sustainability

MDPI

Article

A Data-Driven Risk-Informed Decision Support Framework for Sustainable Municipal Organic Waste Management in Smart Cities

Anatoliy Tryhuba [1,*], Nazarii Koval [2], Inna Tryhuba [1], Ihor Firman [2], Volodymyr Famuliak [1], Andriy Tatomyr [1], Bohdan Hulko [3], Ivanna Rozhko [3], Mykola Rudynets [4] and Valentyna Fedorchuk-Moroz [4]

[1] Department of Information Technologies, Lviv National Environmental University, 1 V. Velykoho Str., 80381 Dublyany, Ukraine; innatrguba@gmail.com (I.T.); vovfam@gmail.com (V.F.); andrew.tatomyr@gmail.com (A.T.)
[2] Department of Information Technologies and Electronic Communications Systems, Lviv State University of Life Safety, 79000 Lviv, Ukraine; kovaln870@gmail.com (N.K.); firmanihor@gmail.com (I.F.)
[3] Department of Horticulture and Vegetable Growing, Lviv National Environmental University, 1 V. Velykoho Str., 80381 Dublyany, Ukraine; bohulko1@gmail.com (B.H.); rozhkoivanka73@gmail.com (I.R.)
[4] Department of Civil Security, Lutsk National Technical University, 75 Lvivska St., 43018 Lutsk, Ukraine; rudinetc@gmail.com (M.R.); fedmor70@ukr.net (V.F.-M.)
* Correspondence: trianamik@gmail.com

Abstract

The rapid growth of organic waste volumes in urban areas and increasing environmental pressures necessitate the transition toward sustainable and risk-informed municipal waste management systems. This study aims to develop a data-driven decision support framework for the risk-informed management of municipal organic waste within the context of sustainable urban development. The proposed approach integrates multi-source municipal data, advanced preprocessing techniques, entropy-based feature weighting, and an ensemble of machine learning models, including Random Forest, Gradient Boosting, and XGBoost. An integrated environmental risk index is formulated to quantify the state of the waste management system and to support predictive analytics. The results demonstrate high predictive performance and reveal that key risk drivers include demographic pressure, transport accessibility, infrastructure characteristics, and seasonal variability of waste generation. The developed framework enables the integration of predictive risk analytics into municipal decision support systems, facilitating optimized waste collection logistics, infrastructure planning, and early identification of critical conditions. The findings confirm that data-driven approaches can significantly enhance the efficiency and adaptability of urban waste management systems. The proposed framework contributes to sustainable urban development by supporting circular economy principles and enabling proactive, risk-aware governance of municipal organic waste systems.

Keywords: municipal organic waste; environmental risk assessment; machine learning; decision support system; data-driven analytics; circular economy; sustainable urban development; smart city; risk index; geospatial analysis

Check for updates

Academic Editor: Antoni Sánchez

Received: 4 May 2026
Revised: 27 May 2026
Accepted: 1 June 2026
Published: 8 June 2026

1. Introduction

Urban areas account for a significant share of global resource consumption, infrastructure demand, and environmental risks, making sustainable urban development a critical priority for modern societies. In this context, the transition toward data-driven governance and digital transformation of urban services has become an essential component of sustainable development strategies [1,2]. In particular, the integration of heterogeneous data sources, transparent performance indicators, and intelligent decision support systems (DSS) enables municipalities to improve the efficiency, adaptability, and resilience of urban infrastructure under conditions of uncertainty [1,3,4].

Solid waste management systems, especially those dealing with organic waste, represent one of the most sensitive and complex elements of urban infrastructure. Inefficiencies in waste collection, transportation, and monitoring can lead to increased methane emissions, environmental degradation, and overload of logistical systems [5–7]. At the same time, organic waste constitutes a valuable resource within the framework of the circular economy, offering opportunities for biogas production, energy recovery, and material reuse [8,9]. The dual role of organic waste as both an environmental burden and a secondary resource highlights the necessity of integrated sustainability-oriented management strategies.

In practice, municipal organic waste management systems rely on coordinated operations involving collection networks, transportation routes, and treatment infrastructure. Their performance depends on the synchronization of operational processes, the ability to respond to seasonal fluctuations, and the availability of monitoring tools for environmental and technological indicators [10]. However, traditional management approaches are often reactive, limiting their ability to anticipate risks and adapt to dynamic urban conditions.

Recent advances in machine learning, big data analytics, and Internet of Things (IoT) technologies have significantly expanded the capabilities for monitoring and optimizing urban services, including waste management [2,4,10]. Some studies emphasize technological innovations and smart infrastructure, while others focus on predictive modeling and algorithmic performance. However, these approaches often remain fragmented, lacking integration into a unified framework that combines data acquisition, risk assessment, predictive analytics, and decision-making processes [1,10]. Moreover, there are diverging perspectives in the literature regarding whether technological optimization alone is sufficient or whether integrated, risk-informed governance frameworks are required to achieve sustainable outcomes [8,11].

Therefore, there is a clear need for comprehensive approaches that integrate data-driven analytics with decision support mechanisms to enable proactive and risk-informed management of municipal waste systems. Such approaches should not only improve prediction accuracy but also ensure practical applicability in real-world governance and infrastructure planning.

This study aims to develop an integrated, data-driven, and risk-informed decision-support framework for sustainable municipal organic waste management. The proposed approach combines multi-source municipal data, entropy-based feature weighting, and ensemble machine learning models to support predictive environmental risk assessment and informed decision-making.

The scientific novelty of this study lies in the development of a unified data-driven digital framework that integrates entropy-based feature relevance assessment, risk index formulation, and ensemble-based predictive analytics within a single analytical architecture. Unlike existing approaches, which typically consider data analytics, risk assessment, and decision support as separate components, the proposed framework ensures their systematic integration and enables a transition from static, expert-based evaluation to adaptive, risk-oriented management supported by continuous monitoring and predictive capabilities.

From a theoretical perspective, the proposed framework extends existing research on smart waste management by introducing a unified risk-oriented analytical architecture in which environmental risk is treated as a dynamic and predictive variable rather than as a retrospective indicator of system performance. Unlike prior studies that separately address IoT monitoring, circular economy governance, machine learning prediction, or multi-criteria evaluation, the proposed approach formalizes their interaction within a closed-loop structure integrating data acquisition, entropy-based feature relevance assessment, predictive modeling, and decision-support mechanisms. This enables a transition from fragmented operational analytics toward adaptive and risk-informed governance of municipal organic waste systems under conditions of spatial and temporal uncertainty.

The main contributions of this study include the development of an integrated digital framework for waste management, the formulation of an entropy-based environmental risk index, the application of ensemble machine learning models for risk prediction, and the integration of predictive analytics into a DSS for municipal governance. The results demonstrate that the proposed framework enables accurate risk forecasting and supports proactive management strategies, contributing to the implementation of circular economy principles and sustainable urban development. The main scientific contributions of this study can be summarized as follows:

(1) The development of a unified data-driven framework integrating risk assessment, predictive analytics, and municipal decision support;
(2) The formalization of an entropy-weighted integrated environmental risk index for municipal organic waste systems;
(3) The integration of heterogeneous socio-economic, environmental, infrastructural, and temporal data into a single analytical architecture;
(4) The implementation and comparative evaluation of ensemble machine learning models for predictive risk assessment;
(5) The incorporation of predictive outputs into a risk-informed DSS for proactive municipal waste management.

The remainder of this paper is organized as follows. Section 2 presents the literature review and identifies the research gap. Section 3 describes the methodological framework, study area, data structure, preprocessing procedures, and predictive modeling approach. Section 4 presents the experimental results and comparative analysis of machine learning models. Section 5 discusses the implications of the proposed framework for sustainable and risk-informed municipal waste management. Finally, Section 6 summarizes the main conclusions and outlines directions for future research.

2. Literature Review and Research Gap

2.1. Smart City Infrastructure and Digitalization of Waste Management

Within the smart city paradigm, the digitalization of waste management systems is increasingly interpreted as a transition from traditional operational logistics to data-driven management, where decisions are based on telemetry streams, service event logs, and integrated analytical platforms [1,2,11]. Such an approach enables the transformation of municipal waste systems into dynamic, data-intensive environments capable of real-time monitoring and adaptive control.

Practical implementations of smart waste management include the deployment of IoT-enabled containers, LPWAN communication technologies, smart routing algorithms, and integration with intelligent transportation systems (ITS). These technologies allow municipalities to monitor the temporal dynamics of waste accumulation, optimize collection schedules, and reduce inefficient operations such as empty vehicle trips [12,13]. As a result, digitalization contributes not only to cost reduction but also to improved service efficiency and resource utilization.

Another important research direction involves the use of cyber-physical systems and multi-agent simulation models, which reproduce complex interactions between waste generation processes, container networks, transportation logistics, and infrastructure capacity [14]. These approaches enable the analysis of system behavior under varying conditions and provide insights into the dynamic nature of urban waste systems.

However, despite the significant progress in the digitalization of waste management, most existing studies primarily focus on operational optimization and infrastructure efficiency. The potential of digital technologies for predictive risk assessment and integration into DSS remains insufficiently explored. In particular, risk factors such as container overflow, infrastructure overload, and seasonal demand fluctuations are often treated as operational incidents rather than as predictable and manageable variables. This limitation reduces the ability of smart waste systems to support proactive and sustainability-oriented urban governance.

2.2. Governance and Circular Economy in an Urban Context

In the urban context, the circular economy is increasingly conceptualized as an institutionally managed transition that requires coordinated interaction among stakeholders, regulatory frameworks, and territorial systems [15]. This transition extends beyond technological implementation and involves the alignment of governance mechanisms, economic incentives, and societal behavior. To support this process, the concepts of «circular cities» and progress monitoring frameworks have been developed, emphasizing the importance of measurable indicators, policy coherence, and long-term strategic planning [16–18].

Recent studies highlight that, despite the availability of advanced technological solutions, many urban strategies fail to adequately account for the social and institutional dimensions of circular transitions. In particular, insufficient attention is given to the feasibility of waste reuse practices, public acceptance, and the distribution of economic benefits among stakeholders [19]. This indicates that circular economy implementation cannot be reduced to infrastructure modernization alone, but requires a comprehensive governance approach that integrates social, economic, and environmental factors.

Comparative analyses of circular economy policies in European cities reveal significant heterogeneity in implementation strategies. While some municipalities prioritize infrastructure development and technological modernization, others focus on regulatory instruments and incentives aimed at supporting local value chains and resource circulation [20]. At the international level, frameworks such as those proposed by the OECD formalize the transition to circular urban systems through the integration of governance structures, economic policies, and performance evaluation mechanisms [21].

For the organic fraction of municipal waste, policy-oriented roadmap approaches play a crucial role. These approaches combine strategies for household waste utilization, development of processing infrastructure, and the definition of circularity scenarios aligned with sustainability objectives. For the organic fraction of waste (biowaste), policy-oriented roadmap approaches are relevant, combining practices for the use of household waste [22,23], processing infrastructure [24,25], and circularity scenario requirements [26,27]. However, despite the strategic orientation of these frameworks, their practical implementation is often limited by the lack of integration with real-time data, predictive analytics, and operational decision-making tools.

Thus, while governance-oriented circular economy models provide a strong conceptual foundation for sustainable urban development, they frequently lack the analytical and technological components necessary for dynamic, data-driven, and risk-informed management. This limitation highlights the need for integrated frameworks that bridge the gap between high-level policy design and operational decision support in municipal waste management systems.

2.3. Decision Support Systems Focused on Risk Assessment and Multi-Criteria Decision-Making in Waste Management

The development of DSS in municipal solid waste (MSW) and organic waste management has evolved from simple technology selection tools to more advanced multi-criteria decision-making (MCDM) frameworks that incorporate environmental, economic, and social objectives [28,29]. These approaches reflect the increasing complexity of waste management systems and the need to balance multiple, often conflicting, sustainability criteria.

Among the most widely used methods, MCDM techniques such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Data Envelopment Analysis (DEA), and their fuzzy extensions dominate in tasks related to technology selection, facility location, and evaluation of alternative waste management strategies [30]. These methods are particularly effective in handling uncertainty in criteria definition and weighting, making them suitable for strategic planning under incomplete or ambiguous information.

However, despite their methodological strengths, most MCDM-based DSS approaches remain static in nature and are weakly connected to real-time operational data and temporal dynamics of waste generation and processing flows [31]. In practice, this limits their ability to support adaptive decision-making in dynamic urban environments. Furthermore, many DSS implementations function primarily as expert-based evaluation tools rather than as data-driven systems integrated with continuous monitoring and predictive analytics [32–36].

Recent developments in decision support models have attempted to expand the analytical scope by comparing conventional waste management solutions, such as landfilling, with innovative approaches, including biorefineries and integrated processing schemes, while incorporating broader sustainability indicators and waste hierarchy principles [15,37]. Although these models provide valuable insights for long-term planning, they often lack mechanisms for real-time data integration and do not explicitly treat environmental risk as a quantifiable and forecastable variable.

Consequently, a significant limitation of existing DSS approaches lies in their insufficient integration with data-driven technologies and their limited capacity to formalize risk as a central element of decision-making. This highlights the need for next-generation decision support frameworks that combine multi-criteria evaluation, real-time data processing, predictive analytics, and risk-oriented modeling to enable proactive and sustainability-driven management of municipal waste systems.

2.4. Using Artificial Intelligence and Big Data for Waste Forecasting and Scenario Modeling

In recent years, artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques have been increasingly applied to municipal waste management tasks, including waste generation forecasting, system performance evaluation, capacity planning, and scenario-based decision support [22,29,38]. These approaches enable the identification of complex nonlinear relationships between socio-economic, environmental, and infrastructural variables, thereby improving the predictive accuracy of waste management models.

Systematic reviews highlight the growing importance of ensemble models and deep learning architectures in this domain. However, they also emphasize several critical challenges, including limited reproducibility of results, low transferability of models across different urban contexts, and the lack of standardized and interoperable datasets [39,40]. These limitations reduce the scalability and practical applicability of AI-driven solutions in real municipal environments.

Although recurrent neural network architectures such as Long Short-Term Memory (LSTM) models are widely used for sequential forecasting tasks, the present study primarily focuses on a structured multifactorial dataset characterized by heterogeneous socio-economic, spatial, infrastructural, environmental, and temporal variables. Therefore, ensemble machine learning methods were selected as the core predictive models due to their robustness in handling tabular heterogeneous data and nonlinear feature interactions.

Temporal dependencies and seasonal variability were partially incorporated into the modeling framework through the inclusion of lag-based variables, rolling statistics, and calendar-related temporal attributes. These engineered features enabled the ensemble models to capture short-term temporal inertia and seasonal fluctuations in waste generation dynamics without requiring fully sequential neural architectures.

Recent studies published in 2024–2025 further emphasize the growing role of spatio-temporal artificial intelligence models and urban resilience analytics in sustainable city management [41–45]. In particular, transformer-based forecasting architectures, graph neural networks, and hybrid spatial–temporal deep learning models are increasingly used for predicting dynamic urban processes, including infrastructure load, environmental risks, and municipal service demand under uncertainty [41,42]. At the same time, urban resilience research highlights the importance of adaptive digital infrastructures capable of integrating heterogeneous real-time data streams and predictive analytics for proactive risk mitigation and sustainable governance [43,44]. These developments demonstrate the transition from static analytical systems toward adaptive, resilience-oriented urban intelligence platforms [45].

For the organic fraction of waste, particular attention has been given to modeling methane emissions and energy recovery potential. On the one hand, deep learning models have been successfully applied to predict landfill gas generation and electricity output [46]. On the other hand, satellite-based monitoring approaches provide facility-level emission estimates, revealing significant discrepancies and uncertainties in emission inventories [47]. This indicates that, despite technological advances, there remains a gap between analytical capabilities and reliable operational implementation.

