

STRATEGIC SPATIAL PLANNING FOR ENHANCING THE ECONOMIC SUSTAINABILITY OF THE TOURISM SECTOR IN GOA, INDIA

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Abstract: Tourism in Goa is concentrated along the coastal belt, generating congestion, environmental stress, and uneven spatial development. This study develops a spatial decision-support framework to identify areas where tourism pressure should be contained and areas where diversification is more feasible. The analysis uses a 1 × 1 km grid across Goa and integrates tourism amenity indicators, environmental conditions, accessibility measures, and regulatory constraints. OpenStreetMap-based tourism and service proxies, Earth observation variables, transport accessibility metrics, and governance overlays are combined to derive three decision dimensions: tourism opportunity, environmental stress, and access. Machine-learning models are used to predict a tourism-opportunity surface, referred to as the Benefit Index, and tourism presence, and these dimensions are then translated into scenario-based development classes for decongestion, diversification, cautious development, and constraint. The results indicate that tourism opportunity is highly concentrated along the coastal belt, where high benefit often coincides with elevated environmental stress and tighter regulatory constraints. In contrast, selected inland areas exhibit moderate opportunity, lower environmental pressure, and adequate access. Scenario testing also indicates that an environment-first approach strengthens the case for directing marginal tourism growth inland rather than intensifying development in already stressed coastal zones. Overall, the results suggest that spatial targeting, rather than uniform expansion, offers a more robust basis for zoning, project appraisal, and phased tourism investment in Goa.

Keywords: tourism diversification, spatial decision support, coastal tourism management, sustainable tourism development, Goa

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INTRODUCTION

Tourism generates employment, income, and public revenue, but its gains and costs are unevenly distributed across space. Activity often concentrates in well-known, well-connected nodes, whereas nearby areas remain weakly integrated into tourism systems. This spatial concentration creates hotspot pressures, including congestion, infrastructure strain, environmental stress, and declining visitor experience, while leaving adjacent areas underused. Sustainable destination performance therefore depends not only on the scale of tourism growth, but also on its spatial distribution.

Fine-grained evidence for local decision-making remains limited. Aggregate indicators such as arrivals and destination-level receipts offer little guidance on where additional development is likely to generate net benefits or where marginal returns may decline. Outside established tourism belts, systematic data on visitation, spending, and business outcomes are often unavailable. Planners therefore rely on indirect spatial indicators, including the distribution of facilities, accessibility, environmental quality, and land-use context. These proxies are uneven and incomplete, which increases uncertainty in prioritisation, sequencing, and regulatory decisions. These problems are especially acute in coastal destinations, where land is scarce, development is concentrated along narrow corridors, and climate-related risks increase the cost of poorly targeted expansion (Butler, 1980; Scott et al., 2016; Scott & Gössling, 2022).

Recent work also treats spatial planning as a core instrument of climate resilience in tourism destinations, especially where extreme weather exposure, coastal pressure, and overtourism interact (Papageorgiou, 2025). In such settings, diversification towards lower-pressure areas becomes both a development strategy and a form of spatial risk management.

Recent tourism research shows wider use of Geographic Information Systems (GIS), remote sensing, volunteered geographic information, and related geospatial technologies in destination planning and management. Yang et al. (2023) argue that geospatial analytical technologies are becoming more important for monitoring, managing, and predicting tourism activity, while also supporting analysis of tourism's social, economic, cultural, and environmental effects. Their

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contribution is mainly methodological. It shows how emerging geospatial data can support multi-scale tourism analysis. However, the paper is a viewpoint article rather than an applied planning framework, so it does not show how these tools can be translated into operational zoning, prioritisation, or development control in specific destinations.

One major stream of recent work focuses on tourism suitability assessment. Acharya et al. (2022) used GIS and the Analytic Hierarchy Process (AHP) to identify geo-ecotourism potential in West Bengal and showed that geospatial techniques can support location-specific planning for sustainable tourism. Harishnaika et al. (2023) applied a similar GIS–AHP framework in Uttara Kannada and found that 53.54% of highly suitable land was located in forest regions, with the most suitable ecotourism sites concentrated in taluks such as Joida and Karwar. These studies show the value of integrating topographic, ecological, and accessibility variables into a spatial planning surface. However, they remain primarily suitability-oriented. Their outputs indicate where tourism development may be possible, but provide less guidance on where further development may be inefficient or undesirable under congestion, environmental stress, or regulatory conflict. They also rely mainly on weighted-overlay or expert-driven decision structures. As a result, uncertainty is not modelled explicitly and trade-offs between opportunity and pressure are only partly addressed. Huang et al. (2024) more recently showed that multisource geospatial data combined with machine-learning techniques can produce more data-driven ecotourism suitability surfaces, although the approach still depends on reliable input data and labelled samples.

A second stream emphasises GIS-based route optimisation and visitor dispersal. Granja-Martins & Fernandez (2024) used ArcGIS and OpenStreetMap data to optimise walking and e-scooter routes across 54 heritage sites in Faro and showed that GIS can improve visitor mobility and support greener urban tourism. Akay (2026) developed one-day cultural-gastronomic route scenarios in Gaziantep and showed that GIS-based network analysis can organise breakfast, museum, heritage, archaeology, and zoo visits more efficiently. Related work continued in 2026. Duran & Doğan (2026) argue that geotourism planning in rural and mountainous regions requires joint attention to accessibility, scenic visibility, and digital awareness, and show that GIS-based route design can extend beyond simple shortest-path logic towards broader spatial feasibility. These studies move tourism GIS research from static mapping towards visitor movement and itinerary design.

