DOI 10.34185/1562-9945-5-166-2026-23
UDC 004.89:528.8

I.M. Udovyk

METHODOLOGY FOR CREATING INTELLIGENT INFORMATION TECHNOLOGIES FOR RECOGNITION AND PROCESSING OF MULTISPECTRAL AEROSPACE IMAGES

Abstract. Heterogeneous Earth-observation data and rapidly expanding machine-learning, multiagent, and multimodal models require a methodology that creates coherent intelligent information technologies rather than isolated processing pipelines. The purpose of the study is to develop and formalize a methodology for creating intelligent information technologies for recognition and processing of multispectral aerospace images through synergistic processing of heterogeneous data. The methodology combines systems analysis, set-theoretic mappings, graph models, multilevel integration, multi-criteria configuration selection, and structural-functional verification. A scene is represented as a multidimensional information object with spatial, spectral, textural, contextual, temporal, and semantic characteristics. The principal scientific result is a methodology that integrates a system of creation principles, the Ψ–Ф–Л cycle of data harmonization, representation formation, and evidence-aware decision integration, adaptive task-dependent configuration, multiagent cooperation, multimodal interpretation, and end-to-end control of quality, uncertainty, and provenance. The creation procedure includes problem formalization, admissible source and component selection, data harmonization, integrated representation, intelligent recognition, evidence reconciliation, explained decision formation, and feedback-driven reconfiguration. Structural-functional verification establishes mechanisms for completeness, consistency, modularity, extensibility, adaptability, traceability, and interpretability. The methodology provides a design basis for monitoring and decision-support systems for natural and anthropogenic objects.

Keywords: *multispectral aerospace images, intelligent information technology, methodology for creation, heterogeneous data, synergistic processing, multilevel integration, spatial-spectral-semantic representation, multiagent analysis, multimodal interpretation, decision support.*

Statement of the problem. Earth observation systems generate multispectral, hyperspectral, radar, thermal, airborne, unmanned-aerial, and very-high-resolution imagery. Their coordinated use is constrained by geometric misalignment, unequal spatial resolution, sensor-specific spectral response, variable acquisition conditions, missing channels, and incompatible taxonomies [1–4]. These factors propagate from source-data quality to feature extraction, recognition, interpretation, and decision support. Therefore, a collection of high-performance

© Udovyk I.M., 2026
Copyright for this paper by its authors. Use permitted under License CC BY 4.0.

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

algorithms does not constitute an intelligent information technology unless the route from observation to an explained and traceable result is methodologically defined.

Multisensor fusion addresses integration at the data, feature, or decision level [5–7], while machine-learning and deep-learning models improve classification, segmentation, and object recognition [8–13]. Foundation models extend these capabilities through multispectral, multitemporal, and multimodal representations [14–18]. However, these advances usually optimize individual stages. Creating a complete technology additionally requires source admissibility, integrated representation, component selection, evidence reconciliation, quality and uncertainty control, provenance preservation, and feedback.

The methodological contradiction is between the expanding diversity of data, models, and application requirements and the predominantly fixed organization of existing processing pipelines. Local improvement of preprocessing, fusion, or recognition cannot guarantee validity of the complete process. The methodological problem is therefore to define invariant principles, information models, interlevel operators, admissibility rules, and feedback mechanisms that jointly determine the creation and operation of an intelligent information technology.

In this study, creation denotes the full methodological lifecycle: formulation of the problem and requirements, construction of the information space, selection and coordination of components, execution of the processing route, verification of the result, and subsequent adaptation. Controlled synthesis is its operational mechanism, which assembles a task-dependent configuration from admissible data sources, transformations, representations, recognition models, agents, multimodal components, and decision rules. The methodology must preserve physical meaning at the data level, information content at the representation level, and evidence consistency at the decision level.

Analysis of recent research and publications. Classical remote-sensing methodology organizes radiometric and geometric correction, spectral analysis, classification, and thematic mapping as consecutive stages [1, 2]. Fusion research distinguishes data-, feature-, and decision-level integration, but these levels are often treated separately and their effect on downstream reliability is not made explicit [5–7].

Random forests and support vector machines remain effective for well-defined feature spaces and limited training samples [8, 9], whereas encoder-decoder networks, atrous models, transformers, and promptable models extend automated interpretation [10–13]. Their performance depends on compatibility of the representation, physical scale, taxonomy, sensor, season, and application domain. Self-supervised and foundation models add multitemporal pretraining, vision-language alignment, and multimodal representations [14–18], but also require control of physical meaning, calibration, evidential support, and reproducibility.

Multiagent systems decompose complex analysis into specialized functions and coordinate local hypotheses [19], while multimodal models combine imagery, text, metadata, and domain knowledge [20]. Previous studies involving the author addressed multichannel preprocessing [21], data integration [22], multiagent object detection [23], multimodal land-cover interpretation [24], and post-training adaptation [25]. These studies demonstrate component feasibility but do not provide a unified methodology that simultaneously defines the scene

model, synergistic Ψ–Φ–Λ integration, adaptive configuration, and end-to-end quality, uncertainty, evidence, and provenance control.