In the context of circular economy planning, system dynamics models have been used to analyze the long-term effects of circular strategies on urban systems, while machine learning-based scenario modeling has been incorporated into decision support frameworks for sustainable planning [48,49]. Nevertheless, these approaches are typically developed independently and lack integration into a unified analytical environment. As a result, their practical use in real-world municipal governance remains limited.

A key limitation of current AI-driven approaches is the absence of integrated frameworks that combine real-time data acquisition, predictive modeling, risk assessment, and decision support within a single system. In particular, digital telemetry from smart infrastructure, circular economy objectives, risk metrics, and scenario-based forecasting are rarely considered simultaneously. This fragmentation prevents the development of proactive, adaptive, and sustainability-oriented waste management strategies.

Therefore, there is a clear need for unified data-driven analytical models that integrate:

- Digital telemetry from smart urban services;
- Governance and circular economy objectives;
- Quantifiable and predictive risk metrics;
- Interpretable forecasting and scenario analysis tools.

Addressing this need is essential for enabling data-driven, risk-informed, and sustainable management of municipal waste systems.

https://doi.org/10.3390/su18125862

2.5. Research Gap

The analysis of contemporary scientific literature (Table 1) demonstrates that three major research directions in municipal organic waste management have been extensively developed:

- Smart infrastructure and digital waste collection systems [1,2,12–14];
- Circular economy governance and policy frameworks [16–18,20,21,25];
- DSS and machine learning-based analytical approaches [30,31,37–40,48,49].

Despite the significant progress achieved within each of these domains, they have largely evolved independently, resulting in a fragmented research landscape (Table 1).

Table 1. Method families aligned with the literature review.

Method Family	Primary Outputs	Core Inputs	Strengths	Limitations
Digital transformation frameworks for municipal SWM [1,2]	Digital architecture, data governance structures, and BI-enabled workflows	Service datasets, asset registries, operational processes	Provides a conceptual foundation for building integrated end-to-end data pipelines	Often lacks formalized risk modeling and predictive analytical components
IoT-based smart waste systems (LPWAN/ITS) [12,13]	Optimized collection operations, fill-level monitoring, service performance indicators	Sensor telemetry, traffic information, and routing datasets	Enables operational efficiency improvements and scalable service management	Risk is typically treated as operational incidents rather than a predictive metric
Multi-agent simulation of smart waste management systems [14]	Operational scenarios and policy simulations	Behavioral rules, agent parameters, waste generation, and collection dynamics	Captures complex system behavior and dynamic interactions	Requires extensive calibration and may have limited linkage with real-world datasets
Circular cities: conceptual frameworks and indicators [16–18]	Circular economy indicators, transition pathways, and sustainability assessment frameworks	Strategic plans, policy documents, statistical datasets	Aligns circular economy objectives with urban planning strategies	Provides limited operational decision signals at the process level
Governance and policy analysis for circular cities [19–21]	Institutional coordination mechanisms, stakeholder roles, policy instruments	Governance frameworks, regulatory, and institutional datasets	Clarifies implementation mechanisms for circular economy transitions	Limited integration with operational datasets and predictive analytics
Organic-waste transition roadmaps (EU pathways) [25,50]	Strategic roadmaps towards circular organic waste management	Regulatory frameworks, infrastructure data, and best practices	Provides actionable policy-oriented transition pathways	Limited incorporation of data-driven analytical and risk evaluation components
DSS and MCDM approaches for technology and routing decisions [30,31,37,51–55]	Ranking of technological alternatives and optimized collection strategies	Multi-criteria indicators, expert judgments, and weighting schemes	Effective for decision-making under multi-criteria uncertainty	Typically, static; limited integration with temporal dynamics and IoT data streams

Table 1. *Cont.*

Method Family	Primary Outputs	Core Inputs	Strengths	Limitations
AI/ML/DL reviews in municipal solid waste management [39,40,55–57]	Structured overview of analytical methods, tasks, and research gaps	Scientific publications, datasets	Consolidates the evidence base for data-driven waste management	Highlights issues related to transferability, data quality, and reproducibility
Emission and methane modeling (deep learning + satellite data) [41,47]	Emission forecasting and detection of discrepancies in waste-related inventories	Field measurements, operational datasets, satellite observations	Strengthens the climate-risk assessment dimension of waste systems	Requires harmonization of spatial and temporal scales across datasets
System dynamics and scenario planning for circular economy transitions [48]	Long-term policy and strategy impact simulations	System parameters, feedback loops, policy scenarios	Captures causal relationships and long-term trade-offs	Often relies on generalized assumptions with limited operational granularity
ML-based scenario DSS for urban planning [49,58]	Policy scenarios, resilience assessments, predictive decision support	Urban datasets integrated with predictive models	Enables scenario-driven strategic planning	Often not specifically tailored to organic waste systems, and lacks a unified data architecture

Table 1 highlights that existing method families differ substantially in their analytical focus, data requirements, and practical applicability. Digital transformation frameworks and IoT-based systems provide a strong foundation for real-time monitoring and operational optimization, yet they typically lack formalized risk modeling and predictive analytical components. Circular economy and governance-oriented approaches offer comprehensive strategic and policy-level guidance; however, they often fail to deliver operational decision signals and lack integration with real-time data and analytical tools. At the same time, DSS, MCDM, and machine learning-based models demonstrate strong capabilities in evaluation, forecasting, and scenario analysis, but are frequently implemented as standalone tools without integration into unified data architectures or municipal information systems.

A critical limitation across these research directions is the absence of a unified framework that systematically integrates data acquisition, predictive modeling, risk assessment, and decision support. First, IoT-oriented studies primarily focus on service optimization, while risk is typically treated as an operational outcome rather than as a predictive and manageable variable [12–14]. Second, governance and circular economy research emphasizes policy design and indicator systems but lacks operational data infrastructures capable of generating actionable risk signals for municipal management [19–21]. Third, DSS and machine learning approaches are often disconnected from real-time telemetry and from each other, limiting their applicability in dynamic urban environments [59–62]. Third, DSS/MCDM and ML models often exist as separate tools without a coordinated data architecture and without a mechanism for integration with urban telemetry data and event flows [15,30,31,37–40]. Although individual studies demonstrate the potential of data-driven approaches, including machine learning, system dynamics, and distributed digital registries, their practical implementation in the form of a unified risk-informed platform for the organic fraction of municipal waste remains underdeveloped [48,59–63]. That is why it is advisable to use an approach where risk-oriented digital management of organic waste is implemented as an integrated data-driven model [64,65] that combines data collection, intelligent forecasting, scenarios, and management decisions.

Furthermore, even emerging approaches that incorporate advanced technologies such as blockchain, distributed registries, or system dynamics modeling tend to address specific aspects of waste management without ensuring their integration into a cohesive analytical and decision-making system. As a result, the practical implementation of data-driven solutions in the form of unified, risk-informed platforms for municipal organic waste management remains underdeveloped.

Therefore, there is a clear need for an integrated data-driven framework that combines:

- Multi-source data acquisition and processing;
- Predictive risk modeling;
- Scenario-based analytical tools;
- Decision support mechanisms tailored to municipal governance.

Addressing this need is essential for enabling proactive, adaptive, and sustainability-oriented management of organic waste systems in urban environments.

The present study addresses these gaps by proposing a risk-informed digital framework that integrates data-driven analytics, machine learning-based prediction, and decision support into a unified architecture for municipal organic waste management.

3. Materials and Methods

3.1. Overview of the Methodological Framework

The proposed methodological approach is based on the concept of risk-oriented digital management of organic waste. It assumes that municipal decisions on organic waste management are made based on formalized, quantifiable, and predictable indicators of environmental and operational risk. Unlike traditional waste accounting systems, which are primarily focused on retrospective reporting (volumes, emissions, compliance with standards), the proposed approach views the organic waste management system as an integrated digital ecosystem in which data, analytics, and management decisions are considered in a single closed loop. Unlike existing approaches, the proposed framework integrates multi-source data processing, entropy-based feature weighting, predictive risk modeling, and decision support mechanisms within a unified analytical architecture.

In this study, risk-oriented management is interpreted as a process in which management actions (route adjustments, optimization of processing capacity loads, monitoring of CH_4 emissions, and generation of warning signals) are based on an integrated risk index that reflects the current and projected state of the system. This index is a function of many factors—environmental, infrastructural, social, and temporal—and serves as the key element in the transition from descriptive analytics to proactive management. This formulation enables environmental and operational risk to be treated as a predictive and manageable variable rather than a retrospective indicator.

The methodological logic of the study is implemented through a sequential integration scheme, which is presented in Figure 1.

In Figure 1, each stage forms a separate analytical level, and feedback loops are provided between levels for adaptive updating of system parameters. This closed-loop structure ensures continuous updating of system parameters and supports adaptive decision-making under dynamic urban conditions. The first level (Data) involves the integration of diverse municipal sources into a single analytical array. It includes operational data on organic waste volumes, methane emission indicators, infrastructure characteristics, demographic parameters, and time indicators. The main requirement is to ensure the temporal consistency and spatial comparability of data.

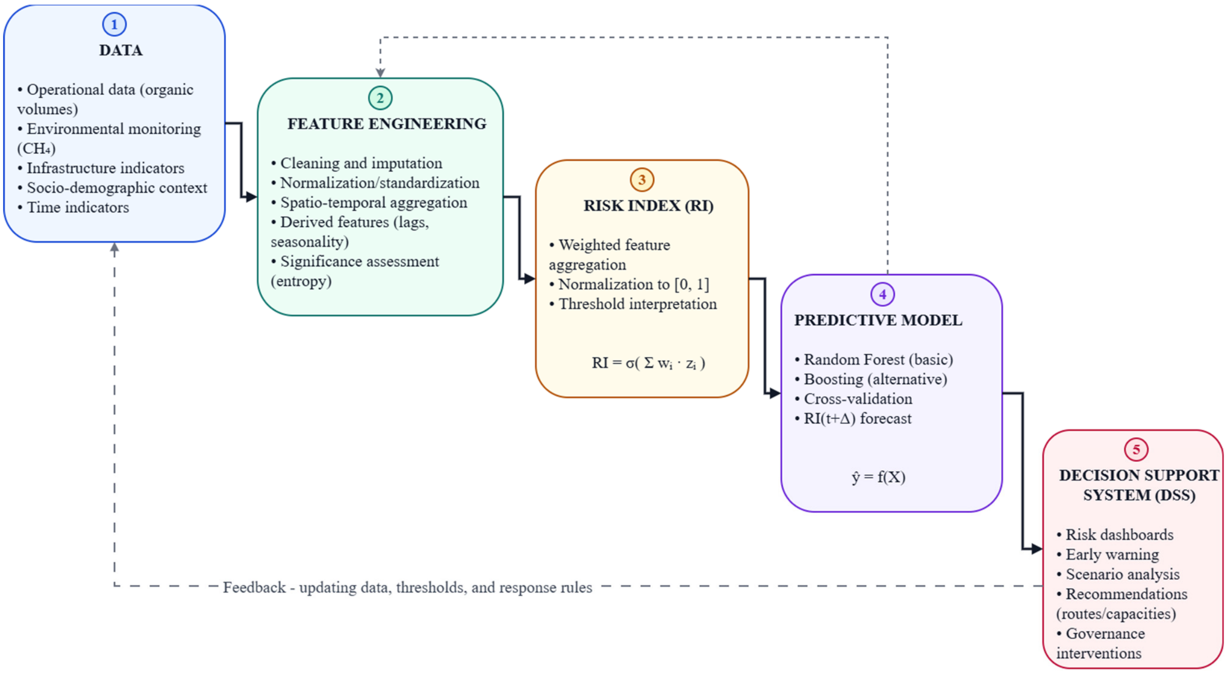


Figure 1. Methodological structure of digital risk-oriented organic waste management in urban communities (the approach reflects the transition from retrospective reporting to predictive management): RI—integrated risk index; DSS—decision support system; weights w_i are formed based on the informativeness of features (entropy assessment).

The second level (Feature Engineering) is aimed at transforming raw data into formalized analytical features. At this stage, cleaning, imputation of missing values, normalization, standardization, construction of derived indicators (seasonality, load intensity, relative indicators), as well as assessment of the significance of variables are performed.

The third level (Risk Index) consists of forming an integral risk indicator RI:

$$RI = \sigma\left(\sum_{j=1}^{m} w_j \cdot z_j\right), \tag{1}$$

where z_j—standardized values of features; w_j—weight coefficients determined based on their informativeness; and $\sigma(\cdot)$—normalization function that limits the index value in the range [0, 1].

The resulting risk index RI acquires an interpretable scale and is used to compare periods or territories. Unlike conventional indicators, the proposed risk index integrates heterogeneous variables into a unified normalized scale, enabling direct comparison across spatial units and time periods.

The fourth level (Predictive Model) provides a predictive assessment of risk dynamics. At this stage, machine learning methods are applied that can consider nonlinear relationships between variables and the temporal variability of the system. The use of ensemble machine learning models ensures robustness to data variability and improves predictive accuracy by capturing complex interactions between socio-economic, environmental, and infrastructural factors.

The fifth level (DSS) transforms the predicted risk values into specific management signals. These can be warnings about exceeding critical thresholds, recommendations for route adjustments, scenario calculations of the load on processing capacities, or the identification of priority monitoring areas. The integration of predictive analytics into the DSS enables a transition from passive monitoring to proactive and risk-informed management, forming a closed-loop structure of «data–analysis–decision–feedback».

The proposed digital framework (Figure 1) enables the transition from fragmented indicator-based analysis to an integrated data-driven management system in which data, analytics, and management decisions operate within a unified analytical logic, supporting proactive, adaptive, and sustainability-oriented municipal organic waste management.

3.2. Study Area and Empirical Data

3.2.1. Study Area Description

The Lviv urban community (Ukraine) is a complex socio-ecological and infrastructural urban system that operates in conditions of high population density and significant concentration of organic waste flows. The administrative center of the community is the city of Lviv, which is characterized by a multi-level spatial structure, a combination of historic buildings, industrial zones, and new residential areas (Figure 2). Such spatial variability creates heterogeneity in the organic fraction of household waste, which directly affects the load on the logistics and processing infrastructure.

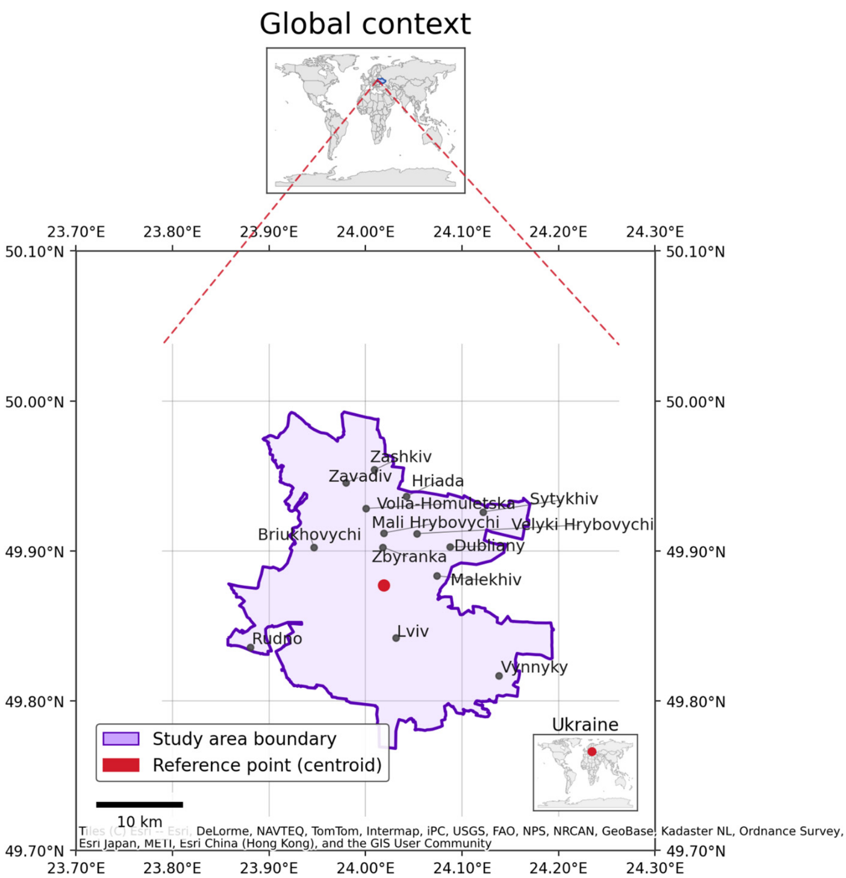


Figure 2. Study area map.

