GIS data and AI-driven environmental monitoring using remote sensing

Aziza Zhidebayeva[1,*], *Alma* Kostangeldinova[2], *Kurbankul* Myrzasseitova[1], *Zhansaya* Sugiraliyeva[2], *Ainash* Aidarkhanova[2], *Marzhan* Tastanova[2], and *Yerkebulan* Uxikbayev[3]

[1]University of Friendship of People's Academician A. Kuatbekov, Shymkent, Kazakhstan
[2]Kokshetau University named after Sh. Ualijhanov, Kokshetau, Kazakhstan
[3]Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkistan, Kazakhstan

Abstract. Amid global climate change and escalating human impact on the environment, the necessity for the development of effective and scalable environmental monitoring systems is intensifying. Conventional observation techniques reliant on terrestrial measurements and expert evaluations exhibit restricted spatial coverage and lack the capacity for swift analysis of dynamic environmental phenomena. The amalgamation of remote sensing data, geographic information systems (GIS), and artificial intelligence techniques signifies a promising domain in contemporary environmental research. This paper introduces an AI-based methodology for environmental monitoring utilizing satellite data and GIS spatial information. The proposed methodology encompasses the preprocessing and integration of multidimensional spatiotemporal data, the extraction of informative features, and the application of machine and deep learning algorithms to analyze environmental conditions. Artificial intelligence techniques facilitate the automation of land cover classification, the identification of environmental changes, and the prediction of potential risks. The study's findings indicate that the incorporation of AI models with remote sensing and GIS data enhances monitoring precision and resilience relative to conventional methods. Moreover, the proposed system improves the interpretability of outcomes and facilitates decision-making in environmental management and sustainable development. The results validate the practicality of employing intelligent technologies for thorough environmental analysis and underscore their considerable potential for environmental monitoring across diverse spatial scales.

1 Introduction

Given the global climate change and escalating human impact on natural ecosystems, the necessity for effective environmental monitoring is particularly pressing. Increasing temperatures, altered precipitation patterns, land degradation, and air and water pollution substantially affect ecosystem resilience and the populace's quality of life. In these circumstances, the prompt identification of environmental alterations and evaluation of their effects are essential components of sustainable development and environmental

* Corresponding author: erkebulan.uxikbayev@ayu.edu.kz

management. Contemporary monitoring systems must deliver elevated spatial and temporal data resolution, alongside the capacity for rapid analysis of substantial information volumes [1].

Remote sensing technologies and geographic information systems (GIS) are integral to environmental analysis on both regional and global scales. Satellite data facilitates ongoing observation of the Earth's surface, atmospheric phenomena, and ecosystems, offering extensive coverage and frequent information updates. GIS technologies facilitate the integration, visualization, and analysis of spatial data, allowing for the identification of spatial patterns and relationships among diverse environmental parameters. The integration of remote sensing and GIS underpins a thorough examination of environmental processes. Although traditional environmental monitoring methods, including ground-based measurements and expert evaluations, are extensively utilized, they possess several notable limitations. These methods are primarily defined by restricted spatial coverage and the substantial expense of field observations. Secondly, the measurement frequency frequently precludes the prompt identification of dynamic environmental changes [2]. Moreover, conventional methods are inadequately suited for handling substantial quantities of heterogeneous data, thereby diminishing their efficacy in addressing the escalating complexity of ecological systems.

The advancement of artificial intelligence and machine learning techniques creates new opportunities for the analysis of remote sensing and GIS data. Artificial intelligence algorithms can efficiently analyze extensive arrays of spatial and temporal data, uncover concealed patterns, and accommodate nonlinear relationships among environmental indicators. Deep learning techniques facilitate the automation of land cover classification, change detection, and environmental risk prediction. Consequently, AI-driven methodologies greatly enhance the analytical capacities of conventional environmental monitoring systems. This study aims to formulate and evaluate a methodology for environmental monitoring that integrates GIS data, remote sensing data, and artificial intelligence techniques. The primary objectives of the study are: to analyze current environmental monitoring methods; to develop a methodology for the integration of spatial data and AI models; to assess the efficacy of AI-driven approaches for environmental analysis; and to illustrate the practical relevance of the proposed solution for environmental monitoring and management. This work primarily contributes a comprehensive framework for intelligent environmental monitoring that offers enhanced accuracy, scalability, and adaptability in environmental assessments [1].

