Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26,JUNE 2026

**DOI: 10.37943/ZACP9086**

**Aigul Mimenbayeva**
Master of Science, Senior Lecturer, Department of Artificial Intelligence and Data Science
A.Mimenbayeva@astanait.edu.kz, orcid.org/0000-0003-4652-470X
Astana IT University, Kazakhstan
**Tamara Zhukabayeva**
PhD, Professor, Department of Information Systems
zhukabayeva_tk@enu.kz, orcid.org/0000-0001-6345-5211
L.N. Gumilyov Eurasian National University, Kazakhstan
**Sherzod Turaev**
PhD, Associate Professor, College of Information Technology
sherzod@uaeu.ac.ae, orcid.org/0000-0001-6661-8469
UAE University, UAE
**Oleg Solovyov**
Master's Degree, Head of the Laboratory of Crop Rotation and Soil Tillage
Solovyev_1990@mail.ru, orcid.org/0000-0002-7341-5851
North Kazakhstan Agricultural Experimental Station LLP, Kazakhstan
**Akgul Naizagarayeva**
PhD, Senior Lecturer, Department of Information Systems
a.naizagaraeva@kazatu.edu.kz, orcid.org/0000-0001-6888-1092
S.Seifullin Kazakh AgroTechnical Research University, Kazakhstan
**Raikhan Kudabayeva**
Master's Degree, Senior Lecturer, Department of Higher Mathematics
Kudabaevaraikhan23@gmail.com, orcid.org/0009-0002-0827-9395
S.Seifullin Kazakh Agro Technical Research University, Kazakhstan

# CLOUD-BASED SYSTEM FOR AGRICULTURAL LAND MONITORING USING REMOTE SENSING DATA IN NORTHERN KAZAKHSTAN

**Abstract:** Satellite remote sensing offers strong opportunities for monitoring agricultural lands, especially in climate-sensitive regions such as Northern Kazakhstan. However, most existing agricultural monitoring platforms rely mainly on optical vegetation indices (e.g., Normalized vegetation index (NDVI) or Enhanced Vegetation Index (EVI)) and provide limited information on soil moisture and surface temperature. As a result, early signs of water and heat stress at the field level are often missed.

This study presents a cloud-based agricultural monitoring system that differs from existing solutions by integrating optical, microwave, and thermal satellite data within a unified framework. The system combines Sentinel-2 vegetation indices, SMAP SM, and land surface temperature (LST) from the MODIS MOD11A2 product, processed using Sentinel Hub and Google Earth Engine. All datasets are harmonized into consistent 10-day composites and aggregated at the field scale.

The Thermo-Moisture Drought Index (TMDI) was calculated by combining LST and soil moisture (SM), enabling improved characterization of drought conditions compared to vegetation indices alone. Integrating TMDI and EVI highlights stress conditions that are not visible in optical data only, demonstrating a clear advantage over traditional NDVI-based platforms.

The developed system provides an operational, cloud-based solution for field-level monitoring, potentially early stress detection, and interactive analysis. Compared to existing systems, it offers improved environmental interpretation by combining multiple satellite sensors, making it a practical decision-support tool for rainfed agriculture in Northern Kazakhstan.


Received: 18.03.2026 Accepted: 17.07.2026 Published: 30.06.2026

This proposed system architecture is adaptable to other agricultural regions with similar characteristics. Furthermore, the framework can be extended with machine learning algorithms to predict crop yields and automatically assess drought risk.

**Keywords**: remote sensing; agricultural monitoring; land surface temperature; soil moisture; Normalized vegetation index (NDVI); Thermo-moisture drought index (TMDI); vegetation indices; multi-sensor fusion; Google Earth Engine; Northern Kazakhstan

**Introduction**

Agricultural production in Northern Kazakhstan is highly sensitive to meteorological variability, including precipitation deficits, temperature extremes, and soil moisture availability. Since agriculture is sensitive to climate, timely and location-specific information on crop conditions is needed to reduce risks. Remote sensing technologies provide continuous, multi-temporal observations of croplands, enabling detailed assessment of vegetation condition and environmental stress at the field level. However, traditional monitoring approaches lack the spatial and temporal resolution required for timely decision-making [1].

Most existing systems and platforms in Kazakhstan (such as Qoldau, Digital Earth, and Egistic) and internationally (EO Browser, Climate Engine) rely predominantly on optical vegetation indices such as NDVI and critically lack the capability for multisensor data fusion. This limitation prevents the early detection of stress signals that can be provided by thermal and microwave indicators [2].

The integration of optical vegetation indices (Vis) with soil moisture and thermal datasets is key to achieving more precise and reliable detection of vegetation stress. Spatio-temporal integration approaches combining MODIS and Sentinel-2 data provide higher spatial resolution and improved identification of drought signals compared to single-sensor approaches [3].

This paper addresses these gaps by presenting the development of an information system for monitoring and analysis of multi-sensor remote sensing indicators across agricultural lands in Northern Kazakhstan. The proposed system integrates Sentinel-2 VIs (NDVI and EVI), SMAP SM, and MODIS LST. Processing this data into 10-day composites provides reproducible statistical data on time series at the polygon level and provides scientifically sound tools that significantly improve the detection of drought in fields, vegetation changes, and stress anomalies [4].

**Research Problem**

Despite advances in remote sensing for crop monitoring, most platforms in Kazakhstan and internationally still rely on a limited set of optical vegetation indices and do not fully exploit microwave or thermal data. Systems such as Qoldau, Digital Earth Kazakhstan, and Egistic typically provide NDVI maps with low temporal resolution and lack field-level information on soil moisture or land surface temperature. As a result, early signs of water and heat stress often go undetected until crop yields are visibly affected, particularly in rainfed agricultural areas of Northern Kazakhstan [5].

Furthermore, existing solutions rarely offer a reproducible cloud-based workflow that combines multiple satellite data sources with field-level metrics and interactive web visualization for local experimental farms. Currently, no system simultaneously integrates Sentinel-2 vegetation indices, SMAP SM, and MODIS LST at the field level with an accessible interface for researchers at the North Kazakhstan Agricultural Experimental Station (NKAES) [6].

These gaps create practical and scientific problems: farmers and researchers in Northern Kazakhstan lack an integrated cloud-based system that can convert various satellite data into operational indicators of plant condition, soil moisture, and heat stress for specific fields. The solution requires the development of a special system architecture, a data fusion pipeline, and visualization tools adapted to the agro climatic conditions of the region [7].

**Research Aim**

This study aims to develop and demonstrate a cloud-based information system, for operational monitoring and analysis of agricultural lands in Northern Kazakhstan. The system

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

integrates multi-sensor remote sensing data, including Sentinel-2 vegetation indices, SMAP SM, and MODIS land surface temperature. This integration enables field-level assessment of crop condition, soil moisture dynamics, and thermal stress.

**Research Objectives**

To achieve this aim, the study sets the following specific objectives:

- To design a framework to harmonize optical, microwave, and thermal satellite data into 10-day composites for rainfed agriculture in Northern Kazakhstan.
- To implement a cloud-based pipeline on Google Earth Engine to generate multi-sensor composites and field-level statistics.
- To develop a modular system and backend for efficient storage, retrieval, and export of satellite-derived indicators.
- To create an interactive dashboard for visualization and temporal analysis of vegetation, soil moisture, and temperature.
- To evaluate the system's effectiveness for crop monitoring, early stress detection, and potential integration with yield-prediction tools.

**Literature review**

In recent years, agricultural remote sensing has advanced rapidly due to improvements in cloud computing, multi-sensor products, and fusion algorithms. The focus has shifted from single-index approaches to operational multi-sensor systems that integrate optical, microwave, and thermal data to improve the detection of water and heat stress.

Sentinel-2 vegetation indices remain central to crop monitoring. While NDVI is widely used, it can saturate under high biomass, whereas EVI is more sensitive in dense vegetation. Sentinel-2 offers high spatial resolution and red-edge bands useful for assessing plant condition and early stress signals.

However, optical vegetation indices reflect the vegetation response to environmental stress rather than the driving environmental factors themselves. This limitation restricts the ability to detect stress conditions at early stages, such as drought and heat stress.

