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Multi-Objective Optimization of Irrigation Canal Network Using Geospatial Computing: A Case Study of the Kadi Narmada Main Canal, Gujarat

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Abstract

This study develops and applies a geospatially driven computational framework to enhance the operational efficiency of irrigation canals, demonstrated through the Kadi branch of the Narmada Main Canal in Gujarat, India. Canal seepage and subsequent waterlogging are major contributors to reduced irrigation efficiency and secondary salinization in command areas. To characterize these processes, multi-temporal Landsat datasets (1990–2024), high-resolution UAV Ortho-mosaics, and ground-based geophysical measurements were analysed to generate long-term vegetation and surface-moisture indices, specifically the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). A multi-objective optimization model, formulated on the principles of the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), was implemented to identify intervention strategies that minimize seepage losses and waterlogged area while sustaining irrigation deliveries. The analysis revealed recurring moisture persistence and vegetative anomalies adjacent to the canal alignment, confirming progressive seepage patterns. Optimization results indicated that selective lining of high-loss segments combined with targeted sub-surface drainage could achieve approximately 20% reduction in seepage without adversely affecting supply reliability. The study demonstrates how the integration of remote sensing, UAV data, and evolutionary algorithms can support data-driven, cost-effective canal management, contributing to more sustainable and resilient irrigation infrastructure planning in India.

1. Introduction

Irrigation canals are critical infrastructure for delivering water to farms, industry, and settlements, especially in arid and semi-arid regions where surface storage and distribution networks provide the backbone of agricultural water supply. In countries such as India—home to roughly one-fifth of the world's population but with access to only a small fraction of global freshwater—efficient use of water is essential; canal inefficiencies therefore directly worsen scarcity and stress on both surface and groundwater systems. The losses caused by seepage and waterlogging are not only a significant volumetric loss of valuable irrigation supply, but they also degrade soil productivity (through salinization and waterlogging), increase groundwater table problems, and raise long-term costs for farmers and water agencies. Traditional canal operation practices—fixed release schedules, empirically based gate operations, and maintenance approaches that rely on periodic physical inspection—are poorly equipped to capture the highly dynamic spatial patterns of soil moisture, vegetation stress, and localized seepage that determine where water is being lost or where soils are being degraded. Climate variability (erratic monsoon timing, more intense dry spells, and floods) and rising water demand from agriculture, industry, and cities make these limits far more consequential: a static schedule or an inspector's snapshot can miss transient leaks, emergent seepage that appears only under certain flow conditions, or progressive salinization that develops over seasons. By contrast, an integrated approach that combines geospatial sensing (satellite multispectral and thermal imagery, airborne/UAV sensors, and ground geophysics), near-real-time analytics, and optimisation algorithms offers a pathway to modernise canal management. Remote sensing and UAV thermal–multispectral surveys can detect anomalous surface moisture, vegetation stress, and thermal signatures associated with leakage; high-resolution UAV imagery or airborne thermal surveys quickly pinpoint candidate seepage stretches for targeted field inspection or remediation. At basin and network scales, satellite time-series (Landsat, Sentinel-2, SAR) support trend detection and seasonal monitoring, while in-field EM/soil conductivity and ground-based sensors validate and quantify subsurface moisture and salinity. Recent reviews and pilot studies show the effectiveness of these sensing chains for leak detection and salinity assessment, and how they reduce reliance on purely manual inspection campaigns.

2. Methodology

The research methodology integrates detailed geospatial observations, ground-based measurements, and computational modelling to evaluate the hydraulic performance of the Kadi branch of the Narmada Main Canal. The workflow proceeds systematically—from data collection and preprocessing to spatial-temporal analysis and finally the development of an optimization model designed to reduce seepage and waterlogging while maintaining adequate irrigation flow.

