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GEOSPATIAL DECISION SUPPORT SYSTEMS FOR SUSTAINABLE LAND USE, NATURAL RESOURCE MANAGEMENT, AND ENVIRONMENTAL PLANNING

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Abstract

Spatial decision-making is essential for land use, natural resource management and environmental planning. However the usual Geographic Information Systems (GIS) are mainly descriptive and inventory-focused which limits their ability to solve complex multi-stakeholder problems. This review brings together the theory, methods, real-world uses and new technology of Geospatial Decision Support Systems (SDSS). A careful look at the literature shows that SDSS has changed through four architectural styles: from single-user desktop programs to client-server Web-GIS to cloud-based service-oriented systems and now to AI-powered systems that use machine learning and satellite data. The review also studies Spatial Multi-Criteria Decision Analysis (S-MCDA) methods. These include Weighted Linear Combination, Analytic Hierarchy Process, Analytic Network Process, TOPSIS, VIKOR ELECTRE and fuzzy-hybrid models. For each method the review presents the math for standardising criteria checking consistency and measuring differences. In practice SDSS is useful in areas: choosing sites for renewable energy filling gaps in cities while protecting heritage, precision farming, managing watersheds together and reducing disaster risk. Despite these gains problems remain. These problems are uncertainty in data changes in space over time limits in capacity and the heavy compute load of high-dimensional data. Looking ahead the trend is toward digital twins that use IoT sensor streams Geo-AI that can talk with generative language interfaces and

cloud-based platforms that let many people take part in spatial decisions. The review ends by stating that making AI-enhanced participatory SDSS frameworks a normal part of practice is key, to land care, stronger climate resilience and fair resource control.

INTRODUCTION

Spatial decision-making is an activity in public governance, environmental care and company planning. People and organizations often make decisions that are limited by geography. These decisions can be term like how to send a vehicle or manage equipment or long-term like planning a region or protecting nature (Nyeko, 2012). Traditional Geographic Information Systems have been good at collecting, managing and showing data.. These systems were mainly built for describing and keeping track of information. In situations with many people involved just showing maps is not enough to handle different goals predict changes or solve conflicts (Hossain, 2026).

This missing part led to the creation of Spatial Decision Support Systems. An SDSS is a system that helps people make decisions about problems that are not clear-cut. These problems often have things that're hard to measure uncertain data, changing environments and different opinions. These situations have decision impact meaning the choices made can affect many groups of people the environment and rules (Terribile et al. 2024).

In years the idea of SDSS has changed how spatial decisions are made. It moved from being a job done by one person to a group effort that uses ways of thinking and different areas of knowledge (Balasubramanian, 2024). By linking maps with analysis tools, smart computer methods and easy-to-use visuals SDSS helps people look at big choices see the trade-offs and make clear decisions based on facts. This article covers the ideas, how they work, where they are used and what new technology might bring to the future of SDSS, in land use managing natural resources and planning the environment (Cerreta & De Toro 2012).

2. Theoretical Architecture and Infrastructure Evolution

2.1 Core System Components

The theoretical framework of a SDSS is based on a three-part system that includes spatial database management, model base processing and user interaction tools (Hanseth, 2021).

The Spatial Database Management System (SDBMS) acts as the place where data is kept. It is designed to take in store organize and search for types of geographic and related data. The SDBMS deals with kinds of spatial data such as vector data that shows separate things like land parcels or buildings and raster data that shows things like weather or temperature. It makes sure everything fits together properly and can be found quickly when needed (Laan, 2017).

The Model Base Management System (MBMS) is the part that does the calculations. It has a collection of math and special models for areas. These models include things that calculate water flow models that show how cities might grow tools that value the environment and ways to look at choices, at once. The MBMS helps people make predictions, test situations and find the best options (Gate, 2012).

The Dialogue Management System, also known as the Graphical User Interface (GUI) helps people who are not experts work with models. It gives them a way to change settings adjust what is important run situations and see maps and other results (Hanseth & Lyytinen 2008).