To overcome these limitations, many scientists have proposed considering thermal indicators such as LST-based heat stress alongside optical indices. Fusing high-resolution vegetation indices with thermal data, using methods such as ESTARFM and machine learning, improves drought detection at the field level compared with optical indices alone.

Soil moisture is important for early drought warning, enabling yield reductions to be predicted weeks before vegetation indices change. Because SMAP has coarse resolution, downscaling methods such as machine learning models and proxies using LST and vegetation cover are used [8]. These produce finer-resolution SM maps (1–3 km), giving better detail and less bias at the field scale. While most studies are international, similar approaches are now being applied in Kazakhstan, showing the importance of high-resolution data for regional agriculture [9]. These studies demonstrate that integrating LST with soil moisture significantly improves the detection of agricultural drought. This approach also better reflects land–atmosphere interactions [10].

In Kazakhstan, remote sensing-based drought monitoring has been actively developing over the past two decades. Most national studies have focused on vegetation indices such as NDVI, EVI, vegetation condition index (VCI), and temperature condition index (TCI) to analyze spatial and temporal patterns of drought and its impact on agricultural productivity [11]. A number of studies have examined vegetation trends and land conditions using NDVI and related indices based on publicly available satellite imagery [12-13].

Chen, S. et al. presented that combining high-resolution vegetation indices with thermal data using fusion models like ESTARFM improves field-level drought monitoring through enhanced spatiotemporal fusion of Sentinel-2 and MODIS, though it requires cloud-free data and computational effort [14]. However, such fusion methods often require the availability of cloud-free satellite imagery. This may limit their practical application in real-time monitoring of large agricultural areas. Moreover, the complexity of spatio-temporal fusion models makes their integration into traditional monitoring systems challenging. In particular, limited computational infrastructure can hinder the implementation of such approaches. Furthermore, the lack of continuous satellite observations may restrict their operational use in certain regions.

Li, J. et al. used machine learning methods such as deep belief networks to downscale SMAP SM data to finer spatial resolutions, improving detail but depending on the quality of auxiliary inputs [15]. However, this method is highly dependent on the quality of the additional input data. However, while downscaling techniques have increased spatial accessibility, it should be noted that remote sensing data on soil moisture is one of the key factors in monitoring agriculture.

Qin, Q. et al. emphasized that integrating optical, soil moisture, and thermal indicators with machine learning allows earlier stress detection than optical indices alone, though combining heterogeneous datasets remains challenging [16]. This study demonstrated that using several variables describing the state of the environment together makes it possible to prevent plant stress.

Gao, G. highlights that temporal aggregation (e.g., 10-day composites) improves the stability and reproducibility of vegetation and moisture metrics, but may obscure short-term stress dynamics [17]. Deriving temporary composites to reduce cloud-induced noise helps ensure accurate and reliable analysis of vegetation index time series.

Gorelick, N. demonstrates that platforms like Google Earth Engine allow scalable processing of large multi-source datasets, but reliance on cloud infrastructure may limit their use in connectivity-restricted regions [18].

Moreover, recent studies have shown the importance of jointly using indices from multiple satellites in drought monitoring. For example, Guria, R. et al. proposed the IDSI multisensory integrated drought index [19]. This index combines optical crop indices with several factors, such as surface temperature and soil moisture. The results of this study demonstrate a validation accuracy of over 85%. However, such indices require additional regional adaptation and validation in the case of Kazakhstan, because the agroclimatic characteristics differ from those of the original model conditions.

Other studies have demonstrated the effectiveness of integrating data from multiple remote sensing satellites. In particular, Khafizova, Z. et al. used vegetation indices, rainfall data, surface temperature, and soil moisture information [20]. The authors suggest using such a multi-index system to monitor long-term changes in agricultural drought. However, approaches like this may not always provide detailed information for precise agricultural monitoring.

More recent studies have applied machine learning algorithms to remote sensing datasets to predict key factors affecting crop yield. Andure, N. et al. developed a framework for drought detection and forecasting using multispectral satellite data [21]. They applied indices such as NDVI, VCI, TCI, LST, and SP-3, as well as rainfall amount, in their machine learning models. In this study, the model was focused on the semi-arid region of India and better demonstrated the impact of vegetation on drought. The ecological factors that cause the drought itself were not taken into account. However, such models are primarily used for predicting individual factors rather than supporting operational agricultural monitoring.

Therefore, there is an increasing demand for simple and scalable systems capable of integrating multisensory satellite datasets. At the same time, maintaining sufficient temporal consistency remains essential for operational agricultural monitoring.

## Materials and methods

### *The study area*

The study area comprises the agricultural lands of the NKAES**,** located in the North Kazakhstan Region of the Republic of Kazakhstan (Figure 1). Geographically, the area is situated approximately between 69°00′–69°45′ E longitude and 54°50′–55°25′ N latitude**.** The region is characterized by predominantly flat terrain formed by alluvial and lacustrine deposits and belongs to the forest–steppe and steppe natural zones of Northern Kazakhstan.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

The climate of the study area is sharply continental, with cold winters and warm summers. The mean annual air temperature ranges from +1 °C to +3 °C, while average air temperatures during the growing season (May–September) vary between 14 °C and 20 °C**.** Annual precipitation averages 300–350 mm, with the majority of rainfall occurring in late spring and summer.

Agricultural production within the NKAES territory is dominated by spring wheat, which is the primary cereal crop in Northern Kazakhstan, along with barley and oilseed crops cultivated under experimental crop rotations. Farming in the region is mostly rainfed, and crop yields depend on year-to-year changes in precipitation and temperature. Irrigation infrastructure is limited and mainly used for research purposes.

The selected study area is suited for remote sensing–based agricultural monitoring due to its pronounced climatic variability, intensive agricultural land use, and availability of long-term experimental observations (Figure 1).

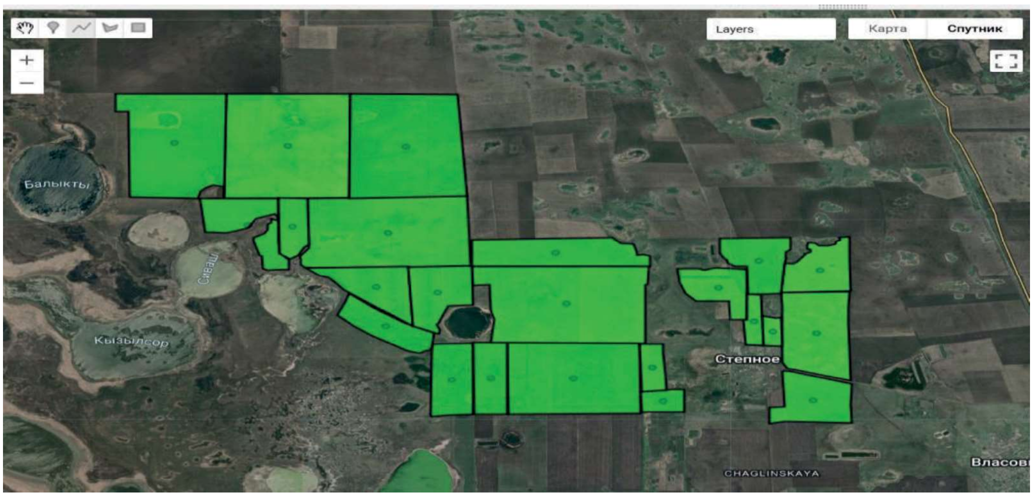



Figure 1. Study area: North Kazakhstan Agricultural Experimental Station (NKAES)

These characteristics provide a reliable basis for assessing vegetation indices, soil moisture dynamics, and their relationships with crop condition and productivity.

*Remote Sensing Data*

Remote sensing data from multiple satellite platforms were employed to monitor vegetation condition, soil moisture dynamics, and surface thermal characteristics of agricultural lands within the study area. The selected datasets provide complementary spatial and temporal information relevant to crop growth and water availability in rainfed agricultural systems.

