Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268
(Print copies up to 2016)
e-ISSN: 2395-3454

Vol. 25 | No. 2 | Article ID B4385 | 2026

Original Research Paper

https://doi.org/10.46488/NEPT.2026.v25i02.B4385

Open Access Journal

Sustainability Assessment of Rural Areas Using Composite Green Rating Score (CGRS) Across Diverse Eco-Geographical Conditions: A Case Study of Villages in Sangli District, Maharashtra

Suhas Bhanudas Mohite[1,2]† and Rohan S. Gurav[1]

[1]Department of Civil Engineering, Visvesvaraya Technological University, Belagavi-590018, Karnataka, India
[2]Department of Civil Engineering, P.V.P. Institute of Technology, Budhgaon-416304, Sangli, Maharashtra, India
†Corresponding author: Suhas Bhanudas Mohite; suhas.mohite80@gmail.com

Abbreviation: Nat. Env. & Poll. Technol.
Website: www.neptjournal.com

Received: 13-08-2025
Revised: 05-10-2025
Accepted: 08-10-2025

Key Words:

Rural sustainability
SWOT analysis
Environmental assessment
Green rating system
Infrastructure disparities
Renewable energy adoption
Sustainable rural development

Citation for the Paper:

Mohite, S.B. and Gurav, R.S., 2026. Sustainability assessment of rural areas using composite green rating score (CGRS) across diverse eco-geographical conditions: A case study of villages in Sangli District, Maharashtra, India *Nature Environment and Pollution Technology*, 25(2), B4385. https://doi.org/10.46488/NEPT.2026.v25i02.B4385

Note: From 2025, the journal has adopted the use of Article IDs in citations instead of traditional consecutive page numbers. Each article is now given individual page ranges starting from page 1.

ABSTRACT

Indian rural development faces multidimensional challenges, including uneven socioeconomic conditions, limited infrastructure, and environmental risks. Recognizing the need for a systematic sustainability assessment, this study proposes a Composite Green Rating System (CGRS) to analyze and compare the ecological, infrastructural, and socio-economic performance of rural settlements. Existing sustainability rating systems, such as LEED, BREEAM, and GRIHA, are designed for city- or industrial-scale contexts and do not account for rural ecological heterogeneity, decentralized infrastructure, and socio-economic inequalities. To address this gap, the CGRS integrates environmental, infrastructural, and socioeconomic factors into a transferable index tailored to rural locations. Primary data were collected via structured questionnaires from 120 respondents across three villages - Dorli, Bilashi, and Padmale - covering environmental conditions, infrastructure, sustainable practices, and risk awareness. Descriptive statistics, Chi-square, ANOVA, and Kruskal-Wallis tests were used to assess differences and the reliability of adoption patterns across villages. The normalized scores were aggregated to compute domain-wise averages, which were then used to derive the CGRS, yielding a single, comparable sustainability ranking for each village. A SWOT analysis was also conducted to identify strengths, weaknesses, opportunities, and threats and provide actionable insights to inform targeted interventions. The results show that Padmale recorded the highest CGRS (64%), followed by Bilashi (59%), while Dorli performed lower (34%) owing to poor environmental and infrastructural performance. The integrated CGRS and SWOT model identifies village-specific strengths and weaknesses, facilitating evidence-based planning and supporting policy-led interventions for sustainable rural development. This model is a workable and transferable tool for tracking and upgrading rural sustainable development. By being parallel to India's rural development plans and the UN SDGs, the CGRS framework offers policymakers with evidence-based recommendations for crafting localized, sustainable interventions.

INTRODUCTION

Sustainable development in rural regions is increasingly recognized as a critical component of national development strategies, particularly in countries such as India, where more than two-thirds of the population resides in villages (Pathak & Deshkar 2023). Despite targeted schemes such as Smart Villages and Gram Panchayat strengthening initiatives, rural areas continue to experience significant disparities in infrastructure, environmental management, and quality of life (Sharma et al. 2024). Traditional development models often overlook local ecological diversity and resource availability, making it imperative to adopt location-sensitive assessment frameworks to ensure sustainable development.

Although city-centric systems such as LEED, BREEAM, and GRIHA offer disciplined environmental appraisals, they are insufficient for the rural realities of farm water use, disjointed infrastructure, and livelihood-bound environmental interventions. This disconnect highlights the necessity for a rural-targeted appraisal model, such as the CGRS, that reflects both ecological vulnerability and locally owned sustainability practices. (Kochhar et al. 2022). Recent literature underscores the need for decentralized, community-centric sustainability assessments (Tholkapiyan et al. 2023) that integrate environmental parameters, such as water conservation, renewable energy utilization, waste management, and biodiversity preservation, along with social infrastructure (Tiwari & Chandra 2023, Patil et al. 2024).

In particular, a growing body of evidence supports the use of SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis for village-level diagnostics. Studies have demonstrated its utility in evaluating environmental and infrastructure readiness in various rural geographies, including riverine, hilly, and arid regions (Ali et al. 2021). For example, Sengupta (2022) found that integrating SWOT analysis with participatory governance frameworks significantly enhances policy targeting in agricultural communities (Sengupta 2022).

Furthermore, advances in smart village concepts, particularly those incorporating renewable energy, IoT-enabled agriculture, and digitized public services, have shown measurable improvements in rural sustainability (Renukappa et al. 2024). However, such models also highlight the necessity of contextual adaptation, especially in regions with varying geographical vulnerabilities, such as flood plains, drought-prone zones, and hilly terrains (Tao & Xiang 2022).

The proposed work is imperative for presenting a structured, evidence-based rural sustainability assessment using environmental, infrastructural, and socioeconomic indicators. Its originality lies in the creation of the Composite Green Rating Score (CGRS) alongside multivariate statistical and SWOT analyses, providing a quantitative and comparative approach to village-level assessment. This study adds a replicable framework for policymakers and planners to determine strengths, weaknesses, and targeted interventions, while the scope is extended to scaling this model across various rural settings to inform sustainable development plans and support improved resource management in the future. This is directly related to India's national programs, such as the Sansad Adarsh Gram Yojana, Smart Village projects, and Gram Panchayat Development Plans, while localizing international SDGs to rural settings.

This study considers villages from the Sangli district of Maharashtra, namely Padmale (river-side), Dorli (drought-affected), and Bilashi (hilly) villages. Using a structured household survey, statistical analysis, and SWOT evaluation, this study offers an evidence-based appraisal of prime sustainability indicators such as environmental conditions, access to infrastructure, and sustainable practice adoption.

The aims of this study are as follows:

- To evaluate the existing environmental, infrastructural, and socioeconomic status of the target villages.
- To examine the trends in sustainability practice adoption and determine areas of strength and vulnerability.
- To construct and utilize a Composite Green Rating Score (CGRS) for comparative analysis of village sustainability performance.
- To combine SWOT analysis with CGRS results to recommend focused strategies for rural development and policy actions.

BACKGROUND RESEARCH

Assessment methodologies tailored to rural settings are essential because of the distinct ecological, economic, and infrastructural characteristics of the villages. In a comparative study, Kochhar et al. (2022) critically evaluated urban green rating systems, such as LEED and GRIHA, and found that these models inadequately address vital rural dimensions such as agricultural water management, decentralized energy supply, sanitation, and social inclusion. They argued for the development of rural-specific frameworks that incorporate both environmental and socio-infrastructural indicators into village governance processes (Kochhar et al. 2022). Following this call, Ali et al. (2021) implemented a SWOT analysis in three varied landscapes across Eastern India—riverine, hilly, and arid. Their mixed-methods approach, using community surveys complemented by resource inventories, demonstrated that such a diagnostic framework can highlight environmental bottlenecks and sociocultural strengths that quantitative indicators often miss (Ali et al. 2021). Their findings underscore the adaptability and participatory nature of SWOT as a rural evaluation tool. This methodology directly informs the analytical design of the present study, which employs similar diagnostic mapping across selected Sangli villages.

