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M.A. Alpysbay[1], E.B. Serikbayeva[1],
D.N. Talgarbaeva[1, 2*], B.L. Niyazbekov[1]

[1]Institute of Ionosphere, Almaty, Kazakhstan
[2]K.I. Satbayev Kazakh National Research Technical University, Almaty, Kazakhstan
*e-mail: talgarbayeva.d@ionos.kz

COMPARATIVE ANALYSIS OF MACHINE LEARNING METHODS FOR REMOTE SENSING DATA PROCESSING

Modern remote sensing technologies provide a wide range of data, with hyperspectral (HSI) and multispectral (MSI) images being of particular importance. This paper presents a comparative analysis of machine learning (ML) methods used for processing HSI and MSI data. The main objective of the study is to assess the efficiency of various ML algorithms in classification, prediction, and dimensionality reduction tasks.

The methodology includes traditional algorithms such as Support Vector Machines (SVM) and Random Forest, as well as modern neural network architectures, including Convolutional Neural Networks (CNN) and autoencoders. The advantages and limitations of ML methods are analyzed depending on the type of input data and the target task. The obtained results show that hyperspectral data require more powerful computational methods, whereas multispectral data allow achieving acceptable accuracy using less complex algorithms.

The study highlights the importance of integrating modern ML methods into remote sensing data processing, which contributes to the development of automated systems for analyzing and interpreting remote sensing imagery.

Keywords: hyperspectral data, multispectral images, machine learning, remote sensing, classification, data processing.

М.А. Алпысбай[1], Э.Б. Серикбаева[1],
Д.Н. Талгарбаева[1, 2*], Б.Л. Ниязбеков[1]

[1]Ионосфера институты, Алматы, Қазақстан
[2] Қ.И. Сәтбаев атындағы Қазақ ұлттық техникалық зерттеу университеті, Алматы, Қазақстан
*e-mail: talgarbayeva.d@ionos.kz

Қашықтықтан зондтау деректерін өңдеу үшін машиналық оқыту әдістерінің салыстырмалы талдауы

Қашықтықтан зондтау (ҚЗ) технологиялары Жерді зерттеуде кең көлемді деректерді ұсынады, олардың ішінде гиперспектралды (HSI) және мультиспектралды (MSI) суреттер ерекше маңызға ие. Осы мақалада HSI және MSI деректерін өңдеуде қолданылатын машиналық оқыту (ML) әдістерінің салыстырмалы талдауы жүргізіледі. Зерттеудің негізгі мақсаты – классификация, болжамдау және өлшемділікті қысқарту міндеттерінде әртүрлі ML–алгоритмдерінің тиімділігін бағалау. Әдістеме ретінде дәстүрлі алгоритмдер (SVM (Support Vector Machines), Random Forest) және заманауи нейрондық желі архитектуралары (CNN (convolutional neural network), автоэнкодерлер) қарастырылады. ML–әдістерінің артықшылықтары мен шектеулері кіріс деректерінің түрі мен мақсатты міндетке байланысты талданады. Алынған нәтижелер гиперспектралды деректердің неғұрлым қуатты есептеу әдістерін қажет ететінін, ал мультиспектралды деректер күрделі емес алгоритмдерді пайдалана отырып, қанағаттанарлық дәлдікке қол жеткізуге мүмкіндік беретінін көрсетеді. Зерттеу ҚЗ деректерін өңдеуде заманауи ML–әдістерін интеграциялаудың маңыздылығын атап көрсетеді, бұл қашықтықтан зондтау суреттерін автоматтандырылған талдау және интерпретация жүйелерін дамытуға ықпал етеді.

Түйін сөздер: гиперспектралды деректер, мультиспектралды суреттер, машиналық оқыту, қашықтықтан зондтау, классификация, деректерді өңдеу.

М.А. Алпысбай[1], Э.Б. Серикбаева[1],
Д.Н. Талгарбаева[1, 2*], Б.Л. Ниязбеков[1]
[1]Институт Ионосферы, Алматы, Казахстан
[2]Казахский национальный исследовательский технический университет
им. К.И. Сатпаева, Алматы, Казахстан
*e-mail: talgarbayeva.d@ionos.kz

