



Applying Machine Learning Models to Predict Population Dynamics of Harmful Non-Gregarious Locusts Across Kazakhstan Agroclimatic Zones

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ABSTRACT

The paper reports the results of studies on the use of models based on machine learning algorithms and IT to predict the population dynamics of harmful, non-gregarious locusts in different agroclimatic zones of Kazakhstan. The research goal was to create a forecasting model for the population of harmful non-gregarious locusts in the agroclimatic zones of Kazakhstan using a machine learning algorithm and climatic predictors. The study covered the highly humid and slightly humid and moderately warm agroclimatic zones. Long-term data (2003-2023) on the number of pests and weather parameters (temperature, precipitation, soil water volume, etc.) were used to create multilinear regression, random forest, gradient boosting SVR, and SARIMA models. Model accuracy was assessed with MSE and R^2 metrics. As a result, Gradient Boosting SVR performed the best in terms of the accuracy and stability of forecasts for both zones. The key climatic parameters were determined: precipitation and soil water volume in July-August in the highly humid zone and spring soil water volume and early summer conditions in the slightly humid zone. Thus, together with GIS data, the highlighted model can make long-term phytosanitary forecasts and plan plant protection measures, considering regional agroclimatic features.

Keywords: Harmful non-gregarious locusts, Agroclimatic zones, Phytosanitary forecasting models, Machine learning algorithms, GIS technologies

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INTRODUCTION

The digital transformation of the agro-industrial complex (AIC) is currently considered a key factor in the sustainable and innovative development of agriculture. The integration of information and communications technologies into the agricultural production processes contributes to labor productivity and the efficiency of resource use and provides for an export-oriented model by increasing the volume of processed agricultural products (Pakhomova *et al.*, 2025). Today, locusts hold their position as troublesome polyphagous plant pests worldwide. Kazakhstan, in particular, is home to about 300 species and subspecies of locusts. Of these, about 15-20 species, both gregarious and non-gregarious, are the most harmful and dangerous for crops and lands (Kambulin, 2000; Childebaev *et al.*, 2004b; Kambulin *et al.*, 2010). It causes an increasing need for preventive control and advanced

forecasting of the population of these pests to objectively plan the scope of protective measures (Yskak *et al.*, 2002; Azhbenov *et al.*, 2015; Yessenbayeva *et al.*, 2025). Our earlier studies (Baibussenov *et al.*, 2021, 2022a, 2022b) provide data on innovative approaches in the phytosanitary monitoring of the complex of harmful non-gregarious locusts, namely, GIS-based modeling of ecological niches or favorable habitats. This technology allows identifying the places with the highest risk of population by locusts, which need to be prioritized in surveys (Al-Dosari *et al.*, 2024; Csep *et al.*, 2024; Homayoun *et al.*, 2024; Khan *et al.*, 2024; Braun *et al.*, 2025; Flores *et al.*, 2025; Nakamura *et al.*, 2025; Pacheco *et al.*, 2025; Park *et al.*, 2025; Wilson *et al.*, 2025).

There is a satisfactory body of research on the improvement of the phytosanitary monitoring of especially dangerous gregarious locusts, such as *Calliptamus italicus* L., *Doclostaurus maroccanus* Thunb., *Locusta migratoria* L., and *Schistocerca gregaria* Fors. (Iranipour *et al.*, 2017; Lachininsky, 2020; Githae & Kuria, 2021; Maeno *et al.*, 2021; Sergeev *et al.*, 2022; Lachininsky *et al.*, 2023; Azhbenov *et al.*, 2024). These studies

were used to create large databases on the distribution and migration of these species, as well as models of their ecological niches using remote sensing of the Earth and GIS technologies (Liao et al., 2013; Klein et al., 2022; Wu et al., 2022).

Predicting the mass reproduction and migration directions of gregarious locust species is the goal of several studies (Gómez et al., 2018; Humphreys et al., 2022; Lawton et al., 2022; Sun et al., 2022). Using indices of vegetation, soil moisture, rainfall, and land surface temperature, African researchers employed generalized linear models to examine the intervals between observations of desert locust presence and absence during remission periods in West Africa. According to the study, when the soil was subsequently moistened, the gap grew by three weeks in comparison to vegetation (Sun et al., 2022).

Using a multistage dynamic population model, researchers from Australia (Humphreys et al., 2022; Lawton et al., 2022) uncovered environmental processes explaining large-scale changes in the distribution of Australian desert locusts, accounting for errors in phase determination during field studies. They found that variations in the probability of accumulation are mainly explained by rainfall and vegetation cover, with the response to rainfall in desert habitats being faster and more robust than in agricultural landscapes. This structure is promising for predicting locust outbreaks because it bridges the gap between process-based models, which often lack empirical support, and data-based models, which tend to overlook causation in the migration mechanisms of gregarious locust species.

It is urgently necessary to create contemporary digital methods for phytosanitary monitoring and forecasting that target dangerous non-gregarious locust species as well as gregarious ones. Using automated population forecasting as a foundation for determining the necessary volume of protective measures, a particularly urgent goal is to develop technology to identify population expansion early and establish appropriate preventive plant protection measures.

Today, global science is heavily invested in introducing artificial intelligence, machine learning, and other digital technologies into various fields, including the AIC. These technologies could be very useful for plant protection in research aimed at developing models for the phytosanitary forecasting of plant pest populations. In our studies, this experience was applied to the complex of harmful non-gregarious locusts as the research subject.

