**Indicator systems and modeling methods for assessing atmospheric air pollution and forecasting environmental risk in southern**

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**Abstract:** This study aims to develop a multi-component indicator system and modeling framework for assessing air pollution and forecasting environmental risk in southern regions. It analyses atmosphere composition (PM₂.₅/PM₁₀, NO₂, SO₂, CO, dust-aerosols), meteorological parameters (temperature, wind, humidity) and anthropogenic sources (industry, transport, agriculture). Using GIS and statistical/regression models, pollution distribution and risk zones are predicted. Results support enhanced regional monitoring, risk assessment, and environmental management strategies.

**INTRODUCTION**

The state of atmospheric air is a crucial indicator of human health, agro-ecosystem sustainability, socio-economic development, and overall environmental stability. The southern regions of Uzbekistan—particularly Kashkadarya and Surkhandarya—are characterized by arid climatic conditions, frequent strong winds, and high temperatures, which create favorable conditions for dust–aerosol processes and the dispersion of air pollutants.

In recent years, climate change has led to a decrease in precipitation, intensification of droughts, and increased soil degradation. At the same time, the growth of industrial activities and transportation flows has contributed to the intensification of both natural and anthropogenic components of air pollution. For example, in October 2025, dust storms and PM₂.₅/PM₁₀ concentrations in these regions exceeded national air quality standards by several times.

However, existing air quality monitoring systems often measure only basic physical and chemical parameters, while pollution sources, aerosol composition, meteorological factors, and landscape characteristics are not analyzed in an integrated manner. Therefore, the implementation of indicator-based systems and modeling approaches is essential for scientifically grounded environmental risk assessment and forecasting [1], [2], [3].

Under local conditions—where drought, dust storms, and anthropogenic emission sources interact—the accurate assessment of air quality and environmental risk forecasting becomes particularly urgent. Air pollution is not limited to urban areas; environmental risks are also increasing in rural regions, industrial zones, and transport corridors. Official statistics and monitoring data are often limited and not subjected to continuous analytical evaluation.

The application of integrated indicator systems and dynamic modeling approaches enables regional environmental risk forecasting, early warning, and the development of effective environmental management measures.

***Objective.*** The objective of this study is to develop a multi-parameter indicator system for assessing air pollution and forecasting environmental risks in southern regions (e.g., Kashkadarya Province), as well as to apply GIS-based and statistical/modeling methods.

**EXPERIMENTAL RESEARCH**

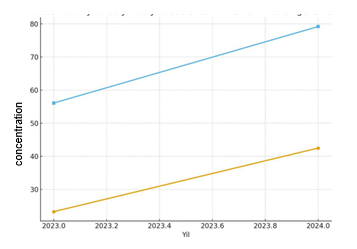
*Methods:*

1. Data Collection

Atmospheric air sampling points are established in different functional zones (industrial areas, proximity to transport routes, and rural areas) to measure PM₂.₅, PM₁₀, NO₂, SO₂, CO, and aerosol composition (e.g., carbonaceous particles, metals, and mineral dust).

Meteorological parameters include air temperature, wind direction and speed, humidity, and atmospheric pressure.

Anthropogenic source statistics are collected, including traffic intensity, industrial emissions, agricultural practices, and construction activities.



**FIGURE 1.** Changes in PM2.5 and PM10 Concentrations in 2023–2024

This graph illustrates the average annual concentrations of PM2.5 and PM10 particles in the southern regions during 2023–2024.

In 2023, the PM2.5 concentration was 23.3 µg/m³, increasing to 42.5 µg/m³ in 2024. This rise indicates intensified anthropogenic activity, particularly related to road construction, agricultural operations, and increased transport loads.

PM10 concentrations increased from 56.1 µg/m³ in 2023 to 79.2 µg/m³ in 2024. This increase was primarily influenced by wind erosion, soil dryness, reduced humidity, and decreased precipitation levels.

The simultaneous increase in both indicators in 2024 is associated with unfavorable meteorological conditions under the influence of climate change.

