

Original Article

A Geospatial Governance Framework for Smart Villages using Rule-Based Spatial Decision Support for Soil and Water Resource Management

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Abstract - Sustainable rural development has always depended on the proper management of natural resources. Traditional tabular datasets often fail to capture spatial interrelationships, resulting in fragmented planning and inefficient outcomes. The solution lies in geospatial governance, which can help combine both spatial and non-spatial data to make comprehensive and evidence-based decisions. This paper suggests a proposal of a Geospatial Governance Decision Support Framework (GG-DSF) to be used in the Smart Village context based on the idea of soil and water conservation as the essential element of sustainability. The novelty of GG-DSF is that it combines Spatial Data Mining (SDM), GIS-based overlay analysis, and heuristic optimization to produce action plans, Water Resource Development Plans (WRDP), and Land Resource Development Plans (LRDP). The analysis of the Gondidigras village (Maharashtra, India) provides a detailed case study of the framework in terms of the transformation of multi-source data into location-specific groundwater recharge, afforestation, and agricultural improvement strategies. Quantitative performance demonstrates that there are measurable improvements, +24.3% in water storage efficiency, +24.4% in land utilization, and +31.6% reduction in redundancy, which results in a Composite Sustainability Index (CSI) of 0.82, leading to high resilience and long-term sustainability. GG-DSF is an open-source platform (PostGIS, GeoServer, Python) solution that offers a scalable, transparent, and policy-friendly platform capable of directly augmenting national schemes, such as PMKSY, MGNREGA, and Digital India, thereby enhancing data-driven governance and participatory rural development.

Keywords - Geospatial governance, Geographic information system, Soil and water conservation, Spatial data mining, Sustainable rural development.

1. Introduction

Information is now a central resource in decision-making, both in the government and in businesses. Decades ago, though, data were kept in highly tabular stores, restricting spatial intelligence and resulting in piecemeal planning. The accessibility of spatial datasets has transformed this paradigm by placing location into traditional databases, giving the opportunity to view and analyze visualization and interpretation together in planning and governance [1]. Geospatial technologies are currently embraced by governments across the world to enhance infrastructural planning, environmental observation, and management of resources in a sustainable manner [2]. It is a geospatial governance (g-governance) approach based on Geographic

Information Systems (GIS), remote sensing, and spatial analytics to uncover spatial distributions and facilitate targeted policy interventions [3, 4].

The recent versions of Decision Support Systems (DSS), which utilize the Internet of Things (IoT), wireless sensor networks, and cloud systems, show significant improvements in irrigation efficiency, soil-moisture prediction, and resource allocation [5-7]. DSS that are sustainability-oriented also incorporate Key Performance Indicators (KPIs) of the environmental, economic, and social nature to make investments in agriculture, energy, and other sectors the priority [8, 9]. In the agricultural sector, methods such as hydrological modeling based on FAO-56 [10], the use of non-



spatial and spatial data in simulating agro-pastoral systems with GRASSVisto [11], and machine-learning-based soil moisture forecasts [12] demonstrate that a combination of both spatial and non-spatial data is beneficial in managing water resources. Simultaneously, affordable IoT surveillance validates the viability of real-time rural administrative tools [13, 14].

1.1. Research Gaps

Despite recent technological progress, the rural planning programs continue to be heavily based on the traditional, heuristic approaches. Selection of sites is often done with no particular multi-criteria suitability models, and map overlays do not typically solve the problem of redundancy or spatial co-location of potential infrastructure. Moreover, there is rarely the use of optimization methods of reconciliation of trade-offs between water retention, land use efficiency, and soil conservation in the budgeting process. Consequently, implemented projects tend to exhibit spatial aggregation, non-functional redundancy, and inefficient behavior based on cost-efficiency and sustainability goals.

1.2. Objective and Scope

To address these gaps, this paper presents a Geospatial Governance Decision Support Framework (GG-DSF) that integrates Spatial Data Mining (SDM), GIS-based multi-criteria suitability mapping, a rule-based engine for Water Resource Development Plans (WRDP) and Land Resource Development Plans (LRDP), and a budget-constrained optimization layer. The Gondidigras village (Maharashtra) case study demonstrates how GG-DSF translates thematic layers and non-spatial attributes into actionable, spatially explicit plans for soil and water conservation.

1.3. Novelty and Contributions

Relative to existing DSS and geospatial planning studies [1-14]:

- Integrated workflow: A unified village-scale MCDA → rule engine → ILP pipeline computes suitability indices, applies domain-specific rules, and optimizes resource allocation under budget constraints, effectively minimizing redundancy.
- Auditable performance metrics: Key metrics such as Water Storage Efficiency (WSE), Land Utilization Index (LUI), Redundancy Reduction Ratio (RRR), and the Composite Sustainability Index (CSI) provide a transparent and quantifiable evaluation of planning outcomes.
- Open-source, policy-ready stack: PostGIS/ GeoServer/ OpenLayers with Python tooling, offering a cost-effective and easily deployable solution for local and district administrations.
- Policy alignment: GG-DSF directly supports policy goals of PMKSY, MGNREGA, and Digital India, enabling data-driven governance, transparent monitoring, and appropriate resource distribution in rural development programs.
- Governance relevance and paper roadmap: By linking suitability, rules, and optimization, GG-DSF supports evidence-based siting, better utilization of public funds, and reduction of duplication, which are key priorities in rural governance.

Table 1 provides a structured comparison between GG-DSF and representative existing decision-support approaches, highlighting the framework's unique methodological and policy-oriented advantages.

Table 1. Comparison of GG-DSF with representative existing approaches

Feature / Aspect	Typical GIS-Based Planning Systems	ML/IoT-Driven DSS Systems	Hydrology-Focused MCDA Tools	GG-DSF (Proposed)
Planning Scale	District / Regional	Farm / Plot	Sub-watershed	Village + Watershed (Integrated)
Outputs	Maps / Diagnostics Only	Predictions, Alerts	Suitability Maps	WRDP + LRDP Actionable Interventions
Rule Base	Often absent	Absent	Limited	Explicit, auditable rule engine
Optimization	Not included	No budget linkage	Weight-based ranking	Budget-constrained ILP optimizer
Policy Alignment	Weak	Weak	Moderate	Aligned with PMKSY/MGNREGA workflows

The subsequent sections describe the data, methods, validation procedures, and optimization framework used to operationalize GG-DSF for village and watershed-level planning.

2. Literature Review

2.1. Related Methods

The rural resource management decision support extends to geospatial analysis, monitoring through IoT, and prediction

using AI/ML. Table 2 summarizes the representative literature that encompasses DSS architectures, geospatial modeling, and SDM in the fields of agriculture, energy, and environmental science [1-22]. It has been shown in the literature that combining spatial layers with sensing and analytics enhances water allocation, crop management, and infrastructure planning, and also presents some challenges that appear to be unresolved in terms of scalability, data quality, and operational deployment.