2 Related work

In recent decades, remote sensing (RS) technologies have become a key tool in environmental monitoring. Satellite data is widely used to monitor land cover, water resources, atmospheric processes, and ecosystems. Multispectral and hyperspectral images make it possible to assess indicators such as vegetation cover, land degradation, pollution levels, and climate change [3]. A significant advantage of remote sensing is the ability to regularly and extensively monitor vast areas, making this approach indispensable for global and regional environmental analysis.

Geographic information systems (GIS) play a vital role in the spatial analysis of environmental data, integrating disparate information sources within a unified spatial context. GIS technologies enable spatial modeling, analysis of environmental indicator distributions, and the identification of spatial patterns. In environmental research, GIS is widely used to assess the impact of anthropogenic factors, analyze land-use changes, and support environmental decision-making [4]. Combining GIS with remote sensing data significantly expands the analytical capabilities of environmental monitoring. With the advancement of computing technologies, machine learning and deep learning methods have become widely used in environmental monitoring. Classification, regression, and clustering algorithms are used to analyze satellite images, detect changes, and predict environmental processes. Deep neural networks, including convolutional and recurrent architectures, demonstrate high efficiency in processing complex spatiotemporal data. The use of AI approaches allows for the automated analysis of large data sets and increases the accuracy of environmental assessments compared to traditional methods.

Despite significant progress, the integration of remote sensing, GIS, and artificial intelligence poses a number of challenges. Key issues include data heterogeneity, differences in spatial and temporal resolution, and the presence of noise and gaps in the source data. Furthermore, the difficulty in interpreting deep learning results limits their application in practical environmental management [5]. These aspects highlight the need to develop comprehensive and interpretable AI-driven frameworks for environmental monitoring.

Satellite data obtained from remote sensing platforms is widely used in environmental monitoring research. These data include optical images, as well as multispectral and hyperspectral data, providing detailed information on the state of the Earth's surface. These data enable the analysis of ecosystem dynamics, land-use change, and environmental risks.

GIS layers include spatial data on land use, topography, climate characteristics, and environmental indicators. Integrating these layers with remote sensing data enables comprehensive spatial analysis and considers the impact of various factors on the environment [3].

The description of the study area, if necessary, includes the geographic, climatic, and environmental features of the region. This allows for consideration of regional differences and increases the reliability of the analysis results.

Remote sensing and GIS data are characterized by high dimensionality and heterogeneity, requiring preprocessing procedures, including noise filtering, normalization, and spatial-temporal harmonisation. High-quality data preprocessing is essential for the effective application of AI models in environmental monitoring.

3 Materials and methods

The initial phase of the research project consisted of preprocessing the data obtained from remote sensing observations in order to enhance the quality of the initial information and get it ready for further analysis. It was necessary to correct satellite images for radiometric and geometric distortions in order to guarantee that the data obtained from various time periods could be compared with one another method [6]. Different techniques, such as normalization and noise filtering, were utilized in order to lessen the impact of atmospheric effects. The following step involved the extraction of informative features that reflected the current state of ecosystems and land cover. Spectral characteristics, vegetation indices, as well as textural and statistical image parameters, are all included in these features. The features that are produced as a result constitute a multidimensional feature space that is utilized in artificial intelligence models.

