

Analytical review of methods for assessing the agroecological potential of agricultural landscapes

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Abstract. Sustainable agricultural development is directly dependent on the efficient use of natural resources, scientifically grounded assessment of climate related risks, and accurate evaluation of the agroecological potential of agricultural landscapes. Under the conditions of global climate change, land degradation, water scarcity, and increasing anthropogenic pressure, improving methods for assessing agroecological potential has become one of the key priorities in contemporary agricultural science. However, the theoretical foundations, application characteristics, and interrelationships of the mathematical, biophysical, energy-based, statistical, and geospatial models used in international scientific research have not yet been comprehensively systematized.

This study provides a systematic analytical review of the contemporary methods used to assess the agroecological potential of agricultural landscapes. The research is based on comparative analysis, scientific synthesis, and methodological systematization of the theoretical foundations, calculation principles, application features, advantages, and limitations of existing assessment approaches.

The literature review demonstrates that methods for assessing agroecological potential have evolved from simple empirical models to integrated approaches combining spatiotemporal analysis, remote sensing, geographic information systems (GIS), ERA5 reanalysis data, statistical modeling, and digital technologies. The review systematically examines the importance of the Miami and Thornthwaite Memorial models for evaluating climatic productivity potential, the role of the Net Primary Productivity (NPP), Potential Net Primary Productivity (PNPP), Human Appropriation of Net Primary Productivity (HNPP), and Climate Regulation Use Efficiency (CRUE) indicators assessing biological productivity, as well as the effectiveness of the Mann-Kendall test, Sen's Slope estimator, Geographically and Temporally Weighted Regression (GTWR), and the Lindeman-Merenda-Gold (LMG) method in identifying spatiotemporal patterns. Furthermore, the study highlights the significant contribution of remote sensing data, geographic information systems, and digital monitoring technologies to improving the accuracy and reliability of agroecological assessments.

The findings systematize the theoretical and methodological foundations of agroecological potential assessment and demonstrate the scientific advantages of integrating multiple assessment approaches. The integration of different models enables more accurate evaluation of the productive potential of natural resources, improves the prediction of

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climate change impacts, and provides a scientific basis for sustainable agricultural planning and management.

Keywords: agroecological potential; agricultural landscapes; climatic productivity potential; climate model; geographic information systems (GIS); remote sensing; sustainable agriculture.

1. Introduction

Contemporary scientific approaches to assessing agroecological potential are the result of scientific schools that have developed over more than a century. The evolution of research in this field has progressed from simple descriptions of natural-climatic evidentiary indicators to comprehensive assessment based on geoinformation technologies and digital monitoring. Therefore, understanding the current methods of agroecological assessment requires an analysis of the stages of their formation.

One of the researchers who made an early contribution to the formation of the scientific foundations for assessing agrolandscapes was G. Vysotsky. In his works devoted to the study of regions of European Russia, climate, soil, vegetation cover, and water regime were, for the first time, considered as a natural system interconnected with one another. The scholar demonstrated that assessing each of the natural components separately is insufficient, and that it is their interaction that determines the potential of agricultural production. This idea subsequently became one of the fundamental principles of landscape ecology and the theory of agroecological assessment. Vysotsky's scientific conclusions indirectly served as a theoretical foundation for the formation of modern climatic productivity potential models, since they relied on the principle of comprehensive assessment of natural evidentiary indicators.

The research conducted by Adilbektegi G.A., Mustafayev J.S., Uvatayeva T.K., Dulatbekova Z.N., and Jozef Mosiej occupies a special place in the information of the Kazakhstan scientific school. These scholars carried out a quantitative assessment of the biological and ecological potential of the landscapes of Southern Kazakhstan, examining natural resources not in isolation but as an interconnected system. The study integrated the assessment of climatic indicators, soil resources, and biological productivity. As a result, it was demonstrated that the natural potential of landscapes is determined not only by the volume of production but also by their ecological sustainability. This research represents one of the first systematized models of comprehensive agroecological potential assessment under Kazakhstan conditions and formed the scientific basis for integrated assessment approaches used in current research.

Akhmetov B.Zh., Kasenova A.Zh., Merzlyakov O.E., and Tatarintsev L.M. incorporated the results of agroecological assessment into the system for planning the sustainable use of agricultural lands. Through a comprehensive assessment of natural-climatic conditions, soil characteristics, and land-use structure, these scholars proposed a model for the rational use of territories. The results of the study showed that agroecological assessment is not merely a scientific description but a key tool for economic decision-making. At the same time, the authors demonstrated that applying identical technologies to regions with differing natural potential intensifies the degeneration of land resources. This conclusion is consistent with the fundamental principles of the modern concept of sustainable land use.

Next, Akimbekova G. and other scholars examined the issues of the efficient use of the resource potential of agricultural production from economic and agroecological perspectives. In the opinion of these scholars, an adequate supply of natural resources does not, by itself, ensure high efficiency in agriculture. The primary outcome is dependent on the system of resource management. In the course of the study, the interrelationship among industrial, natural, and labor resources was assessed, and it was demonstrated that their balanced utilization increases the sustainability of agricultural production (Akimbekova et al., 2025).

These works are distinguished by the introduction of an economic efficiency measure into the assessment of agroecological potential, making it possible to explain the relationship between natural potential and production outcomes.

In recent years, the principles of ESG (Environmental, Social and Governance) have begun to acquire particular significance in the assessment of agroecological potential. The research conducted by Nasiyev B. showed that the sustainable development of agriculture production is directly connected to the long-term, efficient use of soil resources. It was demonstrated that the implementation of ESG principles reduces the rate of soil degradation and increases the efficiency of land resource use. Furthermore, the study concluded that the ecological sustainability of agriculture should now be assessed not only by the volume of production but also by the long-term ecological condition of the soil. This is one of the current international scientific directions (Nasiyev et al., 2025).

Plokhikh R. proposed a landscape-ecological-indicative approach to assessing sustainable pastoral agrolandscapes. The author showed that when assessing the condition of pastures, vegetation cover, erosion processes, soil degradation, and anthropogenic load must be considered simultaneously. The results of the study demonstrated that the use of landscape indicators makes it possible to identify pasture degradation at an early stage, as well as to effectively plan measures for their restoration. This approach strengthened the role of ecological indicators in the assessment of agroecological potential.

Among the studies devoted to the development of digital agriculture in Kazakhstan, the work of Pashkov V. and Mazhitova S. deserves special attention. Having analyzed regional experience in introducing digital technologies into agricultural production, these scholars showed that the use of geoinformation systems, satellite monitoring, and precision farming technologies substantially increases the accuracy of assessing the productivity of agricultural lands. It was further demonstrated that digital technologies enable real-time monitoring, early identification of risks, and rapid management of agricultural production. This study indicates that the future of the agroecological potential assessment system is linked to fully digital systems.

The aim of the research work: An analytical review of methods for assessing the agroecological potential of agricultural landscapes.

Main objectives:

- To analyze current scientific directions in assessing the agroecological potential of agricultural landscapes;
- To examine the theoretical foundations of classical models of climatic productivity potential;
- To analyze the scientific significance of energy-based and agroclimatic indicators for assessing biological productivity;
- To systematize the specific features of the application of statistical and spatiotemporal analysis methods;
- To identify the specific features of applying geoinformation and digital technologies;
- To conduct a comparative assessment of the advantages and disadvantages of the models used in current research.

2. Literature Review

2.1. Classical models of climatic potential productivity

The formation of the theory of assessing the agroecological potential of agricultural landscapes begins with classical studies devoted to modeling the primary productivity of the biosphere. Research in this field is based on identifying quantitative relationships between climatic resources and the productivity of vegetation cover. These models were subsequently widely used applied in assessing the potential of agricultural production, forecasting climate change, and managing natural resources.