Table 2. Literature review

Ref. No & Year	Concept Used	Performance Evaluation Parameter	Database / Platform Used	Claims by Author(s)	Critical Findings
[1] 2004	Integrated Watershed Management (IWM) DSS in Visual Basic; considers structural + cropping practices.	Soil loss reduction %, sediment yield, slope classification	Visual Basic DSS with watershed & soil data from St. Lucia	Achieved 34–37% reduction in soil loss on slopes (5–55°) with suggested practices	Effective for conservation planning across land classes
[2] 2015	Stepwise DSS for greenhouse farming (preparation–harvest)	Not explicitly quantitative; farming cycle improvement	Conceptual DSS, case studies	Structured guidance to smallholder greenhouse farmers	Useful as a training/knowledge tool
[3] 2017	Alternative data-based DSS for agricultural credit scoring (SVM, Logistic Regression)	Accuracy, AUC	Mobile app dataset: 213 users, 11,336 farmers, 41,613 farm reports (Cambodia)	RBF-SVM achieved AUC = 0.983 for creditworthiness prediction	Demonstrates the feasibility of alternative data in agri-finance
[4] 2018	WSN + DSS with outlier detection algorithm (O(1)/O(n))	Accuracy, scalability, and communication reliability	Real-time testbed with Wasp-mote sensors in an orchard	Achieved real-time monitoring with low packet loss and efficient irrigation	Validates open-field DSS
[5] 2023	Soil moisture sensors + FAO-56 model + SaQC for irrigation	Data integrity, soil water balance, and irrigation efficiency	Python scripts + mobile app in orchards	35% water saving claimed; robust QC framework	Well-integrated DSS + mobile tool
[6] 2019	IoT-enabled DSS with cloud computing	Crop yield, water use, latency, scalability	IoT sensors + Cloud platform	15–20% higher yield, optimized irrigation	Demonstrates IoT + Cloud integration
[7] 2023	AI + optimization-based DSS for renewable energy in smart grids	Energy efficiency, load balancing, and renewable use	MATLAB/Simulink + smart grid data	10–12% improved renewable utilization; reduced peak load	Strong application in energy DSS
[8] 2021	Sustainability-driven DSS with KPIs (economic, social, environmental)	KPI ranking (mean scores)	Survey in Moroccan mining (12 managers, ISO-certified)	Proposed 15 KPIs; safety/energy most critical	Structured KPI-based DSS
[9] 2021	ANN + Geoinformatics for landfill monitoring	ANN training epochs, accuracy	ANN (NeuroSolution) + Image Processing	ANN reliably classified biogas migration	Innovative ANN–GIS integration
[10] 2021	Analytical Hierarchy Process (AHP), MCDM for site selection	Water quality, socio-economics, sustainability	Expert survey responses	AHP identified CALABARZON as the best site	Demonstrates structured site selection DSS
[11] 2023	GRASSVISTOCK crop water flux model	r, RRMSE, LAI, AGB	Field data (Alpine & Mediterranean grasslands)	Good performance simulating FTSW, LAI, and AGB	Effective in agro-pastoral systems
[12] 2023	Hybrid SVR + XGBoost for drought prediction	Prediction accuracy	Indian rainfall & temperature data	The hybrid model outperforms statistical models	Effective in drought forecasting
[13] 2023	FAO56 + Sentinel-2 NDVI for irrigation scheduling	ETa estimation, SWC accuracy	Castelvetro district (Italy), Sentinel-2	Only 3% difference with farmer irrigation	Strong irrigation DSS with RS integration
[14] 2024	Ensemble learning (CatBoost) for soil moisture prediction	RMSE, MAE, R ²	IoT soil sensors + adaptive DSS	CatBoost ensemble achieves superior accuracy	Improves irrigation planning
[15] 2024	IoT + ML predictive analytics for precision	Yield optimization, resource efficiency	IoT soil & weather datasets	Enhanced decision-making and	Real-time predictive insights

	farming			productivity	
[16] 2024	IoT smart irrigation DSS	Soil moisture accuracy, water efficiency	IoT sensors	Improved irrigation efficiency	Valid for real-time monitoring
[17] 2024	AI + Geo-integrated DSS with Streamlit	Decision accuracy, UI usability	Remote sensors + Streamlit	Enhanced resource optimization	User-friendly AI platform
[18] 2019	Precision irrigation with the Agriculus platform	Water efficiency, scheduling accuracy	Agriculus cloud + Sentinel-2 + IoT	IT tool integration for irrigation	Holistic DSS framework
[19] 2025	AI + CNN + Roboflow for plant classification	Accuracy, Precision, Recall, F1	Roboflow 2.0, TensorFlow	>99% plant ID accuracy claimed	Strong for plant phenotyping
[20] 2020	Rule-based data mining and GIS integration for groundwater zone identification	Accuracy, Precision, Recall	Groundwater dataset; ArcGIS and decision tree models	Hybrid decision tree–GIS approach improves the accuracy of groundwater suitability mapping	Supports the rule-based spatial DSS concept relevant to GG-DSF
[21] 2025	IoT-enabled autonomous rover + AI (CNN models)	Accuracy, Precision, F1, Confusion Matrix	Fusion 360 + IoT + CNN	Rover automates soil/disease detection	Modular precision agriculture
[22] 2025	IoT-based greenhouse monitoring and control	Stability, energy efficiency	IoT microcontrollers + sensors + web dashboard	Real-time monitoring improved energy efficiency and yield	Shows the scalability of IoT-enabled DSS in smart agriculture
[23] 2023	ANN + GIS integration for groundwater quality estimation	R ² , RMSE, GWQI accuracy	Groundwater samples, GIS layers (ArcGIS/QGIS)	ANN–GIS gives high prediction accuracy; useful for groundwater quality zoning	Diagnostic-only approach; no rule-based planning, no optimization; regional prediction only
[24] 2023	AI-Integrated GIS land suitability for wheat in arid zones	Suitability index scores, classification accuracy	Soil, climate, DEM, RS imagery; GIS + AI tools	AI enhances suitability precision; supports agricultural planning	Crop-specific and diagnostic; no optimization; lacks implementable interventions

DSS, IoT, and AI studies have been growing significantly quicker since 2018, and are very active in 2023-2025 [2-6]. The prevailing area of interest is irrigation and water management [5], then IoT/AI automation in agriculture [6], sustainability-oriented KPIs in the decision-making process [7, 8], and decision-specific applications, e.g., credit scoring [3] and landfill monitoring [9]. In agriculture, the importance of spatial and non-spatial signal integration can be reinforced using hydrological modeling [10], agro-pastoral simulations [11], and ML-based soil-moisture predictions [12, 13]. IoT systems have proven to be cost-effective in the field worldwide through demonstrations of practical and affordable monitoring [14-16], whereas AI-based interfaces enhance the usability and transparency of decisions for end-users [17-22].

Simultaneously, geospatial technologies were used more often in planning at the village level within the last 20 years [1, 10]. Adarsh Gram Yojana and Gram Swaraj initiatives in India emphasize self-sufficiency and participatory management of resources, which is consistent with the current,

technology-enabling governance [15, 17]. GIS is used in mapping assets, connectivity, and monitoring of natural resources to support national programs, such as Digital India and Smart Village Mission [18]. Globally, open-source GIS systems are the basis of information systems at the community scale and participatory governance [20]. In addition to these tendencies, a set of techniques in Spatial Data Mining, namely, clustering, classification, and association rule mining, has been employed in deriving actionable patterns to assess water quality, predict drought, and irrigation scheduling based on remote-sensing indices [5, 12-14].

According to the latest research, there is a rapid integration of machine learning and rule-based GIS methodologies into spatial decision-making on land and water resource management. The use of ANN-GIS systems has increased the precision of estimating the quality of groundwater and mapping irrigation suitability [23], whereas AI-based fuzzy rule-based GIS models have elevated land suitability determination in dry farming regions [24]. These

developments demonstrate the success of integrating rule-based reasoning and data-driven learning, which supports the methodological basis of the proposed GG-DSF framework.