The purpose of the research was to identify patterns and underlying predictors in a specific agroclimatic zone of Kazakhstan to forecast the pest population based on machine learning algorithms and GIS technologies.

MATERIALS AND METHODS

Long-term historical data on the distribution and population of non-gregarious locust pests were collected and processed using the methods of statistical analysis adopted in phytosanitary monitoring, forecasting, and signaling of the emergence and development of plant pests (Suleimenov et al., 2009; Dubrovin et al., 2011; Azhbenov, 2013; Sagitov et al., 2016).

The study utilized the resources of the Center for Technological Competence in the Field of Digitalization of the Agro-Industrial Complex under S. Seifullin Kazakh Agro-Technical Research University, specifically the laboratories of Big Data Analysis,

Artificial Intelligence, and GIS Technologies in Agriculture.

1. *Study location.* Two agroclimatic zones of Kazakhstan were chosen as the location of the study site for subsequent comparison. The research and analysis were conducted within the following agroclimatic zones:

- The highly humid, moderately warm zone spans across the entire territory of the North Kazakhstan region, the northern part of the Kostanay region, the northern and central part of the Akmola region, and the extreme northern part of the Pavlodar region.
- The slightly humid, moderately warm zone, which occupies the territory around Karaganda city and nearby areas in the direction from north to southeast of the Karaganda region.

2. *Data collection and aggregation.* In order to determine the long-term patterns of the population of harmful non-gregarious locusts, we gathered, examined, and processed long-term data on their distribution and population in the regions of Kazakhstan by agroclimatic zones because the necessary patterns and causes of fluctuations in phytophage population dynamics cannot be established over just two to three years of research. This involved forecasting and signaling the emergence of pests in Kazakhstan, as well as the examination of past data from governmental plant protection services.

The density of non-gregarious locusts in various biotopes and the daily and seasonal dynamics of their number was assessed using a set of accounting methods (Dubrovin et al., 2011; Sagitov et al., 2016):

1 — 100 single (or 50 double) sweeps of the entomological net repeated three to four times. Species abundance was determined using the following scale:

m — the species is abundant (mass), sometimes forming clusters (100 specimens per hour of collection);

f — the species occurs frequently but without forming clusters (21-100 spec./hour);

r — the species occurs rarely (3-20 spec./hour);

un. — only unique individuals of the species occur (1-3 spec./hour).

The dominance index was determined as the ratio of the number of individuals of the species to the total number of all individuals in the collection:

$$D = k \times 100 / K \quad (1)$$

where:

D — domination, %;

K — total number of specimens of all species in all samples, spec.;

k — total number of individuals of the specific species, spec.

According to Pravdin (1978), species that make up over 16% of the total number of collected species are considered dominant forms, and those accounting for 4-16% are categorized as subdominant. In all cases, mass species are always dominant.

3. *Building and training the forecasting model.* To predict the population of harmful non-gregarious locusts using neural networks and machine learning, we employed a comprehensive approach involving several stages.

First, long-term historical data on the population of locust pests in various agroclimatic zones of Kazakhstan were collected and processed. These data cover information on climate conditions, crops, and pest presence. Thus, the first stage provides the foundation for the forecasting model.

The indicators of changes in the number of individuals of insects over time include the mass appearance of harmful species in specific years. The phases of pest population dynamics include depression, population growth, mass reproduction, peak number, and decline in number (Baibussenov, 2021). To determine the phase of non-gregarious locust pests in the analyzed years, the main indicators of crop pest population—relative (P_{rel}), average (P_{av}), and absolute (P_{abs}) population—were calculated by the following formula:

$$P_{rel} = A_p 100 / A_s \quad (2)$$

where

P_{rel} — relative population, %

A_p — populated area, thousand ha

A_s — surveyed area, thousand ha

$$P_{av} = [A_p(0-5)N_{av}(0-5)] + [A_p(30)N_{av}(30)] / A_p \quad (3)$$

where

P_{av} — average population, pcs./m²

$A_p(0-5), (>30)$ — populated area (ths. ha) with the given population density (pcs./m²)

$N_{av}(0-5)...030$; — average population density, pcs./m²

A_p — populated area, thousand ha

$$P_{abs} = P_{rel} P_{av} / 100 \quad (4)$$

where

P_{abs} — absolute population, pcs./m²

P_{rel} — relative population, %

P_{av} — average population, pcs./m²

The absolute population indicator (P_{abs}), which best reflects changes in pest abundance, was used as the target variable for model training. The dataset was cleaned, missing values were imputed, categorical variables were encoded, and exploratory data analysis was performed using Python tools (Anand, 2024; Kapoor et al., 2025). Potential climatic and environmental predictors were then screened through correlation analysis and outlier assessment, and the final set of predictors included in the forecasting model is presented in **Table 1**.