Purpose of the study. The purpose of the study is to develop and formalize a methodology for creating intelligent information technologies for recognition and processing of multispectral aerospace images based on synergistic processing and analysis of heterogeneous data. The object is the process of transforming heterogeneous Earth observation data into recognized, interpreted, and traceable information products. The subject is the system of principles, information models, integration operators, admissibility conditions, and structural-functional relations that determine the creation of a task-dependent intelligent information technology.

Systems analysis is used to decompose the technology and establish interlevel relations; set theory and mappings formalize information spaces and integration operators; graph models represent spatial, temporal, functional, and semantic relations; multi-criteria optimization selects a technological configuration; and comparative structural-functional analysis verifies methodological properties.

The study addresses four tasks: to establish the principles for creating intelligent information technologies; to formalize the multispectral scene and its integrated representation; to develop synergistic multilevel integration of data, representations, and decisions; and to define an adaptive creation procedure together with conditions for analytical verification. The scientific novelty consists in a methodology that unites synergistic processing, spatial-spectral-semantic representation, intelligent recognition, multiagent cooperation, multimodal interpretation, and evidence-aware decision support within a single quality-, uncertainty-, and provenance-controlled model.

Presentation of the main research material. The proposed methodology is a system of interconnected conceptual, informational, operational, analytical, and verification provisions that determine how an intelligent information technology is created for a specific recognition or processing task. Its information basis is a multispectral aerospace scene considered as a multidimensional information object rather than as a set of independent channels. The corresponding information space is defined as

$$I = X \times S \times T \times C \times M, \tag{1}$$

where X is the space of spatial and geometric characteristics; S is the spectral feature space; T is the textural feature space; C is the space of contextual, relational, and temporal characteristics; and M is the semantic space containing class taxonomies, textual attributes, and domain knowledge.

For the i-th object, segment, or spatial unit, the integrated representation is formed as

$$F_i = \Phi(X_i, S_i, T_i, C_i, M_i), \tag{2}$$

where Φ denotes the operator for forming, normalizing, selecting, and integrating heterogeneous characteristics after the source data have been harmonized by Ψ. The representation F_i may include a dense feature tensor, object descriptors, class distributions, textual attributes, uncertainty estimates, and links to source metadata. A scene-level representation is defined by

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

the set of object representations, the graph G of spatial and semantic relations, and cross-cutting quality, uncertainty, and provenance information.

Synergistic processing is not interpreted as mechanical concatenation of all available channels or model outputs. It denotes coordinated interaction of complementary data and analytical mechanisms: geometric and spectral harmonization constrains feature formation; feature quality and availability constrain activation of recognition models; model and agent outputs are reconciled together with their uncertainty and provenance; and the final decision provides feedback for reconfiguration. The effect of such coordination is evaluated at the task level by informational completeness, reliability, interpretability, and resource feasibility rather than by the amount of combined data alone.

Table 1

Notation and principal components of the proposed methodology

Notation	Meaning
$D_1, \ldots, D_k$	Heterogeneous aerospace images, auxiliary data, metadata, and reference sources.
X, S, T, C, M	Spatial, spectral, textural, contextual/temporal, and semantic feature spaces.
F_i	Integrated representation of the i-th object, segment, or spatial unit.
G	Graph of spatial, temporal, functional, or semantic relations between scene objects.
Ψ	Operator for compatibility control, harmonization, and integration of primary data.
Φ	Operator for feature formation, normalization, selection, and integrated spatial-spectral-semantic representation.
Λ	Operator for reconciliation of model, agent, multimodal, and domain-rule outputs.
Q, U, μ	Quality, uncertainty, and metadata/provenance propagated throughout the processing route.

The methodology is based on principles that define invariant requirements for creating and operating the technology rather than prescribing a fixed sequence of software procedures. The principles form three interconnected groups: the information basis, intelligent analysis, and decision formation. Quality Q, uncertainty U, and provenance μ are cross-cutting dimensions that accompany all groups and all intermediate products.

The principle of multisource operation requires the technology to accept data of different physical nature and origin, including optical, radar, thermal, multispectral, hyperspectral, airborne, unmanned-aerial, and ground observations. It does not require simultaneous use of every source; an admissible complementary subset is selected according to the task, availability, compatibility, quality, information value, and access constraints.

The principle of multilevel integration establishes explicit links between the data, feature, and decision levels. A lower-level transformation is justified only when it preserves physical meaning and increases or maintains the information value of subsequent recognition and interpretation. For example, visual sharpening is not considered beneficial when it distorts spectral characteristics required for thematic classification.

The principle of spatial-spectral-semantic representation requires object and scene descriptions to combine geometry, spectra, texture, context, temporal relations, and semantic attributes. The principles of adaptability, multiagent cooperation, and multimodality determine how sources, scales, feature composition, recognition models, agent coalitions, and interpretation mechanisms are changed under variable conditions.

The principle of interpretability requires the final result to be linked to verifiable evidence, alternatives, and explicitly stated limitations. Decision support extends the output from a class, mask, or detected object to a recommended action. Trust and traceability require the recording of data sources, model versions, parameters, intermediate products, evidence, and the route by which the decision was obtained.