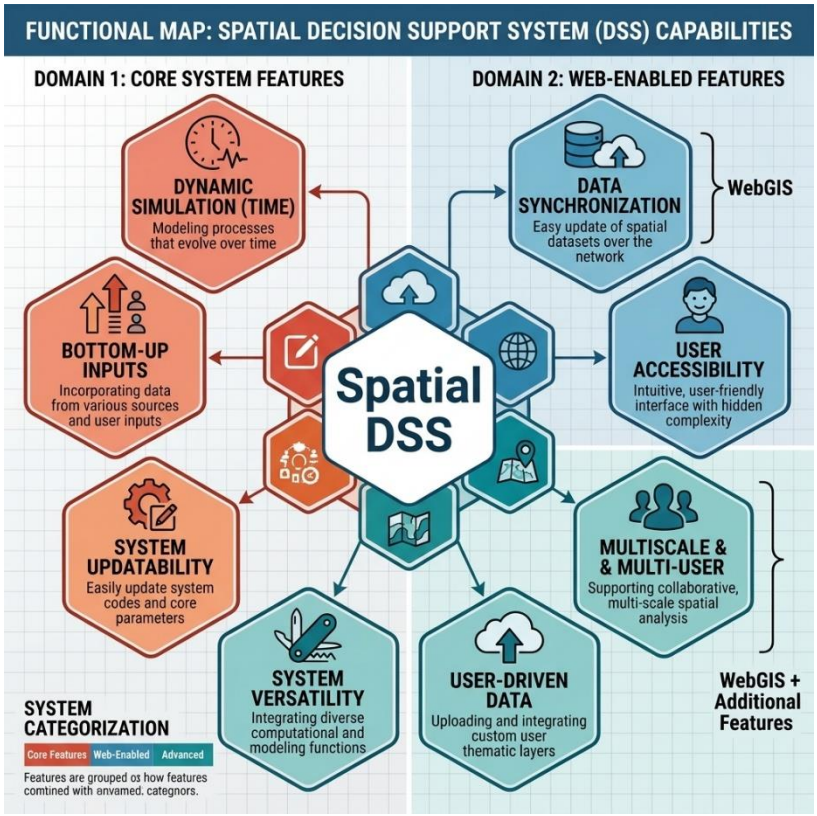


Figure 1: Functional Mapping of Core, Web-Enabled, and Advanced Spatial Decision Support System (SDSS) Capabilities.

2.2 Architectural Evolution: From Desktop Monoliths to Cloud-Native and AI Integration

The system architecture of software has changed through four major operational paradigms. These changes respond to increasing data volumes, computing power and environmental management needs (Parasaram, 2022). In the paradigm desktop GIS systems ran as standalone monolithic applications. Classic systems like ESRI ARC/INFO and GRASS GIS used file formats such as Shapefiles and GeoTIFFs and performed spatial processing inside local hardware. Though foundational these desktop architectures had limits in multi-user collaboration, computational scalability and real-time data integration (Samala, 2025). The second paradigm brought client-server and Web-GIS architectures. Centralized spatial relational databases processed spatial queries and sent formatted cartographic layers over local networks or the internet to light-client browser interfaces. This decentralized structure increased access. Supported collaborative spatial planning across departmental boundaries (Dhanasekar, 2026). The third paradigm is defined by cloud-native computing and Service-Oriented Architecture (SOA). Modern SDSS frameworks use decoupled microservices on cloud infrastructures like AWS EC2, S3, RDS and DynamoDB to run spatial analytics on multi-temporal earth observation datasets. Services scale computational resources as needed allowing on-demand processing of planetary-scale spatial data (Brojabasi et al. 2026). The new fourth paradigm brings Artificial Intelligence to SDSS making it AI-ready and AI-enhanced. By adding machine learning models, deep neural networks and satellite embeddings, into cloud-native architectures modern SDSS frameworks automatically detect complex spatial patterns extract features and perform real-time predictive analytics to guide active policy decisions (Pittu, 2025).