Table 1. Key parameters and predictors used to model the forecast of non-gregarious harmful locust population dynamics

No.	Input parameters and predictors	Description
1	Years of analysis	2003-2023
2	Region code	KAZ002 format
3	Regions under study	Akmola, North Kazakhstan, Kostanay, Karaganda
4	Area code	KAZ008002 format
5	Agroclimatic zone	Slightly humid, moderately warm, highly humid, moderately warm
6	Surface temperature (Skintemp4-10)	April-October

7	Surface solar radiation (Snsr4-10)	April-October
8	Temperature (Temp4-10)	April-October
9	Evaporation (Evap4-10)	April-October
10	Precipitation (Prec4-10)	April-October
11	Soil water volume (Vswl4-10)	April-October
12	Pest population	Absolute population
13	Pest count unit	pcs./m ²
14	Season	1 — spring, 2 — spring-summer, 3 — summer, 4 — autumn
15	Number	Target variable — the subject of the forecast

Model development involved splitting the dataset into training and test sets and evaluating four forecasting approaches: multilinear regression, random forest, gradient boosting SVR, and SARIMA (Durgabai et al., 2018; Xiao et al., 2019; de Oliveira Aparecido et al., 2020; Ibrahim et al., 2022; Da Hye et al., 2024; Lima et al., 2024; Lombardi et al., 2024; Verma et al., 2024; Aoyama et al., 2025; Damaševičius et al., 2025; Møller et al., 2025; Papadopoulos et al., 2025; Shafique et al., 2025; Sørensen et al., 2025; Svendsen et al., 2025). The models were implemented in Google Colab using Python-based tools (Shaik et al., 2024; Swarnkar et al., 2024), and their performance was assessed using mean squared error (MSE) and the coefficient of determination (R^2). To reduce overfitting, multilinear regression included 3-4 key predictors per zone, random forest was limited to 100 trees with a maximum depth of 3, and gradient boosting used 100 trees, a maximum depth of 3, and a learning rate of 0.1. SARIMA models were fitted to annual population series without an explicit seasonal component; based on AIC, the selected specifications were ARIMA(0,1,0) for zone 14 and ARIMA(0,0,2) for zone 15. Together, these procedures formed the methodological basis for forecasting harmful non-gregarious locust populations in Kazakhstan.

RESULTS AND DISCUSSION

Ecological features of harmful non-gregarious locusts in the studied agroclimatic zones

Phytopsanitary services usually monitor gregarious and non-gregarious species separately. Gregarious species of locusts (e.g., in Kazakhstan—*Calliptamus italicus* L., *Dociostaurus maroccanus* Thunb., and *Locusta migratoria* L.) in years of their mass reproduction usually form large swarms consisting of only one biological species and move in them. However, these swarms may not form uniformly across the entire territory of the country, even in the years of population growth and mass reproduction.

For instance, starting in 2022, an increase in *Calliptamus italicus* L. populations was noted in the Aktobe area (Ayteke Bi and Khromtau districts) and districts bordering the Kostanay region with the Aktobe region (Zhetikara and Kamysty districts). The species' population reached its peak in 2024, after which it started to progressively decrease. In the northern and central regions of Kazakhstan, which were selected for our study, *Calliptamus italicus* L. was in the solitary or transitional phase and was primarily observed in a mixed population with harmful non-gregarious locust species, whereas in these regions it saw population growth and transition into the gregarious

phase. As a result, this species and non-gregarious locusts were taken into account in our observations.

In 2023-2024, route surveys were conducted in the chosen districts within the studied agroclimatic zones to establish the species composition, occurrence, and interspecies domination. Namely, in the highly humid, moderately warm agroclimatic zone, surveys were conducted in the Fyodorov and Karabalyk districts of the Kostanay region; the Timiryazev, Akkayin, and Ualikhanov districts of the North Kazakhstan region; and the Burabay, Sandyktau, and Akkol districts of the Akmola region. In the slightly humid, moderately warm agroclimatic zone, our study covered the Arshaly district of the Akmola region and the Bukhar-Zhyrau and Karkaraly districts of the Karaganda region. These areas were chosen as the favorable habitats of the target pests. The results of these surveys were used to clarify and establish the set of harmful non-gregarious locust species, their frequency of occurrence, and dominance in the studied agroclimatic zones of Kazakhstan.

In this process, the species composition of harmful locusts in the studied agroclimatic zones of Kazakhstan was clarified. In the studied areas, among the locusts most harmful and economically significant to the AIC, we identified the main 15 harmful species. All these species were found in a community or a complex of species. Further research as part of this focused exclusively on this set of species.

Calliptamus italicus was common in both of the agroclimatic zones investigated. This gregarious species was found everywhere, primarily on fallow and perennial wormwood-cereal plant associations, and it appeared largely in the solitary phase in a mixed population with dangerous non-gregarious

locust species. *Paracryptera microptera* is a common species in the humid, somewhat warm agroclimatic zone that covers the majority of North Kazakhstan. This species was found in tiny quantities in a slightly humid, fairly warm agroclimatic zone. These locusts like needle grass-cereal and needle grass-Volga fescue-cereal plant communities.

Dociostaurus brevicollis and *Dociostaurus kraussi* occurred frequently in the highly humid, moderately warm agroclimatic zone and moderately often in the slightly humid, moderately warm zone. *Dociostaurus brevicollis* was found primarily in cereal-wormwood and Volga fescue-wild rye plant associations, while *Dociostaurus kraussi* appeared mainly in the Volga fescue-wild rye association. *Stenobothrus fischeri* inhabited the Volga fescue-wormwood association. This species occurred moderately often in the highly humid, moderately warm agroclimatic zone and frequently in the slightly humid, moderately warm zone. *Oedipoda miniata* was observed in the slightly humid, moderately warm agroclimatic zone, predominantly in needle grass-cereal and cereal-wormwood plant associations, whereas *Oedipoda caerulescens* was more common in the highly humid, moderately warm agroclimatic zone, mostly in the cereal-wormwood plant association. The remaining species cited are also economically important but occur less frequently in the considered agroclimatic zones. However, in combination with other frequently encountered species, their harmfulness increases.