Synergistic processing and multilevel integration of heterogeneous data. The operational core of the methodology is represented by a coordinated composition of three operators. The Ψ operator performs compatibility control, harmonization, and integration of primary sources. The Φ operator constructs the integrated spatial-spectral-textural-contextual-semantic representation. The Λ operator reconciles the outputs of statistical and machine-learning models, specialized agents, multimodal components, and domain rules. Their coordinated composition realizes synergy across the data, representation, and decision levels. The generalized representation is

$$SI = \Lambda \circ \Phi \circ \Psi(D1, \ldots, Dk), \quad (3)$$

where $D_1, \ldots, D_k$ are the available sources and SI is the integrated scene representation associated with the resulting recognition or decision. The composition does not imply an irreversible linear sequence. Quality, uncertainty, or evidence control may initiate a return to source selection, harmonization parameters, feature composition, spatial scale, or the set of active models and agents.

At the Ψ level, the technology verifies spatial, temporal, radiometric, and spectral compatibility; transforms data to a common spatial reference; constructs validity masks; and preserves physically interpretable channels. Its output can be a harmonized multichannel data cube or a set of aligned modalities with documented relationships rather than a single fused image.

At the Φ level, spatial, spectral, textural, contextual, temporal, and semantic characteristics are formed, normalized, selected, and linked to object or graph structures. Every feature retains information about its source, spatial support, transformation method, validity, and quality. This prevents an integrated representation from becoming detached from the physical and procedural origin of its elements.

At the Λ level, class distributions, object hypotheses, agent evidence, multimodal descriptions, and domain rules are reconciled. The output contains the preferred class or state,

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

alternatives, reliability, uncertainty, supporting and contradicting evidence, an explanation, and a recommended action. A multimodal output is treated as one evidence source and cannot replace evidence-aware reconciliation.

The complete methodological model for creating an intelligent information technology is defined by the tuple

$$M = (P, I, \Psi, \Phi, A, V, \Lambda, Q, U, \mu), \tag{4}$$

where P is the system of methodological principles; I is the information space; Ψ, Φ, and Λ are the integration operators; A is the set of specialized recognition models and agents; V is the multimodal component; Q is the quality-control system; U is uncertainty; and μ contains metadata, evidence links, and provenance. The tuple specifies the minimum set of components and relations that must be instantiated in a concrete intelligent information technology.

The structural and functional relations are summarized in Fig. 1. The methodology is not a fixed linear pipeline but a controlled process for creating a task-dependent technology. The principles impose invariant requirements; the Ψ–Φ–Λ cycle implements synergistic integration at the data, representation, and decision levels; and Q, U, and μ accompany every transformation and constrain acceptance of the result.