Eco-village frameworks aim to align village infrastructure with ecological principles. Kumavat et al. (2021) examined a semi-arid Maharashtra village, introducing decentralized technologies-rooftop solar, rainwater harvesting, composting toilets-and coupled these with community engagement to reduce energy use by one-quarter and water use by nearly a third over 18 months (Kumavat et al. 2021). By integrating household-level interventions with communal systems, this framework demonstrates measurable sustainability gains. Building on structural design, Mohapatra et al. (2024) studied rural housing retrofitting in three Indian villages, embedding passive cooling techniques, solar water heating, and greywater recycling into the existing housing stock of the villages. Evaluations revealed that 80% of retrofitted homes reached a net-zero energy status and reported 20–35% improvements in indoor comfort, along with reduced energy expenditures (Mohapatra et al. 2024). These models provide technical precedents and performance benchmarks for infrastructure criteria in green-rating exercises.

A growing body of research emphasizes that sustainable rural development relies heavily on community engagement, especially in energy governance and social enterprise ecosystems. Ricket et al. (2023) introduced a "social enterprise ecosystem" model, demonstrating that combining local institutions, entrepreneurial networks, and ecological initiatives significantly enhances rural prosperity by aligning livelihood generation with sustainability objectives (Ricket et al. 2023). CuencaEnrique et al. (202)4conductedn a systematic review of global rural electrification projects and identified social capital, participatory planning, and local governance structures as key determinants of project sustainability, often being more influential than technology type or initial funding (Cuenca-Enrique et al. 2024). Adding another dimension, Katoch et al. (2024) examined community solar microgrids in rural India, highlighting how community-based microenterprises and local ownership models boosted employment by up to 70% while reducing carbon emissions by 40% if they received strong local institutional support (Katoch et al. 2024). Finally, Nasution et al. (2025) synthesized over 100 studies in South Asia and concluded that three pillars-sustainable agriculture, digital inclusion, and active community participation-converge to create self-reliant and resilient villages (Nasution et al. 2025). Together, these studies reinforce that community participation and local governance are indispensable in any village-level green rating framework and must be explicitly captured within the SWOT analysis.

Recent studies have highlighted the transformative potential of integrating information and communication technology (ICT) into rural governance and agricultural systems. Gerli et al. (2022), in a systematic review, defined Smart Villages as those that effectively combine local knowledge, participatory governance, and digital technologies to enhance services and strengthen resilience. They emphasized that while digital tools can improve service delivery, they must be introduced with sensitivity to local capacities and community structures (Gerli et al. 2022). Empirical studies support this view. Sabir et al. (2021) examined pilot programs that used IoT-enabled irrigation systems and mini-solar grids in Indian villages. The results indicated a 30% increase in water-use efficiency and a 25% reduction in the energy costs. The key to successful deployment was village institutions capable of managing maintenance and data interpretation (Sabir et al. 2021). Meanwhile, Renukappa et al. (2024) extended the discussion by analyzing integrated ICT-water-energy interventions across villages in Western and Central India. They highlighted that the resilience of such systems depends on robust community governance, reliable data, and aligned institutional incentives (Renukappa et al. 2024). These studies underscore the importance of assessing not only infrastructure performance but also governance and operational sustainability—elements that inform the SWOT evaluations and comparative village analyses in this study.

Precision agriculture, underpinned by IoT and remote sensing, has had transformative impacts on resource use and production. A 2024 meta-analysis (Shahab et al. 2024) reviewed over 100 rural case studies and reported average yield increases of 20-30% with simultaneous 25–40% reductions in the use of water and fertilizer. Additionally, Dhal and Kar (2024) showcased how AI-driven forecasting models, particularly SARIMA and deep-learning hybrids, enhanced regional yield prediction and supply chain optimization, while acknowledging the need for better data infrastructure in smallholder settings (Dhal & Kar 2024). These findings support the inclusion of technological efficiency and forecasting capabilities in the SWOT analysis when evaluating information and resource management processes.

Recent studies have stressed that sustainability gains must be resilient to climatic and economic uncertainties. Der Tambile et al. (2024) undertook a South Asia-wide bibliometric study, recommending frameworks that combine resource governance, digital systems, and resilience indicators to cope with environmental and market stresses (Der Tambile et al. 2024). A parallel comparative investigation by Sengupta (2022) contrasted flood risks in riverine villages with forest-dependent communities in hilly terrain, finding that resilience frameworks, including early warning systems and ecosystem-based risk management, must be tailored to the ecological context (Sengupta 2022). These insights guided the inclusion of "Resilience" dimensions within the SWOT framework and comparative analysis of villages facing contrasting environmental risks in Sangli.

Despite the acknowledged value of comparative studies, few have been conducted within the same district. Sengupta (2022) utilized participatory SWOT methods across riverine and hilly villages in West Bengal, revealing distinct strengths and limitations, similar to those of Ali et al. (2021) in Odisha. Their approaches demonstrated that cross-village comparisons help in drawing out contextually grounded interventions and adaptive planning strategies (Ali et al. 2021, Sengupta 2022). These comparative diagnostics form the methodological backbone of the present study, which applies a consistent SWOT and survey framework across three geographically diverse Sangli villages to generate data-driven comparisons.

Recent empirical evidence (Liu et al. 2024) from various Indian states demonstrates the diverse approaches adopted for smart village development, particularly in enhancing environmental, energy, water, sanitation, and agricultural sustainability. Across multiple regions, environmental initiatives have prioritized improving livability through afforestation, pollution control, and waste reduction, as observed in villages such as Betul, Payvihir, Anadwan, and Hemalkasa in Madhya Pradesh and Maharashtra. Interventions such as native tree plantations, recycling programs, the adoption of efficient cookstoves, and the promotion of ecotourism hubs have been instrumental in fostering greener rural spaces. Simultaneously, the energy dimension has been addressed through the promotion of clean and renewable energy sources, notably in Chhotkei (Odisha), Odanthurai (Tamil Nadu), and Dharni (Bihar), where smart nanogrids and a combination of solar, wind, and hydropower have transformed village-level energy accessibility. Equally significant are water management practices, exemplified in Ralegaon Siddhi, Hiware Bazar, Dhanora, and Anadwan, where rainwater harvesting, percolation tanks, river rejuvenation efforts, and purification systems have collectively enhanced water security. On the sanitation front, villages such as Ramchandrapur in Telangana have focused on building individual household toilets, wastewater reuse, and potable water quality monitoring, thereby contributing to improved hygiene and better public health. Lastly, in the agriculture sector, villages such as Noorpur Bet (Punjab), Hiware Bazar (Maharashtra), and Eraviperoor (Kerala) have adopted weather monitoring technologies, farmer capacity-building programs, and modern irrigation techniques to bolster productivity and sustainability. This diversity of localized, thematic interventions highlights the growing recognition of village-specific needs and solutions in advancing India's smart and sustainable rural transformation agenda.

Several key gaps emerge in the literature. First, while eco-village and retrofit studies report concrete resource efficiencies, they often lack comparative analyses across various environmental settings. Second, Smart Village initiatives tend to focus on pilot projects without assessing the long-term viability of digital governance and community-led operations. Third, resilience frameworks are typically conceptual, offering limited operational guidance to rural administrators and managers. Finally, few studies have integrated these multiple dimensions, environmental, infrastructural, technological, and resilience, within comparative village-level empirical analyses.

By synthesizing evidence across these domains, the present research advances knowledge through detailed documentation of village typologies, participatory SWOT analysis, cross-contextual benchmarking of environmental, infrastructural, and governance factors, and development of evidence-based insights for future green rating and prioritization, which will be detailed in follow-up studies.

MATERIALS AND METHODS

Proposed Method

This study employs a hybrid evaluation approach using survey-derived sustainability measures, expert-weighted evaluation through the Analytic Hierarchy Process, and multi-village comparative analysis. The indicators were scaled to a 0–1 interval and collated into a Composite Green Rating System, validated statistically (chi-square, ANOVA, PCA), and cross-checked with official development records. The quantitative findings were combined with SWOT analysis to link quantitative scores to real-world strengths, weaknesses, opportunities, and threats for each village type. This quantitative–qualitative approach has the strength of both the precision of measurement and richness of interpretation, rendering it flexible for policy-oriented rural-development planning.