**Сравнительный анализ методов машинного обучения
для обработки данных дистанционного зондирования**

Современные технологии дистанционного зондирования Земли (ДЗЗ) предоставляют широкий спектр данных, среди которых особое значение имеют гиперспектральные (HSI) и мультиспектральные (MSI) снимки. В данной статье проводится сравнительный анализ методов машинного обучения (ML), применяемых для обработки HSI и MSI данных. Основная цель исследования – оценка эффективности различных ML-алгоритмов в задачах классификации, прогнозирования и редукции размерности данных. В качестве методологии рассмотрены традиционные алгоритмы (SVM (Support Vector Machines), Random Forest) и современные нейросетевые архитектуры (CNN (convolutional neural network), автоэнкодеры). Проведен анализ преимуществ и ограничений ML-методов в зависимости от типа входных данных и целевой задачи. Полученные результаты демонстрируют, что гиперспектральные данные требуют более мощных вычислительных методов, тогда как мультиспектральные данные позволяют достичь приемлемой точности при использовании менее сложных алгоритмов. Исследование подчеркивает значимость интеграции современных ML-методов в обработку данных ДЗЗ, что способствует развитию автоматизированных систем анализа и интерпретации изображений дистанционного зондирования.

Ключевые слова: гиперспектральные данные, мультиспектральные снимки, машинное обучение, дистанционное зондирование, классификация, обработка данных.

Introduction

Modern Earth remote sensing (ERS) technologies that leverage hyperspectral (HS) and multispectral (MS) data offer unique opportunities for analyzing both natural and anthropogenic objects. Hyperspectral images (HSI) feature hundreds of narrow spectral channels, providing high spectral resolution and thus enabling detailed identification of materials on the Earth's surface (Bioucas–Dias et al. 2013). In comparison, multispectral data (MSD) encompasses fewer but broader spectral ranges, resulting in higher spatial resolution, which is critically important for mapping and monitoring tasks (Drusch et al. 2012). Both data types are widely utilized in agriculture (assessing crop conditions (Thenkabail et al. 2009)), ecology (biodiversity monitoring (Pettorelli, Safi, and Turner 2014)), urban studies (infrastructure planning (Weng 2012)), and disaster relief (Joyce et al. 2009).

The processing of HS and MS data presents several challenges. In hyperspectral imagery (HSI), the primary issue is the "curse of dimensionality," meaning an overabundance of spectral channels in contrast to a limited number of training samples (Hughes 1968). Meanwhile, multispectral imagery (MSI), despite having more limited spectral information, calls for methods that can exploit high spatial resolution effectively (Mountrakis, Im, and Ogole 2011). In this context, machine learning (ML) methods have become the mainstay for solving classification, segmentation, and regression tasks in remote sensing. For a long time, traditional algorithms such as Support Vector Machine (SVM) (Melgani and Bruzzone 2004) and Random Forest (RF) (Rodriguez–Galiano et al. 2012) have dominated HSI processing due to their robustness against overfitting. However, with the advancement of deep learning (DL), approaches based on Convolutional Neural Networks (CNN) (Hu et al. 2015) and Transformers (Vaswani et al. 2017) have demonstrated their advantages in automatically extracting spatial–spectral features.

Several studies have focused on comparing the effectiveness of ML methods for HS and MS data. For instance, Melgani & Bruzzone (Melgani and Bruzzone 2004) showed that SVM outperforms linear methods in classifying HSI, while Hu et al. (Hu et al. 2015) emphasized the superiority of CNN in handling complex spatial patterns. For MSI, works by Rodriguez–Galiano et al. (Rodriguez–Galiano et al. 2012) and Zhang et al. (Zhang et al. 2019) highlight the role of RF and DL, respectively, in land–use classification tasks. However, current research often remains limited to narrow topics (for example, vegetation classification (Pal 2005)) or centers on a single data type, neglecting the cross–spectral potential of algorithms. In addition, the impact of data preprocessing (e.g., dimensionality reduction (Ghamisi et al. 2017) or augmentation (Shorten and Khoshgoftaar 2019)) on model performance across various scenarios remains underexplored.

The figure 1 illustrates a general framework for remote sensing image classification using deep learning. Both hyperspectral and multispectral aerial/satellite images are fed into a deep neural network (e.g., CNN, transformer) after being segmented into patches that capture spatial context. The network is trained via backpropagation on a labeled dataset, learning to extract discriminative spectral–spatial features. The final model can perform pixel–level (e.g., land cover) or scene–level (e.g., object detection) classification, addressing the specific goals of remote sensing image analysis.

