the same in 11 of 17 units; in 5 of the 6 differing units wheat and barley change places, and the gap between them is less than 1 point. In the Monte Carlo test (10,000 trials for each unit) the leading crop is kept in 96.8% of trials when only the weights change within 0.30–0.70, and in 57.4% of trials when, in addition, the scores are changed by up to 3 points. Therefore, QŪNAR presents the three leading crops as a set of alternatives, and not as a single recommended crop.

Future climate is not forecast by the model. QŪNAR allows user-defined stress scenarios of growing-season temperature, precipitation and available water applied to the historical climatic profile of the district. These scenarios are an analysis of the vulnerability of the production structure. To link them with the climate projections, three warming-level scenarios were calculated for the 2021-2025 district-crop observations: +1.0 °C; +2.0 °C with 10% less growing-season precipitation; +3.0 °C with 20% less precipitation. The global warming expected for 2041-2060 under the intermediate scenario SSP2-4.5 is about 2.0 °C relative to 1850-1900 [114]; for the region, the CMIP6 ensemble gives a similar increase of the April-September temperature (+2.01 °C for 2040-2059 relative to 1995-2014 [115]), so the +2.0 °C scenario represents a comparable regional magnitude rather than an equivalent of the global level. The forecast wheat yield decreases by 2.1%, 3.9% and 4.9%, potato by 0.6-0.9%, while cotton and corn, which are concentrated in the warm southern districts, do not show a decrease (Table E.10). Since the Random Forest does not extrapolate beyond the observed temperature range (in the third scenario 46% of observations exceed it), these estimates have limited reliability outside the historical temperature range and are interpreted as conditional sensitivity results; regionally downscaled CMIP6 projections are a direction of further research. With regard to the topic of the dissertation, preventing climate change at the level of an agricultural region cannot mean a direct regulation of temperature or precipitation. The dissertation addresses the approved topic through two complementary channels: the adaptation of the production structure to water and heat constraints, which reduces the negative consequences of climate change for the agriculture of the region, and the accounting of greenhouse gas emissions from fertilizers, fuel and electricity, which helps to avoid additional anthropogenic

climate load from agriculture (3.35), (3.49). At the level of the region, a wider use of such resource-efficient and lower-emission decisions by farms could reduce the cumulative pressure of agriculture on water and energy resources and its emissions in Turkestan region. The model does not claim to change the regional temperature, and such regional effects remain potential results that require monitoring after implementation. This corresponds to the objectives of the Strategy for Achieving Carbon Neutrality of the Republic of Kazakhstan until 2060.

These warming levels are used as a sensitivity analysis. In addition, the projections of the CMIP6 multi-model ensemble for the former South Kazakhstan region, which includes Turkestan region, were used [115]. For 2040-2059 relative to 1995-2014, the April-September temperature increases by 2.01 °C under SSP2-4.5 and by 2.68 °C under SSP5-8.5, while the median change of precipitation is small (+1.3% and +0.9%) with a wide range between the models (from about −24% to +19%). Under these scenarios the forecast wheat yield decreases by 2.6% and potato by 0.7%, while cotton, corn and rice do not show a decrease; in the hot and dry variant of SSP5-8.5 (90th percentile of temperature and 10th percentile of precipitation) the decrease of wheat reaches 5.4% (Table E.11). The number of days with temperature above 45 °C in April-September increases from 0.05 to 0.54 days under SSP2-4.5 and to 1.01 days under SSP5-8.5. As the Random Forest does not extrapolate beyond the observed temperature range, these estimates have limited reliability outside the historical temperature range, and the results of the CMIP6 and stress scenarios are interpreted as conditional sensitivity results rather than quantitative forecasts of future yields. Since the changes relative to 1995-2014 are added to the 2021-2025 observations, which already include part of this warming, the estimated yield changes should be regarded as an upper bound of sensitivity. The projected warming is consistent with the assessment of agroclimatic resources of Turkestan region for 1941-2020, which showed an increase of heat resources by 10-15% and of the total water consumption of agricultural land by 10-12% [60]; the increase of the reference evapotranspiration by 5.2-6.9% by 2040-2059 estimated for the demonstration plot (Table D.4) continues this trend. At the same time, precipitation decreased by 5-10% in 1941-2020 [60], whereas the median CMIP6 projections show only small changes, so the hot and dry variant of SSP5-8.5 is the more relevant stress case for water planning.

The comparison of QŪNAR with existing agricultural modelling tools is given in Table 3.12.

Table 3.12 shows how QŪNAR differs from existing agricultural modelling tools. Process-based crop models, such as DSSAT and APSIM [63; 64], and the water productivity model AquaCrop [65] describe the growth of a crop on a field in detail, but they require detailed soil and management data and do not choose the structure of the whole farm under a water budget. QŪNAR combines the machine-learning yield reference based on regional statistics, the official water norms of the Republic of Kazakhstan, evidence and confidence diagnostics and constrained optimization of the farm structure. This combination for the conditions of Turkestan region is the main element of the novelty of the model.

Table 3.12 – Comparison of QŪNAR with existing agricultural modelling tools

Characteristic	Crop model (DSSAT, APSIM)	Water productivity model (AquaCrop)	QŪNAR
1	2	3	4
Main purpose	Simulation of crop growth on a field	Yield response to water and field-level irrigation planning	Choice of the farm crop structure under resource constraints
Main input data	Detailed soil, cultivar and management data	Soil, climate and irrigation data of a field	Regional statistics, NASA POWER data, official norms, user inputs
Water budget of the farm as a hard constraint	Field water balance only	Field water balance only	Included (3.33)
Economic objective	Limited (seasonal analysis)	Not included	Contribution margin (3.46), (3.47)
Confidence and evidence diagnostics	Not included	Not included	Evidence hierarchy, forecast guard
Official water norms of the Republic of Kazakhstan	Not included	Not included	Order № 108-NQ (2025)

Note – Compiled by the author based on [63-65].

QŪNAR should also be compared with economic optimization models of agriculture. Bio-economic farm models describe the resource-management decisions of a farmer as a mathematical programming problem with input-output coefficients of production activities and are used to assess technologies and policies [116]. For the Aral Sea basin, to which the irrigated zone of Turkestan region belongs, a hydro-economic optimization model showed that field irrigation efficiency should be fully upgraded in rice-producing areas by drip and alternate wet and dry irrigation, and that the benefits of efficiency improvements increase from about 20% under normal water availability to about 40% under dry conditions [117]. QŪNAR uses the same principle of constrained optimization but at the farm and district level, with yields from the validated machine-learning reference instead of fixed coefficients, the official irrigation norms of the Republic of Kazakhstan and the evidence status of each coefficient. The results agree with [117] in the direction of water saving (the Taimas case, Table D.9), but the farm-level calculation adds what a basin estimate does not show: at the current water tariff, the saving may reduce the margin of the producer (Tables D.2, D.3), so the adoption of water-saving technologies depends on support measures.

Thus, Chapter 3 transformed the results of the empirical analysis into strategic directions, an organizational-economic mechanism and the economic-mathematical model QŪNAR. The model combines a machine-learning yield reference, the resource-climate assessment, official water norms, economic and partial emission indicators and constrained optimization of the crop structure. Its validation showed

that the model is suitable for comparative planning rather than for exact yield forecasts of separate crops, and the scenario calculations, including the published case of LLP «Taimas-2024», showed the trade-offs between the margin, water use and emissions and the need to repeat the optimization when the constraints change. In the yield forecast, climatic variables mainly refine year-to-year deviations, while the long-term effect of climate change is assessed through the warming and CMIP6 scenarios and the related increase of crop water requirements; therefore, the forecasts are used together with their prediction intervals rather than as exact values.

CONCLUSION

The dissertation addressed the problem of increasing the efficiency of natural resources using in agriculture of Turkestan region, preventing climate change, by combining the theory of resource efficiency, empirical territorial diagnostics, modelling under climate change and constrained agricultural decision-making. The results obtained for the six research objectives allow the following conclusions.

