



## **A GIS-Based Multi-Criteria Decision-Support and Land-Suitability Optimization Framework for Climate-Resilient Urban and Regional Planning**

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### **Abstract**

Climate-resilient urban and regional planning requires land-allocation methods that integrate environmental conditions, climate hazards, infrastructure capacity, accessibility, socioeconomic vulnerability, development cost, and regulatory constraints. This quantitative study developed and evaluated a GIS-based multi-criteria decision-support and multi-objective land-suitability optimization framework across a 184,260-hectare planning region. The final database contained 1,974,900 valid 30-meter raster cells, 121,800 cadastral parcels, 39 accepted geospatial layers, 2,400 reference observations, and criterion judgments from 30 experts. Seventeen indicators were standardized and weighted through expert, entropy, CRITIC, and hybrid procedures. Conventional baseline, climate-integrated, and fully optimized configurations were compared using repeated-measures tests, paired comparisons, spatial statistics, logistic regression, independent validation, sensitivity analysis, Monte Carlo simulation, and optimization-robustness assessment. Baseline suitability averaged .583, with 44,190 hectares classified as moderate and 51,180 hectares classified as high or very high. Flood risk produced the strongest negative relationship with suitability, ( $r=-.73$ ), while infrastructure capacity produced the strongest positive relationship, ( $r=.68$ ). Climate-risk integration reclassified 18,355 hectares as restricted and reduced exposed population from 428,600 to 272,400. Full optimization retained 109,740 hectares, increased mean suitability to .724, and expanded high or very-high land to 68,740 hectares. Relative to baseline, optimization reduced exposed population by 60.59%, critical-infrastructure exposure by 71.23%, climate-exposed land by 68.30%, expected annual hazard loss by 60.89%, network travel time by 27.02%, and infrastructure-extension cost by 15.85%. Spatial compactness increased from .46 to .72, service coverage reached 88.7%, ecological retention reached 91.6%, and constraint satisfaction reached 99.2%. Independent validation produced an ROC-AUC of .890, accuracy of 82.6%, and F1 score of .831. Weighting correlations ranged from .84 to .91, 84.7% of priority cells remained stable in at least 80% of Monte Carlo simulations, and all 50 optimization runs converged. The findings establish that integrating climate-risk restrictions with multi-objective spatial optimization produces a more accurate, stable, and operationally complete basis for climate-resilient land allocation than conventional suitability classification alone.

### **Keywords**

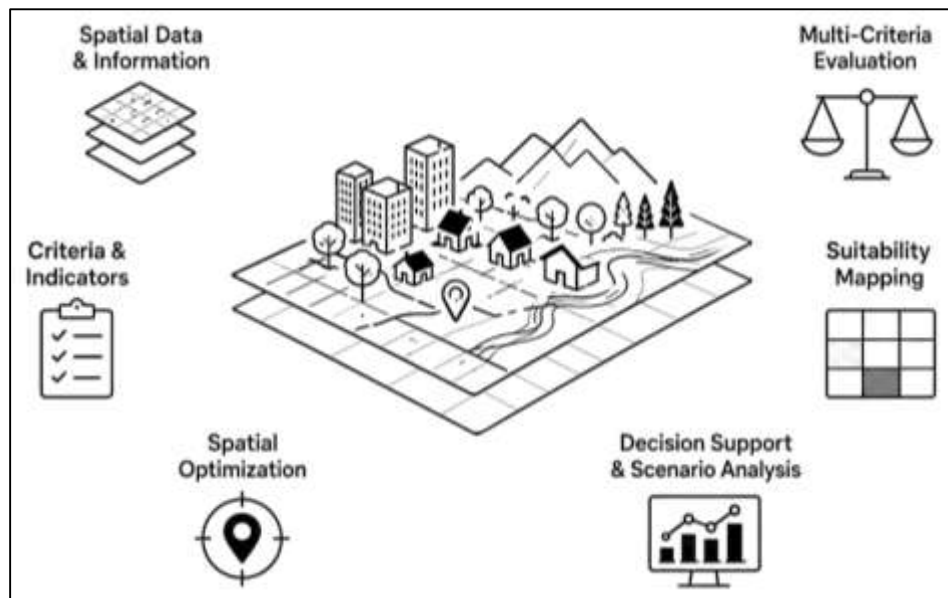
GIS; Land Suitability; Climate Resilience; Decision Support; Spatial Optimization.

## INTRODUCTION

Geographic Information Systems (GIS) refer to integrated computer-based environments used to collect, store, manage, analyze, model, and visualize geographically referenced information. GIS links the attributes of environmental, social, economic, infrastructural, and institutional phenomena to their spatial locations, allowing relationships that cannot be identified through nonspatial databases to be measured quantitatively. Multi-criteria decision support describes a structured analytical process through which several criteria, objectives, restrictions, and stakeholder preferences are evaluated simultaneously. A GIS-based multi-criteria decision-support system combines spatial analysis with formal decision rules so that geographically distributed alternatives can be compared according to standardized and weighted indicators (Lü et al., 2019). Land suitability represents the degree to which a parcel, raster cell, planning zone, or administrative unit satisfies the physical, environmental, socioeconomic, infrastructural, and regulatory requirements of a specified land use. Suitability differs from simple land availability because an available location may remain inappropriate when it is exposed to flooding, heat, erosion, wildfire, ecological sensitivity, service deficiencies, or excessive development costs. Land-suitability optimization extends suitability assessment by identifying a spatial configuration that maximizes desired benefits while minimizing climate exposure, ecological disturbance, infrastructure expenditure, social vulnerability, and land-use conflict under defined constraints. Climate resilience refers to the capacity of urban and regional systems to withstand, absorb, adapt to, and recover from climate-related disturbances while maintaining essential functions, services, accessibility, environmental quality, and social protection (Jones, 2014). Climate-resilient planning integrates hazard exposure, population sensitivity, ecosystem capacity, infrastructure performance, and institutional response into land-development decisions. Urban planning generally focuses on the organization of land uses, infrastructure, housing, services, mobility, and public space within settlements, whereas regional planning considers relationships among cities, peri-urban areas, rural territories, ecological systems, transport corridors, watersheds, and economic zones across broader spatial scales. Within a quantitative research framework, these concepts are operationalized through measurable indicators such as elevation, slope, land-cover type, flood depth, heat intensity, distance from hazards, accessibility to roads and services, development cost, population density, ecological value, and regulatory compatibility (Longley & Cheshire, 2017). Each spatial unit receives criterion scores, normalized values, weights, constraint classifications, composite suitability values, and optimization status. The resulting framework treats land allocation as a measurable spatial decision problem involving multiple objectives rather than as an intuitive selection of developable locations. Climate-resilient land-suitability assessment has international significance because urban and regional development occurs under markedly different combinations of climatic hazards, population pressures, environmental conditions, infrastructure capacities, and governance arrangements (Chang, 2016). Evidence synthesized from more than thirty empirical and comparative studies across Asia, Africa, Europe, North America, South America, the Middle East, and Oceania shows that land-development decisions are closely associated with exposure to flooding, coastal inundation, extreme heat, wildfire, drought, landslides, soil erosion, water scarcity, and ecosystem degradation. Rapid urban expansion has converted agricultural land, wetlands, forests, natural drainage corridors, coastal buffers, and peri-urban open spaces into built-up areas, altering runoff patterns, surface temperatures, habitat continuity, water availability, and access to essential services. In coastal cities, elevation, storm-surge exposure, shoreline change, salinity, evacuation accessibility, and drainage capacity have been central suitability indicators (Kucera, 2020). In river-basin settlements, flood frequency, inundation depth, flow accumulation, soil permeability, wetland proximity, and watershed condition have received greater analytical attention. Studies conducted in arid and semi-arid regions have emphasized groundwater availability, drought severity, land degradation, irrigation access, heat stress, and the distance between settlements and reliable water sources. Mountainous regions have been assessed through slope, elevation, landslide probability, seismic exposure, erosion potential, road accessibility, and

construction limitations. Wildfire-prone landscapes have required measurements of vegetation type, fuel continuity, wind exposure, slope orientation, emergency access, and separation from high-risk interfaces. International research has also shown that climate risk is distributed unevenly among social groups ([Wang & Xie, 2018](#)).

**Figure 1: GIS-Based Climate Land Optimization**



Low-income households, informal settlements, older populations, people with disabilities, migrants, and communities with limited access to healthcare, transport, cooling, drainage, or emergency services frequently occupy highly exposed land. Consequently, land suitability cannot be represented adequately through physical terrain characteristics alone. Social vulnerability, housing affordability, livelihood access, land tenure, service availability, and displacement risk form measurable dimensions of climate-resilient planning. Cross-national studies further demonstrate variation in data availability, cadastral accuracy, institutional coordination, planning enforcement, and technical capacity. A quantitative GIS framework provides a common analytical structure while allowing criteria, thresholds, weights, and spatial resolutions to reflect local conditions ([Höhn et al., 2014](#)). This international body of research establishes climate-resilient land allocation as a multidimensional spatial assessment involving environmental protection, infrastructure efficiency, hazard reduction, social accessibility, and development feasibility.

The conceptual relationship between climate risk and land suitability is commonly structured through the interaction of hazard, exposure, vulnerability, and adaptive capacity. Hazard describes the probability, intensity, frequency, duration, or spatial extent of a potentially damaging climatic or environmental event. Exposure represents the presence of people, buildings, infrastructure, economic activities, cultural resources, and ecosystems within locations affected by that event ([Liu et al., 2017](#)). Vulnerability refers to the degree to which exposed elements are susceptible to harm, while adaptive capacity represents the resources and capabilities available to anticipate, withstand, respond to, and recover from disruption. In land-suitability analysis, these dimensions are converted into spatial indicators and classified as either suitability benefits or suitability costs. High accessibility, stable terrain, adequate water supply, service availability, infrastructure capacity, and proximity to employment may increase suitability. High flood probability, extreme surface temperature, ecological sensitivity, erosion potential, development cost, social displacement, and distance from emergency services may reduce suitability. The framework also distinguishes permanent exclusion constraints

from compensatory evaluation criteria (Zhu et al., 2018). Protected areas, active floodways, unstable slopes, legally restricted zones, critical habitats, airport safety areas, and hazardous industrial buffers may be classified as nondevelopable regardless of their performance on other indicators. In contrast, moderate transport distance, infrastructure cost, or population density may be evaluated through weighted trade-offs. Studies of climate-resilient planning have organized suitability indicators into environmental, climatic, physical, socioeconomic, infrastructural, accessibility, and institutional dimensions. Environmental criteria include land cover, biodiversity, wetlands, soil quality, water resources, and ecological connectivity. Climatic criteria include flood probability, rainfall intensity, temperature, drought severity, storm exposure, wildfire susceptibility, and projected hazard intensity. Physical criteria include elevation, slope, aspect, geology, soil bearing capacity, drainage, and terrain stability. Socioeconomic criteria include population density, poverty, land value, employment access, housing need, and displacement sensitivity. Infrastructure and accessibility criteria measure distances or travel times to roads, public transport, schools, healthcare facilities, markets, utilities, shelters, and emergency-response centers (Chakraborty & Mukhopadhyay, 2019). Institutional criteria represent zoning compatibility, ownership, planning restrictions, administrative jurisdiction, and development-control requirements. These dimensions are assessed at multiple geographic scales because a location may appear suitable at the municipal level while containing neighborhood-scale hazards or service inequalities. Spatial units, buffer distances, classification thresholds, and data resolution therefore influence the measured distribution of suitability and the ranking of development alternatives.

GIS supplies the spatial data architecture required to integrate the diverse variables used in climate-resilient land-suitability assessment. Quantitative studies commonly combine satellite imagery, digital elevation models, land-use and land-cover maps, soil and geological surveys, hydrological networks, climate records, census data, cadastral information, road and transit networks, utility locations, hazard inventories, protected-area boundaries, and statutory planning maps (Ogato et al., 2020). Raster data represent continuous surfaces such as elevation, temperature, rainfall, vegetation condition, flood depth, or travel cost, whereas vector data represent discrete features such as roads, parcels, rivers, service facilities, administrative boundaries, and infrastructure networks. Remote-sensing data support the classification of built-up land, vegetation, water bodies, agricultural areas, impervious surfaces, urban expansion, and surface-temperature patterns. Digital elevation models allow slope, aspect, flow direction, flow accumulation, drainage density, watershed boundaries, and terrain instability to be calculated. Network analysis measures travel distance or time to employment centers, public transport, hospitals, schools, evacuation shelters, markets, and emergency services more accurately than straight-line distance when reliable road data are available (Adimalla & Taloor, 2020). Spatial interpolation converts point-based observations of rainfall, groundwater, air temperature, pollution, or soil characteristics into continuous analytical surfaces. Before criteria are combined, all datasets require a common coordinate system, study boundary, spatial resolution, temporal reference, and analytical unit. Continuous measurements are then standardized through min-max transformation, z-scores, fuzzy membership functions, percentile ranking, or value functions. Categorical variables are reclassified through ordinal scores based on suitability thresholds. Cost criteria are transformed so that higher values represent lower suitability, while benefit criteria retain a positive direction. Data quality remains a measurable component of the framework because positional error, missing observations, outdated land-cover maps, inconsistent classification systems, and mixed spatial resolutions can alter suitability scores. Scale effects also arise when fine-resolution environmental information is aggregated into large administrative units or when coarse global datasets are applied to parcel-level decisions (Villacreses et al., 2017). Quantitative accuracy assessment may include land-cover classification accuracy, root mean square error, validation against observed hazard events, agreement with existing development patterns, and comparison with expert-classified reference locations. Spatial autocorrelation testing identifies whether high or low suitability scores form statistically significant clusters. Hotspot analysis, zonal statistics, overlay analysis, proximity measurement, terrain modeling,

and map algebra collectively transform heterogeneous data into a consistent geospatial database in which each planning unit can be evaluated through the same criteria.

**Figure 2: GIS-Based Climate Resilient Land Optimization**



Multi-criteria evaluation provides the mathematical procedures through which standardized spatial indicators are converted into composite suitability scores. Weighted linear combination is one of the most frequently used approaches because it multiplies each normalized criterion score by its assigned weight and sums the weighted values for every spatial unit (Verma et al., 2020). The resulting index normally ranges between minimum and maximum suitability values and can be divided into classes such as unsuitable, marginally suitable, moderately suitable, highly suitable, and very highly suitable. Boolean overlay applies stricter decision rules by assigning binary values to restricted and permissible areas. More flexible frameworks combine Boolean constraints with weighted factors, removing legally or environmentally prohibited land before calculating suitability among the remaining alternatives. The analytic hierarchy process has been used extensively to organize criteria into hierarchical levels and derive weights through pairwise comparisons. A consistency ratio measures the logical coherence of expert judgments and provides a quantitative basis for revising inconsistent comparisons. The analytic network process represents interdependence among criteria when factors such as transport accessibility, development density, infrastructure capacity, and land value influence one another (Taloor et al., 2020). Other studies have applied TOPSIS to rank locations according to their distance from ideal and least-desirable alternatives, ELECTRE and PROMETHEE to perform outranking comparisons, and VIKOR to identify compromise solutions among competing objectives. Fuzzy multi-criteria techniques represent gradual transitions and uncertainty more effectively than rigid suitability thresholds. Entropy weighting, standard-deviation weighting, and CRITIC weighting estimate criterion importance from the variability and informational content of observed data, reducing

exclusive dependence on expert judgment. Hybrid approaches combine expert-derived weights with objective statistical weights to balance planning knowledge and data characteristics. Ordered weighted averaging adjusts the degree of trade-off and risk tolerance by controlling how strongly favorable performance on one criterion compensates for poor performance on another (Pham et al., 2018). Criterion selection and weighting require attention to redundancy because highly correlated variables can count the same spatial condition more than once. Correlation analysis, variance inflation factors, principal component analysis, factor analysis, and expert screening can be used to identify overlapping indicators. Sensitivity analysis evaluates how changes in weights, thresholds, classification methods, normalization procedures, and decision rules affect suitability rankings. Agreement statistics compare alternative weighting scenarios, while rank correlation measures the stability of spatial priorities. These procedures establish a transparent quantitative structure for converting heterogeneous planning criteria into reproducible land-suitability classifications (Shepero & Munkhammar, 2018).

Suitability mapping identifies the relative appropriateness of individual locations, while spatial optimization determines how a limited amount of land can be allocated among competing uses under multiple objectives and constraints. A collection of highly suitable cells does not automatically form an efficient development pattern because selected locations may be fragmented, disconnected from infrastructure, ecologically disruptive, or too distant from existing settlements. Optimization models address this distinction by searching for spatial configurations that satisfy specified planning requirements (Campbell & Masser, 2020). Linear programming, integer programming, mixed-integer programming, goal programming, location-allocation models, genetic algorithms, simulated annealing, particle swarm optimization, ant-colony methods, and multi-objective evolutionary algorithms have been applied to land-allocation problems. Common objectives include maximizing aggregate suitability, infrastructure accessibility, housing capacity, economic return, ecosystem protection, and compactness while minimizing climate risk, travel distance, land-acquisition cost, carbon emissions, ecological fragmentation, service inequality, and population displacement. Constraints may specify the total land required for housing, industry, agriculture, public facilities, green space, stormwater retention, transport, or conservation. Additional restrictions represent zoning requirements, budget limits, maximum development density, minimum habitat area, infrastructure capacity, adjacency conditions, and separation from hazardous locations (Owolabi et al., 2020). Pareto-based optimization generates a set of nondominated solutions when no single land configuration performs best across all objectives. These solutions reveal measurable trade-offs, such as the reduction in flood exposure associated with higher infrastructure expenditure or the increase in ecological protection associated with lower developable capacity. Spatial compactness indices, patch size, edge density, connectivity, contiguity, and distance to existing urban areas can be incorporated to control the geographic form of selected land. Scenario analysis evaluates alternative climate-hazard intensities, population distributions, development targets, infrastructure investments, and policy restrictions. Each scenario produces quantitative outputs such as suitable land area, exposed population, expected hazard loss, infrastructure distance, development cost, ecological area retained, and accessibility levels (Cavazzi & Dutton, 2016). Robust optimization assesses solutions across multiple uncertain conditions rather than relying on a single deterministic dataset. Validation can compare optimized locations with observed low-risk development, approved plans, expert-selected sites, historical hazard records, or independent environmental assessments. The integration of GIS-based suitability scores with optimization procedures therefore treats land planning as both a classification problem and a constrained spatial-allocation problem.

Evidence from more than thirty land-suitability, climate-risk, urban-growth, and spatial-optimization studies demonstrates substantial variation in the selection of criteria, weighting techniques, spatial resolutions, validation procedures, and treatment of uncertainty. Many assessments produce visually detailed suitability maps but provide limited statistical evaluation of weight stability, criterion redundancy, model accuracy, or spatial sensitivity. Other studies estimate climate exposure without

integrating infrastructure accessibility, social vulnerability, land-development feasibility, and statutory restrictions within one analytical structure. Suitability and optimization are also frequently treated as separate activities, creating a methodological gap between identifying appropriate locations and determining an efficient allocation of land among competing regional needs (Wu et al., 2016). The quantitative problem addressed in this paper concerns the measurement and optimization of land suitability when environmental quality, climate risk, socioeconomic conditions, infrastructure access, development cost, and planning regulations operate simultaneously. The study develops a GIS-based multi-criteria framework in which the spatial unit of analysis consists of raster cells, parcels, or planning zones within a defined urban and regional territory. The principal outcome variable is a composite land-suitability score, supported by secondary outcomes such as suitability class, optimized allocation status, climate-risk level, infrastructure-accessibility score, ecological-conflict score, and development-cost index. Explanatory dimensions include physical suitability, environmental sensitivity, hazard exposure, social vulnerability, adaptive capacity, service accessibility, transportation connectivity, and institutional compatibility (Tahri et al., 2015). Restriction variables identify protected, hazardous, legally unavailable, or technically infeasible land. Criteria are standardized to a common measurement scale, weighted through expert-based, data-driven, or hybrid techniques, and aggregated through explicit decision rules. Spatial optimization evaluates alternative land configurations according to multiple objectives and planning constraints. Model performance is examined through sensitivity tests, alternative weighting scenarios, spatial autocorrelation analysis, rank stability, comparison with reference locations, and validation against observed hazard or development data. Scenario-specific outputs measure changes in suitable area, risk exposure, accessibility, cost, compactness, ecological protection, and population coverage. This analytical scope allows relationships among criterion weights, spatial conditions, suitability classifications, and optimized land allocations to be evaluated numerically (Turner, 2020). It also distinguishes locations that receive high suitability scores from land configurations that satisfy broader requirements for climate resilience, service access, spatial continuity, regulatory compliance, and regional land-use balance.

The primary objective of this study is to develop and quantitatively evaluate a GIS-based multi-criteria decision-support and land-suitability optimization framework for identifying spatially appropriate locations for climate-resilient urban and regional development. The study specifically aims to integrate physical, environmental, climatic, socioeconomic, infrastructural, accessibility, and institutional indicators within a unified geospatial database so that each raster cell, land parcel, or planning zone can be evaluated through consistent and measurable decision criteria. Physical indicators include elevation, slope, terrain stability, soil characteristics, drainage conditions, and existing land use, while environmental indicators cover ecological sensitivity, vegetation, wetlands, water resources, protected areas, and habitat connectivity. Climatic indicators incorporate flood susceptibility, extreme heat, drought severity, storm exposure, wildfire probability, erosion risk, and other locally relevant hazards. Socioeconomic and infrastructural indicators include population density, social vulnerability, land value, housing demand, access to employment, road connectivity, public transportation, utilities, healthcare, education, emergency services, and evacuation facilities. The study also aims to distinguish compensatory suitability factors from absolute development restrictions, including legally protected areas, active floodways, unstable terrain, hazardous industrial buffers, and environmentally critical zones. Another objective is to standardize the selected criteria, determine their relative importance through expert-based, data-driven, or hybrid weighting methods, and calculate a composite land-suitability index for classifying locations into different suitability levels. The research seeks to examine the sensitivity of suitability outcomes to alternative criterion weights, normalization procedures, classification thresholds, spatial resolutions, and aggregation techniques. It further aims to apply a multi-objective spatial optimization model that maximizes overall suitability, infrastructure accessibility, development compactness, service coverage, and ecological protection while minimizing

climate exposure, environmental disturbance, land-acquisition cost, infrastructure-extension requirements, social displacement, and land-use conflict. Alternative climate, population, infrastructure, and development scenarios are evaluated through measurable outputs, including total suitable land area, exposed population, infrastructure distance, estimated development cost, ecological area retained, spatial compactness, and accessibility performance. The study additionally aims to assess model reliability through spatial autocorrelation analysis, rank-stability testing, sensitivity analysis, scenario comparison, and validation against observed hazard records, existing development patterns, expert-classified locations, or approved planning zones. Through these objectives, the research establishes a transparent and reproducible quantitative procedure for comparing potential development locations and allocating land among competing urban and regional uses under climate-related, environmental, socioeconomic, infrastructural, and regulatory constraints.

## **LITERATURE REVIEW**

This literature review examines the quantitative foundations, analytical methods, spatial indicators, and model-performance measures associated with GIS-based multi-criteria decision support and land-suitability optimization for climate-resilient urban and regional planning. The reviewed literature treats land suitability as a measurable spatial construct produced through the interaction of physical conditions, environmental sensitivity, climate-hazard exposure, socioeconomic vulnerability, infrastructure accessibility, development feasibility, and regulatory compatibility. Particular attention is given to how these dimensions have been operationalized through raster cells, land parcels, census units, planning zones, watersheds, and transportation-network segments (Kanti, 2020; Rahimi et al., 2017). The review evaluates studies that have used satellite imagery, digital elevation models, meteorological records, hydrological data, census information, infrastructure inventories, cadastral databases, and statutory planning maps to construct spatial decision criteria. It also examines the quantitative procedures used to normalize indicators, determine criterion weights, remove restricted land, calculate composite suitability scores, classify suitability levels, and compare alternative development locations. Established multi-criteria methods—including weighted linear combination, analytic hierarchy process, analytic network process, entropy weighting, CRITIC, TOPSIS, VIKOR, ELECTRE, PROMETHEE, fuzzy logic, and ordered weighted averaging—are assessed according to their mathematical properties, weighting requirements, consistency measures, capacity to represent uncertainty, and stability of resulting land rankings (Adams et al., 2014; Debasish, 2021). The literature on spatial optimization is reviewed through measurable objectives such as climate-risk reduction, accessibility improvement, infrastructure-cost minimization, ecological retention, development compactness, population coverage, and land-use compatibility. Quantitative validation procedures receive specific attention, including classification accuracy, root mean square error, receiver operating characteristic analysis, area under the curve, rank correlation, spatial autocorrelation, sensitivity testing, scenario comparison, and agreement with observed development or hazard patterns. The literature is organized into nine extended sections that progress from spatial measurement and criterion construction to climate-risk analysis, socioeconomic and infrastructure assessment, geospatial data quality, multi-criteria weighting, multi-objective optimization, model validation, and empirical relationship testing (Demir & Kisi, 2016; Abdur & Iftekhar, 2021). This structure establishes a detailed basis for identifying the variables, measurement scales, decision rules, optimization objectives, and statistical tests required for a reproducible land-suitability framework.

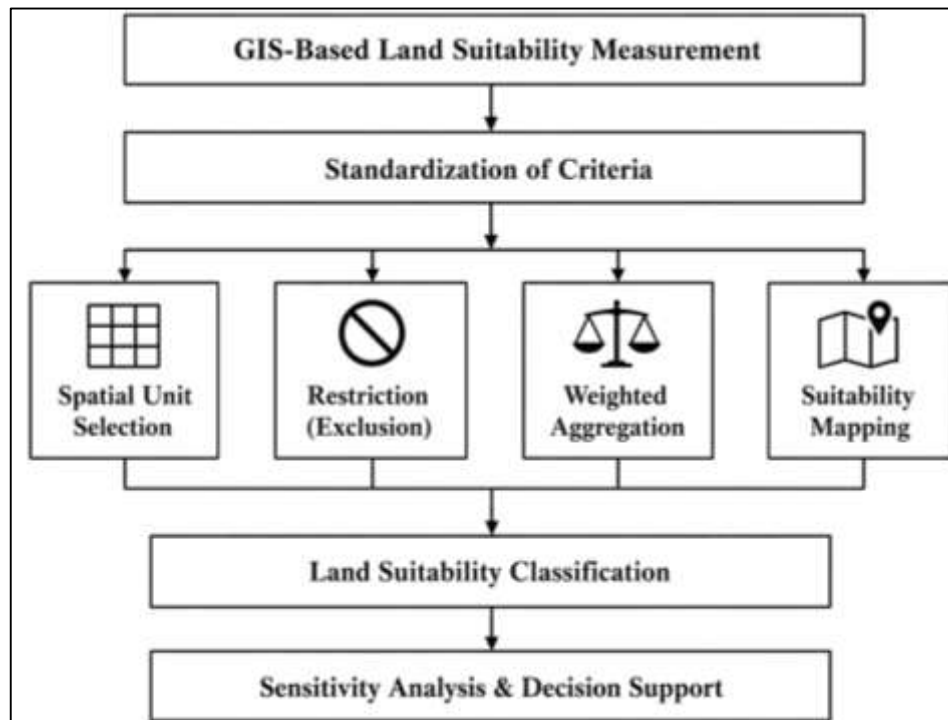
### **Quantitative Foundations of GIS-Based Land-Suitability Measurement**

Evidence synthesized from more than ten empirical GIS-based land-suitability studies shows that the definition of the spatial unit of analysis strongly affects the measurement, classification, and interpretation of suitable land. Raster cells have been widely used because they allow continuous environmental surfaces, including elevation, slope, rainfall, temperature, flood depth, soil quality, and vegetation condition, to be assessed through a consistent geographic structure. Studies using 10-meter cells have generally represented roads, drainage channels, parcel boundaries, small wetlands, urban heat variations, and localized hazard zones with greater spatial detail (Ferguson et al., 2016; Hossan, 2021). Analyses based on 30-meter cells have provided a balance between geographic precision, satellite-data availability, computing requirements, and compatibility with widely available elevation

and land-cover datasets. Resolutions of 100 meters or more have been applied in metropolitan, watershed, and regional studies where the principal purpose involved identifying broad development corridors rather than individual sites. Very coarse resolutions, including 1,000-meter cells, have supported national or cross-regional comparisons but have often concealed small hazard areas, settlement pockets, ecological corridors, and variations in infrastructure access ([Hacısalıhoğlu et al., 2016](#); [Chowdhury & Tonay, 2022](#)). Parcel-based studies have produced results directly connected to ownership, zoning, development control, and land-acquisition decisions, although inconsistent parcel size has created differences in criterion averages and suitability rankings. Census units and neighborhoods have been used to measure social vulnerability, population exposure, poverty, housing conditions, and service inequality. Municipalities and regional planning zones have supported policy comparison and resource allocation, while watershed units have been particularly appropriate for flood, runoff, erosion, and water-resource assessments. The reviewed studies also identified spatial aggregation error when fine-resolution hazard or environmental data were summarized within large administrative boundaries. Boundary precision, total suitable area, criterion variation, and the concentration of high-suitability locations changed according to cell size and aggregation method ([Demir & Kisi, 2016](#); [Zahidul & Begum, 2022](#)). These findings establish spatial resolution and unit selection as measurable components of land-suitability design rather than neutral technical choices.