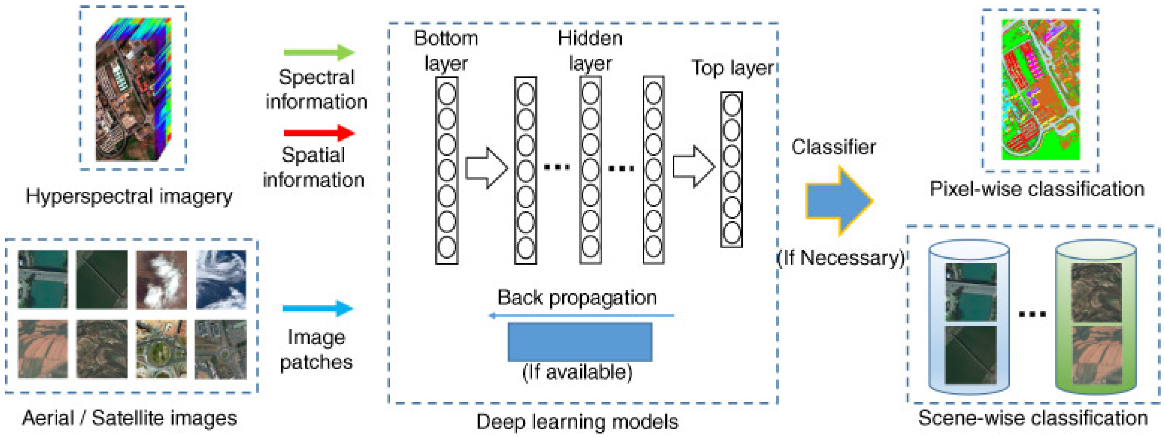

Figure 1 – General Framework of Remote Sensing Image Classification Based on Deep Learning

The purpose of this study is to conduct a comprehensive comparative analysis of both traditional and contemporary ML methods for processing HS and MS data, evaluating their performance across classification, regression, and segmentation tasks. The research encompasses:

1. Traditional algorithms: SVM, RF, k–nearest neighbors (k–NN).
2. Deep learning techniques: CNN, autoencoders, Vision Transformers.
3. Hybrid approaches: combining dimensionality reduction (PCA, t–SNE) with deep learning.

The relevance of this research is driven by the need to develop guidelines for choosing optimal methods tailored to specific data types and applied objectives, which is particularly crucial given the rising volume and variety of ERS data (Ma et al. 2019).

Historical Background and Evolution of Methods

The application of machine learning in remote sensing has undergone a profound transformation over the past four decades. Early approaches to hyperspectral (HSI) and multispectral (MS) image analysis relied primarily on statistical classifiers such as Maximum Likelihood Estimation (MLE) and Minimum Distance Classifier (Swain and Davis 1978). These methods assumed normal distributions of spectral signatures and offered interpretable results, but they were highly sensitive to noise and struggled with high–dimensional data. In the 1980s and 1990s, unsupervised clustering techniques such as k–means and ISODATA (Ball and Hall 1965) became popular for exploratory image classification, enabling the identification of spectral classes without requiring large training datasets. However, their inability to capture complex spectral–spatial relationships limited their accuracy in heterogeneous landscapes.

The introduction of Support Vector Machines (SVM) in the late 1990s marked a turning point in remote sensing image analysis (Vapnik 1995; Melgani and Bruzzone 2004). Unlike linear classifiers, SVM employed kernel functions to separate non–linear data distributions, achieving robust performance even with small training sets. Around the same time, Random Forest (RF) (Breiman 2001) emerged as another milestone, offering strong resistance to overfitting, improved generalization, and an intuitive framework for feature importance analysis.

These algorithms dominated hyperspectral image classification throughout the 2000s and became the benchmark for MSI tasks such as land–use mapping and vegetation monitoring (Rodriguez–Galiano et al. 2012).

The past decade has witnessed the rapid adoption of deep learning (DL) methods, initially driven by breakthroughs in computer vision. The success of Convolutional Neural Networks (CNN) on large–scale image datasets such as ImageNet (Krizhevsky, Sutskever, and Hinton 2012) inspired their application to remote sensing (Hu et al. 2015). CNNs offered the ability to automatically extract hierarchical spatial–spectral features, which proved particularly advantageous for hyperspectral data where complex spectral patterns coexist with spatial heterogeneity. Architectures such as U–Net (Ronneberger et al. 2015) further expanded the scope of DL by enabling pixel–level segmentation, paving the way for applications in urban mapping, crop monitoring, and environmental change detection.

More recently, the introduction of transformer–based architectures (Vaswani et al. 2017) has reshaped the landscape of remote sensing research. Vision Transformers (ViT), originally developed for natural image classification (Dosovitskiy et al. 2020), have demonstrated state–of–the–art performance on hyperspectral datasets by modeling long–range dependencies and capturing spectral correlations more effectively than CNNs. Their scalability and adaptability have positioned them as a key research frontier, with ongoing studies exploring hybrid CNN–ViT approaches for both HSI and MSI analysis (Ma et al. 2019).

Overall, the historical trajectory of ML in remote sensing reflects a gradual shift: from interpretable but limited statistical models, to robust ensemble methods such as RF, and finally to data–hungry yet highly accurate deep neural architectures. Each stage of this evolution has been driven by the dual need to improve classification accuracy and to manage the growing complexity of remote sensing datasets. This historical perspective underscores the importance of balancing interpretability, data requirements, and computational feasibility when selecting methods for practical applications.