In addition, we calculated the percentage of dominance of the considered mass harmful locust species within the studied agroclimatic zones (**Figures 1 and 2**).

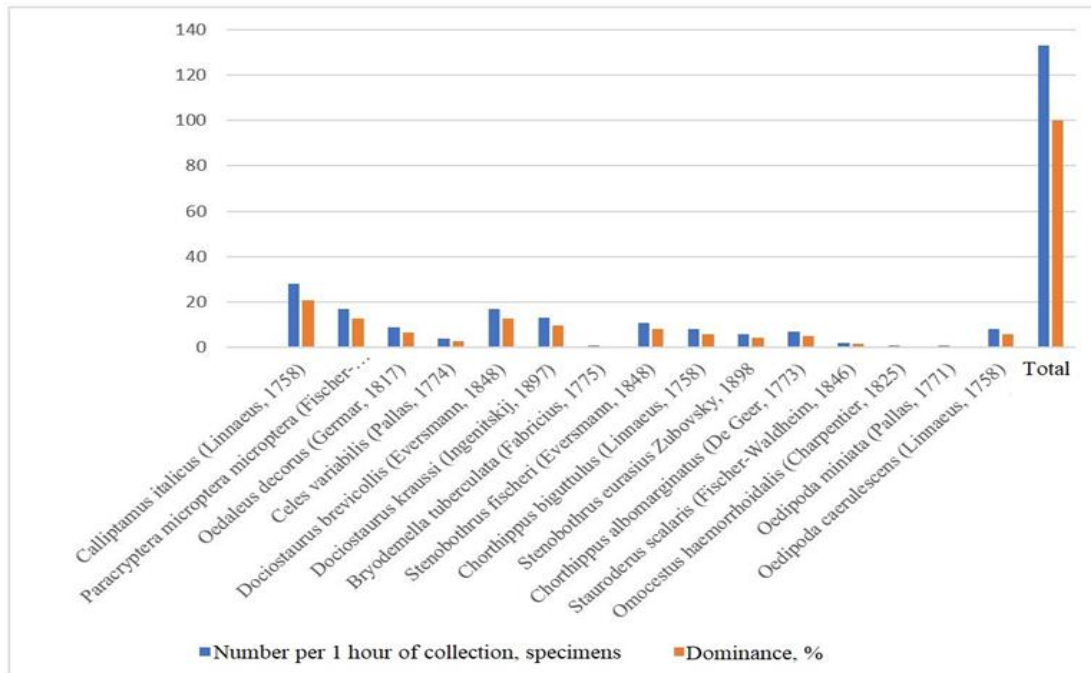


Figure 1. Average numbers and dominance percentage of the mass species of harmful locusts in the highly humid, moderately warm agroclimatic zone (average over 2023-2024)

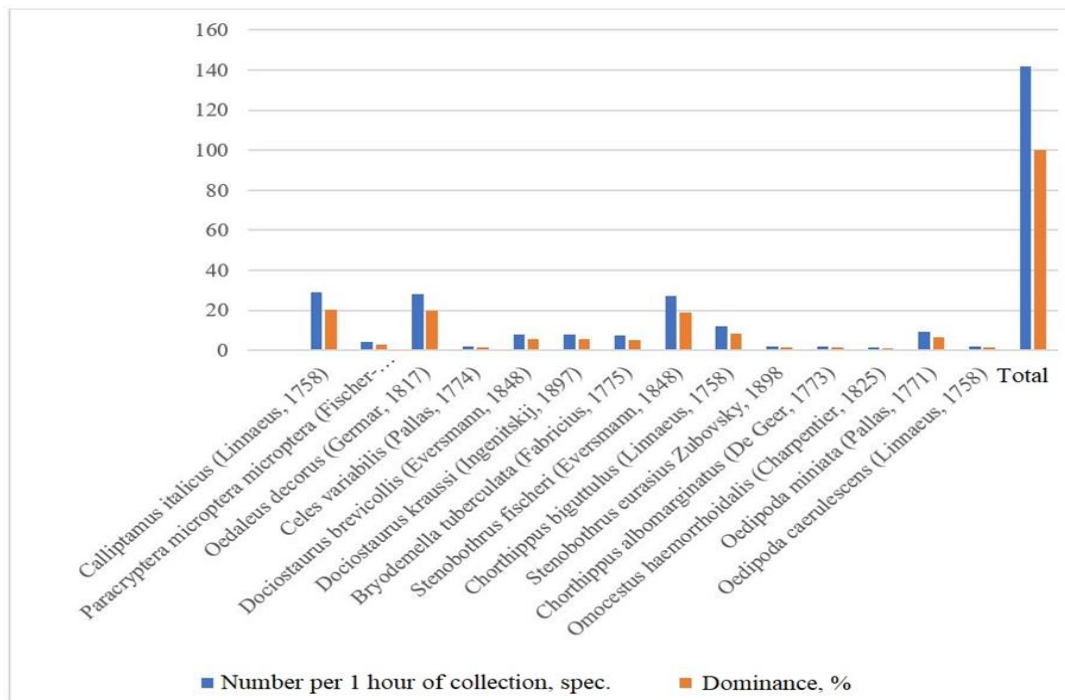


Figure 2. Average numbers and dominance percentage of the mass species of harmful locusts in the slightly humid, moderately warm agroclimatic zone (average over 2023-2024)