This research advances beyond standard rural sustainability evaluations based on descriptive measures or SWOT analyses. This study proposes a Composite Green Rating System (CGRS), a weighted, expert-based index that measures sustainability performance in terms of environmental, infrastructural, sustainability-practice, and risk-resilience dimensions. Combining this quantitative system with a qualitative SWOT analysis, the approach allows for both numerical benchmarking and context-relevant interpretation (Fig. 1). The three-way comparative research design in the contrasting eco-geographical settings of drought-prone, hilly, and riverside areas also adds to the novelty, since few Indian rural research studies have systematically interrelated environmental settings, socio-economic profiles, and sustainability performance in a single evaluation framework.

Materials

This study used both primary and secondary data sources to develop and test the Composite Green Rating System (CGRS). Primary data were gathered through a structured household

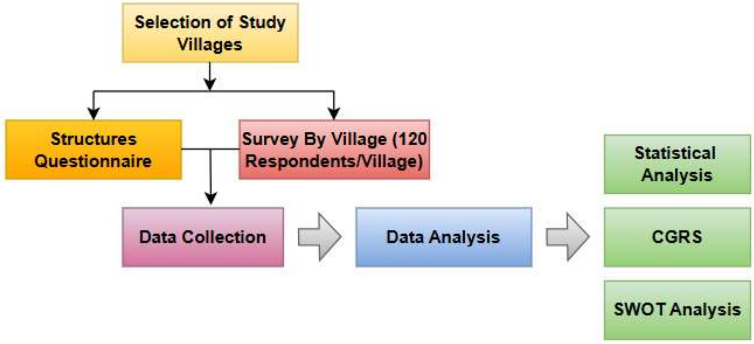

Fig. 1: Proposed methodology for analysis of sustainability and development with CGRS for villages in Sangli District.

survey administered to 360 families (approximately 120 per village) using paper questionnaires and digital entry forms on tablets for precision. The survey tool captured environmental activities, infrastructure access, sustainability, and risk awareness. GPS-equipped devices were used to capture the geographic location and elevation, and field observations were captured using high-resolution digital cameras. Secondary information, such as Gram Panchayat development records, Census 2011 population data, and Google Earth Pro satellite imagery, was used to cross-check the survey responses and supplement the contextual environmental information. Analytical tasks utilized statistical software (SPSS 28.0, R 4.3.2) for cleaning, normalization, weighting, and advanced analysis to promote methodological rigor and replicability of the results.

Selection of Study Villages

Three villages in Maharashtra's Sangli district-Dorli (drought-prone), Bilashi (hilly terrain), and Padmale (riverside)-were purposively selected to represent distinct ecogeographical contexts. This approach ensured that the study captured a broad array of environmental challenges, socioeconomic profiles and infrastructure conditions. Dorli is characterized by long-term water scarcity and heat stress, Bilashi by terrain-related access limitations and scattered settlements, and Padmale by periodic flooding from the Krishna River. The comparative context of these settings enables the evaluation of how context-specific risks and resources affect sustainability outcomes, offering a more complete understanding than single-context rural research.

The research purposively sampled three villages spanning drought-prone, hilly, and riverside eco-geographies to maximize the contextual variety within a tractable range. Although this constrains external validity, the comparative approach offers transferable insights into how the ecological context interacts with sustainability adoption. Additional research with larger samples is needed to examine the generalizability of the findings.

Sampling and Data Collection

A stratified random sampling approach was employed to ensure representation across diverse socioeconomic and demographic groups within each village. Approximately 120 households were surveyed per village, accounting for 20-25% of the total number of households. The stratification criteria included caste or community group, income level, occupation type, and geographic distribution within the village. Data were collected using a structured questionnaire available in Marathi and English. To improve reliability, the enumerators were trained in ethical data collection practices and maintaining impartiality during interviews. The questionnaire comprised closed-ended questions to facilitate quantitative analysis and semi-structured questions to capture the local perspectives. The questionnaire was pilot-tested on 15 households outside the study villages to refine the wording, minimize ambiguities, and ensure consistent responses. The Cronbach's alpha coefficients for the key domains exceeded 0.7, indicating good internal consistency. Triangulation with Gram Panchayat records and census data further strengthened the validity of the study.

Indicator Classification and Domain Grouping

The collected variables were organized into four key analytical domains: Environmental Sustainability, Infrastructure Adequacy, Sustainability Practice Adoption, and Risk and Resilience. Environmental indicators encompassed water treatment, waste management, and vegetation; infrastructure indicators included sanitation, road conditions, and healthcare access; sustainability practices measured the use of renewable energy and organic farming methods; and risk and resilience assessed the awareness of hazards and satisfaction levels. This classification facilitated both a focused domain analysis and the development of an overall sustainability score. The multi-domain approach offers a thorough evaluation that integrates ecological, infrastructural, and social factors.

Development of Composite Green Rating System (CGRS)

A pilot Composite Green Rating System (CGRS) was constructed to measure overall sustainability performance. The indicators were initially normalized to a 0–1 scale for comparability. Weights for every domain were allocated utilizing the Analytic Hierarchy Process (AHP), with the support of 12 domain experts in rural development, environmental engineering, and policymaking. Each village's composite score was computed as the weighted average of its domain scores. This methodology improves conventional descriptive surveys, making it possible to objectively benchmark sustainability performance and inform data-driven policy settings.

Statistical Analysis

Descriptive and inferential statistical techniques were used to enhance analytical strength. Descriptive statistics captured indicator performance at the village level, whereas chi-square tests probed the relationships between categorical indicators (e.g., renewable energy uptake and village type). One-way ANOVA was employed to contrast the mean domain and composite scores between the villages. Principal Component Analysis (PCA) was performed to determine the underlying factors influencing sustainability performance and minimize indicator redundancy. Statistical significance was set at $P < 0.05$. SPSS 28.0 and R 4.3.2 were used to conduct the analyses, ensuring replicability and adherence to best research practices.

While the Chi-square, ANOVA, and Kruskal-Wallis tests yielded non-significant findings, the result was informative rather than passive. This indicates that the diffusion of sustainability practices across varying eco-geographies is influenced more by structural constraints common to eco-geographies than by village-specific heterogeneity. Practically, this implies that interventions could be developed at the regional level rather than village-by-village.

SWOT Analysis and Integration with CGRS

A SWOT (Strengths, Weaknesses, Opportunities, Threats) matrix was also constructed for every village based on the survey results, direct field observations, and appropriate secondary sources, such as Gram Panchayat documents and hazard maps. High-scoring CGRS indicators were attributed to strengths, and low-scoring indicators were mapped to weaknesses. Threats and opportunities were determined based on external factors, such as government schemes, climatic risks, and access to markets. Combining SWOT with CGRS enabled quantitative scores to be augmented with qualitative context-based information, thus bridging the gap between statistical evaluation and actionable planning.

Validation of the Rating System

To verify the pilot CGRS's reliability, the generated village rankings were cross-checked with external measures, such as Gram Panchayat development expenditure data and available census-based quality-of-life indicators. A positive convergence between the CGRS results and external sources was assumed to be an indicator of construct validity. The validation procedure enhances the credibility of the proposed framework and proves its potential to serve as a replicable instrument for rural sustainability evaluations in varying eco-geographical settings.

Mathematical Model

To systematically compare and quantify sustainability performance in a quantifiable manner among villages, a mathematical model was developed for the Composite Green Rating System (CGRS). The model combines several indicators of sustainability, normalizes them to a comparable scale, uses expert-elicited weights, and aggregates them into domain and composite scores. This systematic process assures objectivity, transparency, and replicability in assessing rural sustainability under varying socioecological settings.

Normalization of indicators: Let $x_{i,j}$ be the raw observed value of indicator i for village j, where $i = 1, \ldots, m$ and $j = 1, \ldots, p$ (here, $p = 3$ villages). Indicators may be positively or negatively oriented (higher is better or worse). For positive indicators, the proposed method is normalized using min–max scaling as follows:

$$S_{i,j} = \frac{x_{i,j} - min_j\,(x_{i,j})}{max_j(x_{i,j}) - min_j(x_{i,j})} \quad \ldots(1)$$

For negative indicators (where a lower raw value is better), the following is used:

$$S_{i,j} = \frac{max_j\,(x_{i,j}) - x_{i,j}}{max_j(x_{i,j}) - min_j(x_{i,j})} \quad \ldots(2)$$

Here, $S_{i,j} \in [0,1]$ denotes the normalized score of indicator i for village j; min_j and max_j are taken over the p villages (or over households, if household-level data are used).