However, their main concern is route efficiency rather than broader spatial planning. Granja-Martins & Fernandez (2024) note that route optimisation did not fully address accessibility problems and degraded infrastructure, and Akay (2026) notes that the lack of real-time traffic and visitor-flow data limits route precision.

More importantly, route studies do not usually address hotspot containment, development sequencing, environmental screening, or governance alignment across administrative and regulatory units.

A third stream moves closer to decision-support systems. Mileti et al. (2022) developed a geospatial decision-support system for ecotourism in the Campania region of Italy and showed that such systems can support local actors, planners, and policy implementation in rural tourism contexts. This study moves beyond suitability mapping and proposes an operational support tool with high transferability. However, its focus is ecotourism and rural development rather than the spatial management of mature tourism hotspots. Similarly, Šoltésová et al. (2025), in a GIS-based tourism planning study of Gelnica, showed that spatial analysis and digital data can identify high-demand and underused tourism locations, but also identified a key planning weakness: the absence of systematic visitor-data collection still constrains demand assessment, strategic planning, and monitoring. Recent regional work also points to the importance of tourism spatial structure itself.

Song et al. (2025), using ArcGIS analysis from both government supply and visitor-demand perspectives in Shanxi Province, argue that single-perspective analysis cannot fully capture tourism spatial distribution and propose a reconstructed spatial structure to support higher-quality tourism planning. Together, these studies indicate that geospatial methods are now central to tourism planning, but the literature remains fragmented across suitability assessment, route optimisation, visitor analytics, and decision-support applications. This fragmentation leaves three practical gaps.

First, many studies identify areas of tourism potential but offer limited guidance on where additional development may become inefficient under hotspot pressure, ecological stress, or regulatory constraint. Second, uncertainty is still rarely addressed explicitly, even though open spatial data, proxy indicators, and incomplete visitor information can materially affect prioritisation. Third, outputs are often weakly aligned with the administrative and regulatory units through which tourism development is implemented and controlled. These gaps matter especially in mature coastal destinations, where the policy challenge is not simply to identify attractive places, but to distinguish where pressure should be contained, where diversification is feasible, and where protection is the more defensible long-term option.

Against this background, the present study develops a governance-oriented spatial decision-support framework for sustainable tourism development in Goa. It frames tourism development as a spatial transition under uncertainty and integrates three interpretable dimensions—tourism opportunity, environmental constraint, and access—within a fine-scale 1×1 km grid. These dimensions are translated into implementable planning categories that distinguish areas requiring containment and impact management, feasible diversification zones, emerging locations suitable for cautious nurturing, and constrained areas where expansion should be limited. The framework is applied to Goa, India, a mature coastal destination characterised by strong tourism concentration along the beach belt and explicit policy ambitions to diversify tourism towards the hinterland (Government of Goa, 2020). Rather than treating tourism planning only as a suitability-mapping exercise, the framework is designed to support zoning, prioritisation, and phased intervention under environmental and regulatory constraints. Although grounded in Goa, it relies on widely available data and transparent decision rules, which supports transferability to destinations facing similar concentration-diversification trade-offs and climate-related risks.

The study contributes in three ways. First, it provides fine-scale evidence on the spatial co-location of tourism opportunity, accessibility, environmental constraint, and governance-relevant spatial pressures. Second, it translates sustainability objectives into zoning and prioritisation outputs aligned with planning and regulatory decisions. Third, it

shows how alternative policy emphases reshape diversification priorities and implementation sequencing. Overall, the study offers a planning-oriented basis for spatial targeting, phased intervention, and more defensible long-term tourism governance in a mature coastal destination.

MATERIALS AND METHODS

Methodologically, the study is designed as decision support rather than as a mapping exercise. The aim is to produce (i) a comparable evidence unit (the grid), (ii) three interpretable decision dimensions (opportunity, constraint, access), and (iii) implementable outputs (A–D classes, priority zones, and a model-agreement screen) that match how tourism investments and controls are evaluated across administrative units.

Study area and overall design

This study develops a planning-oriented spatial evidence base for Goa to support three operational decisions: identifying where congestion in saturated coastal zones should be reduced, where tourism can be diversified toward lower-conflict locations, and where expansion should be limited or restricted due to environmental or regulatory constraints.

Goa provides a policy-relevant empirical setting because tourism activity is highly concentrated along the coastal belt, regulatory constraints are substantial, including Coastal Regulation Zone provisions, and state policy explicitly promotes hinterland diversification (Government of Goa, 2020). The analysis is conducted on a uniform 1×1 km grid covering the state of Goa. The grid serves as a consistent spatial unit for integrating heterogeneous datasets and for translating results into governance-relevant summaries aligned with panchayat, taluka, and regulatory boundaries. At the grid-cell level, the study (i) represents observed tourism pull using a proxy derived from the spatial distribution of points of interest, (ii) characterises environmental conditions and accessibility through Earth observation and transport network indicators, and (iii) integrates these dimensions into interpretable indices and decision classes for spatial mapping and aggregation.

A data-driven modelling stage is employed to predict a continuous tourism-opportunity surface from the proxy inputs, referred to hereafter as the Benefit Index, to classify tourism presence, and to reduce information gaps in areas with sparse mapped tourism infrastructure. Model evaluation uses a random train–test split and 5-fold cross-validation on the training set. However, as the folds are not spatially grouped, the reported performance should be interpreted as evidence of predictive consistency under the proxy system rather than as a leakage-free estimate when spatial autocorrelation is present. The overall geospatial–machine-learning workflow used in the study is summarised in Figure 1.

