Prepublished copy

Nature Environment & Pollution Technology

This is a peer-reviewed prepublished version of the paper to be published in Vol. 25, No. 2, June 2026 issue

Original Research

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

ORCID IDs of Authors: 0000-0003-0768-1761[1], 0009-0009-5259-6815[2]

Key Words	Rural sustainability, SWOT analysis, Environmental assessment, Green rating system, Infrastructure disparities, Renewable energy adoption, Sustainable rural development,
DOI	https://doi.org/10.46488/NEPT.2026.v25i02.B4385 (DOI will be active only after the final publication of the paper)
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. *Nature Environment and Pollution Technology*, 25(2), B4385. https://doi.org/10.46488/NEPT.2026.v25i02.B4385

ABSTRACT

Indian rural development is confronted by multi-dimensional challenges such as non-uniform socio-economic conditions, low levels of infrastructure, and environmental risks. To acknowledge the importance of systematic sustainability assessment, this research suggests a Composite Green Rating System (CGRS) to analyze and compare ecological, infrastructural, and socio-economic performance in rural settlements. Current sustainability rating systems like LEED, BREEAM, and GRIHA are city or industrial-scale based and do not account for rural ecological heterogeneity, decentered infrastructure, and socio-economic inequalities. This paper solves this problem by introducing the Composite Green Rating System (CGRS), which combines environmental, infrastructural, and socio-economic factors in one transferable index specific to rural locations. Primary data were obtained using structured questionnaires from 120 respondents in a sample of three villages - Dorli, Bilashi, and Padmale - on parameters of environment, infrastructure, sustainable practices, and risk awareness. Descriptive statistics, Chi-square, ANOVA, and Kruskal-Wallis tests were used to analyze differences and ascertain the reliability of adoption patterns between villages. Normalized scores were tallied to calculate domain-wise averages, which were further utilized to obtain the CGRS, yielding a single, comparable sustainability ranking for every village. A SWOT analysis was also carried out to determine strengths, weaknesses, opportunities, and threats, and provide actionable insights to inform targeted interventions. Results show that Padmale recorded the highest CGRS (64%), followed by Bilashi (59%), while Dorli performed lower (34%) because of 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 in sustainable rural development. This model shows a workable and transferable tool for tracking and upgrading rural sustainability. 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 like India, where more than two-thirds of the population resides in villages (Pathak and 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, Chouhan, and Chandauriya 2024). Traditional development models often overlook local ecological diversity and resource availability, making it imperative to adopt location-sensitive assessment frameworks for sustainability.

Whereas city-centric systems such as LEED, BREEAM, and GRIHA offer a disciplined environmental appraisal, they are insufficient to 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 CGRS that reflects both ecological vulnerabilities and locally owned sustainability practice. (Kochhar et al. 2022). Recent literature underscores the need for decentralized, community-centric sustainability assessments (Tholkapiyan et al. 2023) that integrate environmental parameters like water conservation, renewable energy utilization, waste management, and biodiversity preservation, along with social infrastructure (Tiwari and 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 varied rural geographies, including riverine, hilly, and arid regions (Ali, Anufriev, and Amfo 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 metrics (Renukappa et al. 2024). However, such models also highlight the necessity of contextual adaptation, especially in regions with varying geographical vulnerabilities like flood plains, drought-prone zones, and hilly terrains (Tao and Xiang 2022).

The proposed work is imperative for presenting a structured, evidence-based rural sustainability assessment using environmental, infrastructural, and socio-economic indicators. Its originality is situated in the creation of the Composite Green Rating Score (CGRS) alongside multivariate statistical and SWOT analyses, providing a quantitative and comparative approach for village-level assessment. The 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. This has a direct relation to India's national programs like the Sansad Adarsh Gram Yojana, Smart Village projects, and Gram Panchayat Development Plans, while also localizing international SDGs to rural settings.

This research considers villages from the Sangli district of Maharashtra, namely Padmale (river-side), Dorli (drought-affected), and Bilashi (hilly). With the help of a structured household survey and statistical analysis, and SWOT evaluation, the 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 research are:

- To evaluate the existing environmental, infrastructural, and socio-economic 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 action.

