UDC 004.94:519.876:631.5
DOI: 10.15587/1729-4061.2026.359355

DEVELOPMENT OF A SYSTEM FOR MONITORING AND MANAGING CLIMATE-DEPENDENT PROCESS RISKS BASED ON HIDDEN MARKOV MODELS (USING GRAIN CROP YIELDS AS AN EXAMPLE)

Dulat Kali
Doctoral Student**
ORCID: https://orcid.org/0009-0002-0564-2267
Nurzhamal Kashkimbayeva
Correspondence author
PhD*
E-mail: N.Kashkimbayeva@astanait.edu.kz
ORCID: https://orcid.org/0000-0002-6070-876X
Ayan Kemel
Master of Science (Computer engineering and software)*
ORCID: https://orcid.org/0009-0008-2074-0942
Botagoz Mirzagalikova
Master of Science (Robotics)*
ORCID: https://orcid.org/0009-0002-9201-855X
Zhuldyz Basheyeva
PhD*
ORCID: https://orcid.org/0000-0001-9605-2101
*School of Software Engineering**
**Astana IT University
Mangilik El ave., C1, Astana, Republic of Kazakhstan, 010000

This study focuses on climate-dependent production processes, in particular grain crop yields, under conditions of climatic variability and uncertainty in Northern Kazakhstan. The problem addressed is the low effectiveness of deterministic risk monitoring approaches due to limited predictive power and the lack of formalized risk criteria, which leads to unreliable decision-making under uncertainty.

The results include the development of a three-state hidden Markov model (S_0–S_2) and a TO-BE architecture for continuous risk monitoring and decision support. The model enabled the identification of latent climatic regimes and probabilistic assessment of risk states for 2025. The highest probability of an unfavorable regime was observed in Korgalzhyn (61.2%) and Ereymentau (58.8%), while Arshaly (42.9%) and Zhaksy (38.1%) showed moderate risk levels. The Brier score ranged from 0.106 to 0.199, confirming acceptable calibration of probabilistic estimates.

The key feature of the approach is the representation of climate-dependent processes as transitions between latent probabilistic states, allowing the capture of temporal dependencies (climate memory) and the persistence of unfavorable conditions. Unlike deterministic models, the proposed framework enables dynamic risk tracking through continuously updated probability estimates integrated into a monitoring loop.

The advantage of the approach lies in combining probabilistic modelling with an operational architecture, where risk probabilities serve as formalized decision-support signals. The results can be applied in early warning systems and digital monitoring platforms using remote sensing and IoT

Keywords: hidden Markov models, probabilistic risk monitoring, TO-BE architecture, process management

Received 02.02.2026
Received in revised form 27.03.2026
Accepted 13.04.2026
Published 30.04.2026

***How to Cite:** Kali, D., Kashkimbayeva, N., Kemel, A., Mirzagalikova, B., Basheyeva, Z. (2026). Development of a system for monitoring and managing climate-dependent process risks based on hidden Markov models (using grain crop yields as an example). Eastern-European Journal of Enterprise Technologies, 2 (3 (140)), 15–26. https://doi.org/10.15587/1729-4061.2026.359355*

1. Introduction

Climate-dependent production processes in the Republic of Kazakhstan are largely determined by natural conditions and exhibit interannual variability [1, 2].

Under conditions of increasing climate instability, the timely identification of potential deviations from target indicators becomes critical for effective decision-making and loss minimization [3, 4].

However, such approaches often rely on deterministic, non-probabilistic models that are sensitive to the quality of input data and are limited in their ability to account for the uncertainty of dynamic processes [5, 6].

This shift from deterministic forecasting to probabilistic modelling moves the focus from point prediction to monitoring risk dynamics and supporting decision-making under uncertainty [4, 7].

In practical terms, this requires the development of tools capable of providing early warning signals and supporting continuous risk monitoring in climate-dependent systems.

Traditional approaches to monitoring and forecasting are often based on deterministic models, which are limited in their ability to account for uncertainty and dynamic changes in climatic conditions. As a result, they do not provide sufficient support for adaptive decision-making under uncertainty.

In practice, this leads to delays in risk identification, reduced reliability of forecasts, and limited ability to respond to rapidly changing climatic conditions, which negatively affects the efficiency of climate-dependent production systems.

Therefore, study devoted to the development of probabilistic approaches for monitoring and managing climate-dependent process risks under conditions of uncertainty is relevant, as it enables more reliable decision-making and supports effective management of climate-dependent processes.

2. Literature review and problem statement

Despite the growing interest in probabilistic methods for yield prediction and risk assessment, most existing studies [3, 6] are focused on specific application domains or particular modelling techniques. In paper [3], a systematic review of yield forecasting approaches is presented, highlighting the diversity of data sources and models used; however, the integration of these approaches into continuous risk monitoring systems remains unaddressed. In paper [6], the main data and modelling bottlenecks for yield prediction are analyzed, including limitations related to data availability and model generalization, but the issue of combining probabilistic modelling with operational decision-support mechanisms is not resolved.

The studies [8, 9] further demonstrate that standard approaches to evaluating forecast skill and digitalization of yield prediction may be insufficiently robust under real-world conditions. In particular, [8] shows that conventional forecast skill assessments can be misleading, while [9] highlights limitations in fully digitalizing yield prediction systems. These findings indicate that the reproducibility and reliability of such models in practical applications may be limited. This limitation can be explained by the sensitivity of models to data quality, regional variability and the absence of integrated monitoring frameworks.

In this context, the study [10] confirms the feasibility of yield forecasting for Kazakhstan using statistical models, but does not address the integration of probabilistic estimates into a continuous monitoring and risk management system. Therefore, there remains a need for approaches that not only model yield variability, but also incorporate probabilistic risk assessment into an operational monitoring framework adapted to regional conditions.

The study shows that early monitoring of climate-dependent production risks can be based on climatic and seasonal predictors [11, 12]. In paper [11], global crop yield forecasting is considered using seasonal climate information from a multi-model ensemble. The benefit of this approach is the possibility of obtaining early predictive signals before the end of the production cycle. However, the study is mainly focused on yield forecasting accuracy and does not address the transformation of probabilistic information into an operational risk monitoring mechanism. This limitation can be explained by the complexity of integrating large-scale seasonal forecasts into local decision-support processes.

In paper [12], seasonal predictability of major crop yields is analyzed using a hybrid system that combines dynamical climate prediction and crop-growth simulation. The advantage of this approach lies in combining climate information with crop development mechanisms. At the same time, the study remains focused on yield prediction and does not formalize risk states or decision triggers for continuous monitoring. This unresolved aspect may be related to methodological difficulties in linking crop simulation outputs with operational risk management procedures.

The possibility of obtaining early signals several months before the end of the production cycle is also confirmed in [7, 13]. These studies demonstrate that seasonal climate information and large-scale climate indices can support early assessment of yield anomalies. Their practical benefit is the extension of the decision-making horizon. However, the problem of dynamic risk tracking remains insufficiently developed, because the main result is still a forecast of the target indicator rather than a continuously updated assessment of risk states.

The works [4, 14–16] further develop early-season and preseason forecasting approaches, including the use of probabilistic seasonal climate forecasts and ocean anomaly indices such as the El Niño-Southern Oscillation (ENSO). Their advantage is the possibility of assessing crop yield risks before harvesting and comparing persistence-based and dynamical forecasts. Nevertheless, these studies mainly consider forecasting as a predictive task and do not provide a unified architecture in which uncertainty estimates are integrated into a continuous monitoring and decision-support loop. This gap may be caused by the objective difficulty of combining climate forecast uncertainty, regional agricultural specificity and operational management requirements in one framework.