Multiple datasets were used to capture both surface and subsurface characteristics of the study area. Multi-temporal satellite imagery from Landsat 5 TM, 7 ETM+, and 8 OLI (Path 149/Row 043) covering the period from 1990 to 2024 provided a continuous record of vegetation and surface moisture dynamics at 30-metre resolution. To complement this, high-resolution UAV imagery was acquired using a DJI Mavic Pro platform flown at an average altitude of 100 metres, producing ortho-mosaics with a ground sampling distance of about three centimetres. Differential GPS ground control points established during each flight ensured positional accuracy better than three centimetres in both horizontal and vertical directions. Geophysical investigations using electromagnetic induction and vertical electrical sounding were conducted along representative canal sections to measure electrical conductivity, subsurface moisture, and lithological variations up to about 15 metres depth. These measurements provided a physical reference for verifying the spectral signals of seepage detected from remote sensing. Supplementary information—including rainfall, soil type, and canal discharge records—was collected to define seasonal boundary conditions and to contextualize spatial patterns.

All satellite imagery underwent atmospheric correction through the LEDAPS and LaSRC algorithms and was cloud-masked using the C-F-mask. The scenes were reprojected to UTM Zone 43 N (WGS 84) and resampled to a consistent 30-metre grid. To minimize noise from short-term fluctuations, seasonal composites were produced for the post-monsoon (October–December) and rabi (January–March) periods within each decade. UAV images were processed in PIX4D Mapper using automatic tie-point detection and bundle adjustment, and the resulting ortho-mosaics were rectified with DGPS checkpoints. To maintain consistency with the satellite data, the UAV raster was aggregated to 30 metres using mean-cell averaging while preserving fine-scale variability. Geophysical data were log-transformed and spatially interpolated by ordinary kriging; cross-validation confirmed that interpolation errors remained within ten percent of observed conductivity values.

Spectral indices were computed for every composite to quantify vegetation and moisture behaviour. The Normalized Difference Vegetation Index (NDVI = (NIR – Red)/(NIR + Red)) served as a measure of plant Vigor, whereas the Normalized Difference Water Index (NDWI = (NIR – SWIR)/(NIR + SWIR)) was used to assess surface or near-surface moisture. Each index was normalized to zero mean and unit variance to ensure comparability between sensors and time periods. Statistical summaries—means, variances, and percentile thresholds—were then generated for each decade. Pixels consistently above the 90th-percentile NDWI or exhibiting sustained high NDVI values were classified as potential seepage zones. Temporal change detection applied the non-parametric Mann–Kendall trend test and Sen's slope estimator to identify monotonic increases or decreases in moisture. Positive slopes indicated gradual expansion of saturated areas over time. Spatial clustering was analysed using the Getis–Ord Gi statistic within a 500-metre buffer of the canal to highlight statistically significant hotspots likely associated with seepage or waterlogging.

The satellite-derived indicators were verified through ground measurements. Each electromagnetic and VES reading was matched to its corresponding pixel within a 15-metre tolerance. Correlation analysis revealed a strong positive relationship between apparent electrical conductivity and NDWI ($r \approx 0.65$, $p < 0.01$), confirming that high NDWI values correspond to zones of elevated subsurface moisture. Regression models developed from this relationship were used to estimate seepage intensity for canal reaches lacking direct field data. Lithological interpretation of the VES curves distinguished sandy, silty-clay, and loamy strata, each assigned representative hydraulic-conductivity values to parameterize seepage coefficients for the optimization model.

All processed datasets were integrated into a common geospatial database comprising the canal alignment, NDWI persistence, NDVI anomalies, interpolated conductivity, terrain slope derived from the DEM, and land-use information within a one-kilometre corridor. Each 250-metre canal segment was attributed with its average spectral, topographic, and geophysical parameters, forming the quantitative input for the optimization phase. The optimization model aimed to determine the most efficient combination of lining and drainage interventions that would simultaneously reduce seepage and minimize waterlogging while satisfying irrigation-supply constraints. Decision variables were binary, denoting whether a segment was lined or unlined and whether a particular drainage cluster was installed or omitted. The objective functions represented (1) total seepage loss derived from NDWI persistence and soil type, and (2) total area predicted to be waterlogged based on topography and moisture anomalies. Constraints were imposed on total rehabilitation cost, required downstream discharge, and permissible variation in seasonal water releases.