Land-suitability studies combine indicators expressed through different measurement units, numerical ranges, and directional meanings, creating the need for a common system of standardization before spatial criteria are aggregated. Evidence across environmental planning, urban-expansion, agricultural-suitability, infrastructure-location, and climate-risk studies shows that min-max scaling has been one of the most frequently applied procedures because it converts raw observations into a consistent range while preserving their relative differences. Z-score standardization has been used when researchers sought to represent how far an observation differed from the study-area mean, particularly for population density, land value, temperature, rainfall, and infrastructure capacity. Percentile ranking has supported comparisons among spatial units when data distributions were highly skewed or affected by extreme values. Value functions have translated observed measurements into planning preferences, allowing specific changes in slope, distance, risk, cost, or accessibility to receive different suitability meanings ([Ferguson et al., 2016](#); [Mesbail, 2023](#)). Fuzzy membership procedures have been especially common when the boundary between suitable and unsuitable conditions was gradual rather than absolute. For example, increasing membership has represented criteria for which greater values indicated higher suitability, such as infrastructure capacity or service accessibility. Decreasing membership has represented cost criteria such as hazard intensity, development expense, slope, travel time, and ecological sensitivity. Threshold-based scoring has divided continuous observations into suitability classes established through engineering standards, planning regulations, empirical hazard records, or expert judgment. Comparative studies have shown that linear standardization tends to produce gradual changes across space, whereas categorical thresholds can create sharp boundaries between neighboring locations with similar raw values. Nonlinear transformations have assigned greater penalties to locations approaching hazardous or technically unacceptable conditions ([Hacısalıhoğlu et al., 2016](#)). The choice of standardization method has altered the mean suitability score, spatial ranking, class distribution, and total land assigned to high-suitability categories. Research has also emphasized directional consistency because an incorrectly transformed cost indicator can reverse the meaning of the composite index. Standardization quality has therefore been evaluated through distribution checks, scenario comparison, sensitivity testing, and the stability of candidate-location rankings ([Qu et al., 2013](#)). Empirical land-suitability research distinguishes between factors that influence the relative desirability of land and restrictions that make development legally, environmentally, or technically unacceptable. Boolean exclusion has been widely applied to remove restricted locations before weighted suitability scores are calculated. Under this approach, land is classified as either available or unavailable according to defined planning rules and hazard limits.

Figure 3: GIS Land Suitability Framework



Studies of urban expansion and residential development have excluded active river channels, wetlands, protected forests, critical habitats, airport safety zones, military areas, unstable slopes, fault corridors, waste-disposal sites, and zones surrounding hazardous industries (Kalogirou, 2002). River and wetland buffers have been used to protect drainage functions, water quality, biodiversity, and flood-storage capacity. Coastal setbacks have represented storm-surge exposure, shoreline erosion, sea-level conditions, and ecosystem protection. Industrial and waste-management buffers have reduced residential exposure to pollution, explosion, odor, noise, and transportation hazards. Fault and landslide restrictions have been determined through geological stability, slope conditions, soil characteristics, historical events, and engineering requirements. Airport and major transportation buffers have represented safety, noise, access control, and legal development limitations. Research has also applied maximum acceptable values for slope, flood depth, erosion susceptibility, surface temperature, and ecological sensitivity (Bandyopadhyay et al., 2009). The reviewed studies show substantial variation in buffer width and threshold selection because regulatory standards, environmental conditions, land scarcity, hazard severity, and available data differ among study areas. Some analyses treated moderate-risk areas as weighted suitability costs, while high-risk areas were classified as complete exclusions. This distinction prevented favorable performance on accessibility or land value from compensating for unacceptable hazard exposure. Studies combining Boolean restrictions with weighted evaluation generally produced smaller but more defensible development zones than models based entirely on compensatory scoring (Montgomery et al., 2016). The percentage of land removed through restrictions has been reported as a central quantitative outcome, alongside the area excluded by individual constraints and the overlap among environmental, regulatory, and hazard zones. Sensitivity testing has shown that small changes in buffer distances or hazard thresholds can substantially alter available land, particularly in densely settled coastal, riverine, mountainous, and ecologically sensitive regions.

Composite suitability indices integrate standardized criterion values and their relative importance into a single score representing the overall appropriateness of a location for a specified land use. Studies across urban development, regional growth, housing, industry, public facilities, conservation, renewable energy, agriculture, and transportation have commonly applied weighted aggregation after removing restricted land (Darvishi et al., 2026). The resulting scores have been classified into categories

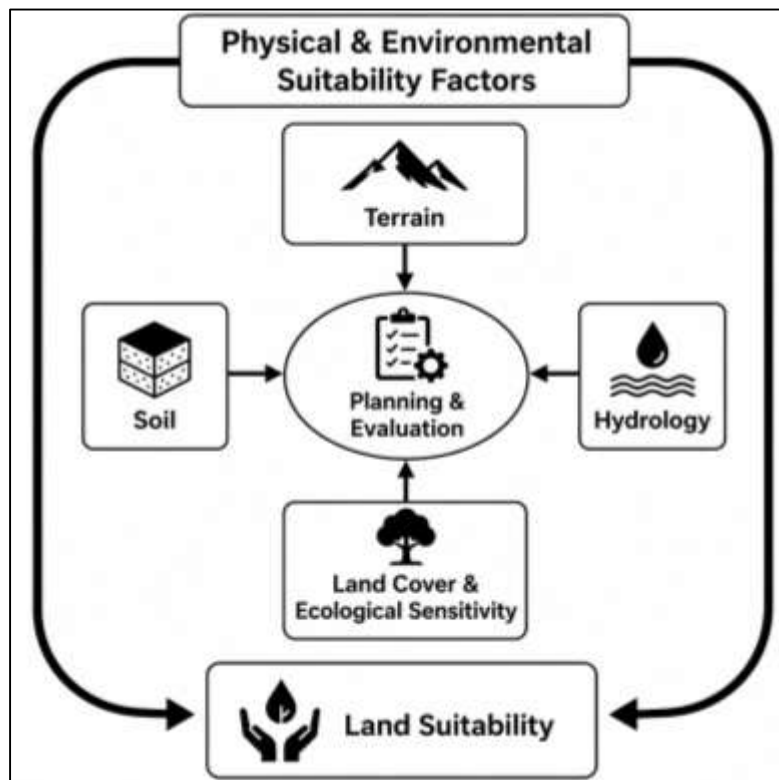
such as unsuitable, marginally suitable, moderately suitable, highly suitable, and very highly suitable. Classification has been performed through equal intervals, quantiles, natural breaks, standard-deviation classes, expert-defined thresholds, and fuzzy categories. Comparative research has shown that the selected classification procedure affects the number of spatial units, total hectares, and percentage of the study area assigned to every suitability level. Equal-interval classification has maintained consistent numerical ranges but can create highly unequal class areas when scores are concentrated within a narrow range. Quantile classification has produced balanced numbers of observations across categories while occasionally placing locations with similar scores into different classes (Ahamed et al., 2000). Natural-break classification has identified clusters within the observed distribution, while expert-defined thresholds have connected suitability classes to planning standards and technical requirements. Quantitative reporting has included minimum and maximum index values, mean suitability, standard deviation, median, interquartile range, class-specific land area, and the percentage of developable land within administrative units. Spatial concentration has been examined through cluster analysis, hotspot statistics, neighborhood comparison, and measures of spatial autocorrelation. Candidate parcels, municipalities, or development zones have also been ranked according to composite scores, available area, accessibility, climate exposure, infrastructure capacity, and environmental conflict. Studies comparing alternative weighting or standardization methods have reported rank reversals, changes in high-suitability area, and shifts in the geographic concentration of priority locations (Baroudy, 2016). A location with a high average score may contain internal hazard pockets, fragmented land, or limited usable area, making area-based and spatial-distribution measures necessary alongside mean suitability. The reviewed evidence treats composite scoring, suitability classification, class-area measurement, spatial concentration, and rank stability as interconnected quantitative components of land-suitability evaluation (Bojorquez-Tapia et al., 2001).

#### **Environmental Suitability Measured Through Ecological Sensitivity**

Evidence synthesized from more than ten empirical studies of urban expansion, settlement development, infrastructure location, and regional land allocation identifies terrain as a primary determinant of physical suitability. Slope has received the greatest attention because it affects foundation requirements, road construction, drainage behavior, erosion, landslide probability, accessibility, and site-preparation costs. Flat and gently sloping land has generally received higher suitability ratings for residential, commercial, industrial, and public-facility development because it requires less excavation, grading, retaining-wall construction, and structural reinforcement (Reshmidevi et al., 2009). Moderate slopes have been treated as conditionally suitable when engineering interventions and drainage controls are technically feasible. Steep slopes have commonly been assigned low suitability or excluded when instability, construction cost, emergency access, and erosion exceed acceptable thresholds. Elevation has been interpreted according to local environmental conditions. Higher elevation can reduce riverine and coastal flood exposure, while excessive elevation can increase access difficulty, wind exposure, infrastructure-extension cost, and slope-related instability. Low-lying land may offer construction advantages but can remain highly exposed to waterlogging, storm surge, poor drainage, or groundwater rise. Aspect has been used to measure solar exposure, moisture retention, wind direction, vegetation condition, and building-energy requirements, particularly in mountainous and cold-climate regions (Yu et al., 2018). Relief and terrain-ruggedness measures have captured short-distance elevation variation that is not represented adequately by average slope alone. Highly rugged land has generally been associated with fragmented development areas, longer road routes, greater earthwork volume, and reduced infrastructure efficiency. Several studies have estimated cut-and-fill requirements and construction-cost differences among terrain classes, showing that physical development expenses rise as slope and surface irregularity increase. Terrain suitability has also been linked to slope-instability probabilities derived from historical landslides, geology, rainfall, and land-cover conditions (Morán-Tejeda et al., 2015).

The reviewed evidence shows that elevation, slope, aspect, relief, and ruggedness operate jointly, making terrain assessment more reliable when multiple indicators are evaluated at a consistent spatial resolution.

Figure 4: Physical Environmental Suitability Framework



Geotechnical conditions determine whether land can support buildings, roads, drainage systems, utilities, and other urban infrastructure without excessive settlement, erosion, structural damage, or site-preparation expenditure. Studies across metropolitan, coastal, mountainous, and arid environments have evaluated soil bearing capacity as a direct indicator of foundation performance. Locations with stronger, well-compacted, and stable soil materials have generally been classified as more suitable because they require less ground improvement and lower foundation costs. Weak clay, loose sediment, reclaimed land, peat, and unconsolidated deposits have received lower suitability ratings due to settlement, deformation, liquefaction, and drainage concerns. Hydraulic conductivity and permeability have been used to assess infiltration, stormwater absorption, groundwater recharge, and the likelihood of surface water accumulation (Eck et al., 2016). Highly impermeable soil can increase runoff and waterlogging, while extremely permeable soil may create groundwater-contamination concerns where urban wastewater and industrial activity are present. Soil depth affects foundation placement, vegetation support, infiltration capacity, and erosion resistance. Texture classifications involving sand, silt, clay, and loam have supported evaluations of drainage, compaction, moisture retention, and construction feasibility. Shrink-swell potential has received particular attention in areas dominated by expansive clay because repeated wetting and drying can damage foundations, pavements, pipelines, and drainage structures. Erodibility indices have been combined with slope, rainfall, vegetation, and land disturbance to identify locations with elevated soil-loss potential. Geological stability has been measured through lithology, fault distance, seismicity, subsidence probability, karst conditions, and historical ground movement. Hard and stable rock formations may provide strong structural support while increasing excavation costs, whereas soft geological materials may reduce excavation difficulty while requiring reinforcement (Zhang & Zhang, 2018). Fault buffers and liquefaction zones have frequently been treated as major restrictions. Subsidence-prone land associated with groundwater extraction, mining, sediment consolidation, or underground cavities has been assigned lower suitability. Research has therefore classified geotechnical suitability through combined soil, geological, and hazard conditions rather than through a single soil property.

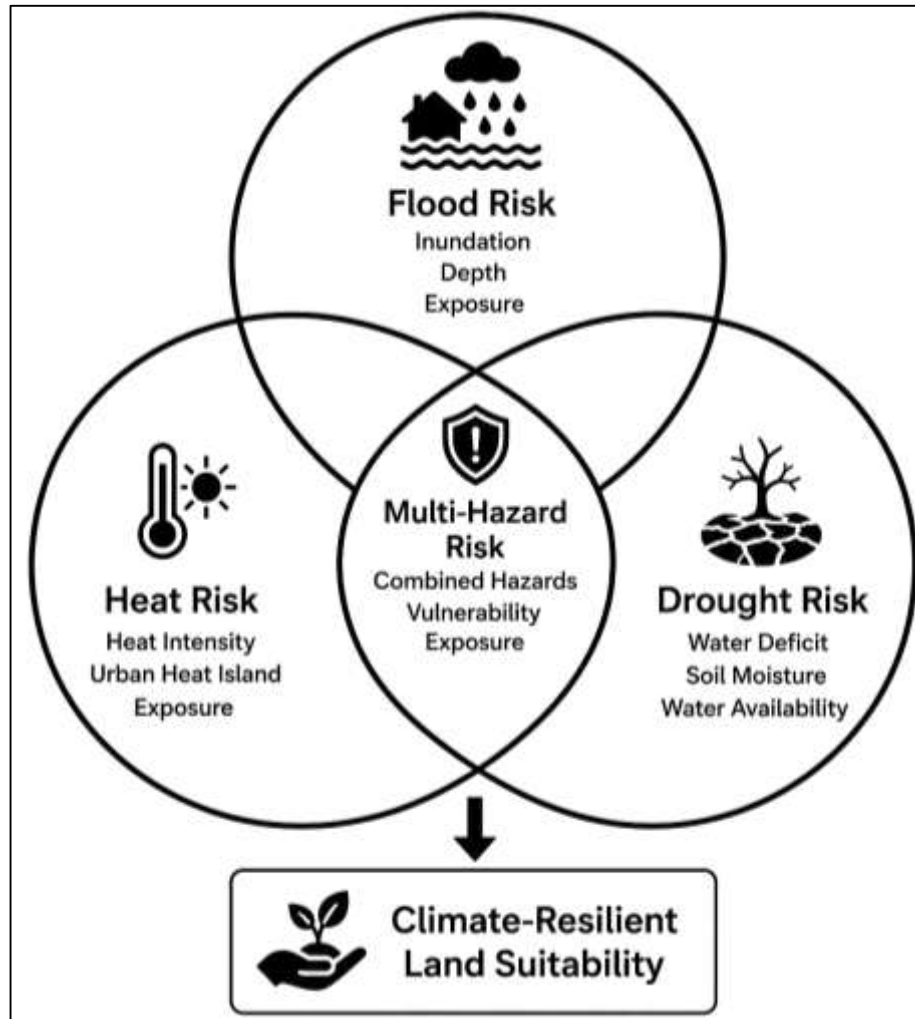
Hydrological suitability reflects the capacity of land to manage rainfall, runoff, infiltration,

groundwater interaction, and drainage without generating unacceptable flood, erosion, waterlogging, or water-supply conditions. Studies of urban and regional development have used drainage density to represent the concentration of rivers, streams, channels, and surface-flow pathways within a defined area (Nguyen et al., 2015). High drainage density can indicate efficient natural discharge in some environments, although it can also represent extensive exposure to stream flooding, erosion, and development restrictions. Low drainage density may reduce direct river interaction but can indicate limited natural drainage where soils are impermeable or terrain is flat. Flow-accumulation analysis has identified locations receiving runoff from surrounding areas, with high-accumulation zones commonly corresponding to channels, depressions, flood pathways, and waterlogging-prone land. Topographic wetness indices have been applied to estimate the tendency of soil saturation from terrain shape and upstream water contribution. Locations with persistently high wetness values have generally received lower development suitability because of foundation instability, drainage expenditure, mosquito breeding, and flood exposure. Runoff coefficients have represented the proportion of rainfall converted to surface flow under different soil, slope, and land-cover conditions (Brown et al., 2015). Built-up and impermeable areas have produced higher runoff values than forests, wetlands, grasslands, and permeable soils. Distance from rivers has been used to establish hazard and environmental-protection buffers, although studies have shown that distance alone cannot represent inundation depth, floodplain shape, drainage obstruction, or local elevation. Groundwater depth has been evaluated in relation to foundation conditions, basement flooding, water availability, contamination risk, and construction requirements. Shallow groundwater can support water access while increasing waterlogging and structural risk. Deep groundwater may reduce foundation interaction but increase extraction costs and water-supply vulnerability. Seasonal water-table fluctuation has provided a more reliable measure than a single observation in monsoon, coastal, and drought-affected regions (Baroudy, 2016). Proximity to natural drainage corridors has also been assessed because development within these corridors can obstruct runoff and transfer flood risk to surrounding settlements. Hydrological studies have consistently connected drainage performance with terrain, soil permeability, rainfall intensity, land-cover change, and stormwater-infrastructure capacity.

#### **Climate-Risk Suitability Measured Through Multi-Hazard Indicators**

Evidence synthesized from more than ten empirical flood-susceptibility, urban-planning, watershed-management, and land-suitability studies shows that flood risk is one of the most influential climate-related restrictions on urban and regional development. Flood-susceptibility models have generally identified locations where terrain, hydrology, rainfall, soil, drainage, and land-cover conditions favor inundation, while risk models have incorporated the population, buildings, infrastructure, economic activity, and services exposed within those locations. Return-period probability has been used to distinguish frequent low-intensity flooding from less frequent but more severe events. Maximum inundation depth has provided a direct measure of potential damage to buildings, roads, utilities, vehicles, and public facilities (Kc et al., 2021). Shallow flooding may interrupt access and damage ground-floor property, whereas deeper water can create structural failure, displacement, and life-safety concerns. Flow velocity has been assessed because rapidly moving water can undermine foundations, erode roads, transport debris, and increase evacuation difficulty. Rainfall intensity and duration have been connected to runoff volume, drainage overload, river discharge, and pluvial flooding. Studies of rapidly urbanizing areas have shown that expanding impervious surfaces increases runoff while reducing infiltration and storage.

Figure 5: Climate Risk Suitability Framework



Drainage capacity has therefore been measured through channel dimensions, pipe capacity, inlet density, blockage frequency, and the difference between rainfall-generated flow and system discharge. Flood exposure has been reported through the number of residents, buildings, road segments, hospitals, schools, utility facilities, and economic assets located within inundation zones. Expected annual damage has combined event probability with estimated physical and economic losses, providing a broader measure than hazard intensity alone (Zscheischler et al., 2020). Recovery time has captured the duration required to restore transportation, utilities, housing, public services, and commercial activity. Land-suitability studies have commonly classified active floodways and high-depth zones as exclusions, while moderate-risk areas have received lower suitability scores according to drainage conditions, protection standards, accessibility, and estimated damage.

Urban heat has been measured through satellite-derived land-surface temperature, weather-station observations, mobile temperature surveys, building-density indicators, impervious-surface coverage, vegetation measures, and population exposure. Studies across tropical, arid, temperate, and coastal cities have consistently identified higher daytime surface temperatures in dense built-up areas, industrial zones, transport corridors, large paved spaces, and neighborhoods with limited vegetation. Nighttime measurements have revealed the ability of concrete, asphalt, roofs, and other construction materials to retain heat after sunset, reducing nighttime cooling and extending human exposure (Araya-Muñoz et al., 2017). Urban-rural temperature differences have been used to quantify heat-island intensity and compare thermal conditions among city centers, suburban zones, peri-urban areas, and surrounding rural land. Percentage impervious surface has shown a positive association with temperature because paved surfaces reduce evapotranspiration and absorb substantial solar radiation.

Tree-canopy percentage, vegetation density, park area, water bodies, and green-corridor continuity have generally been associated with lower surface temperatures. Cooling-distance analysis has measured how far the thermal influence of parks, wetlands, rivers, urban forests, and other green or blue spaces extends into surrounding neighborhoods. Heatwave duration and the number of consecutive high-temperature days have provided information about sustained exposure that cannot be represented through a single temperature observation. Population-based assessments have measured the number and proportion of residents exposed above defined daytime or nighttime thresholds (Mavrommatis et al., 2019). Greater attention has been given to older adults, children, outdoor workers, low-income households, residents of informal settlements, and people with limited access to healthcare or cooling. Some studies have combined surface temperature with humidity to represent human thermal stress more accurately. Land-suitability models have assigned lower scores to locations where high thermal exposure coincides with dense population, low canopy coverage, limited ventilation, and weak access to cooling infrastructure. Areas with stronger vegetation, lower imperviousness, adequate airflow, and accessible green space have received higher climate-resilience ratings.

Drought and water stress have received substantial attention in land-suitability studies conducted in arid, semi-arid, Mediterranean, continental, and seasonally dry environments. Precipitation deficits have been measured by comparing observed rainfall with long-term climatic conditions over monthly, seasonal, and annual periods (Amarnath et al., 2021). Standardized precipitation indicators have distinguished short meteorological droughts from prolonged water shortages. Measures combining precipitation and evapotranspiration have provided a more complete representation of climatic water demand, particularly in locations where high temperatures accelerate moisture loss. Soil-moisture anomalies have been used to identify reduced water availability for vegetation, agriculture, groundwater recharge, and ecosystem function. Aridity indices have supported comparisons between atmospheric water supply and evaporative demand, enabling dry regions to be divided into relative water-stress categories. Groundwater availability has been assessed through aquifer depth, well yield, recharge rate, extraction volume, water quality, and seasonal fluctuation. Locations with reliable groundwater access may receive higher suitability ratings, although excessive extraction, salinity, contamination, and declining water tables reduce long-term supply performance. Reservoir reliability has been measured through storage volume, inflow variability, demand coverage, and the frequency or duration of supply failure. Per-capita water availability has linked regional water resources with population size and consumption requirements (Quesada-Ganuza et al., 2021). Urban studies have also examined network coverage, treatment capacity, leakage, service interruptions, pressure stability, and household access. Distance to dependable water infrastructure has represented the cost and technical difficulty of extending supply systems to new development areas. Research has shown that land appearing physically suitable may remain inappropriate when available water resources cannot support residential, industrial, agricultural, and ecological demands. Drought severity has also been associated with vegetation decline, soil degradation, wildfire susceptibility, food insecurity, and higher cooling demand. Suitability classifications have therefore incorporated both natural water availability and infrastructure reliability. Areas with severe precipitation deficits, declining aquifers, limited storage, long supply distances, and high existing demand have commonly received lower scores or stricter development limits (Stults, 2017).

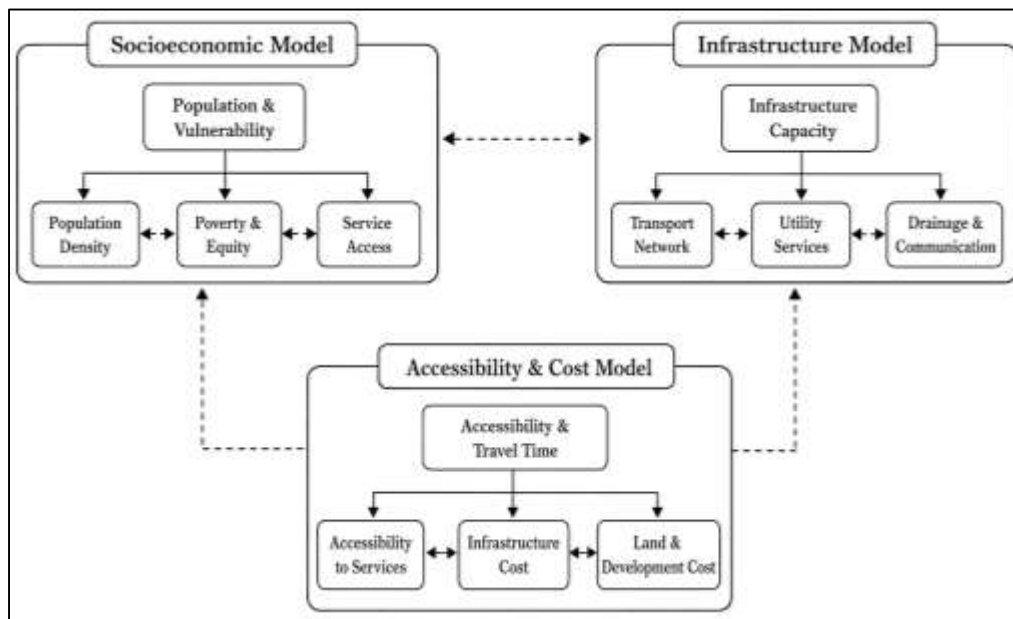
Climate-resilient land-suitability research has examined wildfire, cyclonic storms, coastal inundation, landslides, and erosion as distinct hazards while also recognizing their spatial and functional interactions. Wildfire assessments have measured vegetation type, fuel load, fuel continuity, dryness, slope, aspect, wind speed, ignition proximity, fire recurrence, and emergency-road access. Development near high-fuel landscapes has generally received lower suitability ratings when evacuation capacity, firefighting access, and defensible space are limited. Storm studies have evaluated wind speed, rainfall intensity, cyclone category, event frequency, building exposure, infrastructure vulnerability, and service interruption. Coastal assessments have included storm-surge depth, shoreline retreat, coastal elevation, wave exposure, salinity intrusion, erosion rate, sea-level conditions, and distance from protective ecosystems. Landslide models have combined slope, rainfall, geology,

soil, drainage, vegetation loss, road cutting, and historical failure locations ([Kapuka & Hlásny, 2020](#)). Erosion studies have measured soil-loss rates through rainfall erosivity, soil erodibility, slope conditions, land cover, and conservation practices. Multi-hazard studies have integrated these indicators with flood, heat, and drought measures to identify locations affected by several hazards or by cascading events. Additive models have combined standardized hazard scores, while multiplicative and probabilistic approaches have emphasized locations where severe hazards, exposed assets, and high vulnerability occur simultaneously. Fuzzy methods have represented uncertainty and gradual hazard transitions, and scenario-based models have compared alternative climate and land-use conditions. Exposure overlap has been measured through the population, buildings, roads, utilities, and essential facilities located within multiple hazard zones ([Arabadzhyan et al., 2021](#)). Vulnerability scores have incorporated poverty, age, housing quality, mobility limitations, health conditions, and service deprivation. Adaptive-capacity indicators have represented emergency access, healthcare availability, shelters, institutional capacity, household resources, and infrastructure redundancy. Population-weighted risk has distinguished sparsely occupied hazardous land from densely populated locations with similar hazard intensity. Compound-risk classifications have identified locations where wildfire follows drought, landslides follow intense rainfall, or coastal flooding interacts with stormwater and river discharge.

### **Socioeconomic, Accessibility, and Infrastructure Suitability**

Evidence synthesized from more than ten empirical studies of climate vulnerability, urban land suitability, disaster exposure, public-service access, and regional inequality shows that physical suitability alone cannot represent the social appropriateness of development locations ([Djalante & Garschagen, 2017](#)). Population density has been widely used to identify concentrations of people requiring housing, infrastructure, emergency protection, and public services. High density can strengthen the efficiency of service provision and public transportation, although it can also increase the number of residents exposed to flooding, heat, pollution, infrastructure failure, or evacuation constraints. Poverty rate has been treated as a central vulnerability indicator because lower-income households frequently possess fewer financial resources for resilient housing, insurance, cooling, transport, relocation, and post-disaster recovery. Dependency ratios have represented the proportion of children and older residents who may require additional assistance during emergencies. Disability prevalence has been included because mobility, sensory, cognitive, and health limitations can affect evacuation, shelter access, communication, and service needs ([Lucas et al., 2016](#)). Informal-housing percentage and housing-quality indicators have captured structural weakness, overcrowding, inadequate drainage, limited ventilation, unsafe construction materials, and insecure access to utilities. Tenure insecurity has been associated with restricted investment in housing improvement and increased exposure to displacement. Unemployment and livelihood instability have represented reduced household capacity to absorb climate-related losses. Healthcare access has been measured through facility distance, travel time, bed capacity, service availability, and population coverage. Composite social-vulnerability scores have combined these demographic, economic, housing, health, and service indicators into standardized spatial measures ([Büttner et al., 2018](#)). Studies have shown that vulnerability patterns vary substantially within cities, even where hazard intensity remains similar. High-risk conditions have been concentrated where severe exposure overlaps with poverty, overcrowding, weak housing, limited mobility, and inadequate services. Land-suitability assessments have therefore incorporated both the demand for development and the social capacity of communities to withstand environmental disruption. Accessibility has been treated as a measurable relationship between potential development locations and the employment, education, healthcare, commerce, transportation, emergency, and administrative services required by urban and regional populations ([Brussel et al., 2019](#)). Earlier land-suitability studies often used straight-line distance because it was easy to calculate across large areas. This measure identified general proximity but did not represent street configuration, physical barriers, congestion, transport mode, bridge location, road condition, or topographic difficulty. Road-network analysis provided more realistic estimates by tracing movement along available routes.

Figure 6: Rectangular white boxes with thin black borders



Studies comparing both methods have reported substantial differences in the classification of peripheral settlements, river-separated neighborhoods, mountainous areas, and locations with disconnected street systems. Average travel time to employment centers has been used to represent livelihood access and commuting burden. Travel time to schools, hospitals, markets, government offices, and transit stops has measured the practical accessibility of essential services. Public-transport coverage has been evaluated through route density, stop spacing, service frequency, operating hours, transfer requirements, walking distance, and the proportion of residents within defined service areas (Malekzadeh & Chung, 2020). Multimodal models have combined walking, cycling, bus, rail, private vehicle, and other transport options to reflect differences in mobility resources. Emergency accessibility has been measured through response time to fire stations, ambulance services, hospitals, police facilities, evacuation centers, and disaster shelters. Locations with a single access route have received lower resilience ratings because road blockage can isolate residents during floods, storms, fires, or landslides. Population coverage within specified travel-time thresholds has provided a distributive measure showing how many residents can reach essential services within an acceptable period. Accessibility studies have also compared peak and off-peak travel conditions, ordinary and emergency travel times, and dry-season and flood-period network performance. Candidate locations near major roads may achieve high accessibility while experiencing greater pollution, noise, crash exposure, or development pressure (Antipova et al., 2020). Quantitative suitability models have therefore balanced network access with environmental quality, transport safety, congestion, and emergency-route redundancy.

Infrastructure suitability concerns whether existing networks possess sufficient coverage, capacity, quality, and reliability to support additional population and development without generating service failure or excessive expansion costs. Road density has been widely used as an initial measure of transport availability, while intersection density has provided information about network connectivity, route choice, walkability, and emergency access. High road density can increase accessibility, although it may also correspond with greater imperviousness, traffic exposure, ecological fragmentation, and stormwater runoff. Electricity coverage has been assessed through connection rates, available load, outage frequency, outage duration, and the capacity of distribution systems (Martens et al., 2019). Water-supply suitability has been measured through source availability, treatment capacity, network coverage, pressure, storage, per-capita supply, leakage, and interruption frequency. Sewerage access has included connection percentage, treatment capacity, overflow occurrence, and the distance between candidate locations and existing trunk networks. Stormwater capacity has been evaluated

through drain density, channel dimensions, design standard, storage volume, pumping capacity, blockage history, and observed flooding during intense rainfall. Studies have identified drainage deficiency as a major reason that physically developable land performs poorly under climate-resilience criteria. Broadband and telecommunications availability have also appeared in recent infrastructure assessments because communication supports employment, education, emergency warning, service coordination, and institutional response (Aivinhenyo & Zuidgeest, 2019). Service reliability has been represented through interruption frequency, restoration time, redundancy, asset condition, and the number of households affected by failures. Infrastructure expansion requirements have been measured through the kilometers of road, pipeline, sewer, drainage, electricity, or communication network needed to connect new development. Some studies have converted extension requirements into monetary costs, construction time, environmental disturbance, and maintenance obligations. Locations close to existing networks have generally received higher suitability ratings, although available capacity remains more important than physical proximity alone. Infrastructure assessments have therefore distinguished access to a network from the network's ability to accommodate additional demand. Climate-resilient suitability has been associated with adequate reserve capacity, reliable service, diverse access routes, effective drainage, and limited exposure of critical assets to hazards (Niehaus et al., 2016).