2. LITERATURE REVIEW

Assessment methodologies tailored to rural settings are essential due to the distinct ecological, economic, and infrastructural characteristics of 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 like 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 within 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, Anufriev, and Amfo 2021). Their findings underscored 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, Kumavat, and Bhangale 2021). By integrating household-level interventions with communal systems, the framework demonstrated 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 within the existing housing stock. Evaluations revealed that 80% of retrofitted homes reached net-zero energy status and reported 20–35% improvements in indoor comfort, alongside reduced energy expenditure (Mohapatra, Dwivedi, and Harish 2024). These models provide technical precedents and performance benchmarks for infrastructural 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). Further research by Cuenca-Enrique et al. (2024) in a systematic review of global rural electrification projects identified social capital, participatory planning, and local governance structures as key determinants of project sustainability, often 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 micro-enterprises and local ownership models boosted employment by up to 70% while reducing carbon emissions by 40%, provided 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, resilient villages (Nasution et al. 2025). Together, these works reinforce that community participation and local governance are indispensable in any village-level green-rating framework and must be explicitly captured within your SWOT analysis.

Recent scholarship highlights the transformative potential of integrating information and communication technology (ICT) within 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, Navio Marco, and Whalley, 2022). Empirical studies bolster this insight. Sabir et al. (2021) examined pilot programs using IoT-enabled irrigation systems and mini solar grids in Indian villages. Results indicated a 30% increase in water-use efficiency and a 25% reduction in energy costs. Key to deployment success were 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 just infrastructure performance, but also governance and operational sustainability—elements that inform the SWOT evaluations and comparative village analyses in this paper.

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 water and fertilizer use. Additionally, Dhal & 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 infrastructures in smallholder settings (Dhal and Kar, 2024). These findings support the inclusion of technological efficiency and forecasting capabilities in our SWOT analysis when evaluating information and resource management.

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 ecological contexts (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 executed such analyses within the same district. Sengupta (2022) utilized participatory SWOT methods across riverine and hilly villages in West Bengal, revealing distinct strengths and limitations—findings similar to those by 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, Anufriev, and Amfo 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 in 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 like Betul, Payvihir, Anadwan, and Hemalkasa in Madhya Pradesh and Maharashtra. Interventions such as native tree plantations, recycling programs, adoption of efficient cookstoves, and promotion of eco-tourism hubs have been instrumental in fostering greener rural spaces. Parallelly, 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 nano grids and a combination of solar, wind, and hydro power have transformed village-level energy access. 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 like Ramchandrapur in Telangana have focused on building individual household toilets, wastewater reuse, and potable water quality monitoring, thereby contributing to improved hygiene and 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.

Across this literature, several key gaps emerge. First, while eco-village and retrofit studies report concrete resource efficiencies, they often lack comparative analysis across differing 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 for rural administrators. Finally, few studies integrate these multiple dimensions—environmental, infrastructural, technological, and resilience—within a comparative, village-level empirical analysis.

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, to be detailed in follow-up studies.

3. MATERIALS AND METHODS

3.1 Proposed Method

The 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 are 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 are 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 precision of measurement and richness of interpretation, rendering it flexible for policy-oriented rural development planning.

This research advances beyond the standard rural sustainability evaluations that are based on descriptive measures or SWOT analysis. The 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 qualitative SWOT analysis, the approach allows for both numerical benchmarking as well as context-relevant interpretation. 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 setting, socio-economic profile, and sustainability performance in a single evaluation framework.