The optimization problem was solved using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), which is well-suited to discrete and non-linear decision spaces. Preliminary tests were conducted to tune algorithm parameters; a population size of 150–200, crossover probability of 0.9, and mutation rate of 0.1 were found to yield stable convergence. Each candidate configuration was dynamically linked to the geospatial database so that adjustments to canal-segment status automatically updated seepage and waterlogging estimates. Iterations continued until successive generations produced less than two percent improvement in Pareto-front coverage, indicating convergence.

Model calibration used seventy percent of the canal segments for training and thirty percent for validation. Statistical measures such as the coefficient of determination (R^2), root-mean-square error, and mean absolute percentage error were computed to evaluate predictive accuracy. Sensitivity analysis was performed by varying NDWI thresholds, seepage coefficients, and budget limits by ± 20 percent. The resulting dispersion of Pareto-optimal solutions demonstrated that the seepage-reduction benefits of roughly 20 percent remained consistent under these perturbations.

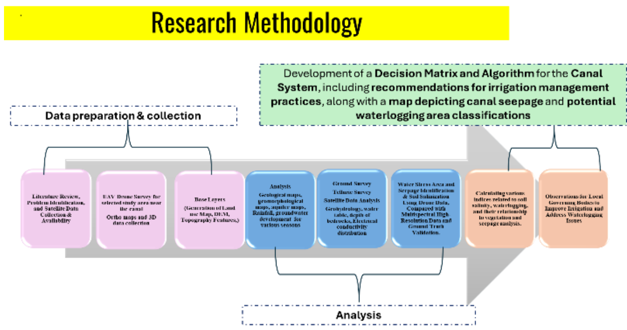

Figure 1 Methodology

3. Geospatial Computing and Multi-Objective Optimization Concepts

Geospatial computing combines remote sensing, GIS analysis, and numerical modelling to describe and quantify spatial patterns in the physical environment. In irrigation studies, this approach enables spatially continuous observation of canal networks, soil moisture, and vegetation dynamics—areas hard to monitor with ground surveys alone.

A typical workflow starts with multi-scale data acquisition

- Satellite imagery provides consistent temporal coverage.
- UAV data offer sub-decimetre detail.

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- Ground geophysical measurements capture subsurface moisture and conductivity variations.

Preprocessing ensures comparability

- Radiometric and geometric corrections.
- Mosaicking and resampling to a common spatial grid so every pixel or vector segment aligns across sensors.
-

Spectral indices form the first interpretive layer

- NDVI (normalized difference vegetation index) measures vegetation vigor by contrasting near-infrared and red reflectance.
- NDWI (normalized difference water index) captures surface or near-surface moisture variations, using the short-wave infrared band.

Complementary terrain attributes are derived from DEMs

- Slope, curvature, flow accumulation, and local relief.

Together, these layers help identify anomalous zones where vegetation growth or surface moisture deviates persistently from the regional baseline, often signalling seepage or inefficient drainage.

Managing an irrigation network involves balancing several sometimes-conflicting goals: conserving water by reducing seepage, preventing waterlogging and salinity buildup, maintaining delivery efficiency, and controlling construction or maintenance costs. Improving one objective can often worsen another, so a single optimization target isn’t sufficient.

A multi-objective optimization approach treats the problem as a set of competing goals evaluated simultaneously. Solutions are compared using Pareto dominance: a configuration is considered superior only if it improves at least one objective without making the others worse. The collection of all non-dominated solutions forms the Pareto frontier, which represents the trade-offs available between cost, efficiency, and environmental impact.

4. Overview of the Kadi Narmada Main Canal Study

4.1 Genesis and Purpose

The Kadi Narmada Main Canal is a branch of the Narmada canal network in Gujarat. Constructed in the 1980s as part of the Narmada Project, its purpose is to convey water from the Sardar Sarovar dam to irrigate arid regions and support socio-economic development. The canal runs through the Kalol region near a Y-junction of the main canal, at approximately 23°18′06″ N and 72°19′35″ E. Despite its importance, the canal suffers from seepage due to ageing lining and variable soils, creating waterlogged patches and soil salinity downstream.