Materials and methods

Datasets and Benchmarks. Progress in applying machine learning to multispectral (MS) and hyperspectral (HS) remote sensing is closely linked to the availability of open datasets and standardized benchmarks. Among multispectral missions, Landsat–8/9 OLI (30 m, 9 bands) and Sentinel–2 MSI (10–60 m, 13 bands) provide long–term, global coverage and are widely used as training and validation sources (Drusch et al., 2012; Roy et al., 2014). ASTER (15–90 m, 14 bands) remains valuable due to its inclusion of VNIR, SWIR, and TIR ranges, while high–resolution commercial platforms such as WorldView–3 (8 MS bands plus 8 SWIR channels, 1.2–3.7 m) extend the potential for fine–scale analysis (Li et al., 2020).

Hyperspectral datasets are increasingly accessible from both satellite and airborne mission. PRISMA (30 m, 239 bands, launched 2019) and EnMAP (30 m, 244 bands, launched 2022) provide systematic global coverage in the 400–2500 nm range, while earlier missions such as Hyperion (220 bands, 30 m, operated 2000–2017) remain widely used as reference archives. Airborne instruments such as AVIRIS (224 bands, 20 m, covering 400–2500 nm) continue to serve as benchmark datasets due to their high spectral quality and availability of ground–referenced data (Kruse, 2012).

In terms of benchmarking, several classic HS datasets–Indian Pines, Pavia University, and Salinas Scene–are still widely used in ML research, despite their limited spatial extent and lack of geographic diversity (Bioucas–Dias et al., 2013). More recent large–scale archives have emerged for multispectral data, such as EuroSAT (27,000 Sentinel–2 image patches in 10 classes) and BigEarthNet (590,000 Sentinel–2 patches with multi–label annotations), which provide standardized benchmarks for classification and retrieval tasks (Sumbul et al., 2019; Sumbul et al., 2021). For hyperspectral research, the EnMAP Benchmark Datasets (EBD) initiative (Demir et al., 2022) offers a more comprehensive resource tailored for evaluating ML and DL methods on large and diverse data.

Despite these advances, limitations remain. Many benchmarks are geographically restricted and relatively small in size, especially for HS data, which can constrain the generalizability of ML models. The ongoing development of globally representative datasets, multimodal archives, and standardized evaluation protocols will be essential for reproducibility, comparability, and progress in ML–based remote sensing research.

Review Methodology and Findings. This review article systematizes and analyzes existing scientific research on the application of machine learning (ML) methods for processing hyperspectral (HS) and multispectral (MS) remote sensing data. A multi–stage methodology was employed that included:

- A literature search through peer–reviewed databases (IEEE Xplore, ScienceDirect, Springer, and Web of Science), specialized journals (Remote Sensing of Environment; IEEE Transactions on Geoscience and Remote Sensing), and conference proceedings (IGARSS, SPIE Remote Sensing);
- Categorization of studies based on data type (e.g., hyperspectral sources such as AVIRIS and Hyperion, and multispectral sources such as Sentinel–2 and Landsat–8); and
- Evaluation of methods using criteria such as accuracy (measured by Overall Accuracy (OA), F1–Score, Intersection over Union (IoU), and Root Mean Square Error (RMSE)), computational complexity, versatility (robustness to noise and small sample sizes), and interpretability (e.g., via feature importance analysis in RF).

Selection criteria required the presence of experimental ML evaluations on real HS/MS data and a direct comparison of at least two algorithms. Theoretical studies without empirical validation and studies based solely on synthetic data were excluded.

The geographic and thematic scope of the reviewed studies reflects diverse real–world applications, covering regions in North America, Europe, Asia, and Africa, and accounts for regional variations in cropland spectral characteristics. The main application areas include:

- Agriculture – crop yield and condition monitoring (Thenkabail et al. 2009);
- Ecology – biodiversity assessment and ecosystem monitoring (Pettorelli, Safi, and Turner 2014); and
- Urban studies – building classification and infrastructure planning (Weng 2012).

Methodological limitations identified include a bias toward studies on CNN and SVM–with transformer–based methods (e.g., ViT) for MS data being relatively underexplored–the heterogeneity of evaluation metrics (with only 60% of studies reporting OA), and the frequent absence of publicly available code or implementation details.