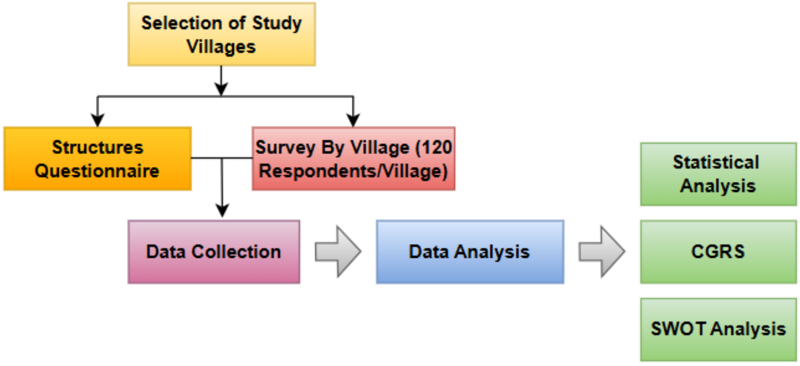

Fig. 1: Proposed Methodology for Analysis of Sustainability and Development with CGRS for Villages in Sangli District

3.2 Materials

The research used both primary and secondary sources of data to come up with and test the Composite Green Rating System (CGRS). The primary data were gathered through a structured household survey given to 360 families (about 120 per village) using paper questionnaires and digital entry forms on tablets for precision. The survey tool captured environmental activities, access to infrastructure, sustainability activities, and risk consciousness. GPS-equipped devices were used to capture geographic location and elevation, whereas field observations were captured with high-resolution digital cameras. Secondary information, such as Gram Panchayat development records, Census 2011 population data, and Google Earth Pro satellite imagery, was utilized to cross-check survey responses and supplement contextual environmental information. Analytical tasks utilized statistical software (SPSS 28.0, R 4.3.2) for cleaning, normalization, weighting, and advanced analysis, promoting methodological rigor and replicability.

3.3 Methodology

a) Selection of Study Villages

Three villages in Sangli district, Maharashtra—Dorli (drought-prone), Bilashi (hilly terrain), and Padmale (riverside)—were purposively chosen in order to represent different eco-geographical contexts. This method ensures that the study reflects a broad array of environmental challenges, socio-economic profiles, and infrastructural conditions. Dorli is defined by long-term water scarcity and heat stress, Bilashi by terrain-based access limitation and scattered settlements, and Padmale by periodic flooding from the Krishna River. The comparative context of these settings enables 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 contextual variety within a tractable range. Although this constrains external validity, the comparative approach offers transferable insights into how ecological context interacts with the adoption of sustainability. Additional research across larger samples can examine generalizability.

b) Sampling and Data Collection

A stratified random sampling design was used to provide representation within varied socio-economic and demographic strata within every village. There were about 120 households surveyed in each place, representing 20–25% of all households in each village. The criteria for stratification comprised caste/community group, income level, occupation type, and geographical spread within the village. Information was gathered using a structured questionnaire, which was conducted in Marathi and English. For enhanced reliability, enumerators underwent training on ethical data collection and impartiality in asking questions. The questionnaire integrated closed-ended ones for quantitative analysis and semi-structured ones to gather local views. The questionnaire was pilot-tested with 15 households from outside the study villages to sharpen wording, reduce ambiguities, and ensure response consistency. Cronbach's alpha coefficients for major domains were above 0.7, reflecting good internal reliability. Triangulation with Gram Panchayat records and census data added to validity.

c) Indicator Classification and Domain Grouping

Variables gathered were classified into four analytical domains: Environmental Sustainability, Infrastructure Adequacy, Sustainability Practice Adoption, and Risk and Resilience. Environmental indicators involved water treatment, waste management, and vegetation; infrastructure indicators involved sanitation, road condition, and access to healthcare; sustainability practice indicators involved the use of renewable energy and organic farming practices; risk and resilience involved awareness of hazards and the level of satisfaction. This typology enabled both domain-specific analysis and creation of an aggregated sustainability score. The multi-domain strategy provides a comprehensive assessment that blends ecological, infrastructural, and social aspects.

d) Development of Composite Green Rating System (CGRS)

A pilot Composite Green Rating System (CGRS) was constructed to measure overall sustainability performance. Indicators were initially normalized into a 0–1 scale to facilitate 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 policy. Each village's composite score was computed as the weighted average of its domain scores. This methodology is an improvement over conventional descriptive surveys, making it possible to objectively benchmark sustainability performance and inform data-driven policy setting.

e) Statistical Analysis

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

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

f) SWOT Analysis and Integration with CGRS

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

g) Validation of the Rating System

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

3.4 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 socio-ecological 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 vs. worse). For positive indicators, the proposed method normalizes by min–max scaling:

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

For negative indicators (where a lower raw value is better), it uses:

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

Here, $S_{i,j} \in [0,1]$ denotes the normalized score of indicators 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, etc. 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:

$$D_{k,j} = \frac{1}{m_k} \sum_{i \in Dk} S_{i,j} \tag{3}$$

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 via 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 expert eigenvectors:

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

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

Composite Green Rating System (CGRS): The village $j's$ composite sustainability score is the weighted average of domain scores with all indicators:

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

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 [0,1] and can be normalized to [0,100] for presentation.