According to these data, within the highly humid, moderately warm agroclimatic zone of Kazakhstan, the more dominant species (**Figure 1**) are *Calliptamus italicus*, *Paracryptera microptera*, and *Dociostaurus brevicollis* (21:12.8:12.8%, respectively). In the slightly humid, moderately warm agroclimatic zone, the most dominant harmful species (**Figure 2**) are *Calliptamus italicus*, *Oedaleus decorus*, and *Stenobothrus fischeri* (20.4:19.7:19%, respectively). The remaining species are not dominant in the studied zones, but their combination with the dominant species increases the damage caused by the overall complex of harmful locusts in the area.

These results are crucial for researchers to fully understand the phytosanitary situation with the occurrence and dominance of a set of harmful locusts in the considered agroclimatic zones of Kazakhstan. However, in the practice of plant protection, it is inexpedient to keep separate records for each species, and population and harmfulness are determined for the entire complex of non-gregarious locust pests. The economic threshold of harmfulness is also set based on the entire complex of non-gregarious locust species.

Consequently, all applied work on phytosanitary control and population forecasting was carried out with respect to the complex of harmful species by the studied agroclimatic zones.

Machine learning-based forecasting models for the population of harmful non-gregarious locusts in the studied agroclimatic zones
The issues of forecasting and preventing the outbreaks of mass reproduction of harmful locusts remain pressing in plant protection to this day due to considerable losses of agricultural products.

In any field of science, the forecasting of a phenomenon is founded on the study of repeated events and the main factors

affecting the course of events. If a pattern is detected, changes in the dynamics of any future event can be predicted based on the suppression or activation of concomitant factors. Today, these processes can be studied automatically using machine learning or neural networks.

To identify the fundamental predictors of the population of harmful non-gregarious locusts in the studied agroclimatic zones based on machine learning algorithms, we processed and analyzed long-term historical data for the period of 2003-2023, describing the population dynamics of the studied pests depending on the influence of weather-climatic and edaphic (soil) factors.

At the stage of preliminary data processing, the input data were adapted for machine learning models. Categorical variables, such as region and district codes, were converted to a numeric format. The missing values discovered, in particular, in temperatures, solar radiation, and soil humidity, were filled with median values, thus avoiding distortion due to outliers.

The set of standard models tested for the forecasting of pest population included multilinear regression, random forest, gradient boosting SVR, and SARIMA.

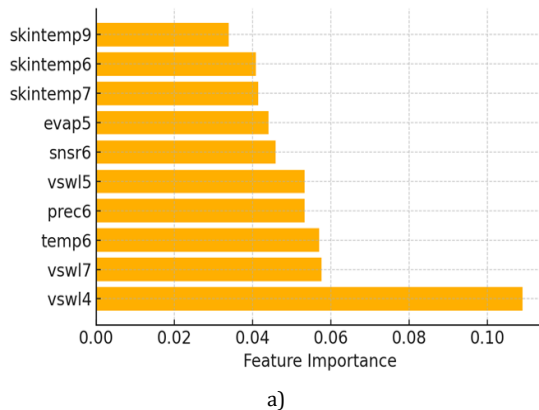
In the process of training the forecasting models, together with the analysis of the population of the studied pests, the accompanying weather and climatic environmental factors for the analyzed years were also considered.

Data for the period from 2003 to 2017 were used to train the models, and the 2018-2023 data were left to test the forecast (validation on unseen data). The quality of the models was assessed by mean squared error (MSE) and the coefficient of determination (R^2).

The correlation heatmap illustrates the structure of relationships between the variables. As expected, climatic indicators have strong internal links: evaporation correlates

positively with air temperatures and "surface temperatures" and negatively with precipitation (forming blocks on the graph with coefficients $|r| > 0.7$ between, for example, Temp, Skintemp, and Evap). Soil water volume (VSWL) is associated negatively with temperature and evaporation (stronger in the summer months) and positively with precipitation, reflecting moisture balance. Thus, many climatic parameters are multicollinear, which needs to be considered when interpreting the impact of individual factors.

Importantly, the linear correlation of population with each of the climatic parameters was very weak ($|r| < 0.1-0.17$). In no agroclimatic zone does any factor show a significant pairwise correlation with the "number" indicator. The highest correlation coefficient is observed in the temperature of late summer/early autumn: for example, in the slightly humid,



moderately warm agroclimatic zone, $r \approx 0.17$ is between "skintemp9" (surface temperature in September) and population. Soil moisture in the spring has a small negative association ($r \approx -0.14$ for VSWL4). However, these relationships do not reach statistical significance at the level of individual correlations. These results imply that the pest population is determined by a combination of factors and nonlinear effects undetectable by simple correlation analysis. This proves the need to use multifactor models to catch hidden dependencies. To identify key climate predictors affecting pest populations, random forest models (at the level of individual districts for all years) were trained, and importance values were calculated for each variable. **Figures 3a and 3b** show the top 10 most significant features by importance in random forest models in the considered agroclimatic zones.