Figure 2. Site Topography

4.2 Data Collection and Study Design

Two representative sites along the canal were selected: Site 1, adjacent to irrigated fields, and Site 2 downstream in a low-lying area. UAV surveys using a Mavic PRO platform were conducted at ~100 m altitude, producing ortho-mosaics with 3 cm resolution processed in PIX4D. Landsat 5, 7, and 8 images between 1990 and 2024 were downloaded and corrected to create NDVI and NDWI time series. Telluric and vertical electrical sounding surveys measured subsurface moisture, salinity, and lithology, validating remote-sensing observations. Precipitation and climate data provided a seasonal context.

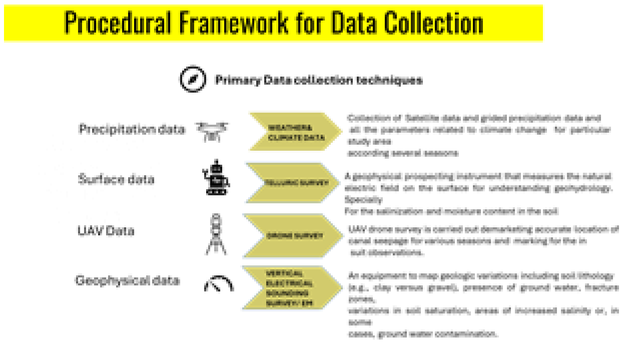

Figure 3. Procedural Framework

5. Evaluation of the Geospatial Optimization Approach

5.1 Data Integration and Indices References

Integrating UAV, satellite, and geophysical data provided a comprehensive picture of canal conditions. UAV ortho-mosaics captured fine-scale features such as embankments, drains, and adjacent fields. Landsat-derived NDVI and NDWI mapped vegetation vigour and moisture across broader time spans. Geophysical surveys confirmed that zones with high NDWI and NDVI corresponded to shallow groundwater and saline soils.

5.2 Spatial and Temporal Analysis

Time-series analyses of NDVI and NDWI enabled the identification of patterns beyond what a single date could reveal. High NDVI values along the canal across decades signalled persistent vegetative growth due to seepage-induced moisture. NDWI patterns showed that waterlogging expanded from localized spots in the 1990s to larger patches by the 2010s and 2020s. These observations support targeted maintenance and highlight the need for periodic monitoring.

NDVI multi-temporal analysis for various years is shown below for the selected site areas:

NDVI (Normalized Difference Vegetation Index):
NDVI = (NIR - Red) / (NIR + Red)

NDVI is a vegetation index used to assess the presence and health of vegetation in a given area. It quantifies the difference between near-infrared (NIR) and red-light reflectance.

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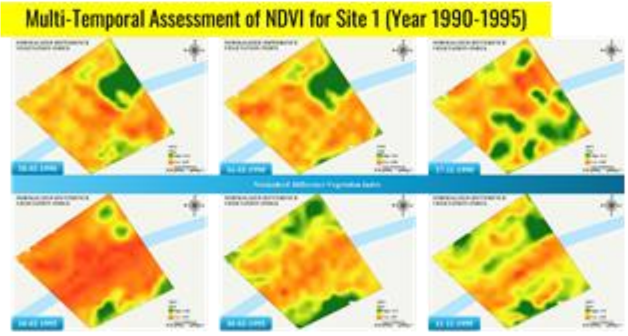

Figure 4. NDVI Assessment site 1 (1990-1995)

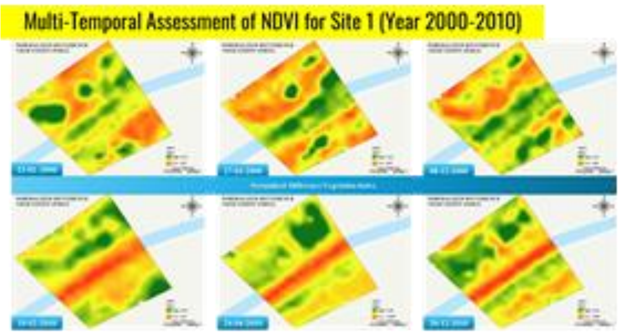

Figure 5. NDVI Assessment site 1 (2000-2010)