Vegetation-related indicators were derived from the Sentinel-2 Surface Reflectance (SR) products acquired from the Copernicus satellite constellation. Sentinel-2 provides multispectral imagery across 13 spectral bands with spatial resolutions of 10 m, 20 m, and 60 m, covering the visible, near-infrared, and shortwave infrared regions. Sentinel-2 SR data were accessed through the Google Earth Engine (GEE) platform and filtered for growing seasons between 2019 and 2025. Before analysis, cloud- and cirrus-contaminated pixels were removed using quality assessment information to ensure the use of high-quality surface reflectance data. Based on the corrected reflectance values, the NDVI and the EVI were calculated to characterize vegetation vigour and crop development at the field scale.

NDVI is a widely used spectral index for monitoring vegetation using remote sensing (satellites, drones, etc.). It indicates the “greenness” or health/vigour of vegetation. It uses two spectral bands: NIR (Near-Infrared) – healthy vegetation reflects strongly in this band, RED (Red) – healthy vegetation absorbs red light for photosynthesis.

$$NDVI = \frac{B_{NIR} - B_{RED}}{B_{NIR} + B_{RED}} \quad (1)$$

where $B_{NIR}$ - reflectance in the near-infrared band, $B_{RED}$ reflectance in the red band.

The EVI is a vegetation index designed to improve the sensitivity of NDVI in areas with dense vegetation, reduce the influence of the atmosphere, and minimize background noise from soil. It is widely used in agriculture, forestry, and ecological monitoring.

$$EVI = \frac{B_{NIR} - B_{RED}}{(B_{NIR} + 6B_{RED} - 7.5B_{BLUE} + 1)} * 2.5 \quad (2)$$

Soil moisture information was obtained from the SMAP Level-4 Surface and Root Zone Soil Moisture product (SPL4SMGP)**.** This dataset provides spatially continuous estimates of surface soil moisture by assimilating satellite observations into a land surface model framework. SMAP Level-4 data have an approximate spatial resolution of 9 km**,** with daily temporal coverage, making them suitable for capturing large-scale soil moisture variability that influences crop water stress in Northern Kazakhstan. SMAP data were retrieved from GEE and used to represent soil water availability during the growing season.

$$SM_{norm} = \frac{(SM - SM_{min})}{(SM_{max} - SM_{min})} \quad (3)$$

where $SM = SMAP$ surface soil moisture *($m^3/m^3$);* $SM_{min}$, $SM_{max}$ –seasonal minimum and maximum soil moisture.

LST was derived from the MODIS MOD11A2 product acquired by the MODIS sensor on board NASA’s Terra satellite. MOD11A2 provides 8-day composite daytime LST at a spatial resolution of 1 km**.** A scale factor was applied to convert digital values into temperature expressed in Kelvin. LST was derived from the MODIS MOD11A2 product acquired by the MODIS sensor onboard NASA’s Terra satellite. MOD11A2 provides 8-day composite daytime LST at a spatial resolution of 1 km. To convert MODIS digital numbers (DN) into physically meaningful temperature values, the standard scale factor was applied using:

$$LST(K) = DN * 2 \quad (4)$$

where *DN* - raw MODIS digital number, 0.02 scale factor specified in the MOD11A2 product, *LST(K)* - land surface temperature in Kelvin.

$$TMDI = \frac{LST - \overline{LST}}{\sigma_{LST}} - \frac{SM - \overline{SM}}{\sigma_{SM}} \quad (5)$$

where $\overline{LST}$, $\overline{SM}$ - long-term mean values, $\sigma_{LST}$, $\sigma_{SM}$ - standard deviations of *LST, SM* vegetation indices.

In this study, the TMDI is defined as a standardized anomaly index based on LST and soil moisture. LST and SM are key variables that determine evapotranspiration and water availability for plants. The formula uses z-score normalization, which is widely used in climate and drought analysis (e.g., SPI and SPEI) [22-23]. It is also consistent with remote sensing methods that combine thermal and moisture variables [24].

To ensure consistency among datasets, all satellite observations were spatially subset to the study area and temporally harmonized. Sentinel-2, SMAP, and MODIS data were aggregated into 10-day composite intervals using median values, reducing the influence of residual cloud contamination, noise, and extreme observations.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

*Quantitative Evaluation Metrics*

The Pearson correlation coefficient is a statistical measure of the relationship between variables. It indicates the strength and direction of the linear relationship between two or more variables [25].

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (6),$$

where:
- $x_i$ – value of the first variable;
- $y_i$ – value of the second variable;
- $\bar{x}$, $\bar{y}$ – mean values of the variables;
- n– number of observations.

The NDVI anomaly was calculated to quantify the deviation of the vegetation index from the norm:

$$\Delta NDVI = NDVI_i - \overline{NDVI} \quad (7),$$

where:
- $NDVI_i$ – NDVI value at a specific time;
- $\overline{NDVI}$ - long-term mean NDVI value.

*Data Integration and Temporal Compositing*

Due to differences in spatial resolution, temporal frequency, and sensing principles among the selected satellite datasets, a unified data integration and compositing strategy was applied before analysis. The primary objective of this step was to harmonize multi-source remote sensing data within a consistent temporal framework suitable for field-scale agricultural monitoring.

All datasets were processed within the Google Earth Engine cloud computing environment, which enables scalable handling of large geospatial data volumes and reproducible analytical workflows. Sentinel-2 vegetation indices, SMAP SM, and MODIS LST data were spatially aligned with agricultural field boundaries using vector-based polygon masking.

To achieve temporal consistency, satellite observations were aggregated into 10-day composite periods throughout the growing season. For each composite interval, all available observations were summarized using median values, effectively minimizing the impact of residual noise, cloud effects, and outliers. This approach ensures a balance between temporal resolution and data stability while preserving key intra-seasonal dynamics.

Following temporal aggregation, the integrated dataset comprised synchronized time series of NDVI, EVI, surface soil moisture, and land surface temperature for each agricultural field. [26].

The adopted data integration framework enables the consistent fusion of optical, microwave, and thermal satellite observations, serving as the methodological foundation of the information system**.** By combining heterogeneous datasets into a unified spatio-temporal structure, the system supports continuous agricultural monitoring and provides a scalable solution for decision support in precision agriculture.

**Results**

As a result of this study, a cloud-based information system was developed for monitoring and analyzing agricultural lands using multi-source remote sensing data. The system integrates optical, microwave, and thermal satellite observations into a unified analytical environment, enabling field-level assessment of vegetation and environmental conditions.

The system was implemented on the Google Earth Engine cloud platform, which provides scalable access to long-term satellite archives and high-performance geospatial processing. The system architecture includes data ingestion, preprocessing, temporal compositing, statistical aggregation by agricultural fields, and web-based visualization.

The system was tested using agricultural fields of the NKAES as a representative study area. Field boundaries were uploaded as polygon layers, enabling consistent spatial aggregation of satellite-derived indicators.

*System Architecture and Web Application Development*

The information system was developed using a modular client–server architecture designed to support scalable processing and visualization of multi-source satellite remote sensing data.

The system consists of three main components: (1) a cloud-based data processing layer, (2) a backend service layer, and (3) a web-based frontend application (Figure 2).

The data processing layer is implemented on the Google Earth Engine (GEE) platform. Sentinel-2 surface reflectance data are utilized to calculate vegetation indices, including the NDVI and EVI. Soil moisture information is obtained from the SMAP Level-4 Surface and Root Zone Soil Moisture product, while thermal conditions are characterized using the MODIS MOD11A2 land surface temperature dataset.