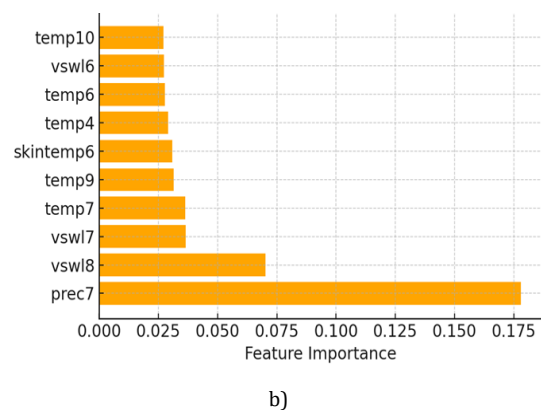


Figure 3. Top 10 predictors in the two agroclimatic zones according to random forest

The heatmap shows that the most influential factor in the slightly humid, moderately warm agroclimatic zone is soil moisture reserve in spring (VSWL4), whose importance reaches ~ 0.11 , noticeably ahead of others. The top ten also includes soil moisture in mid-summer (VSWL7), air temperature in June (Temp6), precipitation in June (Prec6), soil moisture in May (VSWL5), and solar radiation in June (SNSR6). These factors suggest that for the slightly humid, moderately warm agroclimatic zone (more arid), soil moisture at the beginning of the season and conditions in the first half of summer are critical for the development of the pest. Soil water volume in April (VSWL4) leads in importance. Other significant features are soil moisture in July (VSWL7), temperature and precipitation in June (Temp6, Prec6), May moisture (VSWL5), and June solar radiation (SNSR6). These results emphasize the role of the water regime in the arid zone 14 for the development of the studied pests.

The scenario is a little different in the agroclimatic zone that is fairly warm and extremely humid. With a high proportion of ~ 0.18 , precipitation in July (Prec7) is the most significant feature. Soil moisture in August (VSWL8) and July (VSWL7) and air temperature in July (Temp7) and September (Temp9) are next. Therefore, midsummer conditions—including precipitation and soil moisture in July and August as well as temperature during this time—have a substantial impact on population variation in the extremely humid, moderately warm agroclimatic zone. One likely explanation is that excessive humidity and frequent rainfall can either encourage the growth of pests and fodder plants or, on the other hand, repress certain

pests or spread illnesses. Because of this, this feature plays a major role in the model (in this case, the years with greater Prec7 saw a bigger number of the examined pests, according to the model's signals of influence).

Next, to estimate future risks of pest populations, the forecast was extrapolated using the chosen gradient boosting model to the period up to 2030. When constructing the long-term forecast, the climatic parameters of recent years were considered. It was assumed that the average weather conditions would remain within the observed ranges, without extreme anomalies. This allows us to obtain an approximate dynamic of the number of pests in each region, subject to the gradual continuation of current trends. The figures below show the forecast curves for the slightly and highly humid, moderately warm agroclimatic zones, together with actual data until 2023 to illustrate the trends.

The gradient boosting model indicates that after the 2019-2020 decline, the population of pests in the highly humid, moderately warm agroclimatic zone will fluctuate around the average level of $\sim 1.3-1.5$ c.u., with exceptions in individual years. The forecasted population dynamics for the highly humid, moderately warm agroclimatic zone for 2024-2030 are presented in **Figure 4**. The forecast shows a moderate increase in population by the middle of the decade: a maximum is expected around 2026, when the average number can reach $\sim 1.7-1.8$, approaching the values of 2018. Further on, a temporary decrease is likely: minimums are predicted at the end of the decade (around 2029, the number may decrease to ~ 1.2). Nevertheless, even in the years of recession, the model

does not imply such a sharp drop as was observed in 2020. No significant monotonous trend is expected for zone 15. According to the forecast, the number of pests will remain on a relative plateau with some fluctuations, which indicates the continuing threat of periodic outbreaks. In practice, this means that after

the experienced decline in numbers, constant monitoring is vital. The expected new upturn in the mid-2020s signals an increased risk requiring preventive measures in these years, despite possible periods of relief (like the forecasted decline by 2029).