For the Republic of Kazakhstan, the relevance of such approaches requires separate verification. The study [10] demonstrates that wheat yields in Republic of Kazakhstan can be forecasted using statistical crop modelling, which confirms the practical feasibility of climate-based yield prediction for this region. However, it does not solve the problem of continuous probabilistic risk monitoring. In addition, [8, 17] show that the stability and skill of climate forecasts may vary across periods and conditions, which limits the direct transfer of forecasting approaches between regions. Therefore, for Northern Kazakhstan, it is necessary not only to estimate yield-related risks but also to account for uncertainty, regional variability and the need for operational interpretation of risk signals.

Thus, the analyzed studies confirm the practical value of early forecasting based on climatic predictors. However, their common unresolved issue is that they mainly focus on predicting target indicators, while the problem of continuous risk monitoring, formalized risk states and integration of probabilistic outputs into decision-support procedures remains insufficiently addressed.

Within the probabilistic paradigm, a number of studies analyze climate-dependent processes as sequences of regimes characterized by temporal dependence. In paper [18], the concept of soil moisture memory is investigated, demonstrating that climatic variables retain information about previous states over time. The advantage of this approach lies in explaining the persistence of climatic conditions; however, the study focuses on physical processes and does not provide a formal mechanism for integrating this property into risk monitoring systems.

Similarly, [19] analyses long-term persistence in precipitation data and shows that climatic series exhibit significant temporal dependence. While this work provides a theoretical basis for understanding climate memory, it does not address how these dependencies can be used for operational risk assessment or decision-making.

The study [20] examines the evolution of wet and dry spells and confirms that climatic regimes tend to persist over time. This supports the assumption of inertia in climate-dependent processes. However, the work is primarily descriptive and does not formalize risk states or provide probabilistic monitoring tools.

The work [21, 22] demonstrates the phenomenon of synchronized failures in global crop production, highlighting the systemic nature of climate risks. Its strength lies in showing large-scale dependencies between climatic conditions and production outcomes. At the same time, the study does not consider the modelling of latent states or the integration of such knowledge into operational monitoring frameworks.

The papers [4, 20] present the use of hidden Markov models for analyzing sequential climatic data and identifying latent regimes. These models allow climatic dynamics to be represented as transitions between states and provide probabilistic estimates of favorable and unfavorable conditions. Their key advantage is the ability to explicitly model temporal dependencies and latent structures. However, in these studies the application of hidden Markov models is mainly limited to analytical tasks and does not extend to integration into continuous monitoring systems or decision-support architectures.

Thus, although the analyzed studies provide a theoretical and methodological basis for modelling climatic regimes and their temporal dependencies, they do not offer integrated solutions that combine probabilistic modelling with continuous monitoring and operational risk management. This gap is due to methodological difficulties related to the formalization of risk states, the integration of heterogeneous data, and the translation of probabilistic estimates into actionable decision-support signals.

Thus, the analysis of the literature shows that:

– existing approaches provide early forecasting capabilities but are mainly limited to point estimation;

– probabilistic models, including hidden Markov models, allow the representation of climatic dynamics and uncertainty, but are rarely embedded into continuous monitoring processes;

– there is a lack of integrated solutions that combine probabilistic modelling, dynamic updating, and operational decision support within a unified framework.

Therefore, the key unresolved problem is the absence of an integrated framework that combines probabilistic modelling of climate regimes with continuous monitoring and risk management under conditions of uncertainty. This problem determines the need to develop an approach that not only models climatic regimes probabilistically, but also ensures their integration into an operational monitoring architecture capable of supporting adaptive decision-making.

Thus, there is a clear need to develop an integrated probabilistic system for monitoring and managing climate-dependent process risks.

3. The aim and objectives of the study

The aim of this study is to develop a system for monitoring and managing climate-dependent process risks based on a hidden Markov model, which enables the identification of adverse conditions, generation of early warning signals, and support for decision-making under uncertainty. This will enable more effective risk monitoring under conditions of uncertainty in climate-dependent systems and support the implementation of continuous risk-oriented decision-making in practical applications.

To achieve the aim, the following objectives were set:

– to analyze the limitations of the current analytical framework (AS-IS) for yield prediction;

– to estimate transition probabilities between regimes and identify risk states;

– to validate the model using calibration and stability metrics;

– to design a TO-BE (target) architecture for risk monitoring and decision support.

4. Materials and methods

4. 1. The object and hypothesis of the study

The object of the study is the climate-dependent production processes, in particular grain crop yields, under conditions of climatic variability and uncertainty.

The main hypothesis of the study is that probabilistic modelling of climatic regimes using a hidden Markov model allows more effective identification of risk states and improves the reliability of risk monitoring compared to deterministic approaches.

The study assumes that climatic processes exhibit temporal dependence (inertia) and can be represented as transitions between latent states characterized by different risk levels.

The following simplifications were adopted: the transition probabilities between states are assumed to be stationary over time; the climatic variables are sufficient to characterize the system without explicitly incorporating additional agronomic or soil-related factors; and the analysis is performed at the district level using aggregated annual data.

4. 2. Initial data and test objects

The initial information for the analytical model was based on climate predictors from the Kazhydromet State Meteorological Service and official statistics on target indicators for 2004–2024.

The study analysed the districts of Korgalzhyn, Zhaksy, Ereymentau, and Arshaly in the Akmola region of the Republic of Kazakhstan. Multivariate climatic characteristics (air temperature, precipitation, humidity, pressure, wind parameters, etc.) and annual grain crop yields in centners per hectare were used for each district.

4. 3. Regression analysis in the current analytical framework (AS-IS)

In the current analytical framework (AS-IS), climatic features were used to evaluate target indicators using regression models. The relationships between the features were evaluated using Spearman's coefficient [23]. Features with high mutual correlation were excluded, as were features without a statistically significant relationship with the target indicators.

The selection was performed at each time step using only the training data for that step, thereby preventing information leakage from the test set [22].

For comparison, models of different architectures were used that accounted for the possible nonlinearity of the climatic influence [24].

Equation (1) presents a basic multiple linear regression model [10]

$$Y_t = \beta_0 + \sum_{j=1}^{p} \beta_j X_{t,j} + \varepsilon_t. \tag{1}$$

Equation (2) defines the estimation of Ridge regression parameters [13]

$$\widehat{\beta} = \arg\min_{\beta}\left[\sum_{t=1}^{n}\left(Y_t - \beta_0 - \sum_{j=1}^{p}\beta_j X_{t,j}\right)^2 + \lambda\sum_{j=1}^{p}\beta_j^2\right]. \qquad (2)$$

In the above formulas: Y_t – the target indicator in year t; $X_{t,j}$ – the value of predictor j in year t; p – the number of predictors after selection; β_0, β_j – the model parameters (intercept and coefficients for the predictors); ε_t – the error term; n – the number of years in the training sample; $\lambda \geq 0$ – the regularization coefficient and $\widehat{\beta}$ represents the estimates of the model parameters obtained by minimizing the regularized functional.

Since linear models may not capture nonlinear effects, Random Forest and Gradient Boosting ensemble algorithms were additionally applied. Model quality was assessed using RMSE and R2 metrics.

4. 4. Probabilistic modelling of risk states using a hidden Markov model

A hidden Markov model with three states was used to probabilistically detect risk states in the TO-BE monitoring architecture. Equation (3) defines the hidden state at time t

$$S_t \in \left\{S_0, S_1, S_2\right\}. \qquad (3)$$

Here, S_0, S_1, S_2 are three latent states that may correspond to unfavorable, transitional, or favorable conditions. Their interpretation is empirically determined based on the distributions of target indicators and climatic characteristics, and may vary across objects of analysis [25].

Equation (4) defines the transition matrix

$$A = \left\{a_{ij}\right\},\; a_{ij} = P\left(S_{t+1} = S_j \middle| S_t = S_i\right), \qquad (4)$$

where the elements of the matrix satisfy $\sum_j a_{ij} = 1$ for each i and are assumed to be stationary over time.

Equation (5) introduces the vector of observed climatic characteristics in year t

$$X_t \in \mathbb{R}^d, \qquad (5)$$

where d – the number of climatic characteristics after selection.