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

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

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

Dimensionality Reduction: When there are several indicators, PCA extracts orthogonal latent factors. Let S denote the $n \times m$ 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:

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

where S_h is the h-th row. Indicator loadings on principal components tell us which indicators tend to group together and may be used to determine data-driven weights $\omega_i \propto |\ loading\ i\ |$ for an 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)

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

where n_i and n_j are marginal totals and N total sample. For comparing means of continuous domain or CGRS between villages, use one-way ANOVA with MS_{btw} (between) and MS_{wtn} (within):

$$F = \frac{MS_{btw}}{MS_{wtn}} \tag{9}$$

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

Determinants of Adoption: To find predictors of a binary variable, e.g., household adopts solar, $Y_h \in \{0,1\}$, fit:

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

$$\eta_h = \beta_0 + \sum_r \beta_r Z_{r,h} \tag{11}$$

where $Z_{r,h}$ are predictors like demographics, income, road, CGRS domain scores, etc. 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 needed.

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

$$\min_{C_1,\dots,C_k} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{12}$$

where μ_i is the centroid of the C_i cluster. Select k by silhouette score or the elbow method. Centroids of clusters can be profiled to develop typologies, e.g., "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):

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

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

4. RESULTS

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

4.1 Descriptive Analysis

4.1.1 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. Dorli shows a significantly higher proportion of women participants (76%), whereas Padmale has the largest number of men participants (56%), indicating a more balanced or male-biased response there.

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

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. In terms of occupation, Dorli features a wide range of spread, with significant contributions from farmers, pensioners, and own-account workers. Conversely, Padmale has the largest percentage of shopkeepers (21%), showing a relatively more commercial or service-based economy. In terms of income, Dorli holds the largest number of low-income respondents (41%), reflecting its economic condition of being drought-affected, whereas Bilashi holds the highest percentage of high-income respondents (38%), showing relatively higher economic stability in spite of 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. Fig. 2 represents demographic results of participants from three villages.

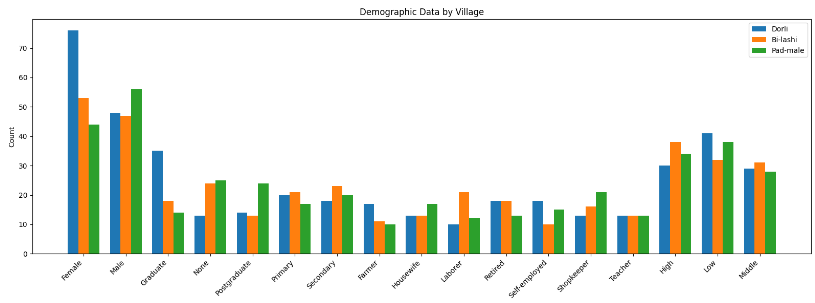

Fig. 2: Demographic Results of Participants from Three Villages

4.1.2 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 of all the parameters for the four domains. It indicates village-specific strengths, i.e., Bilashi is maximum in vegetation (91%), Padmale is maximum in rainwater harvesting (63%), and Dorli is maximum in solar adoption (57%). These are used to create the baseline for the next stage of statistical processing.