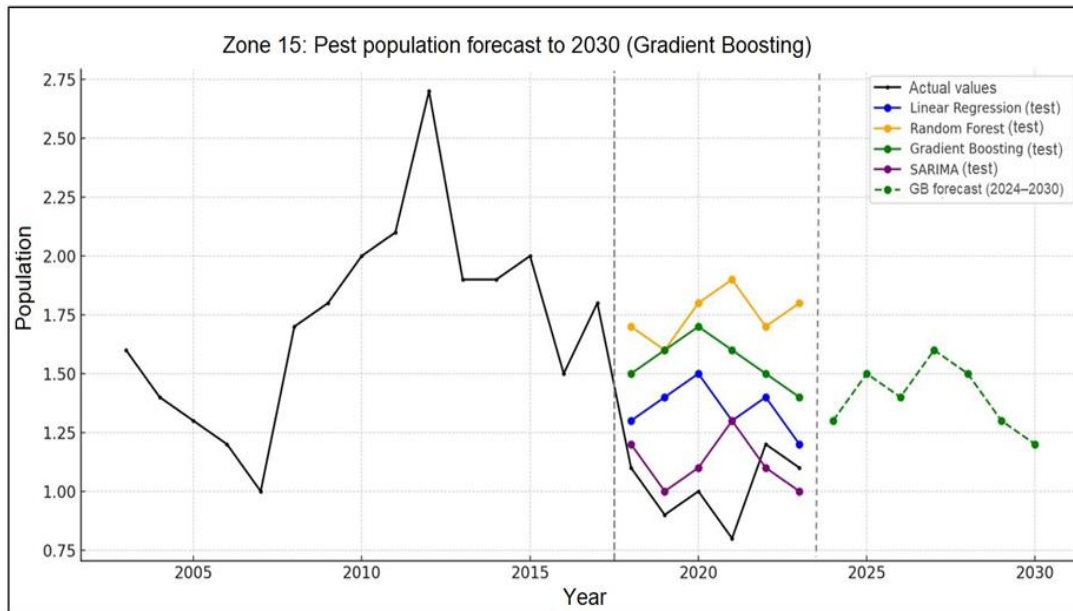


Figure 4. Forecasted dynamics of the population of harmful non-gregarious locusts in the highly humid, moderately warm agroclimatic zone for 2024-2030

As suggested by the model, in the slightly humid, moderately warm agroclimatic zone, the pest population is expected to continue to recover after the long-lasting low level in the 2000s-2010s. The forecasted population dynamics for the slightly humid, moderately warm agroclimatic zone for 2024-2030 are shown in Figure 5. The forecast indicates a general upward trend in population: after a relatively moderate level in 2024 (~

1.5 c.u., which is comparable to 2023), further growth is possible in subsequent years. Maximum values are predicted by 2027 and the end of the decade (2030), when the average number may exceed 2.0 c.u. (twice the 2018-2020 level). In some years, small fluctuations are likely: for example, the model suggests a possible temporary decrease in the growth rate around 2028.

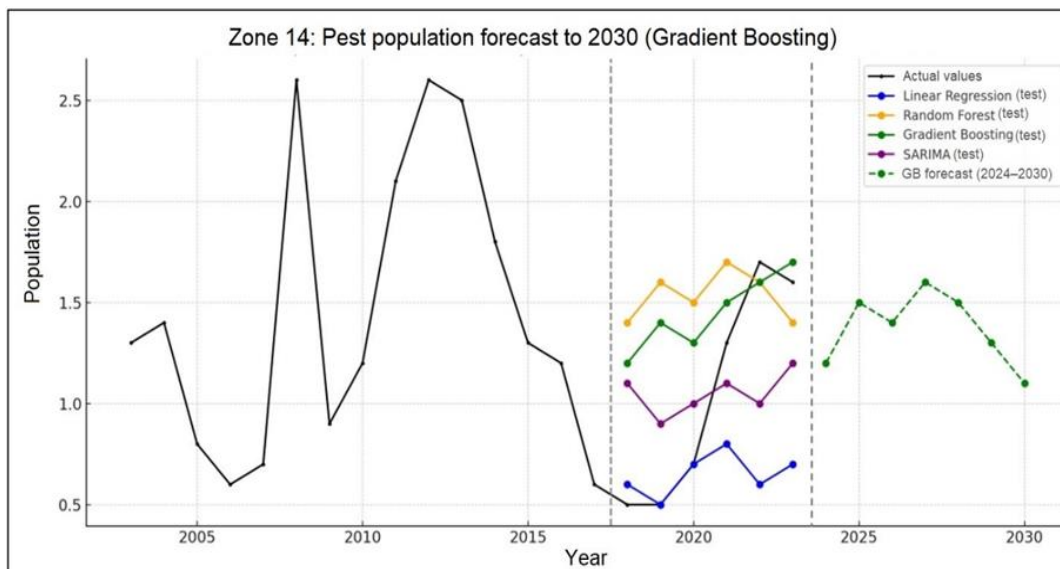


Figure 5. Forecasted dynamics of the population of harmful non-gregarious locusts in the slightly humid, moderately warm agroclimatic zone for 2024-2030

Nevertheless, the overall predicted curve for the slightly humid, moderately warm agroclimatic zone goes up, approaching the values that the model had previously expected by 2023 (but in fact, they are reached later). This suggests that climatic conditions favorable for pests are likely to develop more often, and the population growth will be able to compensate for previous losses. The practical implication is the need for enhanced preparedness. The slightly humid, moderately warm agroclimatic zone, which has had a low pest count for a long time, can enter a period of increased threat of outbreaks. Years with peak forecast values (around 2026-2027 and 2030) appear to be especially high-risk, when preventive measures (planning and preparation of insecticides and informing farms and farmers) should be deployed as much as possible.

For each method, forecast estimates of the number of pests for 2018-2023 were obtained, and error metrics (**Table 2**) were calculated. MSE and R^2 are provided separately for each agroclimatic zone. Overall, the forecast proved to be a difficult task, as most models failed to predict abrupt interannual changes in population, and R^2 was negative (meaning the quality is worse than the trivial mean prediction).