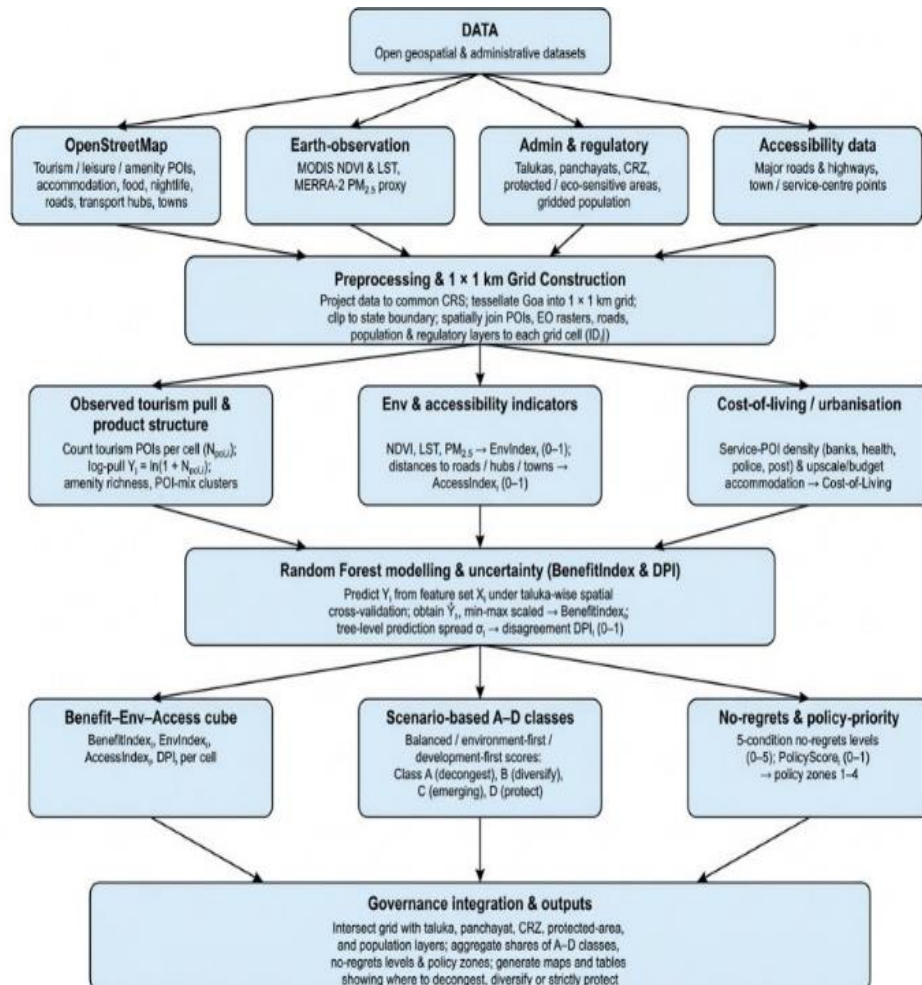


Figure 1. 1×1 km geospatial–machine-learning workflow used to construct the tourism-intelligence grid and policy zones for Goa

Data sources and variables

Tourism-related amenities and infrastructure are derived from OpenStreetMap (OSM) (OpenStreetMap contributors, n.d.), a volunteered geographic information source widely applied in spatial planning and accessibility research (Goodchild, 2007). Tourism-relevant points of interest (POIs) are extracted using OSMnx (Boeing, 2017).

For modelling and interpretation, POIs are classified into three groups.

First, tourism amenities—including accommodation, food and beverage outlets, attractions and viewpoints, and nightlife—are used to construct the observed tourism pull proxy. Second, urban services and cost-of-living proxies, such as financial, health, and civic services, are included as predictors capturing service intensity and urbanisation.

Third, transport and accessibility elements, comprising road network structure and proximity to transport hubs and towns, are used to represent reach and connectivity. These groupings enable consistent representation of tourism opportunity and supporting conditions across space. Environmental conditions are represented using Earth observation products selected for broad spatial coverage and open access. Vegetation greenness is proxied using the MODIS Normalised Difference Vegetation Index (NDVI; Didan, 2015), thermal conditions are captured through MODIS land surface temperature (LST; Wan et al., 2015), and air quality is approximated using aerosol fields from MERRA-2 (Gelaro et al., 2017; Randles et al., 2017). Administrative and regulatory contexts are incorporated through taluka and panchayat boundaries and Coastal Regulation Zone (CRZ) polygons obtained from official sources, supplemented by protected and ecologically sensitive area overlays where available. Population exposure is approximated using gridded population datasets, such as WorldPop (Tatem, 2017), intersected with the 1×1 km analysis grid.

Spatial unit construction

Goa is tessellated into a regular 1×1 km grid in a projected coordinate system suitable for distance calculations. Point, line, and polygon layers are joined to grid cells using spatial intersections and summaries. Grid outputs are subsequently aggregated to taluka and panchayat units to align interpretation with governance and budgeting processes. While any gridded approach is subject to the modifiable areal unit problem (MAUP), the grid provides a transparent and consistent unit for comparing opportunities and constraints across the state.