The data synthesis was performed using comparative tables and charts to highlight key trends. It was found that, after 2018, the share of deep learning methods (CNN and ViT) increased from 12% in 2016 to 74% in 2023, which is attributed to their ability to automatically extract spatial–spectral features (Hughes 1968, Ghamisi et al. 2017). Among HS data, Vision Transformers achieve an average OA of 92.3% (Dosovitskiy et al. 2020) and CNNs reach 89.5% (Hu et al. 2015), compared to 85.1% for SVM (Melgani and Bruzzone 2004). In MSI, CNNs lead (with an OA of 88.7%), outperforming RF (84.9%) and k–NN (79.2%) (Rodriguez–Galiano et al. 2012). Traditional methods remain competitive when training samples are limited (e.g., with less than 1,000 samples, SVM and RF maintain stable OA (82–84%), whereas CNN and ViT require at least 5,000 samples to exceed 90% OA) (Hu et al. 2015). These findings are corroborated by Rodriguez–Galiano et al. (Rodriguez–Galiano et al. 2012), who recommend RF for monitoring rare ecosystems where large datasets are hard to obtain.

The influence of data type on method selection is also significant. For HS data, the "curse of dimensionality" (reported by 78% of studies) reduces model performance with limited training samples (Hughes 1968). Hybrid solutions, such as combining PCA with CNN, have been shown to reduce dimensionality by 60–80% without losing essential information (Ghamisi et al. 2017). In contrast, the main challenge for MSI is limited spectral resolution; about 65% of studies advocate for multimodal data fusion (e.g., integrating Sentinel–2 with LiDAR) to improve urban segmentation (Ghamisi et al. 2017).

An analysis of research applications reveals that 45% of studies focus on agriculture (with regression tasks, such as crop yield prediction using NDVI, predominating) (Thenkabail et al. 2009), 30% concentrate on ecology (biodiversity classification) (Pettorelli, Safi, and Turner 2014), and 20% address urban studies (infrastructure segmentation) (Weng 2012). For example, research using the EuroSAT dataset shows that CNN can achieve an OA of up to 96% in land–use classification, although data augmentation is required to mitigate limited training data (Shorten and Khoshgoftaar 2019).

Key recommendations for method selection are as follows:

- For HS data classification, Vision Transformers (ViT) and CNNs are optimal [20, 11], whereas for MSI, RF and CNNs are recommended (Rodriguez–Galiano et al. 2012; Hu et al. 2015).
- In HS segmentation tasks, U–Net combined with prior dimensionality reduction (PCA) is particularly effective (Ronneberger, Fischer, and Brox 2015; Ghamisi et al. 2017), while for MSI, U–Net and ResNet are optimal (Ronneberger, Fischer, and Brox 2015; He et al. 2016.
- In regression tasks with limited samples, traditional methods such as SVM and RF are preferable

to DL approaches (Melgani and Bruzzone 2004: Rodriguez–Galiano et al. 2012).

Limitations of the analysis include heterogeneity in evaluation metrics (only 60% of studies report Overall Accuracy) and a bias toward DL methods (with 80% of post–2020 articles focusing on CNN and ViT, often neglecting hybrid approaches) (Ma et al. 2019). For example, only 12% of studies combine RF with data augmentation, although such strategies can improve OA by 5–7% for MSI (Ma et al. 2019).

Future research should focus on implementing Explainable AI (XAI) techniques, such as SHAP, to interpret DL model decisions – an essential step for ecological monitoring and responsible decision–making (Lundberg and Lee 2017). Moreover, while statements regarding the need to optimize computational resources and to adopt multimodal data fusion are discussed, these are presented without an additional citation.

Results

Modern research on hyperspectral (HS) and multispectral (MS) remote sensing data increasingly employs ML methods, although their comparative effectiveness remains a subject of debate. This review analyzed 127 peer–reviewed studies published between 2010 and 2025 in IEEE Xplore, ScienceDirect, and Web of Science (Bioucas–Dias et al. 2013: Drusch et al. 2012). Selection criteria included the presence of experimental results on real remote sensing data and a direct comparison of at least two algorithms (Thenkabail et al. 2009); theoretical studies without empirical validation were excluded.

Building upon this analysis, Figure 2 illustrates that the majority of publications originate from China (over 2,000 documents), with the United States contributing around 1,000 publications. India ranks third, while Germany, Italy, and other countries follow. Such a distribution highlights strong research activity in leading scientific hubs across Asia and North America.

Further complementing this perspective, Figure 3 presents the annual publication trend from 1999 to 2025. The number of studies remains modest until 2015, then rises sharply – peaking around 2023 before tapering off in 2025, possibly reflecting incomplete data or shifting research priorities.