Domain aggregation: Indicators are aggregated into K domains, such as Environmental, Infrastructure. Let domain k have m_k indicators with normalized values $S_{i,j}$ for $i \in D_k$. The (unweighted) domain score for village j and domain k is the arithmetic mean.

$$D_{k,j} = \frac{1}{m_k} \sum_{i \in Dk} S_{i,j} \quad \ldots(3)$$

If domain-level weights v_k are applied such that $\sum_{k=1}^{K} v_k = 1$, the weighted domain contribution to the composite is simply $v_k D_{k,j}$.

Analytic Hierarchy Process (AHP): Weights can be elicited from q experts using AHP. Let $A^{(e)}$ be a pairwise comparison matrix from expert e for domains; the principal eigenvector $\omega^{(e)}$ of $A^{(e)}$ provides that expert's domain-weight vector. The aggregated domain weight vector v is the normalized mean of the expert eigenvectors:

$$v = \frac{1}{\sum_k \overline{\omega}_k} \overline{\omega}, \qquad where \qquad \overline{\omega} = \frac{1}{q} \sum_{e=1}^{q} \omega^{(e)} \quad \ldots(4)$$

Every v_k obeys $0 \le v_k \le 1$ and $\sum_k v_k = 1$. The AHP consistency ratios are reported to demonstrate that expert judgments are consistent.

Composite Green Rating System (CGRS): Village *j's* composite sustainability score is the weighted average of the domain scores for all indicators:

$$CGRS_j = \sum_{k=1}^{K} v_k \left(\frac{1}{m_k} \sum_{i \in D_k} S_{i,j}\right) = \sum_{i=1}^{m} \omega_i S_{i,j} \quad \ldots(5)$$

where $\omega_i = v_k(i) / m_k(i)$ is the ultimate weight of indicator i, and $k(i)$ assigns indicator i to its domain. The CGRS is in the range [0,1] and can be normalized to [0,100] for presentation.

Reliability: To check if the indicators within every domain constitute a reliable scale, Cronbach's alpha for domain k from household-level data (if present) is calculated. Let there be n respondents and the domain have m_k items with item variances σ_i^2 and total variance σ_T^2. Cronbach's alpha is:

$$\alpha_k = \frac{m_k}{m_k - 1}\left(1 - \frac{\sum_{i=1}^{m_k} \sigma_i^2}{\sigma_T^2}\right) \quad \ldots(6)$$

Values of αk close to or greater than 0.7 reflect good internal consistency for domain k.

Dimensionality Reduction: When several indicators, PCA extracts orthogonal latent factors. Let S denote an $n \times m$ matrix of household-level standardized indicator scores. The covariance (or correlation) matrix C is decomposed by PCA into eigenvalues $\lambda 1 \ge \lambda 2 \ge \cdots$ and eigenvectors $u1, u2, \ldots$. The r-component approximation of household h is as follows:

$$Z = \sum_{l=1}^{r} (S_h \cdot u_l) u_l \quad \ldots(7)$$

where S_h is the *hth* row. Indicator loadings on principal components tell us which indicators tend to group and may be used to determine data-driven weights $\omega_i \propto |\, loading\ i \,|$ for empirical weighting.

Statistical Tests: For categorical adoption outcomes, such as solar use, construct contingency table counts nij for category i in village j. The chi-square statistic tests independence: (Eq 8)

$$X^2 = \sum_i \sum_j \frac{(n_{ij} - e_{ij})^2}{e_{ij}}, \quad where \ e_{ij} = \frac{n_i \cdot n_j}{N} \quad \ldots(8)$$

where n_i and n_j are the marginal totals and N is the total sample. To compare the means of the continuous domain or CGRS between villages, we used a one-way ANOVA with MS_{btw} (between) and MS_{wtn} (within):

$$F = \frac{MS_{btw}}{MS_{wtn}} \quad \ldots(9)$$

With mean squares based on sums of squares, if the assumptions do not hold, it uses Kruskal–Wallis as a nonparametric alternative.

Determinants of adoption: To find predictors of a binary variable, for example, a household adopts solar, $Y_h \in \{0,1\}$, fit:

$$P_r(Y_h = 1) = \frac{1}{1 + \exp(-\eta_h)} \quad \ldots(10)$$

$$\eta_h = \beta_0 + \sum_r \beta_r Z_{r,h} \quad \ldots(11)$$

where $Z_{r,h}$ are predictors such as demographics, income, road, and CGRS domain scores. Estimate β by maximum likelihood; report odds ratios $exp(\beta_r)$ and 95% confidence intervals with added village fixed effects or cluster-robust standard errors if necessary.

Cluster analysis: To define homogeneous groups, apply k-means to standardized indicator vectors. The algorithm minimizes the within-cluster sum of squares as follows:

$$\min_{C_1, \ldots, C_k} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \quad \ldots(12)$$

where μ_i is the centroid of *cluster Ci*. Select k using the silhouette score or elbow method. Centroids of clusters can be profiled to develop typologies, such as the "high-infrastructure, low-environment" cluster.

Validation: Validate CGRS by calculating Spearman or Pearson correlations ϱ between $CGRS_j$ (or household CGRS) and independent external indicators Y^{ext} (e.g., development, census indicators):

$$\rho = \frac{cov(CGRS,\ Y^{ext})}{\sigma_{CGRS}\, \sigma_{Y^{ext}}} \quad \ldots(13)$$

Report r-values and p-values; a positive and significant correlation indicates construct validity. A sensitivity analysis was conducted by recalculating the CGRS using different weighting schemes (equal, AHP, and PCA-derived) and reporting the score rank stability (Spearman rank correlation between weighting schemes).

RESULTS AND DISCUSSION

Triangulation was employed by correlating survey data with

Table 1: Demographic Outcomes of the Respondents in the Survey.

Parameter	Sub Parameter	Dorli	Bilashi	Padmale
Gender	Female	76	53	44
	Male	48	47	56
Education	Graduate	35	18	14
	None	13	24	25
	Postgraduate	14	13	24
	Primary	20	21	17
	Secondary	18	23	20
Occupation	Farmer	17	11	10
	Housewife	13	13	17
	Laborer	10	21	12
	Retired	18	18	13
	Self-employed	18	10	15
	Shopkeeper	13	16	21
	Teacher	13	13	13
Income	High	30	38	34
	Low	41	32	38
	Middle	29	31	28

Gram Panchayat records and available secondary data (e.g., village census abstracts and public works reports) to confirm the authenticity of responses related to water source types, toilet coverage, and electrification.

Descriptive Analysis

Demographic Results

The population data in Table 1 present a comparative snapshot of respondents across the three villages, Dorli, Bilashi, and Padmale, showing variations in gender, education, occupation, and income levels. Dorli shows a significantly higher proportion of female participants (76%), whereas Padmale has the largest number of male participants (56%), indicating a more balanced or male-biased response.

Educationally, Padmale is at the fore with the highest proportion of postgraduate respondents (24%), while Bilashi has the lowest graduate proportion (18%) and a comparatively high proportion of respondents with no educational qualifications (24%). Bilashi also features a high presence of laborers (21%), highlighting the engagement of economically marginalized segments of society. In terms of occupation, Dorli features a wide range of occupations, with significant contributions from farmers, pensioners, and own-account workers. Conversely, Padmale has the largest percentage of shopkeepers (21%), indicating a relatively more commercial or service-based economy. In terms of income, Dorli has the largest number of low-income respondents (41%), reflecting its economic condition of being drought-affected, whereas Bilashi has the highest percentage of high-income respondents (38%), showing relatively higher economic stability despite its hilly geography. These results provide the underlying knowledge of the socio-economic milieus (Gaikwad & Shinde 2022) in the villages to inform custom-made development strategies for the villages. Fig. 2 represents the demographic results of the participants from the three villages.

Parameter-wise Descriptive Results

The descriptive analysis of various parameters in the three villages of Dorli, Bilashi, and Padmale points to differences in environmental, infrastructure, sustainability, and risk-related parameters. Table 2 shows the raw survey percentages for all parameters in the four domains. This indicates village-specific strengths; for example, Bilashi has the maximum vegetation (91%), Padmale has the maximum rainwater harvesting (63%), and Dorli has the maximum solar adoption (57%). These were used to create a baseline for the next stage of statistical processing.