In assessing the agroecological potential of agricultural landscapes, the concept of Climate Potential Productivity (CPP) is one of the key indicators. This indicator characterizes the highest possible levels of plant productivity that natural climatic resources can generate, and it allows a quantitative assessment of the influence of climate on agricultural production. As a result, Net

Primary Productivity (NPP) and Potential Net Primary Productivity (PNPP) are calculated using the Thornthwaite Memorial model (Bi et al., 2025).

The Miami model, in turn, describes the annual biomass productivity of natural vegetation cover as a function of average annual temperature and precipitation. The main principle of the model is based on treating heat and moisture resources as the primary limiting evidentiary factors that shape plant productivity. Accordingly, climatic potential productivity is calculated through temperature-dependent production potential (Y_t) and precipitation-dependent production potential (Y_r), with the final result determined in accordance with Liebig's law of the minimum (Shei et al., 2025).

The Thornthwaite Memorial model, in turn, occupies a special place in assessing climatic potential productivity. This model treats actual evapotranspiration as the principal limiting factor for plant productivity, describing the relationship between climatic resources and biological productivity through a new mathematical dependency. The model's key feature lies in assessing productivity not solely through temperature or precipitation, but by taking into account the actual amount of evaporation. The results of the study demonstrated that accounting for the water regime substantially increases the accuracy of assessing climatic potential productivity. The model is widely used in assessing agricultural productivity, forest resources, and the productivity of natural ecosystems (Tamru et al., 2025; Zhu et al., 2025; Shi et al., 2025).

Zoure C. and other authors selected degraded soils known as "Zipellé" in the settlement of Northern Burkina Faso, West Africa, and applied two experimental setups using the zaï and half-moon methods. In the course of the work, precipitation levels, soil hydraulic conductivity, crop growth, and yield volume were studied (Zoucre et al., 2025).

2.2. Models for assessing biological productivity

In assessing climatic productivity, integral indices describing energy resources and the heat-moisture balance play an important role. Energy resources determine the following indicators.

Net Primary Productivity (NPP) was calculated using the vegetation productivity assessment model together with the Thornthwaite Memorial model. This model, relying on precipitation and temperature indicators, makes it possible to assess plant productivity. That is, in the model, climatic evidentiary indicators – temperature and precipitation – are used as the primary input parameters. With the help of these indicators, the annual Net Primary Productivity (NPP) of the vegetation cover of a particular region is determined (Zhang et al., 2022; Bouteska et al., 2024).

Using the Thornthwaite Memorial model, Potential Net Primary Productivity (PNPP) indicators are calculated. To increase the accuracy of this indicator, additional variables obtained from the ECMWF Reanalysis v5 (ERA5) dataset – wind speed and solar radiation – are also applied. The resulting altered net primary productivity (HNPP) indicator is calculated by subtracting Annual Net Primary Productivity (ANPP) from Potential Net Primary Productivity (PNPP). In addition, the potential for increasing grain production (Y) is assessed by calculating the difference between climatic potential productivity and the actually obtained yield (Bi et al., 2025).

Mehmood K. studied the variation of Net Primary Productivity (NPP) across altitudinal belts in the ecosystems of a temperate zone. It was shown that the influence of climatic factors changes considerably with altitude, and that the transformation of the temperature regime directly affects the dynamics of productivity. The results of the study indicate that need to account not only for climatic variables but also for terrain and altitude-related evidentiary indicators when assessing the Net Primary Productivity (NPP) indicator (Mehmood et al., 2024).

The FABLE Calculator model performs calculations through interrelated stages. Evidentiary indicators such as population growth, GDP forecasts, dietary structure, food waste, and demand for biofuel – all linked to the demand for agricultural products – are taken into account. Production constraints are then factored in. As a result, the actual supply available for human consumption is determined (Carr et al., 2024).

Anand S. and other scholars proposed a new approach aimed at assessing the efficient use of water resources and the sustainability of agricultural production under conditions of climatic

variability. The scholars considered two directions. In the first direction, only changes in the precipitation regime were assessed, while in the second, changes in precipitation were considered together with parametric uncertainty. For each direction, the results of 1,000 modeled vegetation periods were used, and 10,000 bootstrap resamplings were performed. As a result, 95% confidence intervals were calculated for the Marginal Irrigation Water Productivity index (MIWP) and the Marginal Irrigation Carbon Intensity (MICI) indicators. The results of the study showed that solutions on the Pareto frontier possess high stability and make it possible to select optimal strategies for managing water resources under conditions of climatic variability. This study demonstrates the scientific importance of introducing uncertainty assessment methods alongside classical climatic models in evaluating agricultural productivity (Anand et al., 2025).

Agroecological lighthouses are a type of network model that integrates social, technical, cultural, and economic dimensions of research. As a result, they are used in developing a methodological roadmap for discussion (Garcia et al., 2024).

Landscape agronomists and landscape architects proposed a plan for creating an Agrarian Park. This proposal treats the area, on the one hand, as a place of food production, and on the other hand, as a zone for recreation and walking (Cenet et al., 2024).

An assessment of the ecological condition and sustainability of agrolandscapes was carried out at the local level. In the course of the assessment, more than twenty indicators characterized the qualitative condition of agricultural lands were used. The use of these indicators revealed the need to pay attention to cropland areas and crop rotation systems (Akhmetova et al., 2023).

Furthermore, scientific studies have applied the SLR (Systematic Literature Review) method to determine the influence of climate change on agricultural productivity. As a result, bringing the literature together into a single system demonstrates scientific accuracy and transparency (Farah et al., 2025).

Cossel M. and other authors conducted an experiment in agroforestry practice, growing trees in combination with field crops and pastures. When fertilizers were applied, competition between trees and agricultural crops reduced productivity in some areas. It was shown that, in order to achieve an effective outcome, the level of fertilizer application must also be taken into account (Cossel et al., 2025).

Zhao H. and other authors assessed the climatic potential productivity of forest vegetation in China's Da Hinggan mountainous region over the past 38 years. Analysis based on long-term climatic reconstruction data showed that climatic changes have a periodic effect on productivity. It was demonstrated that a rise in temperature does not lead to an increase in productivity under all conditions, and that its effect is closely related to adequacy of moisture resources. This conclusion scientifically substantiates the need, in current agroecological assessment to consider temperature not in isolation but together with hydrothermal conditions. Furthermore, the study showed that the use of long-term data makes it possible to gain a deeper understanding of the impact of periodic climatic changes on agricultural production (Zhao et al., 2017).

2.3. Statistical and spatiotemporal analysis methods

Xue Y., Bi M., Mehmood K., and other scholars applied the Geographically and Temporally Weighted Regression (GTWR) model to assess the influence of six anthropogenic factors on Gross Primary Productivity (GPP) in China's pasture ecosystems. The scholars implemented the model in the ArcGIS 10.7 environment using the Geographically and Temporally Weighted Regression (GTWR) extension, with the model parameters optimized according to the Akaike Information Criterion (AIC). The results of the study showed that anthropogenic influence is not spatially uniform. In some regions, declines in productivity were mainly driven by climatic factors, while in others, human activity had a predominant influence. This demonstrates that the Geographically and Temporally Weighted Regression (GTWR) model makes it possible to determine the influence of factors not only in general terms but at a specific spatial level. To supplement the Geographically and Temporally Weighted Regression (GTWR) results, the study also applied the Lindeman-Merenda-

Gold (LMG) method. Lindeman-Merenda-Gold (LMG) analysis makes it possible to quantitatively distinguish the contribution of climatic factors and human activity to gross primary productivity over time using the Sen's slope and Mann-Kendall methods, and then assesses the influence of climatic factors using partial correlation analysis. Following this, they used the Geographically and Temporally Weighted Regression (GTWR) model to identify the regional characteristics of anthropogenic influence (Xue et al., 2023; Bi et al., 2025; Mehmod, 2024).