Equation (6) specifies the distribution of observations in each state [25]

$$X_t \middle| S_t = S_i \sim N\left(\mu_i, \Sigma_i\right). \qquad (6)$$

The parameters $\{\pi_i, \mu_i, \Sigma_i, a_{ij}\}$ were estimated by maximum likelihood using the iterative Baum-Welch algorithm, where π_i denotes the initial state probabilities, μ_i – the mean vector, Σ_i – the covariance matrix, and a_{ij} – the transition probabilities.

Based on the estimated parameters, the Viterbi algorithm was used to reconstruct the most probable state sequence. For each year, the probabilities of belonging to states were also calculated and interpreted as quantitative risk signals [20]. A model with $k = 3$ states was used, as it distinguishes three levels of risk and remains interpretable. The choice of k was verified using Akaike information criterion (AIC) and Bayesian information criterion (BIC) criteria, as well as through analysis of the stability of the labelling and metric values.

4. 5. Quality assessment and validation

The verification scheme replicated the cycle of updating the risk assessment for the following year. At step t the model was trained on the years 2004, ..., $t - 1$. The verification was performed at time t.

The quality of the probabilistic forecast of states was assessed using the Brier score, which is calculated according to eq. (7)

$$BS = \frac{1}{N}\sum_{t=1}^{N}\sum_{k=1}^{3}\left(p_{t,k} - y_{t,k}\right)^2, \qquad (7)$$

where $p_{t,k}$ – the predicted probability of state k in year t, $y_{t,k}$ – the indicator of the actual state k in year t according to the restored labelling (1 if state k occurred, 0 otherwise), N – the number of years in the estimation sample.

Additionally, a binary form was used for the ‘unfavorable conditions’ event, where the state with the minimum target indicator was considered a positive class, and the rest were aggregated.

The stability of the results was verified in several ways. First, repeated runs were performed with different initializations. Second, a leave-one-year-out (LOYO) test was applied, excluding one year. Third, the state labels were reconciled between runs. The comparison was performed based on the proximity of the μ_i vectors. After that, the adjusted Rand index (ARI) was calculated.

The implementation of the proposed models and experiments was carried out using standard data analysis and machine learning tools within a unified computational environment, ensuring reproducibility of the results. The experimental setup does not require specialized high-performance computing resources, which confirms the practical applicability of the proposed approach in typical analytical settings.

The choice of methods is justified by the need to account for uncertainty and temporal dependencies in climate-dependent processes. Traditional regression models were used as a baseline to evaluate the limitations of deterministic approaches, while the hidden Markov model was selected due to its ability to represent the system as transitions between latent states and to provide probabilistic estimates of risk. This makes it particularly suitable for modelling processes with inherent variability and incomplete observability, such as climatic dynamics affecting crop yields.

The initial dataset includes multivariate climatic indicators and yield data for the period 2004–2024 at the district level. The use of aggregated annual data allows for a consistent comparison across regions; however, it introduces certain limitations related to spatial and temporal resolution, which are taken into account when interpreting the results.

5. Results of the proposed probabilistic risk monitoring framework

5. 1. Analysis of the limitations of the current analytical framework (AS-IS)

Quantitative assessment within the current analytical framework (AS-IS), with strict rolling validation, showed marked heterogeneity in the quality of regression estimates for target indicators across districts (Table 1). The best result was obtained for Arshaly.

For grains, the Random Forest model achieved the best results in Arshaly: R2 = 0.512 and RMSE = 1.612. For Korgalzhyn, the R2 values were negative, indicating the absence of a reproducible signal for the selected predictors and validation scheme.

Regression experiments revealed limitations of the current analytical framework (Fig. 1).

Table 1

Regression quality in the AS-IS framework (rolling validation)

District	Crop	Model	R2	RMSE
Arshaly	Grain	Random forest	0.512	1.612
Arshaly	Wheat	Random forest	0.468	1.635
Ereymentau	Grain	Ridge	0.130	2.449
Ereymentau	Wheat	Ridge	0.209	2.363
Zhaksy	Grain	Ridge	0.235	2.733
Zhaksy	Wheat	Lasso	0.345	2.528
Korgalzhyn	Grain	Linear regression	–0.347	2.483
Korgalzhyn	Wheat	Linear regression	–0.418	2.433

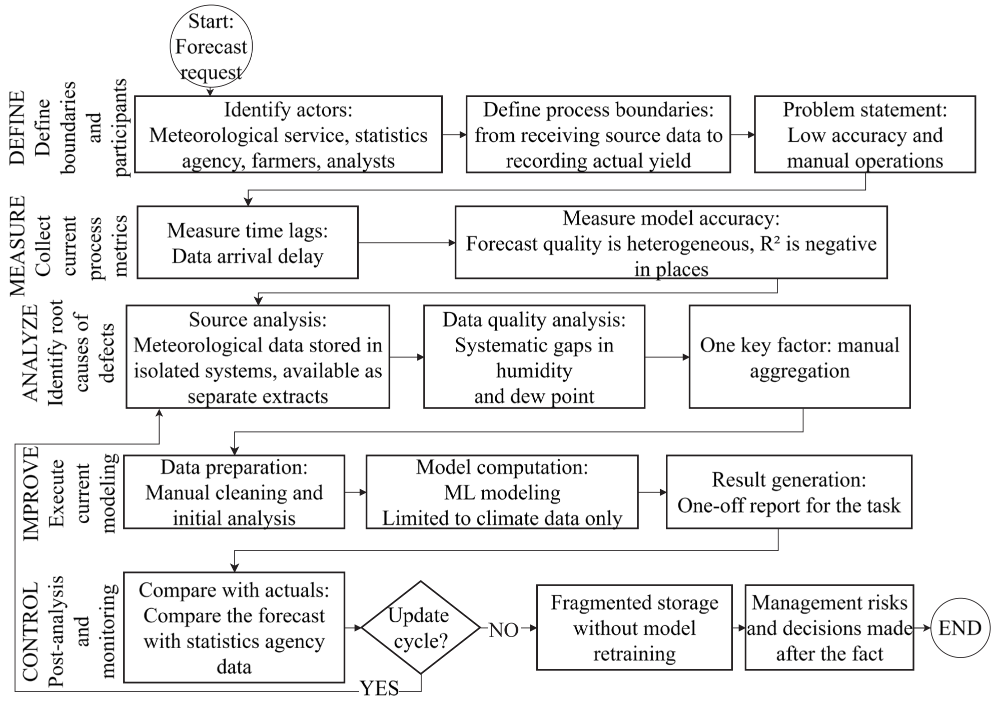
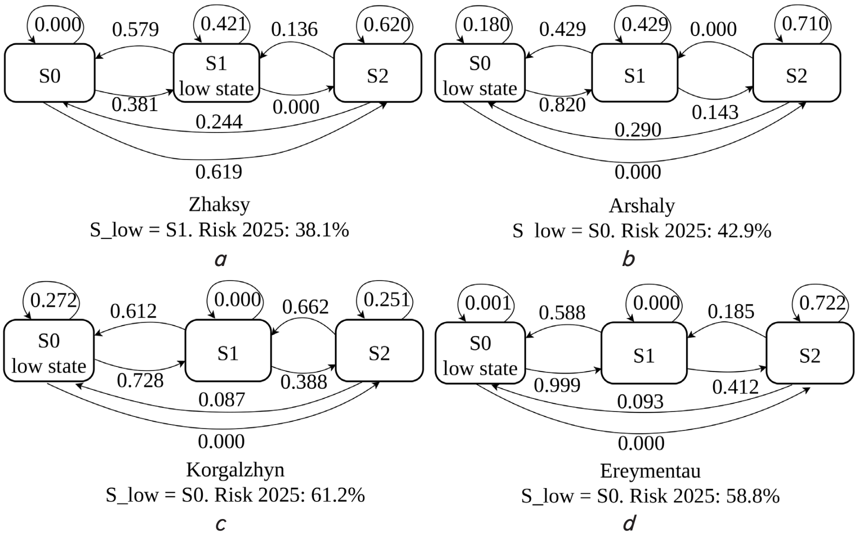


Fig. 1. Diagram of the current (AS-IS) analytical framework

The main barriers are delays in the publication of meteorological data and the lack of convenient mechanisms for bulk data download. The current monitoring process mainly provides reference information and final reports, so forecasting calculations are performed sporadically and manually. Taking these limitations into account, the analysis was shifted from point estimation to probabilistic monitoring of risk states based on hidden Markov models (HMM).