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

In terms of environmental parameters, Padmale excels in water treatment (57%) and rainwater harvesting (63%), whereas Bilashi exhibits the highest vegetation cover (91%), and Dorli exhibits moderate air quality (63%) and noise levels (64%). For infrastructure, Dorli yields the highest road coverage (68%), while Bilashi experiences improved sanitation (56%) and similar health center accessibility (54–58%) between villages. For sustainability, Padmale reports relatively higher rates of organic farming adoption (55%) and use of solar energy (54%), while Bilashi excels marginally in biogas consumption (53%) and renewable energy practice adoption (54%). Risk awareness and satisfaction levels are relatively consistent across villages, with satisfaction highest 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, which mirror localized socio-economic and ecological realities as shown in fig. 3.

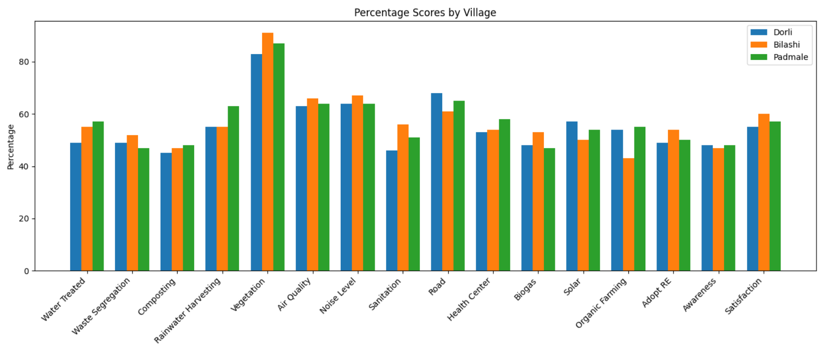

Fig. 3: Villagewise Percentage Score Obtained by Survey Results

4.2 Normalized Scores

Normalization was performed with min–max scaling over the three villages for every parameter (Table 3). Normalized scores scale data to strip units, so data can be compared directly. The best performance of the three villages for each parameter is a score of 1.00, and the worst is 0.00. Bilashi, for instance, rates 1.00 for vegetation, air quality, noise level, sanitation, and satisfaction as shown in Table 3.

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

4.3 Domain Scores

Domain score is an average of normalized indicator scores across each domain. Domain scores aggregate multi-indicator performance. Bilashi sweeps Environmental as a result of uniformly high vegetation, air, and noise scores, with Padmale topping Infrastructure and Risk. Sustainability scores are fairly evenly balanced.

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

Average domain scores in Table 4 indicate significant differences between the three villages in environmental, infrastructure, sustainability, and risk domains. Bilashi scores best in the environmental domain (0.92), reflecting good performance in indicators like vegetation coverage and water management, while the lowest score is that of Dorli (0.07), reflecting relatively poorer environmental conditions. In the infrastructure sector, Padmale scores the highest at 0.72, reflecting improved development in roads, sanitation, and health centers, while Dorli scores 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 of 0.50. Such domain scores identify the strengths and weaknesses of each village, presenting a comprehensive understanding of localized socio-environmental and infrastructural conditions.

4.4 Statistical Analysis

4.4.1 Chi-square test

The Chi-square test results for all the parameters, carried out with 120 people in each village, are presented in the 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 above 0.05. This indicates that technology adoption patterns and associated behaviors are very much similar across Dorli, Bilashi, and Padmale, indicating similar levels of interaction and acceptance in the respective local environments. The results in Table 5 suggest a 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.

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

4.4.2 ANOVA and Kruskal-Wallis Test

The findings of the ANOVA and Kruskal-Wallis tests, as shown in Table 6, are 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 values higher than the normal significance level (0.05).

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

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 the research sites.

Even though statistical differences were not large, the uniformity of villages suggests that there is a consistent baseline of adoption practice. This implies that though context-specific environment and infrastructure vary, even diffusion of sustainability practices is uniformly distributed, which indicates common opportunities for region-wide policy interventions.

4.4.3 Composite Sustainability Score

Composite Sustainability Score, taken as the average percentage positive response for each village, is a composite indicator of overall sustainability performance (Table 7). Dorli achieved 53.27%, lower than Bilashi (55.23%) and Padmale (55.49%). This suggests that all three villages have moderate levels of involvement with 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 among citizens.