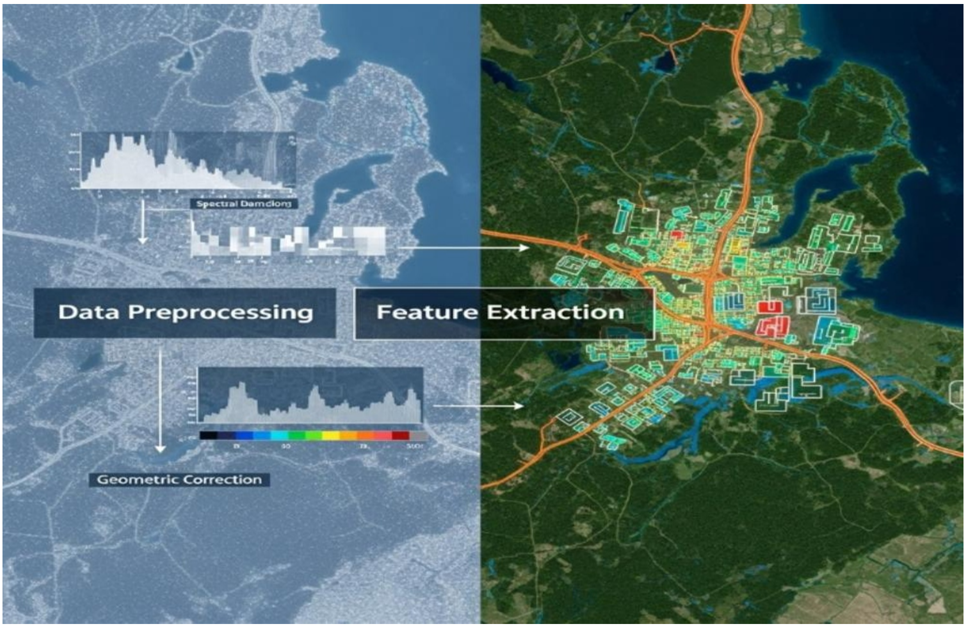

Fig. 1. AI-based environmental monitoring workflow based on remote sensing and GIS data.

The subsequent step consisted of analyzing spatial data through the utilization of geographic information systems (in Figure 1). Information on land use, terrain, climate, and environmental indicators were included in the data that was integrated from remote sensing with the layers of the geographic information system (GIS). The geographic context and the spatial relationships between environmental parameters were able to be taken into consideration thanks to the utilization of spatial referencing and data alignment respectively. The geographic information system (GIS) analysis included the identification of regional patterns, as well as territorial zoning and the analysis of the spatial distribution of environmental indicators [7]. A comprehensive understanding of the current state of the environment is provided by this approach, which also improves the accuracy of the intelligent analysis that is performed in the future.

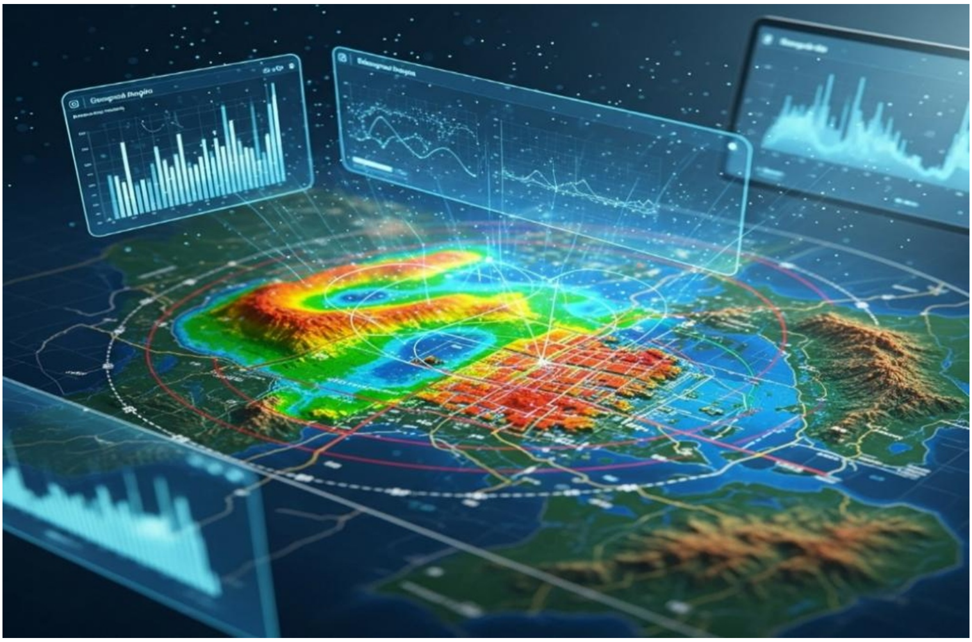

Fig. 2. Integration of GIS and AI for spatial monitoring of environmental conditions.

The analysis and interpretation of integrated spatiotemporal data was accomplished through the utilization of artificial intelligence techniques that were centered on environmental monitoring and classification (Figure 2). In this study, machine learning and deep learning algorithms were utilized. These algorithms were able to process large amounts of data and identify nonlinear relationships between features. Although regression models were utilized for the purpose of quantifying environmental indicators, classification models were utilized for the purpose of identifying different types of land cover and detecting changes in the environment. The application of AI techniques made it possible to automate the process of analyzing data obtained from remote sensing, which resulted in a significant improvement in the efficiency of environmental monitoring [8].