1. In accordance with the first objective, the natural resource architecture of agricultural systems was revealed as the relationship «resource endowment – production configuration – resource pressure» between land and soil, water, climatic, pasture and feed resources and energy inputs. It was shown that natural-resource efficiency in agriculture is a multidimensional and state-dependent property of the whole resource-production configuration, which changes under climate change through irrigation demand, soil moisture, pasture productivity and effective scarcity of resources. Productivity, natural-resource efficiency, environmental stability and climate resilience were distinguished as related but different analytical dimensions.

2. In accordance with the second objective, international experience of economic-mathematical approaches was summarized. The bibliometric analysis of 860 Scopus publications for 1992-2025, 715 of which were published in 2021-2025, showed a shift from process-based simulation to spatial, data-driven, machine-learning and hybrid decision-support systems, while the economic interpretation of model outputs remains comparatively weak. On this basis, the methodological requirements of the model were defined: separation of prediction and optimization, explicit resource constraints, scenario analysis and preservation of evidence status.

3. In accordance with the third objective, the current state and efficiency of natural resource use in agriculture of Kazakhstan and Turkestan region were analysed. No single regional resource-efficiency coefficient can describe the agricultural system of the region. In 2004-2025, the total sown area increased from 762.7 to 911.1 thousand ha; for cereals, the area grew by 52.1% and output by 33.4%, while the yield decreased by 12.7%, so their growth was mainly extensive, whereas vegetables and melons combined area expansion with productivity growth. The 17 territorial units differ significantly in production scale, crop-livestock structure, crop-output intensity and climatic exposure; in 2025, eight units belong to the crop-intensive irrigated type, five to the livestock-oriented type, two to the mixed type and two to the small-area urban type. In the 2026 survey of 208 respondents, 57.7% named water as a scarce resource, 59.6% insufficient financing as a barrier, 50.5% irrigation development as an adaptation priority and 44.7% climatic risks as a constraint.

4. In accordance with the fourth objective, the relationships among natural resource use, agricultural production and climate change were assessed. The climate-yield and area-yield relationships are crop-specific and differ between pooled and within-district comparisons: for wheat, the pooled correlation of yield with growing-season temperature is close to zero, but within districts it is negative

(about -0.288), while the within-district correlation with precipitation is about 0.361. Multicollinearity diagnostics reduced the VIF of growing-season temperature from 11.10 to 2.39 and justified a baseline climate block of growing-season temperature, precipitation, root-zone soil wetness and solar radiation; the duplicated barley series was excluded from inferential analysis.

5. In accordance with the fifth objective, strategic directions and an organizational-economic mechanism were substantiated. The evidence-concordance score showed that six of twelve strategic directions, including irrigation modernization and digital decision support, are supported by all four evidence streams, while energy, human capital and processing directions have less complete territorial evidence. The territorial-production typology links each type of territory with a dominant strategic response. The organizational-economic mechanism is organized as a continuous cycle of monitoring, prediction, resource-feasibility assessment, decision selection, implementation and verification at the farm, district and regional levels; it separates observation, prediction and recommendation and assigns responsibility for decisions to the appropriate actors.

6. In accordance with the sixth objective, an economic-mathematical model was developed and implemented as the QŪNAR digital decision-support tool (Quantified Utilization of Natural Agricultural Resources), which combines machine-learning prediction, resource-climate assessment, evidence hierarchy and constrained optimization. The crop panel includes 1,362 observations for 17 territorial units and six crops in 2004-2025 (1,362 of 2,244 possible district-crop-year combinations). The pooled GroupKFold R^2 is 0.926 compared with 0.914 for the median baseline, the crop-specific R^2 is 0.219-0.516, and the median R^2 of leave-one-district-out validation is 0.863; therefore, the yield forecast is used as a reference with prediction intervals. The decision layer is robust: the mean Spearman correlation is 0.994 under one-at-a-time ±20% perturbations and 0.992 and 0.979 under moderate and stress Monte Carlo perturbations; the optimizer passed 68 automated tests, and all 11 deliberately restrictive scenarios were correctly identified as infeasible. For the pig series, the forecast guard withholds an unsupported numerical forecast. The web application is registered as an object of copyright.

Thus, all six research objectives were fulfilled and the purpose of the research was achieved: the developed model links diagnosis, prediction, feasibility assessment and constrained decision-making in a single reproducible sequence. The research hypothesis was confirmed: taking into account territorial and crop differences and explicit land and water constraints made it possible to find resource-feasible crop structures and to show the trade-offs between margin, water use and emissions that are hidden in region-wide averages, while the evidence hierarchy and the forecast guard kept the uncertainty of the results explicit.

The provisions submitted for defense are substantiated as follows: the first provision – in Sections 1.1-1.2, where the resource architecture and the state-dependent nature of natural resource efficiency are justified; the second – in Sections 2.1-2.3, where territorial and crop-specific heterogeneity is shown by statistical and correlation analysis; the third – in Section 3.1 by the evidence-concordance score

(3.1) and the territorial typology (Table 3.1); the fourth – in Section 3.2 by the functional structure (Table 3.4) and the adaptive management cycle; the fifth and the sixth – in Section 3.3 by the validation, sensitivity and optimizer verification results (Tables 3.9-3.10) and by the implementation of the model in QŪNAR (Appendices C, D).

For practical application, the dissertation recommends differentiated resource-management strategies instead of a uniform regional agricultural target. Planning in irrigation-dependent territories should start with the seasonal water budget and the compatibility of the crop structure with irrigation resources; water-saving technologies should be assessed together with their energy use and potential for expansion; crop allocation should include diversification constraints where excessive concentration increases production and climatic risk; livestock planning should include pasture, feed, drinking water and heat exposure; environmental indicators should not be set to zero when information is missing but included when they are directly observed or supported by reliable sources.

QŪNAR can be used as an applied decision-support tool at the farm, district and regional levels. The minimum input consists of the territorial unit, agricultural activities, available land and water resources and the production conditions of the selected assessment; reliable observations of water and energy use can be added, and clearly identified normative or reference requirements are used where direct measurement is not possible. The system compares alternative crops, evaluates resource-climate compatibility, identifies binding constraints and generates a conditional land-water allocation for the stated territory, season, resource budget, candidate alternatives and structural constraints.

The expected effect of implementation is an improvement in the quality of resource allocation decisions before production: the model identifies infeasible combinations of land, water and structural requirements before resources are committed, reduces the risk of choosing alternatives only by expected yield and provides a formal framework for evaluating production configurations under water stress and climatic uncertainty. The realized monetary effect cannot yet be claimed, since it requires farm-specific costs, actual yields, investment expenses and implementation data; as the recommendations were prepared for the 2027 production season, their actual economic and resource effect can be measured only after the 2027 harvest at the verification stage of the organizational-economic mechanism (Section 3.2). The scenario calculations nevertheless give an estimate of the possible effect. For the representative farm of Maktaaral District, the sustainable compromise keeps the margin close to the economic optimum (20.75 against 21.77 million KZT) without an increase of water use and partial emissions. For the published case of LLP «Taimas-2024», the calculation based on the published data indicates that the transition of 400 ha of rice to drip irrigation may reduce water use by about 4.4 million m^3 (42%), CO_2 emissions from pumping by about 375 t and the costs of water and electricity by about 24 million KZT per season; at the same time, the lower published yield indicates a possible decrease of revenue, so these estimates are scenario calculations based on open data rather than measured effects. The

direction of the recommendations is robust to yield forecast errors: in 86.5% of 1,000 trials within the empirical prediction intervals, the economic optimum remained more profitable than the baseline structure, while the exact crop shares remain conditional.

The scientific level of the research corresponds to the current international transition towards hybrid agricultural decision-support systems that combine spatial information, machine learning, resource assessment, optimization and scenario analysis. The dissertation develops this direction by including resource scarcity directly in the decision problem and by introducing feasible allocation and evidence-status analysis. Unlike purely predictive agricultural models, it treats expected production as an intermediate step, while the final recommendation depends on resource feasibility, evidence quality and explicit decision constraints; the systematic review confirms that this combination of predictive and decision functions is one of the main directions of current agricultural modelling.