Guo X. and other scholars, using Pearson correlation to determine pasture productivity in the eastern, central, and western regions of Mongolia, showed that precipitation indicators influence pasture productivity (Guo et al., 2023).

In a further study, the Pearson correlation method was used to calculate changes in the agrochemical indicators of soil over the years. As a result, it was determined that the formation of soil fertility is dependent on humus content. Its quality and quantity depend on the quantity and quality of plant residues, the soil regime, the intensity of tillage, erosion conditions, and other factors (Almanova et al., 2023).

Dang C., Zhu H., and other scholars determine, through the climatic convergence method, the degree to which temperature and precipitation indicators of the study area approach global average values, using Euclidean distance. Mathematically, applying the method of Lagrange multipliers, it was determined that the uniform distribution of climatic indicators leads to an increase in Net Primary Productivity (NPP). This approach makes it possible to assess the regional structure of climatic changes and to determine their influence on the productivity of ecosystems (Dang et al., 2023; Zhu et al., 2025).

Conserva M. examines current directions in mapping agricultural landscapes through remote sensing. It was shown that automated processing of satellite imagery, machine learning algorithms, and technologies for integrating spatial data make it possible to determine the structure of agricultural lands with high accuracy. The results of the study demonstrate that, compared with traditional field observations, remote sensing technologies make it possible to cover large territories within a short time, to continuously monitor productivity dynamics, and to increase the effectiveness of agroecological monitoring. This approach demonstrates the importance of supplementing climatic potential productivity models with precise spatial data (Conserva et al., 2025).

Net Primary Productivity (NPP) of the study area was calculated on the basis of Remote Sensing (RS) data. The degradation of pastures in the region was examined from the standpoint of the ecosystem's level of carbon sequestration. The actual pasture productivity (NPP_{real}) was compared with the maximum productivity of the given ecosystem (NPP_{max}), and the level of degradation was determined (Zhang et al., 2022).

To reduce soil degradation in agricultural lands, measures such as zero tillage combined with drip irrigation and organic farming are included. In China, programs for "Converting Cropland to Green Areas" have been implemented. Farmers were provided compensation for converting agricultural land into forest and pasture. As a result, conditions were created for the restoration of the ecosystem (Akimbekova et al., 2025).

Saikia R. and other scholars combined geoinformation technologies with soil suitability assessment methods in agroecological assessment. By integrating data on soil properties, terrain, climatic indicators, and productivity through spatial analysis, they identified areas suitable for agricultural production. The results of the study showed that the use of geospatial technologies not only increases the accuracy of assessing agroecological potential but also enables the rational planning of agricultural lands. Furthermore, it was demonstrated that these spatial models serve not merely as mapping tools but as a scientific basis for management decision-making (Saikia et al., 2025).

Borankulova G. and other scholars developed an intelligent monitoring system for real-time observation of water levels in agriculture. As a result of the study, a monitoring system was proposed that is low-cost, powered by autonomous energy sources, and integrated with big data technologies. It was shown that this technology can increase the efficiency of water resource management, reduce

costs in irrigated farming, and enable real-time decision-making. This study demonstrates that assessing agroecological potential should not be limited to the analysis of natural evidentiary factors alone, but must also be integrated with digital monitoring systems (Borankulova et al., 2025).

Cossel M. and other scholars systematized numerous meta-analyses devoted to agroecological farming practices and assessed the influence of sustainable farming technologies on the sustainability of agricultural systems. The introduction of agroecological approaches contributes to preserving soil fertility, increasing biodiversity, and strengthening resilience to climatic risks. At the same time, the scholars show that the universal application of a single technology, without accounting for the natural characteristics of each region, is scientifically incorrect. This conclusion demonstrates the need to adapt agroecological potential assessment models to specific regional conditions (Cossel et al., 2025).

Cenet A. and other scholars proposed a territorial planning methodology to support agroecological transition in local areas. By combining data on soil resources, terrain, agricultural structure, and ecological constraints, they developed an algorithm for assessing agroecological development potential. The results of the study demonstrated that territorial planning serves not only as a tool for assessing natural resources but also as an effective scientific mechanism for managing sustainable land use. This approach shows the need to take socio-economic indicators into account alongside natural evidentiary factors when assessing the agroecological potential of agricultural landscapes (Cenet et al., 2024).

Farah A. and other scholars conducted a systematic literature review of studies published in the Scopus database between 2015 and 2024, showing that climate change has the most significant influence on agricultural productivity. According to the analysis, rising temperatures, instability in the precipitation regime, and extreme climatic events have led to declining productivity in many regions. At the same time, the study demonstrates that the effects of climate are not uniform across all regions and vary depending on natural conditions and adaptation measures. This conclusion demonstrates the necessity of taking regional characteristics into account when assessing agroecological potential (Farah et al., 2025).

Babyenda P., Kaburbo-Mariara J., and Odhiambo S. assessed the impact of climatic variability on agricultural production in Uganda. Through the analysis of long-term climatic and economic data, it was determined that changes in temperature and precipitation directly influence productivity. It was further shown that in farms that had introduced adaptation technologies, the impact of climatic risks was substantially reduced. This study demonstrated that agroecological potential is determined not only by natural resources but also by management decisions (Babyenda et al., 2023).

Bouteska A. and other scholars studied the impact of climate change on agricultural production and food security in Ethiopia. It was shown that the influence of climatic factors on agricultural systems is closely connected with socio-economic conditions. The results of the study demonstrated that, in order to reduce climatic risks, assessing natural resources alone is insufficient and must be accompanied by the development of adaptation strategies. This conclusion reflects the comprehensive nature of the current conception of agroecological potential assessment (Bouteska et al., 2024).

Almanova Z. studied changes in soil fertility indicators under conditions of long-term agricultural use in Northern Kazakhstan. Having demonstrated that changes in the agrochemical properties of soil have a long-term effect on agricultural productivity, the study showed the necessity of mandatorily accounting for soil quality indicators when assessing agroecological potential. This study strengthens the scientific basis for supplementing climatic models with information on soil resources (Almanova et al., 2023).

Mustafayev Zh. Examined measures for improving agricultural lands in Kazakhstan, dividing them into three stages. The results of the study concluded that new, modern methods are still required for carrying out land reclamation measures on agricultural lands (Mustafayev, 2017).

Mustafayev Zh. assessed the soil resources of the agricultural landscapes of the Turkistan region based on agrochemical indicators, determining that regional variability in soil fertility directly affects the efficiency of agricultural production. The assessment approach proposed by the author treats the

agrochemical properties of soil as an important component of agroecological potential and can be applied in regional-level planning work (Mustafayev et al., 2024).

Mustafayev Zh. and other scholars, in a study aimed at improving the methodology for assessing the aggroresource potential of agricultural landscapes, integrated climatic, soil, hydrological, and biological indicators into a unified system. They proposed a methodology for assessing the aggroresource potential of agricultural landscapes, classifying it into groups of agroclimatic resources (ACR), soil-land resources (SLR), agrobiological resources (ABR), and water-based resources. It was scientifically substantiated that assessment of agroecological potential should be carried out not through individual indicators but through a comprehensive system that accounts for the interrelationship of natural resources (Mustafayev et al., 2024).