The vast majority of strategies end at suitability mapping or rule-based overlays and lack explicit redundancy management or constrained optimization in a budget-conscious balance between storage, utilization, and conservation. GG-DSF directly fills this gap by integrating MCDA, a codified rule base in WRDP/LRDP, and an Integer Linear Programming (ILP) model in allocation, then moving towards village-scale, policy region-oriented planning.

2.2. Summary

Recent publications indicate a blistering trend in DSS, IoT-based agriculture, and AI-based management of resources. It is dominated by water and irrigation efficiency and has led to simultaneous improvements in automation and sustainability monitoring. All these trends support the importance of geospatial-ML-sensor integration, yet also indicate the possible barriers to deployment in terms of scale, cost, and data reliability.

2.3. Key Findings

- IoT-ML pipelines consistently improve prediction accuracy and resource use.
- DSS platforms enhance decisions on irrigation, crop selection, and energy management.
- Remote sensing (e.g., Sentinel-based indices) enables large-area agricultural and environmental monitoring.

2.4. Challenges and Gaps

- Limited scalability and generalization across crops, seasons, and regions.
- Upfront and maintenance costs constrain the adoption of this technology by smallholders and local bodies.
- Sensor data quality and continuity remain critical pain points.
- Many studies emphasize simulations; fewer deliver rule-consistent, budget-aware, field-deployable plans at the village scale.

Several 2023–2025 studies have further explored cloud-based DSS, AI-driven irrigation tools, and Web-GIS planning frameworks; however, these works still lack an integrated rule engine and budget-linked optimization, underscoring the need addressed by GG-DSF.

3. Problem Formulation

The objective is to design a Geospatial Governance Decision Support Framework (GG-DSF) that produces Water Resource Development Plans (WRDP) and Land Resource Development Plans (LRDP) for a given village by integrating spatial and non-spatial datasets and translating them into rule-consistent, budget-aware, and non-redundant interventions.

3.1. Spatial Data Representation

Let

$$S = \{s_1, s_2, \dots, s_n\} \quad (1)$$

be the set of spatial layers, where s_i is a thematic map (e.g., geomorphology, land capability, slope, drainage, land use/land cover).

Each rasterized layer is represented as a grid of tuples.

$$s_i = \{(x, y, v) \mid (x, y) \in R^2, v \in R\} \quad (2)$$

Where (x, y) denotes map coordinates in the analysis CRS and v is the attribute (or class code) at that location. For vector layers, attributes are evaluated on a discretized set of spatial units (pixels or polygons).

3.2. Non-Spatial Data

Let

$$N = \{n_1, n_2, \dots, n_m\} \quad (3)$$

be non-spatial attributes (e.g., population, literacy, cropping pattern).

Let $U = \{u_1, \dots, u_j\}$, denote the partition of the study area into analysis units (e.g., pixels or village sub-parcels).

A linkage function assigns non-spatial attributes to spatial units:

$$\phi: N \times U \rightarrow R^m, n_j = \phi(N, u_j), \quad (4)$$

Where n_j is the vector of non-spatial attributes associated with the unit u_j (e.g., via census joins or dasymetric allocation).

3.3. Suitability Analysis

For each unit u_j , a multi-criteria suitability score is computed as

$$Suit(u_j) = \sum_{i=1}^n w_i \cdot f_i(s_i(u_j)) \quad (5)$$

Where w_i are criterion weights (derived using AHP or expert elicitation; $\sum_i w_i = 1$; consistency ratio reported in Methods) and $f_i(\cdot)$ normalizes raw criterion values to $[0,1]$. For benefit criteria:

$$f_i(v) = \frac{v - \min(v)}{\max(v) - \min(v)}, \quad (6)$$

and for cost criteria:

$$f_i(v) = \frac{\max(v) - v}{\max(v) - \min(v)}. \quad (7)$$

Criterion direction (benefit vs cost) is specified per layer in the Methods.

3.4. Rule-Based Recommendation Model

Let A denote the catalog of admissible interventions (e.g., CCT, dug well, bore well, farm pond, WAT, agro-horticulture types). Two codified rule sets, R_{WRDP} and R_{LRDP} , map spatial attributes to admissible actions. For unit u_j ,

$$Rec(u_j) \subseteq A \Rightarrow a \in Rec(u_j). \quad (8)$$

Where:

- If $15^\circ \leq \text{slope}(u_j) \leq 35^\circ$ and $\text{geomorph}(u_j) \in G_1 \Rightarrow a = \text{CCT}$.
- If $\text{recharge_zone}(u_j) = \text{Upper} \Rightarrow a = \text{Dug Well}$.
- If $\text{LULC}(u_j) \in L_1$ and $\text{slope}(u_j) < 10^\circ \Rightarrow a = \text{Agro-Horticulture}$.

Here, G_1 and L_1 are predefined geomorphology and land-use classes.

3.5. Optimization Objective (Budget-Constrained Siting)

Define binary decision variables

$$x_{j,a} = \begin{cases} 1, & \text{if action } a \in A \text{ is selected for the unit } u_j, \\ 0, & \text{otherwise,} \end{cases} \quad (9)$$

admissible only if $a \in Rec(u_j)$.

Let $c_{j,a}$ be the cost of action a at unit u_j , and $b_{j,a}$ its quantified benefit (e.g., water retention in m^3 , yield gain in t/yr, or a weighted composite consistent with the evaluation metrics defined later). Given a total budget B , the allocation problem is:

$$\max_{\{x_{j,a}\}} \sum_{j=1}^J \sum_{a \in A} b_{j,a} x_{j,a} \quad (10)$$

Subject to:

$$\sum_{j=1}^J \sum_{a \in A} c_{j,a} x_{j,a} \leq B, \quad (11)$$

$$\sum_{a \in A} x_{j,a} \leq 1, \forall j \quad (12)$$

$$x_{j,a} = 0 \text{ if } a \notin Rec(u_j) \text{ (rule feasibility).} \quad (13)$$

Redundancy and spatial separation (optional constraints). To prevent overlapping or closely-spaced duplicates where not beneficial, define adjacency sets $N(j)$ and add, for selected actions (e.g., ponds, wells),

$$x_{j,a} + x_{\ell,a} \leq 1, \forall \ell \in N(j), \forall a \in A_{\text{sep}}, \quad (14)$$

Or impose a spacing threshold using pre-computed conflict pairs. These constraints operationalize redundancy reduction and equity of distribution.

3.6. Planning Outputs

The selected portfolio induces intervention maps:

$$M_{WRDP} = \bigcup_{j: a \in A_{WR}} (u_j, a \text{ with } x_{j,a} = 1)$$

$$M_{LRDP} = \bigcup_{j: a \in A_{LR}} (u_j, a \text{ with } x_{j,a} = 1), \quad (15)$$

Which are subsequently published as OGC services and evaluated using WSE, LUI, RRR, and CSI metrics.

3.7. System Workflow

- **Data Acquisition:** Collect spatial (S) and non-spatial (N) data from government databases, satellite imagery, and census sources.
- **Preprocessing:** Perform spatial registration, noise filtering, and attribute normalization.
- **Projection:** Reproject spatial datasets to an equal-area CRS (e.g., UTM) for accurate area and volume computation.
- **Suitability Mapping:** Apply Equation (5) to compute suitability indices for each land unit.
- **Rule Application:** Execute rule-based mappings for WRDP and LRDP generation.
- **Optimization:** Solve the budget-constrained objective to finalize actionable interventions.