Table 7: Comparing the Composite Sustainability Score of Villages

Village	Average % Positive Responses
Dorli	53.27
Bilashi	55.23
Padmale	55.49

4.4.4 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) explains 95.29% of the variance, and a single underlying factor captures most of the variation in sustainability-related parameters (Table 8). The second (PC2) and third (PC3) components explain 3.31% and 1.40% of the variance, respectively, and with minimal additional contribution.

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**

Village-specific PC scores indicate specific contributions along these dimensions: e.g., Bilashi scores highly on PC2 (0.8207), indicating some special variation in some parameters with respect to Dorli and Padmale, which score negatively for PC2. In all, the PCA indicates that most 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).

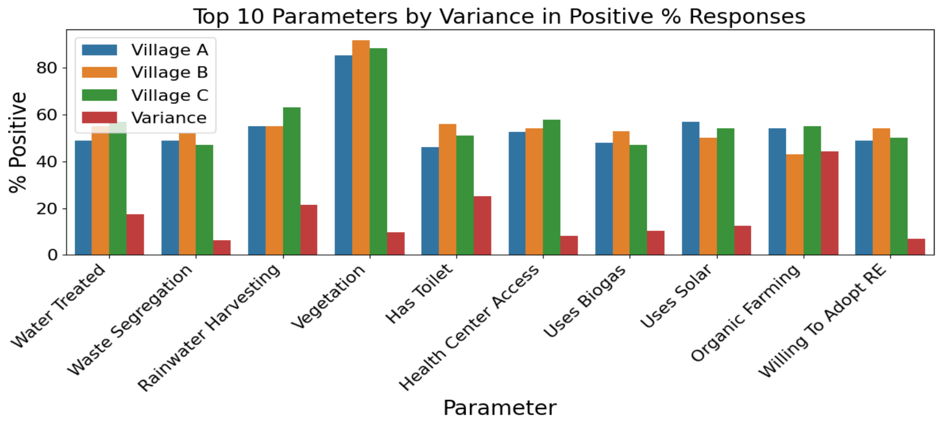

Fig. 4: Variance Parameters in Positive % Responses

4.5 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. From the results in Table 9, Padmale has the highest CGRS at 64%, followed closely by Bilashi at 59%, which means these villages have relatively stronger performance across 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 across multiple domain scores 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.

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

Dorli's markedly lower CGRS score (34%) reflects the compounding effect of drought-induced water stress, inadequate infrastructure, and lower income levels, which constrain sustainability practice adoption. This highlights how ecological vulnerability intersects with socio-economic 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 governance capacity to mobilize them effectively.

The empirical utility of the CP stretches beyond the statistical p-values to present significant insights into the sustainability dynamics among the three villages. In as much as a number of tests, e.g., 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 context have achieved similar exposure to sustainability efforts and are similarly well-placed to take advantage of coordinated, region-wide policy actions rather than disjoined 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 the planning of targeted interventions. Thus, although statistical tests validate homogeneity of responses, observed patterns and relative scores have practical policy significance by pinpointing actionable improvement areas and informing evidence-based rural development interventions.

4.6 SWOT Analysis

Combining CGRS with SWOT analysis gives 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 on the back of its superb environmental performance (0.92), while Dorli trails at 34% on account of low environment (0.07) and infrastructure (0.33) scores.

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

The SWOT table 11 puts these scores into context. Dorli has strengths in solar adoption and knowledge, but weaknesses in sanitation and composting, with 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 of 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 every village.

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

- **Dorli (Drought-prone):** Dorli has impressive sustainability practice strengths like high solar adoption (57%), good awareness (48%), moderate organic farming (54%), and active composting processes, indicating a community practicing eco-friendly measures despite the scarcity of resources. The village, however, has major weaknesses like 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 resilience. Ongoing threats, such as chronic drought and reduced groundwater levels, continue to undermine the village's sustainability initiatives.
- **Bilashi (Hilly Terrain):** 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. The village is still susceptible to landslides and inaccessibility, which threaten both locals and development schemes.
- **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 infrastructure overall 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 overall well-being in the community. Agro-processing, fisheries development, and irrigation-based agriculture are opportunities for economic development and better utilization of resources. Flood risk and possible water contamination from upstream sources are, however, significant threats that can impact livelihoods and environmental health.