The methodology proposed by Mustafayev Zh. provided a comprehensive assessment of the agrobiological resources of landscapes used in agriculture through several levels of productivity. This method takes into account, alongside climatic indicators, temperature-related, radiation-related, and agroecological evidentiary indicators. This approach makes it possible to assess the agrobiological potential of agricultural lands, to identify limiting factors, and to develop solutions (Mustafayev et al., 2024).

The method proposed by Mustafayev Zh. and Adilbektegi G. was developed to assess biological-ecological productivity and to determine the efficient allocation of agricultural productive forces. As a result, it enables a quantitative assessment of qualitative changes in the living environment, the modeling of the transformation of natural systems under conditions of climate change, and natural landscape-ecological zoning (Adilbektegi et al., 2025).

Kong F. and other scholars studied the efficiency of using climatic resources through the introduction of a new farming system in the mountainous regions of southwestern China. It was demonstrated that improving the structure of crop rotation increases the efficiency of using heat and moisture resources. Furthermore, it was shown that new agrothechnological systems make it possible to fully utilize climatic potential alone is insufficient, and that it must be combined with effective agrothechnological management. The scholars' conclusions show that the current level of sustainable agriculture can be improved through evidentiary factors applied to climatic potential productivity (Kong et al., 2024).

Toletayev A. and other authors determined the agroclimatic resources of agricultural landscapes located in various natural zones of the Turkistan region of the Republic of Kazakhstan through energy-based and agroclimatic indicators of biological productivity. The research methodology is based on determining the interdependence of the quantitative and qualitative indicators obtained – that is, the indicators describing the balance between the influx and expenditure of energy. Relying on the law of conservation of energy, it encompasses indicators for assessing energy resources, moisture and heat supply, as well as climatic aridity. Overall, these indicators determine the trend of development of agricultural production (Toletayev et al., 2024).

2.4. Specific features of applying geoinformation and digital technologies

Satellite data make it possible to assess climatic productivity in real time and at the spatial level. The Normalized Difference Vegetation Index (NDVI) is the principal indicator for assessing the photosynthetic activity of vegetation and the volume of green biomass. It is calculated on the basis of the reflectance of the near-infrared (NIR) and red (R) spectral bands. The Vegetation Health Index (VHI), in turn, is one of the satellite indices most widely used in drought analysis. The Temperature Condition Index (TCI) is used to monitor plant stress caused by temperature effects. The Aridity Index (AI), in turn, is calculated on the basis of meteorological data as the ratio of precipitation to evaporation (Karatayev et al., 2025).

The Geographic Information System-Multi-Criteria Decision Making (GIS-MCDM) module evaluates each criterion according to the degree to which it provides favorable conditions for the growth of agricultural crops. Each criterion is then classified on a scale from 0 to 10. The weight of each criterion is determined using the Analytic Hierarchy Process (AHP). A Geographic Information

System (GIS) model is then constructed. All thematic maps are converted into raster format; that is, electronic maps are compiled (Faraslis et al., 2023; Saikia et al., 2025).

To reduce the influence of classification results of spectral similarity arising from the diversity of crop types in the study area, several types of features derived from multi-temporal Sentinel-2 and Sentinel-1 imagery are used. These provide information on the reflective capacity of crops over short intervals of the vegetation period (Fang et al., 2025).

Arystanov A. and other scholars studied the problem of automatically classifying agricultural crops under rain-fed farming conditions in the southern part of Kazakhstan. Using Sentinel-2 satellite data, they developed an algorithm for determining the spatial distribution of various agricultural crops. The results of the study showed that satellite imagery with high spatial resolution makes it possible to accurately determine the structure of agricultural land. Furthermore, it was demonstrated that the automated classification approach substantially reduces time and labor costs compared with traditional field surveys. According to the authors' conclusions, such technologies form a reliable primary database for refining agroecological potential assessment models (Arystanov et al., 2025).

The Eddy Covariance Light Use Efficiency (EC-LUE) and Carnegie-Ames-Stanford Approach (CASA) models, based on light-use efficiency, calculate Gross Primary Productivity (GPP) using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data (Xi et al., 2023; Zhang et al., 2024).

Moderate Resolution Imaging Spectroradiometer (MODIS) data can be used as an optimal tool for the in-depth study of carbon dynamics in ecosystems (Castorena et al., 2025).

The Integrated Terrestrial Ecosystem Assessment Tool (INSTANT) Climate Guide program is a general interactive statistical package designed for microcomputers. This method is applied in determining the trend of dry spells in the first and second periods (Usman et al., 2022).

An ultrasonic sensor for determining water level was built into a microcontroller. This determines the water level in agriculture in real time (Borankulova et al., 2025).

A systematic analysis of scientific works devoted to the agroecological assessment of agricultural landscapes showed that research in this field has changed considerably over the past fifty years. Whereas early studies were limited to determining the influence of climatic factors on plant productivity, current research is aimed at integrating natural, biological, anthropogenic, and digital factors into a unified model system. These changes are connected not only with the increasing complexity of research methods, but also with a deeper understanding of the multilevel organization of agroecological systems.

Analysis. Based on the results of the analysis conducted, all the methods used in the studies can be grouped into four main categories according to their scientific purpose and functional characteristics. The first category comprises the classical models of climatic potential productivity. Here, the Miami model is calculated using the formula shown below (19).

$$NPP = \min(NPPt, NPPp) \quad (1)$$

NPP - net primary productivity,
t - average annual temperature (°C),
p - annual precipitation (mm).

The following indicator of actual evaporation is determined using the Thornthwaite Memorial model (51).

$$Y_e = 3000[1 - e^{-0.0009695(V-20)}] \quad (2)$$

$$V = \frac{1.05r}{\sqrt{1 + \left(\frac{1.05r}{L}\right)^2}} \quad (3)$$

$$L = 300 + 25t + 0.05t^3 \quad (4)$$

Ye - evaporation-based production potential ($\text{kg} \cdot \text{hm}^{-2} \cdot \text{a}^{-1}$).

V - average annual actual evaporation (mm).

L - annual maximum evaporation (mm).

1.05 - a correction coefficient accounting for the relationship between precipitation and evaporation; 300, 25, and 0.05 - empirical parameters used to calculate maximum evaporation based on temperature.

Pasture productivity, in turn, was calculated using the Thornthwaite Memorial model.

$$T_p = 30000 * [1 - e^{-0.0009695(v-20)}] \quad (5)$$

$$V = \begin{cases} 1.05P / \sqrt{1 + (1.05P/L)^2} & (P \geq 0.316L) \\ P & (P < 0.316L) \end{cases} \quad (6)$$

$$L = 300 + 25T + 0.05T^3 \quad (7)$$

T_p - pasture productivity ($\text{g} \cdot \text{m}^{-2} \cdot \text{yr}^{-1}$),

V - actual average annual evapotranspiration, mm,

T - average annual temperature, $^{\circ}\text{C}$,

L - an empirical function of average annual temperature,

and P - average annual precipitation, mm.

Further, the Thornthwaite Memorial model is used to assess Climate Potential Productivity (CPP) according to the following formula. It is widely used in studying changes in climatic potential productivity (25).

$$CPP = 3000 \times (1 - e^{-0.0009695(ET-20)}) \quad (8)$$

$$E_L = 300 + 25T + 0.05T^3 \quad (9)$$

$$E_T = \frac{1.05P}{\sqrt{1 + \left(\frac{1.05P}{E_L}\right)^2}} \quad (10)$$

CPP is expressed in $\text{kg}/\text{ha} \times \text{year}$,

ET - average annual evapotranspiration, mm,

EL - average annual evaporation, mm, and e - the base of the natural logarithm,

T - average annual temperature, $^{\circ}\text{C}$,

P - average annual precipitation, mm.