Construction of pull, environment, and access indicators

Observed tourism pull is proxied by tourism-relevant POI density per grid cell and log-transformed to reduce skewness. Environmental stress is measured with a composite indicator that increases with heat and poorer air-quality proxy values and decreases with greenness. Accessibility combines proximity to roads, transport hubs, and town centres into a single index, with higher values indicating better access. All composite indicators are rescaled to 0–1.

Modelling and uncertainty diagnostics

Random Forest (Breiman, 2001) and Gradient Boosting regression models were used to predict the log-transformed tourism pull proxy from the broader spatial feature set, and a Random Forest classifier was used to model tourism presence (>0 vs 0). The predicted regression surface is referred to here as the Benefit Index and is interpreted as a relative amenity-based tourism-opportunity surface rather than as realised visitation, revenue, or causal impact. Evaluation used a random train–test split (`test_size` = 0.20; `random_state` = 42) and 5-fold cross-validation on the training set. Model agreement was assessed through the absolute difference between the Random Forest and Gradient Boosting regression predictions; cells with smaller differences were treated as higher-agreement areas for implementation, whereas larger differences were flagged for field validation, pilot interventions, or cautious phasing. The modelling stage supports spatial completion and denoising under proxy sparsity rather than causal inference.

Decision classes, governance overlay, and “no-regrets” zones

Benefit, environmental stress, and accessibility are combined into scenario-weighted composite scores for balanced, benefit-oriented, and environment-first scenarios. Each scenario is translated into ordinal A–D classes: (i) high-benefit, high-stress zones requiring decongestion and impact containment; (ii) feasible diversification zones where benefit and access align with lower stress; (iii) emerging areas suitable for cautious nurturing; and (iv) constrained areas where expansion should be limited. The classes define distinct governance and investment postures, including containment, mitigation, enabling investment, cautious piloting, and strict regulation. Results are intersected with CRZ and protected-area overlays to identify legally feasible locations. A policy-priority score identifies no-regrets diversification opportunities by favouring cells with higher benefit, stronger access, lower environmental stress, and stronger model agreement. Cells meeting all core criteria are mapped as no-regrets zones and aggregated to taluka and panchayat summaries for prioritisation, equity discussion, and implementation planning.

Decision rules and threshold definitions

To ensure reproducibility and auditability, all development classes and priority zones are derived from explicit rule-based thresholds applied to rescaled indices. Benefit, environmental stress, and accessibility indices are rescaled to 0–1 across the 1×1 km grid and categorised using empirical quantiles. Benefit and access are tiered using Q33/Q67 cut-offs, and “high environmental stress” is flagged using the top one-third threshold ($\geq$ Q67). These tiers are then used to assign development classes, scenario outcomes, and no-regrets zones through fixed rules defined below. Sensitivity testing uses three alternative rule-sets for assigning A–D classes. Balanced rules follow Table 1. In the benefit-oriented scenario, promotion is less restrictive in access screening among high-benefit cells, while the environment-first scenario treats high-stress cells as

constrained unless they qualify as hotspots requiring containment. No-regrets diversification requires: Class_bal = B, EnvIndex < Q67, AccessIndex $\geq$ Q33, outside CRZ-I and protected/eco-sensitive overlays, and strong model agreement. Model agreement is defined using inter-model similarity: a cell is treated as high agreement if the absolute difference between Random Forest and Gradient Boosting predictions is $\leq$ the median absolute difference across all cells.

Table 1. Decision rules for balanced A–D tourism development classes

Class	Benefit Index (tier)	Env Index (stress flag)	Access Index (tier)	Interpretation
A	High ($\geq$ Q67)	High stress (EnvIndex $\geq$ Q67)	Any	High benefit–high stress (hotspots; decongestion & containment)
B	High ($\geq$ Q67)	Not high stress (EnvIndex < Q67)	Mid/High ($\geq$ Q33)	Feasible diversification zones (high benefit, acceptable stress, adequate access)
C	Mid (Q33–Q67)	Not high stress (EnvIndex < Q67)	Any	Emerging areas; cautious nurturing / phased enablement
D	All remaining cells	Includes low benefit and/or higher constraint cases	Any	Constrained areas; limit expansion / protection-priority depending on overlays

RESULTS AND DISCUSSION

This section presents results in terms of their implications for tourism investment, diversification, and spatial risk management. The analysis identifies where tourism opportunity, measured through amenity-based pull potential, is concentrated, where environmental and physical constraints increase the cost of further expansion, and where diversification opportunities exist with lower economic and regulatory trade-offs. Model performance statistics are reported to establish analytical credibility, while interpretation focuses on decision-relevant spatial patterns. The out-of-sample performance of the tourism pull models is reported in Table 2. Out-of-sample performance is reasonably stable under the proxy-based modelling design, indicating that the tourism pull signal can be identified at the 1-km scale despite strong spatial sparsity. These results support the cautious use of predicted benefit surfaces for zoning and prioritisation decisions, rather than reliance solely on raw POI counts that may under-represent emerging or less mapped areas.

Because the validation design is based on a random split rather than spatially grouped folds, the reported performance should be interpreted as predictive consistency within the proxy system rather than as a leakage-free estimate under spatial autocorrelation. The relative feature importance of the Gradient Boosting model is presented in Table 3.