This can be briefly represented with Strengths, Weaknesses, Opportunities, and Threats as Table 12.

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

4.7 Discussion

The findings of this study give an in-depth insight into the socio-economic, infrastructural, and ecological conditions in Dorli, Bilashi, and Padmale and the intricate nexus among environment, sustainability practices, and community resilience. The survey findings reveal that there are disparate socio-economic conditions in villages with varying income levels, literacy, and technology uptake, which is consistent with Gaikwad & Shinde (2022). Treatment of water 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 & Chandra (2023) on patchy ecological preservation in rural areas. Environmental interventions like waste segregation and composting are in infant stages, indicating the impact of localized environmental practices on strategy adoption (Undurraga & Pokorny, 2024).

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 like solar adoption and biogas are few, although organic farming is experiencing some encouraging uptake, as per Fazal et al. (2025) on incremental green transition 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).

Employment 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 research is a new, combined metric integrating Environmental, Infrastructure, Sustainability, and Risk domains. Padmale has the best CGRS of 64%, with Bilashi following 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 have 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 global rural sustainability benchmarking.

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; 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 (Prabhakar et al. 2023), 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 adoption of renewable energy (SDG 7). The CGRS therefore not only measures local sustainability but also positions Indian rural development in worldwide sustainability models.

Overall, this research contributes to concept and practice by bridging multivariate statistical analysis and an innovative CGRS framework to yield a starting point for a rural Green Rating System. It 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, the study provides a solid foundation for evidence-based rural development planning and strategic green interventions.

5. CONCLUSION AND FUTURE SCOPE

This research introduces an innovative method for assessing rural sustainability by combining a Composite Green Rating System (CGRS) with multivariate statistical analysis and SWOT evaluation. The developed method systematically combines environmental, infrastructural, sustainability, and risk indicators to provide a single, all-encompassing measure to assess and compare rural settlements. The data gathered from structured questionnaires of three villages, namely Dorli, Bilashi, and Padmale, were analyzed employing descriptive statistics, Chi-square, ANOVA, and Kruskal-Wallis tests to ensure observed variations in patterns of adoption and distributions of parameters were statistically significant. The outcomes show considerable village-specific performance. Padmale had the highest CGRS (64%), which captures robust infrastructure, risk preparedness, and environmental practices, followed by Bilashi (59%), which had strengths in vegetation and waste management. Dorli trailed (34%) on account of poor environmental and infrastructure performance. The corresponding SWOT analysis also captured strengths, weaknesses, opportunities, and threats to inform tailored policy advice for each village setting.

The innovation of the study is the integration of a quantitative grading system with comparative and multivariate analysis, which transcends current systems that usually use qualitative or piecemeal evaluations. Through offering a replicable, evidence-based methodology, the research advances rural planning for development, enhances sustainability interventions, and presents a useful instrument for monitoring, benchmarking, and increasing green practices in various rural settings.

Although the present study gives an overall evaluation of rural sustainability using the CGRS and SWOT analysis, numerous limitations need to be considered. Firstly, the survey was conducted in only three villages, which might limit the applicability of the results to wider rural settings. Secondly, certain parameters used self-reported data, where a degree of bias or imprecision may be introduced in reported practices and perceptions. Also, the research was based on quantitative measures, whereas qualitative social dynamics, governance, and cultural issues were not given equal attention. For future study, the framework may be developed over a greater number of villages or areas, and with longitudinal data to be able to account for temporal changes in sustainability. With the addition of geospatial analysis, remote sensing, and sophisticated environmental indicators, further refinement in the assessment can be achieved. In addition, tying CGRS with policy action and actual outcomes, like better health, efficiency in resource utilization, or economic gains, would make it more useful as a decision-support system. In general, the suggested system has high potential to scale, adapt, and integrate with national and regional rural development schemes. Outside of India, the CGRS system can be used in other global rural settings by reconciling indicators to local ecological and socio-economic conditions, thus acting as a comparative worldwide tool for rural sustainability monitoring.