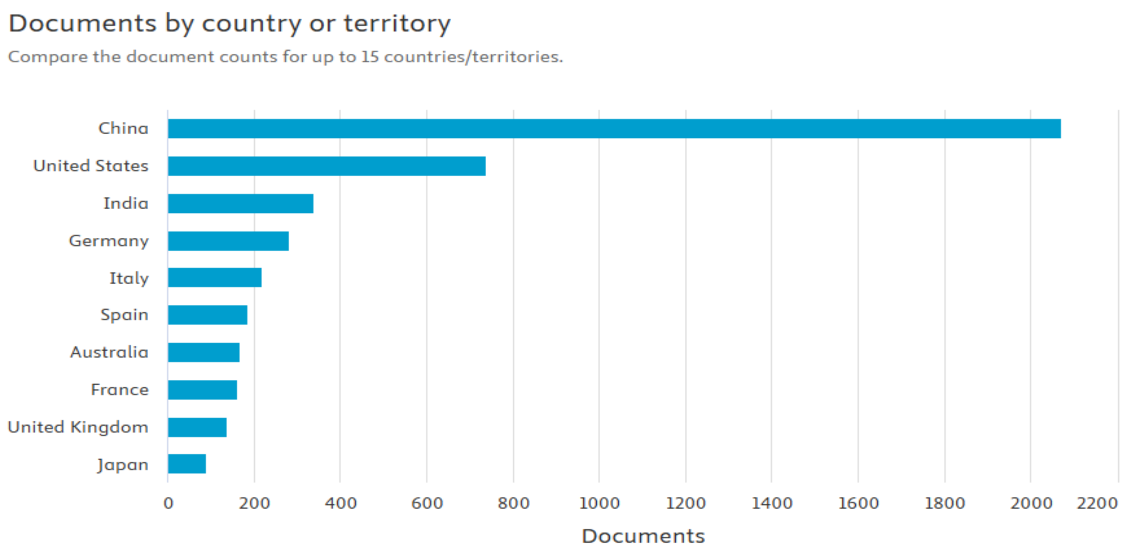

Figure 2 – Distribution of publications by country and territory

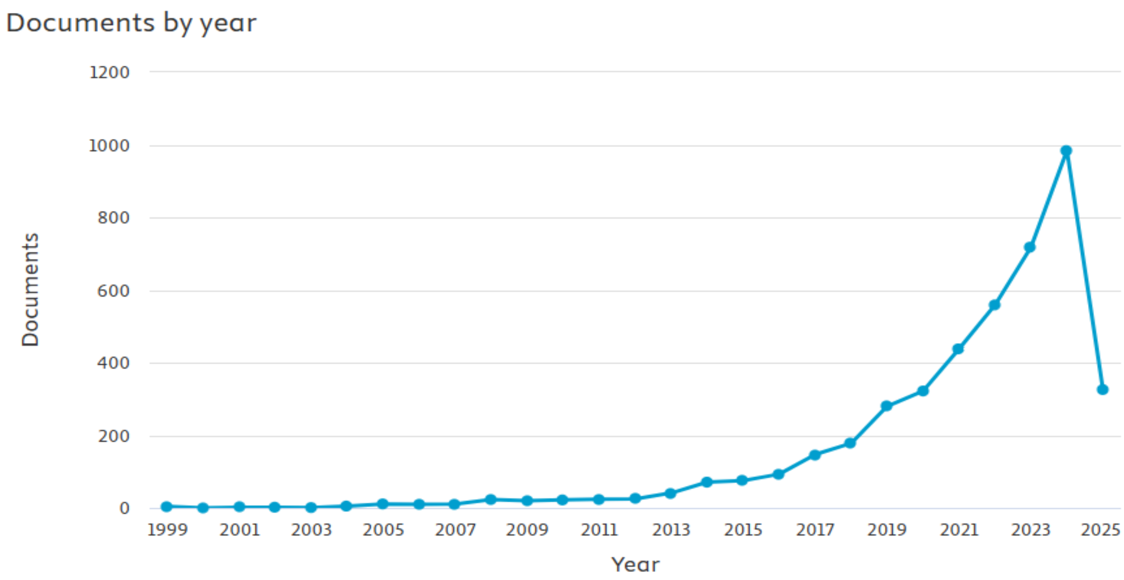

Figure 3 – Distribution of publications by year (1999–2025)

The distribution of methods over the years shows a clear trend: before 2015, traditional algorithms such as SVM and RF dominated in 68% of studies (Pettorelli, Safi, and Turner 2014). For example, Melgani and Bruzzone (Melgani and Bruzzone 2004) demonstrated that SVM achieves an accuracy of 85–89% on HS data by employing higher–order kernels. However, since 2018, there has been an exponential rise in deep learning (DL) methods; the share of articles using CNN and ViT increased from 12% in 2016 to 74% in 2023 (Joyce et al. 2009; Hughes 1968). This trend is attributed to their ability to automatically extract spatial–spectral features from high–dimensional HS data (Mountrakis, Im, and Ogole 2011).