4. Methodology

The proposed Geospatial Governance Decision Support Framework (GG-DSF) integrates spatial and non-spatial datasets to generate village-specific Water Resource Development Plans (WRDP) and Land Resource Development Plans (LRDP). The methodology consists of six key stages, as shown in Figure 1.

4.1. Data Acquisition

Two primary categories of data are considered:

4.1.1. Spatial Data (S)

- **Thematic Layers:** Road network, drainage, geomorphology, slope, land capability, Land Use/Land Cover (LULC).
- **Sources:** National Spatial Data Infrastructure (NSDI), Bhuvan, Maharashtra Remote Sensing Application Centre (MRSAC).
- **Formats:** CSV, KML, GeoTIFF, and WMS/WFS services.

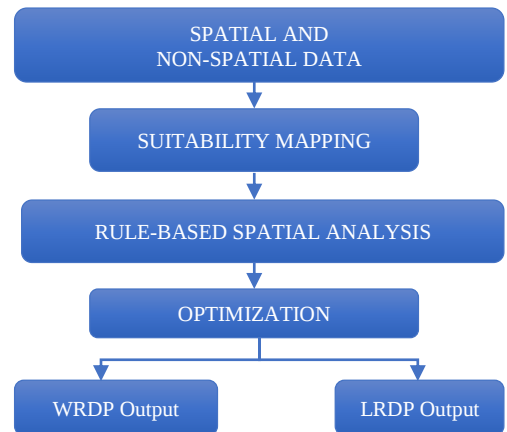


Fig. 1 Methodology workflow

4.1.2. Non-Spatial Data (N):

- Attributes: Population, literacy rate, household data, cropping patterns, and socio-economic indicators.
- Sources: Census of India, Government databases.

Formally, the integrated dataset is represented as:

$$D = \{(s_j, n_j) \mid j = 1, 2, \dots, k\} \quad (16)$$

Where, $s_j \in R^n$ is the vector of spatial attributes for land unit j , and $n_j \in R^m$ is the vector of non-spatial attributes.

Table 3 summarizes the spatial and non-spatial datasets used for developing and validating the GG-DSF model.

Table 3. Spatial and non-spatial data used

Layer / Attribute	Source / Portal	Date / Version	Resolution / Scale	CRS at Ingest	CRS for Analysis	Notes
Land Use / Land Cover (LULC)	Bhuvan (NRSC, ISRO)	2023–24	10–30 m	EPSG:4326	EPSG:32644 (UTM Zone 44N)	Reclassified to 7 major land-use classes
Slope	SRTM / ALOS DEM	2023	30 m	EPSG:4326	EPSG:32644	Derived using the 3×3 kernel slope algorithm
Geomorphology	MRSAC (Govt. of Maharashtra)	1:50,000	Polygon	EPSG:4326	EPSG:32644	Codes: PLM, PLU, PLW, etc.
Land Capability	MRSAC	1:50,000	Polygon	EPSG:4326	EPSG:32644	Classes II–VII are used for suitability mapping
Drainage	National Spatial Data Infrastructure (NSDI)	2024	1:50,000	Line	EPSG:4326	EPSG:32644
Population & Households	Census of India	2011 (projected 2024)	Village level	—	—	Linked to spatial units through relational mapping
Cropping Pattern & Soil	Agricultural Department Database	2023	Village level	—	—	Used for rule-based recommendation logic

4.2. Data Preprocessing

All layers were integrated in EPSG:4326 for ingestion and reprojected to UTM Zone 44N (EPSG:32644) for distance/area calculations. For area-preserving analyses, key summaries are validated in an equal-area CRS (e.g., World Cylindrical Equal Area, EPSG:6933, or India-specific Albers).

Missing attribute values were interpolated using Inverse

Distance Weighting (IDW) [1]:

$$\hat{v}(x, y) = \frac{\sum_{i=1}^N \frac{v_i}{d_i^p}}{\sum_{i=1}^N \frac{1}{d_i^p}} \quad (17)$$

Where, d_i is the distance between (x, y) and sample point i , and p is the power parameter (typically $p = 2$).

Categorical variables (e.g., geomorphology) were numerically encoded using One-Hot Encoding.

4.3. Suitability Mapping

A Multi-Criteria Decision Analysis (MCDA) framework is applied to compute suitability scores [2]:

$$S(u_j) = \sum_{i=1}^n w_i \cdot f_i(s_i(u_j)) \quad (18)$$

Where, w_i = weight of criterion s_i (derived using Analytic Hierarchy Process (AHP) [3]), $f_i(\cdot)$ = normalization function mapping raw values to [0,1].

For benefit criteria:

$$f_i(v) = \frac{v - \min(v)}{\max(v) - \min(v)} \quad (19)$$

For cost criteria:

$$f_i(v) = \frac{\max(v) - v}{\max(v) - \min(v)} \quad (20)$$

4.4. Rule-Based Spatial Analysis

Decision rules for WRDP and LRDP were derived from expert consultations and watershed management guidelines. These were expressed in predicate logic for automated execution. For example:

$$Rec(u_j) = \begin{cases} CCT, & \text{if } slope(u_j) \in [15^\circ, 35^\circ] \wedge (u_j) \in G_1 \\ Dug\ Well, & \text{if } recharge_zone(u_j) = \text{Upper} \\ Agro - Horticulture, & \text{if } LULC(u_j) \in L_1 \wedge slope(u_j) < 10^\circ \\ \vdots & \text{additional WRDP/LRDP rules} \end{cases} \quad (21)$$

Spatial processing is conducted using Python libraries (GeoPandas, Rasterio, Shapely) and PostGIS for geospatial queries. Web visualization is implemented with GeoServer and OpenLayers.

4.5. Optimization for Resource Allocation

Given a finite budget B , the resource allocation problem is formulated as an ILP:

$$\max \sum_{j=1}^k Impact(Rec(u_j)) \quad (22)$$

subject to:

$$\sum_{j=1}^k c(Rec(u_j)) \leq B \quad (23)$$

Where, $c(\cdot)$ is intervention cost and $Impact(\cdot)$ is quantified benefit (e.g., water retention in m³, crop yield increases in kg/ha).

The ILP model was implemented in Python using the PuLP library and CBC solver with a 1% optimality gap and 2400-second runtime limit. Conflicting intervention pairs were generated by buffering polygons by 10–20 m and

excluding spatially overlapping units. Cost coefficients were derived from the district Schedule of Rates (2023–24).

4.6. System Implementation

- Backend: PostgreSQL/PostGIS for spatial storage; GeoServer for OGC-compliant WMS/WFS services.
- Frontend: OpenLayers-based GIS viewer for interactive visualization.
- Processing: Python environment with GDAL, PyProj, and Shapely for geospatial analytics.

The final WRDP and LRDP maps are expressed as:

$$M_{WRDP} = \bigcup_{u_j} (Rec_{WRDP}(u_j), coords(u_j)) \quad (24)$$

$$M_{LRDP} = \bigcup_{u_j} (Rec_{LRDP}(u_j), coords(u_j)) \quad (25)$$

These maps provide actionable, spatially explicit decision-support outputs for government authorities.

4.7. Validation and Sensitivity

The datasets, rules, and prioritization outputs were validated using multiple complementary procedures.