Table 2. Out-of-sample performance of tourism pull models (1-km grid, Goa; n = 3,889)

Task	Model	Cross-validation	Test performance
Regression (log-transformed tourism pull proxy)	Random Forest	$R^2 = 0.750 (\pm 0.038)$	$R^2 = 0.813$; MAE = 0.155
Regression (log-transformed tourism pull proxy)	Gradient Boosting	$R^2 = 0.757 (\pm 0.036)$	$R^2 = 0.812$; MAE = 0.151
Classification (tourism presence; >0 vs 0)	Random Forest classifier	ROC-AUC = 0.930	Accuracy = 0.900; Precision = 0.662; Recall = 0.758; F1 = 0.707; ROC-AUC = 0.931

Table 3. Top predictors of tourism intensity (Gradient Boosting; relative feature importance)

Rank	Feature	Importance
1	cost_of_living_index_cell	0.4679
2	upscale_share_cell	0.1792
3	dist_to_coast_km	0.0652
4	dist_to_airport_km	0.0385
5	service_poi_cell	0.0377
6	road_intersections_density	0.0359
7	ndvi	0.0313
8	dist_to_rail_km	0.0291
9	dist_to_bus_km	0.0199
10	lst	0.0189

The relative importance pattern suggests that the mapped tourism system is associated mainly with commercial-service intensity and proximity to the coast. Cost-of-living and upscale amenity proxies are the most influential variables, followed by proximity to the coast. Accessibility and environmental variables play a smaller role in this model. Because the target is a mapped amenity proxy, the pattern should be read as showing where tourism-oriented service ecosystems cluster spatially, rather than as a direct explanation of observed visitor demand, expenditure, pricing power, or economic returns.

Tourism opportunity (amenity-based pull potential) is highly concentrated along the coastal belt, indicating a hotspot-driven system rather than broad spatial diffusion. This supports the need for managed decongestion in high-intensity zones and redistribution to feasible inland areas. Although the modelling framework relies on open spatial proxies, the mapped pattern is broadly consistent with Goa's well-known coastal concentration of tourism activity and with state policy emphasis on diversification beyond the beach belt (Government of Goa, 2020). This provides a contextual validity check that the mapped opportunity pattern is spatially plausible and policy-relevant, while still being interpreted as a proxy-based surface rather than a direct measure of observed visitor demand, expenditure, or tourism

revenue. Environmental stress is systematically higher in the western/coastal belt, implying tighter ecological constraints where tourism pressure is greatest. Higher environmental stress in the same zones where tourism opportunity concentrates indicates that additional growth is likely to incur higher mitigation, compliance, and public management costs. The spatial patterns of tourism opportunity, environmental stress, accessibility, and the scenario-balanced development classes are presented in Figures 2–5, respectively.

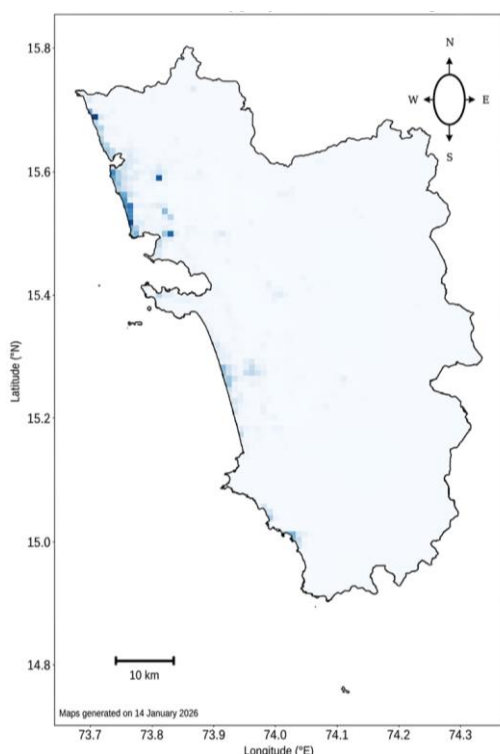


Figure 2. Modelled tourism-opportunity surface (RF Benefit Index; 1-km grid), Goa