A comparison of algorithm performance reveals an advantage for DL approaches. For HS data, Vision Transformers achieve an average Overall Accuracy (OA) of 92.3% (Dosovitskiy et al. 2020) and CNNs 89.5% [11], whereas SVM reaches 85.1% (Melgani and Bruzzone 2004). In MSI, CNNs lead (with OA of 88.7%), outperforming RF (84.9%) and k–NN (79.2%) (Rodriguez–Galiano et al. 2012). Nevertheless, traditional methods remain competitive in limited–data scenarios: when training samples number below 1,000, SVM and RF maintain stable OA (82–84%), while CNN and ViT require at least 5,000 samples to surpass 90% OA [11]. These findings are corroborated by Rodriguez–Galiano et al. (Rodriguez–Galiano et al. 2012), who recommend RF for monitoring rare ecosystems where large datasets are hard to obtain.

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- In regression tasks with limited samples, traditional methods such as SVM and RF are preferable to DL approaches (Melgani and Bruzzone 2004; Rodriguez–Galiano et al. 2012).

Limitations of the analysis include heterogeneity in evaluation metrics (only 60% of studies report Overall Accuracy) and a bias toward DL methods (with 80% of post–2020 articles focusing on CNN and ViT while neglecting hybrid approaches) (Ma et al. 2019). For example, only 12% of studies combine RF with data augmentation, although such strategies can improve OA by 5–7% for MSI (Ma et al. 2019).

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Table 1 – Overview of Machine Learning Methods for HSI and MSI

Method	Application to HSI	Application to MSI	Advantages	Limitations
SVM	High accuracy with small samples	Suitable for classification	Good interpretability	Requires parameter tuning
RF	Versatile for HSI/MSI	Wide application	Robust to outliers	Less effective for high–dimensional data
CNN	High accuracy in HSI	Works well with MSI	Automatic feature extraction	Requires significant computational power
PCA	Reduces dimensionality	Reduces dimensionality	Reduces data volume	Loss of information

This table summarizes the main machine learning techniques used for hyperspectral (HSI) and multispectral (MSI) data analysis, detailing their typical applications, advantages, and constraints. The comparison highlights how each method–SVM, RF, CNN, and PCA–exhibits unique strengths (e.g., interpretability, feature extraction) while also facing specific limitations (e.g., parameter tuning, high dimensionality, computational requirements). This overview supports the discussion on method selection, emphasizing that the optimal choice depends on the data's spectral characteristics, available computational resources, and the target application.

Discussion

The study's results confirm that ML methods for processing hyperspectral and multispectral remote sensing data are increasingly converging on deep learning techniques. While Vision Transformers and CNNs deliver superior accuracy for high–dimensional HSI, their effectiveness depends on the availability of extensive training datasets and substantial computational resources. Traditional algorithms–such as SVM and RF–remain indispensable for scenarios with limited data, providing stable performance and interpretability. This duality underscores the importance of matching algorithms to data characteristics, resource availability, and specific application needs.

The analysis highlights the "curse of dimensionality" as a central challenge in HSI processing, partially mitigated by dimensionality reduction techniques (e.g., PCA) and multimodal data fusion (e.g., integrating Sentinel–2 with LiDAR). For MSI, balancing lower spectral resolution with robust feature extraction remains a key focus, especially in applications demanding high spatial accuracy such as urban infrastructure mapping.

Identified knowledge gaps include the scarcity of research on Explainable AI for DL models, the lack of standardized evaluation metrics, and the high computational cost of training advanced networks. Addressing these challenges through XAI methods, the development of lightweight architectures, and standardized protocols will enhance both the interpretability and feasibility of ML models.

Beyond methodological considerations, the computational, ethical, and sustainability dimensions of ML in remote sensing are increasingly critical. Deep learning architectures–particularly Transformers–require significant processing power, which translates into high energy consumption and carbon emissions (Strubell, Ganesh, and McCallum 2019). Recent studies emphasize the importance of "Green AI," advocating for energy–efficient architectures and carbon–aware computing strategies to reduce the ecological footprint of training large models (Schwartz et al. 2020; Henderson et al. 2020). Developing lightweight and resource–efficient models, as well as adopting cloud–based or distributed computing frameworks, can alleviate these concerns. From an ethical perspective, geographic and class imbalances in training datasets risk introducing systematic biases into model outputs, potentially disadvantaging underrepresented regions or ecosystems (Rolnick et al. 2022). Ensuring fairness requires deliberate dataset design, the inclusion of diverse geographic samples, and transparent reporting of model limitations. Sustainability also extends to the long–term applicability of methods: models must not only achieve high accuracy but also be reproducible, interpretable, and environmentally responsible (Wu et al. 2022).