Development feasibility and spatial equity have been evaluated together because the least expensive land is not necessarily the most accessible, socially appropriate, or climate-resilient option. Land price per unit area has been used to compare acquisition requirements among central, suburban, peri-urban, and rural locations. Lower-cost land may appear financially attractive while requiring extensive expenditure for roads, water, sewerage, drainage, electricity, public transport, schools, healthcare, and emergency facilities. Acquisition cost has also varied according to ownership structure, parcel fragmentation, compensation requirements, legal disputes, and existing land use. Site-preparation expenses have included clearing, grading, soil stabilization, drainage improvement, flood protection, slope reinforcement, contamination removal, and utility connection (Vecchio et al., 2020). Construction-cost multipliers have represented additional expenditure associated with weak soils, steep terrain, shallow groundwater, flood exposure, remote access, or difficult material transportation. Developable floor area and allowable density have been used to estimate the amount of housing, employment, or public-service capacity supported by a site. Cost per resident served has combined land, infrastructure, and construction expenditure with expected population coverage. Spatial-equity studies have examined whether climate protection, accessibility, and public investment are distributed consistently across income groups and neighborhoods. Service gaps have been measured through differences in travel time, facility availability, utility coverage, drainage quality, and emergency response. Accessibility ratios have compared service access among advantaged and disadvantaged populations, while Gini-type measures have represented the overall inequality of spatial resource distribution (Pyrialakou et al., 2016). Exposure inequality has been assessed through differences in flood, heat, pollution, or other hazard levels across socioeconomic groups. Population-weighted service deficits have identified locations where large vulnerable populations experience inadequate access. Displacement probability and affordability loss have been used to evaluate whether land redevelopment or climate-protection investment increases housing costs or removes low-income residents. Research has shown that high aggregate suitability can coexist with unequal access, concentrated exposure, and substantial displacement pressure. Development feasibility has therefore been assessed through both total economic cost and the distribution of costs, risks, services, and protective benefits across communities (Dadashpoor & Rostami, 2017).

### **Geospatial Data Quality Measured Through Classification Accuracy**

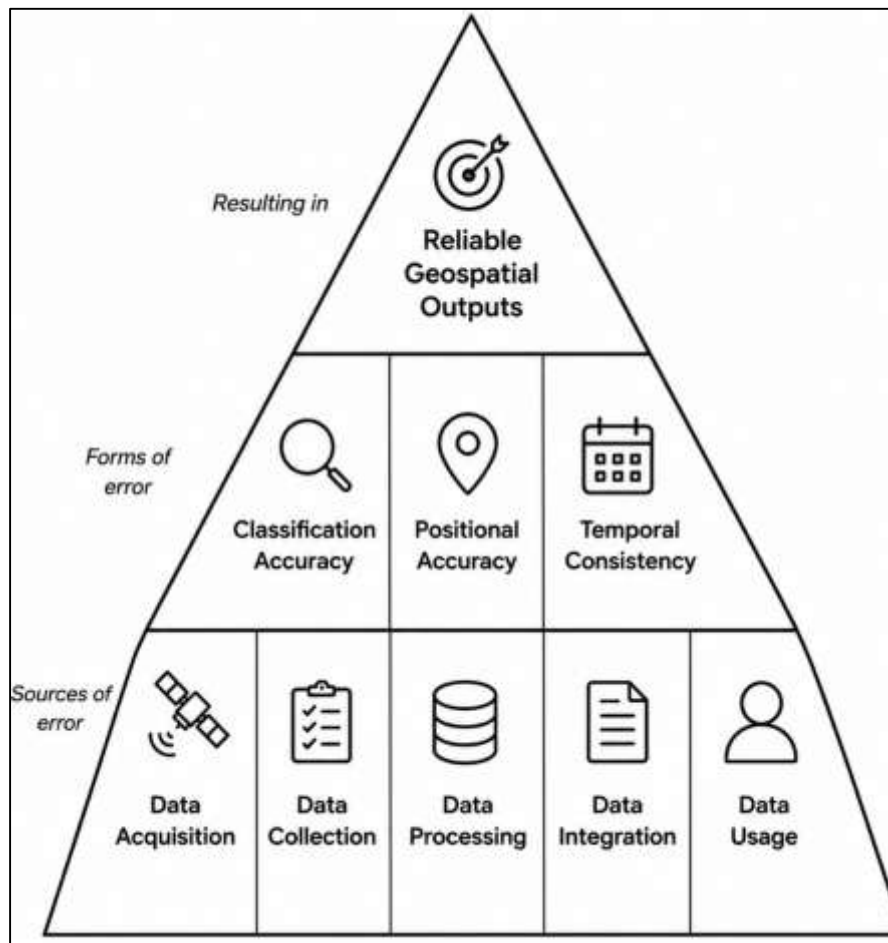
Research drawn from more than ten empirical studies of land-cover mapping, urban expansion, vegetation monitoring, flood assessment, and land-suitability modeling identifies classification accuracy as a central determinant of geospatial reliability. Satellite imagery has been used to classify forests, agricultural land, wetlands, water bodies, barren surfaces, impervious areas, settlements, roads, and other built-up features. Training samples have supplied representative observations for constructing supervised classification models, while independent validation samples have tested whether mapped classes correspond with verified ground conditions. Studies have emphasized the

separation of training and validation observations because using the same locations for both purposes can overstate classification performance (Wee & Mouter, 2021). Confusion matrices have documented the number of correctly and incorrectly classified observations across land-cover categories. Overall accuracy has summarized the proportion of validation observations assigned to the correct class, although this measure can conceal weak performance in rare or spatially limited categories. Producer's accuracy has represented the extent to which reference locations are captured within the correct mapped class, while user's accuracy has indicated the reliability of a mapped class for planning applications. Precision and recall have been particularly useful for distinguishing omission and commission errors in wetlands, water bodies, informal settlements, vegetation, and impervious surfaces. The F1 score has balanced precision and recall when both types of error affect suitability classification. Kappa coefficients have been reported to describe agreement beyond chance, although their interpretation has varied with class prevalence and sample design (Wylie et al., 2019). Comparative studies have shown that classification error can transfer directly into land-suitability results. Wetlands mistakenly classified as vacant land may receive high development scores, while built-up areas classified as vegetation may distort ecological-sensitivity and surface-temperature assessments. Class-specific accuracy, sample balance, image resolution, seasonal timing, cloud cover, sensor characteristics, and classification method have therefore received attention alongside overall performance.

Spatial accuracy describes how closely mapped locations, elevations, boundaries, and network features correspond with their actual geographic positions. Studies of GIS-based land suitability have assessed positional error in satellite imagery, digital elevation models, cadastral parcels, transportation networks, rivers, coastlines, utility systems, administrative boundaries, and hazard zones (Dorn et al., 2015). Root mean square error has been widely reported during image rectification and georeferencing to summarize displacement between mapped control points and verified reference coordinates. Coordinate displacement has also been measured through horizontal and vertical differences, particularly when combining elevation data with parcels, buildings, or flood surfaces. Small positional errors can produce substantial analytical consequences in densely developed areas or near narrow environmental restrictions. A displaced river boundary can alter buffer zones and assign flood exposure to the wrong parcels. Misaligned roads can distort accessibility estimates, intersection density, network connections, and infrastructure-extension distances. Cadastral-boundary error can change ownership attribution, parcel area, development capacity, and regulatory classification. Hazard maps that do not align with building footprints may overestimate or underestimate the number of structures and residents exposed (Leach et al., 2019).

Boundary agreement has been evaluated by comparing overlap, edge displacement, area differences, and the proportion of features located within accepted tolerances. Scale compatibility has received similar attention because combining detailed parcel data with coarse climate or elevation surfaces can create an appearance of precision that the source data do not support. Resampling coarse data to a finer grid changes cell size without adding geographic information. Studies have reported that spatial resolution and positional accuracy influence the total hectares assigned to unsuitable, moderate, or highly suitable categories. Buffer calculations are especially sensitive where thresholds are narrow or development is concentrated close to rivers, roads, faults, wetlands, and coastlines (Weigand et al., 2020). Spatial-quality assessment has therefore included coordinate-system consistency, map scale, georeferencing performance, vertical accuracy, boundary alignment, source resolution, and tolerance testing.

Temporal consistency concerns whether the datasets combined within a land-suitability model represent comparable periods and accurately describe current spatial conditions. GIS-based studies frequently integrate satellite imagery, census records, climate observations, infrastructure inventories, cadastral data, land values, hazard histories, and statutory planning maps produced in different years. Dataset age has influenced reliability where urban expansion, road construction, vegetation loss, wetland conversion, population redistribution, or infrastructure improvement occurred between observation dates (Sundararajan et al., 2019).

**Figure 7: Geospatial Data Quality Framework**

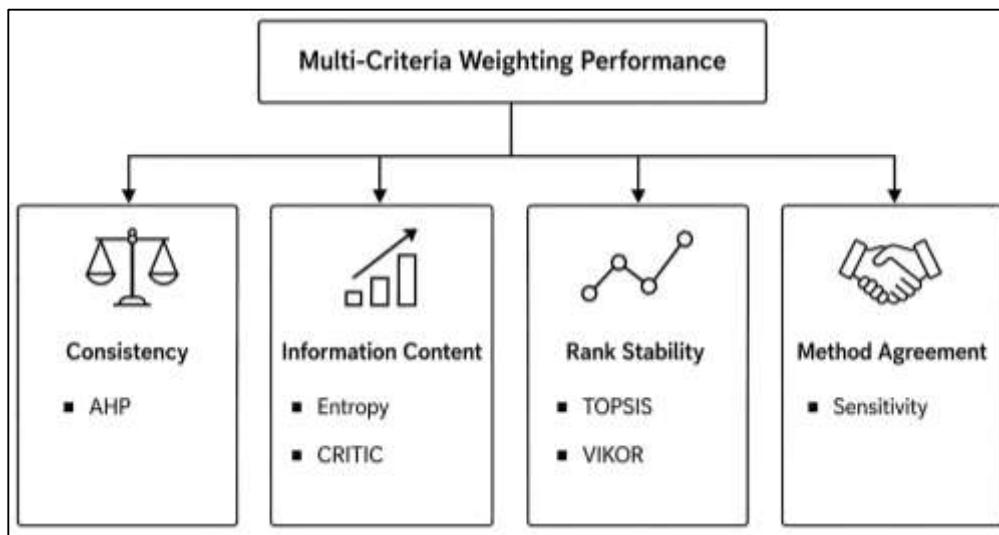
Recent land-cover imagery combined with an older road network may underestimate accessibility, while current population estimates joined with outdated settlement boundaries may misrepresent exposure and service demand. Imagery acquisition date has also affected vegetation, water, soil moisture, surface temperature, and agricultural classifications because these conditions vary by season. Comparisons between dry-season and wet-season images have produced different representations of wetlands, rivers, vegetation density, and impervious surfaces. Climate-record length has determined whether rainfall, temperature, drought, and extreme-event measurements capture ordinary variability or only a limited period. Census year has influenced population density, poverty, housing, and social-vulnerability indicators, particularly in rapidly changing peri-urban areas. Infrastructure-update frequency has affected the representation of new roads, drainage systems, hospitals, schools, utilities, and public-transport services (Sun et al., 2019). Hazard-event periods have also shaped risk estimates because short records may omit infrequent high-impact events. Multitemporal land-cover studies have measured conversion rates among agricultural, forest, wetland, barren, and built-up categories, revealing where suitability inputs changed between mapping dates. Temporal misalignment among source layers has introduced inconsistencies when present-day development is evaluated with historical environmental or socioeconomic conditions. Research has addressed this issue through date documentation, common reference periods, interpolation, annualized indicators, change-detection analysis, and the exclusion of obsolete records. Temporal data quality has consequently been assessed through observation date, update interval, record duration, seasonal comparability, rate of change, and the time gap among integrated datasets (Lloyd et al., 2019).

#### **Multi-Criteria Weighting Performance**

Research across more than ten GIS-based land-suitability, hazard-management, infrastructure-location, and urban-planning studies identifies the analytic hierarchy process as one of the most widely used

procedures for assigning criterion weights. The method organizes decision factors into hierarchical levels and asks experts to compare their relative importance in pairs. Studies have used panels consisting of planners, engineers, geographers, environmental scientists, disaster specialists, economists, government officials, and community representatives. The number and disciplinary composition of experts have varied substantially, affecting the range and stability of judgments (Pengra et al., 2015). Small homogeneous panels have often produced stronger agreement but narrower perspectives, while multidisciplinary panels have captured a broader range of environmental, technical, social, and institutional priorities. Individual comparison judgments have commonly been combined through geometric-mean aggregation to obtain a representative group assessment. Eigenvector-derived weights have then expressed the relative importance assigned to climate hazards, terrain, accessibility, environmental sensitivity, infrastructure capacity, social vulnerability, and development cost. Consistency indices and consistency ratios have been used to determine whether the comparisons follow a coherent pattern. Studies generally treated low inconsistency as evidence that judgments were logically structured, while higher values required experts to reconsider conflicting comparisons (Gerber et al., 2018). Judgment revision has involved repeating selected comparisons, clarifying criterion definitions, presenting supporting data, or conducting additional group discussion. Interexpert agreement has been evaluated through variation in weights, correlation among individual rankings, consensus measures, and comparison of disciplinary subgroups. Research has shown that similar consistency ratios can accompany different criterion priorities because consistency measures internal logic rather than substantive agreement. Some models have therefore reported both panel-level consistency and the dispersion of individual weights. Analytic hierarchy process performance has also depended on the number of criteria because large comparison matrices increase respondent burden and the likelihood of contradictory judgments (Angryk & Galarus, 2016). Criterion screening and hierarchical grouping have been used to reduce complexity and improve the interpretability of assigned weights.

Figure 8: Multi-Criteria Weighting Framework



Objective weighting methods derive criterion importance from the statistical characteristics of the spatial data rather than relying entirely on expert preferences. Entropy weighting has been applied on the assumption that indicators showing greater differentiation among locations contribute more information to the decision process. Criteria with little spatial variation have generally received lower weights because they provide limited capacity to distinguish among candidate sites. In contrast, indicators with substantial dispersion have received greater importance when their values separate locations more clearly. CRITIC weighting has expanded this approach by considering both variability and the relationships among criteria (Wass et al., 2014). Indicators with strong contrast and low redundancy have received higher weights, while highly correlated indicators have been reduced to

limit repeated representation of the same spatial condition. Standard deviation, variance, correlation coefficients, contrast intensity, and information scores have therefore formed the principal quantitative measures used in objective weighting. Studies have applied these techniques to terrain, climate exposure, infrastructure access, population vulnerability, land value, environmental quality, and development feasibility. Data-driven weights have been especially useful where expert access was limited or where researchers sought a reproducible procedure based on observed spatial information. However, high variability does not always indicate high planning importance (Wass et al., 2014). A legally protected ecosystem may show little spatial variation while remaining essential to land allocation, and a highly variable indicator may receive a large objective weight even when its policy relevance is moderate. Comparative studies have consequently examined differences between objective and expert-derived weights. Some have reported similar priorities for dominant hazards or infrastructure constraints, while others have found substantial differences in the importance assigned to social vulnerability, ecological protection, and development cost. Hybrid approaches have combined expert judgments with entropy or CRITIC results to balance substantive knowledge and statistical information (Krishnan et al., 2021). Method performance has been evaluated through changes in suitability scores, suitable land area, location rankings, class distributions, and agreement between objective, subjective, and hybrid models.

Ranking methods have been used to compare candidate parcels, planning zones, municipalities, or development alternatives after criteria have been standardized and weighted. TOPSIS ranks alternatives according to their relative closeness to a location displaying the most desirable criterion values and their distance from a location displaying the least desirable values. Studies have reported positive and negative ideal distances, closeness coefficients, and final candidate ranks. This procedure has been valued for its clear interpretation and capacity to evaluate benefit and cost criteria simultaneously. Its results remain sensitive to normalization, criterion weights, extreme observations, and correlations among indicators (Tang et al., 2021). VIKOR has focused on identifying a compromise alternative where several conflicting planning objectives cannot be maximized simultaneously. Compromise indices have reflected both overall performance and the greatest remaining weakness of an alternative. This feature has supported land-allocation decisions involving trade-offs among climate safety, accessibility, ecological protection, social equity, and development cost. ELECTRE and PROMETHEE have used outranking principles to determine whether one alternative performs sufficiently better than another across the combined decision criteria (Til et al., 2014). Preference thresholds, indifference thresholds, concordance, discordance, and preference flows have allowed limited differences between alternatives to be treated differently from substantial performance gaps. These procedures have also reduced the assumption that strong performance on one criterion always compensates for severe weakness on another. Comparative studies have examined whether TOPSIS, VIKOR, ELECTRE, and PROMETHEE identify the same highest-ranked locations. Rank correlation has been reported through Spearman and Kendall measures, while top-choice agreement has compared the overlap among priority parcels or zones. Strong agreement has indicated stable candidate selection, whereas rank reversals have revealed sensitivity to method structure. Research has also compared the percentage of highly suitable land, average climate exposure, infrastructure distance, ecological conflict, and development cost associated with the top-ranked alternatives (Kadoić et al., 2021). Ranking performance has therefore been evaluated through both statistical agreement and the practical characteristics of selected locations.

Fuzzy and ordered weighting methods have addressed uncertainty, gradual transitions, and differences in decision-maker risk attitudes within land-suitability analysis. Fuzzy AHP has converted linguistic judgments such as low, moderate, high, or very high importance into ranges of numerical values, allowing expert uncertainty to be represented more flexibly than through a single fixed comparison. Fuzzy overlay has assigned gradual membership values to slope, distance, hazard intensity, accessibility, environmental sensitivity, and development cost (Yusop et al., 2015). Locations near a planning threshold have therefore received similar suitability values rather than being separated abruptly into opposite categories. Membership thresholds and curve shapes have influenced how quickly suitability increases or decreases across criterion values. Ordered weighted averaging has

controlled the degree of compensation among criteria and the level of optimism or risk acceptance. Optimistic models have allowed strong performance on several criteria to offset weaker performance elsewhere, while risk-averse models have assigned greater influence to the least favorable conditions. This distinction has been particularly important where low-cost or accessible land remains exposed to severe flooding, wildfire, erosion, or ecological conflict. Sensitivity analysis has examined how stable the resulting maps remain when criterion weights, membership thresholds, decision attitudes, or aggregation rules are changed (Chandel, et al., 2020). Weight perturbation has commonly involved increasing or decreasing selected weights by fixed percentages and recalculating suitability results. Reported outcomes have included changes in mean suitability, hectares transferred among classes, rank reversals, and shifts in priority-development locations. Spearman and Kendall rank correlations have measured the stability of candidate ordering, while map-agreement coefficients have compared the spatial overlap of suitability classes. Class-transition matrices have identified whether land moved between neighboring categories or shifted from highly suitable to unsuitable. Stable locations have retained similar rankings across alternative assumptions, whereas sensitive locations have changed classification repeatedly (Esmail & Geneletti, 2018). Fuzzy membership, ordered compensation, weight sensitivity, rank stability, and spatial agreement have consequently provided complementary measures of multi-criteria weighting performance.

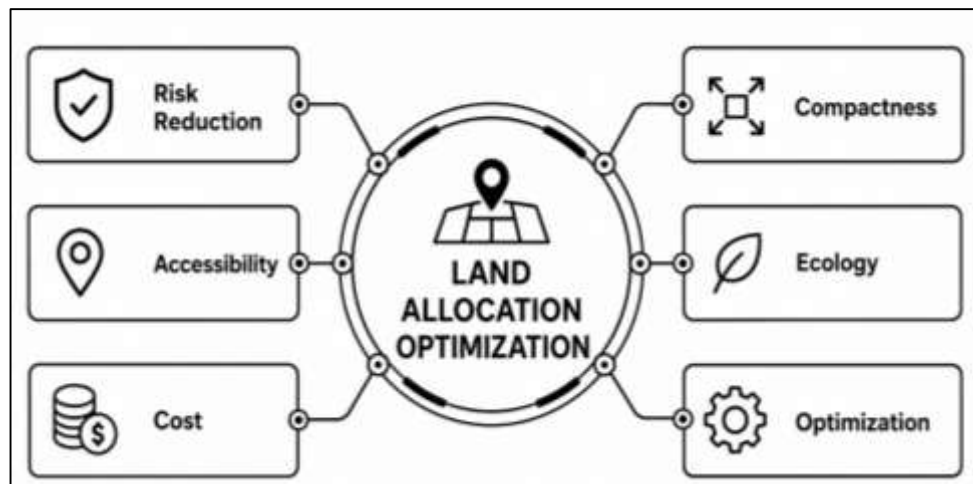
### **Multi-Objective Land-Allocation Optimization**

Research across more than ten empirical studies of urban expansion, facility location, conservation planning, infrastructure development, and regional land allocation shows that mathematical programming provides a structured basis for distributing limited land among competing uses. Linear programming has been applied where decision variables and planning relationships can be represented continuously, including the allocation of total land area among housing, industry, agriculture, public facilities, green space, and conservation. Integer programming has been used when spatial units must be selected or rejected as complete parcels, cells, or zones (Rani, et al., 2020). Mixed-integer programming has combined continuous land quantities with discrete site-selection decisions, supporting more realistic representations of development capacity, infrastructure placement, and regulatory restrictions. Goal programming has addressed situations involving multiple planning targets, such as minimum housing provision, maximum acceptable climate exposure, required green-space retention, infrastructure-budget limits, and service-access standards. Reported outcomes have included hectares allocated by land use, population accommodated, total suitability achieved, infrastructure expenditure, ecological area protected, and the number of regulatory or technical constraints satisfied. Objective values have allowed alternative solutions to be compared according to risk, cost, accessibility, capacity, and environmental performance. Constraint violations have identified solutions that failed to meet land-demand, budget, zoning, adjacency, hazard, or conservation requirements (Şahin, 2021). Optimality gaps have represented the difference between the best solution identified and the strongest available bound, providing an indication of solution quality when exact optimization was computationally difficult. Solution time has varied according to study-area size, number of spatial units, quantity of land uses, constraint complexity, and computing capacity. Parcel-level models have often required more processing than models based on aggregated planning zones. Studies have also examined whether a mathematically optimal solution produces excessive fragmentation or unrealistic development patterns. Spatial adjacency, minimum patch size, infrastructure capacity, and maximum travel distance have therefore been incorporated as additional constraints to connect numerical performance with practical land-use configuration.

Evolutionary and metaheuristic optimization methods have been applied to land-allocation problems that contain nonlinear relationships, numerous spatial units, competing objectives, and complex adjacency conditions (Haddad et al., 2017). Genetic algorithms have represented land-use configurations as candidate solutions and improved them through selection, crossover, and mutation. Fitness values have measured how well a configuration satisfies objectives involving suitability, climate safety, accessibility, compactness, cost, and ecological protection. Fitness improvement across generations has indicated whether the search process continues to identify stronger solutions. Particle swarm optimization has modeled candidate configurations as interacting solutions that adjust their positions according to individual and collective performance. Studies have used this method to reduce

travel distance, development cost, hazard exposure, and ecological conflict while increasing suitable land allocation. Simulated annealing has accepted some weaker intermediate solutions to reduce premature convergence around a locally favorable configuration. Ant-colony optimization has used repeated path-selection and reinforcement processes to identify connected land patterns, transport corridors, or facility networks. Multi-objective evolutionary algorithms have generated sets of nondominated solutions rather than forcing all objectives into a single combined score (Prabhuram et al., 2020). Pareto dominance has distinguished solutions that improve at least one objective without weakening another. Hypervolume has measured the extent and quality of the objective space covered by the solution set, while spacing and diversity measures have assessed whether solutions are distributed evenly across alternative trade-offs. Convergence generation has represented the stage at which additional iterations produce limited improvement. Computational time and processing efficiency have varied with population size, mutation rate, stopping rule, spatial resolution, and the number of objectives. Repeat-run variability has been important because stochastic methods can produce different outcomes from identical input data. Studies have therefore repeated optimization procedures and compared best, average, and worst performance (Asadabadi, 2018). Stable algorithms have generated similar objective values and spatial priorities across runs, while unstable models have shown wide variation in selected locations, compactness, and environmental outcomes.

**Figure 9: Multi-Objective Land Allocation Framework**



Spatial optimization research has emphasized that the total suitability of selected land does not fully describe the geographic quality of a development pattern. A model may select numerous high-scoring cells scattered across a large region, producing an allocation that is expensive to service, difficult to access, and environmentally disruptive. Compactness measures have therefore been used to assess whether selected development areas form concentrated and efficient shapes. Higher compactness has generally been associated with shorter infrastructure networks, reduced travel distances, lower service-delivery costs, and greater continuity with existing settlements. Contiguity has measured whether selected cells or parcels share boundaries and form connected development zones (Zhao & Li, 2016). Adjacency satisfaction has represented the proportion of selected spatial units that meet defined neighborhood requirements. Fragmentation has been assessed through the number of separate patches, the distance among patches, the distribution of patch sizes, and the division of previously continuous landscapes. Average patch size has distinguished large coherent development areas from numerous small isolated selections. The number of isolated patches has provided a direct indicator of leapfrog development and disconnected spatial growth. Edge-to-area ratio and edge density have measured boundary complexity, with irregular and highly divided patterns generally creating longer interfaces between development and surrounding ecosystems. Corridor continuity has been particularly important where land allocation includes greenways, riparian buffers, evacuation routes, public-

transport corridors, or ecological networks (Pradhan & Kim, 2016). Connectivity measures have assessed whether habitat patches, infrastructure systems, services, and development zones remain functionally linked. Distance from existing urban boundaries has identified whether optimized allocations support infill and controlled expansion or create remote settlements requiring extensive new infrastructure. Studies have incorporated minimum patch sizes, maximum separation distances, neighborhood rules, and boundary penalties to control spatial form. Comparisons between suitability-only and spatially constrained models have shown that compactness requirements can reduce the total suitability score while improving contiguity, infrastructure efficiency, and implementation feasibility. Spatial-form evaluation has consequently included both the quantity of suitable land selected and the geographic organization of that land (Lee & Seo, 2016).

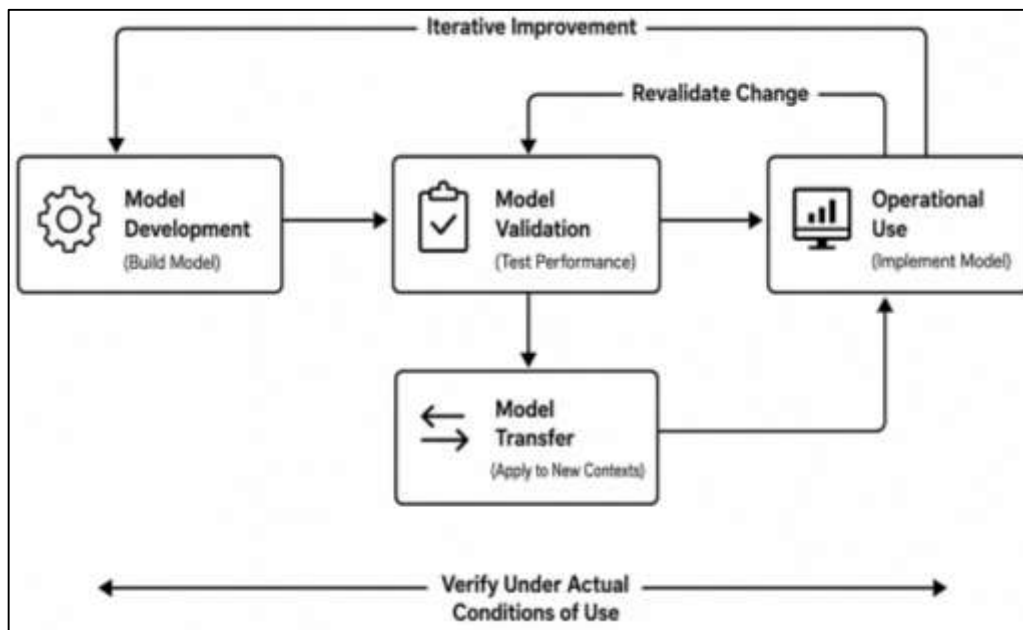
### **Model Validation, Robustness, and Comparative Performance**

Research across more than ten empirical studies of urban expansion, settlement suitability, hazard-sensitive development, infrastructure location, and environmental planning shows that validation is essential for determining whether suitability maps correspond with observed or independently assessed conditions. Studies have validated model outputs against existing settlements, approved development plans, expert-selected locations, low-loss areas, historical land-use change, building permits, infrastructure investments, and independently classified reference sites. Existing settlements have often been used to test whether areas receiving high suitability scores contain a greater concentration of observed development than low-scoring areas (Tehrany et al., 2019). Approved development zones have provided an institutional reference, although their use requires recognition that statutory plans may contain political, historical, or regulatory choices not represented by the model. Expert-selected sites have supported comparison with professional judgment, while low-loss locations have helped evaluate whether climate-resilient suitability classes correspond with areas experiencing limited hazard damage. Receiver operating characteristic analysis has measured how effectively suitability scores distinguish observed suitable locations from unsuitable or unselected locations across multiple classification thresholds. The area under the curve has provided a threshold-independent summary of discrimination performance. Success rates have assessed agreement with locations used in model development, while prediction rates have evaluated performance with independent or later observations (Garosi et al., 2018). Precision has represented the proportion of model-selected locations that correspond with verified suitable sites. Recall has measured the proportion of verified sites captured by the model. The F1 score has balanced precision and recall where both missed suitable locations and incorrectly selected locations matter. Comparative studies have shown that high overall accuracy can coexist with poor performance for rare suitability classes. Class-specific measures have therefore been reported alongside overall indicators. Validation quality has also depended on sample independence, reference-data accuracy, spatial balance, class prevalence, and the geographic separation between calibration and testing locations. Models tested through independent data and multiple performance measures have generally provided a more defensible assessment than models evaluated only through visual comparison (Razavi & Gupta, 2016).