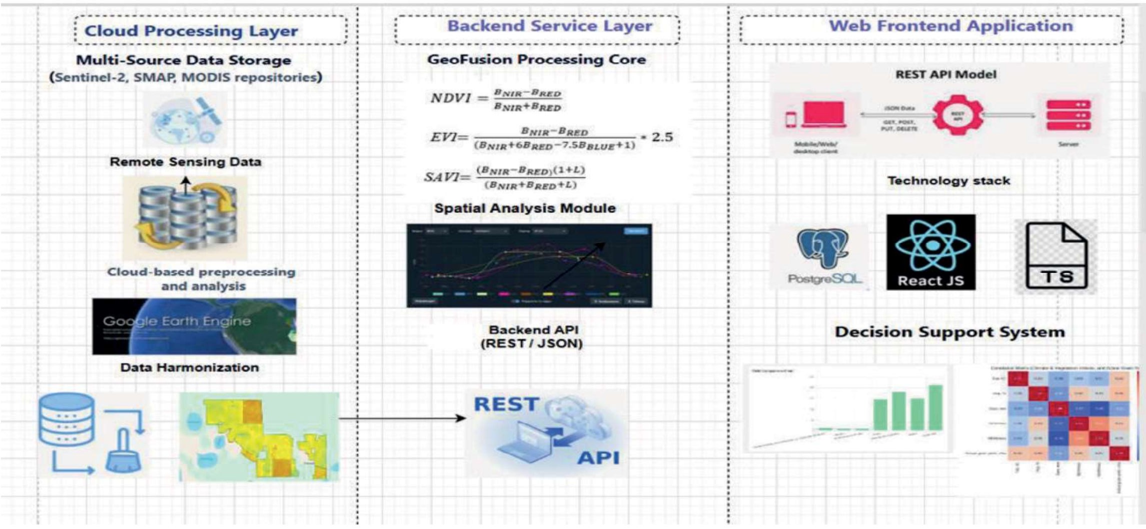



Figure 2. The general architecture of the proposed information system

All satellite observations are aggregated into 10-day composite intervals using median values to ensure temporal consistency and reduce noise.

*NDVI Composite Maps and Vegetation Dynamics*

NDVI composites were generated using Sentinel-2 imagery with a 10-day temporal resolution. Cloud masking and quality filtering were applied to ensure stable vegetation signals. These spatial patterns are important for within-field zoning, experimental analysis, and future precision agriculture applications (Figure 3, (a)).

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

(a) (b)

Figure 3. Temporal composite maps derived from Sentinel-2 data for North Kazakhstan Agricultural Experimental Station LLP fields: (a) NDVI composite map; (b) LST composite map

*Integration of Soil Moisture and Land Surface Temperature*

A key outcome of the proposed system is the integration of SM data from the SMAP Level-4 product and LST data from MODIS. These variables complement optical vegetation indices, provide additional insights into crop water availability, and thermal stress.

Mean soil moisture maps revealed noticeable spatial variability across fields, reflecting differences in soil properties, micro relief, and moisture retention capacity. Periods of reduced soil moisture frequently coincided with declining NDVI values, indicating the sensitivity of crop growth to water stress conditions in the rainfed farming systems of Northern Kazakhstan.

Land surface temperature maps demonstrated clear seasonal patterns, with elevated temperatures during mid-summer periods (Figure 3, (b)). Combined analysis of NDVI and LST data enabled the identification of areas potentially affected by heat stress, even where vegetation cover appeared visually uniform.

*NDVI Trends and Anomaly Analysis*

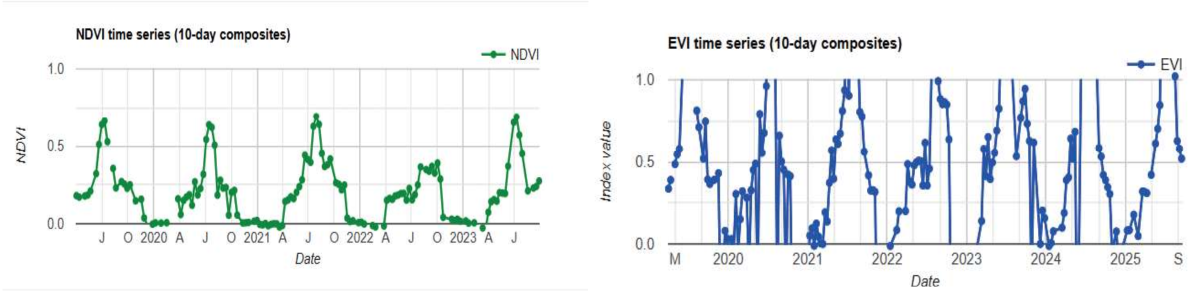
Long-term NDVI trends were calculated using linear regression across the multi-year composite series. The resulting trend maps highlighted areas with positive vegetation dynamics as well as zones exhibiting gradual degradation.

The NDVI and EVI time series for the NKAES exhibit a clearly pronounced seasonal pattern typical of agroecosystems in northern Kazakhstan. Minimum index values occur during the winter–early spring period (November–March), which is associated with the absence of active vegetation, snow cover, and low air temperatures. A steady increase in index values begins in late April to early May, corresponding to the onset of the growing season.

Peak NDVI values, reaching approximately 0.6–0.7, are observed in June–July and correspond to the period of active crop growth and maximum biomass accumulation. Interannual variability in peak amplitudes indicates differences in hydro-meteorological conditions and agricultural practices between years. The subsequent decline in NDVI during August–September reflects crop maturation and harvesting activities (Figure 4, (a)).

The EVI time series shows higher maximum values (up to 0.8–1.0) and greater variability compared to NDVI, which can be attributed to its higher sensitivity to dense vegetation and reduced influence of soil background effects. Short-term sharp decreases in EVI may result from residual cloud contamination, spatial heterogeneity of crop fields, or field management operations (Figure 4, (b)).

A comparison of NDVI and EVI indicates that NDVI provides a more stable representation of overall seasonal vegetation dynamics, while EVI offers improved sensitivity during periods of high biomass.

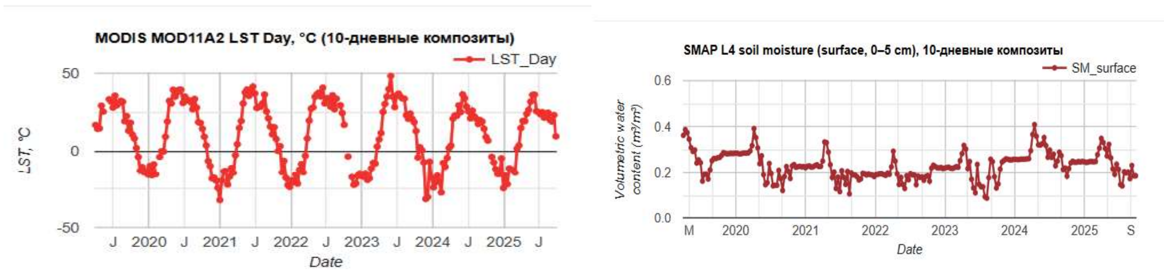



a) b)

Figure 4. Time series composites: a) NDVI time series; b) EVI time series.

The combined use of both indices enhances the robustness of vegetation monitoring and allows for a more comprehensive assessment of crop condition and growth dynamics.

The MODIS MOD11A2 LST daytime time series for the NKAES shows a strong and regular seasonal cycle. Positive temperatures dominate during the warm season, with summer maxima frequently exceeding 35–40 °C, reflecting intense surface heating under continental climatic conditions. In contrast, winter periods are characterized by persistent negative temperatures, often below −20 °C, which correspond to snow cover and frozen soil conditions. The clear annual oscillation indicates the reliability of the 10-day compositing approach for capturing long-term thermal dynamics (Figure 5, (a)).




a) b)

Figure 5. Time series composites: a) MODIS LST time series; b) SMAP L4 soil moisture time series.

Interannual variability in summer LST peaks is evident, suggesting differences in atmospheric conditions, soil moisture availability, and vegetation cover between years. Years with higher summer LST values may indicate drier conditions or reduced evaporative cooling, whereas lower summer peaks can be associated with increased vegetation density or higher soil moisture levels.

The SMAP L4 surface soil moisture (0–5 cm) time series also exhibits pronounced seasonal behavior. Higher soil moisture values are generally observed in spring, associated with snowmelt and early-season precipitation, while lower values dominate in mid to late summer due to increased evapotranspiration and crop water uptake. Typical volumetric water content values range approximately between 0.15 and 0.35 $m^3/m^3$, which is consistent with agricultural soils in the region (Figure 5, (b)). Short-term fluctuations in soil moisture reflect episodic precipitation events and drying periods, while interannual differences point to variability in climatic conditions. Notably, periods of reduced surface soil moisture tend to coincide with

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

elevated land surface temperatures, highlighting the strong coupling between thermal conditions and near-surface moisture dynamics.