Next, the sum of biologically active air temperatures (46) is calculated using the formula below.

$$\sum SBCT_i > 10^{\circ}\text{C} = \sum_{i=1}^n AMT_i N_i \quad (11)$$

AMTi - average monthly air temperature above 10°C ($^{\circ}\text{C}$),

Ni - number of days in the month,

n - number of months in which the average monthly air temperature exceeds 10°C , for the indicator $\sum \text{SBCT}_i$.

The surface radiation balance of air and soil (45) is calculated using the following formula.

$$\text{RB}_i = 4.1868 [13.39 + 0.0079 \sum \text{SBCT}_i > 10^{\circ}\text{C}] \quad (12)$$

RB_i - the surface radiation balance of air and soil.

The De Martonne aridity index (45) is calculated as follows.

$$\text{IA}_i = \text{AAP}_i / (\text{AAT}_i + 10) \quad (13)$$

IA_i - aridity index values,

AAP_i - annual precipitation (mm),

AAT_i - average annual air temperature ($^{\circ}\text{C}$).

The natural moisture coefficient is calculated using the formula below (45).

$$\text{NMC}_i = \text{AAP}_i / \text{TEB}_i \quad (14)$$

NMC_i - natural moisture coefficient,

AAP_i - annual precipitation (mm), TEB_i - total evaporation.

The hydrothermal coefficient is calculated according to the following formula (45).

$$\text{HTC}_i = \text{AAP}_{i>10} / (0.10 \sum \text{SBCT}_i) \quad (15)$$

HTC_i - hydrothermal coefficient,

$\sum \text{SBCT}_i (>10^{\circ}\text{C})$ - sum of active air temperatures,

AAP_i - annual precipitation (mm).

The bioclimatic potential index (45) is determined according to the following calculation.

$$\text{BCP}_i = \text{NMC}_i (\sum \text{SBCT}_i / 1000) \quad (16)$$

BCP_i - bioclimatic potential;

NMC_i - natural moisture coefficient.

N.N. Ivanov's natural moisture coefficient was calculated using the following formula (45).

$$C_m = O_c / E_o \quad (17)$$

C_m - moisture coefficient,

O_c - precipitation amount, mm,

E_o - evaporation amount.

The moisture index was determined using the following formula (45).

$$\text{MI}_{di} = \text{AAP}_i / \sum \text{AAHD}_i \quad (18)$$

MIdi - moisture index,
AAPi - annual precipitation (mm),
 Σ AAHDi - sum of air moisture deficits during the biologically active period of the year.

The formula for the aggroresource potential of landscapes is determined according to the calculation below (29).

$$ARPLi = f(ACRi, SLRi, ABRi, WRi) \quad (19)$$

ACRi - agroclimatic resources,
SLRi - soil-land resources,
ABRi - agrobiological resources, WRi - water resources.

The Horton infiltration equation is expressed in the following form (19):

$$f(t) = (f_c + (f_0 - f_c)e^{-Kt}) \quad (20)$$

$f(t)$ is the infiltration rate at time t (mm/h),
 t is time (h),
 f_0 - initial infiltration rate (mm/hr),
 f_c - steady-state infiltration rate (mm/hr),
 K - infiltration decay coefficient (hr^{-1}),
 e - the base of the natural logarithm (2.71828).

The second group of biological productivity assessment models includes Net Primary Productivity (NPP), Potential Net Primary Productivity (PNPP), and Human Appropriation of Net Primary Productivity (HNPP). Net Primary Productivity (NPP) is calculated using the following equation (26):

$$NPP = 3000[1 - e^{-0.0009695(v-20)}] \quad (21)$$

$$V = \frac{1.05r}{\sqrt{1 + \left(1 + \frac{1.05r}{L}\right)^2}} \quad (22)$$

$$L = 3000 + 25t + 0.05t^3 \quad (23)$$

NPP - net primary productivity ($g\ C\ m^{-2}\ yr^{-1}$),
 V - actual annual evapotranspiration (mm), L - average annual potential evaporation (mm),
 t - average annual temperature ($^{\circ}C$),
 r - annual precipitation (mm).

Potential Net Primary Productivity (PNPP) productivity is determined by the following formula (26).

$$PNPP = C \times (1 - \exp(-d \times (v - 20))) \quad (24)$$

C (3000 mm) - the maximum potential amount of evaporation under ideal conditions,
 v - actual annual evaporation,
 d - the coefficient 0.0009695, which regulates the influence of evapotranspiration on Potential Net Primary Productivity (PNPP).

HNPP productivity is determined according to the following formula (26):

$$\text{HNPP} = \text{PNPP} - \text{ANPP} \quad (25)$$

PNPP - Potential Net Primary Productivity,
HNPP - Human-induced [altered] Net Primary Productivity,
ANPP - Annual Net Primary Productivity.

The third group comprises spatial and temporal statistical models. One of these, the Mann-Kendall (26) trend test, is calculated using the formula below:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(X_j - X_k) \quad (26)$$

$$\text{sgn}(X_j - X_k) = \begin{cases} +1(X_j - X_k) > 0 \\ 0(X_j - X_k) = 0 \\ -1(X_j - X_k) < 0 \end{cases} \quad (27)$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} S > 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} S < 0 \end{cases} \quad (28)$$

S - the statistical indicator of the Mann-Kendall test used to determine a trend,
n - the number of data points in the time series,
k and j - indices used for comparing data ($j > k$), meaning each pair is compared only once),
 X_j and X_k - the data values at positions j and k in the time series,
Z - the standardized Mann-Kendall test statistic used to assess the statistical significance of the trend.

The Sen's Slope model is calculated using the following formula (49).

$$S_{ij} = \frac{y_j - y_i}{x_j - x_i} \text{ where } j > i \quad (29)$$

x_i - denotes the time intervals, y_i - denotes the corresponding Annual Net Primary Productivity (ANPP) values. The Geographically and Temporally Weighted Regression (GTWR) model is calculated according to the following formula (49).

$$Y_j = \beta_0(u_j, v_j, t_j) + \sum_{k=1}^d \beta_k(u_j, v_j, t_j)x_k + \varepsilon_j \quad (30)$$

$\beta_0(u_j, v_j, t_j)$ - the spatiotemporal geographic coordinates of the variable at point j, Y_j - the dependent variable,
 x_k - the k-th independent variable,
 ε_j - the error term,
n! - the factorial of the number of variables,
 R^2 - represents the quality of the regression model,
 $\Delta R^2(\{x_k\}_r)$ - represents the increase in the R^2 value after the variable x_k is introduced into the model in order r.

The Lindeman-Merenda-Gold (LMG) model is calculated using the formula shown below (49).

$$LMG(x_k) = \frac{1}{n!} \sum_{r\text{-premutation}} seqR^2(\{x_k\}|r) \quad (31)$$

$$seqR^2\left(\frac{\{x_k\}}{S_k(r)}\right) = R^2(\{x_k\} \cup S_k(r)) - R^2(S_k(r)) \quad (32)$$

Partial correlation analysis is presented in the following calculation (49).

$$R = \frac{\sum_{i=1}^n [(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (33)$$

R - correlation coefficient,

n - sequential year, x_i - the value of the variable in year i,

$\bar{x}$ - the average value of the variable over the study period,

y_i and $\bar{y}$ - respectively, the influencing factor in year i and the average value of the influencing factor over the study period.