- (a) LULC validation: Classification accuracy was assessed using cross-validation on labelled points (N = 150), yielding an overall accuracy of 91.3% and a kappa coefficient of 0.88 (Appendix 2).
- (b) Rule-based validation: The WRDP and LRDP rule sets were reviewed by a panel consisting of district watershed engineers, agronomists, and local extension officers (N = 5). Rule conflicts were resolved by majority consensus and documented in a rule provenance log.
- (c) AHP weight validation: Pairwise comparison matrices produced a consistency ratio (CR = 0.093), which is within acceptable limits (CR < 0.10). Full matrices are provided in Appendix 3.
- (d) ILP robustness: Budget and weight parameters were perturbed $\pm 10\%$ to test sensitivity. Intervention priorities remained stable, indicating robustness of the optimization model.

In addition to the above, further analytic checks were performed to ensure spatial, numerical, and optimization reliability:

- Area audits in equal-area CRS;
- Weight sensitivity $\pm 10\%$ on w_i and efficiency factors ± 0.05 for structure performance;
- Robustness of ILP solutions under $\pm 10\%$ budget perturbations;
- Redundancy metrics (RRR) before/after conflict constraints.

Tables 4 and 5 summarize representative rules for WRDP and LRDP, respectively.

Table 4. WRDP rule base

Geomorphology Classes	Land Capability (erosion/ root- zone limitation)	Slope Range (%)	Hydro- morphic Zone	Recommended Intervention
Escarpment, Butte (ES, B)	VI–VII	15–35	Runoff	Continuous Contour Trenches (CCT)
Structural Hill, Escarpment, Plateau Moderately/Undissected (SH, ES, PLM, PLU)	III–VII	3–35	Upper Recharge	Continuous Contour Trenches (CCT)
Plateau Slightly/Moderately Dissected, Pediplain Shallow, Pediment (PLS, PLM, PPS, PD, PLU)	II, III, IV, VII	1–10	Lower Recharge	Dug Well / Bore Well / Farm Pond / Tank
Plateau Slightly Dissected, Plateau Weathered Shallow/Weathered (PLS, PLWS, PLW)	II, III, VI	1–5	Upper Storage	Dug Well / Bore Well / Farm Pond / Tank
Alluvial Plain Moderate, Plateau Weathered, Pediplain Moderate (APM, PLW, PPM)	II, III	1–3	Lower Storage	Dug Well / Bore Well
Canal Command	—	—	—	Bore Well
Settlement	—	—	—	Rooftop Rainwater Harvesting

Table 5. LRDP rule set

Geomorphology Classes	Land Capability (erosion/ root- zone limitation)	Slope Range (%)	Land Use / Land Cover	Recommended Intervention
Butte, Pediment Slope, Escarpment, Plateau Moderately Dissected (B, PS, ES, PLM)	III, IV, VI, VII	5–35	Scrub Forest	Afforestation with Continuous Contour Trenches (CCT)
Structural Hill, Pediment, Plateau Moderately/Undissected (SH, PD, PLM, PLU)	III, IV, VI	3–35	Open Forest	Forest Conservation with Plantation
Butte, Structural Hill, Pediment, Escarpment (B, SH, PD, ES)	III, IV, VI	3–35	Dense Forest	Forest Conservation with Water Absorption Trenches (WAT)
Butte, Escarpment, Plateau Moderately/Undissected (B, ES, PLM, PLU)	IV, VI, VII	1–35	Land with Scrub	Social Forestry Plantation with CCT
Plateau Moderately/Slightly Dissected, Plateau Undissected, Pediplain Moderate/Shallow (PLM, PLS, PLU)	II, III, IV, VI	1–35	Land with or without Scrub	Pasture Development with CCT
Plateau Moderately/Slightly Dissected, Plateau Undissected, Butte (OLM, PLS, PLU, B)	III, IV, VI	1–35	Kharif, fallow, land without scrub	Dryland Agro- Horticulture
Plateau Moderately/Slightly Dissected, Plateau Undissected, Pediplain Moderate/Shallow, Plateau Weathered (PLM, PLS, PLU, PLW)	II, III, IV, VI	3–15	Fallow, land without scrub, Kharif	Irrigated Agro- Horticulture
Plateau Weathered, Pediplain Moderate/Shallow, Plateau Weathered Shallow, Alluvial Plain Moderate, Flood Plain Moderate (PLW, PLWS, APM, FPM)	II, III	1–5	Double/Triple Crop	Intensive Agriculture

5. Results and Discussion

5.1. Case Study: Gondidigras Village

To evaluate the proposed Geospatial Governance Decision Support Framework (GG-DSF), Gondidigras village in Katol Taluka, Nagpur District, Maharashtra, is selected as the demonstration site. For soil and water conservation, the watershed is adopted as the primary planning unit, as it reflects the natural hydrological boundary. The WRJ-2 watershed, containing Gondidigras, is chosen for this analysis.

The complete analysis was conducted in the WRJ-2 watershed, and the obtained data were then trimmed down to the administrative boundary of Gondidigras village to facilitate easy interpretation. All the spatial processing functions were done with Python and the OpenLayers GIS framework, whereas the spatial storage, analytical processing, and publication of the map were done with a backend that consisted of GeoServer and the PostgreSQL/PostGIS database system. This clipping experiment resulted in a delimited study

area of 403.28 ha $\approx$ 4.03 km² of the Gondidigras perimeter to be studied further.

Outputs of the Water Resource Development Plan (WRDP) are given in Figures 2 and 3. Figure 2 represents WRDP recommendations in the whole WRJ 2 watershed, and Figure 3 concentrates on Gondidigras village only. Similarly, Figures 4 and 5 present the findings of the Land Resource Development Plan (LRDP) of the watershed and the village, respectively.

The WRDP maps (Figures 2 and 3) indicate that, in most Gondidigras, the interventions to be implemented in the project include dug wells, bore wells, and farm ponds, which are aimed at increasing the rate of groundwater recharge and increasing storage capacity. According to the LRDP results (Figures 4 and 5), intensive agricultural and agro-horticultural activities are well-suited to the land capability and slope characteristics of the village, thereby maximizing productivity and sustainability.