Within the urban community, organic waste is generated by households, commercial entities, and public institutions. The daily volume of organic waste varies significantly, reflecting the presence of both peak and baseline operational modes.

The organic waste management infrastructure in the urban community includes a container collection system, transport logistics, sorting facilities, and composting capacity. Spatial and infrastructure parameters, such as distance to water bodies, road network density, and the proportion of urbanized territory, show significant variability. From a formalization perspective, the urban territorial community is represented by a vector of its state:

$$S_t = \{W_t, C_t, L_t, E_t, U_t\}, \tag{2}$$

where W_t—volume of organic waste at a given moment in time t; C_t—CH_4 concentration; L_t—logistics indicators (transportation duration and distance); E_t—environmental indicators; and U_t—proportion of urbanized territory.

This representation allows the urban system to be analyzed as a multidimensional dynamic structure, where each component reflects a specific aspect of waste generation, environmental impact, or infrastructure performance.

The integral environmental risk in an urban community is formed as a function of the interaction of these parameters:

$$R_t = f(W_t, C_t, L_t, U_t), \quad (3)$$

Expression (3) emphasizes the nonlinear nature of the dependencies between factors influencing risk in the organic waste management system. Such a formulation enables the identification of complex nonlinear interactions between system components and supports the use of predictive analytics for risk estimation.

Within the scope of the study, the Lviv city territorial community is considered as a representative empirical platform for testing a data-driven digital framework for risk-oriented organic waste management. High population density, spatially heterogeneous building structure, the presence of a ramified system for the collection and transportation of bio-waste, as well as the functioning of a centralized waste flow management operator form a complex environment with various types of environmental, logistical, and infrastructural risks. This configuration allows for the integration of heterogeneous data sources (socio-demographic, infrastructural, temporal, and environmental) into a single analytical model. The selection of the Lviv urban community as a case study is justified by the availability of diverse data sources, the complexity of its infrastructure, and the representativeness of its waste management challenges for medium-sized European cities.

The combination of urbanization dynamics, the transformation of the waste management system, and the digitization of management processes provides a robust empirical basis for the formulation of an integrated risk index that captures the probability of accumulation, overload, and inefficient redistribution of organic waste in space and time. This, in turn, supports the development of predictive models and enables the integration of forecasting capabilities into a DSS focused on proactive management, resource optimization, and the minimization of environmental impacts at the municipal level.

3.2.2. Data Structure and Variables

The empirical basis of the study is formed as a structured spatio-temporal dataset covering the period from 1 January 2024, to 23 June 2025. Discretization was carried out using daily observation steps, which resulted in the formation of 10,800 records, each of which corresponds to a specific spatial unit within the Lviv city territorial community and a specific time interval. This ensures enough temporal resolution for capturing dynamic changes in waste generation and environmental conditions. Structurally, the data array is multi-level and includes identification, socio-demographic, spatial-infrastructural, environmental, economic, and time variables. Formally, the set can be represented as a matrix:

$$X = \{x_{ij}\},\ i = 1, \ldots, 10{,}800,\ j = 1, \ldots, m, \quad (4)$$

where i—observation number; j—attribute number; and m—total number of variables describing the state of the organic waste management system at a specific point in time.

Such a representation enables the formalization of the municipal waste management system as a multidimensional analytical space suitable for predictive modeling. Table 2 provides a structured overview of the variables and data sources used for risk-oriented modeling of municipal organic waste management systems.

Table 2. Variables used in the municipal organic waste risk dataset.

Category	Variable	Description	Unit	Data Source
Identification	municipality_id	Unique municipality identifier	–	Municipal registry
	municipality_type	Administrative type of municipality	categorical	Administrative records
Socio-demographic	population	Total population	persons	Municipal statistics
	households	Number of households	units	Municipal registry
	urban_share	Share of urbanized area	fraction	Geographic Information System (GIS) analysis
Spatial	area_km^2	Area of the spatial unit	km^2	Geospatial data
	lat, lon	Geographic coordinates of the municipality centroid	degrees	GIS
	dist_to_region_center_km	Distance to the regional administrative center	km	GIS
	dist_to_water_km	Distance to the nearest water body	km	GIS
	dist_to_housing_km	Distance to residential zones	km	GIS
Infrastructure	roads_density_km_per_km^2	Road network density	km/km^2	OpenStreetMap
Economic	income_index	Relative income index	index	Statistical data
	tourism_index	Tourism activity index	index	Municipal statistics
Environmental	organic_waste_tons	Annual volume of organic waste generated	tons	Waste management operator
	food_waste_tons	Annual volume of food waste generated	tons	Waste management operator
	moisture_pct	Moisture content of organic waste	%	Sensor measurements
	pH	Acidity level of waste substrate	pH	Laboratory analysis
	ch4_ppm	Methane concentration	ppm	Environmental monitoring
	leachate_risk	Estimated leachate generation risk	0–1	Model-based estimation
Integrated indicator	risk_index	Composite environmental risk index	0–1	Model output
Temporal variables	year, month, week, dayofweek	Calendar attributes	–	Time aggregation
	is_weekend	Weekend indicator variable	0/1	Calendar data

The structure of Table 2 demonstrates the integration of more than 20 variables covering social, spatial, economic, and environmental dimensions of the waste management system. This multidimensional representation enables the identification of nonlinear relationships and supports the construction of an integrated risk index based on the interaction of heterogeneous factors.

The structural diagram of the data array (Figure 3) highlights seven interrelated blocks: (1) Social Data X_{soc}; (2) Spatial & Infrastructure Data X_{spat}; (3) Economic Data X_{econ};

(4) Environmental Monitoring X_{env}; (5) Temporal Attributes X_{time}; (6) Integrated Data Matrix; (7) Risk Index & Predictive Module. This structure reflects the transformation of heterogeneous input data into a unified analytical space suitable for subsequent modeling and decision support. Each block forms a corresponding subspace of features X_k, which are aggregated into a single feature matrix:

$$X = [X_{soc}, X_{spat}, X_{econ}, X_{env}, X_{time}], \tag{5}$$

where X_{soc}—subspace of socio-demographic features; X_{spat}—subspace of spatial and infrastructure features; X_{econ}—subspace of economic features; X_{env}—subspace of environmental monitoring features; and X_{time}—subspace of temporal attributes.

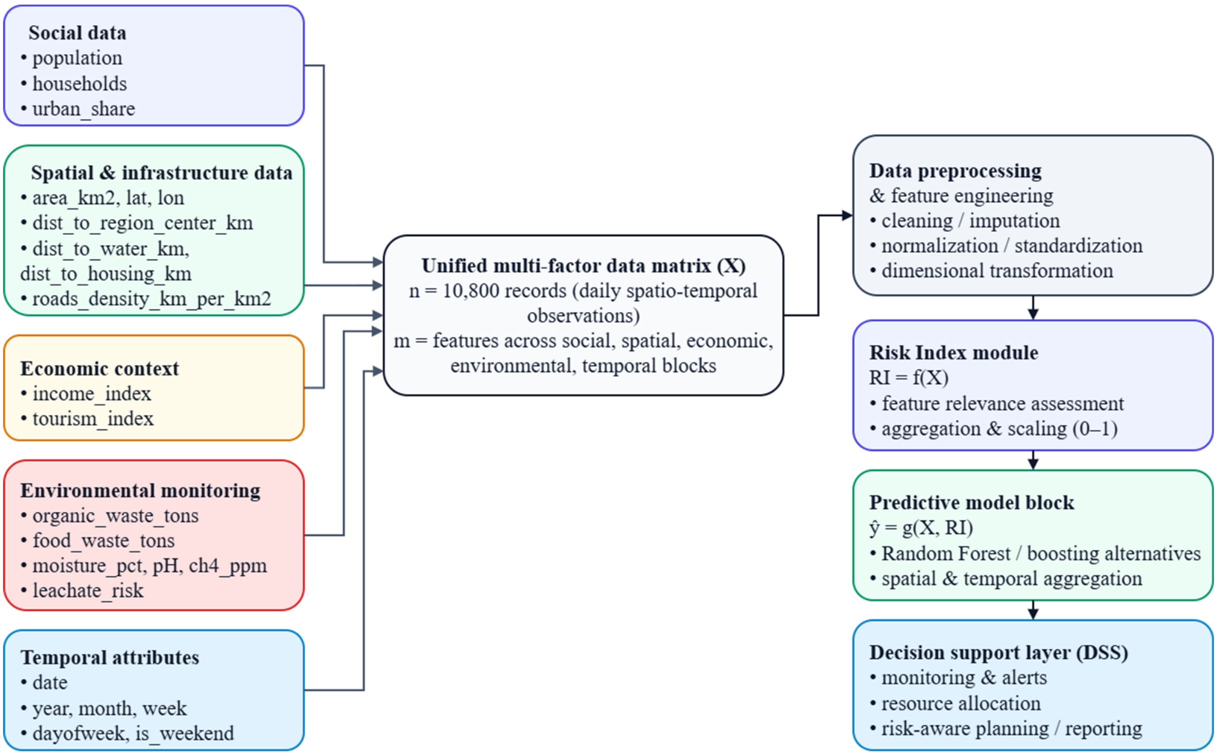


Figure 3. Structure of the multifactorial data array: heterogeneous input data are integrated into a unified feature matrix X and processed to derive the risk index (RI) and predictive outputs, supporting risk-informed decision-making at the municipal level.

This aggregation ensures consistency of the feature space and enables the application of machine learning methods for predictive analytics.

The resulting array (5) serves as the input space for further procedures of cleaning, normalization, and entropy assessment of feature significance.

Thus, the resulting dataset complies with the principles of a data-driven analytical framework and provides a robust foundation for the formulation of an integrated risk index and the development of predictive models within a DSS for municipal organic waste management.

All software tools used in this study were checked and specified with their version numbers where applicable. OpenStreetMap was used as an open geospatial data source (https://www.openstreetmap.org, accessed on 27 May 2026). The data processing and predictive modeling procedures were implemented using Python 3.11, scikit-learn 1.4.2, XGBoost 2.0.3, NumPy 1.26.4, pandas 2.2.2, and Matplotlib 3.8.4.

3.3. Data Preprocessing and Feature Engineering

3.3.1. Data Cleaning and Imputation

The initial multifactorial array X contained variables of heterogeneous origin (social, spatial, economic, environmental, and temporal), so a unified data cleaning and reconciliation procedure was performed before constructing the risk index and forecast block. At this stage, the main goal was to ensure the correctness of variable types, eliminate logical anomalies, process gaps, and bring indicators to comparable scales. This preprocessing stage is essential for ensuring data consistency and reliability of subsequent risk modeling and predictive analysis. Anomalies were defined as values exceeding physically meaningful limits or inconsistent records arising from data merging. In such cases, a strict filtering rule is applied with the removal or correction of values to the limits of the tolerance intervals, which minimizes distribution distortion and prevents incorrect model training.

After validating domain restrictions, missing values were imputed. Since the variables are of different nature and have different mechanisms of occurrence of missing values (some are related to the lack of sensor observations, others to incomplete municipal statistics), a combined strategy was used: interpolation was applied to time-inertial environmental series, and robust estimates of the central tendency within the corresponding spatial unit were applied to socio-economic and infrastructure indicators. Formally, for a continuous variable x within a single municipal unit, imputation g by median is presented as:

$$\widetilde{x}_i = \begin{cases} x_i, & if\ x_i \neq \varnothing, \\ \text{median}\{x_k : k \in g,\ x_k \neq \varnothing\}, & if\ x_i = \varnothing. \end{cases}, \tag{6}$$

For time-dependent environmental variables, in particular *moisture_pct*, *ch*4*_ppm*, as well as derivative risk indicators, imputation was performed using linear interpolation within a single cell time series, preserving the trend and seasonal variations. For a sequence of observations $\{x_t\}$ at time t, this takes the form:

$$\widetilde{x}_t = \begin{cases} x_t, & x_t \neq \varnothing, \\ x_{t_1} + \frac{t-t_1}{t_2-t_1}(x_{t_2} - x_{t_1}), & x_t = \varnothing,\ t_1 < t < t_2, \end{cases}, \tag{7}$$

where t_1 and t_2 are the closest points in time with available values before and after the gap, respectively.

This approach preserves temporal structure and avoids distortion of dynamic patterns in environmental variables.

For categorical variables (e.g., *municipality_type*), mode imputation is applied within the cell or globally across the sample, formally defined as:

$$\widetilde{c}_i = \begin{cases} c_i, & c_i \neq \varnothing, \\ \text{mode}\{c_k : k \in g,\ c_k \neq \varnothing\}, & c_i = \varnothing. \end{cases}, \tag{8}$$

A separate rule was introduced to check for «structural gaps» when the absence of a value is an informative sign (for example, no sensor signal on a certain day). In such cases, a binary indicator of absence $\delta(x)$ was formed, allowing the model to consider the fact of measurement unavailability without distorting the main value:

$$\delta(x_i) = \begin{cases} 1, & x_i = \varnothing, \\ 0, & x_i \neq \varnothing. \end{cases}, \tag{9}$$

After imputation, the data were brought to a consistent scale by normalization. Because the dataset includes heterogeneous variables expressed in different measurement units, such as tons, kilometers, ppm values, indices, and fractional coefficients, normalization was applied to ensure feature comparability and consistency in entropy-based weighting and integrated risk index formulation. For features that have natural lower and upper limits or need to be unified to the interval [0, 1], min-max normalization was applied:

$$x^{(norm)} = \frac{x - \min(x)}{\max(x) - \min(x)}, \tag{10}$$

where x—original value of the feature; $\min(x)$—minimum value of the feature within the dataset; $\max(x)$—maximum value of the feature within the dataset; and $x^{(norm)}$—normalized feature value transformed to the interval [0, 1].

This ensures comparability of heterogeneous variables and supports their integration into a unified analytical framework.

To reduce the influence of extreme values, fissurization at the 1% and 99% levels was applied. As a result, the cleaning and imputation stage ensured the formation of a consistent array X^*, suitable for subsequent standardization, orthogonalization, and relevance assessment procedures in the context of risk-informed digital management of organic waste streams.

3.3.2. Standardization and Dimensional Transformation

After forming the cleaned array, X^* the procedure of standardization and orthogonalization of features was performed in order to eliminate large-scale heterogeneity and reduce multicollinearity between variables. This step is essential for improving model stability and ensuring the robustness of predictive algorithms applied in subsequent stages. This stage is critical for building an integral risk index and further using ensemble algorithms that are sensitive to factor correlation.

In the first step, Z-score standardization was applied, which brings each feature to a zero mean and a standard deviation of one. For an arbitrary feature, the standardized value x_j is defined as:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \tag{11}$$

where z_{ij}—the standardized value of the j-th feature for the i-th observation; x_{ij}—the original value of the j-th feature for the i-th observation; μ_j—is the sample mean; and σ_j—is the standard deviation of the j-th feature.

As a result, a standardized matrix Z is formed:

$$Z = \{z_{ij}\}, \tag{12}$$

The resulting matrix (12) has zero means and the same scale for all variables. This standardization ensures the comparability of heterogeneous variables and reduces the influence of differences in measurement scales.