Climatic convergence was implemented according to the calculations below (49).

$$C_{pre} = |Pre_j - Pre_{mean}| \quad (34)$$

$$C_{tmp} = |Tmp_j - Tmp_{mean}| \quad (35)$$

$$C_{cli} = \sqrt{(C_{tmp})^2 + (C_{pre})^2} \quad (36)$$

Tmp - temperature convergence,

Pre - precipitation convergence,

Ccli - overall climatic convergence.

The Climatic Resource Use Efficiency (CRUE) indicator is calculated using the following formula (49).

$$CRUE = 100\% \times Agp / CPP \quad (37)$$

CRUE - climatic resource use efficiency (%),

Agp - the actual grain yield obtained per unit of cropland area, calculated on the basis of field survey data and statistical data across years.

The fourth group comprises the system of geoinformation and digital technologies. In this group, MODIS data are calculated using the EC-LUE model (26).

$$GPP = \epsilon_{max} \times PAR \times FPAR \times \min(T_s, W_s) \quad (38)$$

GPP - gross primary productivity,

ϵ_{max} 2.25 g C/MJ - represents the maximum value of light-use efficiency,

FPAR - the fraction of photosynthetically active radiation absorbed, T_s - temperature stress,

W_s - water deficit.

The following equations are used to mathematically calculate the FPAR, Ts, and Ws indicators (26).

$$FPAR = a \times NDVI \times b \quad (39)$$

$$T_s = \frac{(T - T_{min})(T - T_{max})}{(T - T_{min})(T - T_{max}) - (T - T_{opt})} \quad (40)$$

$$W_s = \frac{VPD_o}{(VPD_o + VPD)} \quad (41)$$

a and b - empirical coefficients,

Tmin, Tmax, Topt - the minimum, maximum, and optimum temperatures for photosynthesis.

The following formula was used to determine the carbon-use efficiency indicator at the pixel level (26).

$$ANPP = GPP \times CUE \quad (42)$$

ANPP - annual net primary productivity,

GPP - gross primary productivity,

CUE - carbon-use efficiency.

Carbon-use efficiency is determined using the following formula:

$$CUE = \frac{GPP}{NPP} \quad (43)$$

CUE - carbon-use efficiency,

NPP - net primary productivity,

GPP - gross primary productivity.

Thus, the first group of climatic potential productivity assessment model is founded on the Miami model, the Thornthwaite Memorial model, and the Climate Potential Productivity (CPP) approach. The main purpose of these models is to determine the theoretical productivity that the natural environment is capable of generating under unchanged climate conditions, calculated through agroecological indices. The aim of research in this direction is to determine the level of natural resources favorable for agriculture. In the course of reviewing the scientific literature, it was found that the De Martonne aridity index, natural moisture coefficients, the hydrothermal coefficient, bioclimatic potential, and climate favorability indices are the most widely used indicators.

The results of the analysis showed that the Miami model has played a special role in scientific development. Although this model was one of the first universal approaches to assessing climatic potential, current research has demonstrated that it is limited to calculating temperature and precipitation indicators and cannot fully capture all the characteristics of complex natural systems. For this reason, the majority of subsequent studies have shifted toward the Thornthwaite Memorial model, since this model, by accounting for actual evapotranspiration, substantially increases the accuracy of productivity assessment.

However, it was found that in the great majority of current scientific works, neither of these two models is used in isolation. On the contrary, they continue to be used together with the results of satellite monitoring, regional statistics, and biological productivity indicators. This trend does not diminish the scientific significance of the classical models; rather, it demonstrates that they have been retained in current research as the initial element of a comprehensive assessment system.

The second group comprises models for assessing biological productivity and agroecological indices. The main indicators in this direction include Net Primary Productivity (NPP), Potential Net Primary Productivity (PNPP), and Human Appropriation of Net Primary Productivity (HNPP). The research conducted showed that these indicators do not substitute for one another. Net Primary Productivity (NPP) assesses the actual productivity formed under natural conditions. Potential Net Primary Productivity (PNPP) reflects the theoretically possible productivity under fully three indicators together. This approach makes it possible to separately assess the influence of climatic changes and anthropogenic factors. It is even used, applying the Thornthwaite Memorial model, to assess the Potential Net Primary Productivity (PNPP) indicator.

At the same time, scientific works in recent years have shown that Net Primary Productivity (NPP) -based models are also being widely used in studying carbon cycling. This has increased their importance not only in agronomic but also in ecological research.

The third group encompasses methods for assessing the efficiency of using spatial and temporal statistical models. The aim of research in this direction is to determine the extent to which natural potential is actually being utilized. For this purpose, Climate Regulation Use Efficiency (CRUE), the potential for increasing production output, and energy efficiency indicators have been widely applied. The literature analysis conducted showed that the Climate Regulation Use Efficiency (CRUE) indicator has acquired particular importance in current research. Whereas the classical models determine natural potential, Climate Regulation Use Efficiency (CRUE) assesses the extent to which that potential has actually been realized. This indicator has proven highly effective in identifying the reserves of agricultural production. Numerous studies demonstrate that, even where natural potential is high, low actual productivity is attributable to managerial, technological, or social factors. For this reason, Climate Regulation Use Efficiency (CRUE) has come to be regarded in current research as an important indicator of agricultural efficiency.

At the same time, it is observed that these indices, too, are not used in isolation in current research. Many authors have used them together with climatic models. This approach makes it possible to more comprehensively assess the factors influencing productivity.

The direction of spatial and temporal statistical models has been developing with particular intensity over the past decade. Mann-Kendall, Sen's Slope, Geographically and Temporally Weighted Regression (GTWR), Lindeman-Merenda-Gold (LMG), and partial correlation analysis are used in the majority of current international scientific works. The literature reviewed showed that the scientific tasks of these methods differ. Mann-Kendall determines whether a change is present. Sen's Slope calculates the intensity of the change. Geographically and Temporally Weighted Regression (GTWR) reveals regional differences. Lindeman-Merenda-Gold (LMG) assesses the relative contribution of the various factors. Accordingly, current research uses these methods not in isolation but as a single analytical complex.

The fourth group comprises geoinformation and digital technologies. As the literature shows, current work on assessing agroecological potential is not conducted without the Eddy Covariance Light Use Efficiency (EC-LUE) and Carnegie-Ames-Stanford Approach (CASA) models together with Geographic Information System (GIS) and Moderate Resolution Imaging Spectroradiometer (MODIS) technologies. These technologies substantially increase not only the accuracy of research but also the spatial visualization of results. They have also made it possible to conduct real-time monitoring. As a result, agroecological assessment has shifted from statistic research to a dynamic digital monitoring system.

A comparison of scientific works reveals another important feature of current research. In all scientific works of the past decade, agroecological potential is not assessed through a single indicator alone. Nearly all studies apply several methods in parallel. For example, even where the Miami or Thornthwaite Memorial model is used to assess climatic potential, the research does not end there. Scholars subsequently calculate Net Primary Productivity (NPP) indicators as a matter of course, use satellite data, and assess the influence of factors through statistical models. They also determine

regional differences. That is, current agroecological assessment is carried out by integrating the results of several independent methods, as shown in Figure 1 below.