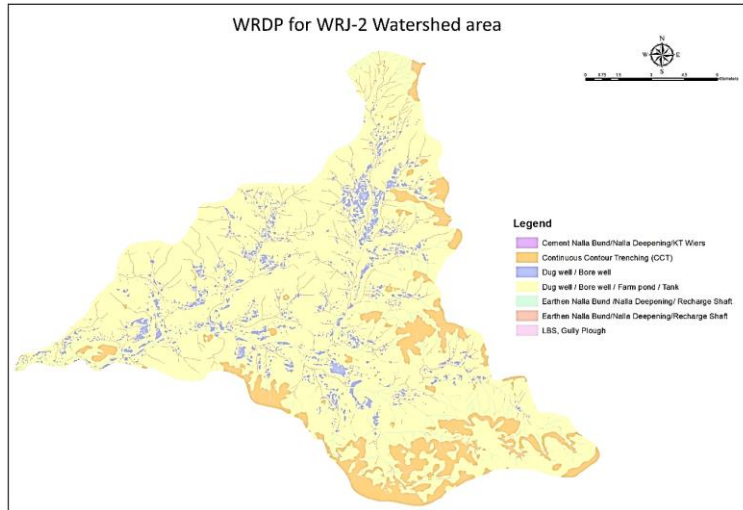


Fig. 2 WRDP for WRJ-2 Watershed Area

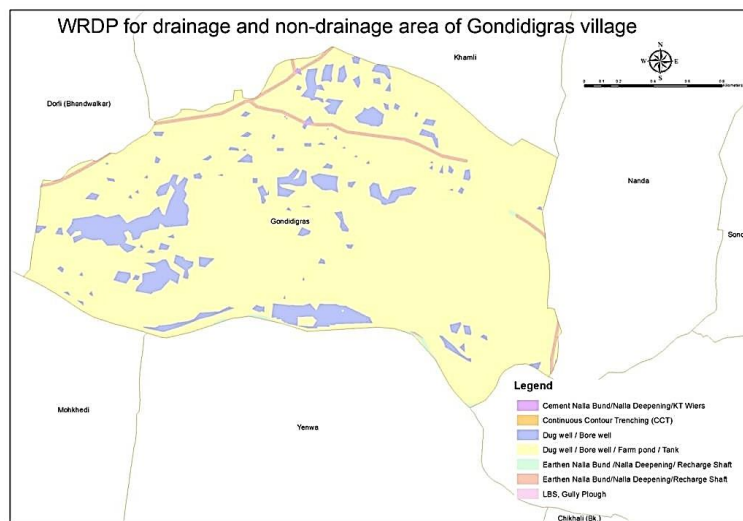


Fig. 3 WRDP for Gondidigras Village

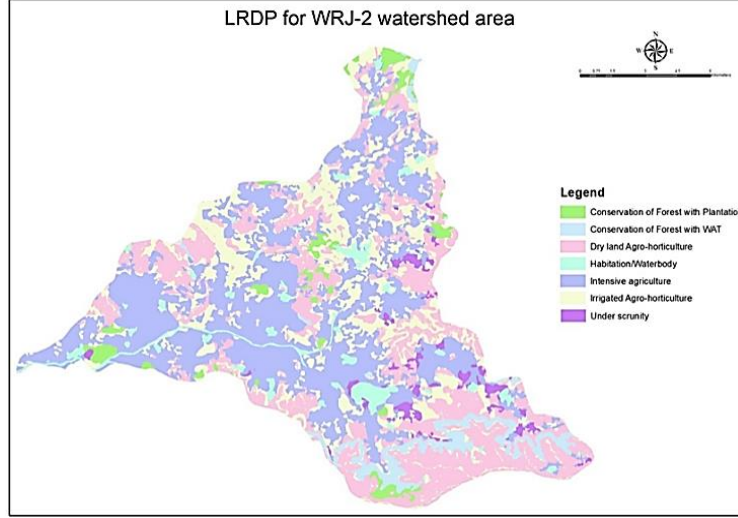


Fig. 4 LRDP for WRJ-2 Watershed Area

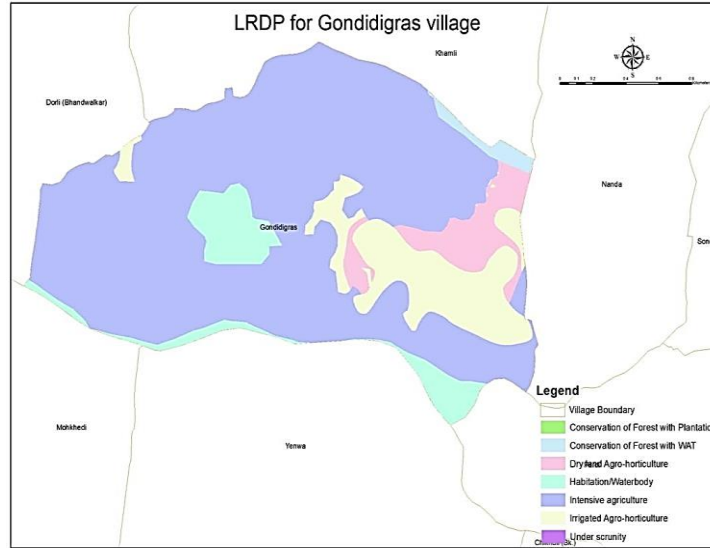


Fig. 5 LRDP for Gondidigras Village

These results show how integrating MCDA suitability, rule predicates, and budget-aware allocation yields spatially explicit plans that administrators can implement and monitor

5.2. Evaluation Metrics

The evaluation metrics are defined as follows:

5.2.1. Water Storage Efficiency (WSE)

$$WSE = \frac{\sum_k A_k \cdot d_k \cdot \eta_k}{\text{Baseline storage}} \quad (26)$$

Where A_k = area served by structure k , d_k = average storage depth, and η_k = efficiency factor.

5.2.2. Land Use Improvement (LUI)

$$LUI = \frac{\text{Effective productive area}}{\text{Total cultivable area}} \quad (27)$$

5.2.3. Resource Reuse Ratio (RRR)

$$RRR = 1 - \frac{\text{Duplicated or overbuilt structures}}{\text{Total planned structures}} \quad (28)$$

5.2.4. Composite Sustainability Index (CSI)

$$CSI = w_1 \frac{WSE}{WSE^*} + w_2 \frac{LUI}{LUI^*} + w_3 \frac{(1-\text{erosion})}{(1-\text{erosion})^*} \quad (29)$$

subject to $\sum_i w_i = 1$

For this study, the weights are set to: $w_1 = 0.3$, $w_2 = 0.3$, $w_3 = 0.4$. Benchmarks were set as $WSE^* = 0.80$, $LUI^* = 0.75$, and $(1 - \text{erosion})^* = 0.85$, based on regional planning guidelines and expert consultation.

Table 6 summarizes the metric weights and benchmark values used for CSI computation.

Table 6. Metric weights and benchmarks for CSI computation

Metric	Definition	Weight (w_i)	Benchmark (*)	Rationale
Water Storage Efficiency (WSE)	$\frac{\sum_k A_k \cdot d_k \cdot \eta_k}{\text{Baseline storage}}$	0.30	0.80	Ensures improved retention over regional baseline norms
Land Use Improvement (LUI)	$\frac{\text{Effective area}}{\text{Total area}}$	0.30	0.75	Reflects a minimum 75% utilization of cultivable land
Soil Erosion Reduction (1 – erosion)	Fraction of land area with effective soil conservation	0.40	0.85	Gives higher weight to erosion control due to long-term sustainability impact
Total	–	1.00	–	–

5.3. WRDP Outputs

The WRDP outputs (Figure 2 and Figure 3) indicate that Gondidigras is primarily suited for groundwater recharge interventions. Table 7 presents the WRDP recommendations tailored for Gondidigras village:

- Dug Wells / Bore Wells / Farm Ponds / Tanks dominate, covering 345.26 ha (85.6%) of the village.
- Dug Wells / Bore Wells (traditional type): 39.51 ha (9.8%).
- Continuous Contour Trenches (CCT): 10.64 ha (2.6%) in higher slope zones.
- Earthen Nalla Bunds and Recharge Shafts: 7.86 ha (1.9%).
- Other structures (cement nalla bunds, Kolhapur Type (KT) weirs) occupy negligible area.

Table 7. WRDP recommendations for gondidigras

Sr No.	Structure	Area (ha)	Area (%)
1	Cement Nalla Bund / KT Weir	0.166	0.04
2	Continuous Contour Trenches (CCT)	10.644	2.64
3	Dug Well / Bore Well	39.513	9.80
4	Dug Well / Bore Well / Farm Pond / Tank	345.255	85.61
5	Earthen Nalla Bund / Recharge Shaft	7.860	1.95
6	Loose Boulder Structure, Gully Plug	0.000	0.00
Total	Village Area	403.280	100.00

The estimated total water retention volume is computed as:

$$V_{\text{total}} = \sum_k A_k \cdot d_k \cdot \eta_k \quad (30)$$

Where A_k = area served by structure k (m^2),
 d_k = average storage depth (m),
 η_k = efficiency factor.