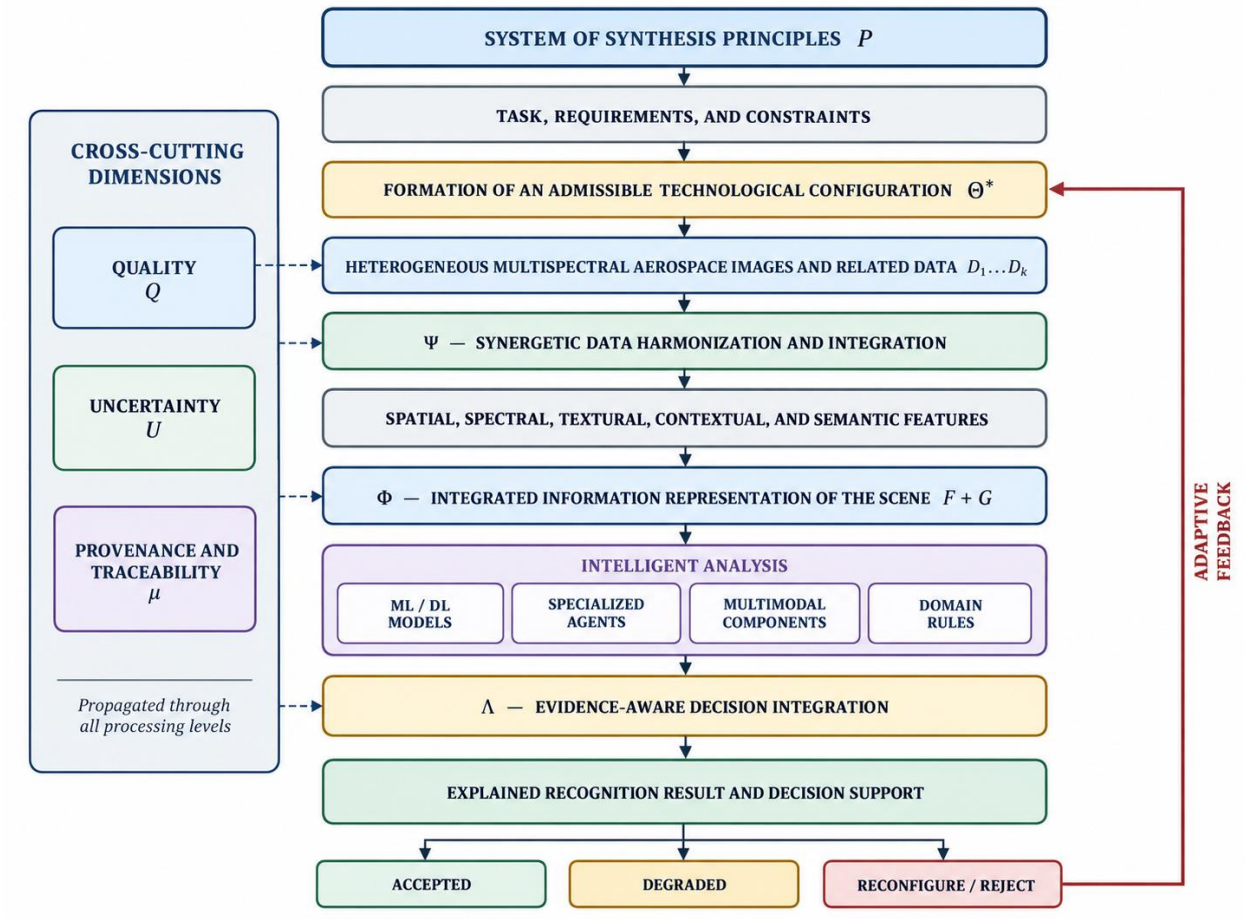


Figure 1 – Methodology for creating intelligent information technologies for recognition and processing of multispectral aerospace images

Figure 1 separates the design and operational levels. The design level establishes principles, task, requirements, constraints, and the admissible configuration Θ*. The operational level implements Ψ–Φ–Λ through ML/DL models, specialized agents, multimodal components, and domain rules. Its output is an explained recognition result with alternatives, uncertainty, supporting and contradicting evidence, limitations, and a recommendation. Accepted results satisfy critical quality, evidence, and traceability conditions; degraded results require explicit limitations or expert verification; and reconfigure/reject activates feedback to data, scale, parameters, features, models, agents, rules, or thresholds. Thus, adaptability is embedded in the creation methodology.

Procedure for creating a task-oriented intelligent information technology. For a specific task of recognition or processing of multispectral aerospace images, creation is operationalized as controlled synthesis and selection of a configuration Θ from an admissible set Ω. A configuration specifies selected data sources, preprocessing operators, feature composition, recognition models, agents, multimodal components, domain rules, resource profile, acceptance thresholds, and trust constraints. The selection criterion is

$$\Theta opt = \arg\max J(\Theta), \Theta \in \Omega, \quad (5)$$

where J(Θ) is a normalized multi-criteria objective combining expected decision reliability *Qdec*, information completeness *I*, explainability *E*, adaptability and transferability *A*, uncertainty *U*, and resource cost *Cres* with application-dependent weights. The expression is a methodological objective rather than a universal numerical metric. Each implementation must define normalized components, critical constraints, and admissible trade-offs for its subject domain.

The procedure for creating a task-oriented intelligent information technology consists of the following steps:

1. define the recognition or processing task, required information products, admissible risks, and acceptance criteria;

2. build registries of available data, transformations, features, models, agents, multimodal components, rules, and computational resources;

3. exclude incompatible components using spatial, spectral, taxonomic, quality, resource, provenance, and access constraints;

4. generate the admissible configuration set Ω and select Θopt according to the multi-criteria objective;

5. construct and execute the Ψ → Φ → analytical components → Λ route while propagating Q, U, and μ;

6. verify recognition quality, evidence completeness, and traceability and assign an accepted, degraded, or reconfigure/reject status;

7. update data requirements, parameters, components, or the processing route using feedback from quality control and expert validation.

This status logic prevents a high confidence score from compensating for low source validity, uncalibrated uncertainty, or incomplete evidence.

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

The methodology is verified structurally and functionally because its principal result is a design framework rather than performance in one application. Verification checks whether the model contains mechanisms required for a coherent, reproducible, adaptive, and explainable information technology. Table 2 compares it with fixed or model-centred approaches.

Table 2

Comparison of fixed approaches and the proposed methodology

Criterion	**Typical fixed or model-centred approach**	**Proposed methodology**
Input organization	One sensor or a predefined data combination.	Task-dependent multisource configuration assembled from registered components.
Integration	One level is usually dominant: pixels, features, or decisions.	Synergistic Ψ–Φ–Λ integration at data, representation, and decision levels.
Scene representation	Pixels, a single feature tensor, or isolated objects.	Object and scene representations linked by graph G and provenance μ.
Analytical components	One model or a fixed ensemble.	Recognition models, specialized agents, multimodal components, and domain rules.
Adaptation	Manual reconfiguration or model retraining.	Configuration selection, status-driven reprocessing, and feedback.
Quality control	Primarily final task accuracy.	End-to-end validity, quality Q, uncertainty U, evidence, and provenance.
Interpretation	Class label, score, or segmentation mask.	Decision, alternatives, evidence, limitations, explanation, and recommendation.
Reproducibility	Parameters may be stored separately from outputs.	Sources, versions, parameters, route, and intermediate provenance are retained.

Structural completeness follows from the explicit presence of all levels from primary data and task requirements to recognition, interpretation, and decision support. Functional consistency is achieved through the defined inputs and outputs of Ψ, Φ, and Λ. Modularity follows from the possibility of replacing an algorithmic implementation without changing the methodological role of the component. Extensibility is provided by registries and admissibility rules that allow new sensors, features, recognition models, agents, multimodal services, and domain rules to be added.