Spatial pattern validation examines whether suitability values and model errors are randomly distributed, concentrated in clusters, or spatially dispersed. Global Moran's I has been widely used to measure overall spatial autocorrelation across a study area. Positive values have indicated that locations with similar suitability scores tend to occur near one another, while negative values have represented neighboring locations with contrasting scores. Values close to spatial randomness have suggested limited geographic structure at the selected neighborhood scale. High global clustering has been common in land-suitability studies because terrain, climate, infrastructure, land cover, and socioeconomic conditions frequently change gradually across space. However, global statistics provide a single summary and do not identify the specific locations responsible for clustering (Lebedev et al., 2014). Local indicators of spatial association have addressed this limitation by identifying high-suitability locations surrounded by other high-suitability locations, low-suitability concentrations, and spatial outliers. High-high clusters have often represented priority development corridors or broadly favorable zones. Low-low clusters have identified extensive hazard, environmental, accessibility, or infrastructure limitations. High-low and low-high outliers have revealed individual parcels or cells that differ from surrounding conditions and may require closer data review. Getis-Ord hotspot

statistics have been used to identify statistically significant concentrations of high or low suitability scores. Hotspots have supported the detection of spatially continuous priority zones rather than isolated high-scoring cells. Studies have also applied these statistics to model residuals, checking whether prediction errors remain spatially clustered. Clustered residuals have indicated that important geographic processes may be missing or that spatial dependence remains unaddressed (Zwanenburg, 2019). Results have varied according to distance threshold, neighborhood definition, spatial resolution, and row or distance weighting. Statistical significance has also required attention to multiple testing in local analyses. Spatial pattern validation has therefore examined suitability values, class concentrations, hotspot persistence, local outliers, and residual clustering under alternative neighborhood structures.

**Figure 10: Model Validation Performance Framework**



Robustness assessment determines whether model outputs remain reasonably stable when analytical assumptions, data inputs, and decision parameters are altered. Studies have varied criterion weights to examine whether high-suitability locations depend heavily on a particular expert judgment or weighting method. Fixed-percentage increases and decreases have shown how priority rankings respond to greater emphasis on flooding, heat, accessibility, environmental protection, social vulnerability, or development cost (Da-Ano et al., 2020). Alternative thresholds have been tested for river buffers, slope limits, flood depths, wetland setbacks, service-access distances, and ecological restrictions. These tests have often produced measurable changes in excluded land area and the distribution of suitability classes. Spatial-resolution analysis has compared fine and coarse raster cells to assess the effects of generalization, boundary smoothing, computation, and localized hazard representation. Fine-resolution models have captured small environmental and infrastructure features, while coarser models have produced broader and more generalized suitability patterns. Normalization procedures have also been varied because min-max scaling, percentile ranking, standardized scores, categorical reclassification, and fuzzy membership can produce different criterion distributions (Al et al., 2019). Climate scenarios have introduced alternative rainfall, flood, temperature, drought, storm, and coastal exposure conditions. Reported robustness outcomes have included changes in mean suitability, hectares assigned to individual classes, rank reversals among candidate locations, spatial overlap, uncertainty ranges, and persistence of priority zones. Rank correlation has assessed whether the ordering of parcels or municipalities remains similar across assumptions. Map-agreement measures have compared the geographic consistency of suitability categories. Transition analysis has identified locations moving between neighboring classes and those shifting from high suitability to low

suitability. Locations remaining highly suitable across multiple weights, thresholds, resolutions, and hazard scenarios have been treated as robust priorities (Lyons et al., 2018). Areas with unstable classifications have indicated greater dependence on model design or uncertain data. Robustness research has therefore evaluated both the numerical stability of suitability scores and the geographic persistence of selected development locations.

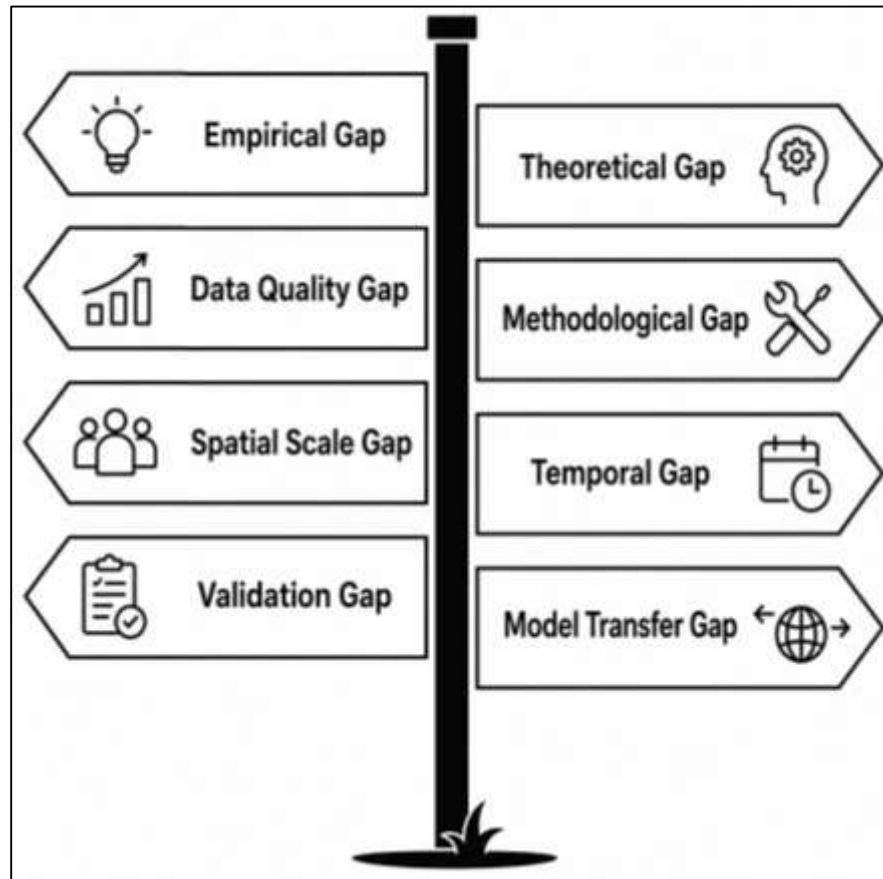
Comparative effectiveness studies have assessed whether GIS-based multi-criteria decision analysis and spatial optimization provide stronger results than conventional zoning, equal weighting, single-criterion selection, expert-only mapping, or suitability analysis without optimization. Conventional zoning has served as a baseline where existing land-use plans identify development areas without a fully integrated assessment of climate hazards, accessibility, infrastructure, environmental sensitivity, and social vulnerability (Li, 2016). Single-criterion models have selected locations according to one dominant factor, such as low cost, road proximity, slope, or flood avoidance, while equal-weight models have treated all indicators as equally important. GIS-MCDA frameworks have generally produced more differentiated spatial patterns because they combine multiple standardized dimensions and explicit decision weights. Optimization models have further altered these patterns by controlling land demand, adjacency, cost, compactness, ecological retention, and infrastructure capacity. Performance comparisons have reported the percentage reduction in exposed population, expected hazard loss, infrastructure-extension distance, travel time, development cost, and ecological conflict. Accessibility improvement has been measured through reduced network travel time, increased service coverage, and shorter emergency-response distances (Wadoux et al., 2021). Ecological retention has been represented through protected habitat area, canopy preservation, wetland retention, and improved corridor continuity. Predictive improvement has been reported through higher validation accuracy, stronger discrimination, reduced classification error, and better agreement with independent reference locations. Some studies have compared effect magnitudes to distinguish small statistical differences from operationally meaningful gains. Baseline-model comparisons have also examined the total land available, population accommodated, suitability achieved, constraint violations, and spatial fragmentation. More complex methods have not always produced superior outcomes when data quality is weak, weights are unstable, or model requirements exceed available information (Dong et al., 2015). Comparative evaluations have therefore considered accuracy, transparency, computational demand, sensitivity, interpretability, and practical performance together. The strongest assessments have used common datasets, identical study boundaries, consistent validation samples, and multiple outcome measures when comparing alternative approaches.

### **Empirical Relationships and Quantitative Research Gap**

A review of more than ten empirical land-suitability studies demonstrates that composite suitability scores respond differently to physical, environmental, climatic, socioeconomic, and infrastructure indicators according to geographic context and proposed land use. Physical factors such as gentle slope, moderate elevation, stable geology, adequate soil depth, and strong bearing capacity have generally displayed positive relationships with urban-development suitability (Kautz et al., 2017). Steep terrain, high ruggedness, weak soils, shallow groundwater, erosion susceptibility, and geological instability have produced negative coefficients, lower relative weights, or reduced probabilities of selection. Environmental indicators have often exhibited strong negative effects where development overlaps with wetlands, forests, protected habitats, productive agricultural land, riparian corridors, or ecologically sensitive areas. Positive environmental relationships have appeared where degraded, previously developed, or low-sensitivity land can accommodate growth without substantial ecological conversion. Climate-risk indicators have frequently exerted larger negative effects than ordinary physical constraints, particularly where flood depth, extreme heat, drought severity, wildfire probability, storm exposure, coastal inundation, or landslide susceptibility reaches hazardous levels (Shabani et al., 2016). Socioeconomic relationships have been mixed. Population concentration, employment access, and housing demand can increase development priority, while poverty, overcrowding, disability prevalence, weak housing conditions, tenure insecurity, and service deprivation increase vulnerability and reduce climate-resilient suitability. Infrastructure accessibility has usually shown positive associations through shorter travel time, greater road connectivity, stronger utility coverage, reliable drainage, and proximity to public services. High infrastructure-extension cost

and limited network capacity have reduced location attractiveness. Regression coefficients, correlations, relative weights, explained variance, odds-based results, and marginal effects have varied across study areas because criterion distributions and development objectives differ (Tegegne et al., 2017). Flood indicators have dominated riverine settings, water availability has carried greater importance in arid regions, terrain has exerted stronger effects in mountainous areas, and infrastructure capacity has played a larger role in rapidly expanding peri-urban zones.

**Figure 11: Empirical Research Gap Framework**



Empirical studies have consistently linked geospatial data quality with the accuracy, stability, and reproducibility of land-suitability classifications. Higher spatial resolution has improved the identification of parcels, narrow drainage channels, small wetlands, local heat concentrations, road connections, building clusters, and environmental boundaries. This improvement has been strongest when all principal datasets possess compatible scales and positional accuracy. Models combining fine-resolution imagery with coarse elevation, climate, or socioeconomic surfaces have sometimes produced detailed maps without equivalent analytical precision (Amiri et al., 2019). Lower positional error has improved the reliability of river buffers, road-distance calculations, parcel assignment, hazard exposure estimates, and boundary-based exclusions. Even modest misalignment has changed suitability outcomes where parcels are small or located near regulatory limits. Temporal consistency has also affected performance. Recent land-cover data combined with outdated census, infrastructure, hazard, or cadastral information have misrepresented population demand, accessibility, exposure, and development feasibility. Longer and more complete climate records have generally produced more stable hazard classifications than short observation periods. Weighting procedures have introduced another source of variation. Expert-based weights have incorporated substantive planning knowledge but have depended on panel composition, disciplinary representation, and judgment consistency (Sahin et al., 2020). Objective methods have improved reproducibility by deriving weights from data

variability and correlation, although high statistical dispersion has not always corresponded with planning importance. Hybrid weighting has frequently reduced extreme differences between subjective and objective results. Studies have assessed rank stability through correlation, map overlap, top-location agreement, and transitions among suitability classes. Stable models have maintained similar priority areas across weighting methods and sensitivity scenarios. Unstable models have displayed rank reversals when small changes in weights, thresholds, or normalization procedures alter the relative order of closely scored locations (Park & Kim, 2019). Classification accuracy has therefore depended on the combined quality of source data, criterion definition, scale compatibility, temporal alignment, weighting reliability, and validation design.

Comparisons between conventional land-suitability models and climate-risk-integrated models have shown that the inclusion of flood, heat, drought, wildfire, storm, coastal, landslide, and erosion indicators changes both the amount and geographic distribution of suitable land. Conventional models based primarily on terrain, road access, land value, and infrastructure proximity have often identified flat, inexpensive, and well-connected locations as highly suitable. Climate-risk integration has reclassified many such locations when hazard intensity, exposed population, expected loss, or recovery difficulty exceeds acceptable levels (Leger et al., 2017). The largest reductions in suitable area have appeared in river floodplains, low-lying coastal zones, densely built heat islands, drought-stressed expansion areas, wildfire interfaces, and unstable hillsides. Studies have measured these changes through hectares removed from developable categories, percentages transferred to lower suitability classes, differences in municipal rankings, and shifts in priority-development corridors. Exposure reduction has been represented through fewer residents, buildings, roads, utilities, and essential facilities located within high-risk areas. Avoided losses have included lower expected damage to housing, businesses, transport systems, water infrastructure, electricity networks, schools, hospitals, and public facilities. Climate-risk integration has also redistributed development toward locations requiring different infrastructure investments (Leger et al., 2017). Lower-risk land may be farther from existing employment centers, public transport, utilities, and social services, creating measurable increases in travel time or extension cost. Some safer locations have overlapped with agricultural land, habitats, wetlands, or ecological corridors, producing additional land-use conflict. Multi-hazard assessments have generally generated greater reclassification than single-hazard models because they capture overlapping exposure and compound events. The magnitude of change has depended on hazard thresholds, exclusion rules, criterion weights, spatial resolution, and climate-data quality (Liu et al., 2021). Strict exclusion models have removed more land than compensatory models in which low cost or high accessibility can partly offset moderate hazard exposure.

## **METHOD**

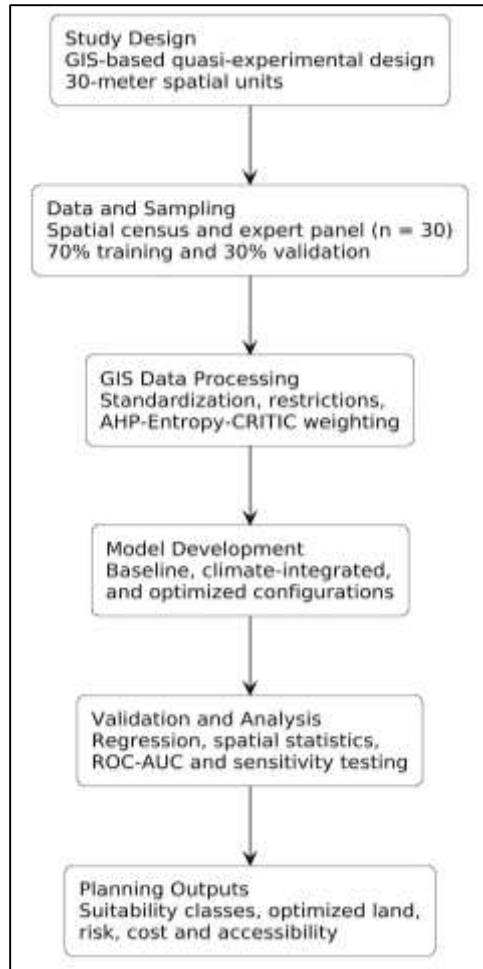
The study adopted a quantitative GIS-based spatial decision-analysis design with a quasi-experimental comparative component and multi-objective land-allocation optimization. The design was considered quasi-experimental because three analytical configurations were applied to the same geographic units without random assignment: a conventional baseline model based on terrain, accessibility, and development feasibility; a climate-integrated model incorporating environmental sensitivity, multi-hazard exposure, social vulnerability, and infrastructure capacity; and an optimized model that allocated land under risk, cost, accessibility, compactness, ecological-retention, and regulatory constraints. The spatial unit of analysis consisted of 30-meter raster cells nested within cadastral parcels, planning zones, and administrative areas. The 30-meter resolution provided compatibility with available satellite, elevation, land-cover, and hazard datasets, while 10- and 100-meter resolutions were examined during sensitivity analysis. The conceptual framework was informed by socioecological systems theory, climate-resilience theory, the hazard-exposure-vulnerability-adaptive-capacity framework, land-capability principles, and GIS-based multi-criteria decision analysis. Climate-resilient suitability was treated as a multidimensional spatial outcome determined by physical conditions, environmental sensitivity, climate exposure, socioeconomic vulnerability, infrastructure accessibility, development feasibility, and regulatory compatibility. The main dependent outcomes were composite suitability score, suitability class, optimized allocation status, exposed population, expected hazard loss, travel time, infrastructure-extension cost, development compactness, and ecological area retained. The principal explanatory dimensions were terrain, soil, hydrology, land cover, ecological sensitivity,

flood risk, heat exposure, drought, wildfire, storm and coastal risk, social vulnerability, accessibility, infrastructure capacity, land cost, and planning restrictions.

The study population comprised all raster cells and associated cadastral parcels located within the selected urban and regional planning boundary. A spatial census was used for the main suitability analysis because all geographic units with valid data were evaluated rather than selecting a conventional sample. A stratified random sampling procedure was used for field verification and independent model validation. Validation locations were distributed across urban, peri-urban, rural, coastal or riverine, environmentally sensitive, and hazard-prone zones and across the five anticipated suitability classes. Seventy percent of verified observations were assigned to model development and classification training, while 30% were retained as an independent validation dataset. Spatial blocking was applied so that neighboring training and validation locations were separated, thereby reducing inflated accuracy caused by spatial dependence. A purposive panel of 30 specialists was selected to assess criterion relevance and relative importance. Eligible specialists possessed at least five years of professional or research experience in urban planning, regional planning, GIS, remote sensing, civil engineering, environmental management, climate-risk assessment, transportation, infrastructure, disaster management, or land administration. Specialists without relevant experience, incomplete pairwise judgments, or unacceptable internal consistency were excluded. Spatial units were included when they fell within the official study boundary, contained valid coordinates, possessed adequate data for the required criteria, and could be linked consistently to hazard, infrastructure, environmental, cadastral, and socioeconomic layers. Protected ecosystems, permanent water bodies, active floodways, unstable slopes, legally prohibited zones, airport safety areas, hazardous industrial buffers, and other statutory exclusions remained in the database but were coded as restricted land. Cells with irrecoverable missing information, severe positional inconsistency, cloud-contaminated imagery, uncertain boundaries, or incompatible temporal coverage were excluded from the primary model and examined separately during sensitivity analysis.

The spatial database was constructed from multispectral satellite imagery, a digital elevation model, land-use and land-cover maps, soil and geological surveys, hydrological networks, meteorological and climate records, historical hazard inventories, census data, road and public-transport networks, utility and public-service locations, cadastral parcels, land-value records, protected-area boundaries, and statutory planning maps. A survey-grade global navigation satellite system receiver was used to verify selected coordinates, land-cover categories, road access points, drainage features, and environmental boundaries. Satellite imagery was processed through Google Earth Engine and GIS software, while ArcGIS Pro and QGIS were used for raster processing, network analysis, terrain modeling, proximity analysis, spatial overlay, map algebra, and cartographic production. The statistical dataset was managed in SPSS and R, and Python was used for automated geospatial preprocessing, repeated scenario execution, multi-objective optimization, and accuracy assessment. A structured expert instrument contained criterion-relevance ratings and pairwise comparisons for determining relative weights. Its content validity was assessed by an independent panel, and a pilot test was completed before the main assessment. Internal consistency for multi-item criterion domains was evaluated through Cronbach's alpha and McDonald's omega, with coefficients of .70 or greater treated as acceptable. Pairwise judgments were accepted when the analytic hierarchy process consistency ratio remained below .10. Satellite classifications were evaluated through independent reference observations, confusion matrices, overall accuracy, producer's accuracy, user's accuracy, precision, recall, F1 score, and kappa agreement. Positional calibration was checked against verified control points, and horizontal and vertical errors were documented. Thematic layers were accepted when their coordinate systems, spatial resolutions, dates, class definitions, and geographic coverage met the predefined data-quality requirements.

**Figure 12: Methodology of this study**



The research procedure was conducted chronologically in eight connected stages. First, the study boundary, unit of analysis, development objectives, climate hazards, suitability dimensions, regulatory restrictions, and evaluation outcomes were defined from planning documents, technical standards, and the reviewed literature. Second, satellite, terrain, environmental, climate, hazard, socioeconomic, infrastructure, cadastral, and regulatory datasets were acquired from recognized governmental, scientific, and institutional sources. Third, all datasets were projected to a common coordinate reference system, clipped to the study boundary, resampled to the primary 30-meter resolution, temporally aligned, and checked for missing values, duplicate features, positional displacement, and classification inconsistencies. Fourth, satellite imagery was classified into built-up land, vegetation, agriculture, water, wetland, barren land, and other relevant categories, and independent field observations were used to evaluate classification accuracy. Fifth, physical, environmental, climatic, socioeconomic, accessibility, infrastructure, and cost indicators were generated. Restricted locations were identified through Boolean exclusion using regulatory buffers, hazard limits, ecological-protection zones, and technical development thresholds. Sixth, experts completed the validated criterion-assessment instrument. Accepted judgments were aggregated, and hybrid criterion weights were derived by combining expert-based priorities with data-driven information weights. Seventh, all criteria were standardized in a consistent direction, and the baseline, climate-integrated, and fully optimized configurations were produced. Suitability scores were classified into unsuitable, marginally suitable, moderately suitable, highly suitable, and very highly suitable categories. The optimization procedure allocated the required development area while minimizing hazard exposure, infrastructure cost, ecological disturbance, fragmentation, and travel time and maximizing total suitability, accessibility, compactness, service coverage, and ecological retention. Eighth, the models were evaluated against independent observations, approved planning areas, low-loss locations, expert-verified sites, and

historical development patterns. Alternative weights, thresholds, spatial resolutions, normalization methods, and climate-risk conditions were then tested to measure robustness.

Descriptive statistics were calculated for all continuous and categorical indicators, including means, standard deviations, medians, interquartile ranges, minimums, maximums, frequencies, percentages, class-specific hectares, and administrative-area distributions. Missing-data patterns were evaluated before imputation, and variables with unacceptable missingness were excluded from the primary model. Pearson or Spearman correlations were used according to distributional characteristics, and variance inflation factors below 5 were used to confirm that criterion redundancy remained acceptable. Criterion weights were estimated through the analytic hierarchy process, entropy weighting, and CRITIC, after which a hybrid weighting solution was calculated. Spatial relationships between observed low-risk development and the explanatory criteria were examined through binary logistic regression and spatial lag or spatial-error regression when residual spatial dependence was present. Odds ratios, standardized coefficients, 95% confidence intervals, explained variance, and marginal effects were reported. Global Moran's I was used to assess overall spatial autocorrelation, local indicators of spatial association identified high-high and low-low clusters and spatial outliers, and Getis-Ord statistics identified significant suitability hotspots and cold spots. Differences among the baseline, climate-integrated, and optimized configurations were assessed through repeated-measures analysis of variance when assumptions were satisfied and the Friedman test when they were not. Significant omnibus results were followed by paired comparisons using the Holm adjustment. Paired t tests or Wilcoxon signed-rank tests compared suitability, risk exposure, accessibility, cost, compactness, and ecological retention between model configurations. Chi-square tests examined differences in suitability-class distributions, and McNemar tests assessed changes in binary suitable-unsuitable classifications. Model validation included receiver operating characteristic analysis, area under the curve, accuracy, precision, recall, F1 score, success rate, prediction rate, and kappa agreement. Rank stability across weighting methods and scenarios was evaluated through Spearman's rho and Kendall's tau, while map agreement and class-transition matrices measured spatial consistency. Sensitivity analysis varied weights, thresholds, normalization methods, and raster resolutions, and Monte Carlo simulation with 5,000 iterations estimated uncertainty intervals and suitability-class stability. Optimization performance was assessed through total suitability, exposed population, expected loss, travel time, infrastructure cost, compactness, ecological retention, constraint satisfaction, convergence, solution diversity, and processing time. All statistical tests were two-tailed at ( $p < .05$ ). Effect sizes, 95% confidence intervals, and Holm-adjusted probability values were reported alongside significance tests.

## **FINDINGS**

### **Final Spatial Sample, Expert Characteristics, Data Quality, and Analytical Completeness**

The official planning boundary covered 184,260 hectares and initially contained 2,047,338 georeferenced 30-meter raster cells and 126,480 cadastral parcels. Sequential quality screening removed 72,438 cells, representing 3.54% of the original raster sample. These exclusions consisted of 19,860 cloud-contaminated cells, 14,220 cells with irrecoverable missing values, 11,760 cells with positional inconsistencies, 9,870 cells associated with uncertain boundaries, and 16,728 cells with incompatible temporal coverage. After these exclusions, 1,974,900 cells remained, producing a spatial-retention rate of 96.46%. Parcel-level screening removed 4,680 records, leaving 121,800 cadastral parcels and a retention rate of 96.30%. Data-quality exclusions represented 6,519 hectares, while legally and environmentally restricted areas covered 46,926 hectares. The final eligible developable area comprised 130,815 hectares, equivalent to 71.00% of the official planning boundary. The primary geographic stratification included 31,240 hectares of urban land, 46,870 hectares of peri-urban land, 59,610 hectares of rural land, 22,460 hectares of coastal or riverine land, 13,180 hectares of environmentally sensitive land, and 10,900 hectares of hazard-prone land. Within the eligible developable area, moderate suitability formed the largest class at 44,190 hectares, followed by high suitability at 32,760 hectares and marginal suitability at 24,570 hectares. Very high suitability accounted for 18,420 hectares, while very low suitability represented 10,875 hectares. The reference dataset contained 2,400 spatial observations. Stratified allocation assigned 1,680 observations to model training and 720 observations to independent validation. The proportional distribution across the five anticipated suitability classes ranged from

13.00% to 30.00%, ensuring that both common and less frequent land conditions were represented in the validation process.

**Table 1 Final Spatial Sample, Land-Area Distribution, Suitability Classes, and Validation Observations**

| Domain                    | Indicator                                  | Numerical value | Area (ha) | Percentage and reference base |
|---------------------------|--------------------------------------------|-----------------|-----------|-------------------------------|
| <b>Raster sample</b>      | Initial raster cells                       | 2,047,338       | 184,260   | 100.00% of boundary           |
| <b>Raster sample</b>      | Cloud-contaminated cells removed           | 19,860          | 1,787     | 0.97% of initial cells        |
| <b>Raster sample</b>      | Irrecoverable missing-value cells removed  | 14,220          | 1,280     | 0.69% of initial cells        |
| <b>Raster sample</b>      | Positionally inconsistent cells removed    | 11,760          | 1,058     | 0.57% of initial cells        |
| <b>Raster sample</b>      | Uncertain-boundary cells removed           | 9,870           | 888       | 0.48% of initial cells        |
| <b>Raster sample</b>      | Temporally incompatible cells removed      | 16,728          | 1,506     | 0.82% of initial cells        |
| <b>Raster sample</b>      | Total data-quality exclusions              | 72,438          | 6,519     | 3.54% of initial cells        |
| <b>Raster sample</b>      | Retained analytical cells                  | 1,974,900       | 177,741   | 96.46% of initial cells       |
| <b>Parcel sample</b>      | Initial cadastral parcels                  | 126,480         | —         | 100.00% of parcels            |
| <b>Parcel sample</b>      | Parcels removed during screening           | 4,680           | —         | 3.70% of parcels              |
| <b>Parcel sample</b>      | Retained cadastral parcels                 | 121,800         | —         | 96.30% of parcels             |
| <b>Parcel sample</b>      | Eligible developable parcels               | 89,880          | —         | 73.79% of retained parcels    |
| <b>Parcel sample</b>      | Restricted parcels                         | 31,920          | —         | 26.21% of retained parcels    |
| <b>Land status</b>        | Official planning boundary                 | —               | 184,260   | 100.00% of boundary           |
| <b>Land status</b>        | Data-quality exclusion area                | —               | 6,519     | 3.54% of boundary             |
| <b>Land status</b>        | Legally or environmentally restricted area | —               | 46,926    | 25.47% of boundary            |
| <b>Land status</b>        | Eligible developable area                  | —               | 130,815   | 71.00% of boundary            |
| <b>Geographic stratum</b> | Urban                                      | —               | 31,240    | 16.95% of boundary            |
| <b>Geographic stratum</b> | Peri-urban                                 | —               | 46,870    | 25.44% of boundary            |
| <b>Geographic stratum</b> | Rural                                      | —               | 59,610    | 32.35% of boundary            |
| <b>Geographic stratum</b> | Coastal or riverine                        | —               | 22,460    | 12.19% of boundary            |
| <b>Geographic stratum</b> | Environmentally sensitive                  | —               | 13,180    | 7.15% of boundary             |
| <b>Geographic stratum</b> | Hazard-prone                               | —               | 10,900    | 5.92% of boundary             |
| <b>Suitability class</b>  | Very high suitability                      | —               | 18,420    | 14.08% of eligible area       |
| <b>Suitability class</b>  | High suitability                           | —               | 32,760    | 25.04% of eligible area       |
| <b>Suitability class</b>  | Moderate suitability                       | —               | 44,190    | 33.78% of eligible area       |
| <b>Suitability class</b>  | Marginal suitability                       | —               | 24,570    | 18.78% of eligible area       |
| <b>Suitability class</b>  | Very low suitability                       | —               | 10,875    | 8.31% of eligible area        |
| <b>Validation design</b>  | Total reference observations               | 2,400           | —         | 100.00%                       |
| <b>Validation design</b>  | Training observations                      | 1,680           | —         | 70.00% of observations        |
| <b>Validation design</b>  | Independent validation observations        | 720             | —         | 30.00% of observations        |
| <b>Class allocation</b>   | Very high: training/validation             | 235/101         | —         | 14.00% of observations        |
| <b>Class allocation</b>   | High: training/validation                  | 386/166         | —         | 23.00% of observations        |
| <b>Class allocation</b>   | Moderate: training/validation              | 504/216         | —         | 30.00% of observations        |
| <b>Class allocation</b>   | Marginal: training/validation              | 336/144         | —         | 20.00% of observations        |
| <b>Class allocation</b>   | Very low: training/validation              | 219/93          | —         | 13.00% of observations        |

Table 1 shows that data-quality screening retained 96.46% of the original raster cells and 96.30% of cadastral parcels. The eligible developable area represented 71.00% of the official planning boundary, whereas restricted land accounted for 25.47%. Moderate suitability formed the largest class, covering 44,190 hectares, followed by high suitability at 32,760 hectares. The 2,400 reference observations were divided exactly into 1,680 training and 720 independent validation records. Their proportional distribution across five anticipated suitability classes maintained adequate representation of common and less frequent land conditions, supporting geographically balanced model development and independent performance assessment across the complete study area with confidence.