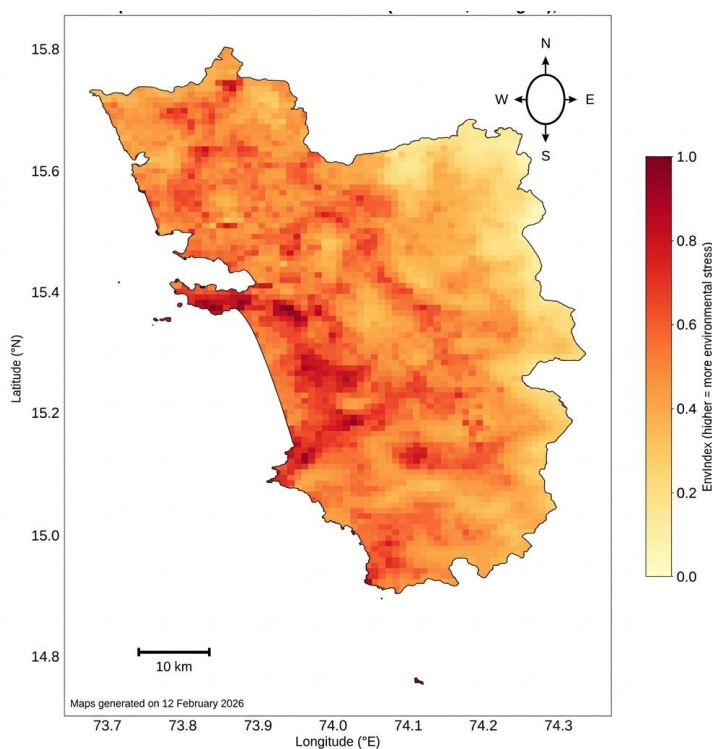


Figure 3. Composite environmental stress index (EnvIndex; 1-km grid), Goa

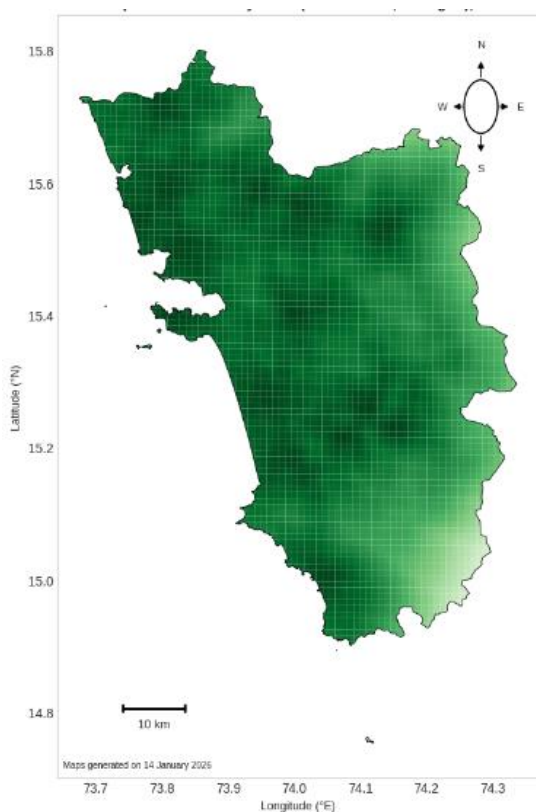


Figure 4. Composite accessibility index (AccessIndex; 1-km grid), Goa

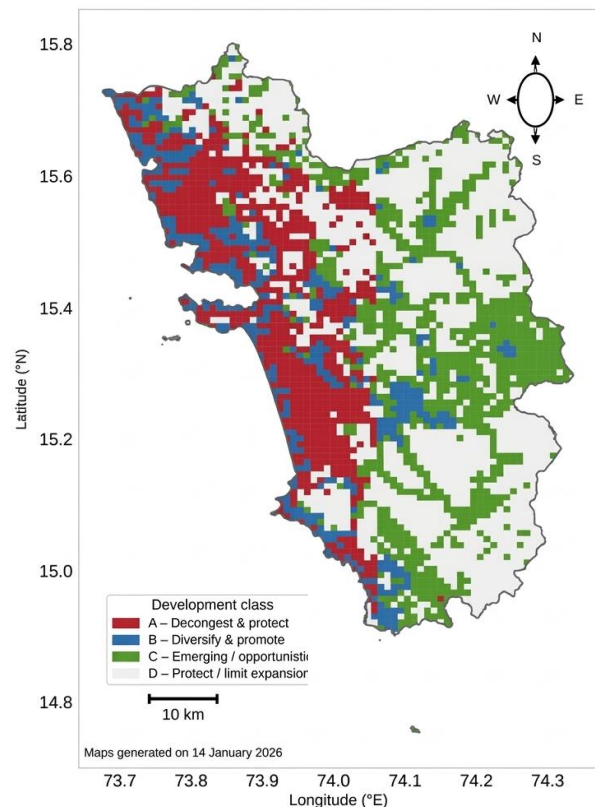


Figure 5. Scenario-balanced A–D tourism development classes (1-km grid), Goa

Accessibility is comparatively widespread across the state, so tourism concentration is not primarily explained by access deficits. The relatively even accessibility pattern implies that diversification barriers are less about transport reach and more about product development, investment focus, and institutional coordination. The classification separates grids into distinct decision regimes: hotspot areas needing decongestion/protection, and non-hotspot areas suitable for diversification/promotion. The A–D classification translates spatial evidence into distinct investment postures: managing and containing pressure in saturated zones, selectively enabling diversification in feasible non-hotspot areas, cautiously nurturing emerging locations, and limiting expansion where constraints dominate. This operationalises a two-track strategy focused on containing pressure and safeguarding viability in hotspots, while expanding opportunity elsewhere.

Comparing the three scenarios shows that the spatial logic of prioritisation is directionally stable: the coastal belt consistently appears as a high-pressure regime requiring containment, while selected inland areas emerge as the main diversification candidates. However, the extent of diversification-ready zones varies with assumptions.

Under the benefit-oriented scenario, a wider set of cells qualifies for promotion, including some areas closer to the coastal belt. Under the environment-first scenario, the prioritisation becomes more selective and shifts further inland, reflecting stricter screening by environmental stress. Cells that remain prioritised across scenarios represent more robust “no-regrets” diversification candidates, while scenario-specific zones are interpreted as higher-discretion choices requiring phased implementation and stronger safeguards. Terrain feasibility and screening indicators for the balanced development classes are reported in Table 4.

Table 4. Terrain feasibility and screening indicators by balanced development class (1-km grid, Goa)

Class_bal	n_cells	elev_mean_m	slope_mean_deg	pct_high_slope	pct_lowlying_coastal	pct_both
A	796	28.393195	4.651214	0.502513	8.291457	0
B	463	37.247893	5.855821	0.863931	12.095032	0
C	973	142.749611	9.180333	15.210689	0.20555	0
D	1657	169.730504	10.596397	24.079662	0.30175	0

Here, `pct_high_slope` denotes the share of cells with 90th percentile slope greater than or equal to 15°, `pct_lowlying_coastal` denotes the share of cells with minimum elevation less than or equal to 10 m and distance to coast less than or equal to 2.0 km, and `pct_both` denotes the share of cells meeting both conditions. The elevation and slope distributions across the balanced development classes are shown in Figure 6.