The main limitations of the model are determined by the available empirical evidence. The crop machine-learning core covers only crops observed in a comparable number of districts and years, the climate block uses a common representation of the active growing season, and some farm-level environmental and resource indicators lack harmonized territorial series. These limitations are stated explicitly through the evidence hierarchy and safeguard rules rather than hidden by imputation or synthetic precision. Further research should expand farm-level water and energy observations, integrate higher-resolution climatic and soil data, introduce crop-specific phenological climate windows where they improve out-of-sample performance, develop the crop and livestock modules as more reliable series become available and assess the economic effects of QŪNAR recommendations through field implementation. Since the crop-specific R^2 values remain moderate, yield forecasts should be used with their prediction intervals, and antecedent and phenological climatic predictors are a direction for further development.

In general, an economic-mathematical system that evaluates production potential together with natural-resource capacity, climatic conditions and evidence quality can support the development of resource-efficient and climate-resilient agriculture in Turkestan region. The developed QŪNAR architecture turns this approach into a repeatable digital decision process and provides a methodological basis for territorially differentiated agricultural planning with explicit natural-resource constraints.

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APPENDIX A
(mandatory)

Act of implementation of the dissertation research results in the agricultural production cooperative «BIO-AGRO» LLP



Докторант Махмуд Динара Марленқызының 8D04110 – «Экономика» білім беру бағдарламасы бойынша философия докторы (PhD) дәрежесін алу үшін дайындаған диссертациялық зерттеу нәтижелерін

ЕНГІЗУ АКТІСІ

Ауыл шаруашылығы өндірістік кооперативі «БИО-АГРО» жауапкершілігі шектеулі серіктестігі М.Әуезов атындағы Оңтүстік Қазақстан университеті докторантының «Климаттық өзгерістерді алдын алу үшін Түркістан облысы ауыл шаруашылығында пайдаланатын табиғи ресурстардың тиімділігін арттырудың моделін жасау» тақырыбындағы диссертациялық зерттеу нәтижелерін қарастырғаны туралы хабарлайды. Зерттеу табиғи ресурстарды пайдалану тиімділігін арттыру және ауыл шаруашылығы өндірісін өзгермелі климаттық жағдайларға бейімдеу қажеттілігімен байланысты аграрлық сектордың өзекті міндеттерін шешуге бағытталған жоғары ғылыми және практикалық маңыздылығымен ерекшеленеді.

Диссертациялық зерттеудің келесі нәтижелері АШӨК «БИО-АГРО» өндірістік-экономикалық практикасына енгізілді:

1) ауыл шаруашылығы өндірісінің нәтижелерімен байланыстыра отырып, табиғи ресурстарды (жер, су, топырақ, жайылым және энергетикалық ресурстар) пайдалану тиімділігін бағалау әдістемесі – кооперативтің өз ресурстық базасын талдау үшін қолданылды;

2) ресурс үнемдейтін және климатқа төзімді ауыл шаруашылығын дамытудың ұйымдастырушылық-экономикалық механизмі («мониторинг – болжау – ресурстық орындалымдылықты бағалау – шешім таңдау – енгізу – тексеру» циклі) – өндірістік жоспарлауда, оның ішінде су үнемдейтін және энергия тиімді технологияларды таңдауда қолданылды;

3) Random Forest әдісімен өнімділікті болжауды жер және су ресурстарының шектеулерімен және егіс алқаптарының құрылымын оңтайландырумен біріктіретін QŪNAR цифрлық шешім қабылдауды қолдау ортасы – егістерді орналастыруды сценарийлік жоспарлау үшін пайдаланылды.

Аталған нәтижелерді пайдалану жер және су ресурстарын неғұрлым ұтымды бөлуге, өндірістік жоспарлаудың негізділігін арттыруға және кооперативтің өсімдік шаруашылығының агроклиматтық тәуекелдерге ұшырауын төмендетуге ықпал етеді.

Ұсынылған ғылыми әзірлемелер аграрлық экономиканың заманауи талаптарына сәйкес келеді және оларды стратегиялық жоспарлау мен ауыл шаруашылығы өндірісінің тиімділігін арттыру үшін негіз ретінде пайдалануға болады деген қорытынды жасалды.

АШӨК «БИО-АГРО» төрағасы: **Акаев Ф.Т.**

APPENDIX B
(mandatory)

Questionnaire for the survey of agricultural producers and specialists of Turkestan region, 2026

This questionnaire was developed by the author and used to collect the empirical data presented in Chapter 2 of this dissertation (N = 208). The questions are reproduced in the original bilingual form (Kazakh / Russian) in which they were presented to respondents; the Russian version is given beneath each Kazakh question.

1 Сіздің ойыңызша, климаттың өзгеруі сіздің аймағыңыздағы ауыл шаруашылығының дамуына қандай дәрежеде әсер етті?
Как вы считаете, в какой мере изменения климата повлияли на развитие сельского хозяйства в вашем регионе?
a) Айтарлықтай әсер етті / Значительно повлияли ☐
b) Орташа әсер етті / Умеренно повлияли ☐
c) Аздап әсер етті / Слабо повлияли ☐
d) Әсер еткен жоқ / Не повлияли ☐

2 Климаттық өзгерістер ауыл шаруашылығы қызметінің қай аспектілеріне көбірек әсер етті?
На какие аспекты сельхоздеятельности климатические изменения повлияли больше всего?
(бірнеше жауап таңдауға болады / можно несколько вариантов)
a) Дақылдардың өнімділігі / Урожайность культур ☐
b) Сумен қамтамасыз ету және суару / Водообеспечение и орошение ☐
c) Жайылымдар мен жем-шөп базасының жағдайы / Состояние пастбищ и кормовой базы ☐
d) Егу және жинау мерзімдері / Сроки посева и уборки ☐
e) Өндіріс өзіндік құны / Себестоимость производства ☐

3 Сіздің ойыңызша, ауыл шаруашылығының орнықты дамуы үшін қандай ресурстар тапшы?
Какие ресурсы, на ваш взгляд, наиболее дефицитны для устойчивого развития сельского хозяйства?
(бірнеше жауап таңдауға болады / можно несколько вариантов)
a) Су ресурстары / Водные ресурсы ☐
b) Қаржыландыру / Финансирование ☐
c) Білікті кадрлар / Квалифицированные кадры ☐
d) Энергетикалық ресурстар / Энергоресурсы ☐
e) Жер ресурстары / Земельные ресурсы ☐

4 Ресурс тиімділігі саласындағы қолданыстағы мемлекеттік қолдауды қаншалықты тиімді деп санайсыз?
Насколько эффективной вы считаете существующую господдержку в области ресурсоэффективности?
a) Жеткілікті тиімді / Достаточно эффективна ☐

b) Ішінара тиімді / Частично эффективна ☐
c) Тиімсіз / Неэффективна ☐
d) Бұл салада мемлекеттік қолдау жоқ / Господдержка в этой области отсутствует ☐

5 Сіздің ойыңызша, ауыл шаруашылығы кәсіпорындары үшін қандай энергия үнемдеу технологиялары перспективті?
Какие энергоэффективные технологии, по вашему мнению, наиболее перспективны для сельхозпредприятий?
(бірнеше жауап таңдауға болады / можно несколько вариантов)
a) Тамшылатып суару / Капельное орошение ☐
b) Күн панельдері / Солнечные панели ☐
c) Жел энергетикасы / Ветроэнергетика ☐
d) Биогаз қондырғылары / Биогазовые установки ☐
e) Энергия тиімді жабдықтар / Энергоэффективное оборудование ☐

6 Аймақтың ауыл шаруашылығы кәсіпорындарының жаңартылатын энергия көздеріне көшуге дайындығын қалай бағалайсыз?
Как вы оцениваете готовность сельхозпредприятий региона к переходу на возобновляемые источники энергии?
a) Өз бетінше дайын / Готовы самостоятельно ☐
b) Мемлекеттік қолдау болса дайын / Готовы при наличии господдержки ☐
c) Әзірге дайын емес / Пока не готовы ☐
d) Жауап беруге қиналамын / Затрудняюсь ответить ☐