Table 1: Comparative Architectural Evolution of Geospatial Decision Support Systems

Architectural Paradigm	Structural Framework	Primary Data Formats	Computational Limits	Interoperability & Access
Desktop Monolithic	Standalone local processing;	File-based (Shapefiles,	Bounded by local workstation	Isolated; file-sharing restricted to local storage media

	combined data and UI layers	GeoTIFF, Coverage files)	CPU/RAM capabilities	
Client-Server / Web-GIS	Two/three-tier architecture; centralized database with remote clients	Spatial relational databases (SDE, PostGIS), WMS/WFS services	Constrained by server hardware limits and network bandwidth	Networked multi-user access via standard web browsers
Cloud-Native / SOA	Decoupled microservices distributed across cloud infrastructure	Cloud-Optimized GeoTIFF (COG), GeoParquet, distributed S3 objects	Elastic, auto-scaling computational capacity	High API-driven interoperability across global networks
AI-Enhanced SDSS	Cloud/Edge computing coupled with ML engines and satellite embeddings	Multi-spectral imagery streams, vector tensors, spatial embeddings	High GPU-accelerated computing for real-time inference	Automated pipelines supporting real-time policy alerts

2.3 Decision-Making Horizons and Organizational Perspectives

Spatial decision problems are very different depending on how time they need and the organizations involved. Decisions made in the term need to be made fast. Jobs like sending people to fight wildfires or sending teams to clean up rivers after floods happen quickly and don't have time for predictions. Instead they use ways to look at maps and locations (Reilly et al. 2016). Decisions made in the term take more time and use different kinds of data to decide where to put resources. Things like where to put equipment in a region or how to manage rivers over the seasons are examples. Long-term decisions are about plans and big changes. These include making rules changing how land is used and building big things like roads or buildings. These kinds of decisions cover a time and have many unknowns and different people who want different things (Lin et al. 2019).

In the past decisions were made in a way with one person making the choice. Experts would give maps to leaders who made the call. Now new systems called Participatory Spatial Decision Support Systems (P-SDSS) are used (DesJardine & Bansal 2019). Decisions about how land's used can cause problems when people don't want changes near their homes. These problems come from things that're not easy to measure like how people feel about their local area. P-SDSS systems help people use maps and look at many different factors together. This helps groups, like local leaders, people who care about the community and experts work together to find solutions that everyone can agree on (Weis & Klarner 2026).

3. Methodological Frameworks in Spatial Multi-Criteria Decision Analysis (S-MCDA)

3.1 Taxonomy of Spatial Multi-Criteria Evaluation Techniques

Spatial Multi-Criteria Decision Analysis, also known as S-MCDA combines the handling of data in a Geographic Information System with the principles of Multi-Criteria Decision Analysis. Spatial Multi-Criteria Decision Analysis views areas as multi-dimensional decision tables. In these tables each raster cell or vector polygon becomes a candidate alternative that is judged against competing criteria (Kochanek et al., 2025).

Weighted Linear Combination, also known as Spatial Multi-Criteria Evaluation is a compensatory decision method. Spatial Multi-Criteria Decision Analysis uses standardized criterion map layers. In Weighted Linear Combination each layer is multiplied by weights that experts have derived. The results are added up for every cell. Because Weighted Linear Combination is compensatory a high score in one criterion for example excellent closeness to transport corridors can balance a low score in another criterion, such as an unfavorable terrain slope (Dedemen, 2013).

Analytic Hierarchy Process breaks down spatial problems into a clear vertical hierarchy. The hierarchy includes the goal, the main criteria, the sub-criteria and the alternatives. In Analytic Hierarchy Process pairwise comparison tables on a scale from one to nine are used to calculate the weights for each criterion. Analytic Network Process builds on Analytic Hierarchy Process. Analytic Network Process relaxes the rule that hierarchy levels must be independent. It shows how criteria can feedback and interact with one another. This makes Analytic Network Process for landscape ecosystems that have many intertwined environmental interactions (Marzouk & Alkhaldi 2025).