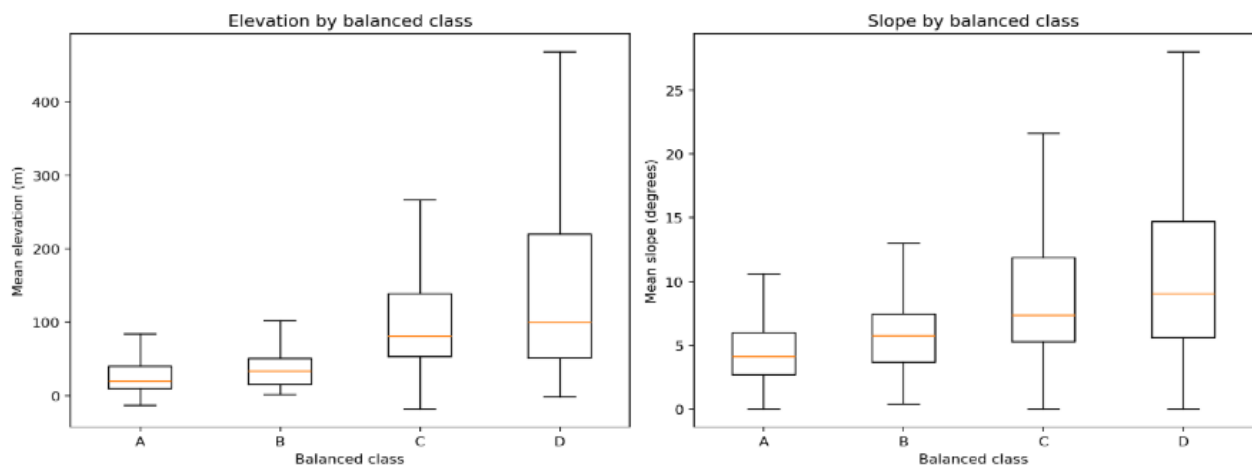


Figure 6. Elevation and slope distributions across balanced development classes

Taken together, the elevation–slope diagnostics show that the balanced A–D zoning is separating areas not only by tourism-development logic but also by physical feasibility. Classes A/B largely fall in low-relief settings, so interventions there are more implementable (management, upgrading, targeted diversification) with lower terrain-related friction. Classes C/D concentrate in higher and steeper terrain, indicating that constraints are structural rather than purely policy-driven; these locations are less suitable for infrastructure-led expansion and are better approached through low-impact, nature-compatible products, phased pilots, and stricter protection where needed. This strengthens the governance interpretation of the zoning: coastal/hotspot actions are feasible and immediate, while inland opportunity must be filtered through terrain-limited capacity. From a commerce and implementation perspective, this implies that diversification strategies should prioritise low- to moderate-relief inland areas where physical feasibility supports scalable investment, while steeper hinterland areas are better suited to low-impact, experience-based products rather than infrastructure-intensive development.

Higher no-regrets scores are more common away from the main hotspot belt, indicating more locations where diversification is feasible with fewer trade-offs. Conversely, hotspot areas show fewer “easy-win” options, reinforcing the case for limits and mitigation. Interpreted economically, higher no-regrets scores indicate locations where diversification investments are comparatively viable under the proxy-based evidence and decision rules, while lower scores signal higher exposure to regulatory, environmental, or demand-side risk.

Priority zones are spatially selective, implying that diversification should be implemented through targeted priority locations rather than uniform statewide investment. This spatial selectivity supports phased sequencing of public and private investment, allowing resources to be concentrated in priority corridors rather than dispersed thinly across the state, which would dilute economic impact and increase coordination costs. The spatial distribution of the no-regrets diversification scores and the resulting tourism-diversification policy zones are shown in Figures 7 and 8.

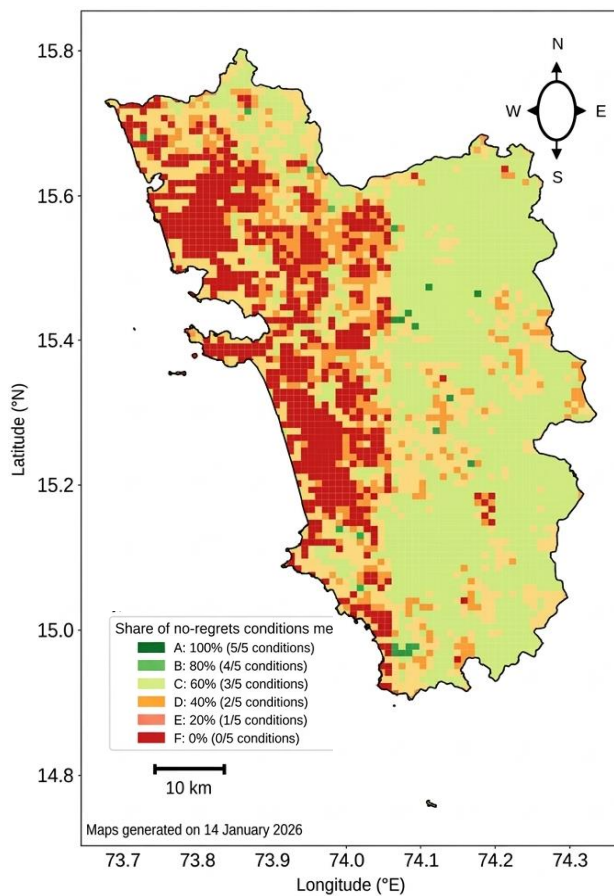


Figure 7. No-regrets diversification score (conditions satisfied; 1-km grid), Goa