In addition, NDVI anomalies were generated by comparing individual composite periods with the multi-year mean NDVI. Positive anomalies indicated above-average vegetation development, while negative anomalies reflected unfavorable conditions potentially linked to drought, delayed emergence, or other stress factors. Figure 6 shows interannual variability in vegetation conditions across the growing season.

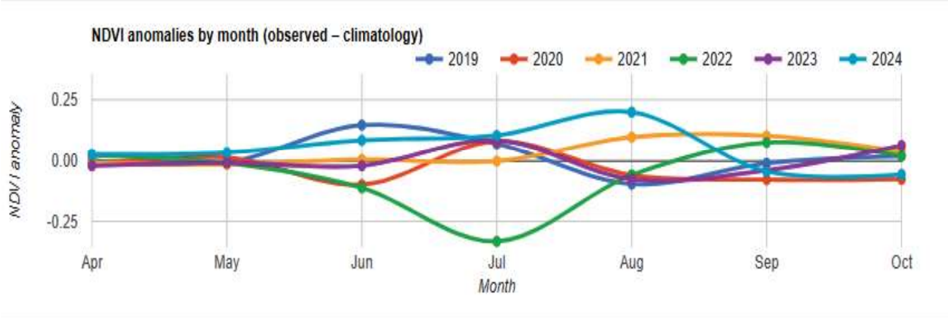



Figure 6. Monthly NDVI anomalies for 2019–2024 (observed minus climatology).

Positive anomalies (above-climatology NDVI) indicate periods of improved vegetation vigor, while negative anomalies reflect stress conditions such as drought, low biomass accumulation, or delayed phenological development. The visualization highlights differing seasonal patterns between years and allows comparison of early-season and mid-season deviations.

*Vegetation Indices Anomaly Maps*

The anomaly map helps to identify spatial differences in crop condition within the experimental station. Such information is useful for detecting stressed fields, assessing variability within the agricultural area, and supporting targeted field inspections and management decisions. Figure 7 illustrates the spatial distribution of NDVI conditions across the agricultural fields of the LLP NKAES in June 2025. The left panel shows mean NDVI values, reflecting the general level of vegetation development across the study area. Higher NDVI values indicate well-developed and healthy crops, while lower values correspond to sparse vegetation, bare soil, or non-agricultural areas.

The right panel presents standardized NDVI anomalies (z-scores), which characterize deviations of vegetation conditions from long-term average values.

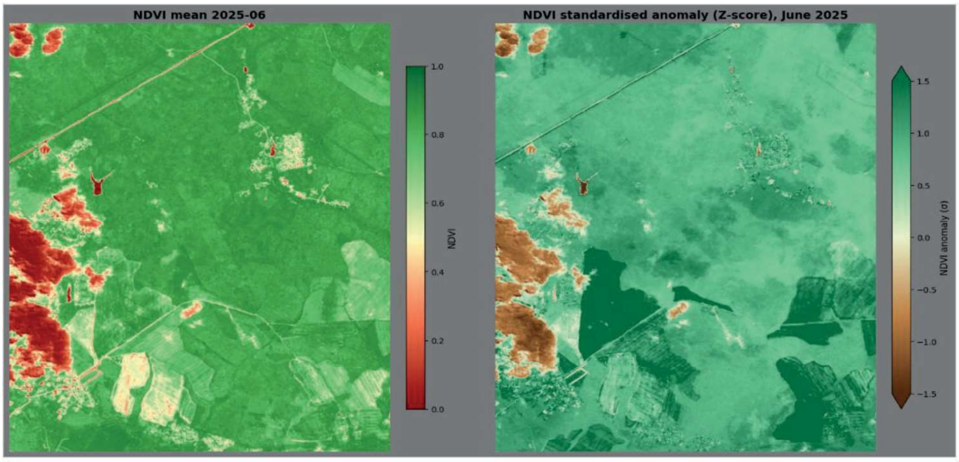



Figure 7. NDVI anomalies of the North Kazakhstan Agricultural Experimental Station LLP

Dark brown areas (−2) indicate strong vegetation stress, orange areas (−1) represent moderate stress, light yellow-green areas (0) correspond to normal conditions, green areas (+1) indicate better-than-average vegetation development, and dark green areas (+2) show vegetation conditions significantly better than the norm.

Figure 8 shows the spatial distribution of EVI conditions across the agricultural fields of the North Kazakhstan Agricultural Experimental Station LLP in June 2025. The left panel presents mean EVI values, which reflect vegetation density and crop vigor. Higher EVI values indicate dense and well-developed crops, while lower values correspond to sparse vegetation, bare soil, or harvested areas.

The right panel displays standardized EVI anomalies (z-scores), representing deviations from long-term average conditions. Dark brown areas (−2) indicate strong vegetation stress, orange areas (−1) show moderate stress, light yellow-green areas (0) correspond to normal vegetation conditions, green areas (+1) indicate better-than-average crop development, and dark green areas (+2) represent vegetation conditions significantly better than the norm.

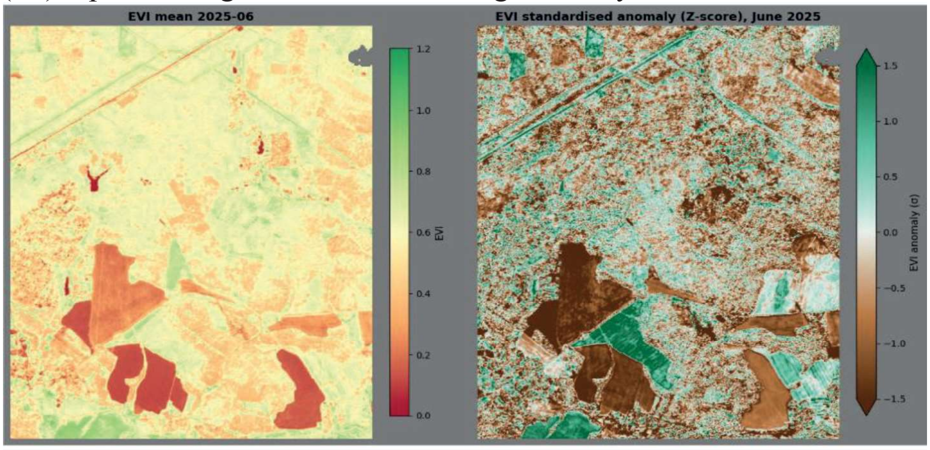



Figure 8. EVI anomalies map of the North Kazakhstan Agricultural Experimental Station LLP

Compared to NDVI, the EVI anomaly map highlights stronger spatial contrasts within the fields, making it particularly useful for identifying areas with high biomass as well as zones experiencing stress during peak growing conditions. This information supports detailed assessment of crop condition and spatial variability within the experimental station.

Figure 9 illustrates the spatial distribution of soil moisture and corresponding anomalies derived from SMAP observations for June in Northern Kazakhstan. Negative soil moisture anomalies dominate the southern part of the study area, indicating the development of moderate moisture deficit conditions, while the northern areas remain relatively wetter.

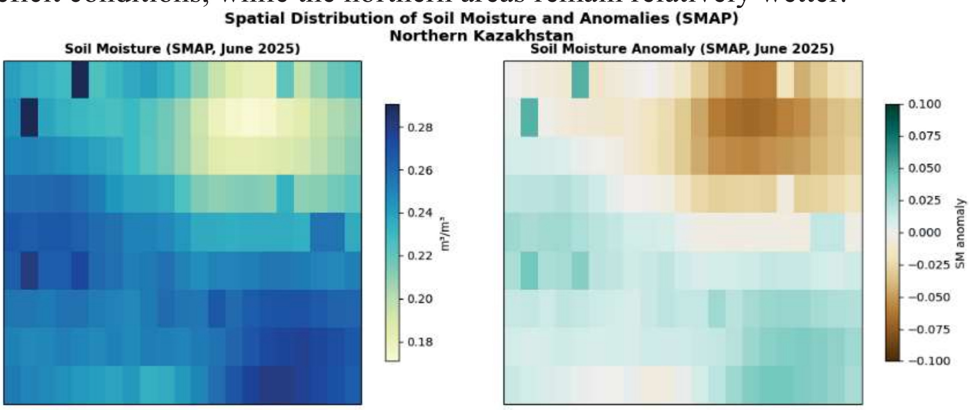



Figure 9. SMAP anomalies of the LLP «North Kazakhstan Experimental Station» by months

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

Further analysis focuses on the relationship between thermo-moisture stress and vegetation response. The scatterplots in Figure 10 illustrate the relationship between the Thermo-Moisture Drought Index (TMDI) and EVI anomalies in June 2025. The correlation between these two variables is very weak, and the correlation coefficient is close to zero ($r \approx -0.01$) in North Kazakhstan Experimental Station LLP. This suggests that the vegetation response may lag behind changes in temperature and humidity conditions. Therefore, TMDI should not be interpreted as directly detecting drought earlier than vegetation indices, but rather as reflecting underlying environmental conditions that may precede vegetation response.