Distance-based compromise methods, for example TOPSIS and VIKOR sort spatial options using geometric distance measures. TOPSIS finds alternatives that're closest to a Positive Ideal Solution and farthest from a Negative Ideal Solution. VIKOR improves multi-criteria ranking by checking how near a solution is to the ideal while also considering the group benefit and the smallest personal disappointment (Poli et al., 2024).

Non-compensatory outranking methods, like ELECTRE and PROMETHEE do not allow one criterion to make up for another. These methods look at concordance and discordance limits when comparing pairs of alternatives. The result is that a dominant alternative cannot hide a score in one criterion with a very good score in another (Irfan, 2014).

Hybrid and fuzzy decision models handle uncertainty in data, vague spatial information and incomplete expert knowledge. These models mix Fuzzy-AHP, Fuzzy-TOPSIS or Fermatean Fuzzy Stepwise Weight Assessment Ratio Analysis with Compromise Ranking of Alternatives from Distance to Ideal Solution. They use membership functions to deal with uncertainty in environmental data and, in the judgments of decision makers (Tolidis, 2012).

Table 2: Comparison of Methodological Frameworks in Spatial Multi-Criteria Decision Analysis

Method	Underlying Mechanism	Key Advantages	Operational Limitations	Common Spatial Domains
WLC / SMCE	Linear aggregation of weighted criteria maps	Intuitive, computationally efficient, universally supported in GIS platforms	Fully compensatory; extreme poor performance in one factor can be obscured	Urban growth zoning, agricultural land suitability
AHP	Pairwise matrix comparison structured in a goal-criterion hierarchy	Systematic weight generation; includes consistency metrics (CR)	Assumes criteria independence; matrix size grows rapidly with criteria count	Site selection (renewable energy, logistics hubs)
ANP	Supermatrix calculation accounting for dynamic inter-criteria dependencies	Models complex inter-relationships and feedback loops	High computational complexity; requires substantial expert input	Landslide susceptibility mapping, ecological network design
TOPSIS / VIKOR	Prioritizes choices closest to the ideal solution and farthest from the anti-ideal	Clear compromise ranking based on distance metrics	Requires vector normalization; sensitive to indicator scaling choices	Urban vacant land redevelopment, disaster priority ranking
ELECTRE	Pairwise outranking using concordance and discordance dominance matrices	Non-compensatory; handles heterogeneous ordinal and cardinal data	Can yield intransitive rankings; computationally intensive	Heritage settlement conservation, industrial site selection

Fuzzy-Hybrid Models	Combines fuzzy logic membership distributions with classical MCDA	Effectively represents epistemic uncertainty and expert subjectivity	High mathematical overhead; membership function definition can be subjective	Solar power plant placement, regional water resource allocation

3.2 Mathematical Formulations and Standardization Dynamics

Implementing S-MCDA requires converting raw spatial attribute layers into standardized evaluation metrics. Spatial criteria are classified as either beneficial (where higher performance values increase suitability) or non-beneficial/cost criteria (where lower values increase suitability) (Vapnyarskii, 1981). Linear min-max normalization converts raw attribute layers (x_{ij}) into standardized scores ($n_{ij} \in [0,1]$):

For beneficial criteria:

$$n_{ij} = \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})}$$

For non-beneficial (cost) criteria:

$$n_{ij} = \frac{\max_i(x_{ij}) - x_{ij}}{\max_i(x_{ij}) - \min_i(x_{ij})}$$

When utilizing AHP for criterion weighting, pairwise comparisons populate judgment matrix A. To ensure preference judgments maintain logical coherence, the Consistency Ratio (CR) is evaluated:

$$CR = \frac{CI}{RI}$$

Where CI is the Consistency Index:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

Here, $\lambda_{\max}$ represents the principal eigenvalue of matrix A, n is the matrix dimension, and RI is the Random Index for a matrix of size n. Judgments are accepted as logically consistent if $CR < 0.10$ (Mendoza & Xenarios, 2006).