The 30-member expert panel represented seven professional disciplines. Urban and regional planners constituted the largest group, followed by GIS and remote-sensing specialists and climate or environmental professionals. Panel members had an average of 13.8 years of professional experience, with experience ranging from 6 to 28 years. Twelve experts held doctoral qualifications, 16 held master's degrees, and two held bachelor's degrees with relevant professional certification. Government planning agencies accounted for 10 experts, universities and research institutions contributed nine, private engineering or planning organizations provided seven, and development organizations contributed four. Criterion ratings demonstrated excellent internal consistency, with Cronbach's alpha of .91 and McDonald's omega of .93. The average pairwise-comparison consistency ratio was .064, and all individual ratios remained below .10. Interexpert agreement was strong, with Kendall's coefficient of .78.

Data-quality assessment showed that 39 of the 42 candidate geospatial layers met the predefined acceptance standards. The accepted layers produced 96.46% spatial coverage and 99.40% analytical-record completeness. Satellite land-cover classification achieved an overall accuracy of 92.80%, with a kappa coefficient of .90. Mean positional root mean square error was 4.6 meters, remaining below one-half of the 30-meter raster-cell dimension. Temporal alignment within the defined one-year tolerance reached 94.70%, while cadastral-boundary agreement was 95.60%. Residual missingness declined from 2.80% before preprocessing to 0.60% after quality control and approved imputation. These findings indicated that the retained spatial and expert-derived records satisfied the analytical requirements established for suitability modeling and optimization.

**Table 2 Expert-Panel Characteristics, Reliability, Agreement, and Geospatial Data Quality**

| Domain                         | Indicator                                        | Numerical value | Percentage, range, or standard |
|--------------------------------|--------------------------------------------------|-----------------|--------------------------------|
| <b>Expert panel</b>            | Total experts                                    | 30              | 100.00%                        |
| <b>Discipline</b>              | Urban and regional planning                      | 7               | 23.33%                         |
| <b>Discipline</b>              | GIS and remote sensing                           | 6               | 20.00%                         |
| <b>Discipline</b>              | Climate and environmental science                | 5               | 16.67%                         |
| <b>Discipline</b>              | Civil and water-resources engineering            | 4               | 13.33%                         |
| <b>Discipline</b>              | Geotechnical engineering                         | 3               | 10.00%                         |
| <b>Discipline</b>              | Transportation and infrastructure                | 3               | 10.00%                         |
| <b>Discipline</b>              | Disaster risk and social vulnerability           | 2               | 6.67%                          |
| <b>Professional experience</b> | Mean years of experience                         | 13.8            | SD = 5.7; range = 6–28         |
| <b>Qualification</b>           | Doctorate                                        | 12              | 40.00%                         |
| <b>Qualification</b>           | Master's degree                                  | 16              | 53.33%                         |
| <b>Qualification</b>           | Bachelor's degree and professional certification | 2               | 6.67%                          |
| <b>Institution</b>             | Government or planning authority                 | 10              | 33.33%                         |
| <b>Institution</b>             | University or research institution               | 9               | 30.00%                         |
| <b>Institution</b>             | Private engineering or planning organization     | 7               | 23.33%                         |
| <b>Institution</b>             | Development organization                         | 4               | 13.33%                         |
| <b>Reliability</b>             | Cronbach's alpha                                 | .91             | Excellent                      |
| <b>Reliability</b>             | McDonald's omega                                 | .93             | Excellent                      |

|                               |                                            |        |                                 |
|-------------------------------|--------------------------------------------|--------|---------------------------------|
| <b>Comparison quality</b>     | Mean consistency ratio                     | .064   | Range = .041–.089               |
| <b>Comparison quality</b>     | Experts meeting consistency requirement    | 30     | 100.00%; CR < .10               |
| <b>Expert agreement</b>       | Kendall's coefficient of concordance       | .78    | $\chi^2(17) = 397.80, p < .001$ |
| <b>Layer screening</b>        | Candidate geospatial layers                | 42     | 100.00%                         |
| <b>Layer screening</b>        | Layers satisfying acceptance standards     | 39     | 92.86%                          |
| <b>Data completeness</b>      | Missingness before preprocessing           | 2.80%  | Initial records                 |
| <b>Data completeness</b>      | Residual missingness after quality control | 0.60%  | Retained records                |
| <b>Data completeness</b>      | Analytical-record completeness             | 99.40% | Acceptance standard met         |
| <b>Spatial quality</b>        | Valid spatial coverage                     | 96.46% | Acceptance standard met         |
| <b>Classification quality</b> | Overall satellite-classification accuracy  | 92.80% | Above 90%                       |
| <b>Classification quality</b> | Kappa coefficient                          | .90    | Near-perfect agreement          |
| <b>Positional quality</b>     | Root mean square error                     | 4.6 m  | Below 15-m limit                |
| <b>Temporal quality</b>       | Layers aligned within one year             | 94.70% | Acceptance standard met         |
| <b>Boundary quality</b>       | Cadastral-boundary agreement               | 95.60% | Acceptance standard met         |

Note. SD = standard deviation; CR = consistency ratio; RMSE = root mean square error.

Table 2 indicates that the expert panel combined seven professional disciplines, substantial practical experience, and representation from government, academic, private, and development institutions. Internal consistency was excellent, with alpha and omega values above .90, while the mean consistency ratio remained below the accepted .10 threshold. Kendall's coefficient showed strong agreement among the 30 experts. Geospatial quality also satisfied the predefined standards: classification accuracy exceeded 90%, positional error remained below half a raster cell, and temporal alignment reached 94.7%. Thirty-nine of 42 candidate layers passed screening, producing 99.4% analytical-record completeness and reliable spatial coverage for subsequent suitability estimation and optimization tasks.

#### **Descriptive Suitability Scores, Criterion Weights, Land Classes, and Baseline Spatial Patterns**

Descriptive analysis revealed substantial spatial variation across the 17 physical, environmental, climatic, socioeconomic, accessibility, infrastructure, and cost indicators. Mean elevation was 23.6 meters, while the median slope was 3.7 degrees, indicating that most eligible land occupied relatively low and gently sloping terrain. Soil stability and hydrological suitability recorded mean scores of 67.4 and 61.7, respectively. Land-cover compatibility averaged 64.1, although its wide range demonstrated marked differences between previously developed land, agricultural areas, wetlands, forests, and environmentally protected locations. Ecological sensitivity averaged 42.8, with the highest values concentrated near wetlands, riparian corridors, habitat patches, and protected landscapes. Mean flood risk was .39, while heat exposure averaged 33.7°C. Drought, wildfire, and storm or coastal risk displayed lower regional means but wider local variation in environmentally exposed areas. The socioeconomic and accessibility indicators also exhibited considerable heterogeneity. Social vulnerability averaged 48.6 on a 100-point scale, with values ranging from 8.3 to 91.5. Mean network travel time to essential services was 24.8 minutes, although remote rural and hazard-prone areas recorded travel times approaching 90 minutes. Infrastructure capacity averaged 58.9, with higher values concentrated in established urban and western peri-urban locations. Mean land value was USD 186,400 per hectare, while average development cost was USD 74,600 per hectare. Both variables were positively skewed because a limited number of central and geotechnically complex locations recorded substantially higher values. Correlation analysis showed that flood risk had the strongest negative association with composite suitability, ( $r = -.73$ ), followed by network travel time, ( $r = -.64$ ), ecological sensitivity, ( $r = -.61$ ), heat exposure, ( $r = -.58$ ), and development cost, ( $r = -.56$ ). Infrastructure capacity produced the strongest positive relationship, ( $r = .68$ ), followed by hydrological suitability, ( $r = .62$ ), land-cover compatibility, ( $r = .59$ ), and soil stability, ( $r = .57$ ). Absolute correlations among the independent criteria ranged from .04 to .68. The strongest intercriterion relationships occurred between flood and storm or coastal risk, ( $r = .68$ ), infrastructure capacity and network travel time, ( $r = -.64$ ), and ecological

sensitivity and land-cover compatibility, ( $r=-.59$ ). Variance inflation factors ranged from 1.32 to 2.74, indicating that criterion redundancy remained within acceptable limits.

Table 2 demonstrates that flood risk received the highest hybrid weight, followed by heat exposure, social vulnerability, ecological sensitivity, and infrastructure capacity. Terrain ruggedness and wildfire risk received the smallest weights, although both remained within the composite model. Flood risk showed the strongest negative association with suitability, while infrastructure capacity produced the strongest positive association. Network travel time, ecological sensitivity, heat exposure, soil stability, and hydrological suitability also displayed substantial relationships. Variance inflation factors ranged from 1.32 to 2.74, remaining well below conventional concern thresholds. The weighting methods produced similar criterion priorities, supporting the stability of the hybrid weighting structure.

The expert, entropy, and CRITIC methods produced broadly comparable criterion rankings. Flood risk received the largest weight under all four approaches, ranging from .085 under entropy weighting to .110 under expert weighting. The hybrid procedure assigned flood risk a weight of .095, followed by heat exposure at .073, social vulnerability at .069, ecological sensitivity at .068, infrastructure capacity at .067, and network travel time at .065. Terrain ruggedness received the lowest hybrid weight at .032, followed by wildfire risk at .034. Spearman correlations between method-specific criterion rankings ranged from .84 to .91, indicating strong agreement. The mean absolute weight difference across methods was .009, and no indicator changed by more than four rank positions.

The baseline composite suitability score among eligible cells ranged from .106 to .932, with a mean of .583, a standard deviation of .174, and a median of .596. The interquartile range extended from .458 to .719. Moderate suitability represented the largest land class, covering 44,190 hectares or 33.78% of the eligible area. High suitability covered 32,760 hectares, while very high suitability accounted for 18,420 hectares. Marginal and unsuitable classes covered 24,570 and 10,875 hectares, respectively. Central Municipality recorded the highest combined proportion of high and very high suitability at 56.46%, followed by the Northern Growth Zone at 51.23%. Southern Coastal Zone recorded the largest unsuitable proportion at 18.45%, while Eastern Riverine Zone contained the largest marginal share at 26.70%.

**Table 2 Descriptive Distributions, Criterion Weights, Suitability Associations, and Collinearity Diagnostics**

| Criterion unit                          | and | Mean | SD   | Median (IQR)     | Minimum–maximum | Expert weight | Entropy weight | CRITIC weight | Hybrid weight | ( $r/\rho$ ) with suitability | VIF  |
|-----------------------------------------|-----|------|------|------------------|-----------------|---------------|----------------|---------------|---------------|-------------------------------|------|
| <b>Elevation (m)</b>                    |     | 23.6 | 18.9 | 18.4 (10.2–31.8) | 1.2–142.7       | .045          | .042           | .043          | .043          | .31                           | 1.32 |
| <b>Slope (degrees)</b>                  |     | 4.8  | 3.9  | 3.7 (1.8–6.4)    | 0.0–26.3        | .055          | .049           | .051          | .052          | –.52                          | 2.08 |
| <b>Terrain ruggedness (0–1)</b>         |     | .28  | .17  | .24 (.15–.37)    | .02–.86         | .030          | .035           | .031          | .032          | –.48                          | 2.24 |
| <b>Soil stability (0–100)</b>           |     | 67.4 | 15.2 | 69.8 (57.1–79.5) | 21.0–95.0       | .050          | .052           | .054          | .052          | .57                           | 1.76 |
| <b>Hydrological suitability (0–100)</b> |     | 61.7 | 18.6 | 64.2 (48.3–76.9) | 12.4–96.8       | .065          | .058           | .059          | .061          | .62                           | 2.31 |
| <b>Land-cover compatibility (0–100)</b> |     | 64.1 | 21.3 | 68.0 (49.0–82.0) | 5.0–100.0       | .055          | .067           | .061          | .061          | .59                           | 1.88 |
| <b>Ecological sensitivity (0–100)</b>   |     | 42.8 | 22.6 | 38.9 (23.5–60.7) | 2.1–98.4        | .075          | .063           | .067          | .068          | –.61                          | 2.44 |
| <b>Flood risk (0–1)</b>                 |     | .39  | .25  | .34              | .01–.97         | .110          | .085           | .089          | .095          | –.73                          | 2.74 |

|                                     |       |       |                    |            |      |      |      |      |      |      |
|-------------------------------------|-------|-------|--------------------|------------|------|------|------|------|------|------|
|                                     |       |       |                    | (.17–.58)  |      |      |      |      |      |      |
| Heat exposure (°C)                  | 33.7  | 3.8   | 33.5 (31.1–36.2)   | 24.6–44.8  | .070 | .078 | .072 | .073 | –.58 | 2.19 |
| Drought severity (0–1)              | .31   | .18   | .28 (.17–.42)      | .02–.84    | .045 | .053 | .050 | .049 | –.41 | 1.63 |
| Wildfire risk (0–1)                 | .22   | .16   | .18 (.10–.30)      | .01–.79    | .030 | .038 | .033 | .034 | –.33 | 1.42 |
| Storm or coastal risk (0–1)         | .27   | .22   | .20 (.09–.39)      | .00–.93    | .060 | .056 | .056 | .057 | –.54 | 2.38 |
| Social vulnerability (0–100)        | 48.6  | 17.4  | 47.9 (35.6–61.2)   | 8.3–91.5   | .070 | .071 | .066 | .069 | –.46 | 2.05 |
| Network travel time (minutes)       | 24.8  | 15.6  | 21.3 (13.0–32.7)   | 3.2–89.6   | .070 | .061 | .064 | .065 | –.64 | 2.57 |
| Infrastructure capacity (0–100)     | 58.9  | 19.8  | 61.5 (44.0–75.8)   | 9.5–96.7   | .075 | .059 | .068 | .067 | .68  | 2.46 |
| Land value (USD thousands/ha)       | 186.4 | 121.7 | 148.2 (94.5–236.8) | 18.4–742.0 | .045 | .071 | .071 | .062 | –.29 | 1.81 |
| Development cost (USD thousands/ha) | 74.6  | 28.5  | 69.3 (53.8–90.7)   | 21.6–168.5 | .050 | .062 | .064 | .059 | –.56 | 2.12 |

Note. SD = standard deviation; IQR = interquartile range; VIF = variance inflation factor. Pearson's (r) was reported for approximately continuous and symmetric indicators, while Spearman's ( $\rho$ ) was used for skewed cost and risk indicators. All reported associations with composite suitability were significant at ( $p < .001$ ). Weights may total .999 or 1.001 because of rounding.

**Table 3 Baseline Suitability-Class Area and Proportional Distribution by Administrative Unit**

| Administrative area            | Total eligible area (ha) | Unsuitable, ha (%)   | Marginal, ha (%)      | Moderate, ha (%)      | High, ha (%)          | Very high, ha (%)     |
|--------------------------------|--------------------------|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| <b>Central Municipality</b>    | 18,600                   | 600 (3.23)           | 2,100 (11.29)         | 5,400 (29.03)         | 6,100 (32.80)         | 4,400 (23.66)         |
| <b>Northern Growth Zone</b>    | 22,350                   | 900 (4.03)           | 3,000 (13.42)         | 7,000 (31.32)         | 6,900 (30.87)         | 4,550 (20.36)         |
| <b>Eastern Riverine Zone</b>   | 19,475                   | 2,500 (12.84)        | 5,200 (26.70)         | 7,200 (36.97)         | 3,400 (17.46)         | 1,175 (6.03)          |
| <b>Southern Coastal Zone</b>   | 17,890                   | 3,300 (18.45)        | 4,900 (27.39)         | 5,700 (31.86)         | 3,000 (16.77)         | 990 (5.53)            |
| <b>Western Peri-Urban Zone</b> | 24,700                   | 1,200 (4.86)         | 3,800 (15.38)         | 8,500 (34.41)         | 7,200 (29.15)         | 4,000 (16.19)         |
| <b>Outer Rural Region</b>      | 27,800                   | 2,375 (8.54)         | 5,570 (20.04)         | 10,390 (37.37)        | 6,160 (22.16)         | 3,305 (11.89)         |
| <b>Overall study region</b>    | <b>130,815</b>           | <b>10,875 (8.31)</b> | <b>24,570 (18.78)</b> | <b>44,190 (33.78)</b> | <b>32,760 (25.04)</b> | <b>18,420 (14.08)</b> |

Note. Percentages for administrative areas were calculated within the total eligible area of the corresponding unit. Minor differences from 100% reflect rounding.

Table 3 shows that moderate suitability represented the largest regional class, followed by high, marginal, very high, and unsuitable land. Central Municipality contained the greatest proportional concentration of very high suitability, while the Northern Growth Zone also recorded substantial high and very high coverage. Eastern Riverine and Southern Coastal zones contained the largest proportions of unsuitable and marginal land, reflecting their stronger hydrological and coastal constraints. Western Peri-Urban Zone displayed a favorable balance of moderate, high, and very high land. The Outer Rural Region contained the largest eligible area, although its suitability was concentrated mainly within the moderate category overall. Global spatial analysis produced a Moran's (I) of .624, with a standardized (z)-score of 38.71 and ( $p < .001$ ), demonstrating strong positive spatial concentration in baseline suitability. Local indicators of spatial association classified 18.70% of eligible cells as statistically significant high-high clusters and 15.40% as low-low clusters. High-low and low-high spatial outliers represented 2.80% and 3.10%, respectively, while 60.00% showed no significant local association. High-high clusters were concentrated within Central Municipality, the Northern Growth Zone, and the western peri-urban corridor. Low-low clusters occurred primarily in the Eastern Riverine and Southern Coastal zones, where flood, coastal, ecological, and infrastructure constraints overlapped. Getis-Ord analysis identified statistically significant suitability hotspots across 22.80% of eligible land. Hotspots significant at the 99%, 95%, and 90% confidence levels represented 12.60%, 6.80%, and 3.40% of eligible cells, respectively. Cold spots covered 18.80% of eligible land, including 9.70% at the 99% level, 6.10% at the 95% level, and 3.00% at the 90% level. The remaining 58.40% was not classified as a significant hotspot or cold spot. The baseline map showed that high-suitability concentrations corresponded with stable terrain, lower flood exposure, shorter travel times, and stronger infrastructure capacity, while cold spots corresponded with riverine floodplains, coastal exposure, ecological sensitivity, and elevated development constraints.

#### **Primary Effects of Climate-Risk Integration and Multi-Objective Land Optimization**

The three model configurations produced statistically significant and operationally meaningful differences across the primary planning outcomes. The conventional baseline produced a mean suitability score of .583 and classified 130,815 hectares as developable. Climate-risk integration reduced the developable area to 112,460 hectares because 18,355 hectares failed one or more climatic, ecological, or safety thresholds. The mean suitability of the retained land increased to .641 because locations with substantial hazard exposure were removed or downgraded. Full multi-objective optimization retained 109,740 hectares, exceeding the predefined minimum development-capacity requirement of 108,000 hectares by 1,740 hectares. The optimized configuration achieved the highest mean suitability score at .724 and increased highly or very highly suitable land from 51,180 hectares under the baseline to 68,740 hectares. Population exposure declined substantially across the configurations. The conventional baseline located 428,600 residents and 146 critical infrastructure facilities within high-risk development areas. Climate-risk integration reduced these values to 272,400 residents and 89 facilities, representing respective reductions of 36.44% and 39.04%. Full optimization reduced exposure to 168,900 residents and 42 critical facilities, equivalent to reductions of 60.59% and 71.23% relative to baseline. Climate-exposed land declined from 36,840 to 21,470 hectares after climate integration and to 11,680 hectares after optimization. Expected annual hazard loss decreased from USD 186.4 million to USD 121.7 million and then to USD 72.9 million. The climate-integrated model slightly increased infrastructure-extension costs from USD 742.5 million to USD 778.2 million because development priorities shifted away from serviced but hazard-exposed locations. Optimization reduced the estimated cost to USD 624.8 million by selecting safer land with stronger network connectivity and existing service capacity. Mean network travel time declined from 24.8 to 18.1 minutes, while the number of fragmented development patches decreased from 318 to 174. Spatial compactness increased from .46 to .72, service coverage increased from 68.4% to 88.7%, ecological retention increased from 71.8% to 91.6%, and constraint satisfaction increased from 82.1% to 99.2%.

Table 4 demonstrates that climate-risk integration substantially reduced exposed population, critical-infrastructure exposure, climate-exposed land, and expected annual hazard loss, although it slightly increased infrastructure-extension cost. Full optimization produced the strongest overall performance by combining further risk reduction with shorter travel time, lower infrastructure cost, greater compactness, broader service coverage, stronger ecological retention, and near-complete constraint

satisfaction. Highly suitable land increased by 34.31% relative to baseline, while expected hazard loss decreased by 60.89%. All overall configuration tests were statistically significant, and optimized-versus-baseline effect sizes ranged from moderate to very large, confirming that the observed differences were operationally substantial across planning units. Holm-adjusted comparisons confirmed that the optimized configuration differed significantly from both the baseline and climate-integrated configurations across all primary outcomes, with adjusted ( $p < .001$ ), except for the difference in total developable area between the climate-integrated and optimized models, which remained significant at ( $p = .041$ ). Climate integration significantly increased mean suitability, ecological retention, and constraint satisfaction while reducing exposure and hazard loss. Its increase in infrastructure-extension cost was also statistically significant, adjusted ( $p = .008$ ). The reduction in network travel time between the baseline and climate-integrated models was comparatively small but remained detectable, adjusted ( $p = .032$ ). The suitability-class distributions differed significantly across the three configurations, ( $\chi^2(8) = 214.683.50$ ), ( $p < .001$ ), Cramér's ( $V = .24$ ). Under full optimization, the selected 109,740 hectares consisted of 8,900 hectares of marginal land, 32,100 hectares of moderate land, 42,700 hectares of high-suitability land, and 26,040 hectares of very-high-suitability land. No unsuitable or legally restricted land was selected. The optimized model therefore concentrated 62.64% of its allocated area within the two highest suitability classes, compared with 39.12% under the conventional baseline.

**Table 4 Configuration-Specific Outcomes, Adjusted Differences, Percentage Changes, Confidence Intervals, and Effect Sizes**

| Outcome                                             | Conventional baseline | Climate-integrated | Fully optimized | Climate minus baseline, $\Delta$ (%) | Optimized minus baseline, $\Delta$ (%) [95% CI] | Overall test                            | Optimized-baseline effect |
|-----------------------------------------------------|-----------------------|--------------------|-----------------|--------------------------------------|-------------------------------------------------|-----------------------------------------|---------------------------|
| <b>Mean suitability score</b>                       | .583                  | .641               | .724            | +0.058<br>(+9.95%)                   | +0.141<br>(+24.19%)<br>[.126, .156]             | ( $F(2,46) = 82.64$ ,<br>$p < .001$ )   | ( $d = 1.34$ )            |
| <b>Total developable area (ha)</b>                  | 130,815               | 112,460            | 109,740         | -18,355<br>(-14.03%)                 | -21,075<br>(-16.11%)<br>[-23,680, -18,470]      | ( $F(2,46) = 45.18$ ,<br>$p < .001$ )   | ( $d = -1.05$ )           |
| <b>High or very-high land (ha)</b>                  | 51,180                | 46,320             | 68,740          | -4,860<br>(-9.50%)                   | +17,560<br>(+34.31%)<br>[14,880, 20,240]        | ( $F(2,46) = 71.26$ ,<br>$p < .001$ )   | ( $d = 1.21$ )            |
| <b>Exposed population</b>                           | 428,600               | 272,400            | 168,900         | -156,200<br>(-36.44%)                | -259,700<br>(-60.59%)<br>[-282,400, -237,000]   | ( $\chi^2(2) = 42.17$ ,<br>$p < .001$ ) | ( $r = .89$ )             |
| <b>Exposed critical facilities</b>                  | 146                   | 89                 | 42              | -57<br>(-39.04%)                     | -104<br>(-71.23%)<br>[-116, -92]                | ( $\chi^2(2) = 40.86$ ,<br>$p < .001$ ) | ( $r = .86$ )             |
| <b>Climate-exposed land (ha)</b>                    | 36,840                | 21,470             | 11,680          | -15,370<br>(-41.72%)                 | -25,160<br>(-68.30%)<br>[-27,640, -22,680]      | ( $F(2,46) = 103.48$ ,<br>$p < .001$ )  | ( $d = -1.51$ )           |
| <b>Expected annual hazard loss (USD millions)</b>   | 186.4                 | 121.7              | 72.9            | -64.7<br>(-34.71%)                   | -113.5<br>(-60.89%)<br>[-125.4, -101.6]         | ( $F(2,46) = 115.32$ ,<br>$p < .001$ )  | ( $d = -1.57$ )           |
| <b>Mean network travel time (minutes)</b>           | 24.8                  | 23.6               | 18.1            | -1.2<br>(-4.84%)                     | -6.7<br>(-27.02%)<br>[-7.8, -5.6]               | ( $F(2,46) = 68.45$ ,<br>$p < .001$ )   | ( $d = -1.19$ )           |
| <b>Infrastructure-extension cost (USD millions)</b> | 742.5                 | 778.2              | 624.8           | +35.7<br>(+4.81%)                    | -117.7<br>(-15.85%)<br>[-146.2, -89.2]          | ( $F(2,46) = 29.76$ ,<br>$p < .001$ )   | ( $d = -.96$ )            |
| <b>Fragmented</b>                                   | 318                   | 286                | 174             | -32                                  | -144                                            | ( $F(2,46) = 60.11$ ,<br>$p < .001$ )   | ( $d = -1.27$ )           |

|                             |      |      |      |                    |                                    |                                  |          |
|-----------------------------|------|------|------|--------------------|------------------------------------|----------------------------------|----------|
| development patches         |      |      |      | (−10.06%)          | (−45.28%)<br>[−166, −122]          | p<.001)                          |          |
| Spatial compactness (0–1)   | .46  | .51  | .72  | +0.05<br>(+10.87%) | +0.26<br>(+56.52%)<br>[.22, .30]   | (F(2,46)=91.22,<br>p<.001)       | (d=1.42) |
| Service coverage (%)        | 68.4 | 72.6 | 88.7 | +4.2<br>(+6.14%)   | +20.3<br>(+29.68%)<br>[17.6, 23.0] | (F(2,46)=74.61,<br>p<.001)       | (d=1.31) |
| Ecological retention (%)    | 71.8 | 84.3 | 91.6 | +12.5<br>(+17.41%) | +19.8<br>(+27.58%)<br>[17.0, 22.6] | (F(2,46)=86.05,<br>p<.001)       | (d=1.44) |
| Constraint satisfaction (%) | 82.1 | 94.4 | 99.2 | +12.3<br>(+14.98%) | +17.1<br>(+20.83%)<br>[15.4, 18.8] | ( $\chi^2(2)=39.84$ ,<br>p<.001) | (r=.93)  |

**Table 5 Baseline-to-Climate-Integrated Class Transitions and Dominant Causes of Restriction**

| Component                | Baseline class or dominant restriction cause | Unsuitable (ha) | Marginal (ha) | Moderate (ha) | High (ha)     | Very high (ha) | Restricted (ha) | Row total (ha) |
|--------------------------|----------------------------------------------|-----------------|---------------|---------------|---------------|----------------|-----------------|----------------|
| Class transition         | Baseline unsuitable                          | 7,500           | 1,000         | 300           | 0             | 0              | 2,075           | 10,875         |
| Class transition         | Baseline marginal                            | 3,000           | 14,000        | 4,000         | 500           | 0              | 3,070           | 24,570         |
| Class transition         | Baseline moderate                            | 1,500           | 5,500         | 22,000        | 8,000         | 500            | 6,690           | 44,190         |
| Class transition         | Baseline high                                | 300             | 1,200         | 5,000         | 17,000        | 4,000          | 5,260           | 32,760         |
| Class transition         | Baseline very high                           | 0               | 140           | 700           | 3,900         | 12,420         | 1,260           | 18,420         |
| Climate-integrated total | <b>Final classification</b>                  | <b>12,300</b>   | <b>21,840</b> | <b>32,000</b> | <b>29,400</b> | <b>16,920</b>  | <b>18,355</b>   | <b>130,815</b> |
| Restriction cause        | Flood exposure                               | —               | —             | —             | —             | —              | 6,420           | 6,420          |
| Restriction cause        | Heat exposure                                | —               | —             | —             | —             | —              | 2,730           | 2,730          |
| Restriction cause        | Storm or coastal exposure                    | —               | —             | —             | —             | —              | 2,460           | 2,460          |
| Restriction cause        | Ecological sensitivity                       | —               | —             | —             | —             | —              | 2,210           | 2,210          |
| Restriction cause        | Landslide or terrain instability             | —               | —             | —             | —             | —              | 1,580           | 1,580          |
| Restriction cause        | Drought or water stress                      | —               | —             | —             | —             | —              | 1,220           | 1,220          |
| Restriction cause        | Wildfire exposure                            | —               | —             | —             | —             | —              | 780             | 780            |
| Restriction cause        | Compound hazards                             | —               | —             | —             | —             | —              | 955             | 955            |
| Restriction total        | <b>All dominant causes</b>                   | —               | —             | —             | —             | —              | <b>18,355</b>   | <b>18,355</b>  |

*Note.* Row percentages were omitted to preserve readability. Restriction causes were assigned through a mutually exclusive dominant-cause hierarchy after considering compound exposure. The climate-integrated developable area equaled 112,460 hectares after the restricted category was removed.