Most data points are clustered around near-zero EVI anomalies, even across a wide range of TMDI values. This suggests that variations in thermal and moisture conditions did not uniformly translate into immediate vegetation response across the region. In many areas, vegetation conditions remained close to their long-term average despite differing levels of drought stress indicated by TMDI.

The LOWESS-smoothed curve confirms this pattern, showing only a slight downward tendency in EVI anomalies with increasing TMDI. This weak non-linear response implies that higher thermo-moisture stress was associated with marginally reduced vegetation activity, but the effect was limited.

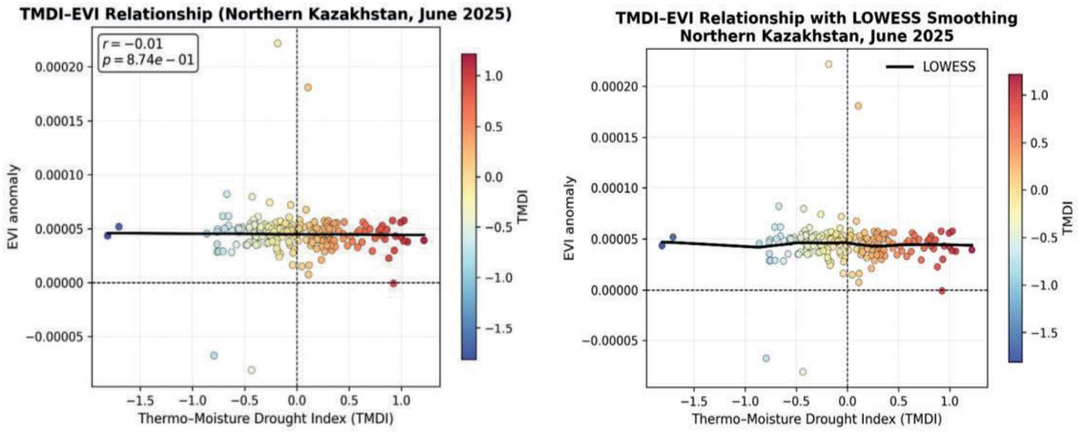



Figure 10. NDVI anomalies of the North Kazakhstan Experimental Station LLP by months

These results indicate that vegetation response to drought conditions in Northern Kazakhstan is influenced by additional factors such as crop type, phenological stage, soil properties, and short-term precipitation events. The weak relationship also suggests a possible time lag between the onset of thermo-moisture stress and detectable changes in vegetation indices.

The bar chart (Figure 11) shows mean EVI anomalies across TMDI-based drought severity classes. Differences between classes are small, indicating a weak vegetation response to increasing drought severity during the study period. Extremely wet and near-normal conditions exhibit slightly higher EVI anomalies, while moderate drought conditions show somewhat lower values. However, the overlap of error bars suggests that these differences are not statistically significant. Overall, vegetation in Northern Kazakhstan remained relatively resilient in June 2025, likely due to phenological stage and short-term moisture availability.

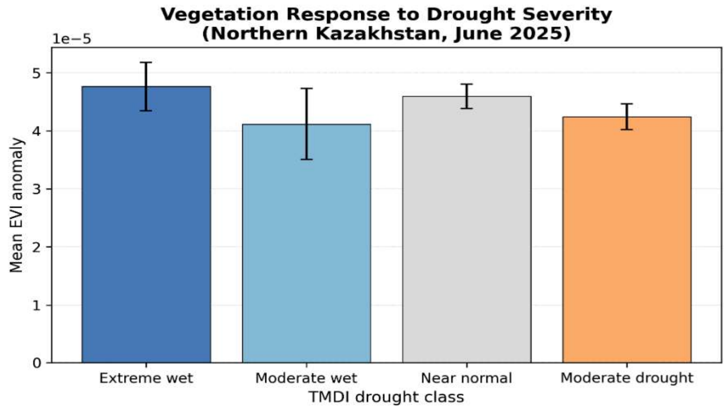



Figure 11. NDVI anomalies of the North Kazakhstan Experimental Station LLP by months

The table below summarizes different approaches used for crop monitoring and assessment (Table 1). Traditional monitoring based on the most widely used NDVI vegetation index in agriculture is only helpful when certain stress factors are detected in the vegetation canopy. Monitoring based on optical indices such as NDVI and EVI allows for average monitoring over a 5–10-day period. This table summarizes the quantitative characteristics derived from remote sensing data for the North Kazakhstan Agricultural Experimental Station.

The maximum values of the NDVI index ranged from 0.6 to 0.7, while EVI values reached approximately 0.8–1.0. These values correspond to the period of maximum plant biomass development in the region during June–July. However, these indices primarily reflect the physiological response of crops rather than the environmental factors that cause stress. As a result, optical vegetation indices alone may not accurately detect drought or heat stress during the early stages of vegetation development.

Table 1. Quantitative evaluation of satellite-based monitoring approaches

| **Monitoring approach** | **Data sources** | **Indicators used** | **Temporal resolution** | **Quantitative metrics** | **Stress detection capability** |
|---|---|---|---|---|---|
| NDVI-based monitoring | Sentinel-2 | NDVI | 5–10 days | $r_{NDVI,SM} = -0.24$ | Detects stress after vegetation decline |
| Optical monitoring | Sentinel-2 | NDVI, EVI | 5–10 days | $r_{NDVI,EVI} = 0.87$ | Moderate detection capability |
| Thermal–moisture indicators | MODIS + SMAP | LST, Soil moisture | 8–10 days | $r_{LST,\ SM} = -0.23$ $r_{LST_{anom},SM_{anom}} = -0.26$ | Early environmental stress signals |
| Proposed GeoFusion system | Sentinel-2 + SMAP + MODIS | NDVI, EVI, TMDI, anomaly indices | 10-day composites | $r_{NDVI,\ SM} = -0.24$ $\Delta NDVI \in [-0.15, 0.12]$ $\Delta NDVI_{min} \approx -0.35$ $r_{TMDI,EVI_{anom}} = -0.04$ | Indicates early environmental stress conditions |

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 26, JUNE 2026

In this context, additional information can be obtained from SMAP Level-4 soil moisture and MODIS MOD11A2 land surface temperature products. Under the conditions of Northern Kazakhstan, soil moisture typically varies between 0.15 and 0.35 $m^3/m^3$, while land surface temperatures during summer can exceed 35–40 °C. These values indicate the strong climatic variability characteristic of rainfed agricultural systems in the region.

The observed negative relationship between land surface temperature and soil moisture ($r \approx -0.24$) indicates that increasing temperature is generally associated with decreasing soil moisture. Another important indicator used in the proposed system is the Thermo-Moisture Drought Index (TMDI), which enables earlier detection of thermo-hydrological stress conditions before visible crop degradation occurs.

The correlation between TMDI and EVI anomalies is very weak ($r = -0.04$), suggesting that vegetation's response to thermo-humid stress may occur with a time lag.

Analysis of NDVI anomalies shows that most deviations fall within the range $\Delta NDVI \in [-0.15; 0.12]$, with extreme anomalies reaching approximately $\Delta NDVI\_min \approx -0.35$.