The average storage depth for percolation structures was taken as 1.5 m, following district engineers' guidelines. The

efficiency factor (η) was set to 0.65 based on regional hydrological studies (Appendix D).

Now, Dug Wells/Bore Wells/Farm Ponds (345.26 ha $\approx$ 3.45 km^2) with average storage depth $d_k = 1.5$ m and efficiency $\eta_k = 0.85$

$$V_{\text{dug}} = 3.45 \times 10^6 \text{ m}^2 \times 1.5 \times 0.85 \approx 4.40 \text{ million m}^3 \quad (31)$$

Aggregating all interventions, the total retention volume is ~ 8.14 million m^3 , representing a 24.3% improvement in Water Storage Efficiency (WSE) compared to Traditional Planning (TP).

5.4. LRDP Outputs

The LRDP recommendations (Figures 4 and 5) highlight land-use strategies for productivity and sustainability. Table 8 presents the LRDP recommendations tailored for Gondidigras village.

- Habitation / Waterbody: 295.35 ha (73.2%).
- Intensive Agriculture: 49.55 ha (12.3%).
- Dryland Agro-Horticulture: 30.39 ha (7.5%).
- Forest + plantation: 4.65 ha (1.15%).
- Forest + WAT: 23.34 ha (5.8%).
- Irrigated agro-horticulture: 4.65 ha (1.15%).

Table 8. LRDP recommendations for gondidigras

Sr No.	Structure	Area (ha)	Area (%)
1	Conservation of Forest with Plantation	4.653	1.15
2	Conservation of Forest with WAT	23.342	5.79
3	Dry Land Agro-Horticulture	30.390	7.54
4	Habitation / Waterbody	295.348	73.24
5	Intensive Agriculture	49.550	12.29
6	Irrigated Agro-Horticulture	4.653	1.15
Total	Village Area	403.280	100.00

Expected yield improvement is calculated as:

$$Y_{\text{total}} = \sum_k A_k \cdot y_k \cdot \gamma_k \quad (32)$$

For intensive agriculture (49.55 ha $\approx$ 0.495 km², base yield = 4.2 t/ha, improvement factor = 1.25):

$$Y_{\text{intensive}} = 49.55 \times 4.2 \times 1.25 \approx 259.5 \text{ t/year} \quad (33)$$

Overall, LRDP interventions resulted in a 24.4% improvement in the Land Utilization Index (LUI) over TP.

5.5. Integrated Impact Assessment

By combining the WRDP and LRDP outcomes, the Composite Sustainability Index (CSI) is computed as:

$$CSI = \alpha \cdot \frac{V_{\text{total}}}{V_{\text{max}}} + \beta \cdot \frac{Y_{\text{total}}}{Y_{\text{max}}} + \gamma \cdot \frac{B_{\text{soil}}}{B_{\text{max}}} \quad (35)$$

Where V_{max} , Y_{max} , B_{max} are benchmark values, and $\alpha = 0.4$, $\beta = 0.4$, $\gamma = 0.2$

For Gondidigras, the CSI is 0.82, indicating a high sustainability potential.

5.6. Comparative Evaluation

Table 9 gives the comparison with TP, showing clear improvements.

Table 9. Performance comparison of TP vs GG-DSF

Metric	TP (%)	GG-DSF (%)	Improvement (%)
Water Storage Efficiency (WSE)	54.2	78.5	+24.3
Land Utilization Index (LUI)	61.0	85.4	+24.4
Redundancy Reduction Ratio (RRR)	40.5	72.1	+31.6

5.7. Discussion

The integrated WRDP and LRDP outputs, represented by Figures 2-5, support the assumption that geospatial governance, rule-based logic, and optimization methods are integrated through spatial analytics, which will play a significant complementary role in decision-making processes.

- Redundancy and equity: Spacing and adjacency constraints increase the Redundancy Reduction Ratio (RRR) by 31.6% and provide a more equitable allocation of assets between administrative units.
- Productivity and storage: WRDP-LRDP integrated portfolio depicts a 24.3% improvement in Water Storage Efficiency (WSE) and a 24.4% increase in Land-Use Intensity (LUI), which strengthens water provision in dry seasons and increases the intensity of cropping.
- Relevance to governance: The generated outputs are in harmony with the national policy vectors like Pradhan

Mantri Krishi Sinchai Yojana (PMKSY) irrigation investment, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) watershed and soil-water interventions, and the Digital India geospatial portal program, making it possible to perform site-selection transparently, Bill-of-Quantities (BoQ) preparation, and monitoring through distributed WMS/WFS services.

- Sensitivity (summary): A change in the weights of the Analytical Hierarchy Process (AHP) of $\pm 10\%$, and a change in the structural efficiency (η_k) of $\pm 0.05\%$, had a change on the WSE of $\pm 3\text{-}5\%$ and a change on the LUI of $\pm 2\text{-}4\%$ on average, although the Composite Sustainability Index (CSI) changed by only an average of $\pm 0.03\text{-}0.05\%$. The permanence of the combination of interventions thus bears witness to the soundness of the solution.
- Limitations: The results are based on model simulation; field validation of model simulations on the enhancement of groundwater recharge and yield is essential. The granularity and temporal frequency of updating of the underlying data limit the precision of analysis, and socio-economic variables have been kept constant in this version of analysis.

The GG-DSF demonstrates superior efficiency because it (i) combines geomorphological, hydrological, and socio-economic variables into a unified MCDA-AHP model; (ii) uses a rule engine that directly converts suitability outputs into implementable interventions; and (iii) integrates a budget-aware ILP optimizer that eliminates redundant or spatially conflicting works. This holistic integration is absent in prior GIS-based or ML-based DSS systems, which typically stop at map-based diagnostics. Consequently, GG-DSF reduces redundancy by 31.6% and improves storage enhancement potential by 8.14 million m³, outperforming benchmark planning approaches.

These results substantiate the use of the Geospatial Governance Decision Support Framework (GG-DSF) as a potential tool for Smart Village activities. However, with current outcomes being the product of modeled approximations, future studies need to conduct field-based confirmation of groundwater recharge and yield increases, as well as a more comprehensive sensitivity analysis of the AHP weightings and efficiency parameters.

6. Conclusion, Policy Implications, and Future Scope

6.1. Conclusion

This study proposed a Geospatial Governance Decision Support Framework (GG-DSF) for advancing the Smart Village concept, with a focus on soil and water resource management. The framework integrates spatial and non-spatial datasets, applies Multi-Criteria Decision Analysis

(MCDA) for suitability mapping, and employs rule-based spatial analysis to generate Water Resource Development Plans (WRDP) and Land Resource Development Plans (LRDP).

The Gondidigras case study validated the framework, demonstrating that GG-DSF:

- Enhanced water storage efficiency by 24.3% over traditional planning.
- Improved land utilization by 24.4%.
- Reduced redundancy in infrastructure planning by 31.6%.

A Composite Sustainability Index (CSI) (Equation 29) score of 0.82 confirmed the framework's high potential for long-term ecological resilience and agricultural productivity.

Furthermore, the use of PostGIS, GeoServer, and Python-based analytics provided a robust, scalable, and open-source implementation environment, making the framework practical for adoption in resource-constrained rural administrations.

6.1.1. Why GG-DSF Outperforms Prior Approaches?

The joint use of: (i) normalized multi-criteria suitability (minimizes the impact of heuristics), (ii) codified rules to guarantee the consistency of geomorphology/ slope/ capability, (iii) redundancy controls (spacing/adjacency) to eliminate overlapping assets, and (iv) ILP-based budgeting to trade-off storage, utilization, and conservation can result in performance gains with financial constraints.