In terms of environmental parameters, Padmale excelled in water treatment (57%) and rainwater harvesting (63%), whereas Bilashi exhibited the highest vegetation cover (91%), and Dorli exhibited moderate air quality (63%) and noise levels (64%). For infrastructure, Dorli yields the highest road coverage (68%), whereas Bilashi experiences improved sanitation (56%) and similar health center accessibility (54–58%) between villages. For sustainability, Padmale reported relatively higher rates of organic farming

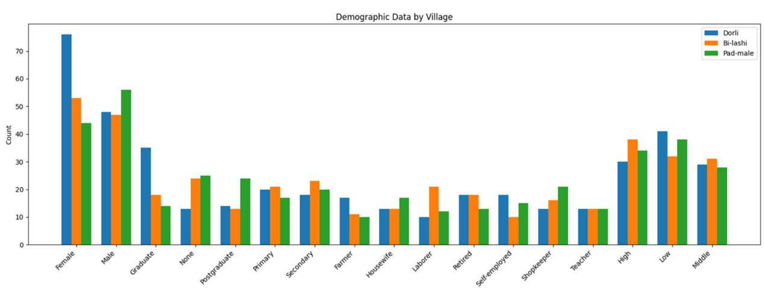

Fig. 2: Demographic Results of Participants from Three Villages.

Table 2: Descriptive Analysis Indicating Percentage of Different Parameters in Three Villages.

Type	Parameter	Dorli	Bilashi	Padmale
Environmental	Water Treated	49	55	57
	Waste Segregation	49	52	47
	Composting	45	47	48
	Rainwater Harvesting	55	55	63
	Vegetation	83	91	87
	Air Quality	63	66	64
	Noise Level	64	67	64
Infrastructure	Sanitation	46	56	51
	Road	68	61	65
	Health Center	53	54	58
Sustainability	Biogas	48	53	47
	Solar	57	50	54
	Organic Farming	54	43	55
	Adopt RE	49	54	50
Risk	Awareness	48	47	48
	Satisfaction	55	60	57

adoption (55%) and the use of solar energy (54%), whereas Bilashi excelled marginally in biogas consumption (53%) and renewable energy practice adoption (54%). Risk awareness and satisfaction levels were relatively consistent across villages, with the highest satisfaction in Bilashi (60%). Overall, the table suggests that whereas all the villages have moderate to high levels of activity around environmental, infrastructure, and sustainability parameters, each village has unique strengths that mirror localized socio-economic and ecological realities, as shown in Fig. 3.

Normalized Scores

Normalization was performed with min–max scaling over the three villages for every parameter (Table 3). Normalized score scale data to strip units so that the data can be compared

Table 3: Normalized Score for Each Parameter for Three Villages.

Domain	Parameter	Dorli	Bilashi	Padmale
Environmental	Water Treated	0.00	0.75	1.00
	Waste Segregation	0.50	1.00	0.00
	Composting	0.00	0.67	1.00
	Rainwater Harvesting	0.00	0.00	1.00
	Vegetation	0.00	1.00	0.50
	Air Quality	0.00	1.00	0.33
	Noise Level	0.00	1.00	0.00
Infrastructure	Sanitation	0.00	1.00	0.50
	Road	1.00	0.00	0.67
	Health Center	0.00	0.33	1.00
Sustainability	Biogas	0.20	1.00	0.00
	Solar	1.00	0.00	0.67
	Organic Farming	0.69	0.00	1.00
	Adopt RE	0.00	1.00	0.33
Risk	Awareness	1.00	0.00	1.00
	Satisfaction	0.00	1.00	0.40

directly. The best performance of the three villages for each parameter was a score of 1.00, and the worst was 0.00. For instance, Bilashi rated 1.00 for vegetation, air quality, noise level, sanitation, and satisfaction, as shown in Table 3.

Domain Scores

The domain score is the average of the normalized indicator scores across each domain. The domain scores aggregate the multi-indicator performance. Bilashi sweeps Environmental due to uniformly high vegetation, air, and noise scores, with Padmale topping Infrastructure and Risk. The sustainability scores were fairly evenly balanced.

The average domain scores in Table 4 indicate significant differences between the three villages in the environmental, infrastructure, sustainability, and risk domains. Bilashi scored the highest in the environmental domain (0.92), reflecting

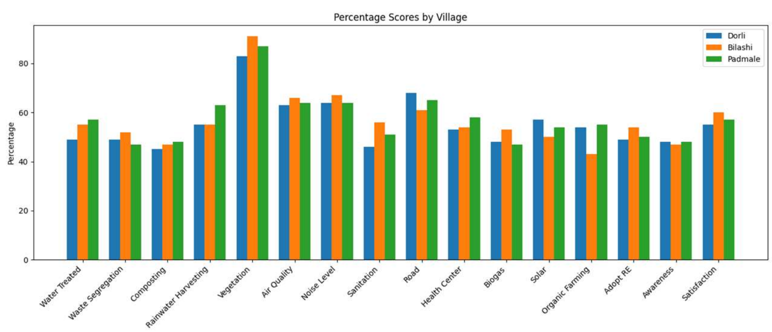

Fig. 3: Villagewise Percentage Score Obtained by Survey Results.

Table 4: Average Domain Score Based on Parameters Score.

Domain	Dorli	Bilashi	Padmale
Environmental	0.07	0.92	0.62
Infrastructure	0.33	0.44	0.72
Sustainability	0.47	0.50	0.50
Risk	0.50	0.50	0.70

good performance in indicators such as vegetation coverage and water management, while the lowest score was that of Dorli (0.07), reflecting relatively poorer environmental conditions. In the infrastructure sector, Padmale scored the highest at 0.72, reflecting improved development in roads, sanitation, and health centers, while Dorli scored the lowest at 0.33. The sustainability sector reflects quite balanced scores in villages, with Dorli, Bilashi, and Padmale all between 0.47–0.50, reflecting moderate participation in renewable energy use, organic agriculture and biogas utilization. For the risk domain, Padmale leads with the highest value of 0.70, suggesting higher awareness and satisfaction with risk management, while Dorli and Bilashi record moderate values (0.50). These domain scores identify the strengths and weaknesses of each village, providing a comprehensive understanding of localized socio-environmental and infrastructural conditions.

Statistical Analysis

Chi-square Test

The Chi-square test results for all parameters, conducted with 120 people in each village, are presented in table. The results of the analysis present evidence that none of the adoption rates among the different technologies or practices differ significantly among the three villages, as all the p-values are greater than 0.05. This indicates that technology adoption patterns and associated behaviors are very similar across Dorli, Bilashi, and Padmale, indicating similar levels of interaction and acceptance in the respective local environments. The results in Table 5 suggest consistency in responses from participants, and it is clear that the differences one might see in adoption are not statistically significant and could be due to random variation and not systemic differences.

ANOVA and Kruskal-Wallis Test

The ANOVA and Kruskal-Wallis test results, as shown in Table 6, indicate that no statistically significant differences exist between the three villages for the parameters being tested. The ANOVA provided an F-statistic value of 0.1693 with a corresponding p-value of 0.8448, and the Kruskal-Wallis test provided an H-statistic value of 0.6643 with a p-value of 0.7174, both of which were higher than the normal significance level (0.05).

These non-significant values (NS) indicate that the measured variable distributions are the same in Dorli, Bilashi, and Padmale, thus affirming that any differences found in parameter scores must be a result of random variation and not due to systematic village-to-village differences. This supports the conclusion of similar patterns of adoption and participation at research sites.

Although the statistical differences were not large, the uniformity of the villages suggests that there is a consistent baseline of adoption practice. This implies that although

Table 5: Results achieved by Chi-square test.