**Limitation and Discussion**

In the proposed work, the potential for integrating Sentinel-2, SMAP, and MODIS remote sensing data into a single system in the North Kazakhstan region for efficient agricultural research is described. Compared with traditional vegetation indices such as NDVI, this system offers certain advantages. This system provides the capability for in-depth study of crops and environmental conditions through integrated analysis of optical, thermal, and microwave observations.

Although most studies in this field have focused on single-source data, several authors have demonstrated the effectiveness of using multisensor data. For example, Vreugdenhil, M. et al. noted that microwave-based soil moisture monitoring complements optical vegetation indices [7]. Furthermore, it was noted that using additional environmental information, beyond the information obtained from vegetation indices, is beneficial for drought monitoring in agriculture.

Similarly, Guria, R. et al. studied the issue of improving drought assessment and proposed an Integrated Drought Severity Index (IDSI) that combines vegetation indices, surface temperature, and soil moisture [19]. Our research is based on the same multisensor concept. It focuses on the development of a cloud-based operational monitoring system for large-scale field-level analysis.

In recent years many researchers have highlighted challenges related to multisensor monitoring. For example, Gao, G. et al. noted that airborne LiDARs provide detailed information on vegetation cover [17]. However, they pointed out that collecting such data is expensive and that it is more appropriate to use them for large-scale operational monitoring. In contrast, the proposed system is suitable for daily monitoring in agriculture, as it uses simple and freely available satellite products.

Despite these advantages, several limitations of this study should be noted. First, the data fusion strategy relies primarily on temporal composition and joint analysis of multisensor fusion. Although this ensures computational efficiency and practical applicability, it does not include the most advanced fusion methods. Future research will explore spatiotemporal fusion methods (e.g., STARFM, ESTARFM), SMAP statistical data downscaling, and data assimilation approaches to improve the integration of heterogeneous sources.

Another limitation of this study is the difference in spatial resolution between SMAP SM data (~9 km) and high-resolution Sentinel-2 data (~10 m) used for field-level analysis. Aggregating coarse SMAP data to field-scale polygons may introduce uncertainty due to sub-pixel variability.

In the North Kazakhstan cropland area under consideration, the correlation between anomalies in the TMDI and EVI indices was weak. This indicates that agricultural crops do not always respond immediately to heat and moisture stress.

Nevertheless, SMAP data were included to capture large-scale soil moisture patterns relevant to regional drought conditions, which cannot be obtained from optical data alone. Thus, combining datasets with different resolutions allows balancing spatial detail and environmental completeness.

In future work, we will address this issue by applying downscaling and other methods to improve data consistency and field-level accuracy.

Furthermore, as shown in Table 2, most existing remote sensing platforms, such as “Qoldau”, “EO Browser,” and “Egistic,” rely primarily on optical vegetation indices such as NDVI and EVI, while some also use MSAVI, ReCI, or NDWI. Although these approaches are effective for general vegetation monitoring, they typically do not incorporate soil moisture or thermal data. This limits their ability to detect early signs of water and heat stress at the field level.

In contrast, the proposed system integrates Sentinel-2 vegetation indices, SMAP SM data, and MODIS LST data within a single 10-day composite framework. This integration enables a more comprehensive assessment of crop condition.

Table 2. Comparative Analysis of Existing Platforms

| Platform / System | Country / Scope | Data Sources | Vegetation & Other Indices | Temporal Resolution | Spatial Resolution | Notes / Critical Features |
|---|---|---|---|---|---|---|
| **Qoldau** | Kazakhstan | Sentinel-2 | NDVI, EVI, MSAVI | 10–15 days | 10 m | Only optical VIs; no soil moisture or thermal integration; limited field-level analytics |
| **Egistic** | Kazakhstan | Sentinel-2, Landsat | NDVI, EVI, MSAVI | 10–16 days | 10–30 m | Optical only; coarse temporal resolution; no TCI/VCI integration |
| **EO Browser (Sentinel Hub)** | Global | Sentinel-2, Landsat, MODIS | NDVI, EVI, NDWI, MSAVI, ReCI | Daily–weekly | 10–30 m | Provides MODIS data, but no automated field-level aggregation or 10-day composites |
| **Climate Engine** | USA / Global | MODIS, Landsat | NDVI, EVI, VCI, TCI, NDWI | 8–16 days | 250 m – 1 km | Supports multiple indices beyond NDVI; lacks full integration with SMAP SM and MODIS LST as in GeoFusion |
| **Google Earth Engine (GEE) Custom Apps** | Global | Sentinel-2, Landsat, MODIS, SMAP | NDVI, EVI, MSAVI, ReCI, NDWI, LAI, VCI, TCI | Daily–10-day | 10 m – 1 km | Highly flexible; supports multisensor fusion; field-level aggregation requires custom setup |
| **Proposed System** | Kazakhstan | Sentinel-2, SMAP, MODIS | NDVI, EVI, TMDI, integrated | 10-day composites | 10 m – 1 km | Integrates optical, thermal, and microwave data; reproducible 10- |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | multi-sensor indicators, anomaly indices | | | day composites; potentially early stress detection at the field scale |

This multisensor approach provides more accurate and timely assessments of crop conditions, capturing complementary environmental signals that single-index platforms may miss. As a result, our proposed system offers a practical tool for field-level monitoring, potentially early stress detection, and interactive visualization, supporting better decision-making for researchers and farmers.

**Conclusion**

This proposed system for agricultural lands in Northern Kazakhstan using multi-sensor remote sensing data for monitoring and analysis. The cloud-based information system integrates optical, microwave, and thermal satellite observations from Sentinel-2 (NDVI and EVI), SMAP (SM), and MODIS (LST, TMDI) data. These datasets are aggregated into 10-day composites and summarized at the field scale. The approach enables continuous monitoring of vegetation dynamics and environmental conditions in agricultural systems.

The pipeline developed on the Google Earth Engine platform enables automated processing of statistics on agricultural fields using multi-sensor indicators. The cloud-based architecture provides repeatable analytical workflows for long-term monitoring. A modular server architecture was developed to analyze key agro-ecological indicators during the plant's vegetative stage. Additionally, an interactive web dashboard was created to visualize these indicators.

The results obtained for the NKAES demonstrate the effectiveness of integrating multiple satellite datasets. This approach provides more reliable monitoring compared with traditional NDVI-based methods. During this study, it was determined that the maximum NDVI values approached approximately 0.6–0.7, while EVI values neared 0.8–1.0 during the plants' most developed stages. Soil moisture fluctuated between 0.15 and 0.35 $m^3/m^3$, and surface temperatures exceeded 35–40 °C during the summer months. These values indicate high seasonal variability of temperature and moisture conditions in the agricultural fields of the study area. The use of 10-day composites enables consistent and reliable monitoring of these changes throughout the growing season.

Furthermore, TMDI allows improved identification of drought-related stress conditions based on combined environmental indicators

Compared to existing platforms such as Qoldau, Egistic, or EO Browser, the system integrates optical, thermal, and microwave data at the field scale. It provides reproducible 10-day composites, calculates field-level statistics, and offers an interactive dashboard for visualization and temporal analysis. These features address the study objectives of harmonizing multi-sensor data, implementing a cloud-based pipeline, developing a modular backend, visualizing indicators, and evaluating the system for operational crop monitoring. The system offers a practical, scalable solution for potentially early detection of vegetation stress and supports better decision-making for farmers and researchers.

Despite the results obtained in this study, several limitations should be noted. The spatial resolution of SMAP SM data (approximately 9 km) is considerably coarser than the 10 m spatial resolution of Sentinel-2 vegetation indices. Therefore, this may limit the accuracy at the field level. The use of 10-day composites may also smooth out short-term ecological fluctuations. Since the study was conducted within the NKAES, the generalizability of the results to other regions may be limited.

Future work will focus on expanding the monitoring framework to larger regions and integrating additional environmental datasets. One important direction is the development of study was conducted within the NKAES, the generalizability of the results to other regions may be limited.

Future work will focus on expanding the monitoring framework to larger regions and integrating additional environmental datasets. One important direction is the development of predictive models based on satellite-derived indicators. These models can be combined with meteorological and crop phenology data to improve yield forecasting and drought risk assessment.

Furthermore, in order to enhance the generalizability of the results across various agroclimatic conditions, future studies will extend the analysis to several regions of Kazakhstan.