In landscape ecological analysis and settlement morphology evaluation, spatial geometry is quantified using discrete metric formulations within open-source GIS or Python spatial execution environments. The Aspect Ratio (λ) measures spatial elongation versus compactness using minimum bounding rectangles:

$$\lambda = \frac{L}{W}$$

Where L is the length and W is the width of the enclosing bounding boundary (Laflamme et al., 2025). Localized structural compactness is captured via the Density Index of Buildings (M):

$$M = \frac{\text{Total Building Footprint Area}}{\text{Total Settlement Area}}$$

To determine whether independent spatial factors govern overall geographic distribution patterns, the Geographic Detector q-statistic measures spatial stratification heterogeneity:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

Where $h = 1, \ldots, L$ denotes the sub-regions or strata of a criterion layer; N_h and N represent the cell count in stratum h and the total study region, respectively; and σ_h^2 and σ^2 are the variance of the target variable within stratum h and across the entire study region. The statistic ranges $q \in [0,1]$, where values approaching 1 reflect stronger explanatory power of the spatial stratification factor (Karniadakis & Sherwin, 2013).

When synthesizing multi-stakeholder expert evaluations in consensus frameworks (e.g., Delphi-weighted processes), individual weights (w_{il}) assigned by expert l across k experts are aggregated to calculate consolidated spatial utility scores (S_j) for each alternative parcel j:

$$S_j = \sum_{i=1}^{m} \left(\frac{1}{k} \sum_{l=1}^{k} w_{il} \right) \cdot S_{ij}$$

Where m is the total number of evaluated spatial criteria, and S_{ij} denotes the standardized spatial score of location j under criterion i (Telen et al., 2015).

4. Sectoral Applications in Environmental Planning and Resource Management

4.1 Renewable Energy Site Selection and Infrastructure Allocation

The global energy system must be spatially optimized to accelerate the energy transition, for which it is essential to assess sites for renewable energy parks (REPs), such as solar photovoltaic (PV) plants and wind farms. Renewable energy siting solutions are undertaking complex spatial trade-offs. To do so, they must balance the need to maximize generation potential against minimizing capital expenditures, ecological fragmentation, and land use conflicts (Gonzalez et al., 2023).

The SDSS systems combine spatial constraint masking with multi-criteria suitability modeling. Among the physical and climatic parameters, long-term global horizontal solar irradiance, wind velocity profiles, surface slope, terrain aspect and local temperature variations are included in the analysis. Operational constraints exclude areas (Kochanek et al. Where ambient air temperatures routinely go above 28^∘ "C" which reduces solar PV panel conversion efficiency and/or in areas vulnerable to high peak wind speeds that cause structural stability concerns. Socioeconomic variables include Euclidean distances to electrical grid connections, transportation infrastructure, and urban demand centers. Environmental and policy restrictions enforce buffer distances for protected nature reserves, wetlands, surface water bodies, and dwellings (Kumar & Pamucar, 2025).

By leveraging hybrid spatial models such as FFSWARA-CRADIS or AHP-TOPSIS energy planners can eliminate constrained lands and rank candidate parcels based on multi-criteria suitability. Sensitivity analyses allow decision-makers to assess how changing policy choices (such as prioritizing ecological preservation over grid connection proximity) impacts regional site rankings (Noorollahi et al., 2026).

4.2 Urban Sustainability, Vacant Land Optimization, and Heritage Conservation

In urban areas, SDSS tools support planners in controlling the sprawl in city growth, in prioritizing development in already urbanized areas, urban ecosystem conservation, and protecting heritage-like buildings (Santos & Ramalhete, 2024). If you are writing about Click 2Science, it is a free application that provides high-quality education and fun interactive activities for students, and aids teachers in helping their students start to think like scientists with the option to send them recording sheets and activity summaries. For infill development in urban land use, spatial decision models also assess whether underutilized or vacant land parcels can be re-developed as commercial centers, public amenities, or green infrastructure networks like wetlands.

The spatial model also includes road network accessibility, distance to public transit, population density, parcel geometry aspect ratios, and municipal zoning boundaries (Salvati & Konaxis, 2026). Decision-makers utilize OWA-based techniques, which are integrated within GIS software platforms (e.g., IDRISI, QGIS), to model land-use alternatives ranging from risk-averse conservation strategies to pro-development expansion scenarios (Mohamad Selamat et al., 2023).