Author Contributions: Conceptualization, S.B.M. and R.S.G.; methodology, S.B.M.; software, S.B.M.; validation, S.B.M. and R.S.G.; formal analysis, S.B.M.; investigation, S.B.M.; resources, S.B.M.; data curation, S.B.M.; writing—original draft preparation, S.B.M.; writing—review and editing, R.S.G.; visualization, S.B.M.; supervision, R.S.G.; project administration, S.B.M.; funding acquisition, R.S.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: All participants provided their informed consent.

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

REFERENCES

1. 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.
2. Cuenca-Enrique, C. et al., 2024. Sustainability of Rural Electrification Projects in Developing Countries: A Systematic Literature Review. Energies 2024, Vol. 17, Page 5925, 17(23), p. 5925. https://doi.org/10.3390/EN17235925.
3. Der Tambile, E. et al., 2024. Rural livelihoods sustainability in South Asia and Africa: a systematic review with bibliometric analysis. Discover Sustainability, 5(1), pp. 1–22. https://doi.org/10.1007/S43621-024-00651-2/METRICS.
4. Dhal, S.B. and Kar, D., 2024. Transforming Agricultural Productivity with AI-Driven Forecasting: Innovations in Food Security and Supply Chain Optimization. Forecasting 2024, Vol. 6, Pages 925-951, 6(4), pp. 925–951. https://doi.org/10.3390/FORECAST6040046.
5. 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.
6. 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. https://doi.org/10.1108/TG-07-2021-0126/FULL/XML.
7. 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. https://doi.org/10.1109/DASA63652.2024.10836507.
8. Katoch, O.R. et al., 2024. Promoting sustainability: tackling energy poverty with solar power as a renewable energy solution in the Indian energy landscape. Discover Energy 2024 4:1, 4(1), pp. 1–16. https://doi.org/10.1007/S43937-024-00043-7.
9. Kochhar, P. et al., 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. https://doi.org/10.12688/f1000research.108826.1.
10. Tholkapiyan, M., Ramadass, S., Seetha, J., Ravuri, A., Vidyullatha, P., Shankar, S. S., & 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.
11. 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. https://doi.org/10.1007/978-981-16-1186-5_13.
12. 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. https://doi.org/10.3389/fenvs.2023.1323688.

13. 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. https://doi.org/10.1007/S10668-024-04786-0/TABLES/7.
14. Nasution, M.S. et al., 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. https://doi.org/10.18280/IJSDP.200123.
15. 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. https://doi.org/10.3390/su15097536.
16. 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. 10.46488/NEPT.2024.v23i03.003
17. Renukappa, S. et al., 2024. Evaluation of smart village strategies and challenges. Smart and Sustainable Built Environment, 13(6), pp. 1386–1407. https://doi.org/10.1108/SASBE-03-2022-0060.
18. Ricket, A.L. et al., 2023. Rural Sustainable Prosperity: Social Enterprise Ecosystems as a Framework for Sustainable Rural Development. Sustainability 2023, Vol. 15, Page 11339, 15(14), p. 11339. https://doi.org/10.3390/SU151411339.
19. Sabir, B. et al., 2021. Smart Villages: Application of Internet-of-Things in the Development of Rural India. Lecture Notes in Electrical Engineering, 788, pp. 147–155. https://doi.org/10.1007/978-981-16-4149-7_12.
20. 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.
21. Sengupta, A., 2022. Sustainable Development in India With Reference to the Agricultural Sector. SSRN Electronic Journal [Preprint]. https://doi.org/10.2139/ssrn.4199047.
22. Shahab, H. et al., 2024. IoT-based agriculture management techniques for sustainable farming: A comprehensive review. Computers and Electronics in Agriculture, 220, p. 108851. https://doi.org/10.1016/J.COMPAG.2024.108851.
23. 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.
24. 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. https://doi.org/10.1007/s12665-022-10398-6.
25. 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. https://doi.org/10.69974/glslawjournal.v5i2.98.
26. Fazal, N., Eryildiz, D. I., Salahuddin, S., Mohsin, N., & Javaid, M., 2025. Eco Village; Social Sustainable Stability with the Eco-cities. Qlantic Journal of Social Sciences and Humanities, 6(1), pp. 326-335.