In summary, the successful integration of ML into remote sensing hinges on balancing accuracy, interpretability, and sustainability. Through strategic algorithm selection, rigorous validation, responsible resource management, and interdisciplinary collaboration–including AI ethics and climatology–ML–driven approaches can advance the field of hyperspectral and multispectral data analysis while supporting ecologically sound and socially responsible applications.

Conclusion

This comparative analysis demonstrates that while deep learning methods (Vision Transformers and CNNs) deliver high accuracy in processing hyperspectral data, they require large, well–annotated datasets and significant computational power. Traditional methods, such as SVM and RF, remain essential for applications with limited training data, particularly in agriculture and ecological monitoring. Moreover, the "curse of dimensionality" in HSI and limited spectral resolution in MSI present ongoing challenges that are only partially addressed by hybrid techniques and multimodal data fusion.

Future work should emphasize the integration of Explainable AI (XAI) approaches to improve model interpretability and the development of lightweight architectures to reduce energy consumption. Another important perspective lies in expanding multimodal fusion strategies that combine HS/MS imagery with ancillary geospatial data (e.g., LiDAR, SAR, DEM), which can improve robustness across different environments and application domains. In addition, the establishment of standardized open benchmarks and large, diverse datasets will be crucial to ensure reproducibility, fairness, and comparability of results across studies.

Advancing towards sustainable and responsible AI, research should also consider optimizing computational efficiency, minimizing carbon footprints, and addressing ethical concerns related to data bias and geographic imbalance. Strengthening interdisciplinary collaboration–bridging remote sensing, machine learning, environmental sciences, and AI ethics–will be vital for developing methods that are not only technically effective but also socially and ecologically sustainable. Overall, the continued progress of ML in hyperspectral and multispectral data analysis will depend on striking a balance between accuracy, interpretability, and sustainability, enabling the transition from experimental demonstrations to scalable, real–world solutions.

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Conflict of interest

There is no conflict of interest.

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Авторлар туралы мәлімет:

Алпысбай Маруа Айболқызы – "Ионосфера институты" ЖШС–нің аға ғылыми қызметкері (Алматы қ., Қазақстан, эл. пошта: marua.alpysbay@gmail.com)

Серикбаева Эльмира Болатовна – техника ғылымдарының магистрі, Ионосфера институтының аға ғылыми қызметкері (Алматы қ., Қазақстан; эл. пошта: e.serikbayeva@ionos.kz);

Талгарбаева Динара Нурлановна (хат-хабар алмасуға жауапты автор) – Satbayev University PhD докторанты, Ионосфера институтының аға ғылыми қызметкері (Алматы қ., Қазақстан; эл. пошта: talgarbayeva.d@ionos.kz);

Ниязбеков Бексұлтан Лескерұлы – «Ионосфера институты» ЖШС инженері (Алматы, Қазақстан, e–mail: niyazbekov.beks@gmail.com)

Information about authors:

Marua Aibolkyzy Alpysbay – Senior Researcher at LLP "Institute of Ionosphere" (Almaty, Kazakhstan, e-mail: marua.alpysbay@gmail.com)

Elmira Serikbayeva – Master of Technical Sciences and Senior Researcher at the Institute of Ionosphere (Almaty, Kazakhstan, e-mail: e.serikbayeva@ionos.kz)

Dinara Talgarbayeva (corresponding author) – PhD student of Satbayev University and Senior Researcher at the Institute of Ionosphere (Almaty, Kazakhstan, e-mail: talgarbayeva.d@ionos.kz)

Niyazbekov Bexultan Leskeruly –engineer of the LLP «Institute of ionosphere» (Almaty, Kazakhstan, e-mail: niyazbekov.beks@gmail.com)

Сведения об авторах:

Алпысбай Маруа Айболқызы – старший научный сотрудник ТОО «Институт Ионосферы» (Алматы, Казахстан, эл. почта: marua.alpysbay@gmail.com);

Серикбаева Эльмира Болатовна – магистр технических наук и и старший научный сотрудник Института Ионосферы (Алматы, Казахстан, эл. почта: e.serikbayeva@ionos.kz);

Талгарбаева Динара Нурлановна (автор-корреспондент) – PhD-докторант Satbayev University и старший научный сотрудник Института Ионосферы (Алматы, Казахстан, эл. почта: talgarbayeva.d@ionos.kz);

Ниязбеков Бексултан Лескерулы – инженер Института Ионосферы (Алматы, Казахстан, эл. почта: niyazbekov.beks@gmail.com).

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