Parameter	Chi-square	p-value	df	Sig.	Dorli	Bilashi	Padmale
Water Treated	1.394	0.4980	2	NS	49.0	55.0	57.0
Waste Segregation	0.507	0.7762	2	NS	49.0	52.0	47.0
Composting Done	0.188	0.9105	2	NS	45.0	47.0	48.0
Rainwater Harvesting	1.748	0.4173	2	NS	55.0	55.0	63.0
Vegetation	7.040	0.1338	4	NS	85.47	91.74	88.50
Air Quality	1.324	0.8573	4	NS	62.38	66.0	64.0
Noise Level	0.724	0.9484	4	NS	64.0	67.0	63.37
Has Toilet	2.001	0.3677	2	NS	46.0	56.0	51.0
Road Type	2.086	0.7200	4	NS	33.0	33.0	37.0
Health Center Access	0.660	0.7191	2	NS	52.48	54.0	58.0
Uses Biogas	0.827	0.6614	2	NS	48.0	53.0	47.0
Uses Solar	0.992	0.6090	2	NS	57.0	50.0	54.0
Organic Farming	3.547	0.1697	2	NS	54.0	43.0	55.0
Willing To Adopt RE	0.560	0.7557	2	NS	49.0	54.0	50.0
Risk Awareness	0.027	0.9867	2	NS	48.0	47.0	48.0
Overall Satisfaction	1.674	0.7954	4	NS	55.0	60.0	57.0

Table 6: Results of ANOVA and Kruskal-Wallis Test.

Test	Statistic	df	p-value	Significance
One-way ANOVA	F = 0.1693	2,357	0.8448	NS
Kruskal–Wallis	H = 0.6643	2	0.7174	NS

context-specific environments and infrastructure vary, even the diffusion of sustainability practices is uniformly distributed, indicating common opportunities for region-wide policy interventions.

Composite Sustainability Score

Composite Sustainability Score, taken as the average percentage of positive responses for each village, is a composite indicator of overall sustainability performance (Table 7). Dorli achieved 53.27%, which was lower than Bilashi (55.23%) and Padmale (55.49%). This suggests that all three villages have moderate levels of involvement in sustainable practices, but Padmale and Bilashi have marginally higher overall use of environmentally and socially good practices than Dorli. The results indicate a fairly consistent trend of sustainability across the research zones, indicating equivalent awareness, involvement, and practice of sustainable measures by citizens.

PCA Components and Variance Explained

Principal Component Analysis (PCA) finds underlying factors in the parameter scores and compresses data into lower dimensions while preserving the majority of the variance. For the three villages, the first principal component (PC1) explained 95.29% of the variance, and a single underlying factor captured most of the variation in sustainability-related parameters (Table 8). The second (PC2) and third (PC3) components explained 3.31% and 1.40% of the variance, respectively, with minimal additional contribution.

Village-specific PC scores indicate specific contributions in these dimensions. For example, Bilashi scored highly on PC2 (0.8207), indicating some special variation in some parameters with respect to Dorli and Padmale, which scored negatively for PC2. In all, the PCA indicates that most of the variation in sustainability performance can be explained by a strong underlying factor, with small differences between villages being apparent in the secondary PCs (Fig. 4).

Table 7: Comparing the Composite Sustainability Score of Villages.

Village	Average % Positive Responses
Dorli	53.27
Bilashi	55.23
Padmale	55.49

Table 8: Achieved PCA Component and Variance Explained by Villages.

Village	Score		
	PC1	PC2	PC3
Dorli	0.5804	-0.3975	0.7107
Bilashi	0.5713	0.8207	-0.0077
Padmale	0.5802	-0.4105	-0.7034
Variance [%]	**95.29**	**3.31**	**1.40**

CGRS Score

The Composite Green Rating Score (CGRS) is the average of the four domain scores per village and is an overall measure of sustainability performance. The results in Table 9 show that Padmale has the highest CGRS at 64%, followed closely by Bilashi at 59%, indicating that these villages have relatively stronger performance across the environmental, infrastructure, sustainability, and risk domains. Dorli, on the other hand, reports a much lower CGRS of 34%, mainly based on its poorer Environmental and Infrastructure ratings. By aggregating multiple domain scores

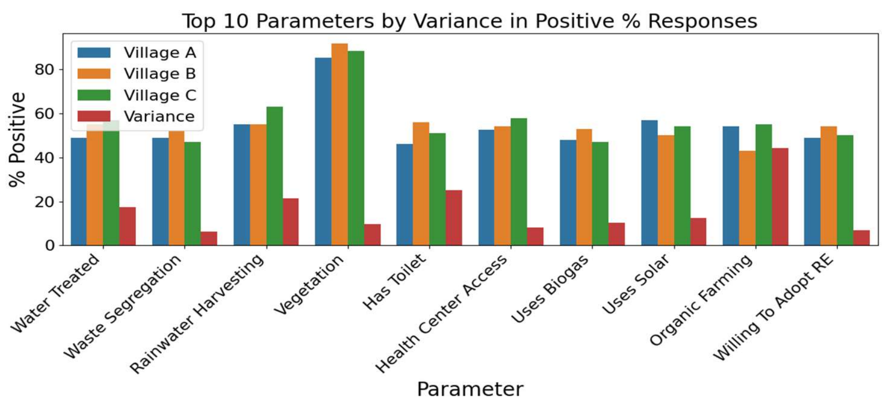

Fig. 4: Variance Parameters in Positive % Responses.

Table 9: Comparing CGRS Score and Percentage of Villages.

Village	CGRS (0–1)	CGRS (%)
Dorli	0.34	34.0
Bilashi	0.59	59.0
Padmale	0.64	64.0

into one measure, the CGRS provides a simple, comparable measure of sustainability, with a focus on relative strengths and weaknesses between and among study villages and with a clear foundation for focused developmental interventions.

Dorli's markedly lower CGRS score (34%) reflects the compounding effect of drought-induced water stress, inadequate infrastructure, and lower income levels, which constrain the adoption of sustainability practices. This highlights how ecological vulnerability intersects with socioeconomic disadvantage, suggesting that targeted interventions, such as water security programs and low-cost infrastructure upgrades, are critical for lifting underperforming villages. More broadly, the findings reveal that rural sustainability is contingent not only on ecological resources but also on the governance capacity to mobilize them effectively.

The empirical utility of the CP stretches beyond the statistical p-values to provide significant insights into the sustainability dynamics among the three villages. Although a number of tests, such as the Chi-square, ANOVA, and Kruskal–Wallis, provided non-significant findings, the uniformity of adoption levels among the environmental and infrastructural indicators points to a common regional baseline of knowledge and participation in sustainable practices. This consistency means that villagers across ecological contexts have achieved similar exposure to sustainability efforts and are similarly well-placed to take advantage of coordinated, region-wide policy actions rather than disjointed village-level programs. In addition, differences in domain scores, especially the better infrastructural and risk preparedness performance in Padmale and the poorer environmental domain in Dorli, provide useful guidance for investment prioritization and planning of targeted interventions. Thus, although statistical tests validate the homogeneity of responses, the observed patterns and relative scores have practical policy significance by pinpointing actionable improvement areas and informing evidence-based rural development interventions.

SWOT Analysis

Combining the CGRS with SWOT analysis provides a multifaceted perspective of every village's sustainability profile by correlating overall performance with unique strengths, weaknesses, opportunities, and threats. Based on Table 10, the highest CGRS of 64% is posted by Padmale, which has high scores for infrastructure (0.72) and risk & resilience (0.70), as well as middle-level environment and sustainability ratings. Bilashi leads with a 59% CGRS owing to its superb environmental performance (0.92), while Dorli trails at 34% due to low environment (0.07) and infrastructure (0.33) scores.

Table 11 presents these scores in context. Dorli has strengths in solar adoption and knowledge but weaknesses in sanitation and composting, with the potential to enhance water treatment and the ongoing risk of drought. Bilashi has robust vegetation, air quality, and waste management, but weaknesses in road conditions and organic agriculture, with promise in eco-tourism and alternative energy, balanced by landslide hazards. Padmale's strengths include rainwater collection and facilities, with moderate weaknesses in waste segregation, potential in agro-processing, and flood hazards as possible dangers. By integrating CGRS with SWOT, the analysis not only measures sustainability performance but also determines actionable areas to address and minimize risks for each village.

- **Dorli (drought-prone):** Dorli has impressive sustainability practice strengths, such as high solar adoption (57%), good awareness (48%), moderate organic farming (54%), and active composting

Table 10: Results of CGRS and SWOT Integration.