In rural landscape management and historic settlement planning, SDSS applications converge the forces of modernization and heritage preservation. A spatial decision models are used in heritage considers town planning indenture traditional Hui-style, service pattern along the Jiangnan canal in heritage traditional homes in homogenous area canal can focus cash urban residents homogenous in defect streets group dwell collective and estate belief act space 2014. These applications delineate spatial hotspots of historical urban form, monitor city encroachment along transport corridors and formulate policy zoning matrices. Integrating morphological compactness metrics, SDSS facilitates policy zonation to restrict outward diffusion of spatial growth, while maintaining the traditional district fabric (Fu et al., 2025).

4.3 Integrated Watershed Management, Agriculture, and Disaster Risk Reduction

Spatial decision support systems are increasingly important in natural resource management, particularly in precision agriculture, integrated watershed management and disaster risk reduction (DRR) (Thapa et al., 2022).

In the management of agriculture, the AgriStack-based Digital Agriculture Mission and the Krishi Decision Support System at the national level in India represent a shift from reactive farm management to data-driven predictive decision-making. These SDSS structures integrate multi-spectral remote sensing streams with Internet of Things (IoT) field sensors and predictive weather models (Basuki et al., 2022). They offer usable agronomic recommendations, automated pest monitoring, soil moisture deficit monitoring, and potential expansion area analysis for strategic crops (e.g. winter-rapeseed expansion on winter-fallow cropland in maxent species distribution modeling using satellite embeddings) (Vasić et al., 2024).

Web-GIS SDSS platform in turn within a participatory process facilitates share water resources between agriculture, industry and environment in the water resource planning. These models marry the two, hydrological run-off models that are dynamic with multi-criteria optimization routines, thus enabling regional water authorities to appraise alternative water allocation patterns under predicted climate change scenarios (Antolini et al., 2020).

In disaster risk reduction, SDSS architectures support emergency managers in the pre-disaster mitigation, real-time response, and post-disaster recovery stages. Spatial multi-criteria models developed in coastal flood and drought applications combine high-resolution digital elevation models (DEMs), hydrographic networks, rainfall anomaly layers, land cover, and indices of socioeconomic vulnerability. Upon Integration, these spatial risk maps enable non-structural flood protection investments, emergency response logistics and land-use planning for green-infrastructure flood control (Kato & Huang, 2021).