5. 2. Estimation of transition probabilities and identification of risk states

Based on the estimated transition matrix, probabilistic estimates of the states for 2025 were obtained, from which the risk of an unfavorable state was then interpreted (Fig. 2).



Zhaksy
S_low = S1. Risk 2025: 38.1%
a

Arshaly
S low = S0. Risk 2025: 42.9%
b

Korgalzhyn
S_low = S0. Risk 2025: 61.2%
c

Ereymentau
S_low = S0. Risk 2025: 58.8%
d

Fig. 2. Diagram of hidden Markov models:
a – in Zhaksy; *b* – in Arshaly; *c* – in Korgalzhyn; *d* – in Ereymentau

In the Korgalzhyn district, the probability of transition to the unfavorable state S_0 is highest, reaching 61.2%. In Ereymentau, the risk is also high (58.8%), while the probability of remaining in state S_1 is practically zero. In Arshaly, the situation is characterized by uncertainty, as the probabilities of transition to S_0 and remaining in S_1 are equivalent (42.9% each). For Zhaksy, where S_1 is the unfavorable regime, the risk of transition is estimated at 38.1%, while the probability of remaining in the current state S_0 is zero.

Analysis of transition dynamics allows to identify stable cycles and quantitatively estimate the frequency of their preservation or change [20].

5. 3. Validation of the model using calibration and stability metrics

The reliability of these estimates is confirmed by the Brier score (Fig. 3).

In Fig. 3, Ereymentau demonstrates the best calibration of the three states (BS = 0.119) at high risk (58.8%), while Zhaksy demonstrates the worst (BS = 0.168) at moderate risk (38.1%). Arshaly and Korgalzhyn have average BS values of 0.147 and 0.139, respectively, at significant risk levels (42.9%, 61.2%).

The semantic meaning of states S_0–S_2 is revealed through the median values of the target indicator and climate (Fig. 4).

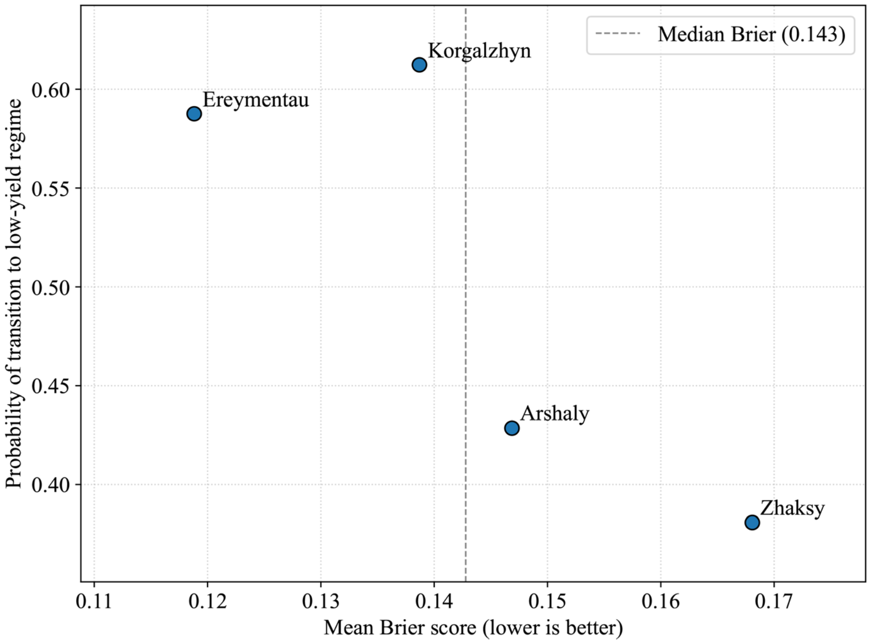
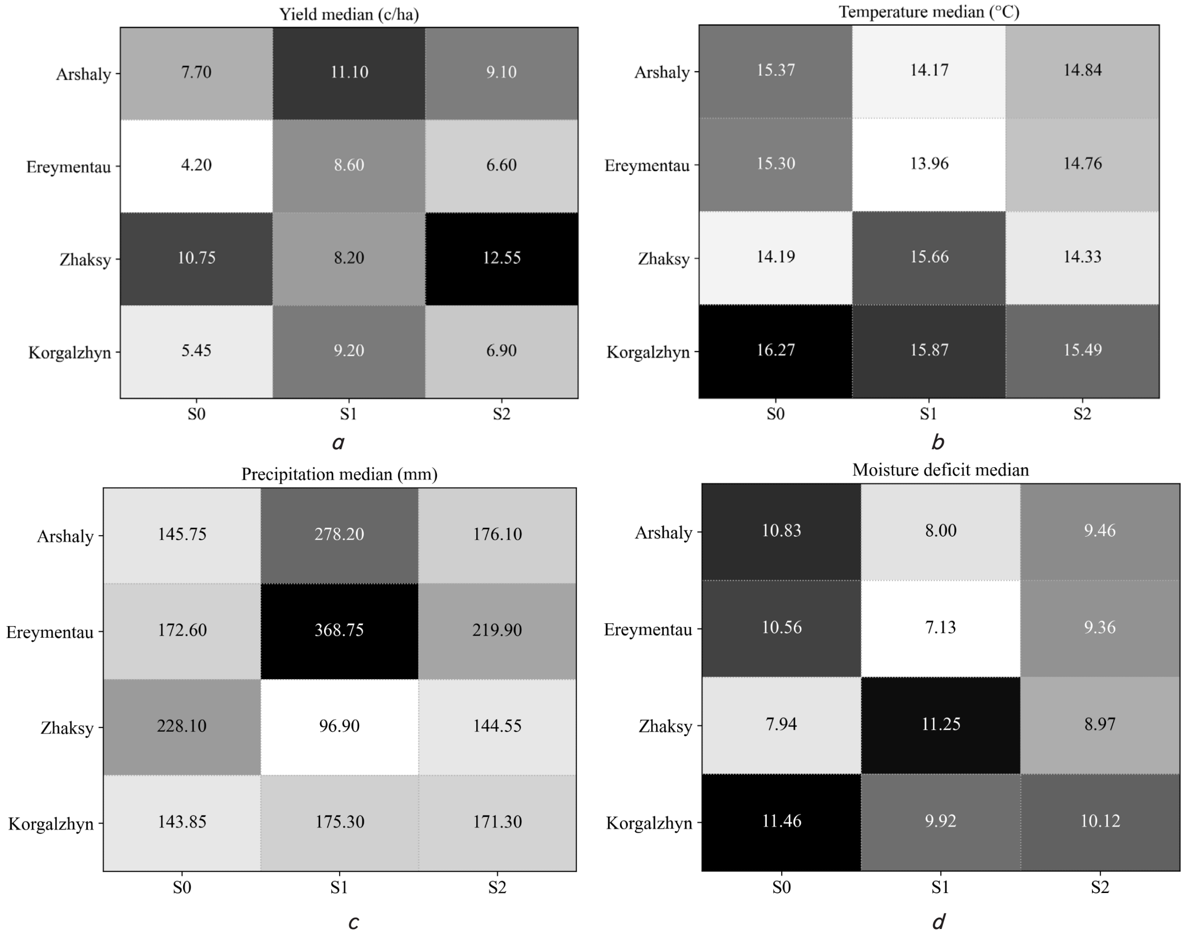


Fig. 3. Risk of transition to an unfavorable regime and calibration quality



Yield median (c/ha)