The next stage involves the orthogonalization of the feature space using Principal Component Analysis (PCA). The goal is to transition from a correlated feature space to a system of uncorrelated latent components. This transformation improves computational efficiency and enhances the interpretability of the underlying data structure. Let Σ be the covariance matrix of standardized features Z. The solution to the spectral decomposition problem is as follows:

$$\Sigma v_k = \lambda_k \cdot v_k\ , \tag{13}$$

where Σ—the covariance matrix of standardized features; λ_k—the k-th eigenvalue of the covariance matrix; and v_k—the eigenvector corresponding to eigenvalue λ_k.

Equation (13) allows us to obtain eigenvectors v_k and eigenvalues λ_k, which determine the directions of maximum dispersion. The principal components Y are formed as:

$$Y = Z \cdot V, \tag{14}$$

where V—is the matrix of selected eigenvectors.

The study retains principal components that explain at least 85–90% of the total variance, ensuring an optimal balance between dimensionality reduction and information preservation, while maintaining the stability and interpretability of subsequent predictive models. In practice, this means compressing the multidimensional feature space into a compact latent subspace, which is used to form the Risk Index and make further predictions. Table 3 presents the sequential stages of the preprocessing framework together with the corresponding mathematical formulations.

Table 3. Stages of data processing.

No.	Stage	Mathematical Framework	Purpose	Result
1	Data Cleaning	Filtering, imputation	Elimination of anomalies and missing values	Cleaned dataset X^*
2	Standardization	Z-score (11)	Removal of scale heterogeneity	Standardized variables Z
3	Covariance Analysis	Covariance estimation $\Sigma = \frac{1}{n-1} Z^T Z$	Assessment of correlation structure	Covariance matrix
4	PCA	Spectral decomposition (13)	Orthogonalization of features	Latent components
5	Component Selection	Variance threshold ($\geq$85%)	Dimensionality reduction	Compact factor space

Table 3 demonstrates a structured transformation from raw heterogeneous data to a compact and analytically consistent feature space. This pipeline integrates data cleaning, normalization, decorrelation, and dimensionality reduction, ensuring the reliability and stability of subsequent risk modeling and predictive analysis within the proposed data-driven framework.

3.4. Entropy-Based Feature Relevance Assessment

To assess the contribution of individual features to the formation of the risk profile, an entropy-based analytical approach was employed. Unlike correlation methods, entropy assessment allows for the uncertainty of feature distribution and their contribution to reducing information uncertainty regarding the integral risk index. Unlike expert-based weighting schemes commonly used in MCDM approaches, the entropy-based method provides a fully data-driven and objective mechanism for feature relevance assessment.

For a discrete feature X_j, entropy is defined as:

$$H(X_j) = -\sum_{i=1}^{k} p_{ij} \log_2 p_{ij}, \tag{15}$$

where p_{ij}—is the probability of a feature value falling into the i-th interval; and k—is the number of intervals.

A high entropy value corresponds to greater uncertainty in the distribution, while a low value corresponds to a concentration of values in a narrow range. In the context of risk modeling, features with higher informational variability are considered more influential for capturing system dynamics. To quantify the contribution of each feature to reducing uncertainty in the risk modeling process, the information gain metric $IG(X_j)$ was introduced. To ensure comparability among features, the information gain values were normalized as follows:

$$w_j = \frac{IG(X_j)}{\sum_{j=1}^{m} IG(X_j)}, \tag{16}$$

where $IG(X_j)$—is the information gain of the j-th feature X_j; and m—is the total number of features included in the analysis.

In Expression (16), $IG(X_j)$ represents the information gain associated with feature X_j and reflects the reduction in uncertainty achieved by including this feature in the risk modeling process. The denominator represents the total information gain across all considered features. Therefore, Expression (16) converts the individual information gain values into normalized feature importance scores, which can be further used in the construction of the integrated risk index.

The resulting entropy-based weights define a data-driven hierarchy of factors influencing the risk profile, enabling the reduction in subjectivity during feature selection and improving the robustness of subsequent modeling. This approach ensures that the integrated risk index and predictive models are constructed on the most informative and dynamically relevant variables within the municipal waste management system.

3.5. Risk Index Formulation

Within the proposed data-driven digital framework, the integrated risk index (Risk Index, RI) is considered as a generalized measure of the potential instability of the organic waste management system at a specific point in space and time. Conceptually, the index integrates social load, infrastructure capacity, environmental parameters, and time factors into a single dimensionless scale [0, 1]. Unlike conventional risk indicators, the proposed index integrates heterogeneous variables into a unified analytical construct, enabling the treatment of risk as a predictive and manageable variable within a data-driven framework.

Let Z_j be the standardized features after the processing stage (Section 3.3), and w_j their weights, determined on the basis of entropy relevance (Section 3.4). The basic formalization of the index RI takes the form of a weighted additive model:

$$RI_i = \sum_{j=1}^{m} w_j Z_{ij}, \tag{17}$$

where i—observation number; and m—number of selected features.

This formulation ensures interpretability of the index and allows the contribution of each feature to the overall risk level to be explicitly quantified.

Given the need for interpretation and comparability of results, the obtained value is normalized to the interval [0, 1] according to the min-max scheme:

$$RI_i^* = \frac{RI_i - \min(RI)}{\max(RI) - \min(RI)}, \tag{18}$$

Thus, $RI_i^* \in [0, 1]$, where values close to 0 correspond to a low level of risk, and values close to 1 correspond to an increased risk concentration. This normalization enables consistent comparison of risk levels across spatial units and temporal intervals.

The general logic of aggregation corresponds to the principle of risk-oriented management. In particular, social and infrastructure variables form the potential load on the system,

https://doi.org/10.3390/su18125862

environmental variables form the sensitivity of the environment, and time variables form the seasonal modification of the impact. Formally, the aggregation structure is described as follows:

$$RI = f(Z_{soc}, Z_{spat}, Z_{env}, Z_{time}), \tag{19}$$

where $f(\cdot)$—is a function implemented through a weighted linear combination of standardized factors.

This structure reflects the multidimensional nature of the system, where risk emerges because of interactions between social pressure, infrastructure capacity, environmental sensitivity, and temporal variability.

The proposed approach ensures transparency of computation and facilitates seamless integration into DSS. The interpretation of the integral risk index is further enhanced through its mapping onto discrete categories, which support operational decision-making and enable the practical application of the model in municipal waste management (Table 4).

Table 4. Interpretation of the integral risk index scale.

Risk Index Interval	Risk Category	Recommended Management Actions
0.00–0.25	Low	System operates under stable conditions; routine monitoring and standard management practices are enough.
0.25–0.50	Moderate	Increasing system pressure; enhanced monitoring and trend analysis are recommended.
0.50–0.75	High	Elevated risk level requiring the implementation of preventive and mitigation measures.
0.75–1.00	Critical	Severe risk conditions; immediate and priority management intervention is required.

To support practical interpretation of the integrated risk index (RI), four risk categories were introduced based on normalized threshold intervals: low risk (RI < 0.25), medium risk (0.25 ≤ RI < 0.50), high risk (0.50 ≤ RI < 0.75), and critical risk (RI ≥ 0.75). The threshold values were selected according to a quartile-based partitioning of the normalized risk scale [0, 1], which enables consistent interpretation of increasing system instability levels and facilitates decision-making within the proposed risk-oriented management framework. Such threshold-based categorization provides an interpretable transition between operationally acceptable conditions and critically unstable system states requiring immediate management intervention.

The proposed scale (Table 4) transforms the risk index into an operational tool, enabling prioritization of resources, planning of waste collection logistics, and implementation of preventive management actions. A sensitivity analysis of the adopted risk thresholds was additionally performed by varying the interval boundaries within ±0.05 of the baseline values. The analysis demonstrated that the overall distribution of municipalities across the defined risk categories remained stable, confirming the robustness of the proposed threshold configuration for practical risk-oriented decision support.

Figure 4 illustrates the integrated process of risk index RI formation within the proposed framework. The pipeline includes data standardization, entropy-based weighting, aggregation into a raw risk score, and normalization to a unified scale. The resulting index is directly integrated into the DSS, where it enables real-time monitoring, early warning generation, and proactive planning of waste management operations.

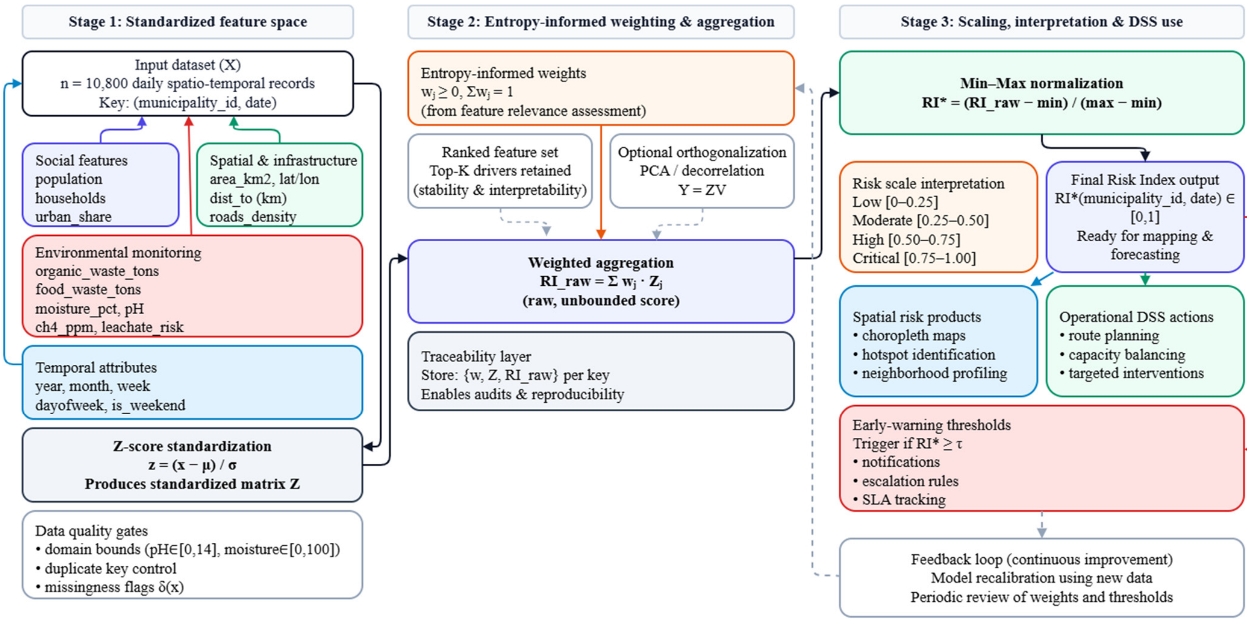


Figure 4. Risk Index formation scheme: transformation of the input dataset X into standardized features Z, weighted aggregation into RI_raw, normalization into RI*, and integration into decision support through threshold-based alert mechanisms (τ).

3.6. Ensemble-Based Predictive Analytics for Municipal Risk Forecasting

The forecasting unit is implemented as an integrated ensemble module that combines two conceptually different approaches (bagging (Random Forest (RF)) and boosting (Gradient Boosting (GB)/XGBoost)) within a single municipal data processing architecture. The input basis is a model matrix that includes socio-demographic, infrastructure, environmental, and time indicators, while the target variable is a normalized integral risk index. This structure allows predictive analytics to be directly linked to the pre-formed Risk Index, which is the central element of the study. The selection of ensemble learning methods is justified by their ability to capture complex nonlinear relationships, handle heterogeneous data, and provide robust predictions under conditions of uncertainty typical for municipal systems. The combination of bagging and boosting approaches ensures a balance between variance reduction and bias minimization, improving the overall predictive performance of the model.

Within the bagging approach, the ensemble of trees is formed in parallel on data subsamples, and the final forecast is determined as their average. This ensures reduced dispersion and high noise resistance, which is especially important for municipal environmental indicators with varying observation quality. In contrast, the boosting model builds a sequence of weak regressors that learn from the residuals of previous steps, which reduces bias and better reflects the nonlinear effects of seasonality, threshold loads, and interactions between indicators.

The architecture shown in Figure 5 demonstrates a symmetrical structure of two ensemble branches with subsequent comparison of results. A distinctive feature of the model is the use of a unified train/test split combined with cross-validation to ensure the stability of performance metrics, as well as the inclusion of a diagnostic layer for assessing the consistency of predictions across approaches. A key novelty of the proposed framework lies in the integration of predictive models with the previously defined risk index, enabling direct interpretation of forecasting results within a risk-oriented management context. Thus, the final model is selected not only based on predictive accuracy, but also considering generalization performance and robustness under varying data conditions.

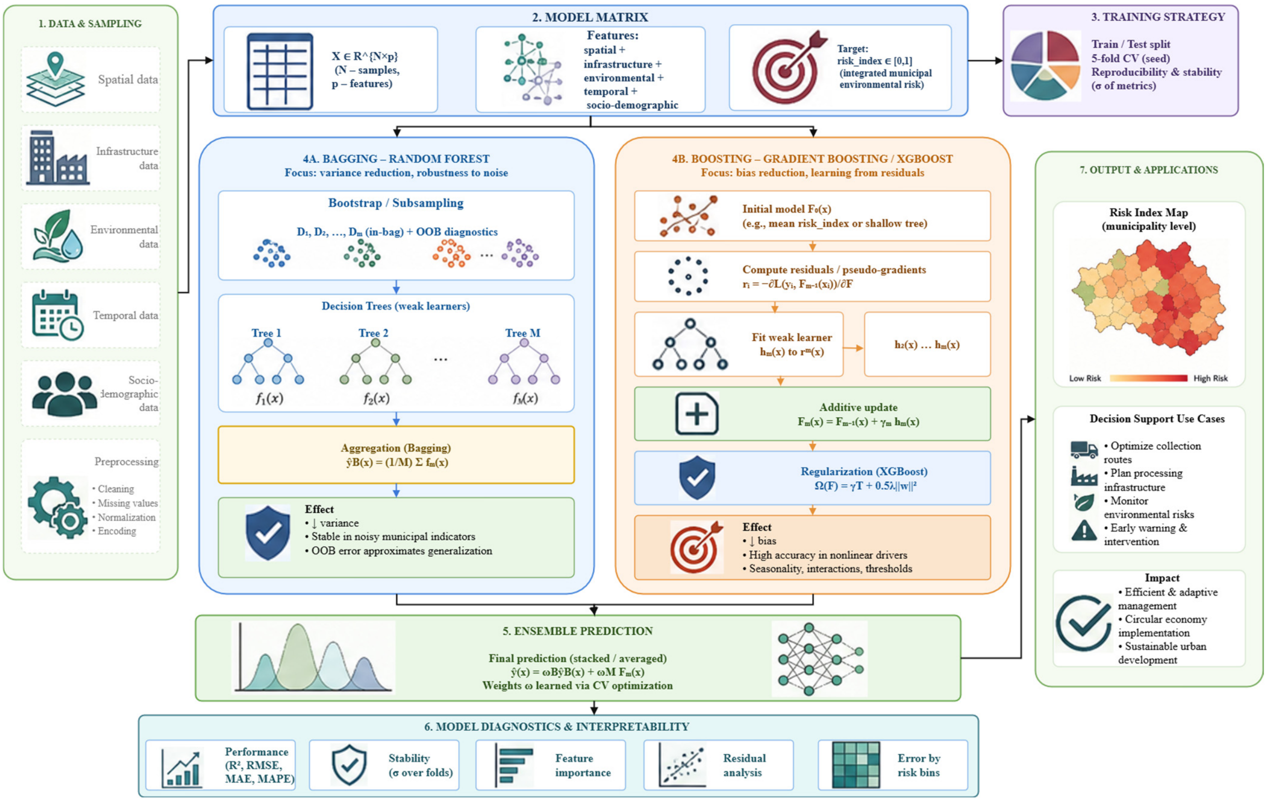


Figure 5. Ensemble learning architecture for predicting the municipal environmental risk index: integration of bagging (RF) and boosting (GB/XGBoost) models within a unified analytical framework.