7 Сіздің ойыңызша, ауыл шаруашылығының орнықты дамуын қандай факторлар көбірек тежейді?
Какие факторы, на ваш взгляд, больше всего сдерживают устойчивое развитие сельского хозяйства?
(бірнеше жауап таңдауға болады / можно несколько вариантов)
a) Қаржыландырудың жетіспеушілігі / Недостаток финансирования ☐
b) Климаттық тәуекелдер / Климатические риски ☐
c) Инфрақұрылымның әлсіздігі / Слабая инфраструктура ☐
d) Ақпарат пен білімнің жетіспеушілігі / Недостаток информации и знаний ☐
e) Заңнаманың жетілмегендігі / Несовершенство законодательства ☐

8 Сіздің ойыңызша, математикалық модельдеу ауыл шаруашылығының орнықты дамуын жоспарлауда қаншалықты көмектесе алады?
Насколько, по вашему мнению, математическое моделирование может помочь в планировании устойчивого развития сельского хозяйства?
a) Өте көмектеседі / Очень поможет ☐
b) Ішінара көмектеседі / Частично поможет ☐
c) Бағалауға қиналамын / Затрудняюсь оценить ☐
d) Көмектеспейді / Не поможет ☐

9 Климаттық өзгерістерге бейімделудің қандай шараларын ең қажетті деп санайсыз?
Какие меры адаптации к климатическим изменениям вы считаете наиболее необходимыми?
(бірнеше жауап таңдауға болады / можно несколько вариантов)
a) Ирригациялық жүйелерді дамыту / Развитие ирригационных систем ☐
b) Қуаңшылыққа төзімді сорттарды енгізу / Внедрение засухоустойчивых сортов ☐

c) Ауыл шаруашылығы тәуекелдерін сақтандыру / Страхование сельхозрисков ☐
d) Кадрларды оқыту және біліктілігін арттыру / Обучение и повышение квалификации кадров ☐
e) Өндірісті әртараптандыру / Диверсификация производства ☐

10 Ауыл шаруашылығын ресурстиімді дамыту үшін мемлекеттік қолдаудың қандай құралдары тиімдірек болар еді?
Какие инструменты господдержки были бы наиболее эффективны для ресурсоэффективного развития сельского хозяйства?
(бірнеше жауап таңдауға болады / можно несколько вариантов)
a) Жеңілдікті несиелеу / Льготное кредитование ☐
b) Энергия тиімді жабдықтарға субсидиялар / Субсидии на энергоэффективное оборудование ☐
c) Ақпараттық-консультациялық қолдау / Информационно-консультационная поддержка ☐
d) Салықтық жеңілдіктер / Налоговые льготы ☐
e) Оқыту бағдарламалары / Обучающие программы ☐

Note – Compiled by the author. Summary results of the survey are presented in Chapter 2 of this dissertation.

APPENDIX C
(informative)

Evidence base of the strategic directions and interface of the QŪNAR decision-support model

Table C.1 – Evidence streams supporting the strategic directions (basis of Figure 3.1)

Strategic direction	S	C	Q	P	Score	Basis
1	2	3	4	5	6	7
Water-use efficiency and irrigation modernization	1	1	1	1	4	S: water abstraction and losses (Table 2.2); C: growing-season temperature and precipitation and crop yields (Table 2.14); Q: water as a scarce resource (57.7%), development of irrigation (50.5%) (Table 2.12); P: Concept for the Development of the Water Resources Management System for 2024-2030, Water Code; illustration: drip-irrigation case of LLP «Taimas-2024» (Table D.9)
Climate-adaptive crop and varietal management	1	1	1	1	4	S: crop yields in Kazakhstan and Turkestan region (Tables 2.4-2.5); C: crop-specific climate-yield relationships (Table 2.14); Q: drought-resistant varieties (38.9%); P: Concept for the Development of the Agro-Industrial Complex for 2021-2030
Crop-structure and land-use optimization	1	1	1	1	4	S: crop structure and area-yield decomposition (Tables 2.3, 2.6-2.7); C: different climate responses of crops (Table 2.14); Q: production diversification (21.2%); P: Concept for the Development of the Agro-Industrial Complex for 2021-2030
Livestock pasture-feed-water resource balance	1	1	1	1	4	S: livestock share of agricultural output (Table 2.9); C: dependence of pasture and fodder on precipitation and soil moisture (Section 2.2); Q: state of pastures and fodder base (Appendix B, question 2); P: Land Code, Concept for the Development of the Agro-Industrial Complex for 2021-2030
Energy-efficiency and renewable-energy integration	0	0	1	1	2	S: no harmonized district-level data on energy use; C: not addressed by the climate analysis; Q: energy resources as a scarce resource (29.8%), readiness to use renewable energy (Appendix B, questions 5-6); P: Strategy for Achieving Carbon Neutrality until 2060

Continuation of Table C.1

1	2	3	4	5	6	7
Digital monitoring and model-based decision support	1	1	1	1	4	S: territorial differentiation of output and resource use across 17 units, not captured by regional averages (Tables 2.9-2.10); C: crop- and district-specific climate effects requiring monitoring (Section 2.3); Q: mathematical modelling will help (52.4% greatly, 26.4% partially); P: Concept for the Development of the Agro-Industrial Complex for 2021-2030 (digitalization of agriculture)
Environmental and soil-risk monitoring	0	1	1	1	3	S: no harmonized district-level data on soil and environmental pressure; C: root-zone soil wetness in the climate analysis (Section 2.3); Q: land resources as a scarce resource (21.2%); P: Environmental Code, Land Code
Storage, logistics and post-harvest loss reduction	1	0	1	1	3	S: growth of crop output (Table 2.6); C: not addressed by the climate analysis; Q: weak infrastructure (39.4%); P: Concept for the Development of the Agro-Industrial Complex for 2021-2030
Human-capital and advisory capacity	0	0	1	1	2	S: no comparable district-level data; C: not addressed by the climate analysis; Q: qualified personnel (33.2%), lack of information and knowledge (26.9%), staff training (23.1%); P: Concept for the Development of the Agro-Industrial Complex for 2021-2030
Climate-risk management, insurance and diversification	1	1	1	1	4	S: interannual variability of yields (Table 2.5); C: climate-yield relationships (Table 2.14); Q: climatic risks (44.7%), agricultural risk insurance (35.1%); P: Law on State Regulation of the Development of the Agro-Industrial Complex
Processing and circular resource-use integration	0	0	1	1	2	S: no comparable district-level data; C: not addressed by the climate analysis; Q: biogas installations (Appendix B, question 5); P: Environmental Code
Cooperation and shared resource infrastructure	1	0	1	1	3	S: water losses in shared irrigation networks (Table 2.2); C: not addressed by the climate analysis; Q: weak infrastructure (39.4%); P: Water Code

Note – Compiled by the author. S – statistical evidence; C – climate-relationship evidence; Q – stakeholder-survey evidence; P – project-implementation evidence; 1 – the direction is supported by the evidence stream, 0 – not supported. The score is the sum of the four indicators according to formula (3.1).

The software implementation of the QŪNAR economic-mathematical model is available as a web interface at: https://qunar-turkestan.streamlit.app/. The interface implements the computational sequence described in Chapter 3 (in accordance with Figure 3.13): intake of verified input data, machine-learning yield

forecasting, the resource-climate feasibility layer, constrained optimization, and generation of the final recommendations.