In conclusion, the proposed cloud-based system demonstrates the potential of multi-sensor remote sensing integration for operational agricultural monitoring in Northern Kazakhstan.

**References:**

[1] Mimenbaeva, A., Yessen, A., Nurbekova, A., Suleimenova, R., Ospanova, T., Kasymova, A., & Niyazova, R. (2024). Development of a linear regression model based on vegetation indices of agricultural crops. *Scientific Journal of Astana IT University*, 15(15), 101–110. https://doi.org/10.37943/15EMUB4283

[2] Kabzhanova, G. R., Rakhimzhanov, B. K., & Tuleukulova, D. T. (2024). Assessment of the possibilities of remote monitoring of soil moisture in the territory of northern Kazakhstan. *Herald of Science of S. Seifullin Kazakh Agrotechnical University: Multidisciplinary*, 4(123), 1788. https://doi.org/10.51452/kazatu.2024.4(123).1788

[3] Rafikov, T., & Yerbolkyzy, M. (2024). Primenenie dannykh distantsionnogo zondirovaniya zemli i analiza NDVI v Vostochno-Kazakhstanskoi oblasti [Application of remote sensing data and NDVI analysis in the East Kazakhstan Region]. *Issledovaniya, rezul'taty*, **1**(101). https://doi.org/10.37884/1-2024/18

[4] Vitkovskaya, I., Batyrbayeva, M., Berdigulov, N., & Mombekova, D. (2024). Prospects for drought detection and monitoring using long term vegetation indices series from satellite data in Kazakhstan. *Land*, 13(12), 2225. https://doi.org/10.3390/land13122225

[5] Mimenbaeva, A. B., & Akanova, A. S. (2022). Soltüstik Qazaqstan oblysynyñ auylsharuashylyq daqyldarynyñ küiin NDVI syzyqtyq trendteri arqyly zertteu [Study of the condition of agricultural crops in the North Kazakhstan Region using NDVI linear trends]. *Academic Scientific Journal of Computer Science*, (3), 185–197. https://doi.org/10.32014/2022.2518-1726.146

[6] Qin, Q., Wu, Z., Zhang, T., Sagan, V., Zhang, Z., Zhang, Y., Ren, H., Sun, Y., & Xu, W. (2021). Optical and thermal remote sensing for monitoring agricultural drought. *Remote Sensing*, 13(24), 5092. https://doi.org/10.3390/rs13245092

[7] Vreugdenhil, M., Greimeister-Pfeil, I., Preimesberger, W., Camici, S., Dorigo, W., Enenkel, M., van der Schalie, R., Steele-Dunne, S., & Wagner, W. (2022). Microwave remote sensing for agricultural drought monitoring: Recent developments and challenges. *Frontiers in Water*, 4, Article 1045451. https://doi.org/10.3389/frwa.2022.1045451

[8] Pilia, S.; Fontanelli, G.; Santurri, L.; Palchetti, E.; Ramat, G.; Baroni, F.; Santi, E.; Lapini, A.; Pettinato, S.; Paloscia, S. Integration of Optical and Microwave Satellite Data for Monitoring Vegetation Status in Sorghum Fields. (2025). *Remote Sensing*, 17(9), 1591. https://doi.org/10.3390/rs17091591

[9] Li, M. Q., Wang, P. X., Tansey, K., & Sun, Y. F. (2025). Improved field-scale drought monitoring using MODIS and Sentinel-2 data for vegetation temperature condition index generation through a fusion framework. *Computers and Electronics in Agriculture*, 234, 110256. https://doi.org/10.1016/j.compag.2025.110256

[10] Cai, Y., Fan, P., Lang, S., Li, M., Muhammad, Y., & Liu, A. (2022). Downscaling of SMAP SM data by using a deep belief network. *Remote Sensing*, 14(22), 5681. https://doi.org/10.3390/rs14225681

analysis. *Remote Sensing Applications Society and Environment*, 29, 100907. https://doi.org/10.1016/j.rsase.2022.100907

[13] Alshehri, B., Zhang, Z., &Liu, X. (2025). A review of Google Earth Engine for Land Use and Land Cover Change Analysis: Trends, Applications, and Challenges. *ISPRS International Journal of Geo-Information*, 14 (11), 416. https://doi.org/10.3390/ijgi14110416

[14] Chen, S., Zhang, L., Hu, X., Meng, Q., Qian, J., & Gao, J. (2023). A spatiotemporal fusion model of land surface temperature based on pixel long time-series regression: expanding inputs for efficient generation of robust fused results. *Remote Sensing*, 15(11), 5211. https://doi.org/10.3390/rs15215211

[15] Li, J., Wei, Y., Lin, L., Yuan, Q., & Shen, H. (2025). Two-stage downscaling and correction cascade learning framework for generating long-time series seamless soil moisture. *Remote Sensing of Environment*, 321, 114684. https://doi.org/10.1016/j.rse.2025.114684

[16] Qin, Q., Wu, Z., Zhang, T., Sagan, V., Zhang, Z., Zhang, Y., Zhang, C., Ren, H., Sun, Y., Xu, W., et al. (2021). Optical and thermal remote sensing for monitoring agricultural drought. *Remote Sensing*, 13, 5092. https://doi.org/10.3390/rs13245092

[17] Gao, G., Qi, J., Lin, S., Hu, R., & Huang, H. (2023). Estimating plant area density of individual trees from discrete airborne laser scanning data using intensity information and path length distribution. International Journal of Applied Earth Observation and Geoinformation, 118, Article 103281. https://doi.org/10.1016/j.jag.2023.103281

[18] Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

[19] Guria, R., Mishra, M., da Silva, R. M., dos Santos, C. A. C., & Santos, C. A. G. (2025). Multisensor Integrated Drought Severity Index (IDSI) for assessing agricultural drought in Odisha, India. *Remote Sensing Applications: Society and Environment*, 37, Article 101399. https://doi.org/10.1016/j.rsase.2024.101399

[20] Khafizova, Z., Umarov, N., Gulmurodov, F., Raximov, U., Yoqubov, A., & Yarkulov, Z. (2025). Drought analysis using cropland surface temperature and NDVI data. *AIP Conference Proceedings*, 3286(1), 040023. https://doi.org/10.1063/5.0280104

[21] Andure, N., Kadam, A., Jadhav, S., Raut, S., Shafiyoddin, S., & Fulani, A. (2025). Real-time drought monitoring and prediction using multispectral remote sensing and machine learning. *International Journal of Environmental Sciences*, 11(8), 3921–3928. https://doi.org/10.64252/y0bxsk22

[22] Qin, Q., Wu, Z., Zhang, T., Sagan, V., Zhang, Z., Zhang, Y., Zhang, C., Ren, H., Sun, Y., Xu, W., & Zhao, C. (2021). Optical and Thermal Remote Sensing for Monitoring Agricultural Drought. *Remote Sensing*, 13(24), 5092. https://doi.org/10.3390/rs13245092

[23] Peng, L., Sheffield, J., Wei, Z., Ek, M., & Wood, E. F. (2024). An enhanced Standardized Precipitation–Evapotranspiration Index (SPEI) drought-monitoring method integrating land surface characteristics. Earth System Dynamics, 15(5), 1277–1300. https://doi.org/10.5194/esd-15-1277-2024

[24] Le, M. S., & Liou, Y. (2021). Spatio-Temporal assessment of surface moisture and evapotranspiration variability using remote sensing techniques. *Remote Sensing*, 13(9), 1667. https://doi.org/10.3390/rs13091667

[25] Sun, D., Li, Y., Zhan, X., Yang, C., & Yang, R. (2021). Integrating optical and microwave satellite observations for high-resolution soil moisture estimation and applications in drought analyses. *Journal of Geospatial Science*, 4(1), 1–13. https://doi.org/10.24294/jgc.v4i1.1313

[26] Lakshmi, V., Kir, E. G., Kir, A., & Fang, B. (2025). Remote Sensing-Based Monitoring of Agricultural Drought and Irrigation Adaptation Strategies in the Antalya Basin, Türkiye. *Hydrology*, 12(11), 288. https://doi.org/10.3390/hydrology12110288