Adaptability is supported by task-dependent configuration selection, status-driven reprocessing, and feedback. Traceability is ensured because quality, uncertainty, evidence, metadata, and provenance remain associated with each intermediate and final product. Interpretability is not reduced to a generated textual description; it is defined as the correspondence between a conclusion, supporting and contradicting evidence, alternatives, limitations, and the processing route.

Table 3

Analytical verification of the methodology

Property	**Verification condition**	**Methodological mechanism**
Structural completeness	All required stages from data acquisition to decision support are represented.	The methodological model includes principles, information space, Ψ–Φ–Λ operators, analytical components, Q, U, and μ.
Functional consistency	Outputs of one level are valid inputs to the next and retain their meaning.	Formal roles of Ψ, Φ, and Λ and documented interlevel contracts.
Modularity	An implementation can be replaced without changing the role of the component.	Registries, admissibility rules, and operator-level interfaces.
Extensibility	New data sources, features, models, or agents can be added.	Open component sets A and V and task-dependent configuration Θ created from registered components.
Adaptability	The route changes when data quality, resources, or task constraints change.	Multi-criteria selection, feedback, and accepted/degraded/reconfigure statuses.
Traceability	Every decision can be linked to sources, transformations, and versions.	Provenance μ and end-to-end recording of the processing route.
Interpretability	The decision is supported by evidence, alternatives, and limitations.	Evidence-aware Λ reconciliation and structured decision output.

Component-level feasibility is supported by the author's previous studies: multichannel preprocessing [21], data harmonization and fusion [22], multiagent object detection [23], multimodal land-cover interpretation [24], and post-training neural adaptation [25]. These works confirm the implementability of the principal methodological levels, but they do not substitute for unified evaluation of a complete task-dependent configuration.

The methodology has limitations. The configuration criterion and its weights must be instantiated for a particular domain; reliability depends on complete model registries, quality

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

metadata, provenance records, and domain-specific uncertainty calibration. Synergistic interaction does not guarantee automatic accuracy improvement. The contribution is to define the conditions, information relations, and feedback mechanisms under which heterogeneous data, models, agents, and evidence are combined in a controlled, reproducible, and explainable manner.

Conclusions. A methodology for creating intelligent information technologies for recognition and processing of multispectral aerospace images has been developed. Its scientific novelty lies in replacing a fixed pipeline with a controlled, task-dependent creation process based on synergistic processing of heterogeneous data. A system of principles and a multidimensional scene model have been formulated. They combine multisource operation, multilevel integration, spatial-spectral-semantic representation, adaptability, multiagent cooperation, multimodality, interpretability, decision support, quality, uncertainty, trust, and traceability. The Ψ–Φ–Λ model coordinates harmonization of primary data, formation of integrated spatial-spectral-textural-contextual-semantic representations, and evidence-aware reconciliation of recognition models, agents, multimodal components, and domain rules. Creation of a task-oriented technology has been formalized as multi-criteria selection from an admissible configuration set, followed by quality-aware execution, evidence verification, status assignment, and feedback-driven reconfiguration. Structural-functional verification established mechanisms for completeness, consistency, modularity, extensibility, adaptability, traceability, and interpretability, and clarified the distinction between methodological validity and performance in a particular application. Previous component-level studies confirm implementability of the principal levels. Further research should provide unified experimental evaluation of complete configurations, domain-dependent uncertainty calibration, and quantitative assessment of recognition reliability, explanation quality, and decision-support effectiveness.

Acknowledgments. This research was funded by the Ministry of Education and Science of Ukraine from the state budget under grant No. 0126U000995, ‘Intelligent technologies for the analysis of spatiotemporal changes in aerospace imagery to support decision-making under conditions of armed aggression’.

Declaration on the use of generative artificial intelligence tools. OpenAI tools were used for language editing, and final preparation of the figure. The author critically reviewed and revised all content and assumes full responsibility for the scientific statements, references, interpretations, and conclusions.

LITERATURE

1. Richards J. A. Remote Sensing Digital Image Analysis: An Introduction. 5th ed. Berlin; Heidelberg: Springer, 2013. 494 p. DOI: https://doi.org/10.1007/978-3-642-30062-2.

2. Schowengerdt R. A. Remote Sensing: Models and Methods for Image Processing. 3rd ed. Burlington: Academic Press, 2007. 560 p.

3. Zhu X. X., Tuia D., Mou L., Xia G.-S., Zhang L., Xu F., Fraundorfer F. Deep learning in remote sensing: a comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine. 2017. Vol. 5, no. 4. P. 8-36.
DOI: https://doi.org/10.1109/MGRS.2017.2762307.