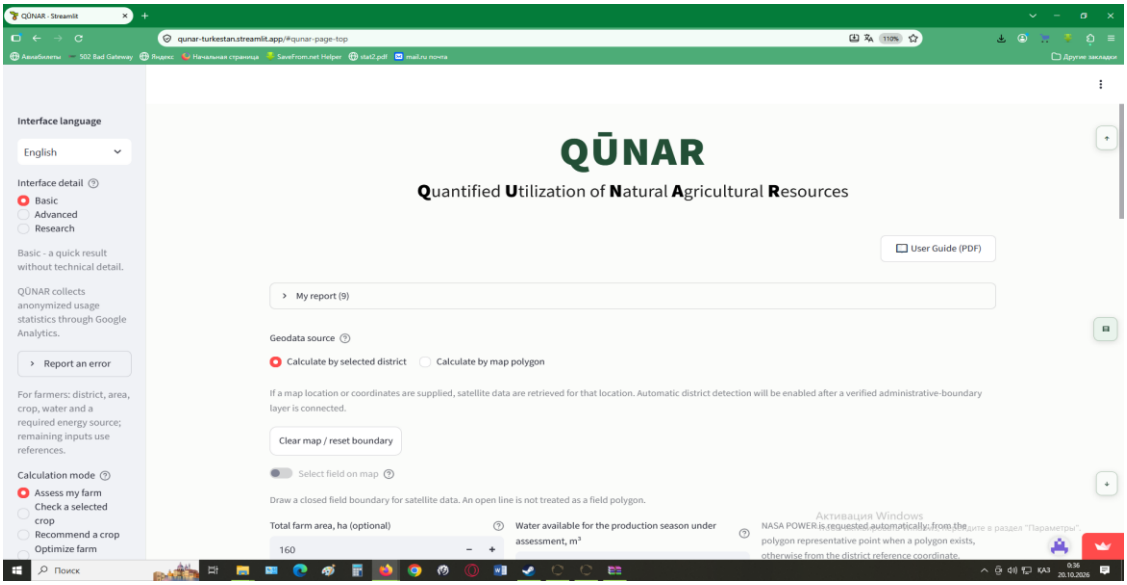


Figure C.1 – QŪNAR start screen: interface language, calculation mode and geodata source

Note – Screenshot of the QŪNAR web application.

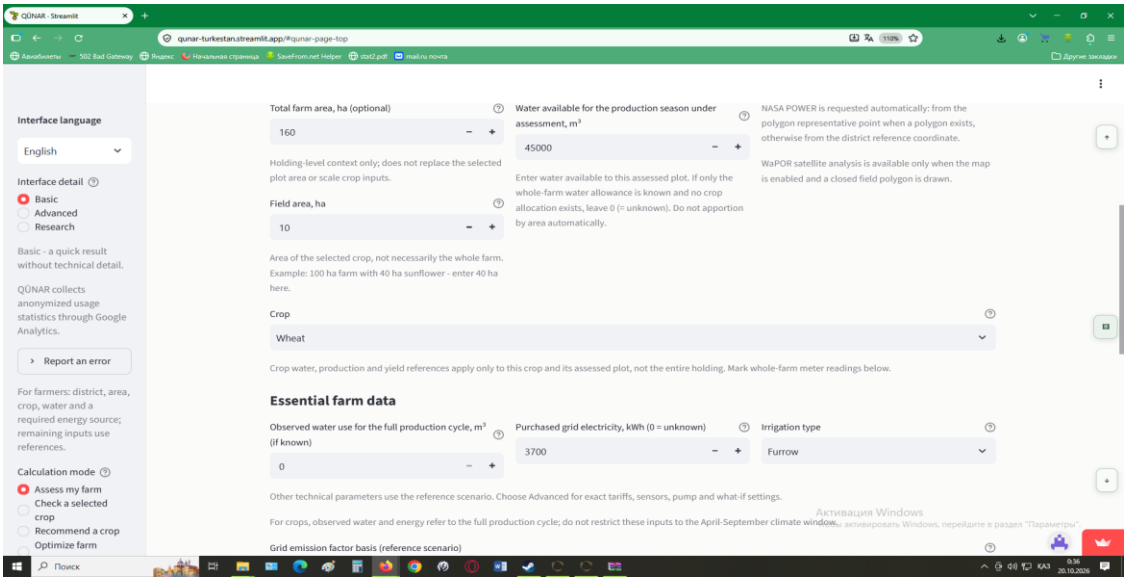


Figure C.2 – Input screen: field area, available water, crop and essential farm data

Note – Screenshot of the QŪNAR web application.

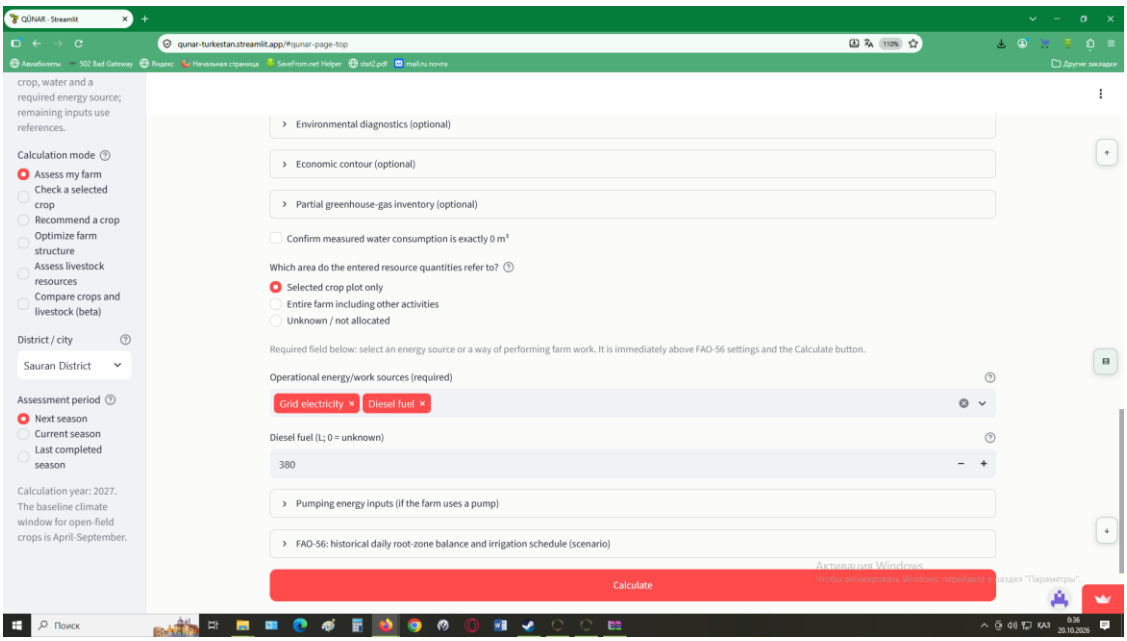


Figure C.3 – Operational energy sources, optional panels and the Calculate button

Note – Screenshot of the QŪNAR web application.

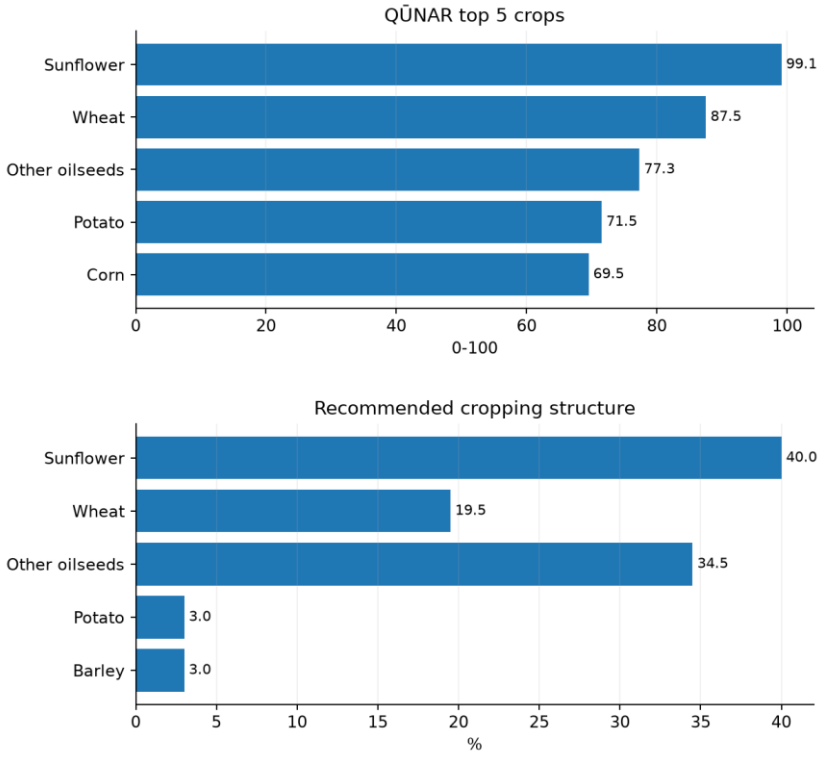


Figure C.4 – Results: crop ranking and recommended cropping structure (Sauran District)

Note – Generated by the author in the QŪNAR web application (v0.8.1).