Table 2. Quality of pest population forecasting models (error in the 2018-2023 test period)

Model	Slightly humid, moderately warm agroclimatic zone		Highly humid, moderately warm agroclimatic zone	
	MSE	R^2	MSE	R^2
Multilinear regression	1.2365	-10.19	0.5802	-4.61
Random forest	1.1191	-9.13	0.3794	-2.668
Gradient boosting SVR	0.5765	-3.27	0.3143	-2.039
SARIMA	0.6494	-3.352	0.3606	-2.486

Lower MSE generally means more accurate prediction. $R^2 > 0$ indicates that the model explains part of the variation. Negative R^2 values suggest an insufficient explanation of variance (the model is worse than just the average of the actual numbers over the test period).

The climate-oriented models (multilinear regression and random forest) for the slightly humid, moderately warm agroclimatic zone produced major errors (**Table 2**) and had very low negative R^2 . This indicates that they overestimated the population in years when it was very low. Likewise, most of the models were insufficiently reliable in predicting dynamics for the highly humid, moderately warm agroclimatic zone. That being said, Gradient Boosting SVR had the lowest MSE (0.5765 and 0.3143, respectively) and the best R^2 (-3.27 and -2.486, respectively) in both of the examined climatic zones.

Our modeling revealed both important patterns and methodological limitations. Correlation analysis showed no strong linear relationships between individual climatic variables and pest abundance, indicating that population responses are shaped by combined and likely nonlinear climatic effects. This also explains the weak performance of linear regression in our study (**Table 2**), consistent with previous work showing that simple regression models often oversimplify pest dynamics. Feature-importance analysis further demonstrated clear differences between the agroclimatic zones.

In the slightly humid, moderately warm zone, early-season soil moisture, especially in April, was the most influential factor, likely because severe spring dryness reduces egg survival and slows host plant development. In contrast, in the highly humid, moderately warm zone, midsummer conditions—particularly July precipitation—were more important, suggesting that both excessively wet and dry summers may limit pest development and food availability.

Unfortunately, the direction of influence cannot be directly derived from the random forest model. However, the results suggest that in the highly humid, moderately warm agroclimatic zone, years with low July precipitation were associated with lower pest abundance. From a practical perspective, both drought and excessively wet seasons may therefore signal a decline in pest numbers in this zone. In the slightly humid, moderately warm agroclimatic zone, by contrast, outbreak risk appears to be associated with low soil moisture in spring, which may reflect mild winters with limited snow cover, early warming, and dry weather favorable for locust development.

These findings are generally consistent with previous studies, although they highlight a more specific role of water balance variables. In most studies, the main meteorological predictors are air temperature and humidity, since heat accelerates reproduction and optimal moisture improves survival. Our results do not contradict this view, but show that precipitation and soil moisture were more informative under the agroclimatic conditions considered here. These parameters are also critical for successful larval hatching. In addition, solar radiation may contribute indirectly by affecting leaf temperature, evaporation, and plant productivity. Previous machine-learning studies on cotton pests emphasized that, besides temperature and precipitation, solar radiation and other seasonal variables should also be considered (Xiao *et al.*, 2019; Shafique *et al.*, 2025). Similar conclusions were reported for rice pests, where total solar radiation and dew point were identified as important predictors (Skawsang *et al.*, 2019; Latif *et al.*, 2022). Thus, our results support the need for a multifactor climatic interpretation rather than reliance on temperature alone.

Model comparison showed that machine-learning approaches outperformed multilinear regression, although their predictive quality remained limited. This is likely due to the small dataset and the fact that pest dynamics depend not only on abiotic but also on anthropogenic and biotic factors, including crop rotation, chemical treatments, natural enemies, and insect diseases. As a result, the negative R^2 values indicate that short-term forecasts still remain unstable. Nevertheless, Gradient Boosting SVR produced the most consistent forecasts for both agroclimatic zones and was closer to observed dynamics than the other models. This suggests that combining climatic predictors with temporal structure may be more effective than relying on a single modeling strategy.

Long-term zonal forecasts are valuable for phytosanitary planning, as they help identify periods requiring intensified monitoring and preventive action (Frolov, 2019; Islam *et al.*, 2024; Lopez-Ramos *et al.*, 2024; Novak *et al.*, 2024; Saif *et al.*, 2024; Zielinska *et al.*, 2024; Castellano-Rioja, 2025; Gurung *et al.*, 2025; Klein *et al.*, 2025). Although such forecasts should be interpreted cautiously, they provide a useful basis for moving from reactive control toward preventive pest management under changing climatic conditions.

CONCLUSION

This study forecast the dynamics of harmful non-gregarious locust populations in two agroclimatic zones of Kazakhstan using multilinear regression, random forest, gradient boosting SVR, and SARIMA based on long-term weather, climate, and soil water data. Correlation analysis showed that water-related variables were the most influential predictors, especially soil water volume at the beginning of the season and summer precipitation. Overall, the water regime played a decisive role in population dynamics, while the effect of temperature was mainly expressed through its interaction with moisture. Among the tested approaches, Gradient Boosting SVR produced forecasts closest to observed values in both the validation period and long-term projections. By contrast, multilinear regression and SARIMA showed larger errors or overly smooth trends that failed to capture local peaks and declines. Therefore, Gradient Boosting SVR was selected as the most accurate and stable model for forecasting up to 2030 and for supporting phytosanitary planning in Kazakhstan.

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