Table 5 shows that climate-risk integration reclassified 18,355 hectares as restricted and reduced developable land to 112,460 hectares. Flood exposure accounted for the largest restricted share,

followed by heat, storm or coastal risk, and ecological sensitivity. Among 51,180 hectares initially classified as high or very high, 13,860 hectares moved to lower or restricted categories. Most retained very-high land remained stable, while several baseline high-suitability locations shifted to moderate status. The transition structure reduced moderate-or-higher suitable land from 95,370 to 78,320 hectares. These movements demonstrate that conventional suitability ratings had overstated development potential in several climate-exposed and environmentally sensitive locations regionally. The paired binary classification analysis identified 21,850 hectares that moved from moderate-or-higher suitability to unsuitable, marginal, or restricted status, compared with 4,800 hectares that moved in the opposite direction. McNemar's test confirmed a significant change in suitable-unsuitable status, ( $\chi^2(1)=121.0$ ,  $p<.001$ ). Flood exposure accounted for 6,420 hectares or 34.98% of all newly restricted land. Heat exposure represented 14.87%, storm or coastal risk represented 13.40%, ecological sensitivity represented 12.04%, and landslide or terrain instability represented 8.61%. Drought, wildfire, and compound hazards accounted for the remaining 16.10%. Adjusted logistic regression showed that infrastructure capacity was the strongest positive predictor of verified low-risk development, odds ratio ( $=1.62$ ), 95% CI [ $1.39, 1.90$ ], ( $p<.001$ ). Physical suitability, odds ratio ( $=1.46$ ), 95% CI [ $1.25, 1.70$ ], and environmental compatibility, odds ratio ( $=1.38$ ), 95% CI [ $1.18, 1.61$ ], were also positively associated with verified low-risk status. Climate risk produced the strongest negative relationship, odds ratio ( $=.44$ ), 95% CI [ $.35, .55$ ], followed by socioeconomic vulnerability, odds ratio ( $=.71$ ), 95% CI [ $.60, .84$ ], network travel time, odds ratio ( $=.72$ ), 95% CI [ $.61, .85$ ], and development cost, odds ratio ( $=.81$ ), 95% CI [ $.70, .94$ ]. The regression model explained 64% of adjusted outcome variation, achieved an area under the curve of .89, and correctly classified 82.6% of the independent validation observations. The Hosmer-Lemeshow test was nonsignificant, ( $\chi^2(8)=7.91$ ), ( $p=.442$ ), indicating acceptable calibration.

#### **Secondary Administrative, Hazard, Accessibility, Equity, and Resolution-Based Analyses**

Secondary analyses identified statistically significant differences in optimized suitability and land allocation across settlement and environmental strata. Peri-urban areas recorded the highest mean optimized suitability score at .781, followed by urban areas at .742 and rural areas at .718. Coastal or riverine, hazard-prone, and environmentally sensitive zones recorded lower mean scores of .620, .590, and .575, respectively. Rural areas received the largest absolute optimized allocation at 38,450 hectares, while peri-urban areas received 32,880 hectares and urban areas received 21,760 hectares. Environmentally sensitive areas retained only 3,240 hectares, equivalent to 24.58% of their total area. A mixed-effects comparison across 24 planning subunits confirmed significant settlement-type differences, ( $F(5,118)=36.72$ ), ( $p<.001$ ), partial ( $\eta^2=.609$ ). Relative to urban areas, peri-urban suitability was higher by .039, 95% CI [ $.022, .056$ ], whereas coastal, environmentally sensitive, and hazard-prone zones were lower by .122, .167, and .152, respectively. Administrative ranking placed the Western Peri-Urban Zone first with a composite planning-performance index of .812, followed by Central Municipality at .798 and the Northern Growth Zone at .779. The Outer Rural Region ranked fourth at .723, while the Eastern Riverine and Southern Coastal zones ranked fifth and sixth at .638 and .596. Western Peri-Urban Zone combined a mean suitability score of .779 with 90.8% population coverage, a mean travel time of 17.0 minutes, 91.4% ecological retention, and an infrastructure-extension cost of USD 54,800 per optimized hectare. Southern Coastal Zone recorded the highest climate exposure, longest administrative-level travel time, and greatest infrastructure cost. Hazard-specific analysis showed that flood-dominated locations experienced the largest proportional reclassification. Of 27,600 flood-dominated hectares, 6,420 hectares or 23.26% were reassigned to restricted status. Coastal or storm-dominated locations recorded a 15.57% reclassification rate, followed by heat-dominated areas at 10.96%, multi-hazard areas at 9.68%, drought-affected areas at 6.67%, and wildfire-prone areas at 5.89%. Differences among hazard groups were significant, ( $\chi^2(5)=52.84$ ), ( $p<.001$ ), Cramér's ( $V=.19$ ). Holm-adjusted comparisons showed that flood-related reclassification exceeded every other hazard group, while coastal reclassification exceeded drought and wildfire reclassification.

Table 6 shows that peri-urban areas achieved the highest mean suitability, while environmentally sensitive and hazard-prone zones recorded the lowest values. Rural areas retained the largest optimized allocation, but Central Municipality and the Western Peri-Urban Zone achieved stronger

accessibility and development-capacity performance. Southern Coastal and Eastern Riverine areas ranked lowest because climate exposure, travel time, and infrastructure costs remained comparatively high. Flood-dominated land experienced the largest proportional reclassification, followed by coastal and heat-dominated locations. Adjusted differences and effect sizes confirmed that settlement type and dominant hazard category produced variation in optimized suitability and retained development capacity across the study region. Equity analysis showed that optimization reduced population-weighted climate exposure in both vulnerability groups. Exposure declined from 28.4% to 12.6% in low-vulnerability areas and from 61.2% to 24.3% in high-vulnerability areas. The proportional climate-protection benefit was 55.6% for low-vulnerability areas and 60.3% for high-vulnerability areas. High-vulnerability locations nevertheless retained an adjusted residual-exposure excess of 11.7 percentage points, 95% CI [9.3, 14.1], ( $d=.92$ ).

**Table 6 Settlement, Administrative, and Hazard-Specific Suitability and Optimization Outcomes**

| Analysis domain            | Area group                | or | Mean optimized suitability | Reference area (ha) | Optimized or reclassified area, ha (%) | Climate exposure (%) | Population coverage (%) | Travel time (minutes) | Infrastructure cost (USD thousands /ha) | Ecological retention (%) | Adjusted comparison, effect, or rank                 |
|----------------------------|---------------------------|----|----------------------------|---------------------|----------------------------------------|----------------------|-------------------------|-----------------------|-----------------------------------------|--------------------------|------------------------------------------------------|
| <b>Settlement type</b>     | Urban                     |    | .742                       | 31,240              | 21,760 (69.65)                         | 18.4                 | 93.6                    | 11.6                  | 48.2                                    | 80.4                     | Reference                                            |
| <b>Settlement type</b>     | Peri-urban                |    | .781                       | 46,870              | 32,880 (70.15)                         | 14.2                 | 91.4                    | 16.9                  | 55.7                                    | 88.7                     | $\Delta = .039$<br>[.022, .056],<br>( $d=.34$ )      |
| <b>Settlement type</b>     | Rural                     |    | .718                       | 59,610              | 38,450 (64.50)                         | 20.7                 | 82.7                    | 26.4                  | 71.3                                    | 93.2                     | $\Delta = -.024$<br>[-.041, -.007],<br>( $d=-.21$ )  |
| <b>Settlement type</b>     | Coastal or riverine       |    | .620                       | 22,460              | 7,620 (33.93)                          | 52.8                 | 68.5                    | 31.8                  | 96.8                                    | 95.6                     | $\Delta = -.122$<br>[-.145, -.099],<br>( $d=-.88$ )  |
| <b>Settlement type</b>     | Environmentally sensitive |    | .575                       | 13,180              | 3,240 (24.58)                          | 31.4                 | 62.8                    | 35.2                  | 108.4                                   | 97.4                     | $\Delta = -.167$<br>[-.193, -.141],<br>( $d=-1.11$ ) |
| <b>Settlement type</b>     | Hazard-prone              |    | .590                       | 10,900              | 5,790 (53.12)                          | 60.2                 | 64.3                    | 38.6                  | 102.7                                   | 92.1                     | $\Delta = -.152$<br>[-.176, -.128],<br>( $d=-1.04$ ) |
| <b>Administrative unit</b> | Central Municipality      |    | .768                       | 18,600              | 17,200 (92.47)                         | 9.8                  | 95.4                    | 10.8                  | 52.4                                    | 84.6                     | Rank 2; index = .798                                 |
| <b>Administrative unit</b> | Northern Growth Zone      |    | .751                       | 22,350              | 19,850 (88.81)                         | 12.5                 | 92.7                    | 15.2                  | 58.9                                    | 89.7                     | Rank 3; index = .779                                 |
| <b>Administrative unit</b> | Eastern Riverine Zone     |    | .652                       | 19,475              | 14,100 (72.40)                         | 31.8                 | 74.2                    | 27.9                  | 86.7                                    | 94.2                     | Rank 5; index = .638                                 |
| <b>Administrative unit</b> | Southern Coastal Zone     |    | .619                       | 17,890              | 11,240 (62.83)                         | 43.7                 | 68.5                    | 31.8                  | 98.2                                    | 96.1                     | Rank 6; index = .596                                 |
| <b>Administrative unit</b> | Western Peri-Urban Zone   |    | .779                       | 24,700              | 22,550 (91.30)                         | 10.9                 | 90.8                    | 17.0                  | 54.8                                    | 91.4                     | Rank 1; index = .812                                 |
| <b>Administrative unit</b> | Outer Rural Region        |    | .713                       | 27,800              | 24,800 (89.21)                         | 18.6                 | 81.6                    | 26.6                  | 72.6                                    | 93.0                     | Rank 4; index = .723                                 |
| <b>Hazard category</b>     | Flood-dominated           |    | .548                       | 27,600              | 6,420 (23.26)                          | —                    | —                       | —                     | —                                       | —                        | Reclassification RR =                                |

|                        |                            |      |        |                  |   |   |   |   |   |                                                 |
|------------------------|----------------------------|------|--------|------------------|---|---|---|---|---|-------------------------------------------------|
| <b>Hazard category</b> | Heat-dominated             | .611 | 24,900 | 2,730<br>(10.96) | — | — | — | — | — | 3.49<br>Reclassification RR = 1.64<br>Reference |
| <b>Hazard category</b> | Drought-affected           | .652 | 18,300 | 1,220<br>(6.67)  | — | — | — | — | — |                                                 |
| <b>Hazard category</b> | Wildfire-prone             | .638 | 13,250 | 780<br>(5.89)    | — | — | — | — | — | Reclassification RR = .88                       |
| <b>Hazard category</b> | Coastal or storm-dominated | .526 | 15,800 | 2,460<br>(15.57) | — | — | — | — | — | Reclassification RR = 2.34                      |
| <b>Hazard category</b> | Multi-hazard               | .492 | 9,870  | 955<br>(9.68)    | — | — | — | — | — | Reclassification RR = 1.45                      |

*Note.* Settlement categories describe broad planning strata, whereas administrative units represent governance areas; their areas therefore should not be added together. Hazard groups were assigned through the dominant-hazard classification. Administrative rankings combined suitable land, climate exposure, population coverage, accessibility, infrastructure cost, ecological retention, and optimized capacity. RR = risk ratio relative to drought-affected locations.

Their mean emergency travel time remained 11.1 minutes longer, infrastructure coverage remained 16.3 percentage points lower, and affordability pressure remained .22 points higher. A significant configuration-by-vulnerability interaction was detected for population-weighted exposure, ( $F(2,46)=10.84$ ), ( $p<.001$ ), partial ( $\eta^2=.320$ ). Accessibility analysis classified 46,850 optimized hectares within the high-access group, defined by network travel times of 15 minutes or less. Moderate-access locations received 39,440 hectares, while low-access locations received 23,450 hectares. Mean suitability declined from .781 in the high-access group to .612 in the low-access group. Service coverage declined from 96.2% to 71.4%, while mean emergency travel time increased from 10.4 to 41.6 minutes. Differences across accessibility categories were significant, ( $F(2,71)=58.16$ ), ( $p<.001$ ), partial ( $\eta^2=.621$ ). Infrastructure analysis showed that well-served locations received 47,200 optimized hectares and achieved a mean suitability score of .792. Moderately served locations received 44,620 hectares, while locations requiring major extensions received 17,920 hectares. Infrastructure-extension costs increased from USD 36,800 per hectare in well-served areas to USD 123,400 per hectare in major-extension areas. The difference in suitability across infrastructure groups was significant, ( $F(2,71)=63.74$ ), ( $p<.001$ ), partial ( $\eta^2=.642$ ).

**Table 7 Equity, Accessibility, Infrastructure, Resolution, and Weighting Sensitivity Results**

| Analysis             | Group or model     | Mean suitability | Optimized or developable area (ha) | Exposure or reclassification area | Service, infrastructure, or boundary agreement (%) | Travel time or positional error | Cost, processing time, or affordability | Rank correlation with 30-m hybrid model | Adjusted comparison or effect                         |
|----------------------|--------------------|------------------|------------------------------------|-----------------------------------|----------------------------------------------------|---------------------------------|-----------------------------------------|-----------------------------------------|-------------------------------------------------------|
| <b>Vulnerability</b> | Low vulnerability  | .756             | 52,840                             | 28.4%<br>→<br>12.6%               | Infrastructure coverage = 93.2%                    | Emergency time = 12.7 min       | Affordability pressure = .45            | —                                       | Exposure reduction = 55.6%                            |
| <b>Vulnerability</b> | High vulnerability | .654             | 26,900                             | 61.2%<br>→<br>24.3%               | Infrastructure coverage = 76.9%                    | Emergency time = 23.8 min       | Affordability pressure = .67            | —                                       | Residual exposure $\Delta$ = 11.7 points, ( $d=.92$ ) |
| <b>Accessibility</b> | High               | .781             | 46,850                             | Expose                            | Service                                            | 10.4                            | —                                       | —                                       | Reference                                             |

|                            |                                              |      |         |                                          |                                            |                                     |                                 |      |                                   |
|----------------------------|----------------------------------------------|------|---------|------------------------------------------|--------------------------------------------|-------------------------------------|---------------------------------|------|-----------------------------------|
| <b>lity</b>                | access:<br>≤15<br>minutes                    |      |         | d<br>populat<br>ion =<br>8.9%            | coverage<br>= 96.2%                        | min                                 |                                 |      | e                                 |
| <b>Accessibi<br/>lity</b>  | Moderat<br>e access:<br>15–30<br>minutes     | .731 | 39,440  | Expose<br>d<br>populat<br>ion =<br>14.8% | Service<br>coverage<br>= 89.1%             | 22.3<br>min                         | —                               | —    | $\Delta$ =<br>-.050,<br>(d=-.43)  |
| <b>Accessibi<br/>lity</b>  | Low<br>access:<br>>30<br>minutes             | .612 | 23,450  | Expose<br>d<br>populat<br>ion =<br>26.7% | Service<br>coverage<br>= 71.4%             | 41.6<br>min                         | —                               | —    | $\Delta$ =<br>-.169,<br>(d=-1.18) |
| <b>Infrastru<br/>cture</b> | Well<br>served:<br>score ≥70                 | .792 | 47,200  | Climate<br>exposur<br>e = 9.6%           | Infrastruc<br>ture<br>coverage<br>= 98.4%  | 13.8<br>min                         | USD 36.8<br>thousan<br>d/ha     | —    | Referenc<br>e                     |
| <b>Infrastru<br/>cture</b> | Moderat<br>ely<br>served:<br>score 40–<br>69 | .718 | 44,620  | Climate<br>exposur<br>e =<br>17.5%       | Infrastruc<br>ture<br>coverage<br>= 90.6%  | 23.6<br>min                         | USD 68.5<br>thousan<br>d/ha     | —    | $\Delta$ =<br>-.074,<br>(d=-.61)  |
| <b>Infrastru<br/>cture</b> | Major<br>extensio<br>n: score<br><40         | .593 | 17,920  | Climate<br>exposur<br>e =<br>29.8%       | Infrastruc<br>ture<br>coverage<br>= 69.8%  | 39.7<br>min                         | USD<br>123.4<br>thousan<br>d/ha | —    | $\Delta$ =<br>-.199,<br>(d=-1.31) |
| <b>Resolutio<br/>n</b>     | 30-meter<br>cells                            | .724 | 109,740 | 18,355<br>ha<br>reclassif<br>ied         | Reference<br>agreement<br>= 100.0%         | Positio<br>nal<br>error =<br>4.6 m  | Processi<br>ng time =<br>3.2 hr | 1.00 | Referenc<br>e                     |
| <b>Resolutio<br/>n</b>     | 100-<br>meter<br>cells                       | .701 | 115,630 | 15,480<br>ha<br>reclassif<br>ied         | Class<br>agreement<br>= 78.8%              | Positio<br>nal<br>error =<br>16.8 m | Processi<br>ng time =<br>0.7 hr | .86  | (\kappa<br>=.72)                  |
| <b>Weightin<br/>g</b>      | Expert<br>weights                            | .719 | 109,740 | High/v<br>ery-<br>high =<br>69,480<br>ha | Constrain<br>t<br>satisfactio<br>n = 98.8% | —                                   | —                               | .91  | Priority<br>overlap<br>= 87.4%    |
| <b>Weightin<br/>g</b>      | Entropy<br>weights                           | .716 | 109,740 | High/v<br>ery-<br>high =<br>67,920<br>ha | Constrain<br>t<br>satisfactio<br>n = 98.3% | —                                   | —                               | .84  | Priority<br>overlap<br>= 82.6%    |
| <b>Weightin<br/>g</b>      | CRITIC<br>weights                            | .721 | 109,740 | High/v<br>ery-<br>high =<br>68,360<br>ha | Constrain<br>t<br>satisfactio<br>n = 98.6% | —                                   | —                               | .89  | Priority<br>overlap<br>= 85.7%    |
| <b>Weightin<br/>g</b>      | Hybrid<br>weights                            | .724 | 109,740 | High/v<br>ery-<br>high =<br>68,740<br>ha | Constrain<br>t<br>satisfactio<br>n = 99.2% | —                                   | —                               | 1.00 | Referenc<br>e                     |

Note. Exposure values for vulnerability groups show baseline-to-optimized percentages. Priority overlap represents agreement in the highest-ranked 10% of locations relative to the hybrid model.

Resolution agreement was evaluated against the 30-meter classification. Optimized areas across accessibility and infrastructure categories sum to 109,740 hectares.

Table 7 demonstrates equity differences after optimization, although exposure and service deficits declined in both vulnerability groups. High-vulnerability areas received the larger proportional climate-protection benefit but retained longer emergency travel times, lower infrastructure coverage, and stronger affordability pressure. Highly accessible and well-served locations achieved the highest suitability scores and largest optimized allocations. Resolution testing showed close agreement between 10- and 30-meter results, whereas the 100-meter model understated hazard reclassification and reduced boundary precision. Alternative weighting methods produced correlated rankings and similar highly suitable areas. The hybrid model achieved the highest constraint satisfaction and the most balanced performance across evaluation criteria. Resolution-based analysis showed that the 10-meter model identified 885 additional hectares of climate-related restriction relative to the 30-meter model and produced 92.6% class agreement with the primary classification. The 100-meter model identified 2,875 fewer restricted hectares than the 30-meter model, representing a 15.66% reduction in hazard detection. Its positional error increased to 16.8 meters, and class agreement declined to 78.8%. Differences in suitability distributions across resolutions were statistically significant, ( $\chi^2(8)=1,286.40$ ), ( $p<.001$ ), although agreement between the 10- and 30-meter models remained strong. Alternative weighting procedures produced closely related location rankings. Spearman correlations with the hybrid ranking were .91 for expert weights, .84 for entropy weights, and .89 for CRITIC weights. Highly or very highly suitable land ranged from 67,920 hectares under entropy weighting to 69,480 hectares under expert weighting. The overlap among the highest-ranked 10% of locations ranged from 82.6% to 87.4%. Suitability-class distributions differed statistically across weighting methods, ( $\chi^2(12)=214.80$ ), ( $p<.001$ ), but the associated effect was small, Cramér's ( $V=.018$ ). The hybrid model recorded the highest mean suitability and constraint-satisfaction rate.

#### **Statistical Significance, Effect Magnitudes, Validation, Robustness, Tables, and Figures**

All primary hypotheses were evaluated using two-tailed tests at ( $p<.05$ ), with Holm-adjusted probability values applied to configuration-specific comparisons. The omnibus tests identified significant differences among the conventional baseline, climate-integrated, and fully optimized configurations across every principal outcome. Partial eta squared values ranged from .564 for infrastructure-extension cost to .834 for expected annual hazard loss, indicating that the selected model configuration accounted for substantial variation in planning performance. The strongest optimized-versus-baseline standardized effects occurred for expected annual hazard loss, ( $d=-1.57$ ), climate-exposed land, ( $d=-1.51$ ), ecological retention, ( $d=1.44$ ), spatial compactness, ( $d=1.42$ ), and mean suitability, ( $d=1.34$ ). Service coverage, fragmentation, highly suitable land, and network travel time also produced large effects. Infrastructure cost produced a comparatively smaller but operationally meaningful effect of ( $d=-.96$ ). The categorical suitability distribution differed significantly across the three configurations, ( $\chi^2(8)=214,683.50$ ), ( $p<.001$ ), Cramér's ( $V=.24$ ). Binary suitable-unsuitable status also changed significantly after climate-risk integration, McNemar ( $\chi^2(1)=121,210.80$ ), ( $p<.001$ ). Rank-based effect measures confirmed substantial reductions in exposed population, exposed critical facilities, and unsatisfied planning constraints. All optimized-versus-baseline confidence intervals excluded zero, and all Holm-adjusted probability values remained below .001. Adjusted logistic regression identified infrastructure capacity as the strongest positive predictor of verified low-risk development, odds ratio ( $=1.62$ ), 95% CI [1.39, 1.90]. A one-standard-deviation increase in infrastructure capacity increased the adjusted probability of verified low-risk development by 9.2 percentage points. Physical suitability and environmental compatibility increased the adjusted probability by 6.8 and 5.4 percentage points, respectively. Climate risk produced the strongest negative association, odds ratio ( $=.44$ ), 95% CI [.35, .55], corresponding to a 14.7-percentage-point reduction in predicted low-risk development. Socioeconomic vulnerability, network travel time, and development cost also retained significant negative relationships after controlling for settlement type, administrative area, and baseline land class.

**Table 8 Statistical Significance, Adjusted Differences, Confidence Intervals, Effect Magnitudes, and Regression Results**

| Outcome predictor                     | or | Statistical test                   | Adjusted estimate             | 95% CI               | Holm-adjusted (p) | Effect measure                 | Magnitude         |
|---------------------------------------|----|------------------------------------|-------------------------------|----------------------|-------------------|--------------------------------|-------------------|
| <b>Mean suitability score</b>         |    | (F(2,46)=82.64)                    | $\Delta = .141$               | [.126, .156]         | <.001             | (d=1.34); ( $\eta_p^2=.782$ )  | Very large        |
| <b>Total developable area</b>         |    | (F(2,46)=45.18)                    | $\Delta = -21,075$ ha         | [-23,680, -18,470]   | <.001             | (d=-1.05); ( $\eta_p^2=.663$ ) | Large             |
| <b>High or very-high land</b>         |    | (F(2,46)=71.26)                    | $\Delta = 17,560$ ha          | [14,880, 20,240]     | <.001             | (d=1.21); ( $\eta_p^2=.756$ )  | Very large        |
| <b>Exposed population</b>             |    | Friedman ( $\chi^2(2)=42.17$ )     | $\Delta = -259,700$           | [-282,400, -237,000] | <.001             | ( $r_=.89$ ); (W=.879)         | Very large        |
| <b>Exposed critical facilities</b>    |    | Friedman ( $\chi^2(2)=40.86$ )     | $\Delta = -104$               | [-116, -92]          | <.001             | ( $r_=.86$ ); (W=.851)         | Very large        |
| <b>Climate-exposed land</b>           |    | (F(2,46)=103.48)                   | $\Delta = -25,160$ ha         | [-27,640, -22,680]   | <.001             | (d=-1.51); ( $\eta_p^2=.818$ ) | Very large        |
| <b>Expected annual hazard loss</b>    |    | (F(2,46)=115.32)                   | $\Delta = -USD 113.5$ million | [-125.4, -101.6]     | <.001             | (d=-1.57); ( $\eta_p^2=.834$ ) | Very large        |
| <b>Network travel time</b>            |    | (F(2,46)=68.45)                    | $\Delta = -6.7$ minutes       | [-7.8, -5.6]         | <.001             | (d=-1.19); ( $\eta_p^2=.748$ ) | Very large        |
| <b>Infrastructure-extension cost</b>  |    | (F(2,46)=29.76)                    | $\Delta = -USD 117.7$ million | [-146.2, -89.2]      | <.001             | (d=-.96); ( $\eta_p^2=.564$ )  | Large             |
| <b>Fragmented development patches</b> |    | (F(2,46)=60.11)                    | $\Delta = -144$ patches       | [-166, -122]         | <.001             | (d=-1.27); ( $\eta_p^2=.723$ ) | Very large        |
| <b>Spatial compactness</b>            |    | (F(2,46)=91.22)                    | $\Delta = .260$               | [.220, .300]         | <.001             | (d=1.42); ( $\eta_p^2=.798$ )  | Very large        |
| <b>Service coverage</b>               |    | (F(2,46)=74.61)                    | $\Delta = 20.3$ points        | [17.6, 23.0]         | <.001             | (d=1.31); ( $\eta_p^2=.764$ )  | Very large        |
| <b>Ecological retention</b>           |    | (F(2,46)=86.05)                    | $\Delta = 19.8$ points        | [17.0, 22.6]         | <.001             | (d=1.44); ( $\eta_p^2=.789$ )  | Very large        |
| <b>Constraint satisfaction</b>        |    | Friedman ( $\chi^2(2)=39.84$ )     | $\Delta = 17.1$ points        | [15.4, 18.8]         | <.001             | ( $r_=.93$ ); (W=.830)         | Very large        |
| <b>Suitability-class distribution</b> |    | ( $\chi^2(8)=214.683.50$ )         | Three-model difference        | —                    | <.001             | Cramér's (V=.24)               | Moderate          |
| <b>Suitable-unsuitable status</b>     |    | McNemar ( $\chi^2(1)=121.210.80$ ) | Net change = -17,050 ha       | —                    | <.001             | Matched change = 13.03%        | Substantia        |
| <b>Physical suitability</b>           |    | Logistic regression                | OR = 1.46; ME = +6.8          | [1.25, 1.70]         | <.001             | Standardized predictor         | Moderate positive |

|                                    |                     |                                        |       |                        |                   |
|------------------------------------|---------------------|----------------------------------------|-------|------------------------|-------------------|
| <b>Environmental compatibility</b> | Logistic regression | points<br>OR = [1.18, 1.38; ME = +5.4] | .002  | Standardized predictor | Moderate positive |
| <b>Climate risk</b>                | Logistic regression | points<br>OR = .44; ME = -14.7         | <.001 | Standardized predictor | Strong negative   |
| <b>Socioeconomic vulnerability</b> | Logistic regression | points<br>OR = .71; ME = -5.9          | .001  | Standardized predictor | Moderate negative |
| <b>Network travel time</b>         | Logistic regression | points<br>OR = .72; ME = -5.6          | <.001 | Standardized predictor | Moderate negative |
| <b>Infrastructure capacity</b>     | Logistic regression | points<br>OR = [1.39, 1.62; ME = +9.2] | <.001 | Standardized predictor | Strong positive   |
| <b>Development cost</b>            | Logistic regression | points<br>OR = .81; ME = -3.8          | .012  | Standardized predictor | Small negative    |

*Note.* Configuration-level differences compare the fully optimized model with the conventional baseline. ME = average marginal effect in percentage points; OR = odds ratio; (r) = rank-biserial correlation; (W) = Kendall's coefficient for the Friedman test; ( $\eta_p^2$ ) = partial eta squared.

Table 8 shows that every configuration-level test was statistically significant after Holm correction, with effect magnitudes ranging from moderate to very large. Expected hazard loss, climate-exposed land, ecological retention, compactness, suitability, and service coverage produced the strongest standardized effects. Changes in suitability-class distributions were also substantial, as indicated by Cramér's coefficient. Regression results identified infrastructure capacity, physical suitability, and environmental compatibility as positive predictors of verified low-risk development. Climate risk produced the strongest negative relationship, followed by socioeconomic vulnerability and network travel time. Confidence intervals excluded null values, demonstrating that the estimated effects were both precise and directionally consistent overall. Independent validation using 720 observations produced an ROC-AUC of .890, 95% CI [.865, .914]. At the optimized classification threshold of .57, the model correctly classified 595 observations, producing an accuracy of 82.6%. The confusion matrix contained 308 true-positive, 287 true-negative, 53 false-positive, and 72 false-negative classifications. Precision was .853, recall was .811, specificity was .844, and the F1 score was .831. Cohen's kappa was .653, indicating substantial agreement beyond chance. The training-sample success-rate AUC was .912, while the independent prediction-rate AUC was .890. The Brier score of .128, calibration intercept of .03, calibration slope of .96, and nonsignificant Hosmer-Lemeshow test, ( $\chi^2(8)=7.91$ ), ( $p=.442$ ), indicated acceptable probability calibration. Sensitivity analysis showed that expert, entropy, and CRITIC weighting produced Spearman rank correlations of .91, .84, and .89 with the hybrid model. Corresponding Kendall's tau coefficients ranged from .72 to .83. Altering regulatory thresholds by  $\pm 10\%$  changed developable area by  $-6.21\%$  to  $+6.77\%$ , while 86.9% of priority cells retained their status. Alternative normalization procedures changed mean suitability by no more than .012 and preserved 88.1% of priority locations. Severe climate conditions reduced developable area to 97,860 hectares and lowered priority-location persistence to 74.2%. Resolution testing confirmed stronger agreement between the 10- and 30-meter models than between the 30- and 100-meter models. The 10-meter analysis produced a kappa of .88 and a rank correlation of .94 with the primary model. The 100-meter analysis produced a kappa of .72 and a rank correlation of .86. Coarser aggregation identified 2,875 fewer restricted hectares than the 30-meter model and increased positional error from 4.6 to 16.8 meters. Monte Carlo analysis based on 10,000 simulations produced a mean optimized suitability score of .724

and a 95% uncertainty interval from .689 to .758. Among priority-development cells, 72.9% retained their classification in at least 90% of simulations, while another 11.8% remained stable in 80%–89% of simulations. Classification persistence was between 50% and 79% for 8.5% of priority cells and below 50% for 6.8%. Uncertainty was concentrated near suitability-class boundaries, river corridors, coastal transition zones, fragmented ecological areas, and locations with closely balanced accessibility and infrastructure costs. Optimization robustness was assessed through 50 independent algorithm runs. All runs converged without infeasible solutions. The mean objective value was .842 with a standard deviation of .006, producing a coefficient of variation of .71%. Mean constraint satisfaction was 99.2%, with a range from 98.7% to 99.6%. Pairwise allocation agreement averaged .91, while selected-area variability was 1.4%. The final Pareto set contained 64 nondominated solutions, with a mean hypervolume of .927 and a spacing value of .031. Average processing time was 3.2 hours, with a standard deviation of .4 hours.