From a practical perspective, the predicted risk index is directly integrated into the municipal DSS as a dynamic analytical layer. This enables the transition from static risk assessment to predictive and proactive management, supporting early warning mechanisms, adaptive planning, and resource optimization in organic waste management.

3.7. Implementation Environment and DSS Integration

The proposed digital framework was implemented in Python 3.11 using Pandas 2.2.2 and NumPy 1.26.4 libraries for data processing, Scikit-learn 1.4.2 for ensemble model implementation, and GeoPandas 1.0.1 and matplotlib 3.8.4 and folium 0.16.0 for spatial risk visualization. This stack ensures compatibility with municipal open data, scalability, and integration with geoinformation services. The selected technology stack ensures flexibility, scalability, and compatibility with heterogeneous municipal data sources, supporting the deployment of the framework in real-world urban environments. The computational process is organized as a sequential pipeline including data preparation, Risk Index formation, predictive modeling, spatial–temporal aggregation, and integration of results into the DSS.

Integration with the municipal DSS is implemented through an API module, which provides automatic updating of the predicted risk index RI_i^* in periodic synchronization mode. In the management system, the indicator is used as an analytical layer for monitoring risk areas, forming warning triggers, and supporting operational planning (waste collection logistics, capacity balancing, targeted interventions). Thus, predictive analytics is directly linked to management decisions. This integration enables real-time updating of risk indicators and supports continuous monitoring and adaptive management.

An important feature of the implementation environment is the reproducibility of results. This is ensured through version control of libraries, recording random seeds in model training procedures, and documentation of experimental configurations. Computational workflows are implemented as structured notebooks and scripts, enabling full reproducibility of the analytical pipeline from raw data processing to risk index generation and DSS integration (Figure 6).

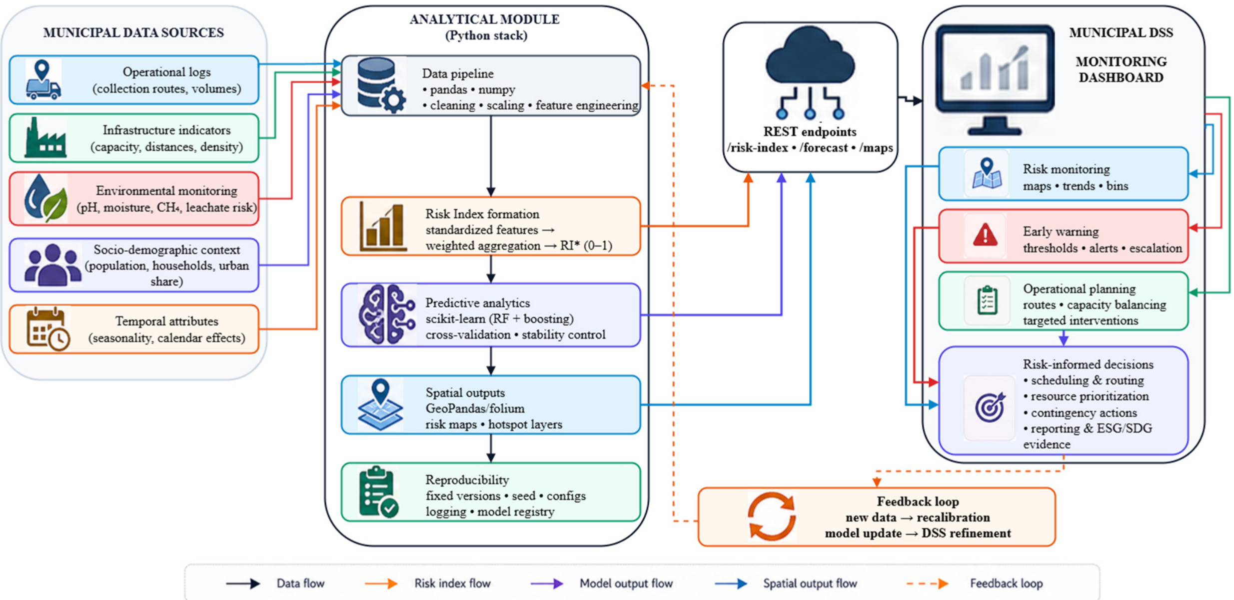


Figure 6. Architecture of integration of the data-driven risk analytics framework into the municipal DSS, including data processing, predictive modeling, and operational decision layers.

The presented DSS architecture reflects the practical implementation of a data-driven digital structure for risk-based municipal organic waste management. It provides for the transformation of city data into a forecast-oriented tool for organic waste management at the municipal level. The system combines a multi-source array of municipal data with an analytical module (Risk Index formation and forecasting), after which the results are transferred via the API level to the DSS monitoring panel. This integration ensures a seamless transition from data collection to management decision-making—enabling monitoring of risk areas, early warning, and operational planning in the field of organic waste. The feedback mechanism forms a closed cycle of «data–analysis–decision–update» which corresponds to the concept of risk-oriented digital organic waste management and enhances the adaptability of the municipal management system in a dynamic urban environment.

4. Results

4.1. Descriptive Dynamics of Municipal Organic Waste Indicators

The descriptive analysis of the multifactorial dataset provides an initial understanding of the variability and structural characteristics of the municipal organic waste management system. The statistical summary (Table 5) highlights significant heterogeneity across socio-demographic, spatial, and waste generation variables, which justifies the use of a data-driven and multivariate modeling approach. Socio-demographic indicators exhibit substantial variability, reflecting differences in population size, household structure, and urbanization levels across spatial units.

Table 5 highlights the pronounced spatial and structural heterogeneity characterizing the municipal organic waste management system. Such variability creates conditions for nonlinear interactions between variables and directly influences the formation of environmental risks, reinforcing the need for integrated analytical modeling.

Spatial and environmental variables further reflect the heterogeneity of the study area, including differences in infrastructure accessibility, environmental conditions, and waste-related parameters. In particular, variability in methane concentration and waste generation indicates the presence of localized zones with increased environmental pressure.

Table 5. Descriptive statistics of socio-economic, spatial and waste generation variables used in the modelling framework.

Variable	N	Mean	SD	Min	Q1	Median	Q3	Max
Socio-economic variables								
Population	10,800	118,767.4	57,238.13	21,111	77,426.75	120,613	167,387	213,905
Households	10,800	46,382.45	23,120.44	7423	28,405.25	47,759	64,130	90,962
Income index	10,800	0.941	0.250	0.611	0.721	0.821	1.162	1.377
Tourism index	10,800	0.513	0.292	0.025	0.265	0.568	0.721	0.956
Urban share	10,800	0.503	0.226	0.128	0.301	0.555	0.710	0.815
Spatial and infrastructure variables								
Area (km^2)	10,800	207.25	99.36	20.96	129.73	241.67	285.63	334.34
Latitude	10,800	49.0447	0.65	48.0568	48.5067	49.0186	49.6563	50.1335
Longitude	10,800	24.5491	1.49	22.4383	23.3532	24.2388	25.6618	26.8459
Distance to regional center (km)	10,800	123.84	46.15	44.60	89.85	125.38	151.83	213.12
Distance to water bodies (km)	10,800	7.81	4.24	0.94	3.69	8.10	10.84	15.45
Distance to residential areas (km)	10,800	4.77	2.74	0.27	3.19	4.87	5.86	9.59
Road density (km/km^2)	10,800	2.80	1.10	0.97	1.85	2.71	3.77	4.47
Waste generation variables								
Organic waste (tons)	10,800	11.44	6.54	1.01	7.06	10.05	15.22	93.91
Food waste (tons)	10,800	10.04	5.44	0.90	6.23	8.91	13.52	26.56
Green waste (tons)	10,800	1.30	0.78	0.10	0.74	1.12	1.78	4.08

Temporal variables capture seasonal and behavioral patterns, enabling the analysis of dynamic changes in waste generation and associated environmental risks.

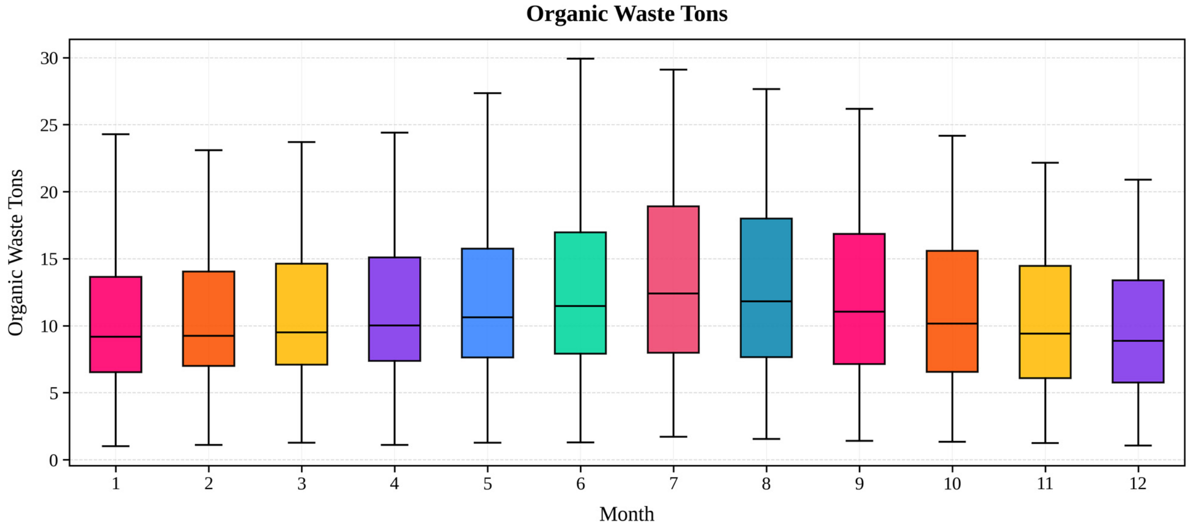
To analyze the temporal dynamics of the municipal organic waste management system, seasonal variability of key indicators was studied, including organic waste volumes, methane concentration, and the integral environmental risk index. Based on the aggregation of monthly data, distributions of indicators were formed, allowing for the assessment of both average values and parameter variability within the year.

To analyze temporal dynamics, key indicators–including organic waste volumes, methane concentration, and the integrated risk index–were aggregated at the monthly level. Figure 7 presents their seasonal distributions using boxplot visualization, which captures median values, interquartile ranges, and extreme observations across different months of the year.

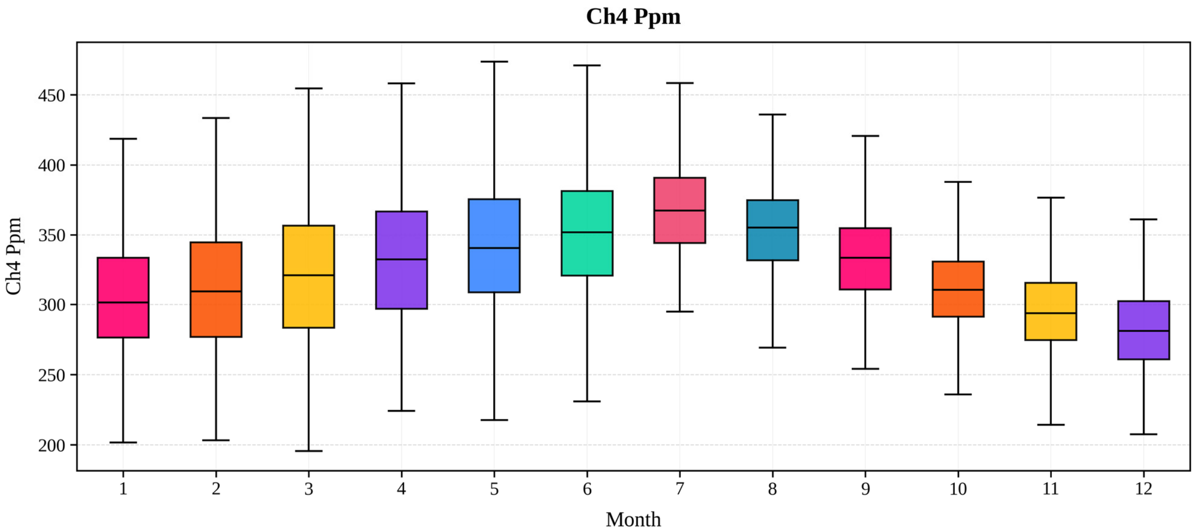
The results reveal pronounced seasonal variability across all key indicators (Figure 7). Organic waste volumes increase significantly during the summer period, reflecting higher consumption patterns and intensified biological waste generation. This seasonal growth leads to increased pressure on collection and processing infrastructure.

A similar pattern is observed for methane concentration, indicating enhanced anaerobic activity under higher temperature conditions. The alignment of waste volumes and CH_4 levels suggests a strong coupling between waste generation and environmental impact processes.

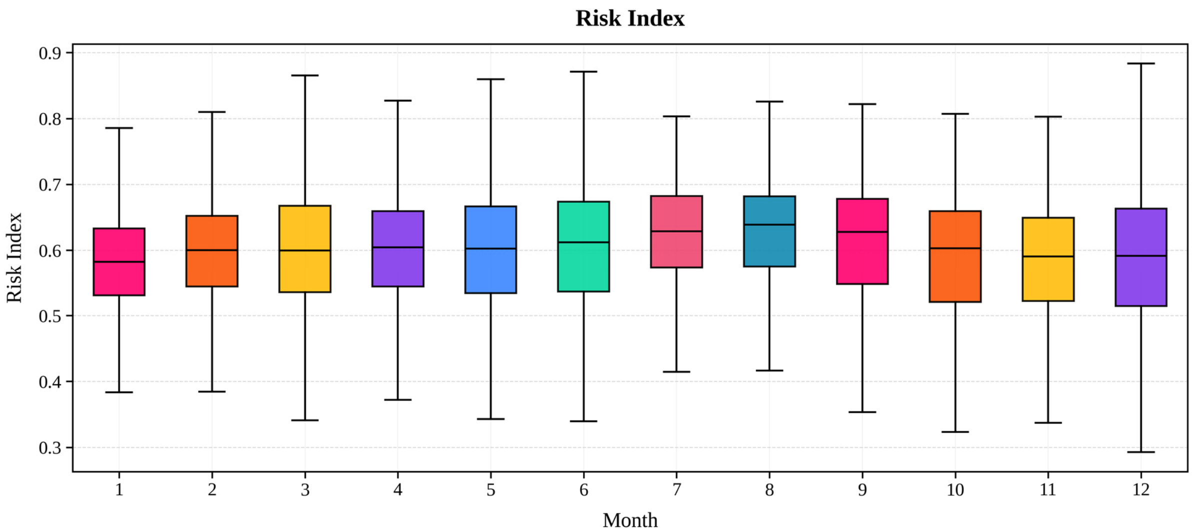
https://doi.org/10.3390/su18125862



(a)



(b)



(c)

Figure 7. Seasonal variability of key indicators of the organic waste management system: (**a**) organic waste volumes; (**b**) methane concentration (CH_4, ppm); (**c**) environmental risk index.

The integrated risk index exhibits consistent seasonal behavior, with peak values observed during periods of maximum system load. This confirms the validity of the proposed risk formulation and demonstrates its sensitivity to both operational and environmental factors.

Overall, the results demonstrate that the municipal organic waste management system is characterized by significant seasonal variability, leading to temporal concentrations of environmental risks. This confirms the necessity of integrating predictive analytics and data-driven tools for the early identification of risk periods and for supporting proactive and adaptive municipal management.

4.2. Entropy-Based Feature Relevance Results

To determine the informativeness of factors influencing environmental risks in the municipal organic waste management system, an entropy-based approach using mutual information was applied. This method quantifies the dependence between individual features and the target variable (the integrated risk index), enabling the ranking of predictors according to their contribution to explaining risk variability.