	S0	S1	S2
Arshaly	7.70	11.10	9.10
Ereymentau	4.20	8.60	6.60
Zhaksy	10.75	8.20	12.55
Korgalzhyn	5.45	9.20	6.90

a

Temperature median (°C)

	S0	S1	S2
Arshaly	15.37	14.17	14.84
Ereymentau	15.30	13.96	14.76
Zhaksy	14.19	15.66	14.33
Korgalzhyn	16.27	15.87	15.49

b

Precipitation median (mm)

	S0	S1	S2
Arshaly	145.75	278.20	176.10
Ereymentau	172.60	368.75	219.90
Zhaksy	228.10	96.90	144.55
Korgalzhyn	143.85	175.30	171.30

c

Moisture deficit median

	S0	S1	S2
Arshaly	10.83	8.00	9.46
Ereymentau	10.56	7.13	9.36
Zhaksy	7.94	11.25	8.97
Korgalzhyn	11.46	9.92	10.12

d

Fig. 4. Median values of indicators by hidden Markov model states:
a — yield median; *b* — temperature median; *c* — precipitation median; *d* — moisture median

In all districts, the unfavorable regime (S_{low}) correlates with precipitation deficit and increased moisture deficit, confirming the physically meaningful interpretation of HMM regimes.

Based on median values and the Viterbi algorithm, the dynamics of state changes for 2004–2024 have been reconstructed (Fig. 5).

Analysis of Fig. 5 shows that the Korgalzhyn and Zhaksy districts have experienced high climate volatility with an increase in arid (*D*) periods in recent years. Arshaly is characterized by stable alternating regimes, while Ereymentau is dominated by a transitional regime (*N*).

To confirm the reliability of the dynamics of state changes, an analysis of the stability of the models (Fig. 6) with respect to initialization parameters, feature composition, and verification schemes was carried out [16].

In 50 independent runs, the adjusted Rand index (ARI) revealed interregional differences. The Arshaly district showed the highest stability of labelling (ARI = 0.68), followed by Zhaksy (0.52), Ereymentau (0.33), and Korgalzhyn (0.16). The LOYO test showed moderate model sensitivity.

In the LOYO test, the median ARI values range from 0.41 to 0.58, with the highest stability observed for the Ereymentau district. The analysis of feature significance using the exclusion method supports the physical interpretation of regimes as states of water stress. In Arshaly, excluding temperature has almost no effect on stability (ARI = 0.87). When precipitation is excluded, stability drops sharply (ARI = 0.19). A similar decrease (ARI = 0.21) is observed when moisture deficit is excluded. For the Korgalzhyn district, precipitation is the key factor. Its exclusion leads to a drop in stability to ARI = 0.06.

AIC supports the selection of a three-state model (AIC = = 169.5 at $k = 3$ versus 174.7 at $k = 2$). The selection of $k = 3$ is justified by the high stability of state labelling (ARI = 0.68), acceptable LOYO results, and the physical interpretability of the states as water-stress conditions.

Although BIC prefers $k = 2$, in all districts, the three-state model better fits the objective and maintains stability in terms of ARI and LOYO.

5. 4. Design of a TO-BE architecture for risk monitoring and decision support

Additionally, based on the restored sequence of states (Viterbi algorithm), the empirical probability of maintaining a dry regime $a_{dry,dry} = P(S_{t+1} = \text{dry}|S_t = \text{dry})$ was estimated for a 10-year sliding window (Fig. 7).

Over the last 10 years (2014–2024), there has been a sharp increase in the coefficient ($a_{dry,dry}$).

The most pronounced increase in this coefficient is observed in the Zhaksy district, from virtually zero to 0.75 in 2020–2022, indicating the formation of the strongest inertia of arid conditions. In the Korgalzhyn district, a steady upward trend to 0.50 has been observed since 2016, indicating a systematic increase in the duration of drought periods. The Arshaly district is characterized by non-linear dynamics, with a peak of 0.60 in 2018 and a subsequent decline to 0.33, reflecting the episodic nature of the inertia. In Ereymentau, the values remain close to zero, confirming the relative stability of climatic conditions and the weak manifestation of prolonged drought cycles. At the same time, it is important to note that for Ereymentau, the high final risk may not be due to inertia, but rather to the high probability of transitioning to an unfavorable regime.

Overall, the identified trends confirm the existence of the climate memory effect and justify the use of probabilistic models to assess the risks of deviation from target indicators, using the example of grain crop yields [18, 20].

Generalizing the modelling results enabled differentiation of districts by risk type and the creation of a final 2025 map (Fig. 8).

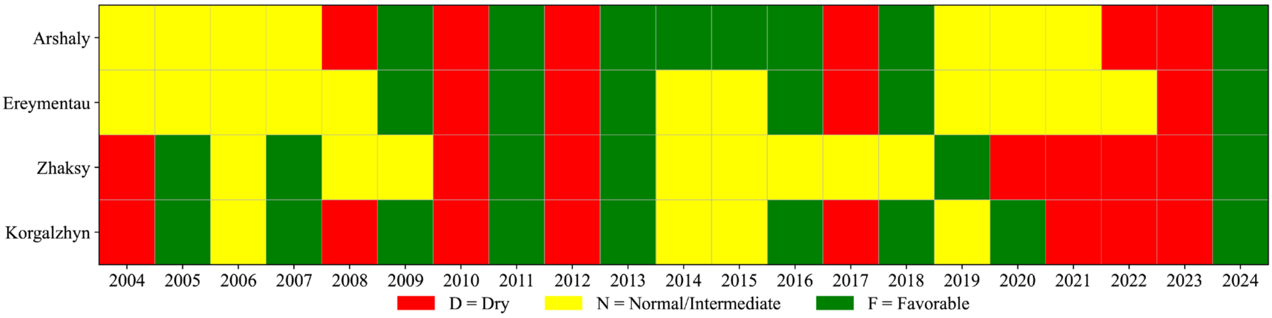
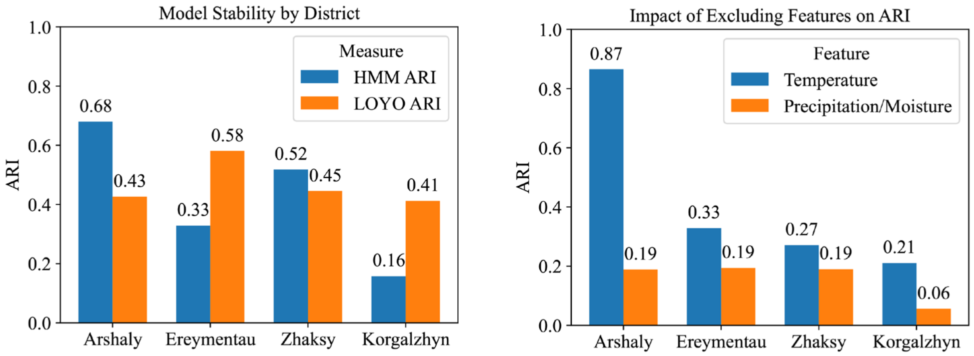


Fig. 5. Dynamics of hidden Markov model states by districts



a *b*

Fig. 6. Stability of state change dynamics:
a — model stability by district; *b* — impact of excluding features on the adjusted rand index