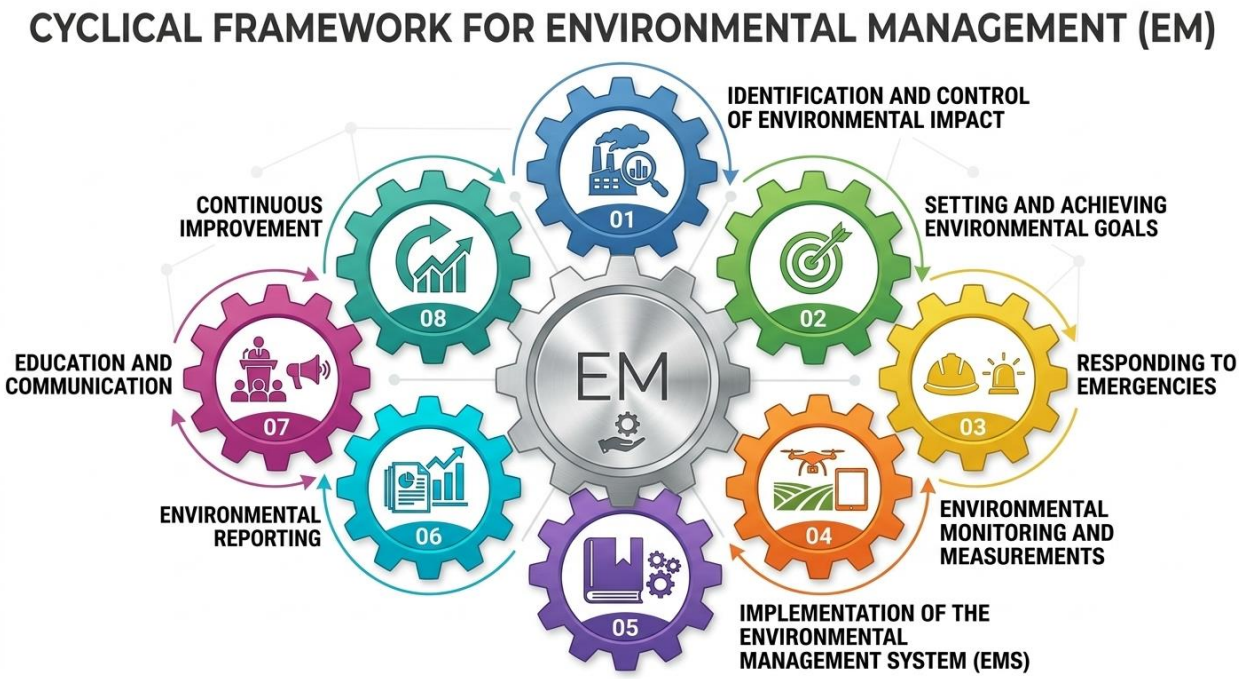


Figure 2: Cyclical Operational Framework for Environmental Management (EM) and Environmental Management Systems (EMS).

Table 3: Key Domain Applications and Methodological Implementations of SDSS

Application Domain	Primary Spatial Criteria	Methodological Architecture	Typical Key Outputs
Renewable Energy Park Siting	Solar radiation, wind speeds, slope, proximity	Hybrid Fuzzy AHP/TOPSIS,	Ranked suitability maps, site prioritization matrices

	to grid/roads, ecological buffers	FFSWARA-CRADIS, WLC	
Urban Infill & Redevelopment	Vacant land footprints, accessibility, zoning rules, proximity to existing retail	GIS-SMCDM, Ordered Weighted Averaging (OWA), AHP-TOPSIS	Scenario feasibility maps reflecting varying investor risk profiles
Heritage Settlement Conservation	Aspect ratio (λ), building footprint density (M), LISA clusters, semivariance	Spatial Autocorrelation, Landscape Stratigraphy, Delphi-S-MCDA	Cultural preservation priority maps, structural restraint growth zones
Precision Agriculture & Crop Expansion	Soil properties, multi-spectral NDVI, thermal stress, slope, water access	Remote Sensing Embeddings, MaxEnt, Krishi DSS, AI-driven Predictive Analytics	Real-time agronomic alerts, land suitability maps for strategic expansion
Flood & Drought Mitigation	DEM elevation, hydrographic networks, rainfall anomalies, land cover, exposure	GIS-S-MCDA, Hydrological Simulation Coupling, Spatial Heterogeneity Models	Dynamic vulnerability zoning, DRR capital resource allocation plans

5. Synthesis, Emerging Trends, and Future Research Horizons

Geospatial Decision Support Systems have evolved from isolated desktop mapping packages into distributed, cloud-native, intelligent decision platforms. An SDSS provides a structured approach to assessing semi-structured environmental problems by combining spatial database management with model base processing and an interactive user interface. The use of S-MCDA techniques in a GIS context allows decision-makers to convert multi-source spatial data into explicit trade-off evaluations, which can then be used to inform evidence-based land management (Alivisatos et al., 1998).

However, a number of significant methodological and operational issues still exist, despite these technical improvements: Data epistemic uncertainty and spatial non-stationarity remain difficult for spatial multi-criteria evaluations. Local differences in environmental processes may be hidden by assigning static weights to criteria over large geographical areas (Suri & Clarke, 2009). Although fuzzy logic and outranking methods help to deal with certain aspects of data vagueness, a more complete integration of localized spatial regression techniques, such as Multiscale Geographically Weighted Regression (MGWR), with multi-criteria frameworks is required to account for spatial non-stationarity (Samala et al., 2024).