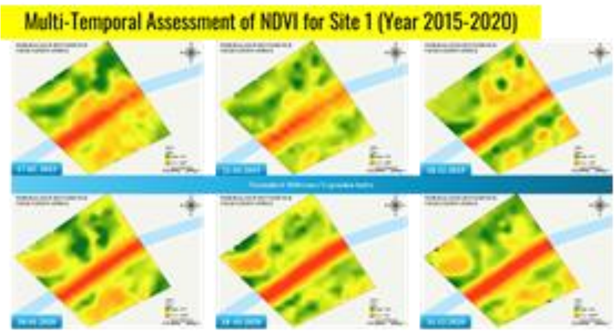

Figure 6. NDVI Assessment site 1 (2015-2020)

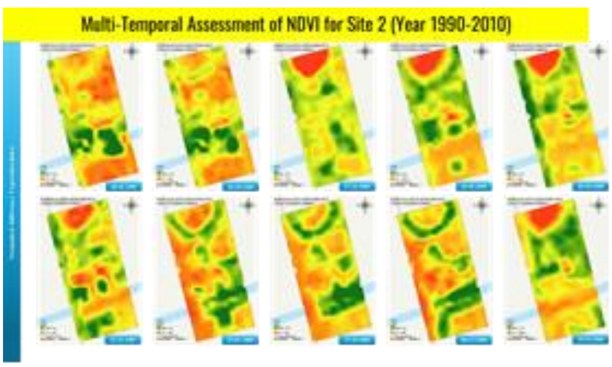

Figure 7. NDVI Assessment site 2 (1990-2010)

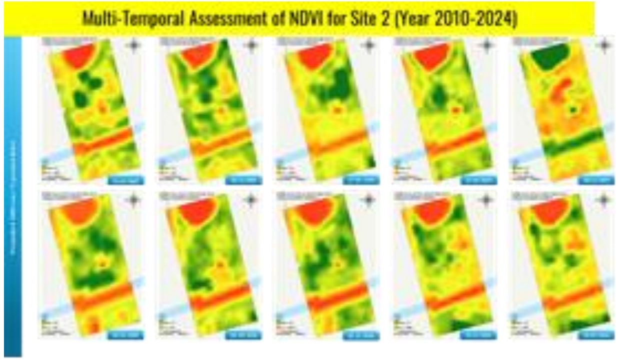

Figure 8. NDVI Assessment site 2 (2015-2020)

NDWI multi-temporal analysis for various years is shown below for the selected site areas:

NDWI (Normalized Difference Water Index):
NDWI = (Green - NIR) / (Green + NIR)

NDWI is a vegetation index employed to highlight the presence of water. It capitalizes on the differences in reflectance by the green and near-infrared bands.

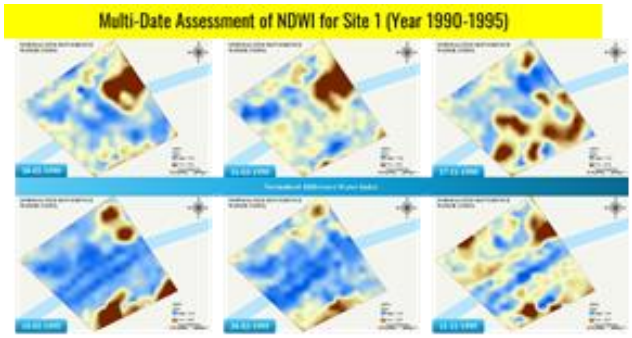

Figure 9. NDWI Assessment site 1 (1990-1995)