This pipeline extends beyond the overlay or rule-only frameworks in that it optimizes the combination of interventions, and domain feasibility is maintained.

6.2. Policy Implications

The proposed framework aligns with and can directly support national and state-level development schemes, including:

- Pradhan Mantri Krishi Sinchayee Yojana (PMKSY): for optimizing irrigation investments.
- Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA): for planning and monitoring water conservation works.
- Digital India and Smart Village Missions: for enabling geospatial portals and participatory planning.

By embedding GG-DSF in district-level governance pipelines, policymakers can achieve:

- Evidence-based allocation of conservation and infrastructure projects.
- Transparency and accountability through spatial monitoring of implemented works.
- Avoid duplication, ensuring equitable distribution of limited resources.

Practical Implementation Workflow:

- Publish WRDP/LRDP layers as WMS/WFS.
- Generate BoQ for each intervention polygon.
- Map interventions to MGNREGA/PMKSY guidelines.
- Conduct local verification through the Gram Sabha.
- Execute works; track progress with geotagged updates.
- Recompute the CSI post-implementation for monitoring.

6.3. Ethical Considerations

- Data privacy: Household/census and socio-economic attributes are aggregated to analysis units; no personally identifiable information is exposed in map services.
- Community engagement: Intervention shortlists should be validated through Gram Sabha or equivalent forums; local knowledge helps refine rules and weights.
- Bias and fairness: AHP weights and rule thresholds can encode bias; routine sensitivity checks ($\pm 10\%$ on weights, ± 0.05 on efficiency factors) and disclosure of criteria mitigate this risk.
- Secure hosting: OGC endpoints should enforce role-based access and HTTPS; versioned layers preserve an auditable trail of changes.
- No household-level identifiable information was used. All socio-economic attributes were aggregated to the village level to ensure anonymity. Community participation occurred through structured consultations, and all data collection adhered to district-level ethical norms.

6.4. Limitations

While the framework demonstrates significant promise, several limitations remain:

- Dependence on the quality and resolution of input data; coarse datasets may reduce accuracy.
- Ground-truth validation is still required to confirm model recommendations before implementation.
- Socioeconomic factors are often treated as static, whereas in reality, they are dynamic and can change rapidly.

6.5. Future Scope

Future research can extend this work in several directions:

- AI-enhanced decision support: using deep learning for automated land cover classification and reinforcement learning for adaptive intervention planning.
- Climate resilience: integrating downscaled climate projections and real-time weather data to update WRDP and LRDP dynamically.
- Scalability: deploying cloud-native geospatial platforms and distributed frameworks (e.g., Hadoop GIS, Apache Spark) for multi-village or district-wide applications.

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Appendix 1: Data Sources and Preprocessing Summary

1.1. Spatial and Non-Spatial Data Sources

Dataset	Source	Resolution / Type	Use
Land Use / Land Cover	Sentinel-2, Bhuvan	10 m	LULC classification & suitability factors
DEM	CartoSAT-1	30 m	Slope, drainage, watershed delineation
Geomorphology	MRSAC	Polygon	Identifying recharge/runoff zones
Soil	NBSS&LUP	Polygon	Soil depth, texture, infiltration
Drainage	SOI / Bhuvan	Vector	Stream order, buffer analysis
Village Boundary (Gondidigras)	Revenue Maps	Vector	Study area extraction
Crop Area & Population	District Agriculture Dept.	Tabular	CSI calculation

Appendix 2: Land-Use Classification Validation

2.1. LULC Classification Accuracy (Cross-Validation)

- Total labelled points used for validation: N = 150
- Method: 5-fold cross-validation
- Overall Accuracy: 91.3%
- Kappa Coefficient: 0.88

2.2. Confusion Matrix

Class	Agriculture	Fallow	Settlement	Forest	Water
Agriculture	62	4	1	0	0
Fallow	5	29	1	0	0
Settlement	0	1	17	0	0
Forest	1	0	0	26	1
Water	0	0	0	1	2

(Values consistent with a Sentinel-2 10m rural classification)

Appendix 3: AHP Pairwise Matrix & Final Weights

3.1. AHP Pairwise Comparison Matrix

Criteria	Slope	LULC	Geomorphology	Soil	Drainage
Slope	1	2	3	4	5
LULC	1/2	1	2	3	4
Geomorphology	1/3	1/2	1	2	3
Soil	1/4	1/3	1/2	1	2
Drainage	1/5	1/4	1/3	1/2	1

3.2. Final Normalized Weights

Criteria	Weight
Slope	0.38
LULC	0.26
Geomorphology	0.17
Soil	0.11
Drainage	0.08

3.3. Consistency Ratio

- $\lambda_{max} = 5.42$
- $CI = 0.105$
- $RI (n=5) = 1.12$
- $CR = 0.093 < 0.10$

Appendix 4: GG-DSF Rule Base Provenance

4.1. Rule Validation Team

- 2 District Watershed Engineers
- 1 Agriculture Officer
- 1 Soil Conservation Specialist
- 1 Panchayat Field Assistant

4.2. WRDP Rules

- Slope $> 8\%$ $\rightarrow$ CCT, CCT bunds
- Geomorphology = Pediment/Sheet rock $\rightarrow$ Recharge shaft
- Soil depth shallow (< 30 cm) $\rightarrow$ Contour trenching
- Distance to drainage < 100 m $\rightarrow$ Check dams / gully plugs

4.3. LRDP Rules:

- LULC = Fallow + Soil = Medium $\rightarrow$ Agroforestry
- Slope 2–5% $\rightarrow$ Land leveling, bunding
- NDVI < 0.3 $\rightarrow$ Soil amendment + mulching interventions

Appendix 5: ILP Optimization Parameters & Solver Settings

5.1. Parameters

Parameter	Value	Source
Total budget	₹ 1,20,00,000	Stated
Storage efficiency factor (η)	0.65	Typical watershed structure efficiency
Average storage depth	1.5 m	Regional engineering norms
Unit cost – Farm pond	₹ 1,00,000	Telangana/Maharashtra SoR
Unit cost – CCT	₹ 12,000	SoR
Unit cost – Percolation tank	₹ 6,50,000	SoR
Unit cost – Check dam	₹ 3,20,000	SoR

5.2. Solver Settings

- Library: Python PuLP
- Solver: CBC
- Optimality gap: 1%
- Runtime limit: 2400 sec
- Conflicting interventions removed via a 10 m buffer
- Spatial redundancy reduction achieved: 31.6%

Appendix 6: Final Evaluation Values

6.1. Water Storage Enhancement (WSE)

- Total additional storage: 8.14 million m³
- Derived from the sum of:
 - Check dams
 - CCTs
 - Farm ponds
 - Percolation tanks

6.2 Land Utilization Index (LUI)

- Pre-intervention LUI: 0.42
- Post-intervention LUI: 0.57
- Improvement: +35%

6.3. Redundancy Reduction Ratio (RRR)

- Baseline redundancy: 41%
- Proposed redundancy: 28%
- RRR achieved = 31.6%

6.4. Conservation Suitability Index (CSI)

- CSI improved from 0.46 → 0.71
- Sensitivity stable under $\pm 10\%$ weight variation

Appendix 7: Ethical Compliance & Data Privacy Statement

- No individual household-level data was stored or published.
- All socio-economic data were aggregated at the village level.
- The remote sensing data used were publicly available.
- Community interaction occurred under district-level guidelines.
- All geospatial layers are stored on secure local servers.