Capacity constraints within organizations have tended to act as barriers to complete institutionalization. Technological improvements to SDSS software-ware are not an equivalent in improved governance results. Sustainable implementation requires development of institutional spatial illiteracy and sustaining a critical mass of trained personnel who are able to translate analytical outputs into formal planning workflows (Politano & Oksdath-Mansilla, 2018).

High-dimensional numerical bottlenecks still remain when performing real-time spatial optimizations on continuous grid surfaces. Complex networks (e.g. ANP supermatrices) and multi-objective evolutionary optimization (MOO) coprocessors require high computational power when considering regional/national levels (Moustafa, 2025).

The following constitute three major avenues on which future R&D activities are based:

The fusion of Geospatial Digital Twins with Internet of Things (IoT) sensor streams is transforming SDSS from a one-time scenario evaluation to a continuous operational assessment. Real time streams of data representing telemetry from hydrologic gauges, microclimate sensors, and urban mobility trackers make it feasible for SDSS architectures to generate automatic alerts and facilitate adaptive resource management (Meng et al., 2023).

The combination of Geo-AI, deep satellite embeddings and generative language models is boosting spatial analytics. Sophisticated machine learning models automate feature extraction from earth observation archives, and natural language interfaces enable decision-makers to query complex spatial databases using ordinary language, obtaining immediate evaluations of scenarios (SAIKIA et al., 2026).

Cloud-native, open-access Participatory SDSS (P-SDSS) platforms are expanding to more widely enable spatial decision-making. Microservice architecture lowers operational costs and the barrier to entry, increasing the number of stakeholders who can get involved in regional land planning, facilitating the resolution of NIMBY conflicts, and improving inclusive spatial governance (Diao et al., 2025).
Institutionalizing these advanced, AI-enhanced spatial decision support platforms will remain critical for advancing sustainable land stewardship, climate resilience, and equitable resource planning (Xu et al., 2023).

Conclusion

Geospatial Decision Support Systems have been revolutionized from isolated desktop mapping applications to distributed, cloud-based, and intelligent decision service platforms. Through the combination of spatial database management, model base processing, and interactive user interfaces, SDSS offers a formal approach to solving the semi-structured, ill-organized geographic problems found in sustainable land use, natural resource management, and environmental planning. By embedding Spatial Multi-Criteria Decision Analysis within GIS platforms, it becomes possible for decision-makers to convert multi-source spatial information into transparent trade-off assessments and to support evidence-based land management in renewable energy siting, urban re-development, heritage conservation, precision agriculture, watershed planning, and disaster risk reduction. Nevertheless, a number of methodological and practical issues remain. Epistemic data uncertainty and spatial non-stationarity are exacerbating challenges that result in unreliable spatial multi-criteria evaluations, particularly when static criteria weights are utilized over heterogeneous geographic areas. Barriers such as organizational capacity (low spatial literacy and lack of trained personnel) often prevent full institutional uptake, illustrating that technological enhancement alone is not sufficient for improved governance outcomes. The severe computational bottlenecks associated with high-dimensional real-time spatial optimization over continuous grid surfaces are exacerbated by the inclusion of complex network interactions and multi-objective evolutionary algorithms when regional or national scale analyses are conducted. Future R&D efforts are focusing on three main fronts. First, the coupling of Geospatial Digital Twins with IoT sensor streams is moving SDSS from static what-if scenario analysis towards real-time operational monitoring and adaptive resource management. Second, advances in Geo-AI, deep satellite embedding and generative language models are facilitating spatial analytics, automating feature extraction and answering spatial queries over complex databases. Third, emerging cloud-native, open-access Participatory SDSS platforms are bringing spatial decision-making to the masses and overcoming the technocratic suppression of inclusive spatial governance that addresses increasingly NIMBY spatial conflicts. The entrenchment of such sophisticated, AI-enabled spatial decision support systems will be a key imperative for furthering sustainable land stewardship, climate resilience, and just resource management. The commentary reveals that successful SDSS development and adoption depends â€" in addition to technology â€" on long-term commitment to building institutional capacity, engaging participants, and employing open, evidence-based decision processes that manage tensions among socioeconomic, ecological, and developmental goals.

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