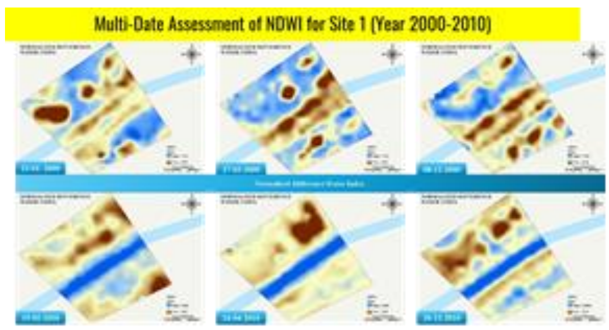

Figure 10. NDWI Assessment site 1 (2000-2010)

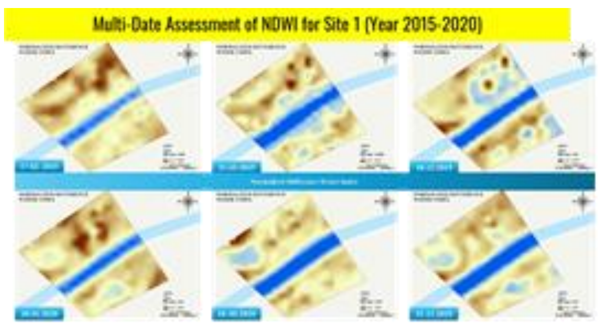

Figure 11. NDWI Assessment site 1 (2015-2020)

5.3 NDVI/NDWI Patterns and Observations

Analysis of NDVI and NDWI maps revealed that Site 1's NDVI increased from roughly 0.2 in the early 1990s to around 0.4 in the 2000s, reflecting improved vegetation due to irrigation. High NDVI values persisted along the canal embankment and irrigated fields across 2015–2024. NDWI maps showed moisture hotspots (> 0.1) coinciding with these high NDVI zones, indicating seepage. Site 2 exhibited similar increases in NDVI but greater spatial variability; NDWI identified waterlogged pockets in low-lying areas. Temporal differencing highlighted a progressive expansion of seepage and waterlogging, particularly after 2000, when canal flow increased

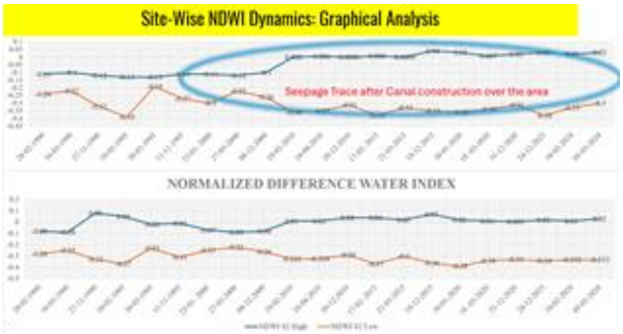

Figure 12. NDWI Graphical Analysis

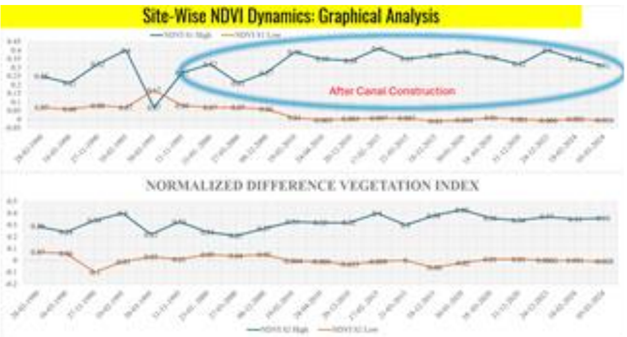

Figure 13. NDVI Graphical Analysis

5.4 Optimization and Decision Support

Optimization was performed using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to balance seepage reduction, waterlogging control, and irrigation reliability. Each population member represented a unique combination of canal-segment lining, drainage placement, and seasonal discharge schedule. Two objective functions were minimized simultaneously: total seepage loss, derived from NDWI-based moisture persistence weighted by local hydraulic conductivity, and predicted waterlogged area estimated from terrain and NDWI anomalies.