Figure 8 presents the distribution of feature relevance scores based on mutual information. The results indicate that socio-economic and spatial characteristics–such as tourism_index, income_index, area_km^2, and spatial coordinates–exhibit the highest explanatory power. Infrastructure-related variables, including road network density and treatment capacity, also demonstrate significant influence. Additionally, lagged variables (e.g., organic_waste_tons_lag_1 and lag_7) confirm the presence of temporal inertia in waste generation processes.

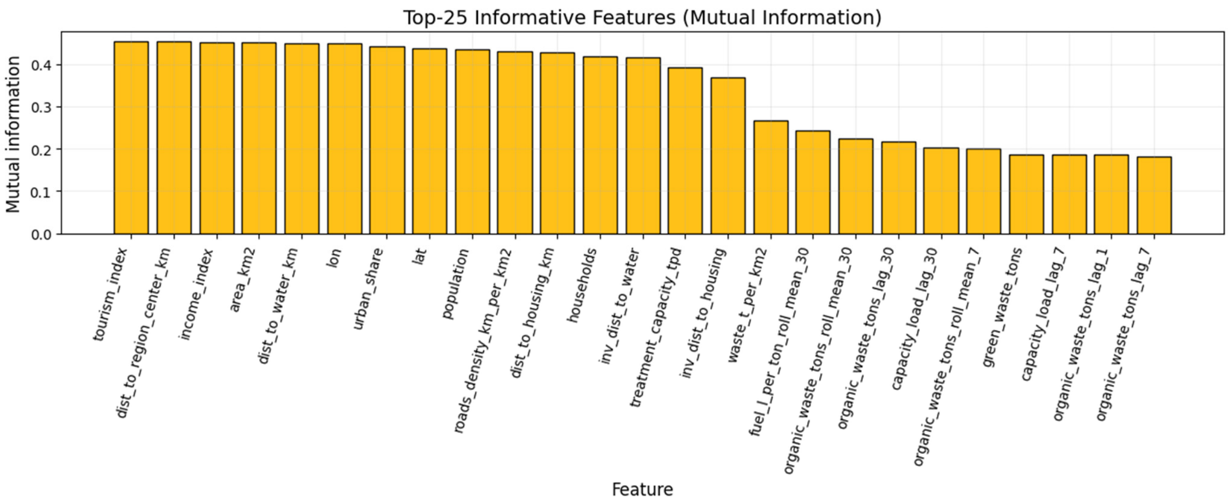


Figure 8. Distribution of feature relevance scores based on mutual information.

The significance of lag-based predictors additionally confirms the presence of temporal dependence and seasonal inertia within the municipal organic waste generation process. This demonstrates that the proposed feature-engineering strategy partially captures sequential dynamics within the ensemble-learning framework.

These findings highlight the multidimensional nature of environmental risk formation and confirm the importance of integrating heterogeneous predictors in the modeling framework.

Table 6 summarizes the sequential stages of constructing the model matrix used for predictive risk modeling within the proposed framework.

Table 6. Stages of forming a model matrix for a hybrid data-driven organic waste management system.

Stage	Input	Output
Load dataset	municipal_organic_waste_multifactor_dataset.csv	df_raw
EDA & quality checks	raw data	figures + diagnostics
Feature engineering	raw + derived ratios + lags + rolling	df (expanded feature set)
Outlier handling (soft IQR)	numeric features	winsorized df
Missing value imputation	numeric & categorical features	cleaned df
Encoding & scaling	X (num + cat)	X_matrix
Model matrix export (no leakage)	X_matrix + risk_index	model_matrix.csv

Table 6 summarizes the structured pipeline for forming the model matrix, including exploratory analysis, feature engineering, outlier handling, imputation, and feature transformation. The final dataset is constructed without target leakage, ensuring the validity and reliability of subsequent predictive modeling.

4.3. Risk Index Dynamics and Seasonal Patterns

For integrated assessment of environmental risks, the proposed Risk Index was applied to capture spatial, socio-economic, and infrastructural factors within a unified framework. The index enables dynamic evaluation of risk levels and identification of temporal patterns in the waste management system.

Analysis of the distribution of risk_index values (Figure 9) shows a near-normal distribution with a center in the range of 0.58–0.62. The bulk of observations are concentrated in the interval 0.50–0.70, which characterizes a moderate level of environmental risk for most municipalities. The presence of a right tail of the distribution with values above 0.80 indicates the existence of individual periods of increased risk, which may be associated with seasonal loads on the organic waste management system or local infrastructure constraints.

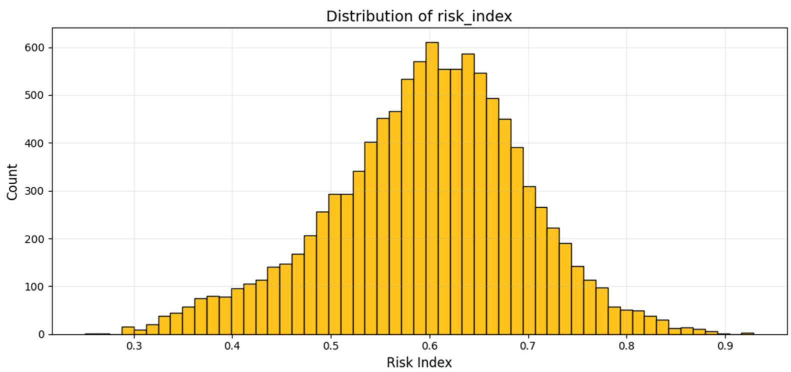


Figure 9. Distribution of the municipal environmental risk index (risk_index).

The temporal dynamics of the Risk Index (Figure 10) reveal pronounced seasonal fluctuations, with higher values observed during the summer–autumn period and lower levels during winter. This pattern reflects increased biological activity and waste generation in warmer periods.

Comparative analysis across municipalities indicates heterogeneous risk trajectories. Some areas exhibit increasing trends, suggesting accumulation of systemic constraints, while others demonstrate stable or declining patterns, reflecting more efficient waste management practices or better infrastructure conditions.

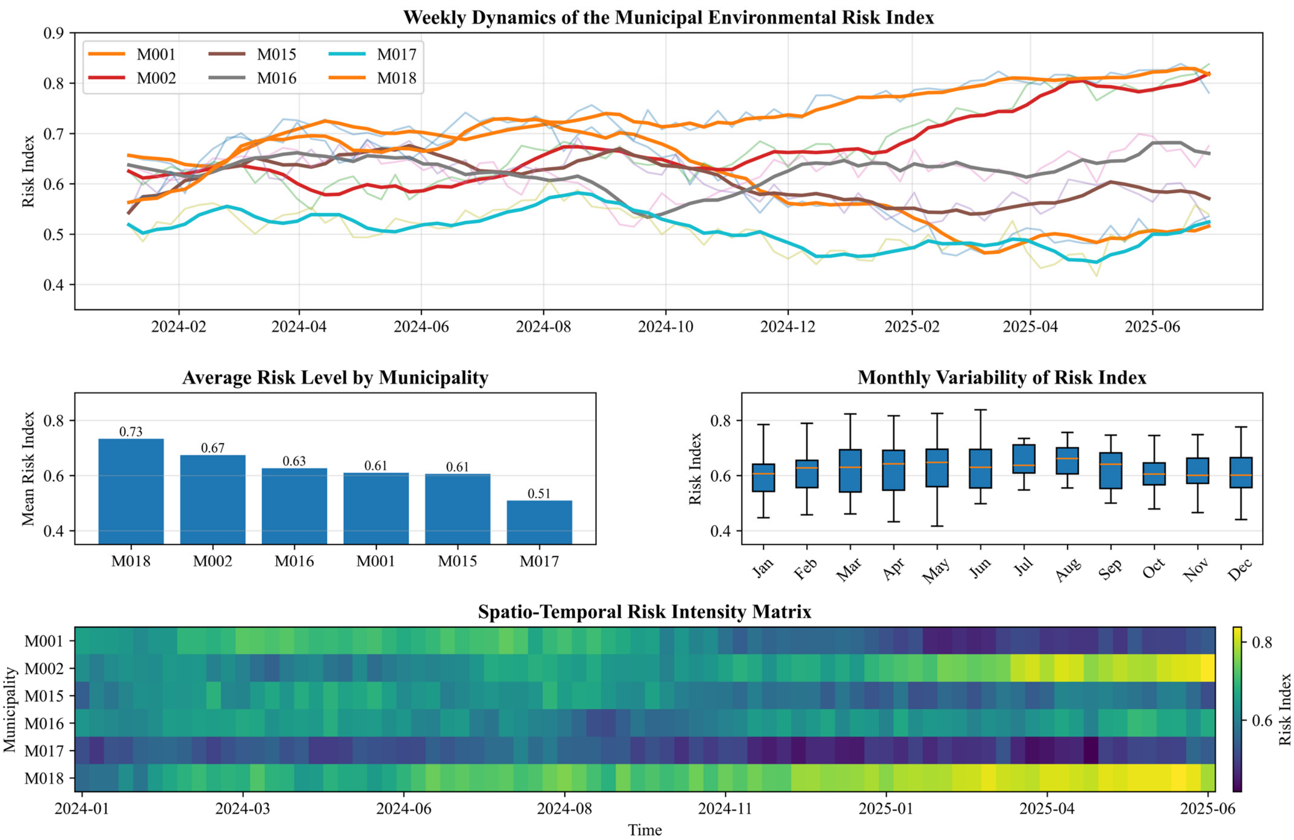


Figure 10. Temporal, statistical, and spatio-temporal analysis of the municipal environmental Risk Index: weekly dynamics, average risk levels, monthly variability, and risk intensity matrix.

The results confirm the effectiveness of the proposed Risk Index as an integrated tool for monitoring and forecasting environmental risks in municipal waste management systems. Its application enables timely identification of high-risk periods and supports the development of proactive and adaptive management strategies.

4.4. Spatial Differentiation of Municipal Risk Levels

Spatial analysis of the Risk Index enables the identification of territorial patterns of environmental risk in municipal organic waste management systems. By integrating geographic, infrastructural, and socio-economic variables, the proposed framework supports spatial interpretation of risk formation and highlights areas of potential system vulnerability.

For spatial differentiation, risk_index values were aggregated at the municipal level and visualized using a geospatial mapping approach (Figure 11).

The spatial distribution of the Risk Index reveals pronounced territorial variability, reflecting the influence of demographic, infrastructural, and environmental factors. Distinct clusters of elevated risk indicate localized pressure on municipal waste management systems. High-risk municipalities are typically associated with higher population density, increased volumes of organic waste generation, and intensified economic activity, including tourism. In contrast, lower-risk areas exhibit more balanced infrastructure conditions, reduced demographic pressure, and lower waste generation intensity.

These findings confirm that spatial heterogeneity is a key determinant of environmental risk formation and demonstrate the applicability of the proposed Risk Index for identifying priority intervention zones. The integration of spatial analytics into the framework supports risk-informed decision-making, including infrastructure planning, resource allocation, and the development of targeted environmental policies at the municipal level.

https://doi.org/10.3390/su18125862

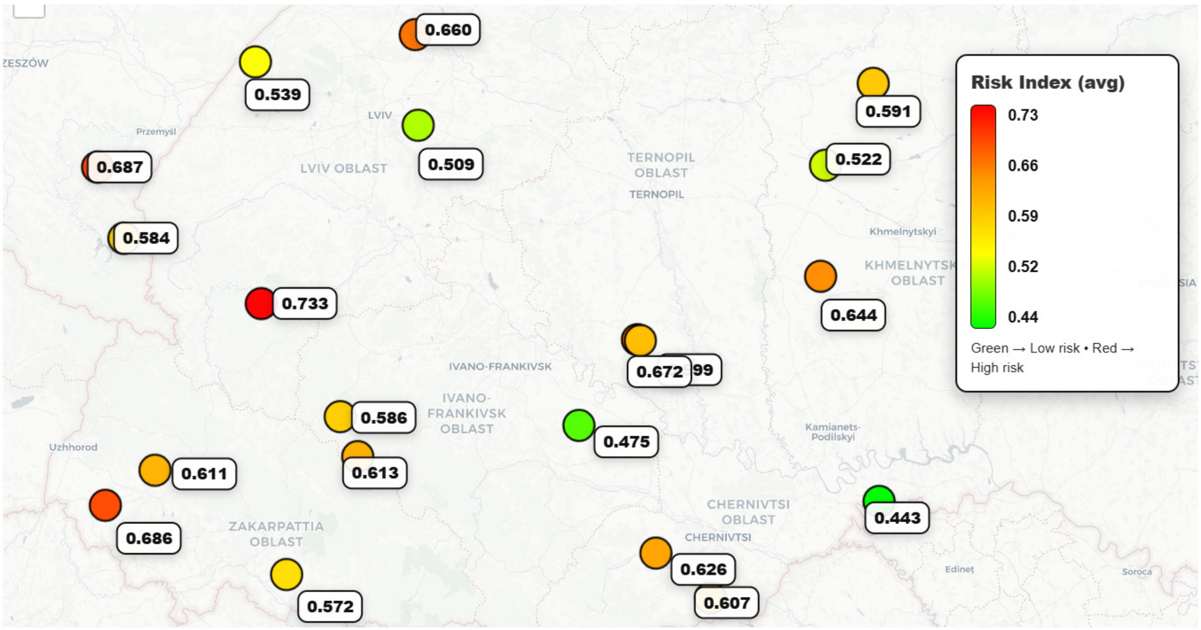


Figure 11. Spatial distribution of the integrated Risk Index across municipalities, highlighting zones of low, moderate, and high environmental risk.

4.5. Predictive Performance of the Analytical Framework

Predictive modeling of the environmental risk index was implemented in Python using ensemble learning methods, including RF, GB, and XGBoost. The models were evaluated using 5-fold cross-validation to ensure robustness and reliability of predictions. Table 7 presents the comparative predictive performance of the evaluated ensemble learning models across the selected accuracy metrics.

Table 7. Predictive performance metrics of the risk forecasting model.

Model	R^2_Mean	RMSE_Mean	MAE_Mean	MAPE_Mean
RandomForest	0.891	0.0403	0.0320	0.0552
XGBoost	0.819	0.0418	0.0332	0.0573
GradientBoosting	0.776	0.0465	0.0368	0.0640

It has been established that ensemble methods have an advantage, in particular the RandomForest model, which showed the highest coefficient of determination (R^2 = 0.891) and the lowest error values (RMSE = 0.0403; MAE = 0.0320). This indicates the model's high ability to reproduce nonlinear relationships between the spatial, socioeconomic, and infrastructural characteristics of municipalities.

A graphical comparison of actual and predicted risk index values is presented in Figure 12.

Most of the points in Figure 12 are concentrated along the diagonal line, indicating a high degree of consistency between the forecasts and the actual risk indicator values and confirming the adequacy of the constructed model for municipal environmental analysis tasks.

The results demonstrate the superiority of ensemble methods, with the RF model achieving the highest predictive performance (R^2 = 0.891) and the lowest error metrics (RMSE = 0.0403; MAE = 0.0320). This indicates its strong ability to capture nonlinear relationships and complex interactions between spatial, socio-economic, and infrastructural variables.