2. Chemical and Aerosol Analyses

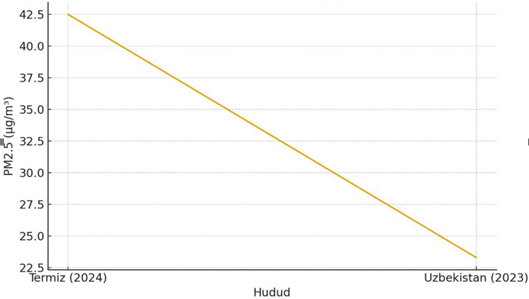
PM samples are analyzed for organic and elemental carbon content, as well as elemental composition (metals and mineral ions). Numerous studies have demonstrated the importance of carbonaceous aerosol analysis for source identification.

To differentiate between natural (soil/mineral) and anthropogenic dust components, elemental analysis and mineralogical analytical methods are applied.

Monitoring results from 2023–2024 indicate that climate change has significantly altered meteorological parameters, leading to increased PM2.5, PM10 concentrations, and dust storm indices in southern regions.

In particular, reduced relative humidity, decreased precipitation, increased air temperature, and intensified wind speed are directly linked to enhanced dust uplift processes.

Therefore, within environmental safety monitoring systems in southern regions, meteorological indicators and dust concentration parameters should be assessed jointly.



**FIGURE 2.** PM2.5 Indicators

3. Modeling and GIS Analysis

The collected data are geospatially mapped using GIS platforms to identify and visualize air pollution zones.

Statistical and regression models (e.g., multivariate regression analysis) are employed to evaluate the combined influence of anthropogenic, meteorological, and landscape factors on air pollution levels.

Where available, integration with remote sensing and satellite data (AOD—Aerosol Optical Depth) is performed. International experience and models applied in other regions—combining satellite, meteorological, and GIS data—can be adapted to local conditions.

4. Risk Assessment and Forecasting

Based on the integrated indicator system, an environmental risk index is developed, incorporating air pollution levels, anthropogenic load, natural aerosol contributions, and meteorological conditions.

Modeling is used to identify high-risk zones and forecast periods (e.g., seasonal variations, dry and wet periods, dust storm seasons).

As a result, detailed data on pollution sources and aerosol composition in southern regions are obtained, allowing for the determination of the relative contributions of natural dust (mineral/soil) and anthropogenic components.

GIS-based mapping enables the identification of high environmental risk zones, including major transport corridors, industrial areas, and regions affected by forest and soil degradation.

Forecasts linked to meteorological factors and climate change trends—such as rising temperatures, increasing drought frequency, and intensified winds—are developed to support proactive environmental management.



**FIGURE 3.** A modern indicator for measuring PM2.5 and PM10

Based on the indicator system and modeling framework, a scientific foundation is established for air quality monitoring and environmental risk assessment.

The obtained results may serve as a basis for developing regional environmental management and environmental protection strategies.

Challenges and limitations:

At present, sufficient publicly available statistical data on dust/aerosol concentrations and chemical composition in southern regions are lacking; therefore, field studies and sample analyses are required.

The integration of remote sensing data (AOD, satellite observations) with ground-based monitoring systems may face technical, financial, and institutional barriers.

Indicators and models need to be adapted not to generalized territories but to specific microzones (urban areas, industrial zones, rural areas) [6].

Uncertainties may arise in long-term forecasting of climate change trends and meteorological variables.

**CONCLUSIONS**

Southern regions are highly sensitive to air pollution due to their climatic conditions, landscape characteristics, and anthropogenic load. Therefore, a multi-parameter indicator system and dynamic modeling are essential components of modern environmental monitoring.

When applied in combination with GIS-based and statistical/regression models and remote sensing data, these approaches enable the identification of pollution zones, forecasting, and proactive planning of environmental management measures.

The differentiation between natural (dust/mineral) and anthropogenic aerosol components, as well as the analysis of structural and chemical composition, plays a crucial role in accurate environmental risk assessment.

Recommendations for local authorities and environmental agencies:

establish permanent monitoring stations;

develop GIS-based environmental risk maps;

formulate environmental management measures grounded in climate change projections and anthropogenic load assessments.

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