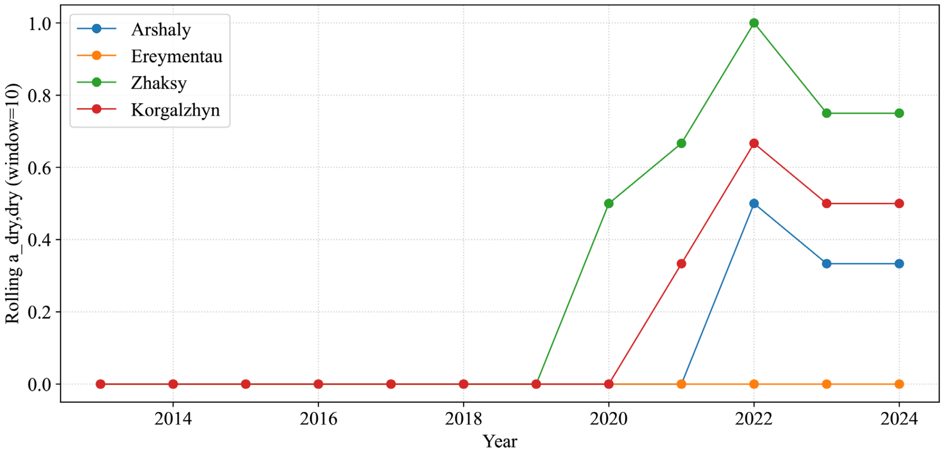


Fig. 7. Probability of continued arid conditions (10-year sliding estimate)

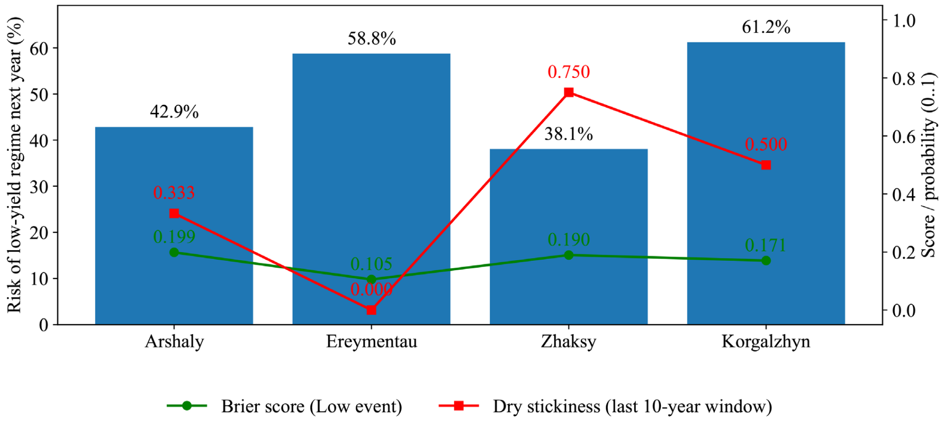


Fig. 8. Risk map of deviation from target indicators for 2025 and drought inertia indicators

As shown in Fig. 8, the assessments for the Korgalzhyn and Ereymentau districts are characterized by consistently high risk, and the quality of the probabilistic assessment is confirmed by the Brier score values.

Zhaksy stands out in this respect. Despite a moderate probability of unfavorable conditions, it shows a high level of climatic inertia (0.75), which should be taken into account when interpreting the forecast for 2025. In contrast, Arshaly is characterized by less pronounced inertia and more frequent regime changes, which require adaptive monitoring under uncertainty.

Based on the results obtained, a target architecture for risk monitoring and management (TO-BE) is proposed, as shown in Fig. 9.

The architecture shown in Fig. 9 outlines the sequence of stages, from data collection and integration through to risk assessment, validation and the formulation of management decisions.

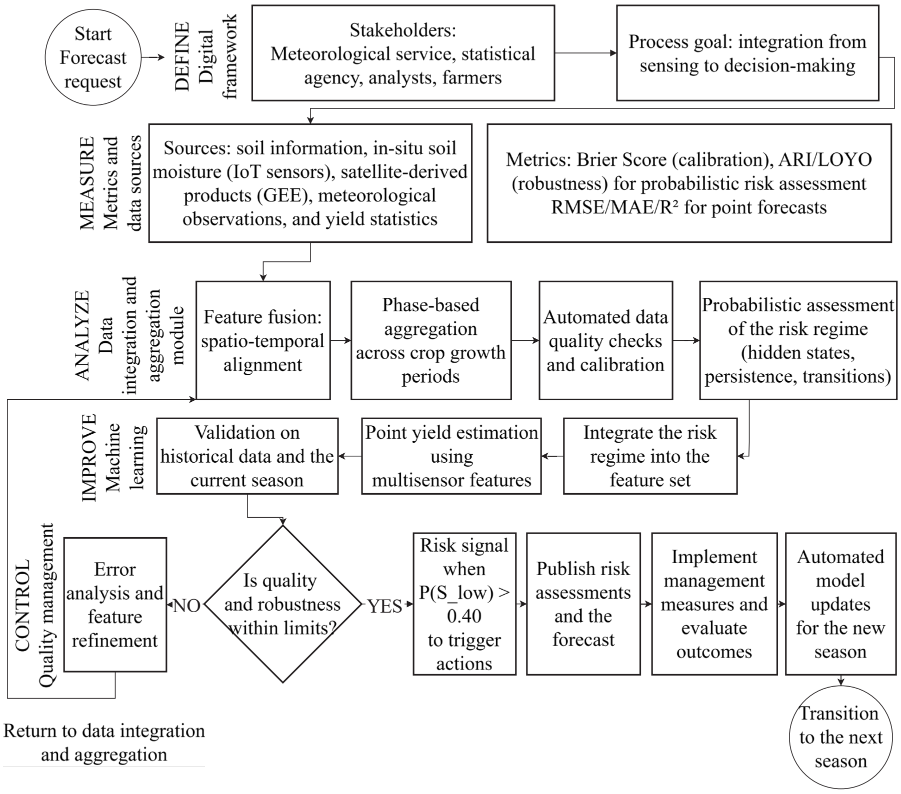


Fig. 9. TO-BE architecture of the risk monitoring and control process

A comparison of the AS-IS, HMM and TO-BE approaches is presented in Table 2.

The comparison presented in Table 2 demonstrates clear differences in the functional roles of the considered approaches within the risk monitoring process. The AS-IS framework is limited to retrospective evaluation of target indicators and does not support continuous monitoring. The HMM approach enables the identification of latent climatic states and provides probabilistic estimates of their occurrence, thereby introducing a mechanism for detecting risk dynamics.

Table 2

Comparison of risk forecasting and monitoring models

Approach	Monitoring objective	Model	Uncertainty	Dynamics consideration	Quality check	Operational limitations
AS-IS (point estimate)	Point estimate of target indicators based on predictors	Point estimate $Y = f(X)$	Usually not explicitly represented (no probabilities or intervals)	Generally not modelled; reflected indirectly through seasonal aggregates	RMSE/ MAE/R^2	Sensitivity to data shifts; limited interpretability of regimes
HMM	Identification of climatic states and their changes	Latent states S_t and transitions $P(S_{t+1}\|S_t)$	State probabilities, including $P(S_{low})$	Explicitly, through the transition matrix	Calibration (Brier score), stability checks (ARI/LOYO)	Climate only; sensitivity to time-series length and transition stationarity
TO-BE (risk monitoring)	Operational risk monitoring	HMM-based risk assessment with update and recalibration based on new data	Risk probabilities over time with calibration control	Explicitly, updating based on new data	Calibration control (Brier score over time), external validation	Requires updating infrastructure; risk of data shifts and source inconsistency

The TO-BE framework integrates these probabilistic outputs into an operational context, ensuring their use within a continuous monitoring cycle with periodic updates and recalibration. This integration transforms probabilistic estimates into actionable signals, linking model outputs with decision-making procedures.

Thus, Table 2 confirms that the proposed framework not only improves the representation of uncertainty, but also extends the functionality of monitoring systems by incorporating dynamic risk tracking and operational applicability.

6. Discussion of results of probabilistic risk monitoring

The results indicate the inertia of climatic regimes, in which unfavorable periods tend to form sequences, increasing the probability of their continuation [18, 19]. This is confirmed by the transition probabilities and state dynamics presented in Fig. 5, 7, where prolonged dry regimes are observed. This justifies the use of an early warning system, in which the probability of an unfavorable regime is refined as new data become available [4].