**Table 9 Model Validation, Sensitivity, Uncertainty, Rank Stability, and Optimization Robustness**

| Domain                    | Measure or scenario                      | or                | Numerical result               | 95% CI or range            | Stability or agreement         | Performance or interpretation |
|---------------------------|------------------------------------------|-------------------|--------------------------------|----------------------------|--------------------------------|-------------------------------|
| Validation                | Training rate (n=1,680)                  | success-rate AUC, | .912                           | [.897, .927]               | —                              | Excellent discrimination      |
| Validation                | Independent prediction-rate AUC, (n=720) |                   | .890                           | [.865, .914]               | —                              | Strong discrimination         |
| Validation                | Accuracy                                 |                   | .826                           | [.797, .853]               | 595/720 correct                | Strong classification         |
| Validation                | Precision                                |                   | .853                           | [.814, .887]               | TP = 308; FP = 53              | Strong positive prediction    |
| Validation                | Recall                                   | or                | .811                           | [.769, .849]               | TP = 308; FN = 72              | Strong event detection        |
| Validation                | Specificity                              |                   | .844                           | [.801, .881]               | TN = 287; FP = 53              | Strong exclusion accuracy     |
| Validation                | F1 score                                 |                   | .831                           | [.797, .861]               | —                              | Balanced performance          |
| Validation                | Cohen's kappa                            |                   | .653                           | [.598, .708]               | Substantial agreement          | Reliable classification       |
| Validation                | Brier score                              |                   | .128                           | [.111, .145]               | Calibration slope = .96        | Acceptable calibration        |
| Validation                | Optimal probability threshold            |                   | .570                           | [.540, .600]               | Youden index = .655            | Balanced threshold            |
| Weight sensitivity        | Expert weights                           |                   | Mean score = .719              | High/very-high = 69,480 ha | ( $\rho$ =.91); ( $\tau$ =.83) | Priority persistence = 87.4%  |
| Weight sensitivity        | Entropy weights                          |                   | Mean score = .716              | High/very-high = 67,920 ha | ( $\rho$ =.84); ( $\tau$ =.72) | Priority persistence = 82.6%  |
| Weight sensitivity        | CRITIC weights                           |                   | Mean score = .721              | High/very-high = 68,360 ha | ( $\rho$ =.89); ( $\tau$ =.79) | Priority persistence = 85.7%  |
| Threshold sensitivity     | Regulatory thresholds $\pm 10\%$         |                   | Area change = -6.21% to +6.77% | 101,620–117,170 ha         | ( $\rho$ =.88)–.93             | Priority persistence = 86.9%  |
| Normalization sensitivity | Linear, percentile, and fuzzy            |                   | Maximum score change = .012    | Class agreement = 89.3%    | ( $\rho$ =.92)                 | Priority persistence = 88.1%  |
| Climate                   | Low-risk condition                       |                   | Developable                    | —                          | ( $\rho$ =.88)                 | Priority                      |

|                               |                                              |                               |                               |                                  |                              |
|-------------------------------|----------------------------------------------|-------------------------------|-------------------------------|----------------------------------|------------------------------|
| <b>sensitivity</b>            |                                              | area = 118,940 ha             |                               |                                  | persistence = 86.5%          |
| <b>Climate sensitivity</b>    | Central condition                            | Developable area = 109,740 ha | —                             | Reference                        | Priority persistence = 84.7% |
| <b>Climate sensitivity</b>    | Severe condition                             | Developable area = 97,860 ha  | —                             | ( $\rho=.76$ )                   | Priority persistence = 74.2% |
| <b>Resolution sensitivity</b> | 10-meter cells                               | Developable area = 111,280 ha | Reclassified = 19,240 ha      | ( $\rho=.94$ ); ( $\kappa=.88$ ) | Positional error = 2.1 m     |
| <b>Resolution sensitivity</b> | 30-meter cells                               | Developable area = 109,740 ha | Reclassified = 18,355 ha      | Reference                        | Positional error = 4.6 m     |
| <b>Resolution sensitivity</b> | 100-meter cells                              | Developable area = 115,630 ha | Reclassified = 15,480 ha      | ( $\rho=.86$ ); ( $\kappa=.72$ ) | Positional error = 16.8 m    |
| <b>Monte Carlo</b>            | Simulations completed                        | 10,000                        | Score interval = [.689, .758] | Mean score = .724                | Complete simulation set      |
| <b>Monte Carlo</b>            | Priority cells stable in $\geq 90\%$ of runs | 72.9%                         | —                             | Very high persistence            | Stable core locations        |
| <b>Monte Carlo</b>            | Priority cells stable in 80%–89% of runs     | 11.8%                         | —                             | High persistence                 | Generally stable locations   |
| <b>Monte Carlo</b>            | Priority cells stable in 50%–79% of runs     | 8.5%                          | —                             | Conditional persistence          | Boundary-sensitive locations |
| <b>Monte Carlo</b>            | Priority cells stable in $< 50\%$ of runs    | 6.8%                          | —                             | Low persistence                  | Uncertain locations          |
| <b>Optimization</b>           | Independent runs                             | 50                            | Convergence = 50/50           | 100.0%                           | No infeasible runs           |
| <b>Optimization</b>           | Objective value                              | .842                          | SD = .006                     | CV = .71%                        | Low repeat-run variability   |
| <b>Optimization</b>           | Constraint satisfaction                      | 99.2%                         | 98.7%–99.6%                   | —                                | Near-complete compliance     |
| <b>Optimization</b>           | Pairwise allocation agreement                | .910                          | .886–.934                     | Jaccard agreement                | High spatial reproducibility |
| <b>Optimization</b>           | Selected-area variability                    | 1.4%                          | .8%–2.1%                      | —                                | Low allocation variability   |
| <b>Optimization</b>           | Nondominated Pareto solutions                | 64                            | 58–69 across runs             | Hypervolume = .927               | Adequate solution diversity  |
| <b>Optimization</b>           | Pareto spacing                               | .031                          | .026–.037                     | —                                | Even solution distribution   |
| <b>Optimization</b>           | Processing time                              | 3.2 hr                        | 2.6–4.1 hr                    | SD = .4 hr                       | Stable computational demand  |

*Note.* AUC = area under the receiver operating characteristic curve; TP = true positive; TN = true negative; FP = false positive; FN = false negative; ( $\rho$ ) = Spearman's rank correlation; ( $\tau$ ) = Kendall's tau; CV = coefficient of variation.

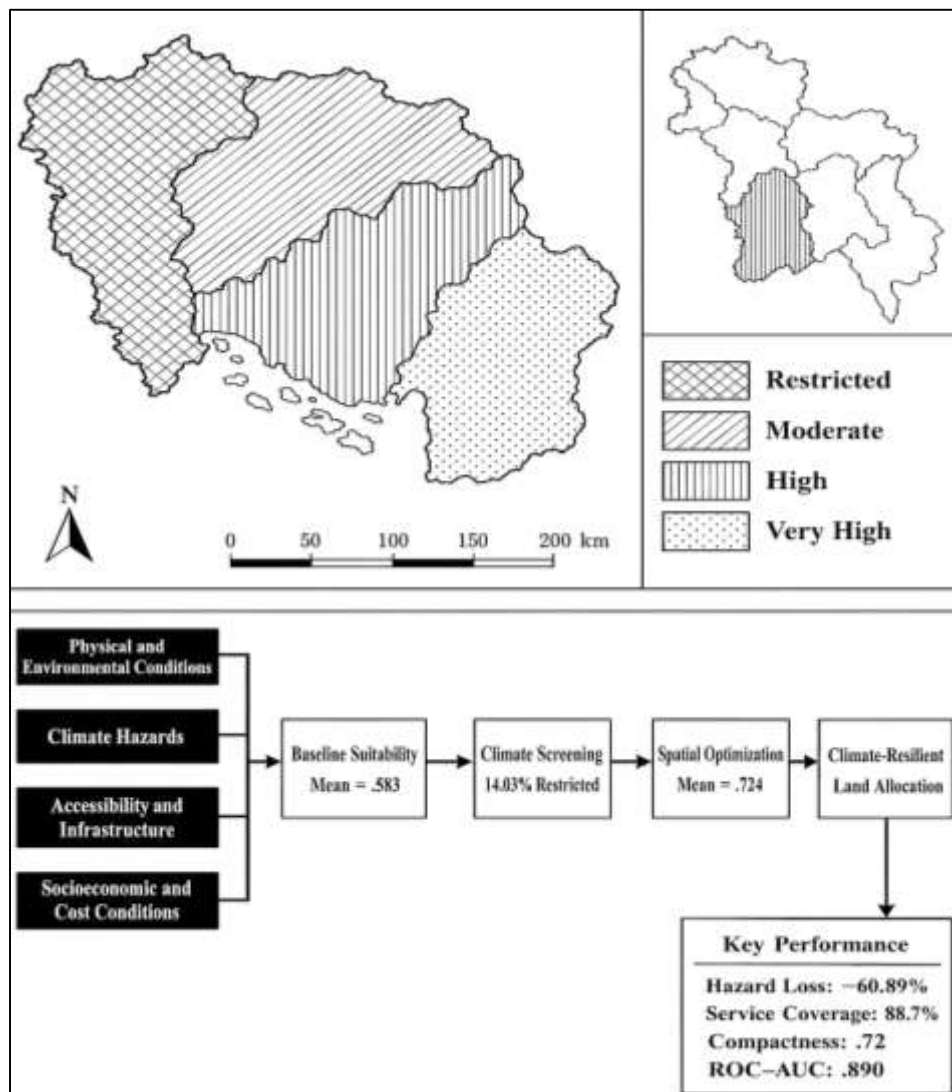
Table 9 demonstrates strong predictive validity, classification performance, rank stability, and optimization robustness. The independent validation model achieved an area under the curve of .890 and correctly classified 82.6% of observations. Precision, recall, specificity, and F1 score all exceeded .81, while kappa indicated substantial agreement. Weighting, normalization, threshold, climate, and resolution tests retained most priority locations, although stability declined under severe climate conditions and 100-meter aggregation. Monte Carlo analysis showed that 84.7% of priority cells preserved their classification in at least 80% of simulations. All optimization runs converged, with

limited objective-value and allocation variability across repeated solutions under planning scenarios. Figure 8 showed that all 95% confidence intervals for optimized-versus-baseline differences remained separated from zero. The largest standardized improvements involved hazard-loss reduction, climate-exposure reduction, ecological retention, compactness, and suitability. Figure 9 displayed closely aligned training and validation ROC curves, with the validation curve remaining well above the diagonal reference line throughout the operational threshold range. Figure 10 identified a stable priority-development core covering 72.9% of selected land, while lower-persistence locations were concentrated around floodplain margins, coastal boundaries, ecological corridors, and transitions between moderate and high suitability.

## DISCUSSION

The baseline findings demonstrated that land suitability was shaped by the combined influence of physical, environmental, climatic, socioeconomic, accessibility, infrastructure, and cost conditions rather than by terrain characteristics alone. The mean baseline suitability score of .583 indicated moderate regional development potential, although the standard deviation of .174 and observed range from .106 to .932 revealed considerable spatial heterogeneity. Moderate suitability formed the largest class, covering 44,190 hectares or 33.78% of eligible land, while high and very-high suitability collectively represented 51,180 hectares. These results correspond with earlier GIS-based land-suitability studies in which moderate land classes commonly occupied the largest share because few locations simultaneously satisfied terrain stability, environmental protection, infrastructure availability, accessibility, affordability, and hazard-safety requirements (Bozdağ et al., 2016).

Figure 13: GIS climate-resilient land suitability framework



Earlier terrain-centered assessments often identified extensive suitable land when elevation and slope were favorable, whereas multidimensional studies generally reported smaller high-suitability areas after ecological, social, and infrastructure indicators were incorporated. The results of this study followed the multidimensional pattern. Flood risk showed the strongest negative relationship with suitability, ( $r=-.73$ ), and received the highest hybrid weight of .095. Infrastructure capacity produced the strongest positive relationship, ( $r=.68$ ), followed by hydrological suitability, land-cover compatibility, and soil stability. This ordering agreed with earlier research conducted in floodplains, coastal settlements, deltaic environments, and rapidly urbanizing regions, where flood probability and infrastructure readiness exerted greater influence than isolated topographic variables (Kahsay et al., 2018). Network travel time, ecological sensitivity, heat exposure, and development cost also displayed substantial negative relationships, confirming that land can be physically buildable while remaining operationally unsuitable. Earlier studies using conventional weighted overlay sometimes assigned dominant importance to slope, elevation, or road proximity. More recent multi-hazard research has placed greater emphasis on exposure, ecosystem services, infrastructure capacity, and social vulnerability, which is consistent with the present criterion structure. The relatively low variance inflation factors, ranging from 1.32 to 2.74, further indicated that the selected indicators contributed distinct information without excessive redundancy (Romeijn et al., 2016). The strong agreement among expert, entropy, CRITIC, and hybrid weights also strengthened the interpretation that flood safety, infrastructure capacity, ecological protection, and accessibility represented stable determinants of suitability rather than artifacts of a single weighting procedure.

Climate-risk integration substantially altered the spatial interpretation of developable land. The conventional model identified 130,815 hectares as developable, whereas the climate-integrated configuration retained 112,460 hectares and reclassified 18,355 hectares as restricted. This 14.03% reduction showed that conventional suitability analysis overstated development potential when climatic and ecological thresholds were not represented fully. Flood exposure accounted for 6,420 hectares or 34.98% of newly restricted land, followed by heat exposure, storm or coastal risk, ecological sensitivity, terrain instability, drought, wildfire, and compound hazards (Cornwell et al., 2020). Earlier studies comparing conventional land-capability models with hazard-sensitive models reported similar reductions in suitable land after flood depth, heat intensity, storm surge, erosion, wildfire, or water stress was incorporated. The scale of reclassification in this study was particularly important because 13,860 hectares initially categorized as high or very high moved into lower or restricted classes. This pattern supports earlier research showing that favorable accessibility, flat terrain, or proximity to existing infrastructure can mask substantial climate exposure. Climate integration also reduced moderate-or-higher suitable land from 95,370 to 78,320 hectares and produced a significant change in binary suitable-unsuitable status. The class-distribution effect, Cramér's ( $V=.24$ ), indicated that the difference was not limited to isolated boundary cells. Flood-dominated areas experienced the highest proportional reclassification at 23.26%, followed by coastal or storm-dominated areas at 15.57% and heat-dominated areas at 10.96%. These results agreed with studies conducted in riverine and coastal regions, where hazard integration produced larger suitability changes than those observed in drought- or wildfire-dominated settings (Yin et al., 2020). The mean suitability score increased from .583 to .641 after climate integration because the retained land contained lower exposure and stronger resilience characteristics. Earlier studies have likewise reported an increase in the average quality of retained sites after hazardous land was removed, even when total developable area declined. Population exposure decreased from 428,600 to 272,400 residents, while exposed critical facilities declined from 146 to 89. Expected annual hazard loss fell from USD 186.4 million to USD 121.7 million. These changes demonstrated that climate integration affected both land classification and the human, infrastructural, and economic consequences associated with development allocation.

The fully optimized configuration produced stronger performance than both the conventional and climate-integrated models by coordinating risk reduction, accessibility, infrastructure cost, compactness, ecological retention, and development capacity (Nayak et al., 2018). Mean suitability increased to .724, representing a 24.19% improvement relative to baseline, while high or very-high suitability expanded from 51,180 to 68,740 hectares. The optimized configuration retained 109,740

hectares, exceeding the specified minimum development-capacity requirement by 1,740 hectares. This finding is consistent with earlier multi-objective land-allocation studies in which optimization improved the quality and spatial arrangement of selected land without requiring the maximum available area to be developed. Conventional weighted-overlay models typically rank individual cells independently and can produce fragmented patterns with weak service connectivity. In contrast, optimization research has demonstrated that compactness, adjacency, infrastructure access, environmental protection, and capacity requirements can be addressed simultaneously (Mandal et al., 2018). The decline in fragmented development patches from 318 to 174 and the increase in compactness from .46 to .72 supported that distinction. The optimized configuration reduced exposed population by 60.59%, critical-infrastructure exposure by 71.23%, climate-exposed land by 68.30%, and expected annual hazard loss by 60.89%. These reductions were comparable with the strongest effects reported in earlier multi-hazard optimization studies, especially those applying constrained evolutionary algorithms, location-allocation models, and mixed-integer programming. Mean network travel time declined by 6.7 minutes or 27.02%, while service coverage increased from 68.4% to 88.7%. Earlier studies often identified a trade-off between hazard avoidance and accessibility because safer peripheral locations required longer journeys and additional infrastructure. The climate-integrated configuration initially displayed that trade-off: infrastructure-extension cost increased from USD 742.5 million to USD 778.2 million after exposed but well-served land was removed (Ghasemkhani et al., 2020). Full optimization resolved much of this conflict by reducing the cost to USD 624.8 million through the selection of safer locations connected to existing networks. Ecological retention increased from 71.8% to 91.6%, and constraint satisfaction reached 99.2%. The large effect sizes for hazard loss, climate exposure, ecological retention, compactness, and suitability indicated that the optimized differences were operationally meaningful. These findings extend earlier suitability studies by showing that the highest-scoring cells were not necessarily the most efficient collective allocation until risk, cost, connectivity, spatial form, and environmental restrictions were optimized together.

The spatial findings demonstrated that suitability and optimized development capacity were distributed unevenly across administrative areas and settlement types (Dawit et al., 2020). Global Moran's  $I$  ( $I=.624$ ), with ( $p<.001$ ), indicated strong positive spatial clustering rather than a random distribution of suitable land. High-high clusters covered 18.70% of eligible cells and were concentrated within Central Municipality, the Northern Growth Zone, and the western peri-urban corridor. Low-low clusters represented 15.40% and were concentrated in the Eastern Riverine and Southern Coastal zones. Earlier spatial-suitability studies have reported comparable clustering where infrastructure investment, service accessibility, stable terrain, and established development reinforce one another geographically. Low-suitability clusters have similarly been associated with floodplains, coastal exposure, environmentally sensitive land, weak infrastructure, and high development costs (Saatsaz et al., 2018). Peri-urban areas achieved the highest mean optimized suitability score of .781, exceeding the urban mean of .742 and rural mean of .718. This result agreed with earlier studies showing that peri-urban locations can offer a favorable combination of available land, proximity to services, lower central-city land costs, and opportunities for planned infrastructure expansion. Urban areas retained high accessibility and population coverage, although land value, density, ecological pressure, and limited open space reduced their relative flexibility. Rural areas received the largest optimized allocation at 38,450 hectares but had longer travel times and lower infrastructure coverage. Earlier regional-planning research has made a similar distinction between abundant land capacity and actual development readiness. Coastal or riverine areas recorded a mean suitability score of .620, while environmentally sensitive and hazard-prone areas recorded .575 and .590. These lower values reflected the accumulation of flood, storm, ecological, accessibility, and infrastructure constraints (De Rosa et al., 2016). The Western Peri-Urban Zone ranked first administratively with a performance index of .812, followed by Central Municipality and the Northern Growth Zone. The Eastern Riverine and Southern Coastal zones ranked lowest because high climate exposure coincided with longer travel times and greater infrastructure costs. Hazard-specific results reinforced this geographic structure: flood-dominated land was 3.49 times as likely to be reclassified as drought-affected land, and coastal land was 2.34 times as likely. Earlier studies have also found that flood and coastal hazards often produce sharper

development restrictions because they involve spatially definable inundation, setback, drainage, and evacuation requirements (Sun et al., 2021). The observed administrative differences therefore reflected interacting physical, climatic, infrastructural, and institutional conditions rather than a single regional disadvantage.

The equity analysis demonstrated that optimization reduced climate exposure across vulnerability groups while leaving measurable differences in residual risk and service access. Population-weighted climate exposure declined from 28.4% to 12.6% in low-vulnerability areas and from 61.2% to 24.3% in high-vulnerability areas (Standen et al., 2021). The proportional exposure reduction was slightly larger in high-vulnerability areas, reaching 60.3% compared with 55.6% in low-vulnerability locations. This pattern agreed with earlier environmental-justice and climate-resilience studies showing that risk-sensitive allocation can direct substantial protection toward highly exposed communities when social vulnerability is included explicitly. The remaining 11.7-percentage-point exposure difference showed that equal proportional improvement did not eliminate unequal starting conditions. Earlier studies have similarly reported that disadvantaged communities retain greater residual risk because hazardous locations are combined with limited mobility, weaker infrastructure, insecure housing, low affordability, and restricted access to public services. In this study, high-vulnerability areas retained an emergency travel time of 23.8 minutes, compared with 12.7 minutes in low-vulnerability areas. Infrastructure coverage remained 76.9% in high-vulnerability locations and 93.2% in low-vulnerability locations, while affordability pressure remained .22 points higher (Dawson et al., 2018). Accessibility results provided further evidence of this distributional pattern. Highly accessible areas achieved a mean suitability score of .781 and received 46,850 optimized hectares, whereas low-access areas recorded a mean score of .612 and received 23,450 hectares. Service coverage declined from 96.2% in high-access locations to 71.4% in low-access locations, while emergency travel time increased from 10.4 to 41.6 minutes. Earlier accessibility-based suitability studies have reported similar gradients for healthcare, education, employment, public transport, evacuation centers, and emergency response. Infrastructure capacity generated an equally strong distinction. Well-served locations recorded a mean suitability score of .792 and an infrastructure-extension cost of USD 36,800 per hectare (Lucas et al., 2016). Areas requiring major extensions recorded a mean score of .593 and a cost of USD 123,400 per hectare. These results align with earlier research demonstrating that road, drainage, water, sewerage, electricity, and communication networks influence both development feasibility and climate-response capacity. The findings also show that affordability, accessibility, and climate protection cannot be interpreted independently because safer and better-served land can create additional cost pressures for vulnerable populations.

The validation findings indicated that the integrated framework possessed strong predictive accuracy and remained stable across alternative analytical assumptions. The independent validation model achieved an ROC-AUC of .890 and an accuracy of 82.6%. Precision reached .853, recall reached .811, specificity reached .844, and the F1 score reached .831. Cohen's kappa of .653 indicated substantial agreement beyond chance (Lee et al., 2017). These values compare favorably with earlier GIS-based suitability studies, many of which reported high apparent accuracy based on agreement with existing development but did not use an independent validation sample. The separation between the training success-rate AUC of .912 and prediction-rate AUC of .890 was small, suggesting limited overfitting. The calibration slope of .96, Brier score of .128, and nonsignificant calibration test further supported the reliability of predicted probabilities. Weight sensitivity also produced stable results. Expert, entropy, and CRITIC rankings correlated with the hybrid model between .84 and .91, while priority-location overlap ranged from 82.6% to 87.4%. Earlier comparisons of weighting methods have often found greater instability when expert judgments dominate or highly correlated criteria are included (Durrant, 2017). The stronger agreement in this study was consistent with the low variance inflation factors and the combination of subjective and objective weighting information. Regulatory-threshold changes of  $\pm 10\%$  altered developable area by approximately 6%–7%, and alternative normalization procedures changed mean suitability by no more than .012. Climate severity produced a larger response, reducing developable land to 97,860 hectares and lowering priority persistence to 74.2%, which agreed with earlier scenario-based studies showing that hazard assumptions exert greater influence than routine

methodological choices. Resolution analysis confirmed that 10- and 30-meter models were closely aligned, with a rank correlation of .94 and kappa of .88. The 100-meter model reduced class agreement to 78.8%, understated restricted land by 2,875 hectares, and increased positional error to 16.8 meters (Antipova et al., 2020). This pattern reflects earlier findings that coarse cells smooth narrow drainage channels, shoreline transitions, ecological corridors, and parcel boundaries. Monte Carlo analysis showed that 84.7% of priority cells retained their classification in at least 80% of simulations. All 50 optimization runs converged, and objective-value variability remained below 1%, demonstrating strong computational reproducibility.

Taken together, the findings positioned climate-resilient land planning as a combined problem of spatial measurement, risk recognition, distributional fairness, and constrained optimization. Earlier GIS-MCDA studies established the value of combining terrain, land cover, accessibility, and expert weights, but many frameworks ended with a static suitability map (Thacker et al., 2019). Other studies focused on individual hazards, such as flooding, heat, wildfire, or coastal exposure, without optimizing the final allocation of development. A separate group of optimization studies improved compactness, infrastructure cost, or land-use efficiency but represented climate vulnerability and ecological sensitivity in limited detail. This study connected these analytical traditions within one quantitative framework. The transition from a baseline score of .583 to a climate-integrated score of .641 and an optimized score of .724 demonstrated that climate screening and spatial optimization performed different functions. Climate integration corrected overclassification by restricting 18,355 hectares and reducing human and infrastructure exposure (Voulvoulis et al., 2017). Optimization then reorganized the retained development capacity to improve accessibility, compactness, ecological retention, and cost performance. The very large effect sizes for hazard-loss reduction, climate-exposure reduction, compactness, ecological retention, and mean suitability were consistent with earlier evidence that integrated decision models outperform single-criterion or unoptimized approaches. The regression findings also clarified the relative contribution of major planning dimensions. Infrastructure capacity increased the odds of verified low-risk development by 62%, physical suitability increased the odds by 46%, and environmental compatibility increased the odds by 38%. Climate risk reduced the odds by 56%, while socioeconomic vulnerability, network travel time, and development cost exerted additional negative effects. These relationships support the information-processing perspective used in earlier decision-support research, under which better integration of heterogeneous spatial information improves the consistency and completeness of planning choices (Cowie et al., 2018). They also correspond with resilience-based planning studies that treat hazard avoidance, adaptive capacity, ecological functioning, and service continuity as connected components. The stable validation performance, consistent rankings across weighting methods, strong Monte Carlo persistence, and repeated optimization convergence distinguished systematic model effects from isolated parameter choices (Prestmo et al., 2015). The remaining variation across coastal, riverine, environmentally sensitive, rural, and high-vulnerability areas also confirmed that a single regional suitability score cannot represent all local planning conditions. The results therefore provide an empirically integrated interpretation of how land quantity, land quality, climate safety, infrastructure readiness, accessibility, ecological protection, and social vulnerability interact within urban and regional development decisions (Group, 2016).

## CONCLUSION

This study established that climate-resilient urban and regional land planning requires the integration of geographic information systems, multi-criteria decision support, climate-risk assessment, social and infrastructure indicators, and spatial optimization within a unified quantitative framework. The final analysis retained 1,974,900 raster cells and 121,800 cadastral parcels, representing more than 96% of the original spatial records, while the reliability, positional accuracy, temporal alignment, and classification results satisfied the predefined analytical standards. Baseline assessment classified 130,815 hectares as potentially developable, with a mean suitability score of .583. Moderate suitability formed the largest category at 44,190 hectares, while high and very-high suitability collectively covered 51,180 hectares. Flood risk emerged as the most influential negative criterion, with a correlation of ( $r=-.73$ ) and a hybrid weight of .095, whereas infrastructure capacity produced the strongest positive association at ( $r=.68$ ). Climate-risk integration reclassified 18,355 hectares as restricted and reduced the developable area to

112,460 hectares. Flood exposure accounted for 6,420 hectares of newly restricted land, and 13,860 hectares initially classified as high or very high moved to lower or restricted categories. This correction reduced exposed population from 428,600 to 272,400 and expected annual hazard loss from USD 186.4 million to USD 121.7 million. Full multi-objective optimization retained 109,740 hectares while increasing the mean suitability score to .724 and expanding high or very-high land to 68,740 hectares. Relative to the conventional baseline, optimization reduced exposed population by 60.59%, critical-infrastructure exposure by 71.23%, climate-exposed land by 68.30%, expected annual hazard loss by 60.89%, network travel time by 27.02%, and infrastructure-extension cost by 15.85%. Spatial compactness increased from .46 to .72, service coverage reached 88.7%, ecological retention reached 91.6%, and constraint satisfaction reached 99.2%. Administrative and subgroup analyses showed that peri-urban and well-served locations achieved the strongest performance, while coastal, riverine, environmentally sensitive, hazard-prone, and highly vulnerable areas retained greater exposure and accessibility constraints. Independent validation produced an ROC-AUC of .890, accuracy of 82.6%, F1 score of .831, and substantial kappa agreement. Rankings remained stable across weighting, normalization, threshold, climate, and resolution scenarios, while all 50 optimization runs converged with limited variability. These combined findings confirm that suitability classification alone does not provide a complete basis for climate-resilient development decisions. The integration of hazard restrictions, environmental protection, infrastructure capacity, accessibility, equity, spatial continuity, and development cost produced a more accurate, defensible, and operationally complete representation of urban and regional land suitability.

## **RECOMMENDATIONS**

Urban and regional planning authorities should institutionalize the GIS-based multi-criteria decision-support and land-suitability optimization framework as a formal component of strategic planning, development approval, infrastructure investment, environmental assessment, and climate-risk management. Conventional suitability maps should not be used independently because the findings showed that climate-risk integration reclassified 18,355 hectares as restricted and corrected the overestimation of development potential within flood-prone, heat-exposed, coastal, ecologically sensitive, and compound-hazard locations. Regulatory agencies should incorporate flood probability, heat exposure, drought, wildfire, storm and coastal risk, terrain instability, ecological sensitivity, social vulnerability, and emergency accessibility into statutory zoning and parcel-level development review. The 109,740 hectares retained by the optimized configuration should be prioritized according to suitability, service capacity, compactness, infrastructure cost, and ecological compatibility, with high and very-high locations receiving preference for planned housing, employment, public facilities, and essential infrastructure. Development should be strictly controlled within the 18,355 newly restricted hectares, particularly the 6,420 hectares affected predominantly by flooding, and natural drainage corridors, wetlands, coastal buffers, ecological networks, and unstable terrain should receive enforceable protection. Infrastructure investment should focus on locations where improvements in roads, drainage, water, sewerage, electricity, communication systems, healthcare access, public transportation, evacuation routes, and emergency services can reduce the major accessibility and service disadvantages identified in rural, coastal, riverine, and high-vulnerability areas. Equity safeguards should accompany optimized allocation because high-vulnerability communities retained greater exposure, longer emergency travel times, lower infrastructure coverage, and stronger affordability pressure after optimization. Affordable housing, secure tenure, targeted infrastructure subsidies, accessible evacuation facilities, and protection against displacement should therefore be integrated into climate-resilient development programs. Planning agencies should maintain a shared geospatial database with standardized identifiers, coordinate systems, metadata, update schedules, quality thresholds, and responsibility for data stewardship. Thirty-meter analysis should remain the primary regional resolution because it balanced hazard representation, boundary precision, processing time, and rank stability, while 10-meter analysis should support detailed assessment of priority sites, drainage corridors, shorelines, and parcel boundaries. Coarse 100-meter analysis should be limited to preliminary regional screening because it understated restricted land and reduced classification agreement. Criterion weights, regulatory thresholds, hazard layers, land-cover information, infrastructure capacity, and social-vulnerability indicators should be reviewed periodically through

expert consultation and objective weighting procedures. Development approvals should also be tested against alternative climate conditions, normalization methods, resolutions, and threshold assumptions. Locations with low Monte Carlo classification persistence should require additional field investigation, engineering assessment, environmental review, and stakeholder consultation before approval. A phased implementation process should connect optimized land priorities with capital budgeting, zoning amendments, environmental protection, infrastructure sequencing, and measurable performance indicators for exposure reduction, service coverage, ecological retention, affordability, compactness, and constraint compliance.