Figure C.5 – QR code for access to the QŪNAR web application

Note – Compiled by the author. The web interface is built on the model and algorithms described in Chapter 3 of this dissertation.

APPENDIX D
(informative)

Examples of QŪNAR analytical reports

The reports were generated in the QŪNAR web application (v0.8.1) on 25 August 2026 for a demonstration farm in Sauran District: 160 ha in total, a wheat plot of 10 ha drawn on the map and 100 ha of crops for optimization. The input data are scenario assumptions for the demonstration of the model and not the indicators of a real enterprise (Table D.1). Sauran District is assigned to the Turkestan City water-management zone by geographic proximity, because Order № 108-NQ does not list it separately.

Table D.1 – Input data and reference values

Parameter	Value	Source / role
District, assessment period	Sauran District; next season (2027)	User input
Assessed plot	10 ha of wheat, map polygon (43.442° N, 67.836° E), 1 NASA POWER cell	User input; NASA POWER monthly data, 1995-2025
Water available for the plot	45,000 m³	User input
Water requirement	3,550 m³/ha (35,500 m³)	Order № 108-NQ, table 3 (zone norm)
Irrigation	Furrow; proposed scenario – drip	User input
Electricity	3,700 kWh (own pump, head 25 m, efficiency 65%)	Scenario assumption
Diesel fuel	380 L	Scenario assumption
Electricity tariff	41.06 KZT/kWh without VAT	«Ontustik Zharyk Tranzit», November 2025
Water tariff	1.16 KZT/m³	RSE «Kazvodkhoz», gravity supply
Emission factor of electricity	0.813 kg CO_2/kWh	Ember, 2025
Yield for the margin	29.0 c/ha	District mean yield, 2024-2025
Producer price of wheat	100,044 KZT/t	BNS, Turkestan region, 2025
Other variable costs	120,000 KZT/ha; extra costs of drip 10,000 KZT/ha	Scenario assumption
Activities for GHG (baseline / scenario)	N 550 / 495 kg; diesel 380 / 340 L; electricity 3,700 / 3,700 kWh; April-September	Scenario assumption; IPCC EF1 = 0.01

Note – Compiled by the author; scenario inputs and reference values used in the QŪNAR web application (v0.8.1).

D.1 Assess my farm

Generated: 2026-08-25 18:38 | Calculation year: 2027 | prospective planning scenario.

Table D.2 – Key results

Indicator	Value	Note
Freshwater requirement	35,500 m³	Norm × area
Water balance	+9,500 m³ (reserve)	Water budget 45,000 m³
Energy use / operational CO_2	3,700 kWh / 3,008 kg CO_2	Factor 0.813 kg CO_2/kWh
Yield: historical reference / Random Forest	29.5 / 25.68 c/ha	Historical median selected for the plot
ML forward R^2 for 2021-2025; coverage of the 90% interval	0.267; 84.7%	Warning: limited crop-specific validity
Contribution margin (furrow)	150,817 KZT/ha	
Partial GHG: baseline / scenario / change	6,384.7 / 6,041.7 / −343.0 kg CO_2e	N −10%, diesel −40 L

Note – Generated by the author in the QŪNAR web application (v0.8.1). Historical reference – median district yield for 2004-2025 (29.5 c/ha); the margin is calculated with the district mean for 2024-2025 (29.0 c/ha, Table D.1). ML forward R^2 and interval coverage refer to wheat in the 2021-2025 forward test; for GroupKFold validation, $R^2 = 0.516$ and coverage = 0.898 (Table E.2).

Key recommendations.

1) Irrigation switch: water and economic risk

The switch saves water but reduces calculated margin. Do not recommend it as a profit improvement under these assumptions.

Table D.3 – Irrigation switch from furrow to drip

Indicator	Furrow (baseline)	Drip (scenario)
Water delivery, m³/ha	3,550	2,840
Water per season, m³	35,500	28,400
Freshwater balance, m³	+9,500	+16,600
Contribution margin, KZT/ha	150,817	141,641
Margin under the stress test, KZT/ha	81,762	71,668
Seasonal margin change, KZT	–	−91,764 (stress test −100,940)

Note – Generated by the author in the QŪNAR web application (v0.8.1). Electricity use is kept at 3,700 kWh in the drip scenario, because drip irrigation requires additional pressure; therefore, the margin change does not include possible energy savings.

Table D.4 – Climate scenarios for the plot: CMIP6

Indicator	NASA POWER, 1995-2014	SSP2-4.5, 2040-2059	SSP5-8.5, 2040-2059
Temperature change, April-September, ℃	–	+2.01	+2.68
Days above 35 ℃	–	63.04	–
Days above 40 ℃	–	16.55	–
Days above 45 ℃	–	0.54	–
Reference evapotranspiration ET0, April-September, mm	1,590.4	1,672.6	1,699.8
Change in reference evapotranspiration ET0, %	–	+5.2	+6.9

Note – ET0 is calculated in QŪNAR for the April-September climate of the plot; it characterizes the climatic water demand and is not a water norm. The days with high temperature are given by QŪNAR for the selected scenario SSP2-4.5.

Table D.5 – Water indicators used in the reports and their meaning

Indicator	What it measures	Area and period	Value in the example
Official irrigation norm (Order № 108-NQ, the same in № 288-NQ)	Gross water delivery to the field for the crop under standard conditions (surface irrigation, 50% probability)	Per hectare, growing season	3,550 m³/ha; 35,500 m³ for 10 ha
Water delivery under drip irrigation (scenario)	Gross water delivery reduced by 20% relative to the norm (Table D.3)	Per hectare, growing season	2,840 m³/ha
Seasonal water requirement of the plot	Official norm multiplied by the plot area	10 ha, growing season	35,500 m³
Water budget of the farm	Seasonal water limit entered by the user	Farm, growing season	45,000 m³

Note – Compiled by the author. The indicators have different boundaries (delivery, requirement, consumption) and assumptions, therefore only changes of the same indicator between scenarios are compared.

D.2 Check a selected crop

Generated: 2026-08-25 18:38 | Calculation year: 2027 | prospective planning scenario.

For wheat on the same plot the QŪNAR score is 87.5/100 (climate 89.8, resource efficiency 84.1, assessment confidence 86.5); no single critical constraint is dominant.

D.3 Recommend a crop

Generated: 2026-08-25 18:40 | Calculation year: 2027 | prospective planning scenario. The ranking of crops for the plot is given in Table D.6.

Table D.6 – Ranking of crops for the plot (first 10 of 15)

Rank	Crop	Climate	Water pressure	Assessment confidence	QŪNAR overall score	Default water norm, m³/ha
1	Sunflower	98.4	100.0	83.0	99.1	2,675
2	Wheat	89.8	84.1	86.5	87.5	3,550
3	Other oilseeds	62.2	100.0	67.0	77.3	2,675
4	Potato	98.3	31.4	86.5	71.5	6,450
5	Corn	94.8	31.4	86.5	69.5	6,450
6	Barley	65.7	75.0	70.5	69.4	4,050
7	Pome and stone fruits	60.4	31.4	70.5	48.8	6,450
8	Cotton	58.6	26.9	86.5	45.9	6,700
9	Melons	72.7	0.0	61.8	43.6	8,182
10	Forage crops	48.2	17.8	70.5	36.1	7,200

Note – Generated by the author in the QŪNAR web application (v0.8.1).

Sunflower ranks first under the current criteria. Treat it as the priority option for further verification and compare the top three options against water availability, production technology and market conditions.

D.4 Optimize farm structure

Generated: 2026-08-25 18:45-18:49 | Calculation year: 2027 | prospective planning scenario.