4. Ma L., Liu Y., Zhang X., Ye Y., Yin G., Johnson B. A. Deep learning in remote sensing applications: a meta-analysis and review. ISPRS Journal of Photogrammetry and Remote Sensing. 2019. Vol. 152. P. 166-177. DOI: https://doi.org/10.1016/j.isprsjprs.2019.04.015.
5. Pohl C., Van Genderen J. L. Multisensor image fusion in remote sensing: concepts, methods and applications. International Journal of Remote Sensing. 1998. Vol. 19, no. 5. P. 823-854. DOI: https://doi.org/10.1080/014311698215748.
6. Li S., Kang X., Fang L., Hu J., Yin H. Pixel-level image fusion: a survey of the state of the art. Information Fusion. 2017. Vol. 33. P. 100-112.
DOI: https://doi.org/10.1016/j.inffus.2016.05.004.
7. Luo X., Tong X., Pan H., Shen H., Du P. A critical review on multi-sensor and multi-platform remote sensing data fusion approaches: current status and prospects. International Journal of Remote Sensing. 2025. Vol. 46, no. 3. P. 1327-1402.
DOI: https://doi.org/10.1080/01431161.2024.2429784.
8. Belgiu M., Drăguţ L. Random forest in remote sensing: a review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing. 2016. Vol. 114. P. 24-31. DOI: https://doi.org/10.1016/j.isprsjprs.2016.01.011.
9. Mountrakis G., Im J., Ogole C. Support vector machines in remote sensing: a review. ISPRS Journal of Photogrammetry and Remote Sensing. 2011. Vol. 66, no. 3. P. 247-259. DOI: https://doi.org/10.1016/j.isprsjprs.2010.11.001.
10. Ronneberger O., Fischer P., Brox T. U-Net: convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention - MICCAI 2015. Cham: Springer, 2015. P. 234-241.
DOI: https://doi.org/10.1007/978-3-319-24574-4_28.
11. Chen L.-C., Zhu Y., Papandreou G., Schroff F., Adam H. Encoder-decoder with atrous separable convolution for semantic image segmentation. Computer Vision - ECCV 2018. Cham: Springer, 2018. P. 833-851. DOI: https://doi.org/10.1007/978-3-030-01234-2_49.
12. Xie E., Wang W., Yu Z., Anandkumar A., Alvarez J. M., Luo P. SegFormer: simple and efficient design for semantic segmentation with transformers. Advances in Neural Information Processing Systems. 2021. Vol. 34. P. 12077-12090.
13. Kirillov A., Mintun E., Ravi N. et al. Segment Anything. Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023. P. 4015-4026.
DOI: https://doi.org/10.1109/ICCV51070.2023.00371.
14. Cong Y., Khanna S., Meng C., Liu P., Rozi E., He Y., Burke M., Lobell D. B., Ermon S. SatMAE: pre-training transformers for temporal and multi-spectral satellite imagery. Advances in Neural Information Processing Systems. 2022. Vol. 35. P. 197-211.
15. Liu F., Chen D., Guan Z., Zhou X., Zhu J., Ye Q., Fu L., Zhou J. RemoteCLIP: a vision-language foundation model for remote sensing. IEEE Transactions on Geoscience and Remote Sensing. 2024. Vol. 62. P. 1-16. DOI: https://doi.org/10.1109/TGRS.2024.3390838.
16. Guo X., Lao J., Dang B. et al. SkySense: a multi-modal remote sensing foundation model towards universal interpretation for Earth observation imagery. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2024. P. 27672-27683.

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

17. Huo C., Chen K., Zhang S. et al. When remote sensing meets foundation model: a survey and beyond. Remote Sensing. 2025. Vol. 17, no. 2. Article 179.
DOI: https://doi.org/10.3390/rs17020179.
18. Xiao A., Xuan W., Wang J., Huang J., Tao D., Lu S., Yokoya N. Foundation models for remote sensing and Earth observation: a survey. IEEE Geoscience and Remote Sensing Magazine. 2025. Vol. 13, no. 4. P. 297-324. DOI: https://doi.org/10.1109/MGRS.2025.3576766.
19. Wooldridge M. An Introduction to MultiAgent Systems. 2nd ed. Chichester: John Wiley & Sons, 2009. 461 p.
20. Li C., Gan Z., Yang Z., Yang J., Li L., Wang L., Gao J. Multimodal foundation models: from specialists to general-purpose assistants. Foundations and Trends in Computer Graphics and Vision. 2024. Vol. 16, no. 1-2. P. 1-214. DOI: https://doi.org/10.1561/0600000110.
21. Олевський В. І., Удовик І. М., Грищак Д. Д., Олевська Ю. Б., Журавльова Ю. С. Методологічні основи інформаційних технологій аналізу багатоканальних аерокосмічних зображень. Information Technology: Computer Science, Software Engineering and Cyber Security. 2024. № 4. С. 159-168. DOI: https://doi.org/10.32782/IT/2024-4-19.
22. Гнатушенко В. В., Грищак Д. Д., Олевська Ю. Б., Олевський В. І., Удовик І. М. Методологія об’єднання даних багатоканальних зображень. Системні технології. 2025. Вип. 6 (161). С. 158-171. DOI: https://doi.org/10.34185/1562-9945-5-161-2025-16.
23. Литвинов Є. В., Гнатушенко В. В., Удовик І. М. Виявлення нелегальних сміттєзвалищ на супутникових зображеннях із використанням мультиагентного підходу. Herald of Khmelnytskyi National University. Technical Sciences. 2026. № 361 (1). С. 523-530.
DOI: https://doi.org/10.31891/2307-5732-2026-361-73.
24. Гончаров О. Г., Удовик І. М., Гнатушенко В. В. Конструювання запитів для класифікації земного покриву без навчальних прикладів за допомогою мультимодальних мовних моделей на знімках Sentinel-2. Системні технології. 2026. Вип. 4 (165). С. 130-147. DOI: https://doi.org/10.34185/1562-9945-4-165-2026-13.
25. Udovyk I., Khabarlak K. Improved small agricultural plant segmentation using post-training adaptive neural network. Computer Systems and Information Technologies. 2026. No. 1. P. 118-124. DOI: https://doi.org/10.31891/csit-2026-1-11.