The obtained results show that climatic processes can be effectively represented as transitions between latent states with distinct characteristics. The estimated transition probability matrix demonstrates a pronounced persistence of regimes, indicating that the current state is strongly dependent on the previous one. In particular, the probability of remaining in the same state is significantly higher than transitioning to other states, especially for the unfavorable regime, which reflects the tendency of adverse climatic conditions to persist over time.

The probabilistic state estimates enable the dynamic assessment of risk levels across different districts. Regions can be differentiated based on the probability of belonging to unfavorable or moderate regimes. For example, higher probabilities of unfavorable conditions are observed in districts such as Korgalzhyn and Ereymentau, while Arshaly and Zhaksy demonstrate moderate risk levels.

Significant spatial heterogeneity has been identified (Fig. 8). The Korgalzhyn and Zhaksy districts are characterized by persistent drought sequences, reflected in an increased probability of persistence over a 10-year period. The Ereymentau district shows low drought inertia with a persistently high risk of returning to an unfavorable state. Arshaly is characterized by changing regimes without pronounced, prolonged unfavorable phases. These differences are illustrated in Fig. 5, 7 and indicate the necessity of region-specific risk management strategies. Consequently, a unified risk-oriented management strategy (Fig. 9) requires adaptation to local dynamics [7].

A comparison of the approaches reveals differences in problem formulation and uncertainty representation (Table 2). The AS-IS control loop focuses on point estimates of yield and does not typically formalize uncertainty. The HMM framework (Fig. 1) provides probabilistic estimates of regimes, enables the use of warning thresholds at $P(S_{low}) > 0.40$, and allows calibration to be assessed using the Brier score. The TO-BE control loop translates probabilistic estimates into a regular monitoring cycle through updated input data and model recalibration, and, where infrastructure is available, can be extended with operational data sources such as remote sensing and IoT.

Unlike traditional regression-based approaches, which provide only point estimates without explicit representation of uncertainty, the proposed HMM-based framework enables probabilistic interpretation of climatic regimes and supports continuous risk monitoring through dynamic updating of state probabilities (Fig. 2). This advantage is achieved through the use of latent state modelling and transition matrices, which explicitly capture temporal dependencies in climatic processes.

In contrast to existing studies focused on early yield forecasting using climatic predictors [4, 15], where the main objective is to improve predictive accuracy at a fixed time horizon, the proposed approach shifts the emphasis towards continuous monitoring of risk dynamics. This allows not only the prediction of outcomes, but also the tracking of transitions between risk states over time, which is not explicitly addressed in traditional forecasting frameworks.

Interpretability is ensured by comparing the unfavorable S_{low} regime with historically low target values and corresponding climatic conditions while controlling the model calibration using the Brier score [26] (Fig. 3). In practice, $P(S_{low})$ serves as a formalized signal in the risk management loop, including changes in crop rotation structure and the use of insurance mechanisms, especially in areas prone to prolonged adverse series [6, 7].

Compared to studies applying hidden Markov models for the analysis of climatic sequences [4, 20], where the focus is primarily on identifying latent regimes and describing their statistical properties, the proposed framework extends this approach by embedding probabilistic state estimation into a decision-support architecture. This integration enables the transformation of model outputs into operational risk signals, which can be directly used in management processes.

The obtained results demonstrate that probabilistic modelling of climatic regimes can be effectively combined with continuous monitoring, enabling the identification of risk states and their use in operational decision-making.

Thus, the main contribution of this study, in comparison with the analyzed literature, lies in the integration of probabilistic modelling, temporal dynamics, and operational implementation within a unified framework, which bridges the gap between analytical modelling and practical risk management in climate-dependent systems.

The proposed architecture can be adapted to other climate-dependent processes that require early detection of adverse conditions. This extends the applicability of the approach beyond grain crop yields and highlights its potential for use in broader climate-sensitive domains.

The limitations of the study include data aggregation at the district level, the relatively short time series (21 years), the focus on climatic predictors without accounting for soil, technological, and management factors, and the assumption of stationary transitions. The disadvantages of the study are related to the dependence of the model on the quality and availability of input data, as well as its sensitivity to structural changes in climate patterns. These disadvantages can be mitigated by incorporating additional data sources and extending the modelling framework. In addition, the proposed approach may be sensitive to structural changes in climate patterns and data availability constraints, which should be considered when applying the model in different regions or under rapidly changing environmental conditions.

Further study may include updating risk monitoring using satellite data [27–30]. In addition, it is advisable to expand the geographical coverage of the analysis [3]. Mandatory independent verification in subsequent seasons is also important [10].

However, this development may involve methodological and computational difficulties related to data heterogeneity, model scalability, and validation under changing environmental conditions.

7. Conclusion

1. The analysis of the current analytical framework (AS-IS) revealed its limitations, including low predictive performance in several districts ($R^2 < 0$ for Korgalzhyn) and sensitivity to data variability, which confirms the lack of a stable and reproducible signal. This result explains the need to shift from deterministic point estimation to probabilistic approaches for risk monitoring.

2. The estimation of transition probabilities made it possible to identify risk states and quantify the inertia of unfavorable conditions, with the probability of maintaining a dry regime over a 10-year sliding window ranging from 0.57 to 0.76. This result confirms the presence of climate memory and explains the persistence of adverse conditions in specific regions.

3. The validation of the model demonstrated acceptable calibration and stability, with Brier scores in the range of 0.106–0.199 and ARI values from 0.16 to 0.68, while LOYO cross-validation showed median values of 0.41–0.58. These results indicate reliable probabilistic estimates and robustness of state identification under different validation conditions.

4. A system for risk monitoring and decision support was proposed, including a TO-BE architecture that integrates probabilistic estimates into a continuous monitoring loop. The practical significance of this result lies in the use of the probability of an unfavorable regime as a formalized control signal, based on the estimated persistence of climatic states. In particular, the results show that the probability of maintaining an unfavorable (dry) regime reaches 0.75 in the Zhaksy district, while a steady increase to 0.50 is observed in Korgalzhyn, and non-linear dynamics ranging from 0.60 to 0.33 are characteristic of Arshaly. These quantitative indicators reflect the variability of climatic inertia across regions and enable adaptive management decisions and timely implementation of preventive measures under conditions of uncertainty.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

Artificial intelligence tools were used in this study in a limited and supporting manner.

The authors used the ChatGPT (OpenAI, GPT-5.3) model for assistance in language editing and structuring of the manuscript, including refinement of the wording in the Introduction, Literature Review, and Discussion sections.

AI tools were applied specifically for:

– improving the clarity and readability of the text;

– restructuring sentences and paragraphs;

– ensuring consistency of academic style and terminology.

The AI tool was not used for generating scientific results, modelling, data analysis, or interpretation of results. All scientific content, including methodology, experiments, results, and conclusions, was developed exclusively by the authors.

All outputs provided by the AI tool were carefully reviewed, verified, and edited by the authors.

The authors ensured that the final text accurately reflects the study conducted and complies with scientific standards.

The use of AI tools did not influence the results or conclusions of the study, but only improved the presentation quality of the manuscript.

Authors' contributions

Dulat Kali: Software, Investigation, Writing – original draft**;** **Nurzhamal Kashkimbayeva**: Conceptualization, Methodology**;** **Ayan Kemel**: Validation, Formal analysis**;** **Botagoz Mirzagalikova**: Data Curation, Writing – review & editing**;** **Zhuldyz Basheyeva**: Resources, Project administration, Conceptualization.