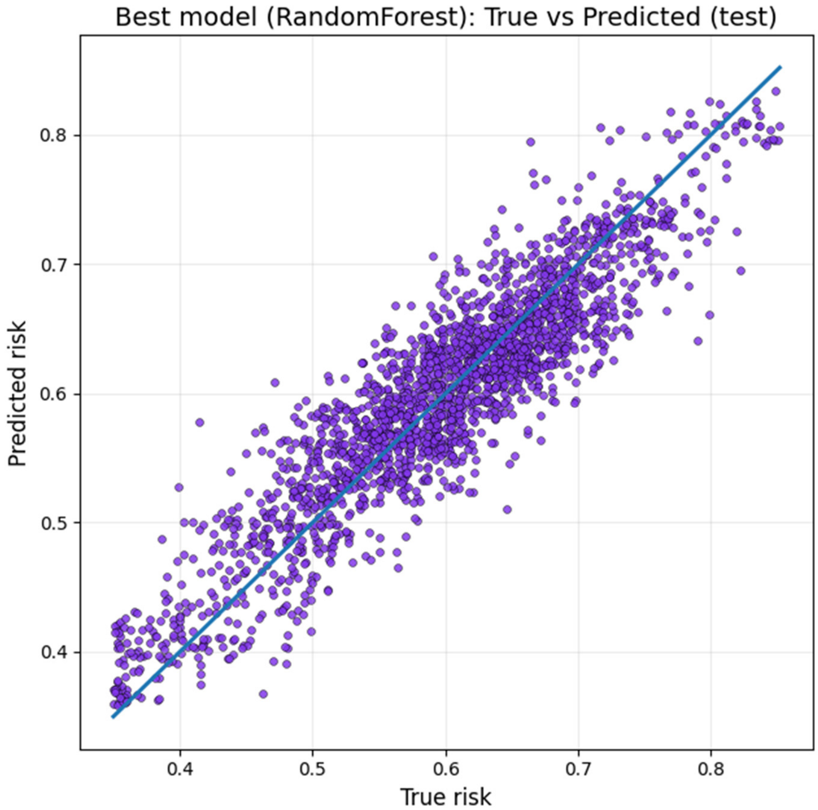


Figure 12. Predicted versus observed values of the environmental Risk Index using the RF model.

In comparison, boosting-based models (XGBoost and GB) demonstrate slightly lower performance, which may be attributed to their sensitivity to data variability and parameter tuning in heterogeneous municipal datasets.

The results confirm that the integration of ensemble learning models into the proposed data-driven framework provides a robust and reliable basis for environmental risk forecasting. This enables early identification of high-risk conditions and supports the development of proactive and adaptive management strategies in municipal organic waste systems.

4.6. Recommendations for Integrating Digital Risk Analytics into the Municipal Decision Support System (DSS)

The results demonstrate the practical feasibility of integrating data-driven risk analytics into municipal DSS for organic waste management. The proposed framework, which combines data integration, feature engineering, risk index formulation, and machine learning–based forecasting, can be deployed as an analytical module within a DSS. Its implementation enables a transition from reactive management to risk-informed governance, where infrastructure planning and operational decisions are guided by predictive assessments of environmental risk (Table 8).

The integration of data-driven analytics into the DSS establishes a structured link between data processing, risk assessment, and decision-making processes. By combining risk index monitoring, predictive modeling, spatial analysis, and scenario evaluation, the system enables a coordinated and proactive management approach to organic waste flows. This integration transforms the DSS from a passive information system into an active decision-support tool capable of responding to dynamic changes in the municipal environment.

Overall, the integration of digital risk analytics into municipal DSSs provides a foundation for data-driven and risk-informed management of organic waste systems. This contributes to improved environmental policy effectiveness, optimized infrastructure planning, and the advancement of circular economy principles in urban communities.

Table 8. Integration of risk-informed analytics within the DSS for municipal organic waste management.

DSS Component	Analytical Implementation	Decision-Making Implication
Data integration	Integration of socio-demographic, infrastructural and geospatial indicators within a unified municipal data platform	Establishes a comprehensive information base for waste management governance
Risk index assessment	Application of an integrated Risk Index for monitoring the state of the organic waste management system	Enables identification of territories with increased environmental pressure
Risk forecasting	Machine learning-based prediction of risk indicators using the RF model	Provides early warning of potential environmental risks
Spatial analytics	GIS-based visualization of risk levels across municipal territories	Supports spatial planning and infrastructure allocation
Scenario analysis	Evaluation of alternative waste management strategies within the DSS environment	Improves effectiveness of strategic planning and policy decisions

5. Discussion

5.1. Spatial and Temporal Patterns of Environmental Risk in Municipal Organic Waste Management Systems

The results reveal pronounced spatial and temporal variability in environmental risk levels associated with municipal organic waste management systems. The constructed Risk Index captures both seasonal fluctuations and spatial clustering of elevated risk, indicating that risk formation is inherently heterogeneous across territories and time. Higher risk levels are observed in municipalities characterized by greater population density, intensified tourism activity, and reduced accessibility to regional centers. This suggests that demographic pressure, economic intensity, and infrastructural constraints are key drivers of environmental vulnerability in organic waste systems.

These findings are consistent with previous studies, which highlight that environmental risks in urban waste management systems are spatially uneven due to differences in infrastructure availability, service efficiency, and socio-economic conditions [66,67]. Similar spatial disparities have been reported in European contexts, where peripheral and infrastructure-limited areas tend to experience higher environmental stress due to logistical inefficiencies and insufficient treatment capacity [57].

The temporal analysis further demonstrates clear seasonal patterns in the Risk Index, driven by fluctuations in organic waste generation. Peak risk levels during summer and early autumn are associated with increased consumption, tourism activity, and biological waste decomposition processes. These results align with existing research showing that organic waste streams exhibit strong seasonality and are closely linked to socio-economic and behavioral dynamics [68].

Overall, the identified spatial and temporal patterns confirm the validity of the proposed data-driven framework and highlight the importance of integrating both spatial and temporal dimensions into risk assessment and management strategies for municipal organic waste systems.

5.2. Validation of the Predictive Model and Scientific Contribution of the Study

The predictive modeling results confirm the high effectiveness of ensemble machine learning algorithms for environmental risk assessment. In particular, the RF model demonstrated the best performance, explaining approximately 89% of the variance in the integrated Risk Index. This indicates its strong capability to capture nonlinear relationships and complex interactions among heterogeneous variables characterizing municipal waste management systems.

These findings are consistent with previous studies highlighting the advantages of machine learning approaches in modeling environmental processes and waste management systems [52,56]. Compared to traditional statistical methods, machine learning models enable the integration of diverse data sources, including socio-demographic, geospatial, and infrastructural indicators, thereby improving the accuracy and flexibility of environmental risk analysis in complex urban systems.

The main scientific contribution of this study lies in the development of an integrated data-driven framework for environmental risk assessment in municipal organic waste management. The proposed approach combines feature engineering, entropy-based weighting, risk index formulation, machine learning, based forecasting, and spatial analysis within a unified analytical structure. Unlike existing studies that primarily focus on waste generation prediction or life-cycle assessment [50,53], the proposed framework introduces a risk-oriented perspective, enabling the identification and forecasting of environmental vulnerabilities.

Furthermore, the integration of feature relevance analysis and geospatial visualization enhances the interpretability of machine learning outputs and facilitates their application in real-world DSS. This bridges the gap between predictive analytics and practical municipal management, supporting the transition toward data-driven and risk-informed governance.

The results confirm the scientific contribution of this study, which lies in the integration of data-driven analytics, entropy-based feature weighting, and predictive modeling into a unified risk-oriented framework for municipal waste management.

5.3. Implications for Urban Planning and Organic Waste Management Systems

The results have important practical implications for urban planning and the management of municipal organic waste systems. The integration of digital risk analytics into DSS enables the optimization of waste collection logistics by identifying high-risk areas and zones of intensified waste generation. This supports adaptive route planning, reduces transportation costs, and improves the efficiency of infrastructure utilization.

Another key implication concerns the planning of waste treatment infrastructure capacities, including composting and biogas facilities. Predictive modeling of organic waste volumes enables alignment of processing capacities with actual demand, reducing the risk of system overload or underutilization. This approach is consistent with circular economy principles and sustainable resource management strategies [54].

Environmental monitoring and greenhouse gas management represent an additional area of application. Organic waste is a major source of methane (CH_4) emissions in urban systems [69], and the proposed framework enables the identification of zones with increased emission potential. This supports targeted mitigation strategies and improves environmental risk control at the municipal level.

Furthermore, the integration of predictive models into municipal systems enables the development of early warning mechanisms for environmental risks. This enhances the ability of local authorities to respond proactively to emerging system pressures, prevent environmental degradation, and improve the effectiveness of urban environmental policies.

Overall, the findings demonstrate that data-driven approaches significantly enhance the adaptability and efficiency of municipal waste management systems. The integration of machine learning, geospatial analytics, and risk-based monitoring supports the transition toward proactive, data-driven, and risk-informed governance, which is essential for sustainable urban development.

5.4. Limitations and Future Work

This study has several limitations that should be considered when interpreting the results. First, although the proposed data-driven framework integrates a wide range of demographic, infrastructural, and geospatial indicators, certain socio-economic and behavioral factors are not explicitly represented due to the lack of consistent and high-resolution data. Household-level behaviors related to waste sorting, environmental awareness, and local management practices may significantly influence risk formation but remain difficult to formalize within standard statistical datasets.

Second, the temporal resolution of the available data limits the analysis of short-term system dynamics. As a result, the integrated Risk Index primarily reflects medium- to long-term structural patterns and may not fully capture rapid system responses to extreme events, seasonal peaks, or policy changes.

Third, while machine learning models effectively identify nonlinear relationships, they primarily capture statistical dependencies rather than causal mechanisms. Despite the use of feature relevance and interpretability techniques, a deeper understanding of causal interactions in complex urban socio-ecological systems requires further investigation.

Future research should focus on several directions. First, expanding the dataset through high-resolution time series, remote sensing data, and real-time sensor monitoring would enhance model accuracy and responsiveness. Second, integrating machine learning with causal inference and system dynamics approaches could improve the understanding of risk formation mechanisms. Third, comparative studies across different urban contexts are needed to evaluate the generalizability and scalability of the proposed framework under varying socio-economic and infrastructural conditions.

Nevertheless, the integration of deep sequential architectures such as LSTM or Temporal Convolutional Networks (TCN) represents a promising direction for future research, particularly for long-term forecasting tasks involving continuous temporal streams and higher-frequency monitoring data.

6. Conclusions

This study developed a data-driven digital framework for assessing and forecasting environmental risks in municipal organic waste management systems. The proposed approach integrates data processing, risk index formulation, entropy-based feature weighting, ensemble machine learning prediction, and spatial analysis within a unified analytical structure, enabling comprehensive evaluation of system performance in urban environments.

The results revealed significant spatial and temporal variability of environmental risks across municipalities. The average value of the integrated Risk Index was approximately 0.38, indicating moderate risk levels, while seasonal dynamics demonstrated increased risk concentrations during peak waste generation periods.

Predictive modeling confirmed the high effectiveness of ensemble learning methods. The RF model achieved the best performance, with a coefficient of determination $R^2 = 0.891$, RMSE = 0.0403, and MAE = 0.0320, demonstrating strong capability to capture nonlinear relationships and provide reliable risk forecasting in complex municipal systems.

The scientific novelty of the study lies in the development of a unified, risk-oriented data-driven framework that integrates entropy-based feature relevance assessment, risk index modeling, and predictive analytics within a DSS. Unlike existing approaches, the proposed model ensures the systematic integration of data analytics and decision-making processes, enabling a transition from static evaluation to adaptive and predictive risk management.

From a practical perspective, the proposed framework can be directly integrated into municipal DSS, enabling a transition from reactive to proactive management. Its

https://doi.org/10.3390/su18125862

application supports optimization of waste collection logistics, planning of processing infrastructure, spatial monitoring of environmental risks, and implementation of early warning mechanisms. The scalability of the approach allows its application to other urban systems with similar data structures, enhancing its relevance for sustainable urban development and circular economy implementation.

Author Contributions: Conceptualization, A.T. (Anatoliy Tryhuba) and I.T.; methodology, A.T. (Anatoliy Tryhuba), N.K. and I.F.; software, I.F. and N.K.; validation, A.T. (Anatoliy Tryhuba), I.T. and M.R.; formal analysis, N.K. and I.F.; investigation, I.F., V.F. and A.T. (Andriy Tatomyr); resources, B.H. and I.R.; data curation, I.F. and N.K.; writing—original draft preparation, A.T. (Anatoliy Tryhuba) and I.F.; writing—review and editing, I.T., M.R. and V.F.-M.; visualization, I.F. and A.T. (Andriy Tatomyr); supervision, A.T. (Anatoliy Tryhuba); project administration, A.T. (Anatoliy Tryhuba); funding acquisition, A.T. (Anatoliy Tryhuba) and M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this study are derived from municipal and aggregated datasets that are not publicly available due to administrative and data protection restrictions. Data may be available from the corresponding author upon reasonable request.

Acknowledgments: The authors would like to thank the municipal authorities and data providers for access to aggregated datasets and technical support during the study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DSS	Decision Support System
RI	Risk Index
ML	Machine Learning
DL	Deep Learning
RF	Random Forest
GB	Gradient Boosting
XGB	Extreme Gradient Boosting
LSTM	Long Short-Term Memory
TCN	Temporal Convolutional Network
PCA	Principal Component Analysis
GIS	Geographic Information System
MCDM	Multi-Criteria Decision-Making
AHP	Analytic Hierarchy Process
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
DEA	Data Envelopment Analysis
LPWAN	Low-Power Wide-Area Network
ITS	Intelligent Transportation Systems
IoT	Internet of Things
MSW	Municipal Solid Waste
CH_4	Methane
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
R^2	Coefficient of Determination