The artificial intelligence models were trained with a data set that was divided into training and test sets. This allowed for an objective evaluation of the quality of the models through the training process. Cross-validation techniques were utilized in order to lessen the impact of random factors and prevent overfitting, which ultimately led to an improvement in the robustness of the reported findings. As part of the training process, the parameters of the model were tuned and their structure was optimized in order to achieve the highest possible level of accuracy. Through the use of independent datasets, the models were validated, which enabled us to evaluate their generalizability and determine whether or not they are applicable to environmental monitoring conditions that occur in the real world.

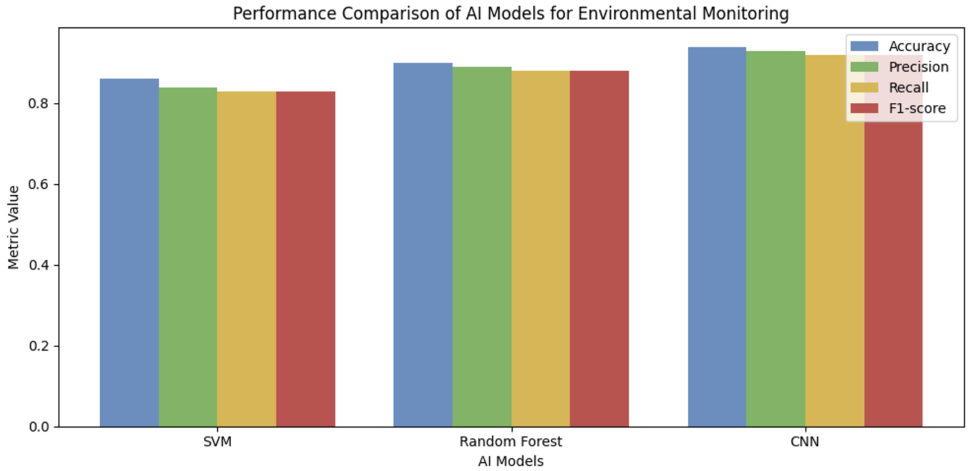

Fig. 3. Performance comparison of AI models environmental monitoring.

For the purpose of determining whether or not the proposed models are effective, standard metrics that are utilized iт classification and regression tasks were utilized. While performing classification tasks, precision, recall, and the F-score were utilized (Figure 3). These metrics were used to reflect the recognition quality of different environmental classes [9]. For the purpose of determining the degree to which the predicted values deviated from the actual data, the root-mean-square and mean absolute error metrics were utilized for the regression tasks. The use of a variety of metrics in conjunction with one another allowed for a comprehensive evaluation of the performance of the artificial intelligence models and enabled a comparison of those models with more conventional approaches to environmental analysis [10-11]. As a basis for further discussion regarding the efficacy of the proposed AI-driven approach to environmental monitoring, the results that were obtained serve as a basis.

4 Result

When applied to environmental monitoring, the results of applying the proposed AI-driven approach demonstrate the high efficiency of automated analysis of data from remote sensing and geographic information systems (GIS). On the basis of multidimensional spatiotemporal data, the machine learning and deep learning models that were utilized ensured an accurate classification of the environmental conditions and land cover types. The classification maps that were produced as a result reflected the spatial distribution of environmental indicators and made it possible to identify areas that could potentially be hazardous to the environment.

It has been demonstrated through experiments that the artificial intelligence models are able to successfully identify complex nonlinear relationships between the spectral characteristics of satellite images and environmental parameters. The stability of the models is demonstrated by high accuracy metrics and F1 scores when the models are processing data with varying spatial resolutions and temporal depths. The fact that this is the case demonstrates that the proposed method of environmental monitoring is applicable in situations where natural processes are highly variable.

Using geographic information systems (GIS), spatial analysis of the results enabled a clear visualization of the environmental patterns that were identified. The output of the AI model was integrated with the layers of the geographic information system, which allowed for the creation of thematic maps that reflected environmental conditions in a variety of geographic zones. These kinds of visualizations make it possible to conduct an analysis of the spatial heterogeneity that exists in environmental processes and to locate regions that are experiencing elevated levels of stress.