References

1. Karatayev, M., Clarke, M., Salnikov, V., Bekseitova, R., Nizamova, M. (2022). Monitoring climate change, drought conditions and wheat production in Eurasia: the case study of Kazakhstan. Heliyon, 8 (1), e08660. https://doi.org/10.1016/j.heliyon.2021.e08660
2. Teleubay, Z., Yermekov, F., Rustembayev, A., Topayev, S., Zhabayev, A., Tokbergenov, I. et al. (2023). Comparison of Climate Change Effects on Wheat Production under Different Representative Concentration Pathway Scenarios in North Kazakhstan. Sustainability, 16 (1), 293. https://doi.org/10.3390/su16010293
3. Schauberger, B., Jägermeyr, J., Gornott, C. (2020). A systematic review of local to regional yield forecasting approaches and frequently used data resources. European Journal of Agronomy, 120, 126153. https://doi.org/10.1016/j.eja.2020.126153
4. Anderson, W., Shukla, S., Verdin, J., Hoell, A., Justice, C., Barker, B. et al. (2024). Preseason maize and wheat yield forecasts for early warning of crop failure. Nature Communications, 15 (1). https://doi.org/10.1038/s41467-024-51555-8
5. van Klompenburg, T., Kassahun, A., Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, 105709. https://doi.org/10.1016/j.compag.2020.105709
6. Corcoran, E., Afshar, M., Curceac, S., Lashkari, A., Raza, M. M., Ahnert, S. et al. (2023). Current data and modeling bottlenecks for predicting crop yields in the United Kingdom. Frontiers in Sustainable Food Systems, 7. https://doi.org/10.3389/fsufs.2023.1023169
7. Ceglar, A., Toreti, A. (2021). Seasonal climate forecast can inform the European agricultural sector well in advance of harvesting. Npj Climate and Atmospheric Science, 4 (1). https://doi.org/10.1038/s41612-021-00198-3
8. Risbey, J. S., Squire, D. T., Black, A. S., DelSole, T., Lepore, C., Matear, R. J. et al. (2021). Standard assessments of climate forecast skill can be misleading. Nature Communications, 12 (1). https://doi.org/10.1038/s41467-021-23771-z
9. Darra, N., Anastasiou, E., Kriezi, O., Lazarou, E., Kalivas, D., Fountas, S. (2023). Can Yield Prediction Be Fully Digitilized? A Systematic Review. Agronomy, 13 (9), 2441. https://doi.org/10.3390/agronomy13092441
10. Romanovska, P., Schauberger, B., Gornott, C. (2023). Wheat yields in Kazakhstan can successfully be forecasted using a statistical crop model. European Journal of Agronomy, 147, 126843. https://doi.org/10.1016/j.eja.2023.126843
11. Iizumi, T., Shin, Y., Kim, W., Kim, M., Choi, J. (2018). Global crop yield forecasting using seasonal climate information from a multi-model ensemble. Climate Services, 11, 13–23. https://doi.org/10.1016/j.cliser.2018.06.003
12. Doi, T., Sakurai, G., Iizumi, T. (2020). Seasonal Predictability of Four Major Crop Yields Worldwide by a Hybrid System of Dynamical Climate Prediction and Eco-Physiological Crop-Growth Simulation. Frontiers in Sustainable Food Systems, 4. https://doi.org/10.3389/fsufs.2020.00084
13. Iizumi, T., Takaya, Y., Kim, W., Nakaegawa, T., Maeda, S. (2021). Global Within-Season Yield Anomaly Prediction for Major Crops Derived Using Seasonal Forecasts of Large-Scale Climate Indices and Regional Temperature and Precipitation. Weather and Forecasting, 36 (1), 285–299. https://doi.org/10.1175/waf-d-20-0097.1
14. Jin, H., Li, M., Hopwood, G., Hochman, Z., Bakar, K. S. (2022). Improving early-season wheat yield forecasts driven by probabilistic seasonal climate forecasts. Agricultural and Forest Meteorology, 315, 108832. https://doi.org/10.1016/j.agrformet.2022.108832
15. Ding, H., Newman, M., Alexander, M. A., Wittenberg, A. T. (2019). Diagnosing Secular Variations in Retrospective ENSO Seasonal Forecast Skill Using CMIP5 Model-Analogs. Geophysical Research Letters, 46 (3), 1721–1730. https://doi.org/10.1029/2018gl080598
16. Bento, V. A., Russo, A., Dutra, E., Ribeiro, A. F. S., Gouveia, C. M., Trigo, R. M. (2022). Persistence versus dynamical seasonal forecasts of cereal crop yields. Scientific Reports, 12 (1). https://doi.org/10.1038/s41598-022-11228-2
17. Lou, J., Newman, M., Hoell, A. (2023). Multi-decadal variation of ENSO forecast skill since the late 1800s. Npj Climate and Atmospheric Science, 6 (1). https://doi.org/10.1038/s41612-023-00417-z
18. Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H. et al. (2024). Soil Moisture Memory: State-Of-The-Art and the Way Forward. Reviews of Geophysics, 62 (2). https://doi.org/10.1029/2023rg000828
19. O'Connell, E., O'Donnell, G., Koutsoyiannis, D. (2023). On the Spatial Scale Dependence of Long-Term Persistence in Global Annual Precipitation Data and the Hurst Phenomenon. Water Resources Research, 59 (4). https://doi.org/10.1029/2022wr033133
20. Ho, M., Lall, U., Cook, E. R. (2018). How Wet and Dry Spells Evolve across the Conterminous United States Based on 555 Years of Paleoclimate Data. Journal of Climate, 31 (16), 6633–6647. https://doi.org/10.1175/jcli-d-18-0182.1
21. Mehrabi, Z., Ramankutty, N. (2019). Synchronized failure of global crop production. Nature Ecology & Evolution, 3 (5), 780–786. https://doi.org/10.1038/s41559-019-0862-x
22. Hewamalage, H., Ackermann, K., Bergmeir, C. (2022). Forecast evaluation for data scientists: common pitfalls and best practices. Data Mining and Knowledge Discovery, 37 (2), 788–832. https://doi.org/10.1007/s10618-022-00894-5

23. Petropoulos, T., Benos, L., Berruto, R., Miserendino, G., Marinoudi, V., Busato, P. et al. (2025). Interpretable Machine Learning for Legume Yield Prediction Using Satellite Remote Sensing Data. Applied Sciences, 15 (13), 7074. https://doi.org/10.3390/app15137074
24. Jabed, Md. A., Azmi Murad, M. A. (2024). Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. Heliyon, 10 (24), e40836. https://doi.org/10.1016/j.heliyon.2024.e40836
25. Gold, D. F., Gupta, R. S., Reed, P. M. (2024). Exploring the Spatially Compounding Multi-Sectoral Drought Vulnerabilities in Colorado's West Slope River Basins. Earth's Future, 12 (11). https://doi.org/10.1029/2024ef004841
26. Lenssen, N. J. L., Goddard, L., Mason, S. (2020). Seasonal Forecast Skill of ENSO Teleconnection Maps. Weather and Forecasting, 35 (6), 2387–2406. https://doi.org/10.1175/waf-d-19-0235.1
27. Ryssaliyeva, L., Salnikov, V., Lin, Z., Raimbekova, Z. (2025). Seasonal Sensitivity of Drought Indices in Northern Kazakhstan: A Comparative Evaluation and Selection of Optimal Indicators. Sustainability, 17 (21), 9413. https://doi.org/10.3390/su17219413
28. Nurgaliyeva, S., Amangali, M., Basheyeva, Z., Kashkimbayeva, N., Amantayev, D. (2025). Design and evaluation of an intelligent waste monitoring system based on RGIS integration for smart cities. Eastern-European Journal of Enterprise Technologies, 4 (9 (136)), 70–78. https://doi.org/10.15587/1729-4061.2025.337033
29. Zhao, Y., Potgieter, A. B., Zhang, M., Wu, B., Hammer, G. L. (2020). Predicting Wheat Yield at the Field Scale by Combining High-Resolution Sentinel-2 Satellite Imagery and Crop Modelling. Remote Sensing, 12 (6), 1024. https://doi.org/10.3390/rs12061024
30. Becker-Reshef, I., Barker, B., Whitcraft, A., Oliva, P., Mobley, K., Justice, C., Sahajpal, R. (2023). Crop Type Maps for Operational Global Agricultural Monitoring. Scientific Data, 10 (1). https://doi.org/10.1038/s41597-023-02047-9