REFERENCES

1. Richards, J. A. (2013). Remote sensing digital image analysis: An introduction (5th ed.). Springer. https://doi.org/10.1007/978-3-642-30062-2
2. Schowengerdt, R. A. (2007). Remote sensing: Models and methods for image processing (3rd ed.). Academic Press.
3. Zhu, X. X., Tuia, D., Mou, L., Xia, G.-S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine, 5(4), 8-36.
https://doi.org/10.1109/MGRS.2017.2762307
4. Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep learning in remote sensing applications: A meta-analysis and review. ISPRS Journal of Photogrammetry and Remote Sensing, 152, 166-177. https://doi.org/10.1016/j.isprsjprs.2019.04.015

5. Pohl, C., & Van Genderen, J. L. (1998). Multisensor image fusion in remote sensing: Concepts, methods and applications. International Journal of Remote Sensing, 19(5), 823-854. https://doi.org/10.1080/014311698215748
6. Li, S., Kang, X., Fang, L., Hu, J., & Yin, H. (2017). Pixel-level image fusion: A survey of the state of the art. Information Fusion, 33, 100-112.
https://doi.org/10.1016/j.inffus.2016.05.004
7. Luo, X., Tong, X., Pan, H., Shen, H., & Du, P. (2025). A critical review on multi-sensor and multi-platform remote sensing data fusion approaches: Current status and prospects. International Journal of Remote Sensing, 46(3), 1327-1402.
https://doi.org/10.1080/01431161.2024.2429784
8. Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24-31. https://doi.org/10.1016/j.isprsjprs.2016.01.011
9. Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 66(3), 247-259.
https://doi.org/10.1016/j.isprsjprs.2010.11.001
10. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In Medical Image Computing and Computer-Assisted Intervention - MICCAI 2015 (pp. 234-241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28
11. Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation. In Computer Vision - ECCV 2018 (pp. 833-851). Springer. https://doi.org/10.1007/978-3-030-01234-2_49
12. Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., & Luo, P. (2021). SegFormer: Simple and efficient design for semantic segmentation with transformers. Advances in Neural Information Processing Systems, 34, 12077-12090.
13. Kirillov, A., Mintun, E., Ravi, N., et al. (2023). Segment Anything. Proceedings of the IEEE/CVF International Conference on Computer Vision, 4015-4026.
https://doi.org/10.1109/ICCV51070.2023.00371
14. Cong, Y., Khanna, S., Meng, C., Liu, P., Rozi, E., He, Y., Burke, M., Lobell, D. B., & Ermon, S. (2022). SatMAE: Pre-training transformers for temporal and multi-spectral satellite imagery. Advances in Neural Information Processing Systems, 35, 197-211.
15. Liu, F., Chen, D., Guan, Z., Zhou, X., Zhu, J., Ye, Q., Fu, L., & Zhou, J. (2024). RemoteCLIP: A vision-language foundation model for remote sensing. IEEE Transactions on Geoscience and Remote Sensing, 62, 1-16. https://doi.org/10.1109/TGRS.2024.3390838
16. Guo, X., Lao, J., Dang, B., et al. (2024). SkySense: A multi-modal remote sensing foundation model towards universal interpretation for Earth observation imagery. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 27672-27683.
17. Huo, C., Chen, K., Zhang, S., et al. (2025). When remote sensing meets foundation model: A survey and beyond. Remote Sensing, 17(2), Article 179.
https://doi.org/10.3390/rs17020179

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)