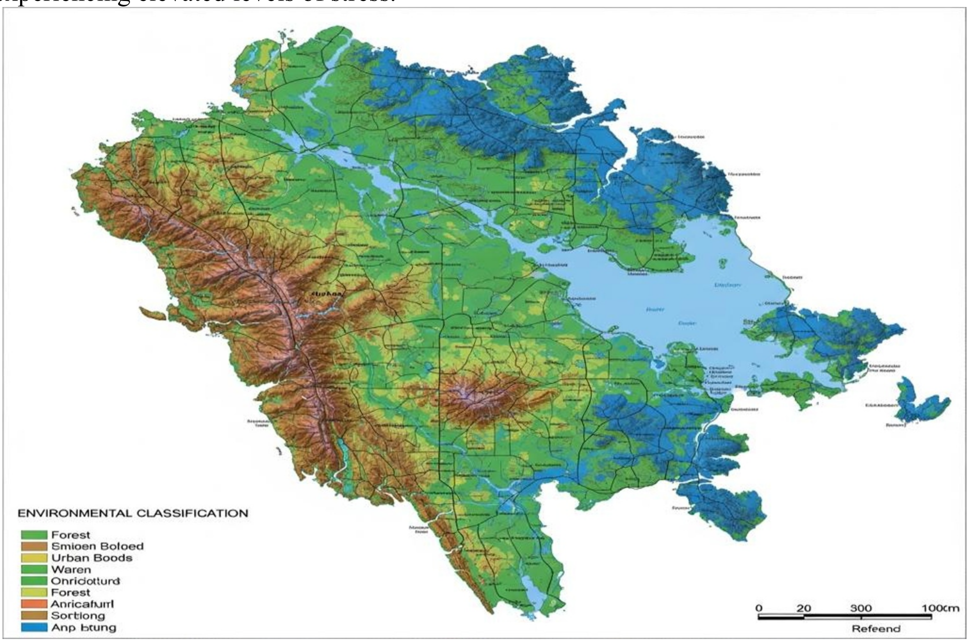

Fig. 4. Ecological classification of landscapes of the Republic of Kazakhstan based on spatial analysis.

When it comes to data interpretation and decision support, the visualization of results using GIS (Figure 4) is an extremely important factor. There is a correlation between spatial representation of results and a deeper understanding of the relationships between natural and anthropogenic factors. Additionally, spatial representation makes it easier to evaluate the dynamics of environmental change over time. By utilizing Geographic Information System (GIS) tools, the practical relevance of the study is increased, and the results are made available to professionals who specialize in environmental management and planning.

The results of a comparison between the AI-driven approach that was proposed and the conventional methods of environmental monitoring revealed that the proposed approach has significant advantages. Traditional methods, which are characterized by limited spatial coverage and a high dependence on manual data processing, are characterized by ground-based measurements and statistical analysis. Intelligent models, on the other hand, are able to perform automated analysis of large amounts of information and enable the rapid detection of changes in the environment.

Artificial intelligence models have been shown to have higher accuracy and robustness when compared to traditional methods, as demonstrated by quantitative evaluation of the results. The use of remote sensing and geographic information systems (GIS) also helps to reduce the costs of field research and ensures that monitoring can be scaled up. In light of this, the combination of artificial intelligence with spatial data constitutes a powerful alternative to the traditional approaches to environmental analysis.

One of the most significant aspects of the results that were obtained is the interpretability of the AI models that were utilized. The spectral characteristics of vegetation cover, land-use parameters, and climate indicators were found to be the most important factors that influence the classification of environmental states, according to the findings of a feature significance analysis. Both the scientific validity of the proposed method and the consistency of these results with previously established ecological theories are confirmed by these findings.