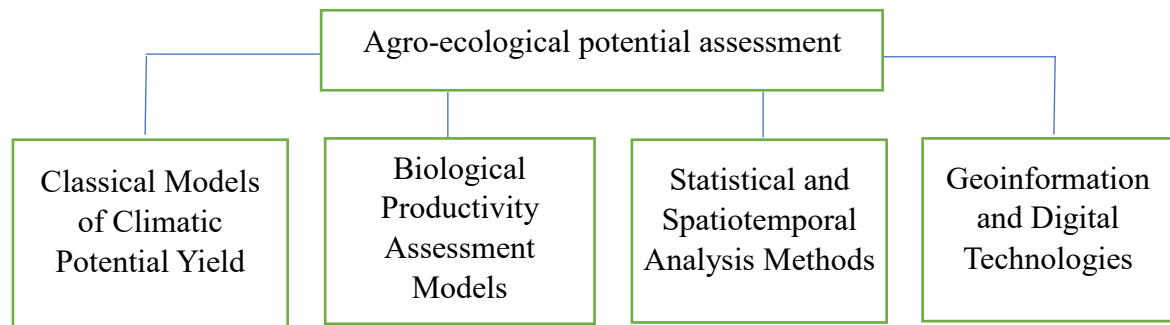


Figure 1. Comprehensive framework for agroecological potential assessment

This trend is clearly evident in works published after 2020. In current research, classical empirical models are used only at the initial assessment stage. The principal scientific results are obtained through regional statistics, remote sensing, and the processing of large volumes of geospatial data. The occurrence of such changes indicates that the science of agroecological potential assessment has entered a new digital stage.

The following table 1 examines the methods and compares their advantages and disadvantages depending on their conditions of use.

Table 1. Strengths and limitations of methods

№	Names of methods	Advantages	Limitations
Classical models of climatic potential productivity			
1	Miami models	Simple and efficient in application. Convenient for limited data availability. Effectively demonstrates the impact of climatic conditions. Computationally light and straightforward.	Fails to account for all ecosystem indicators. Highly dependent on rainfall. Provides inaccurate estimates under extreme climate conditions. Less precise than contemporary complex models.
2	Thornthwaite Memorial models	Effective for assessing water-scarce regions. Based on climatic parameters and well-suited for capturing temporal shifts. Incorporates water balance metrics. Suitable for regional-scale studies.	Dependent on precipitation and temperature parameters. Lacks precise accounting of solar radiation. Does not fully incorporate soil properties and vegetation features.
3	Agro-resource potential of landscapes	It is determined by integrating agro-climatic, soil and land, agro-biological, and water resources. It is calculated by comprehensively considering agro-climatic, soil-land, agro-biological, and water resources.	It difficult to accurately predict the future potential of the landscape due to global climate change.

4	De Martonne aridity index	Simple index and straightforward computation. Convenient for limited climatic data availability. Well-suited for large-scale regional comparisons. Effectively demonstrates aridity and moisture indicators. Suitable for evaluating multi-year climatic parameters. Effective for GIS and cartographic analysis.	Considers precipitation and temperature parameters. Excludes other environmental factors. Fails account for seasonal variations. Does not consider soil moisture, vegetation cover, or land use characteristics.
Models for assessing biological productivity			
5	Net Primary Productivity (NPP)	Describes the intrinsic capacity of plants to produce biomass. Evaluates the carbon sequestration potential of the ecosystem. Applied to assess the impacts of climate change, drought, and anthropogenic drivers on vegetation cover.	Determining Net Primary Productivity (NPP) is time-consuming. Different models may yield varying Net Primary Productivity (NPP) values for the same study area. Estimating Net Primary Productivity (NPP) requires significant computational time.
6	Annual Net Primary Productivity (ANPP)	Enables accurate visualization of annual productivity dynamics. Effective for interannual comparisons. A crucial indicator for comparing productivity across spatial areas.	Annual indicators may mask seasonal fluctuations. They fail to fully capture the actual impact of short-term extreme events within a year. Interannual metrics do not account for intra-annual seasonal variability.
7	Potential Net Primary Productivity (PNPP)	Enables the assessment of the ecosystem's maximum potential productivity in natural state. Human impact on ecosystems can be quantified by comparing potential natural NPP with actual NPP. Serves to evaluate the potential peak productivity of unmanaged ecosystems.	Without considering specific soil, topographic, vegetation type, and water resource parameters, potential productivity risks being overestimated. This indicator reflects model-based theoretical potential rather than actual observed yield.
Statistical and spatiotemporal analysis methods			
8	Mann-Kendall	Determines the statistical significance of trends in climate time series (e.g., temperature, precipitation).	May yield false positives or inaccurate results if serial autocorrelation e.g., seasonality is present in the time series. Requires pre-whitening or data pre-processing to eliminate autocorrelation.

9	Geographically and Temporally Weighted Regression (GTWR)	Models climate change by simultaneously accounting for spatial and temporal non-stationarity. Accurately models how relationships and processes vary across different regions and change over time.	Computationally intensive and requires significant processing power. It is also sensitive to multicollinearity among independent variables.
10	Partial Correlation Analysis	Identifies the net linear relationship between two climate variables e.g., temperature and productivity while controlling for the effect of other confounding factors (e.g., humidity).	Only effective for evaluating linear relationships. It may misrepresent complex, non-linear interactions between factors.
11	Sen's Slope	Calculates the magnitude or rate of change of climate parameters over time (trend slope). Extreme values or anomalies in dataset do not distort the slope calculation.	Strong serial autocorrelation e.g., seasonality or strong multi-year dependencies can lead to an overestimation of trend significance.
12	Climate Convergence	The study of how climate indicators or adaptation performance across different regions converge or equalize over time.	Requires high-quality, long-term hydro-meteorological data series. Insufficient or patchy data can significantly distort the analysis results.
13	Lindeman-Merenda-Gold (LMG)	Evaluates the relative importance of different explanatory factors (e.g., CO ₂ , elevation, latitude) in regression models.	Computation time increases exponentially if the number of independent variables is too high (e.g., exceeding 10 variables).
Specific features of applying geoinformation and digital technologies			
14	Eddy Covariance Light Use Efficiency (EC-LUE)	Calculates Gross Primary Productivity (GPP) with high accuracy since it is grounded in real-world surface measurements.	Dependent on the network of ground Eddy Covariance towers (such towers are not available in all regions, especially in developing countries).
15	Carbon sequestration	Helps combat climate change, supports the development of carbon credit markets, and promotes sustainable land management.	Physically measuring exact amounts on the ground is extremely expensive and complex stored carbon can be released back into the atmosphere during wildfires or deforestation.
16	Moderate Resolution Imaging Spectroradiometer MODIS	Free global-level data, high temporal resolution (daily acquisition) and offers many ready-to-use products for studying vegetation cover, temperature, fires and the carbon cycle.	Low spatial resolution (250 m – 1 km), making it unsuitable for detailed analysis of small fields or fragmented landscapes.
17	Carnegie-Ames-Stanford Approach (CASA)	Accurately estimates carbon flux at regional and global scales; allows	Requires a vast amount of climatic data and soil parameters; high

		simulation of various climate scenarios.	probability of error in data – scarce regions.
18	Normalized Difference Vegetation Index (NDVI)	Easy to calculate, available in most satellite datasets, and ideal for comparing biomass dynamics across large areas over long periods.	Experiences a «saturation» effect in dense forests (the index stops increasing); sensitive to soil color and atmospheric interference (clouds, smoke).

At the same time, the analysis of scientific works reveals that certain methodological contradictions persist even within current research.

The first contradiction relates to the absence of a unified definition of the concept of agroecological potential. Some scholars regard agroecological potential solely as a sum of climatic resources.

A second group of researchers interprets it as the overall capacity of natural resources.

A third scientific direction links agroecological potential to the sustainability of actual agricultural production.

Representatives of a fourth direction incorporate into this concept the influence of anthropogenic factors and digital technologies as well.