Table D.7 – Optimization of 100 ha under water and climate scenarios

Indicator	Baseline (300,000 m³)	Water budget −20%	CMIP6 SSP2-4.5	SSP2-4.5 and water −20%
Sunflower, ha	40.0	–	40.0	–
Other oilseeds, ha	34.5	–	34.5	–
Wheat, ha	19.5	–	19.5	–
Potato, ha	3.0	–	–	–
Corn, ha	–	–	3.0	–
Barley, ha	3.0	–	3.0	–
Water demand / budget, thousand m³	300.0 / 300.0	– / 240.0	300.0 / 300.0	– / 240.0
Structure QŪNAR score	87.6	–	87.2	–
Climate resilience	83.3	–	82.7	–
Resource efficiency	94.1	–	94.1	–
Status	Feasible	No feasible allocation	Feasible	No feasible allocation

Note – In this table the CMIP6 scenario changes only the climatic scores of crops, while the crop water requirements are kept at the official norm; the increase of water requirements under SSP scenarios (+4.6% and +6.1%) is analysed for the representative farm in Table D.8. With 240,000 m³ no feasible structure exists, because 100 ha even under the least water-intensive crops (2,675 m³/ha) require about 267,500 m³.

Table D.8 – Representative farm of 100 ha in Maktaaral District: baseline, economic optimum, sustainable compromise and combined stress

Indicator	Baseline	Economic optimum	Sustainable compromise (δ=0)	SSP2-4.5 (δ≤5%)	SSP5-8.5 (δ≤5%)	Combined stress (optimized)
Cotton, ha	50.0	60.0	60.0	60.0	60.0	41.8
Corn, ha	30.0	24.5	16.3	10.5	8.7	3.0
Wheat, ha	20.0	15.5	23.7	29.5	31.3	55.2
Water budget, thousand m³	750.0	750.0	750.0	750.0	750.0	600.0
Irrigation water, thousand m³	725.5	750.0	722.5	735.6	739.9	600.0
Contribution margin, million KZT	20.42	21.77	20.75	19.86	19.57	8.82
Partial emissions, t CO_2e	116.2	120.2	116.2	116.2	116.2	97.8

Note – Calculated by the author in QŪNAR v0.8.1: producer prices of 2025 [84], district yields for 2023-2025, water norms of Order № 108-NQ (the same values in Order № 288-NQ); water tariff 1.16 KZT/m³ [110] and electricity tariff 41.06 KZT/kWh [111] without VAT; own pump with a head of 25 m and an efficiency of 65% (0.105 kWh/m³) [106]; emission factor 0.813 kg CO_2/kWh [105]. The baseline shares, variable costs (cotton 350, corn 210, wheat 120 thousand KZT/ha), nitrogen (110, 90, 55 kg N/ha) and diesel (60, 55, 38 l/ha) are scenario assumptions. Under SSP scenarios the water requirement is increased by 4.6% and 6.1% and yields are kept unchanged; without a decrease of the margin (δ=0) there is no feasible solution.

Table D.9 – Published case of LLP «Taimas-2024» (Otyrar District, rice, 400 ha): flood and drip irrigation

Indicator	Flood irrigation (traditional)	Drip irrigation	Change
Area, ha	400	400	–
Water use, m³/ha	26,000	15,000	−11,000 (−42.3%)
Water per season, million m³	10.40	6.00	−4.40
Electricity for pumping, thousand kWh	1,090.0	628.8	−461.2
CO_2 from electricity, t	886.2	511.3	−374.9
Cost of water, million KZT	12.06	6.96	−5.10
Cost of electricity, million KZT	44.76	25.82	−18.93
Yield, c/ha	60 (district average, proxy)	50 (published)	−10
Revenue at the BNS price of 2025, million KZT	440.9	367.4	−73.5

Note – Compiled by the author from the published data of LLP «Taimas-2024» [113] and calculations in QŪNAR v0.8.1 (25.08.2026): own pump with a head of 25 m and an efficiency of 65%; tariffs 1.16 KZT/m³ and 41.06 KZT/kWh without VAT; emission factor 0.813 kg CO_2/kWh; rice price 183,699 KZT/t (BNS, Turkestan region, 2025). The yield before the transition was not published, therefore the district average of 2025 is used as a proxy. Capital costs of the drip system, additional pressure energy, other variable costs and methane emissions from flooded rice are not included.

APPENDIX E
(informative)

Additional validation results and reference coefficients of the QŪNAR model

Table E.1 – Leave-one-district-out validation of the crop yield model

Territorial unit	N	MAE, c/ha	RMSE, c/ha	R^2
Arys City	100	16.26	28.71	0.806
Baydibek District	109	12.05	23.92	0.780
Kazygurt District	81	6.35	8.75	0.977
Keles District	38	13.86	23.77	0.914
Kentau City	94	18.39	30.31	0.728
Maktaaral District	124	14.94	22.36	0.712
Ordabasy District	110	12.63	21.97	0.887
Otyrar District	11	20.91	35.88	-0.987
Sairam District	90	9.23	12.69	0.959
Saryagash District	105	9.16	14.94	0.956
Sauran District	24	32.45	53.25	0.657
Shardara District	128	16.24	23.84	0.794
Suzak District	71	16.76	24.27	0.703
Tolebi District	76	7.40	14.29	0.956
Tulkibas District	87	13.02	22.04	0.863
Turkestan City	77	7.81	11.67	0.955
Zhetysay District	37	6.33	8.86	0.968

Note – Calculated by the author using the QŪNAR crop panel, 2004-2025. For Otyrar District only 11 observations are available.

Table E.2 – Crop-specific accuracy and empirical 90% prediction intervals

Crop	N	R^2	Half-width of 90% interval, c/ha	Empirical coverage
Corn	289	0.458	14.8	0.900
Cotton	181	0.287	7.8	0.901
Potato	290	0.412	56.7	0.900
Rice	53	0.219	20.9	0.887
Sunflower	255	0.354	5.4	0.898
Wheat	294	0.516	7.9	0.898

Note – Calculated by the author from grouped out-of-sample residuals (GroupKFold by year).

Table E.3 – Out-of-fold permutation importance of the predictors

Predictor	Mean decrease in R^2	Standard deviation
Crop	1.887	0.072
District	0.041	0.012
Sown area, th. ha	0.041	0.005
Apr-Sep root-zone wetness	0.008	0.002
Apr-Sep solar radiation, MJ/m²/day	0.008	0.005
Apr-Sep temperature, °C	0.005	0.002
Apr-Sep precipitation, mm	0.001	0.003

Note – Calculated by the author: GroupKFold by year, 5 folds, 5 permutations per fold.

Table E.4 – Sequential time validation of yield forecasting methods, MAE, c/ha

Method	2011-2015 (n=292)	2016-2020 (n=318)	2021-2025 (n=326)
Random Forest (main model)	7.18	11.94	16.71
Random Forest for separate crops	7.34	12.00	16.81
ExtraTrees	7.83	12.61	15.90
CatBoost	8.32	13.22	17.20
HistGradientBoosting	8.08	13.38	18.14
Ridge regression	12.75	15.74	18.76
Historical median of the district and crop	7.75	13.31	16.88

Note – Calculated by the author: each model is trained on all earlier years (from 2004) and tested on the given five-year period; n is the number of test observations. The results are not directly comparable with the GroupKFold validation in Table 3.9. The values of the main Random Forest model in this table were obtained in the common multi-model run and differ from Table 3.9 by no more than 0.04 c/ha.

Table E.5 – Sensitivity of the optimal structure of the representative farm to the economic weight λ

Economic weight λ	Cotton, ha	Corn, ha	Wheat, ha	Margin, million KZT	Water, thousand m³	Partial emission, t CO_2e
0	3.0	37.0	60.0	11.69	546.9	88.5
0.25	37.0	3.0	60.0	14.40	579.2	94.6
0.35	60.0	3.0	37.0	19.10	678.1	109.8
0.50	60.0	24.5	15.5	21.77	750.0	120.2
0.70	60.0	24.5	15.5	21.77	750.0	120.2
1.00	60.0	24.5	15.5	21.77	750.0	120.2

Note – Calculated by the author for the representative farm of Table D.8 with the same coefficients; a separate linear calculation with the same objective function and constraints was used for λ from 0 to 1, the code of QŪNAR was not changed.