Village	CGRS (%)	Environmental	Infrastructure	Sustainability	Risk
Dorli (Drought-prone)	34.0	0.07	0.33	0.47	0.50
Bilashi (Hilly terrain)	59.0	0.92	0.44	0.50	0.50
Padmale (Riverside)	64.0	0.62	0.72	0.50	0.70

Table 11: SWOT analysis of study villages.

Village	Strengths	Weaknesses	Opportunities	Threats
Dorli	Solar adoption, Awareness	Low sanitation, composting	Improve water treatment	Drought
Bilashi	Vegetation, Air quality, Waste mgmt	Road quality, Organic farming	Eco-tourism, renewables	Landslide risk
Padmale	Rainwater harvesting, Infrastructure	Waste segregation	Agro-processing	Flood risk

processes, indicating a community practicing eco-friendly measures despite the scarcity of resources. However, the village has major weaknesses, such as poor sanitation (46%), low water treatment (49%), poor waste segregation (49%), and poor infrastructure, which hamper development as a whole. There are opportunities to increase renewable energy schemes and enhance water harvesting and treatment, which could increase the resilience of the region. Ongoing threats, such as chronic drought and reduced groundwater levels, continue to undermine the village's sustainability initiatives.

- **Bilashi (Hilly Terrain):** The Strengths of Bilashi are reflected in its superior vegetation cover (91%), high waste segregation (52%) and composting (47%) performance, good air and noise quality, and sanitation (56%), reflecting a fairly healthy infrastructural and ecological environment. However, the village is beset by lower road quality (61%), poor organic farming (43%), and low utilization of rainwater harvesting potential. Development opportunities for eco-tourism based on its picturesque topography and government infrastructure schemes would increase socio-economic returns to the region. The village is still susceptible to landslides and inaccessibility, which threaten both locals and development schemes in the area.
- **Padmale (Riverside):** Padmale indicates excellent sustainability and infrastructure performance, the highest rainwater harvesting (63%), satisfactory water treatment (57%), good organic farming (55%), and the best overall infrastructure scores among the villages under study. It has weaknesses, such as weak waste segregation (47%), reduced quality of noise, and moderate levels of satisfaction (57%), which can impact the overall well-being of the community. Agro-processing, fisheries development, and irrigation-based agriculture are opportunities for economic development and better resource utilization. Flood risk and possible water contamination from upstream sources are significant threats that can impact livelihoods and environmental health.

This can be briefly represented with strengths, weaknesses, opportunities, and threats, as shown in Table 12.

DISCUSSION

The findings of this study provide in-depth insight into the socio-economic, infrastructural, and ecological conditions in Dorli, Bilashi, and Padmale and the intricate nexus among the environment, sustainability practices, and community resilience. The survey findings revealed disparate socioeconomic conditions in villages with varying income levels, literacy, and technology uptake, consistent with Gaikwad & Shinde (2022). Water treatment is still inadequate in many areas and represents health and environmental concerns, in line with Mohapatra et al. (2024) on ongoing inadequacies in rural water supply systems. Vegetation cover, although comparatively greater on hilly landscapes like Bilashi, is patchy in all villages, affirming Tiwari and Chandra's (2023) findings on patchy ecological preservation in rural areas. Environmental interventions, such as waste segregation and composting, are in their infancy, indicating the impact of localized environmental practices on strategy adoption.

Infrastructure indicators such as sanitation, roads, and health centers exhibit notable differences, supporting Memo & Pieńkowski (2023), who stress the imperative necessity for focused investment in basic services. Sustainability-oriented metrics such as solar adoption and biogas are few, although organic farming is experiencing some encouraging uptake, as per Fazal et al. (2025) on incremental green transition

Table 12: Summary of SWOT Analysis by Village.

Parameter	Dorli (Drought-prone)	Bilashi (Hilly terrain)	Padmale (Riverside)
Strengths	• High solar adoption (57%) • Strong awareness (48%) • Moderate organic farming (54%) • Active composting initiatives	• Best vegetation cover (91%) • Top in waste segregation (52%) & composting (47%) • High air & noise quality • Good sanitation (56%)	• Highest rainwater harvesting (63%) • Good water treatment (57%) • Best infrastructure score • Strong organic farming (55%)
Weaknesses	• Poor sanitation (46%) • Low water treatment (49%) • Weak waste segregation (49%) • Limited infrastructure	• Lower road quality (61%) • Low organic farming (43%) • Low rainwater harvesting relative to potential	• Poor waste segregation (47%) • Lower noise quality • Moderate satisfaction (57%)
Opportunities	• Expansion of renewable energy programs • Improved water harvesting & treatment	• Eco-tourism based on scenic terrain • Government infrastructure projects	• Agro-processing & fisheries development • Irrigation-based agriculture
Threats	• Chronic drought • Declining groundwater	• Landslide risk • Accessibility challenges	• Flood risk • Water pollution from upstream

progress. Risk consciousness is differential with respect to exposure, with villages exposed to drought, flood, or erosion having comparatively higher community preparedness, in accordance with Indriani et al. (2024).

The use of multivariate and comparative statistical testing, such as Chi-square, ANOVA, and Kruskal-Wallis analyses, enhances the validity of these results by affirming that adoption patterns and parameter distributions between villages are generally similar, yet accentuating subtle differences that guide targeted interventions. The Composite Green Rating Score (CGRS) derived in this study is a new, combined metric that integrates the Environmental, Infrastructure, Sustainability, and Risk domains. Padmale has the best CGRS of 64%, followed by Bilashi at 59%, while Dorli is last at 34%, mainly because of poor Environmental and Infrastructure scores. This framework provides a solid, evidence-based measure of relative sustainability performance, allowing policymakers to establish a clear benchmark for prioritizing interventions and allocating resources effectively. Thus, Beyond Sangli, the CGRS framework can be used to inform district planning, feed into state-level rural sustainability indices, and be coordinated with national initiatives such as SDG localization and the Smart Village mission. Globally, the CGRS can be repurposed by re-weighting indicators to local settings, providing an adaptable measure for benchmarking global rural sustainability.

The SWOT analysis fills out the quantitative findings by providing village-specific strengths, weaknesses, opportunities and threats. For example, Dorli has high solar adoption and awareness but low sanitation and water treatment limitations; Bilashi has high vegetation and waste management but road and organic farming constraints; and Padmale has rainwater harvesting and good infrastructure but waste segregation and flood problems. These findings are consistent with wider rural sustainability literature, such as environmental quality advantages in low-vehicle zones, the late adoption of renewable energy technology (Cuenca-Enrique et al. 2024), and innovation difficulties on farms (Nasution et al. 2025), highlighting the need for policy interventions that are context dependent (Katoch et al. 2024).

The results support worldwide sustainability agendas, especially the SDGs, by emphasizing the necessity of holistic strategies that support environmental stewardship (SDG 13), sanitation and infrastructure (SDG 6 and 11) at the same time, and the adoption of renewable energy (SDG 7). Therefore, the CGRS not only measures local sustainability but also positions Indian rural development in worldwide sustainability models.

Overall, this research contributes to the concept and practice by bridging multivariate statistical analysis and an innovative CGRS framework to yield a starting point for a rural Green Rating System. This illustrates how cross-village comparative evaluation can maximize development interventions based on geographical and socio-economic conditions to increase sustainability, environmental responsiveness, and resource utilization. By triangulating empirical findings with theory, policy, and existing studies, this study provides a solid foundation for evidence-based rural development planning and strategic green interventions.

CONCLUSIONS

This study presents an innovative approach to evaluating rural sustainability by integrating a Composite Green Rating System (CGRS) with multivariate statistical analysis and SWOT evaluation. This method systematically combines environmental, infrastructural, sustainability, and risk indicators into a comprehensive measure for assessing and comparing rural settlements. Data collected from structured questionnaires in three villages-Dorli, Bilashi, and Padmale-were analyzed using descriptive statistics, Chi-square, ANOVA, and Kruskal-Wallis tests to confirm that the observed differences in adoption patterns and parameter distributions were statistically significant. The results highlight notable village-specific performances: Padmale achieved the highest CGRS score of 64%, reflecting strong infrastructure, risk preparedness, and environmental practices, followed by Bilashi at 59%, with strengths in vegetation and waste management. Dorli lagged at 34% because of weaker environmental and infrastructural performance. The accompanying SWOT analysis identified strengths, weaknesses, opportunities, and threats, providing tailored policy guidance for each village in the study.