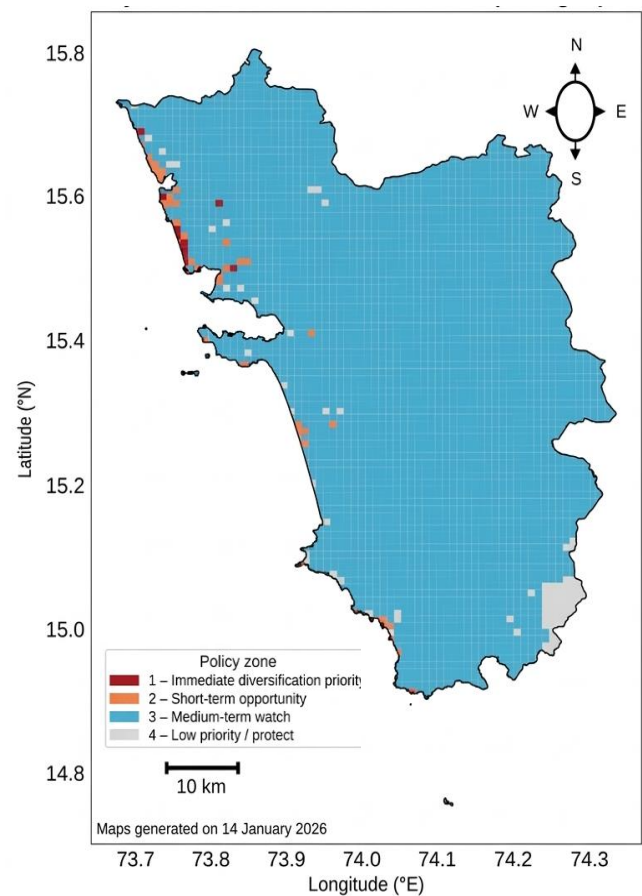


Figure 8. Policy zones for tourism diversification (1-km grid), Goa

CONCLUSION

This study develops a governance-oriented spatial evidence base for Goa to support three operational decisions: managing congestion and limiting incremental pressure in saturated corridors; staging diversification toward lower-conflict locations; and identifying where environmental or regulatory constraints justify protection rather than expansion. Tourism opportunity is represented through a proxy-based latent surface inferred from open spatial indicators. The analysis maps a Benefit–Environment–Access (BEA) decision space and translates it into A–D development classes, policy-priority zones, and a no-regrets screening layer.

These outputs can be intersected with regulatory overlays and aggregated to administrative units used for budgeting, appraisal, and programme design. The resulting pattern suggests that tourism opportunity and environmental stress often co-locate along the coastal belt. Sustainable tourism development therefore depends on spatial targeting that limits additional pressure where constraints are greatest while selectively enabling inland locations where accessibility and tourism opportunity align with lower environmental stress and less binding regulatory constraints.

The findings also have direct implications for tourism governance and investment planning in Goa. Rather than applying uniform destination-wide development strategies, the framework supports a differentiated approach in which saturated coastal and other high-pressure areas are prioritised for containment, mitigation, and quality improvement, while suitable inland locations are considered for phased diversification.

Aggregating grid-level results to taluka and panchayat levels and combining them with regulatory overlays can support zoning, investment sequencing, and resource allocation. Model-agreement screening further provides a risk-management mechanism by distinguishing higher-agreement areas for implementation from locations requiring field verification, stakeholder engagement, or pilot testing before substantial investment.

These results should be interpreted in light of the limitations of proxy-based spatial planning. The tourism pull proxy derived from OpenStreetMap points of interest reflects mapped supply and amenity presence rather than observed visitation, expenditure, or crowding. Variation in mapping completeness and tagging practices may therefore affect measured intensity. Although the modelling stage supports spatial completion under data sparsity, the resulting Benefit

Index remains a proxy-based opportunity surface rather than a substitute for direct demand measures. The 1×1 km grid also introduces unavoidable scale effects, including the modifiable areal unit problem, while some environmental impacts and regulatory sensitivities operate at finer resolutions. The environmental and accessibility indices provide consistent statewide coverage but do not fully capture seasonal dynamics, hazard exposure, or local carrying-capacity mechanisms. The framework should therefore be interpreted as a policy-oriented decision-support system rather than as a direct measure of realised tourism demand or economic outcomes.

Future research can strengthen the framework by improving demand representation and extending its temporal and governance dimensions. Calibration against higher-fidelity demand indicators, such as accommodation occupancy, mobile-location aggregates, ticketing data, traffic counts, or transaction-based measures, would improve interpretability and help distinguish mapped tourism supply from realised use. Repeated temporal observations would allow modelling of seasonality and shock responses, including monsoon conditions, heat stress, and extreme rainfall.

Implementation effects should also be assessed by linking priority zones to monitored outcomes such as visitor redistribution, congestion reduction, environmental conditions, and local income effects, alongside stakeholder-grounded feasibility assessments. Systematic taluka- and panchayat-level reporting and equity-oriented diagnostics could further strengthen the governance interface and help ensure that spatial prioritisation remains technically credible, institutionally actionable, and socially defensible.

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