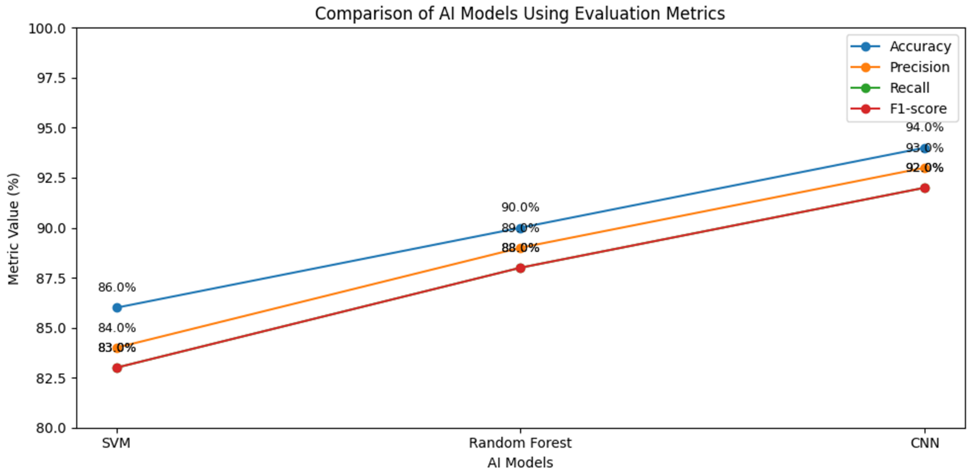

Fig. 5. Comparison of AI models using evaluation metrics.

Artificial intelligence models are compared using classification quality metrics like accuracy, precision, recall, and F1 score (Figure 5). A support vector machine (SVM), random forest ensemble algorithm, and deep convolutional neural network were analyzed.

When switching from traditional machine learning algorithms to deep learning, all metrics increase. The SVM model had 86.0% accuracy, 84.0% precision, 83.0% recall, and 83.0% F1 score. Remote sensing and GIS data analysis baseline classification quality is shown by these metrics.

Compared to SVM, Random Forest has 90.0% accuracy, 89.0% precision, 88.0% recall, and 88.0% F1-score. These improvements show that ensemble methods can better account for spatial-spectral nonlinear relationships.

CNN model yields the highest rankings for all metrics. Accuracy is 94.0%, Precision 93.0%, Recall 92.0%, and F1-score 92.0%. These findings show that convolutional neural networks efficiently process complex spatial structures and multichannel remote sensing data.

The illustration shows that deep neural networks outperform traditional machine learning methods in environmental monitoring. CNN's accuracy, robustness, and balance of classification increased across all metrics, proving its suitability for integrated GIS- and AI-driven environmental monitoring systems.

The results that were obtained have a great deal of practical significance when viewed from an environmental point of view. Not only does the system that is being proposed make it possible to identify ongoing changes in the environment, but it also serves as the foundation for predicting how potential risks might develop. Opportunities for early warning of environmental problems and the development of sustainable strategies for the management of natural resources are made available as a result of this action. Therefore, artificial intelligence-driven environmental monitoring that is based on geographic information systems (GIS) and remote sensing can be considered an effective decision support tool in the field of environmental protection.

5 Discussion

The study confirms the effectiveness of integrating remote sensing data, geographic information systems (GIS), and artificial intelligence (AI) for environmental monitoring. AI methods, particularly convolutional neural networks (CNNs), show superior performance in processing spatiotemporal data with high accuracy (94.0%), precision (93.0%), recall (92.0%), and F1-score (92.0%). Meanwhile, Random Forest and Support Vector Machine (SVM) models show lower metrics, emphasizing the impact of model choice on monitoring quality. The integration of AI results with GIS enhances spatial analysis, enabling identification of environmental risks. Interpretability of AI models is crucial, revealing that land cover and climatic features are significant for classification, bolstering model trustworthiness. However, limitations include dependency on data quality and the need for considerable computational resources. Future studies should focus on dataset expansion and hybrid model exploration. The research indicates that AI-based environmental monitoring is a practical tool for addressing sustainability challenges.

6 Conclusion

This study evaluates an integrated approach to environmental monitoring utilizing Earth remote sensing data, geographic information systems (GIS), and artificial intelligence (AI). The AI-driven framework processes large spatiotemporal datasets, providing accurate environmental assessments amid anthropogenic impact and climate change. Results indicate that machine learning and deep learning methods, particularly convolutional neural networks, outperform traditional approaches, with notable metrics such as 94.0% accuracy. Integrating AI analysis with GIS enhances spatial visualization and aids in identifying environmental risk zones, informing management decisions for sustainability. The study suggests further development in data integration, Explainable AI methods, and real-time monitoring systems, emphasizing the potential for improved environmental management through AI, remote sensing, and GIS synergy.

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