The innovation of this study lies in the combination of a quantitative grading system with comparative and multivariate analyses, surpassing existing methods that often rely on qualitative or fragmented assessments. By offering a replicable, evidence-based framework, this study advances rural planning, improves sustainability initiatives, and provides a valuable tool for monitoring, benchmarking, and promoting green practices in rural areas.

Although this study provides an overall evaluation of rural sustainability using CGRS and SWOT analyses, several limitations must be acknowledged. The survey's scope was limited to three villages, which may restrict the generalizability of these findings. Additionally, some parameters were based on self-reported data, which may have introduced potential bias or inaccuracies. This research emphasized quantitative metrics, with less focus on qualitative social dynamics, governance, and cultural factors. Future research could extend the framework to more villages or regions and incorporate longitudinal data to capture these temporal changes. Integrating geospatial analysis, remote sensing, and advanced environmental indicators can further refine these assessments. Moreover, linking CGRS outcomes to policy actions and tangible results, such as improved health, resource efficiency, or economic benefits, would enhance its utility as a decision-support tool. Overall, the proposed system has great potential for scaling, adaptation, and integration with national and regional rural-development initiatives. Beyond India, the CGRS can be tailored to diverse global rural settings by adjusting indicators to local ecological and socio-economic contexts, serving as a comparative tool for worldwide rural sustainability monitoring.

REFERENCES

Ali, E.B., Anufriev, V.P. and Amfo, B., 2021. Green economy implementation in Ghana as a road map for a sustainable development drive: A review. *Scientific African*, 12, p.e00756.

Cuenca-Enrique, C., del-Río-Carazo, L., Acquila-Natale, E. and Iglesias-Pradas, S., 2024. Sustainability of rural electrification projects in developing countries: A systematic literature review. *Energies*, 17(23), p.5925. [DOI]

Der Tambile, E., Ramachandran, V.S., Rajendrakumar, S., Remesh, M., Ramaswamy, J. and Ramesh, M.V., 2024. Rural livelihoods sustainability in South Asia and Africa: a systematic review with bibliometric analysis. *Discover Sustainability*, 5(1), pp.1–22. [DOI]

Dhal, S.B. and Kar, D., 2024. Transforming agricultural productivity with AI-driven forecasting: Innovations in food security and supply chain optimization. *Forecasting*, 6(4), pp.925–951. [DOI]

Fazal, N., Eryildiz, D.I., Salahuddin, S., Mohsin, N. and Javaid, M., 2025. Eco village; Social sustainable stability with the eco-cities. *Qlantic Journal of Social Sciences and Humanities*, 6(1), pp.326–335.

Gaikwad, S.B. and Shinde, N.G., 2022. Role of MGNREGP in rural development of the Sangli District. *IJFANS International Journal of Food and Nutritional Sciences*, 11(1), pp.1888–1895.

Gerli, P., Navio Marco, J. and Whalley, J., 2022. What makes a smart village smart? A review of the literature. *Transforming Government: People, Process and Policy*, 16(3), pp.292–304. [DOI]

Indriani, M., Nadirsyah, Fahlevi, H. and Evayani, 2024. Village SDGs: ‘The future we want’—descriptive analysis of an area sampling from Aceh Province. In: *2024 International Conference on Decision Aid Sciences and Applications (DASA)*. IEEE, pp.1–8. [DOI]

Katoch, O.R., Sehgal, S., Nawaz, A. and Cash, T.A., 2024. Promoting sustainability: tackling energy poverty with solar power as a renewable energy solution in the Indian energy landscape. *Discover Energy*, 4(1), pp.1–16. [DOI]

Kochhar, P., Mahal, N., Seth, S. and Singh, M., 2022. Green Rating for Integrated Habitat Assessment—A green-building rating system for catalysing climate-change mitigation/adaptation in India. *F1000 Research*, 11, p.153. [DOI]

Kumavat, H.R., Kumavat, R.V. and Bhangale, H.V., 2021. Proposed framework for sustainable village strategy in the semi-arid region of Maharashtra, India. *Lecture Notes in Electrical Engineering*, 760, pp.161–171. [DOI]

Liu, H., Zhang, Y., Wang, S. and Zhao, H., 2024. Comprehensive evaluation of digital village development in the context of rural revitalization: A case study from Jiangxi Province of China. *PLOS ONE*, 19(5), p.e0303847.

Memo, U. and Pieńkowski, D., 2023. Sustainable rural development indicators in Bulgaria, Germany, Poland, Romania and the Netherlands: a review of data. *Frontiers in Environmental Science*, 11, p.1323688. [DOI]

Mohapatra, S., Dwivedi, G. and Harish, V.S.K.V., 2024. Development of a multi-vector framework to translate group housing to eco-housing for rural communities. *Environment, Development and Sustainability*, 26(12), pp.31897–31920. [DOI]

Nasution, M.S., Rusli, Z., Heriyanto, M., Syahza, A., Mashur, D., Ananda, F. and Ikhsan, M., 2025. Bibliometric analysis of rural economic development: Convergence between sustainable agriculture, digital technology, and community engagement for village self-reliance. *International Journal of Sustainable Development and Planning*, 20(1), pp.245–262. [DOI]

Pathak, V. and Deshkar, S., 2023. Transitions towards sustainable and resilient rural areas in revitalising India: A framework for localising SDGs at Gram Panchayat level. *Sustainability*, 15(9), p.7536. [DOI]

Patil, A.A., Arora, R., Arora, R. and Sridhara, S.N., 2024. Techno-economic analysis of solar, wind, and biomass hybrid renewable energy systems to meet electricity demand of a small village in Bihar state of India. *Nature Environment and Pollution Technology*, 23(3), pp.1261–1283. [DOI]

Renukappa, S., Suresh, S., Abdalla, W., Shetty, N., Yabbati, N. and Hiremath, R., 2024. Evaluation of smart village strategies and challenges. *Smart and Sustainable Built Environment*, 13(6), pp.1386–1407. [DOI]

Ricket, A.L., Jolley, G.J., Knutsen, F.B. and Davis, S.C., 2023. Rural sustainable prosperity: Social enterprise ecosystems as a framework for sustainable rural development. *Sustainability*, 15(14), p.11339. [DOI]

Sabir, B., Hameed, A., Faizan, M., Rawat, V.K. and Tariq, M., 2021. Smart villages: Application of internet-of-things in the development of rural India. *Lecture Notes in Electrical Engineering*, 788, pp.147–155. [DOI]

Sengupta, A., 2022. Sustainable development in India with reference to the agricultural sector. *SSRN Electronic Journal* [Preprint]. [DOI]

Shahab, H., Iqbal, M., Sohaib, A., Khan, F.U. and Waqas, M., 2024. IoT-based agriculture management techniques for sustainable farming: A comprehensive review. *Computers and Electronics in Agriculture*, 220, p.108851. [DOI]

Sharma, P.K., Chouhan, K.R. and Chandauriya, M., 2024. Analysis of regional disparities in the level of development of Gram Panchayats identified under the Sansad Adarsh Gram Yojana (SAGY) in Rajasthan, India. *The Indian Geographical Journal*, 99(2), pp.103–119.

Tao, Z. and Xiang, G., 2022. Empirical measurement and evaluation of rural green development: take Hunan Province, China as an example. *Environmental Earth Sciences*, 81(9), p.268. [DOI]

Tholkapiyan, M., Ramadass, S., Seetha, J., Ravuri, A., Vidyullatha, P., Shankar, S.S. and Gore, S., 2023. Examining the impacts of climate variability on agricultural phenology: a comprehensive approach integrating Geoinformatics, satellite Agrometeorology, and artificial intelligence. *International Journal of Intelligent Systems and Applications in Engineering*, 11(6s), pp.592–598.

Tiwari, P.K. and Chandra, T.J., 2023. Policy intervention and legislative framework relating to the sustainability of built structures in India. *GLS Law Journal*, 5(2), pp.1–13. [DOI]