References

1. Rihm, A.; Piamonte, C.; Restrepo Lagos, E.A.; Correal, M.; Guerra Morán, P.G.; Basani, M. *Digital Transformation of Solid Waste Management: Waste Collection Innovation, Business Intelligence, and Digital Technologies to Transition Waste Management towards Circularity in Latin America and the Caribbean; Inter-American Development Bank Technical Note IDB-TN-0301*; Inter-American Development Bank: Washington, DC, USA, 2024. [CrossRef]
2. OECD. *The Circular Economy in Cities and Regions: Synthesis Report*; OECD Publishing: Paris, France, 2020. [CrossRef]
3. Anagnostopoulos, T.; Kolomvatsos, K.; Anagnostopoulos, C.; Zaslavsky, A.; Hadjiefthymiades, S. Assessing dynamic models for high priority waste collection in smart cities. *J. Syst. Softw.* **2015**, *110*, 178–192. [CrossRef]
4. El Jaouhari, A.; Samadhiya, A.; Kumar, A.; Mulat-Weldemeskel, E.; Luthra, S.; Kumar, R. Turning trash into treasure: Exploring the potential of AI in municipal waste management–An in-depth review and future prospects. *J. Environ. Manag.* **2025**, *373*, 123658. [CrossRef] [PubMed]
5. Vara-Vela, A.L.; Rojas Benavente, N.; Nielsen, O.-K.; Pinto Nascimento, J.; Alves, R.; Gavidia-Calderon, M.; Karoff, C. Quantifying methane emissions using satellite data: Application of the integrated methane inversion model to assess Danish emissions. *Remote Sens.* **2024**, *16*, 4554. [CrossRef]
6. Adu, T.F.; Mensah, L.D.; Rockson, M.A.D.; Kemausuor, F. Forecasting municipal solid waste generation and composition using machine learning and GIS techniques: A case study of Cape Coast, Ghana. *Clean. Waste Syst.* **2025**, *10*, 100218. [CrossRef]
7. Kondysiuk, I.; Tryhuba, A.; Bashynsky, O.; Grabovets, V.; Dembitskyi, V.; Myskovets, I. Formation and risk assessment of stakeholders value of motor transport enterprises development projects. In Proceedings of the International Scientific and Technical Conference on Computer Science and Information Technologies, Lviv, Ukraine, 22–25 September 2021; Volume 2, pp. 303–306. [CrossRef]
8. Korhonen, J.; Honkasalo, A.; Seppälä, J. Circular economy: The concept and its limitations. *Ecol. Econ.* **2018**, *143*, 37–46. [CrossRef]
9. Rabbi, M.F.; Amin, M.B. Circular economy and sustainable practices in the food industry: A comprehensive bibliometric analysis. *Clean. Responsible Consum.* **2024**, *14*, 100206. [CrossRef]
10. Nourani, V.; Baghanam, A.H.; Samadi, E.; Uzelaltinbulat, S. Predicting municipal solid waste generation using artificial intelligence: A hybrid approach of entropy analysis and SHAP for optimal feature selection. *Waste Manag.* **2025**, *205*, 115012. [CrossRef]
11. Bibri, S.E. The social shaping of the metaverse as an alternative to the imaginaries of data-driven smart cities: A Study in Science, Technology, and Society. *Smart Cities* **2022**, *5*, 832–874. [CrossRef]
12. Henaien, A.; Ben Elhadj, H.; Chaari Fourati, L. A sustainable smart IoT-based solid waste management system integrating trending technologies. *Future Gener. Comput. Syst.* **2024**, *157*, 587–602. [CrossRef]
13. Taşkın, A.; Demir, N. Life cycle environmental and energy impact assessment of sustainable urban municipal solid waste collection and transportation strategies. *Sustain. Cities Soc.* **2020**, *61*, 102339. [CrossRef]
14. Hussain, I.; Elomri, A.; Kerbache, L.; Omri, A. Smart city solutions: Comparative analysis of waste management models in IoT-enabled environments using multi-agent simulation. *Sustain. Cities Soc.* **2024**, *110*, 105247. [CrossRef]
15. Tryhuba, A.; Hutsol, T.; Tryhuba, I.; Tabor, S.; Kwasniewski, D. Risk assessment of investments in projects of production of raw materials for bioethanol. *Processes* **2021**, *9*, 12. [CrossRef]
16. Paiho, S.; Mäki, E.; Wessberg, N.; Paavola, M.; Tuominen, P.; Antikainen, M.; Heikkilä, J.; Rozado, C.A.; Jung, N. Towards circular cities–Conceptualizing core aspects. *Sustain. Cities Soc.* **2020**, *59*, 102143. [CrossRef]
17. Henrysson, M.; Papageorgiou, A.; Björklund, A.; Vanhuyse, F.; Sinha, R. Monitoring progress towards a circular economy in urban areas. *Sustain. Cities Soc.* **2022**, *84*, 104245. [CrossRef]
18. Vanhuyse, F.; Fejzić, E.; Ddiba, D.; Henrysson, M. The lack of social impact considerations in transitioning towards urban circular economies. *Sustain. Cities Soc.* **2021**, *75*, 103394. [CrossRef]
19. Vanhuyse, F.; Haddaway, N.R.; Henrysson, M. Circular cities: An evidence map of research between 2010 and 2020. *Discov. Sustain.* **2021**, *2*, 59. [CrossRef]
20. Calisto Friant, M.; Vermeulen, W.J.V.; Salomone, R. Sustainable circular cities: Urban circular economy policies in Amsterdam, Glasgow and Copenhagen. *Local Environ.* **2023**, *28*, 1331–1369. [CrossRef]
21. Celestino, É.; Palma-Oliveira, J.M.; Carvalho, A. Innovative roadmap for household organic waste management in the European Union. *J. Clean. Prod.* **2025**, *536*, 147153. [CrossRef]
22. Tryhuba, I.; Tryhuba, A.; Hutsol, T.; Cieszewska, A.; Andrushkiv, O.; Glowacki, S.; Bryś, A.; Slobodian, S.; Tulej, W.; Sojak, M.; et al. Prediction of biogas production volumes from household organic waste based on machine learning. *Energies* **2024**, *17*, 1786. [CrossRef]
23. Boyarchuk, V.; Ftoma, O.; Francik, S.; Rudynets, M. Method and software of planning of the substantial risks in the projects of production of raw material for biofuel. In *Proceedings of the 1st International Workshop on Information Technologies: Theoretical and Applied Problems (ITTAP 2019)*; CEUR-WS.org: Aachen, Germany, 2020; p. 2565. Available online: https://ceur-ws.org/Vol-2565/paper11.pdf (accessed on 10 January 2026).

24. Batyuk, B.; Dyndyn, M. Coordination of configurations of complex organizational and technical systems for development of agricultural sector branches. *J. Autom. Inf. Sci.* **2020**, *52*, 63–76. [CrossRef]
25. Zachko, O.; Grabovets, V.; Pavlova, I.; Rudynets, M. Examining the effect of production conditions at territorial logistic systems of milk harvesting on the parameters of a fleet of specialized road tanks. *East.-Eur. J. Enterp. Technol.* **2018**, *5*, 59–69. [CrossRef]
26. Gutierrez-Lopez, J.; McGarvey, R.G.; Costello, C.; Hall, D.M. Decision Support Frameworks in Solid Waste Management: A Systematic Review of Multi-Criteria Decision-Making with Sustainability and Social Indicators. *Sustainability* **2023**, *15*, 13316. [CrossRef]
27. Tryhuba, A.; Komarnitskyi, S.; Tryhuba, I.; Yermakov, S.; Muzychenko, A.; Muzychenko, T.; Horetska, I. Planning and risk analysis in projects of procurement of agricultural raw materials for the production of environmentally friendly fuel. *Int. J. Renew. Energy Dev.* **2022**, *11*, 569–580. [CrossRef]
28. Tryhuba, A.; Hutsol, T.; Tryhuba, I.; Mudryk, K.; Kukharets, V.; Głowacki, S.; Dibrova, L.; Kozak, O.; Pavlenko-Didur, K. Assessment of the condition of the project environment for the implementation of technologically integrated projects of the European Green Deal using maize waste. *Energies* **2022**, *15*, 8220. [CrossRef]
29. Tryhuba, A.; Mudryk, K.; Tryhuba, I.; Kotsylovskyi, M.; Sorokin, D.; Bezaltychna, O.; Pysz, P.; Hutsol, T. Models for sustainable management of livestock waste based on neural network architectures. *Sci. Rep.* **2025**, *15*, 28082. [CrossRef] [PubMed]
30. Govind Kharat, M.; Murthy, S.; Kamble, S.J.; Raut, R.D.; Kamble, S.S. Fuzzy multi-criteria decision analysis for waste treatment selection. *Technol. Soc.* **2019**, *57*, 20–29. [CrossRef]
31. Clasen, A.P.; Agostinho, F.; Almeida, C.M.; Giannetti, B.F. A decision-making model for sustainable municipal solid waste management. *Environ. Impact Assess. Rev.* **2026**, *118*, 108258. [CrossRef]
32. Goulart Coelho, L.M.; Lange, L.C.; Coelho, H.M.G. Multi-criteria decision making to support waste management: A critical review of current practices and methods. *Waste Manag. Res.* **2017**, *35*, 3–28. [CrossRef]
33. Namoun, A.; Tufail, A.; Khan, M.Y.; Alrehaili, A.; Syed, T.A.; BenRhouma, O. Solid Waste Generation and Disposal Using Machine Learning Approaches: A Survey of Solutions and Challenges. *Sustainability* **2022**, *14*, 13578. [CrossRef]
34. Prata, J.; Simões, C.L.; Simoes, R. Improvements to Municipal Solid Waste Collection Systems Using Real-Time Monitoring. *Sustainability* **2025**, *17*, 1405. [CrossRef]
35. Mullane, P.; Fitzpatrick, C.; Grua, E.M. Rethinking Machine Learning Evaluation in Waste Management Research. *Sustainability* **2025**, *17*, 10707. [CrossRef]
36. Alhathlaul, N. Assessing Waste Management Using Machine Learning Forecasting for Sustainable Development Goal Driven. *Sustainability* **2025**, *17*, 8654. [CrossRef]
37. Dawar, I.; Srivastava, A.; Singal, M.; Dhyani, N.; Rastogi, S. A systematic review on MSW management using ML and DL. *Artif. Intell. Rev.* **2025**, *58*, 183. [CrossRef]
38. Zou, Q.; Duan, H.; Yang, Z.; Wang, X.; Tian, Y.; Hou, H.; Yang, J. Machine learning-assisted waste life-cycle management. *Resour. Conserv. Recycl.* **2025**, *219*, 108320. [CrossRef]
39. Munir, M.T.; Li, B.; Naqvi, M.; Nizami, A.-S. Optimizing municipal waste management using data science. *Environ. Res.* **2024**, *243*, 117786. [CrossRef]
40. Vega, D.I.; Bautista-Rodriguez, S. Impact of circular economy strategies on waste management. *Clean. Eng. Technol.* **2024**, *21*, 100761. [CrossRef]
41. Mrabet, M.M.; Sliti, M.S. Integrating Machine Learning for the Sustainable Development of Smart Cities. *Front. Sustain. Cities* **2024**, *6*, 1449404. [CrossRef]
42. Wu, Z.; Pan, S.; Chen, F.; Long, G.; Zhang, C.; Philip, S.Y. Graph Neural Networks: Foundations, Frontiers, and Applications in Urban Intelligence Systems. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, *35*, 421–438. [CrossRef]
43. Guo, Z.; Li, Z.; Lu, C.; She, J.; Zhou, Y. Spatio-Temporal Evolution of Resilience: The Case of the Chengdu–Chongqing Urban Agglomeration in China. *Cities* **2024**, *153*, 105226. [CrossRef]
44. Agarwal, A.; Patil, S.; Sahu, P.K.; Jeny, E. AI-Driven Predictive Analytics for Smart Cities and Urban Planning. *Int. J. Basic Appl. Sci.* **2025**, *14*, 314–318. [CrossRef]
45. Wu, P.; Zhang, Z.; Peng, X.; Wang, R. Deep Learning Solutions for Smart City Challenges in Urban Development. *Sci. Rep.* **2024**, *14*, 5176. [CrossRef]
46. Askr, H.; Gomaa, M.M.; Rizk-Allah, R.M.; Snasel, V.; Hassanien, A.E. Prediction of methane emissions using deep learning. *Energy Rep.* **2024**, *12*, 5462–5472. [CrossRef]
47. Dogniaux, M.; Maasakkers, J.D.; Girard, M.; Jervis, D.; McKeever, J.; Schuit, B.J.; Sharma, S.; Lopez-Noreña, A.; Varon, D.J.; Aben, I.; et al. Global satellite survey of landfill methane emissions. *Nature* **2025**, *647*, 397–402. [CrossRef] [PubMed]
48. Wang, Z.; Ren, F. Developing a decision support system for sustainable urban planning using machine learning-based scenario modeling. *Sci. Rep.* **2025**, *15*, 13210. [CrossRef] [PubMed]
49. Chau, K.Y.; Moslehpour, M.; Pan, S.-H.; Akhundzada, A. Advanced predictive modeling of municipal solid waste management using robust machine learning. *Sci. Rep.* **2025**, *15*, 43247. [CrossRef] [PubMed]

50. Laurent, A.; Bakas, I.; Clavreul, J.; Bernstad, A.; Niero, M.; Gentil, E.; Christensen, T.H.; Hauschild, M.Z. Review of LCA studies of solid waste management systems–Part I: Lessons learned and perspectives. *Waste Manag.* **2014**, *34*, 573–588. [CrossRef]
51. Sharma, H.B.; Vanapalli, K.R.; Cheela, V.R.S.; Ranjan, V.P.; Jaglan, A.K.; Dubey, B.; Goel, S.; Bhattacharya, J. Challenges, opportunities, and innovations for effective solid waste management during and post COVID-19 pandemic. *Resour. Conserv. Recycl.* **2020**, *162*, 105052. [CrossRef]
52. Yang, L.; Zhao, Y.; Niu, X.; Song, Z.; Gao, Q.; Wu, J. Municipal solid waste forecasting in China based on machine learning models. *Front. Energy Res.* **2021**, *9*, 763977. [CrossRef]
53. Hoornweg, D.; Bhada-Tata, P. *What a Waste: A Global Review of Solid Waste Management*; World Bank: Washington, DC, USA, 2012. Available online: https://openknowledge.worldbank.org/handle/10986/17388 (accessed on 15 January 2026).
54. Ellen MacArthur Foundation. *Cities and Circular Economy for Food*; Ellen MacArthur Foundation: Cowes, UK, 2019. Available online: https://ellenmacarthurfoundation.org/cities-and-circular-economy-for-food (accessed on 20 January 2026).
55. Tryhuba, A.; Ratushny, R.; Tryhuba, I.; Koval, N.; Androshchuk, I. The model of projects creation of the fire extinguishing systems in community territories. *Acta Univ. Agric. Silvic. Mendel. Brun.* **2020**, *68*, 419–431. [CrossRef]
56. Munir, M.T.; Naqvi, M.; Nizami, A.-S.; Li, B. Revolutionizing municipal solid waste management with machine learning as a clean resource: Opportunities, challenges and solutions. *Fuel* **2023**, *348*, 128548. [CrossRef]
57. Pires, A.; Martinho, G.; Chang, N.-B. Solid waste management in European countries: A review of systems analysis techniques. *J. Environ. Manag.* **2011**, *92*, 1033–1050. [CrossRef]
58. Benitez-Bravo, R.; Gomez-González, R.; Rivas-García, P.; Botello-Álvarez, J.E.; Huerta-Guevara, O.F.; García-León, A.M.; Rueda-Avellaneda, J.F. Optimization of municipal solid waste collection routes in a real setting. *J. Air Waste Manag. Assoc.* **2021**, *71*, 1415–1427. [CrossRef]
59. Rastegari Kopaei, H.; Nooripoor, M.; Karami, A.; Ertz, M. Modeling consumer home composting intentions for sustainable municipal organic waste management in Iran. *AIMS Environ. Sci.* **2021**, *8*, 1–17. [CrossRef]
60. Chentouf, F.Z.; El Alami Hasoun, M.; Bouchkaren, S. Blockchain for sustainable smart cities: Motivations and challenges. *Comput. Sci. Math. Forum* **2025**, *10*, 2. [CrossRef]
61. Abdullahi, A. Blockchain technology for sustainable waste management. *Front. Polit. Sci.* **2020**, *2*, 590923. [CrossRef]
62. Wong, P.F.; Chia, F.C.; Kiu, M.S.; Lou, E.C. Potential integration of blockchain technology into smart sustainable city (SSC) developments: A systematic review. *Smart Sustain. Built Environ.* **2022**, *11*, 559–574. [CrossRef]
63. Hutsol, T.; Kuboń, M.; Hohol, T.; Tomaszewska-Górecka, W. Taxonomy and stakeholder risk management in integrated projects of the European Green Deal. *Energies* **2022**, *15*, 2015. [CrossRef]
64. Tryhuba, A.; Boyarchuk, V.; Tryhuba, I.; Pavlikha, N.; Kovalchuk, N. Study of the Impact of the Volume of Investments in Agrarian Projects on the Risk of Their Value. In *CEUR Workshop Proceedings*; CEUR-WS.org: Aachen, Germany, 2021; Volume 2851, pp. 303–313. Available online: https://ceur-ws.org/Vol-2851/paper28.pdf (accessed on 12 January 2026).
65. Boyarchuk, V.; Tryhuba, I.; Boiarchuk, O. Evaluation of risk value of investors of projects for the creation of crop protection of family dairy farms. *Acta Univ. Agric. Silvic. Mendel. Brun.* **2019**, *67*, 1357–1367. [CrossRef]
66. Kaza, S.; Yao, L.; Bhada-Tata, P.; Van Woerden, F. *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*; World Bank: Washington, DC, USA, 2018. [CrossRef]
67. Ferronato, N.; Torretta, V. Waste mismanagement in developing countries: A review of global issues. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1060. [CrossRef]
68. Edjabou, M.E.; Petersen, C.; Scheutz, C.; Astrup, T.F. Food waste from Danish households: Generation and composition. *Waste Manag.* **2016**, *52*, 256–268. [CrossRef]
69. IPCC. *Climate Change 2021: The Physical Science Basis*; Cambridge University Press: Cambridge, UK, 2021. [CrossRef]