Constraints were imposed on total rehabilitation cost, minimum delivery at distributary outlets, and permissible variation in seasonal releases. The model was dynamically linked to the spatial database, allowing real-time recalculation of seepage and waterlogging for every candidate solution. A population of 150 with crossover and mutation probabilities of 0.9 and 0.1, respectively, achieved convergence within ~180 generations.

The resulting Pareto frontier defined feasible trade-offs between seepage and waterlogging reduction. The balanced, knee-point solution—lining about 15 % of the canal and adding ten drainage clusters—yielded approximately 20 % reduction in seepage and 17 % in waterlogged area without affecting deliveries. Sensitivity analysis confirmed model stability under ± 20 % parameter perturbations. Final outputs were visualized as decision maps indicating optimal lining and drainage zones, providing a quantitative, spatially explicit support tool for canal-rehabilitation planning.

6. Conclusion and Recommendations

This study demonstrates the effectiveness of integrating multi-source geospatial data and evolutionary optimization for improving irrigation canal performance. Multi-temporal Landsat and UAV datasets, supported by electromagnetic and VES surveys, provided a detailed spatial representation of vegetation Vigor, moisture persistence, and subsurface conductivity along the Kadi branch of the Narmada Main Canal. The strong correlation between NDWI and ground conductivity confirmed the reliability of remote-sensing indices for identifying seepage-affected zones.

The NSGA-II-based multi-objective optimization framework enabled the simultaneous minimization of seepage losses and waterlogged area under realistic operational and budget constraints. Pareto-optimal solutions indicated that selective lining of about 15 % of the canal length, combined with targeted sub-surface drainage, could achieve a roughly 20 % reduction in seepage without compromising irrigation delivery. Temporal NDWI trends revealed progressive expansion of moisture zones since the 1990s, emphasizing the need for localized interventions rather than uniform canal rehabilitation.

The results validate the use of geospatial computing as a quantitative decision tool for irrigation management. The methodology is computationally scalable, adaptable to other canal systems, and capable of continuous updating as new satellite or UAV data becomes available. Future integration with SAR-derived soil-moisture indices and hydrodynamic simulation models can further enhance predictive accuracy and support data-driven, cost-effective canal maintenance planning.

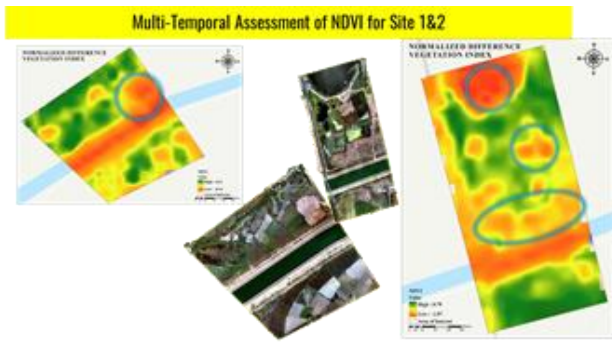

Figure 14. NDVI comparison for Sites 1 and 2: Seepage identification

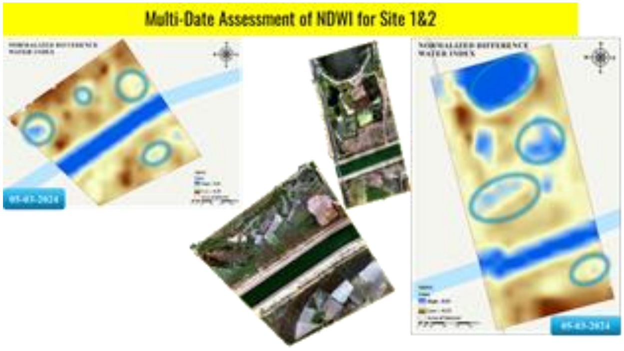

Figure 15. NDWI comparison for Sites 1 and 2: Seepage identification

Acknowledgements

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Edge computing and GIS integration—combining edge computing and GIS produced water resource scheduling models with predictive accuracies exceeding 90.

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