Thus, single scientific term is found to have several definitions. While this diversity of scientific opinion reflects the complexity of the object of study, it also indicates that a unified theoretical foundation for assessing agroecological potential has still not been fully established.

A second important contradiction concerns the assessment methods themselves. The classical models make it possible to assess natural potential simply and quickly. However, they do not adequately account for regional characteristics. Current digital models, by contrast, operate with high accuracy. But their application requires satellite data, large volumes of informational resources, and complex software. This situation complicates the development of a universal model for assessing agroecological potential.

3. Conclusion

In the period ahead, the development of the science of assessing agroecological potential is expected to be connected with the integration of high-spatial-precision satellite observations, machine learning algorithms, and digital data-processing systems. Such technologies will make it possible not only to monitor changes in natural resources in real time, but also to model their future development scenarios and to formulate scientifically grounded management decisions aimed at increasing the sustainability of agricultural production.

In conclusion, at the present stage, the assessment of agroecological potential should be regarded not as a collection of individual scientific methods or separate indicators, but as a multilevel, integrated scientific system that combines natural, climatic, biological, spatial, and digital components. Only such a systemic approach makes it possible to objectively assess the actual capabilities of agricultural landscapes, to rationally manage natural resources under conditions of climate change, and to scientifically ensure the long-term sustainable development of agricultural production.

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5. Author Contributions:

Conceptualization - G.A., L.K.; methodology - G.A.; validation - G.A., L.K.; formal analysis - G.A.; investigation - L.T.; resources - L.T.; data curation - G.A., L.K.; writing - original draft

preparation - G.A., L.K.; writing - review and editing - G.A., L.K.; visualization - L.K.; supervision - G.A. All authors have read and agreed to the published version of the manuscript.

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Ауыл шаруашылығы ландшафттарының агроэкологиялық әлеуетін бағалау әдістеріне аналитикалық шолу

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Аңдатпа. Ауыл шаруашылық өндірісінің тұрақты дамуы табиғи ресурстарды тиімді пайдалануға, климаттық тәуекелдерді ғылыми негізде бағалауға және ауыл шаруашылық ландшафттарының агроэкологиялық әлеуетін дұрыс анықтауға тікелей байланысты. Климаттық жаһандық өзгеріс, жер ресурстарының деградациясы, су тапшылығы мен антропогендік қысымның күшеюі жағдайында агроэкологиялық әлеуетті бағалау әдістерін жетілдіру қазіргі аграрлық ғылымның маңызды бағыттарының біріне айналды. Соған қарамастан халықаралық ғылыми әдебиеттерде қолданылатын математикалық, биофизикалық, энергетикалық, статистикалық және геоақпараттық модельдердің теориялық негіздері, қолданылу ерекшеліктері мен өзара байланыстары бірыңғай жүйеде жеткілікті деңгейде жинақталмаған.

Бұл зерттеуде ауыл шаруашылық ландшафттарының агроэкологиялық әлеуетін бағалауда қолданылатын қазіргі ғылыми әдістерге жүйелі аналитикалық шолу жүргізумен қатар олардың негіздерін, қолданылу ерекшеліктерін, артықшылықтары мен кемшіліктерін салыстырмалы түрғыда талдау, ғылыми синтездеу және әдіснамалық жүйелеу тәсілдеріне негізделді.

Ғылыми жұмыстарды талдау нәтижесінде агроэкологиялық әлеуетті бағалау әдістерінің қарапайым эмпирикалық модельдерден кеңістіктік-уақыттық талдау, қашықтықтан зондтау, географиялық ақпараттық жүйелер, ERA5 қайта талдау материалдары, статистикалық модельдер және сандық технологияларды біріктіретін кешенді тәсілдерге дейінгі даму бағыты анықталды. Miami және Thornthwaite Memorial модельдерінің климаттық әлеуетті бағалаудағы маңызы, NPP, PNPP, HNPP және CRUE көрсеткіштерінің биологиялық өнімділікті бағалаудағы рөлі, сондай-ақ Mann-Kendall, Sen's Slope, GTWR және LMG әдістерінің кеңістік-уақыттық заңдылықтарды анықтаудағы тиімділігі жүйелі түрде талданды. Сонымен қатар қашықтықтан зондтау деректері, геоақпараттық жүйелер мен сандық мониторинг технологияларын қолданудың агроэкологиялық бағалаудың дәлдігін арттырудың маңызы айқындалды.

Зерттеу нәтижесінде агроэкологиялық әлеуетті бағалау әдістерінің теориялық және әдіснамалық негіздері жүйеленіп, оларды кешенді қолданудың ғылыми артықшылықтары негізделді. Өртүрлі модельдерді интеграциялау табиғи ресурстардың өнімділік әлеуетін неғұрлым дәл бағалауға, климаттық өзгерістердің ықпалын нақты болжауға және ауыл шаруашылық өндірісін ғылыми негізде жоспарлауға мүмкіндік беретіні көрсетілді.

Түйін сөздер: агроэкологиялық әлеует; ауыл шаруашылық ландшафттары; климаттық әлеуетті өнімділік; климаттық модель; географиялық ақпараттық жүйелер; қашықтықтан зондтау; тұрақты ауыл шаруашылығы.

Аналитический обзор методов оценки агроэкологического потенциала сельскохозяйственных ландшафтов

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Аннотация. Устойчивое развитие сельскохозяйственного производства напрямую зависит от эффективного использования природных ресурсов, научно обоснованной оценки климатических рисков и правильного определения агроэкологического потенциала сельскохозяйственных ландшафтов. В условиях глобального изменения климата, деградации земельных ресурсов, дефицита воды и усиления антропогенной нагрузки совершенствование методов оценки агроэкологического потенциала стало одним из важных направлений современной аграрной науки. Несмотря на это, теоретические основы, особенности применения и взаимосвязи математических, биофизических, энергетических, статистических и геоинформационных моделей, используемых в международной научной литературе, до сих пор не были в достаточной мере обобщены в единой системе.

В данном исследовании, наряду с проведением системного аналитического обзора современных научных методов, применяемых при оценке агроэкологического потенциала сельскохозяйственных ландшафтов, использовались подходы сравнительного анализа их основ, особенностей применения, преимуществ и недостатков, а также методы научного синтеза и методологической систематизации.

В результате анализа научных работ было установлено, что методы оценки агроэкологического потенциала прошли путь развития от простых эмпирических моделей до комплексных подходов, объединяющих пространственно-временной анализ, дистанционное зондирование, географические информационные системы, материалы реанализа ERA5, статистические модели и цифровые технологии. Были систематически проанализированы значение моделей Miami и Thornthwaite Memorial в оценке климатического потенциала, роль показателей NPP, PNPP, HNPP и CRUE в оценке биологической продуктивности, а также эффективность методов Mann-Kendall, Sen's Slope, GTWR и LMG в выявлении пространственно-временных закономерностей. Кроме того, было определено значение применения данных дистанционного зондирования, геоинформационных систем и технологий цифрового мониторинга для повышения точности агроэкологической оценки.

В результате исследования были систематизированы теоретические и методологические основы методов оценки агроэкологического потенциала и обоснованы научные преимущества их комплексного применения. Показано, что интеграция различных моделей позволяет более точно оценивать продуктивный потенциал природных ресурсов, точнее прогнозировать влияние климатических изменений и осуществлять научно обоснованное планирование сельскохозяйственного производства.

Ключевые слова: агроэкологический потенциал; сельскохозяйственные ландшафты; климатический потенциал продуктивности; климатическая модель; географические информационные системы; дистанционное зондирование; устойчивое сельское хозяйство.