18. Xiao, A., Xuan, W., Wang, J., Huang, J., Tao, D., Lu, S., & Yokoya, N. (2025). Foundation models for remote sensing and Earth observation: A survey. IEEE Geoscience and Remote Sensing Magazine, 13(4), 297-324. https://doi.org/10.1109/MGRS.2025.3576766
19. Wooldridge, M. (2009). An introduction to multiagent systems (2nd ed.). John Wiley & Sons.
20. Li, C., Gan, Z., Yang, Z., Yang, J., Li, L., Wang, L., & Gao, J. (2024). Multimodal foundation models: From specialists to general-purpose assistants. Foundations and Trends in Computer Graphics and Vision, 16(1-2), 1-214. https://doi.org/10.1561/0600000110
21. Olevskyi, V., Udovyk, I., Hryshchak, D., Olevska, Y., & Zhuravlova, Y. (2024). Metodolohichni osnovy informatsiinykh tekhnolohii analizu bahatokanalnykh aerokosmichnykh zobrazhen [Methodological foundations of information technologies for the analysis of multichannel aerospace images]. Information Technology: Computer Science, Software Engineering and Cyber Security, (4), 159-168. https://doi.org/10.32782/IT/2024-4-19 [in Ukrainian].
22. Hnatushenko, V., Hryshchak, D., Olevska, Y., Olevskyi, V., & Udovyk, I. (2025). Metodolohiia obiednannia danykh bahatokanalnykh zobrazhen [Methodology for multichannel image-data fusion]. System Technologies, 6(161), 158-171. https://doi.org/10.34185/1562-9945-5-161-2025-16 [in Ukrainian].
23. Lytvynov, Y., Hnatushenko, V., & Udovyk, I. (2026). Vyiavlennia nelehalnykh smittiezvalyshch na suputnykovykh zobrazhenniakh iz vykorystanniam multyahentnoho pidkhodu [Detection of illegal dumpsites in satellite images using a multiagent approach]. Herald of Khmelnytskyi National University. Technical Sciences, 361(1), 523-530. https://doi.org/10.31891/2307-5732-2026-361-73 [in Ukrainian].
24. Honcharov, O. H., Udovyk, I. M., & Hnatushenko, V. V. (2026). Konstruiuvannia zapytiv dlia klasyfikatsii zemnoho pokryvu bez navchalnykh prykladiv za dopomohoiu multymodalnykh movnykh modelei na znimkakh Sentinel-2 [Prompt engineering for zero-shot land-cover classification using multimodal language models on Sentinel-2 imagery]. System Technologies, 4(165), 130-147. https://doi.org/10.34185/1562-9945-4-165-2026-13 [in Ukrainian].
25. Udovyk, I., & Khabarlak, K. (2026). Improved small agricultural plant segmentation using post-training adaptive neural network. Computer Systems and Information Technologies, (1), 118-124. https://doi.org/10.31891/csit-2026-1-11

Received 29.06.2026.
Accepted 31.08.2026.
Published 30.10.2026

Методологія створення інтелектуальних інформаційних технологій розпізнавання та обробки багатоспектральних аерокосмічних зображень

Аналіз останніх досліджень і публікацій. Сучасні системи дистанційного зондування Землі формують різнорідні багатоспектральні, гіперспектральні, радіолокаційні, теплові й безпілотні дані. Методи їх корекції, інтеграції, розпізнавання, мультиагентного та мультимодального аналізу переважно розвиваються окремо. Невирішеною є проблема єдиної методології, що визначає вибір джерел і компонентів, формування представлень, узгодження рішень, контроль якості й невизначеності, збереження походження та адаптацію маршруту обробки.

Мета дослідження. Розробити й формалізувати методологію створення інтелектуальних інформаційних технологій розпізнавання та обробки багатоспектральних аерокосмічних зображень на основі синергетичної обробки різнорідних даних, багаторівневої інтеграції й адаптивного формування предметно залежної конфігурації.

Виклад основного матеріалу дослідження. Багатоспектральну сцену подано як багатовимірний інформаційний об'єкт, що поєднує просторові, спектральні, текстурні, контекстні, часові й семантичні характеристики. Запропонована методологія інтегрує систему принципів створення, формальну інформаційну модель, цикл Ψ–Ф–Л узгодження даних, формування представлення та доказового узгодження рішень, адаптивний вибір конфігурації, інтелектуальне розпізнавання, мультиагентну кооперацію, мультимодальну інтерпретацію й наскрізний контроль якості Q, невизначеності U та походження μ. Процедура створення охоплює постановку задачі, формування реєстрів компонентів, перевірку сумісності, вибір допустимої конфігурації, виконання маршруту, верифікацію результату й реконфігурацію за зворотним зв'язком.

Висновки. Розроблена методологія, на відміну від фіксованих конвеєрних підходів, визначає керований процес створення предметно залежної технології на основі синергетичної обробки, інтегрованого просторово-спектрально-семантичного представлення, кооперації моделей і агентів, доказового узгодження рішень та адаптивного зворотного зв'язку. Структурно-функціональна верифікація встановила механізми повноти, узгодженості, модульності, розширюваності, адаптивності, простежуваності та інтерпретованості.

Ключові слова: багатоспектральні аерокосмічні зображення, інтелектуальна інформаційна технологія, методологія створення, різнорідні дані, синергетична обробка, багаторівнева інтеграція, просторово-спектрально-семантичне представлення, мультиагентний аналіз, мультимодальна інтерпретація, підтримка прийняття рішень.

Udovyk Iryna Mykhailivna - Candidate of Technical Sciences, Associate Professor, Dean of the Faculty of Information Technologies, Dnipro University of Technology, Dnipro, Ukraine.
ORCID: https://orcid.org/0000-0002-5190-841X

Удовик Ірина Михайлівна - кандидат технічних наук, доцент, деканка факультету інформаційних технологій Національного технічного університету «Дніпровська політехніка», м. Дніпро, Україна.
ORCID: https://orcid.org/0000-0002-5190-841X

ISSN 1562-9945 (Print)
ISSN 2707-7977 (Online)