Table E.6 – Comparison of planning strategies for the representative farm (fixed crop structure under stress and SSP2-4.5)

Strategy	Cotton / corn / wheat, ha	Margin, million KZT	Water, thousand m³	Partial emission, t CO_2e	Combined stress (limit 600.0): water deficit (−) or reserve (+), thousand m³ / margin, million KZT	SSP2-4.5 (limit 750.0): water deficit (−) or reserve (+), thousand m³ / margin, million KZT
Traditional structure 50/30/20	50 / 30 / 20	20.42	725.5	116.2	−125.5 / 12.34	−8.9 / 20.24
Maximum of margin	60 / 24.5 / 15.5	21.77	750.0	120.2	−150.0 / 13.18	−34.5 / 21.58
Minimum of water	3 / 37 / 60	11.69	546.9	88.5	+53.2 / 6.72	+178.0 / 11.55
QŪNAR sustainable compromise (δ=0)	60 / 16.3 / 23.7	20.75	722.5	116.2	−122.5 / 12.43	−5.7 / 20.57

Note – Calculated by the author for the representative farm of Table D.8. The stress and SSP2-4.5 columns test the same structure without re-optimization: under the combined stress the water limit is 600,000 m³ (yield −10%, costs +10%), under SSP2-4.5 the water requirement is increased by 4.6% with the limit of 750,000 m³. All values are scenario estimates; emissions are partial.

Table E.7 – Robustness of the representative farm structure to yield forecast errors

Indicator	Value
Number of Monte Carlo trials	1,000
Yield perturbation (half-width of the 90% interval), c/ha: cotton / corn / wheat	±7.8 / ±14.8 / ±7.9
Share of trials in which the economic optimum is more profitable than the baseline structure, %	86.5
Margin of the economic optimum minus the baseline, million KZT: median (5th; 95th percentile)	1.34 (−0.80; 3.49)
Loss of margin compared with the ex-post optimal structure, %: median (90th percentile)	0.5 (23.4)
Share of trials with a loss of not more than 5%, %	63.0
Share of trials in which cotton remains the leading crop, %	56.7
Share of trials in which the sustainable compromise is more profitable than the baseline, %	56.9
Margin of the sustainable compromise minus the baseline, million KZT: median (5th; 95th percentile)	0.28 (−2.55; 3.05)

Note – Calculated by the author in QŪNAR v0.8.1 for the representative farm of Table D.8: yields of the three crops are perturbed independently with normal errors (standard deviation equal to the half-width of the 90% interval divided by 1.645); the loss compared with the ex-post optimal structure is estimated by re-optimization for the first 300 trials.

Table E.8 – Reference irrigation water requirements used in QŪNAR, m³/ha

Water-management zone (districts)	Wheat (winter)	Corn	Cotton	Potato	Vegetable	Melon	Oilseed***	Forage crop
Maktaaral, Zhetysay, Arys City, Otyrar, Shardara	4,100	7,450	8,400	7,600	9,100	5,650	4,400	11,000
Saryagash, Kazygurt, Keles*	2,950	5,350	5,500	5,350	6,400	8,181.6**	2,350	8,181.6**
Turkestan City, Sauran*, Kentau City*	3,550	6,450	6,700	6,450	8,181.6**	8,181.6**	2,675	7,200
Ordabasy, Sairam, Baydibek	3,100	5,600	5,350	5,850	6,900	4,150	3,375	8,200
Tolebi, Tulkibas	2,600	5,250	4,750	5,050	6,050	3,550	4,050	7,450
Suzak	8,181.6**	8,181.6**	8,181.6**	8,181.6**	8,181.6**	8,181.6**	8,181.6***	8,181.6**

Note – Compiled by the author based on Order of the Minister of Water Resources and Irrigation of the Republic of Kazakhstan № 108-NQ of 4 June 2025 (surface irrigation, automorphic soils, 50% probability). * – zone assigned by geographic fallback; ** – regional benchmark used where the order gives no value for the zone; *** – mean of the official norms for rapeseed and safflower. Norms for barley (4,050 m³/ha) and fruit crops (6,450 m³/ha) used in Table D.6 are taken from the same order (table 3) for the Turkestan City zone.

Table E.9 – Robustness of the crop ranking in 17 territorial units: weighted sum, TOPSIS and Monte Carlo

Territorial unit	Leader, weighted sum	Leader, TOPSIS	Same set of three leading crops	Leader kept, weights only, %	Leader kept, weights and scores, %
Sauran District	Sunflower	Sunflower	Yes	100.0	63.3
Turkestan City	Sunflower	Sunflower	Yes	100.0	62.2
Saryagash District	Sunflower	Sunflower	Yes	100.0	61.6
Keles District	Sunflower	Sunflower	Yes	100.0	61.1
Zhetysay District	Wheat	Barley	Yes	91.9	39.3
Maktaaral District	Wheat	Barley	Yes	88.6	38.6
Shardara District	Wheat	Barley	Yes	87.2	36.6
Otyrar District	Wheat	Barley	Yes	86.1	37.0
Ordabasy District	Wheat	Sunflower	Yes	95.9	52.7
Arys City	Wheat	Barley	Yes	96.7	41.0
Sairam District	Wheat	Wheat	Yes	100.0	56.9
Kazygurt District	Sunflower	Sunflower	Yes	100.0	56.1
Tolebi District	Wheat	Wheat	Yes	100.0	85.7
Tulkibas District	Wheat	Wheat	Yes	100.0	85.6
Baydibek District	Wheat	Wheat	Yes	100.0	55.4
Suzak District	Melons	Melons	Yes	100.0	84.0
Kentau City	Sunflower	Sunflower	Yes	100.0	59.5

Note – Calculated by the author: 15 crops, criteria of climatic suitability and water pressure with the weights 0.60/0.40; Monte Carlo – 10,000 trials for each unit, weights from 0.30 to 0.70, in the second variant scores are changed by up to 3 points. In most units where the leaders differ, wheat and barley change places with a gap of less than 1 point.

Table E.10 – Change of the forecast crop yield under warming-level scenarios, %

Crop	S1: +1.0 °C	S2: +2.0 °C, −10% precipitation	S3: +3.0 °C, −20% precipitation
Wheat	−2.1	−3.9	−4.9
Corn	0.0	+0.5	+1.9
Cotton	+0.6	+3.2	+3.9
Sunflower	−0.1	−0.1	+0.7
Potato	−0.6	−0.8	−0.9
Rice	0.0	+0.3	+0.5
Observations beyond the historical temperature range, %	6.1	23.6	46.3

Note – Calculated by the author with the QŪNAR Random Forest model for 326 district-crop observations of 2021-2025; the scenario changes are applied to the growing-season temperature and precipitation. Conditional stress tests relative to the 2021-2025 data.

Table E.11 – Change of the forecast crop yield under CMIP6 scenarios for 2040-2059, %

Crop / indicator	SSP2-4.5 (median)	SSP5-8.5 (median)	SSP5-8.5 (hot and dry)
Wheat	−2.6	−2.6	−5.4
Corn	+0.3	+1.4	+2.4
Cotton	+1.5	+1.4	+5.4
Sunflower	0.0	+0.6	+1.0
Potato	−0.7	−0.7	−1.0
Rice	+0.3	+0.3	+0.6
Temperature change, April-September, °C	+2.01	+2.68	+3.72
Precipitation change, April-September, %	+1.3	+0.9	−24.4
Observations beyond the historical temperature range, %	26.4	38.7	58.0

Note – Calculated by the author with the QŪNAR Random Forest model for 326 district-crop observations of 2021-2025 using CMIP6 ensemble projections for the former South Kazakhstan region (reference period 1995-2014) [115]. The changes are added to the 2021-2025 observations, which already include part of the warming since 1995-2014; therefore, the results are an upper-bound estimate.