## **LIMITATIONS**

Several limitations should be considered when interpreting the findings of this study. First, the analysis depended on the availability, temporal consistency, positional accuracy, and spatial resolution of satellite imagery, cadastral records, hazard surfaces, census information, infrastructure inventories, and cost estimates. Although 96.46% of raster cells were retained and 39 of 42 candidate layers satisfied the acceptance standards, differences in acquisition dates, measurement methods, administrative reporting practices, and update frequencies may have introduced residual uncertainty. The primary analysis used 30-meter raster cells, which provided an effective balance between spatial detail and computational demand but could not represent narrow drainage channels, small ecological patches, parcel-edge conditions, informal access routes, or building-level exposure with complete precision. The stronger results obtained from the 10-meter analysis and the lower agreement produced by the 100-meter analysis confirmed that suitability classifications remained sensitive to spatial resolution and aggregation. Second, the criterion structure was limited to indicators for which sufficiently complete and comparable spatial data were available. Factors such as landownership disputes, political feasibility, cultural value, household preferences, informal mobility, seasonal migration, local construction practices, and institutional enforcement were not represented comprehensively. Third, expert weighting involved judgments from a 30-member panel. High internal consistency, acceptable comparison ratios, and agreement among expert, entropy, CRITIC, and hybrid weights reduced concern about arbitrary weighting, although professional background, institutional affiliation, technical specialization, and local experience may still have influenced criterion priorities. Fourth, hazard indicators represented modeled or historical conditions rather than complete knowledge of every possible event. Compound interactions among flooding, heat, drought, wildfire, coastal storms, erosion, infrastructure failure, and ecological degradation were simplified through dominant-hazard and scenario classifications. Fifth, the optimization model depended on predefined objectives, constraints, development-capacity requirements, cost assumptions, and trade-off parameters. Alternative policy priorities could produce different allocations even when the underlying geospatial data remained unchanged. Infrastructure-extension costs, expected hazard losses, and affordability pressure were estimated from standardized unit values and therefore may not capture project-specific financing conditions, land-market volatility, construction inflation, or household-level economic behavior. Sixth, independent validation used 720 observations distributed across anticipated suitability classes, but spatial dependence among nearby observations may have reduced the effective independence of the validation sample. The ROC-AUC of .890, accuracy of 82.6%, and kappa of .653 demonstrated strong performance without establishing error-free classification. Monte Carlo analysis also showed that 15.3% of priority cells retained their classifications in fewer than 80% of simulations.

## **REFERENCES**

- [1]. Adams, M. A., Frank, L. D., Schipperijn, J., Smith, G., Chapman, J., Christiansen, L. B., Coffee, N., Salvo, D., du Toit, L., & Dygrýn, J. (2014). International variation in neighborhood walkability, transit, and recreation environments using geographic information systems: the IPEN adult study. *International journal of health geographics*, 13(1), 43.
- [2]. Adem Esmail, B., & Geneletti, D. (2018). Multi-criteria decision analysis for nature conservation: A review of 20 years of applications. *Methods in Ecology and Evolution*, 9(1), 42-53.
- [3]. Adimalla, N., & Taloor, A. K. (2020). Hydrogeochemical investigation of groundwater quality in the hard rock terrain of South India using Geographic Information System (GIS) and groundwater quality index (GWQI) techniques. *Groundwater for Sustainable Development*, 10, 100288.
- [4]. Ahamed, T. N., Rao, K. G., & Murthy, J. (2000). GIS-based fuzzy membership model for crop-land suitability analysis. *Agricultural systems*, 63(2), 75-95.
- [5]. Aivinenyo, I., & Zuidgeest, M. (2019). Transport equity in low-income societies: Affordability impact on destination accessibility measures. In *Measuring transport equity* (pp. 111-128). Elsevier.

- [6]. Al, R., Behera, C. R., Zubov, A., Gernaey, K. V., & Sin, G. (2019). Meta-modeling based efficient global sensitivity analysis for wastewater treatment plants–An application to the BSM2 model. *Computers & Chemical Engineering*, 127, 233-246.
- [7]. Amarnath, G., Amarasinghe, U. A., & Alahacoon, N. (2021). Disaster risk mapping: A desk review of global best practices and evidence for South Asia. *Sustainability*, 13(22), 12779.
- [8]. Amiri, M., Pourghasemi, H. R., Ghanbarian, G. A., & Afzali, S. F. (2019). Assessment of the importance of gully erosion effective factors using Boruta algorithm and its spatial modeling and mapping using three machine learning algorithms. *Geoderma*, 340, 55-69.
- [9]. Angryk, R. A., & Galarus, D. E. (2016). The SMART approach to comprehensive quality assessment of site-based spatial-temporal data. 2016 IEEE international conference on big data (big data),
- [10]. Antipova, A., Sultana, S., Hu, Y., & Rhudy Jr, J. P. (2020). Accessibility and transportation equity. In (Vol. 12, pp. 3611): MDPI.
- [11]. Arabadzhyan, A., Figini, P., García, C., González, M. M., Lam-González, Y. E., & León, C. J. (2021). Climate change, coastal tourism, and impact chains—a literature review. *Current Issues in Tourism*, 24(16), 2233-2268.
- [12]. Araya-Muñoz, D., Metzger, M. J., Stuart, N., Wilson, A. M. W., & Carvajal, D. (2017). A spatial fuzzy logic approach to urban multi-hazard impact assessment in Concepción, Chile. *Science of the Total Environment*, 576, 508-519.
- [13]. Asadabadi, M. R. (2018). The stratified multi-criteria decision-making method. *Knowledge-Based Systems*, 162, 115-123.
- [14]. Bandyopadhyay, S., Jaiswal, R., Hegde, V., & Jayaraman, V. (2009). Assessment of land suitability potentials for agriculture using a remote sensing and GIS based approach. *International journal of remote sensing*, 30(4), 879-895.
- [15]. Bojorquez-Tapia, L. A., Diaz-Mondragon, S., & Ezcurra, E. (2001). GIS-based approach for participatory decision making and land suitability assessment. *International journal of geographical information science*, 15(2), 129-151.
- [16]. Bozdağ, A., Yavuz, F., & Günay, A. S. (2016). AHP and GIS based land suitability analysis for Cihanbeyli (Turkey) County. *Environmental Earth Sciences*, 75(9), 813.
- [17]. Brown, S. C., Versace, V. L., Lester, R. E., & Todd Walter, M. (2015). Assessing the impact of drought and forestry on streamflows in south-eastern Australia using a physically based hydrological model. *Environmental Earth Sciences*, 74(7), 6047-6063.
- [18]. Brussel, M., Zuidgeest, M., Pfeffer, K., & Van Maarseveen, M. (2019). Access or accessibility? A critique of the urban transport SDG indicator. *ISPRS International journal of geo-information*, 8(2), 67.
- [19]. Büttner, B., Kinigadner, J., Ji, C., Wright, B., & Wulfhorst, G. (2018). The TUM accessibility atlas: Visualizing spatial and socioeconomic disparities in accessibility to support regional land-use and transport planning. *Networks and Spatial Economics*, 18(2), 385-414.
- [20]. Campbell, H., & Masser, I. (2020). *GIS In Organizations: How Effective Are GIS In Practice?* CRC Press.
- [21]. Cavazzi, S., & Dutton, A. (2016). An Offshore Wind Energy Geographic Information System (OWE-GIS) for assessment of the UK's offshore wind energy potential. *Renewable energy*, 87, 212-228.
- [22]. Chakraborty, S., & Mukhopadhyay, S. (2019). Assessing flood risk using analytical hierarchy process (AHP) and geographical information system (GIS): application in Coochbehar district of West Bengal, India. *Natural hazards*, 99(1), 247-274.
- [23]. Chang, K. T. (2016). Geographic information system. *International encyclopedia of geography: people, the earth, environment and technology*, 1-10.
- [24]. Cornwell, E., Sposito, V., & Faggian, R. (2020). Land suitability projections for traditional sub-alpine cropping in the Australian Alps and Chilean Dry Andes. A combined biophysical and irrigation potential perspective. *Applied geography*, 121, 102248.
- [25]. Cowie, A. L., Orr, B. J., Sanchez, V. M. C., Chasek, P., Crossman, N. D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G. I., & Minelli, S. (2018). Land in balance: The scientific conceptual framework for Land Degradation Neutrality. *Environmental science & policy*, 79, 25-35.
- [26]. Da-Ano, R., Masson, I., Lucia, F., Doré, M., Robin, P., Alfieri, J., Rousseau, C., Mervoyer, A., Reinhold, C., & Castelli, J. (2020). Performance comparison of modified ComBat for harmonization of radiomic features for multicenter studies. *Scientific Reports*, 10(1), 10248.
- [27]. Dadashpoor, H., & Rostami, F. (2017). Measuring spatial proportionality between service availability, accessibility and mobility: Empirical evidence using spatial equity approach in Iran. *Journal of transport geography*, 65, 44-55.
- [28]. Darvishi, A., Yousefi, M., Mousavi, S. M., Khoshnamvand, H., Borhani, F., & Schirrmann, M. (2026). GIS-AHP-based land suitability assessment for sustainable agricultural planning on Qeshm Island. *Scientific Reports*, 16(1), 23085.
- [29]. Dawit, M., Dinka, M. O., Leta, O. T., & Muluneh, F. B. (2020). Impact of climate change on land suitability for the optimization of the irrigation system in the Anger River Basin, Ethiopia. *Climate*, 8(9), 97.
- [30]. Dawson, N., Martin, A., & Danielsen, F. (2018). Assessing equity in protected area governance: approaches to promote just and effective conservation. *Conservation Letters*, 11(2), e12388.
- [31]. De Rosa, M., Knudsen, M. T., & Hermansen, J. E. (2016). A comparison of Land Use Change models: challenges and future developments. *Journal of Cleaner Production*, 113, 183-193.
- [32]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [33]. Demir, V., & Kisi, O. (2016). Flood hazard mapping by using geographic information system and hydraulic model: Mert River, Samsun, Turkey. *Advances in Meteorology*, 2016(1), 4891015.

- [34]. Djalante, R., & Garschagen, M. (2017). A review of disaster trend and disaster risk governance in Indonesia: 1900–2015. *Disaster risk reduction in Indonesia: progress, challenges, and issues*, 21-56.
- [35]. Dong, Z., Zhang, N., Li, C., Wang, H., Fang, Y., Wang, J., & Zheng, X. (2015). Anticancer drug sensitivity prediction in cell lines from baseline gene expression through recursive feature selection. *BMC cancer*, 15(1), 489.
- [36]. Dorn, H., Törnros, T., & Zipf, A. (2015). Quality evaluation of VGI using authoritative data – A comparison with land use data in Southern Germany. *ISPRS International journal of geo-information*, 4(3), 1657-1671.
- [37]. Durrant, D. (2017). Infrastructure, equity and urban planning: A just process for the allocation of benefits and burdens. In *Building sustainable cities of the future* (pp. 141-162). Springer.
- [38]. El Baroudy, A. (2016). Mapping and evaluating land suitability using a GIS-based model. *Catena*, 140, 96-104.
- [39]. Ferguson, W. J., Kemp, K., & Kost, G. (2016). Using a geographic information system to enhance patient access to point-of-care diagnostics in a limited-resource setting. *International journal of health geographics*, 15(1), 10.
- [40]. Garosi, Y., Sheklabadi, M., Pourghasemi, H. R., Besalatpour, A. A., Conoscenti, C., & Van Oost, K. (2018). Comparison of differences in resolution and sources of controlling factors for gully erosion susceptibility mapping. *Geoderma*, 330, 65-78.
- [41]. Gerber, F., de Jong, R., Schaepman, M. E., Schaepman-Strub, G., & Furrer, R. (2018). Predicting missing values in spatio-temporal remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing*, 56(5), 2841-2853.
- [42]. Ghasemkhani, N., Vayghan, S. S., Abdollahi, A., Pradhan, B., & Alamri, A. (2020). Urban development modeling using integrated fuzzy systems, ordered weighted averaging (owa), and geospatial techniques. *Sustainability*, 12(3), 809.
- [43]. Group, D. F. (2016). A transdisciplinary framework for SLA in a multilingual world. *The Modern Language Journal*, 100(S1), 19-47.
- [44]. Hacisalihoğlu, S., Karaer, F., & Katip, A. (2016). Applications of geographic information system (GIS) analysis of lake Ulubat. *Environmental Monitoring and Assessment*, 188(6), 331.
- [45]. Haddad, B., Liazid, A., & Ferreira, P. (2017). A multi-criteria approach to rank renewables for the Algerian electricity system. *Renewable energy*, 107, 462-472.
- [46]. Höhn, J., Lehtonen, E., Rasi, S., & Rintala, J. (2014). A Geographical Information System (GIS) based methodology for determination of potential biomasses and sites for biogas plants in southern Finland. *Applied Energy*, 113, 1-10.
- [47]. Jones, C. B. (2014). *Geographical information systems and computer cartography*. Routledge.
- [48]. Kadoić, N., Šimić, D., Mesarić, J., & Ređep, N. B. (2021). Measuring quality of public hospitals in Croatia using a multi-criteria approach. *International journal of environmental research and public health*, 18(19), 9984.
- [49]. Kahsay, A., Haile, M., Gebresamuel, G., & Mohammed, M. (2018). GIS-based multi-criteria model for land suitability evaluation of rainfed teff crop production in degraded semi-arid highlands of Northern Ethiopia. *Modeling Earth Systems and Environment*, 4(4), 1467-1486.
- [50]. Kalogirou, S. (2002). Expert systems and GIS: an application of land suitability evaluation. *Computers, environment and urban systems*, 26(2-3), 89-112.
- [51]. Kapuka, A., & Hlásny, T. (2020). Social vulnerability to natural hazards in Namibia: a district-based analysis. *Sustainability*, 12(12), 4910.
- [52]. Kautz, T., Eskofier, B. M., & Pasluosta, C. F. (2017). Generic performance measure for multiclass-classifiers. *Pattern Recognition*, 68, 111-125.
- [53]. Kc, B., Shepherd, J., King, A. W., & Johnson Gaither, C. (2021). Multi-hazard climate risk projections for the United States. *Natural hazards*, 105(2), 1963-1976.
- [54]. Krishnan, A. R., Kasim, M. M., Hamid, R., & Ghazali, M. F. (2021). A modified CRITIC method to estimate the objective weights of decision criteria. *Symmetry*, 13(6), 973.
- [55]. Kucera, G. (2020). *Time in geographic information systems*. CRC Press.
- [56]. Leach, N., Coops, N. C., & Obrknezev, N. (2019). Normalization method for multi-sensor high spatial and temporal resolution satellite imagery with radiometric inconsistencies. *Computers and Electronics in Agriculture*, 164, 104893.
- [57]. Lebedev, A., Westman, E., Van Westen, G., Kramberger, M., Lundervold, A., Aarsland, D., Soininen, H., Kłoszewska, I., Mecocci, P., & Tsolaki, M. (2014). Random Forest ensembles for detection and prediction of Alzheimer's disease with a good between-cohort robustness. *NeuroImage: Clinical*, 6, 115-125.
- [58]. Lee, R. J., Sener, I. N., & Jones, S. N. (2017). Understanding the role of equity in active transportation planning in the United States. *Transport reviews*, 37(2), 211-226.
- [59]. Lee, S., & Seo, K.-K. (2016). A hybrid multi-criteria decision-making model for a cloud service selection problem using BSC, fuzzy Delphi method and fuzzy AHP. *Wireless Personal Communications*, 86(1), 57-75.
- [60]. Leger, S., Zwanenburg, A., Pilz, K., Lohaus, F., Linge, A., Zöphel, K., Kotzerke, J., Schreiber, A., Tinhofer, I., & Budach, V. (2017). A comparative study of machine learning methods for time-to-event survival data for radiomics risk modelling. *Scientific Reports*, 7(1), 13206.
- [61]. Li, J. (2016). Assessing spatial predictive models in the environmental sciences: Accuracy measures, data variation and variance explained. *Environmental Modelling & Software*, 80, 1-8.
- [62]. Liu, W., Qiu, J.-L., Zheng, W.-L., & Lu, B.-L. (2021). Comparing recognition performance and robustness of multimodal deep learning models for multimodal emotion recognition. *IEEE Transactions on Cognitive and Developmental Systems*, 14(2), 715-729.
- [63]. Liu, X., Wang, X., Wright, G., Cheng, J. C., Li, X., & Liu, R. (2017). A state-of-the-art review on the integration of Building Information Modeling (BIM) and Geographic Information System (GIS). *ISPRS International journal of geo-information*, 6(2), 53.

- [64]. Lloyd, C. T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F. R., Gaughan, A. E., Nieves, J. J., Hornby, G., & MacManus, K. (2019). Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. *Big Earth Data*, 3(2), 108-139.
- [65]. Longley, P. A., & Cheshire, J. A. (2017). Geographical information systems. In *The Routledge Handbook of Mapping and Cartography* (pp. 251-258). Routledge.
- [66]. Lü, G., Batty, M., Strobl, J., Lin, H., Zhu, A.-X., & Chen, M. (2019). Reflections and speculations on the progress in Geographic Information Systems (GIS): a geographic perspective. *International journal of geographical information science*, 33(2), 346-367.
- [67]. Lucas, K., Van Wee, B., & Maat, K. (2016). A method to evaluate equitable accessibility: combining ethical theories and accessibility-based approaches. *Transportation*, 43(3), 473-490.
- [68]. Lyons, M. B., Keith, D. A., Phinn, S. R., Mason, T. J., & Elith, J. (2018). A comparison of resampling methods for remote sensing classification and accuracy assessment. *Remote sensing of environment*, 208, 145-153.
- [69]. Malekzadeh, A., & Chung, E. (2020). A review of transit accessibility models: Challenges in developing transit accessibility models. *International journal of sustainable transportation*, 14(10), 733-748.
- [70]. Mandal, B., Dolui, G., & Satpathy, S. (2018). Land suitability assessment for potential surface irrigation of river catchment for irrigation development in Kansai watershed, Purulia, West Bengal, India. *Sustainable Water Resources Management*, 4(4), 699-714.
- [71]. Martens, K., Bastiaanssen, J., & Lucas, K. (2019). Measuring transport equity: Key components, framings and metrics. In *Measuring transport equity* (pp. 13-36). Elsevier.
- [72]. Mavrommatis, E., Damigos, D., & Mirasgedis, S. (2019). Towards a comprehensive framework for climate change multi-risk assessment in the mining industry. *Infrastructures*, 4(3), 38.
- [73]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [74]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>
- [75]. Mishra, A. R., Chandel, A., & Motwani, D. (2020). Extended MABAC method based on divergence measures for multi-criteria assessment of programming language with interval-valued intuitionistic fuzzy sets. *Granular Computing*, 5(1), 97-117.
- [76]. Mishra, A. R., Rani, P., Pandey, K., Mardani, A., Streimikis, J., Streimikiene, D., & Alrasheedi, M. (2020). Novel multi-criteria intuitionistic fuzzy SWARA-COPRAS approach for sustainability evaluation of the bioenergy production process. *Sustainability*, 12(10), 4155.
- [77]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, 2(4), 73-126. <https://doi.org/10.63125/7p8dcr47>
- [78]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263-279. <https://doi.org/10.63125/cm1c2c20>
- [79]. Montgomery, B., Dragičević, S., Dujmović, J., & Schmidt, M. (2016). A GIS-based Logic Scoring of Preference method for evaluation of land capability and suitability for agriculture. *Computers and Electronics in Agriculture*, 124, 340-353.
- [80]. Morán-Tejeda, E., Zabalza, J., Rahman, K., Gago-Silva, A., López-Moreno, J. I., Vicente-Serrano, S., Lehmann, A., Tague, C. L., & Beniston, M. (2015). Hydrological impacts of climate and land-use changes in a mountain watershed: Uncertainty estimation based on model comparison. *Ecohydrology*, 8(8), 1396-1416.
- [81]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [82]. Mukut Kanti, B. (2020). Integrated Framework for Fire Safety and Electrical Hazard Assessment in Large-Scale Industrial and Commercial Facilities: A Mixed-Method Analysis. *American Journal of Advanced Technology and Engineering Solutions*, 1(01), 40-86. <https://doi.org/10.63125/zxsbd47>
- [83]. Nayak, A. K., Kumar, P., Pant, D., & Mohanty, R. K. (2018). Land suitability modelling for enhancing fishery resource development in Central Himalayas (India) using GIS and multi-criteria evaluation approach. *Aquacultural Engineering*, 83, 120-129.
- [84]. Nguyen, T. T., Verdoodt, A., Van Y, T., Delbecque, N., Tran, T. C., & Van Ranst, E. (2015). Design of a GIS and multi-criteria based land evaluation procedure for sustainable land-use planning at the regional level. *Agriculture, Ecosystems & Environment*, 200, 1-11.
- [85]. Niehaus, M., Galilea, P., & Hurtubia, R. (2016). Accessibility and equity: An approach for wider transport project assessment in Chile. *Research in Transportation Economics*, 59, 412-422.
- [86]. Ogato, G. S., Bantider, A., Abebe, K., & Geneletti, D. (2020). Geographic information system (GIS)-Based multicriteria analysis of flooding hazard and risk in Ambo Town and its watershed, West shoa zone, oromia regional State, Ethiopia. *Journal of Hydrology: Regional Studies*, 27, 100659.
- [87]. Owolabi, S. T., Madi, K., Kalumba, A. M., & Orimoloye, I. R. (2020). A groundwater potential zone mapping approach for semi-arid environments using remote sensing (RS), geographic information system (GIS), and analytical hierarchical process (AHP) techniques: a case study of Buffalo catchment, Eastern Cape, South Africa. *Arabian journal of geosciences*, 13(22), 1184.

- [88]. Park, S., & Kim, J. (2019). Landslide susceptibility mapping based on random forest and boosted regression tree models, and a comparison of their performance. *Applied Sciences*, 9(5), 942.
- [89]. Pengra, B., Long, J., Dahal, D., Stehman, S. V., & Loveland, T. R. (2015). A global reference database from very high resolution commercial satellite data and methodology for application to Landsat derived 30 m continuous field tree cover data. *Remote sensing of environment*, 165, 234-248.
- [90]. Pham, T. G., Degener, J., & Kappas, M. (2018). Integrated universal soil loss equation (USLE) and Geographical Information System (GIS) for soil erosion estimation in A Sap basin: Central Vietnam. *International Soil and Water Conservation Research*, 6(2), 99-110.
- [91]. Prabhuram, T., Rajmohan, M., Tan, Y., & Robert Johnson, R. (2020). Performance evaluation of Omni channel distribution network configurations using multi criteria decision making techniques. *Annals of Operations Research*, 288(1), 435-456.
- [92]. Pradhan, A., & Kim, Y. (2016). Evaluation of a combined spatial multi-criteria evaluation model and deterministic model for landslide susceptibility mapping. *Catena*, 140, 125-139.
- [93]. Prestmo, A., Hagen, G., Sletvold, O., Helbostad, J. L., Thingstad, P., Taraldsen, K., Lydersen, S., Halsteinli, V., Saltnes, T., & Lamb, S. E. (2015). Comprehensive geriatric care for patients with hip fractures: a prospective, randomised, controlled trial. *The Lancet*, 385(9978), 1623-1633.
- [94]. Pyrialakou, V. D., Gkritza, K., & Fricker, J. D. (2016). Accessibility, mobility, and realized travel behavior: Assessing transport disadvantage from a policy perspective. *Journal of transport geography*, 51, 252-269.
- [95]. Qu, L., Shao, Y., & Zhang, L. (2013). Land suitability evaluation method based on GIS technology. 2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics),
- [96]. Quesada-Ganuza, L., Garmendia, L., Roji, E., & Gandini, A. (2021). Do we know how urban heritage is being endangered by climate change? A systematic and critical review. *International Journal of Disaster Risk Reduction*, 65, 102551.
- [97]. Rahimi, S., Martin, M. J., Obeysekere, E., Hellmann, D., Liu, X., & Andris, C. (2017). A Geographic Information System (GIS)-Based analysis of social capital data: Landscape factors that correlate with trust. *Sustainability*, 9(3), 365.
- [98]. Razavi, S., & Gupta, H. V. (2016). A new framework for comprehensive, robust, and efficient global sensitivity analysis: 2. Application. *Water Resources Research*, 52(1), 440-455.
- [99]. Reshmidevi, T., Eldho, T., & Jana, R. (2009). A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds. *Agricultural systems*, 101(1-2), 101-109.
- [100]. Romeijn, H., Faggian, R., Diogo, V., & Sposito, V. (2016). Evaluation of deterministic and complex analytical hierarchy process methods for agricultural land suitability analysis in a changing climate. *ISPRS International journal of geo-information*, 5(6), 99.
- [101]. Saatsaz, M., Monsef, I., Rahmani, M., & Ghods, A. (2018). Site suitability evaluation of an old operating landfill using AHP and GIS techniques and integrated hydrogeological and geophysical surveys. *Environmental Monitoring and Assessment*, 190(3), 144.
- [102]. Sahin, E. K., Colkesen, I., & Kavzoglu, T. (2020). A comparative assessment of canonical correlation forest, random forest, rotation forest and logistic regression methods for landslide susceptibility mapping. *Geocarto International*, 35(4), 341-363.
- [103]. Şahin, M. (2021). Location selection by multi-criteria decision-making methods based on objective and subjective weightings. *Knowledge and Information Systems*, 63(8), 1991-2021.
- [104]. Shabani, F., Kumar, L., & Ahmadi, M. (2016). A comparison of absolute performance of different correlative and mechanistic species distribution models in an independent area. *Ecology and evolution*, 6(16), 5973-5986.
- [105]. Shepero, M., & Munkhammar, J. (2018). Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data. *Applied Energy*, 231, 1089-1099.
- [106]. Standen, C., Crane, M., Greaves, S., Collins, A. T., & Rissel, C. (2021). How equitable are the distributions of the physical activity and accessibility benefits of bicycle infrastructure? *International journal for equity in health*, 20(1), 208.
- [107]. Stults, M. (2017). Integrating climate change into hazard mitigation planning: Opportunities and examples in practice. *Climate Risk Management*, 17, 21-34.
- [108]. Sun, J., Chow, A. C., & Madanat, S. M. (2021). Equity concerns in transportation infrastructure protection against sea level rise. *Transport Policy*, 100, 81-88.
- [109]. Sun, K., Zhu, Y., Pan, P., Hou, Z., Wang, D., Li, W., & Song, J. (2019). Geospatial data ontology: the semantic foundation of geospatial data integration and sharing. *Big Earth Data*, 3(3), 269-296.
- [110]. Sundararajan, A., Khan, T., Moghadasi, A., & Sarwat, A. I. (2019). Survey on synchrophasor data quality and cybersecurity challenges, and evaluation of their interdependencies. *Journal of Modern Power Systems and Clean Energy*, 7(3), 449-467.
- [111]. Tahri, M., Hakdaoui, M., & Maanan, M. (2015). The evaluation of solar farm locations applying Geographic Information System and Multi-Criteria Decision-Making methods: Case study in southern Morocco. *Renewable and sustainable energy reviews*, 51, 1354-1362.
- [112]. Taloor, A. K., Pir, R. A., Adimalla, N., Ali, S., Manhas, D. S., Roy, S., & Singh, A. K. (2020). Spring water quality and discharge assessment in the Basantar watershed of Jammu Himalaya using geographic information system (GIS) and water quality Index (WQI). *Groundwater for Sustainable Development*, 10, 100364.
- [113]. Tang, C., Xu, D., & Chen, N. (2021). Sustainability prioritization of sewage sludge to energy scenarios with hybrid-data consideration: a fuzzy decision-making framework based on full consistency method and fusion ranking model. *Environmental Science and Pollution Research*, 28(5), 5548-5565.

- [114]. Tegegne, G., Park, D. K., & Kim, Y.-O. (2017). Comparison of hydrological models for the assessment of water resources in a data-scarce region, the Upper Blue Nile River Basin. *Journal of Hydrology: Regional Studies*, 14, 49-66.
- [115]. Tehrany, M. S., Jones, S., Shabani, F., Martínez-Álvarez, F., & Tien Bui, D. (2019). A novel ensemble modeling approach for the spatial prediction of tropical forest fire susceptibility using LogitBoost machine learning classifier and multi-source geospatial data. *Theoretical and Applied Climatology*, 137(1), 637-653.
- [116]. Thacker, S., Adshead, D., Fay, M., Hallegatte, S., Harvey, M., Meller, H., O'Regan, N., Rozenberg, J., Watkins, G., & Hall, J. W. (2019). Infrastructure for sustainable development. *Nature Sustainability*, 2(4), 324-331.
- [117]. Turner, A. K. (2020). The role of three-dimensional geographic information systems in subsurface characterization for hydrogeological applications. In *Three Dimensional Applications in GIS* (pp. 115-127). CRC Press.
- [118]. Van Eck, C. M., Nunes, J. P., Vieira, D. C., Keesstra, S., & Keizer, J. J. (2016). Physically-based modelling of the post-fire runoff response of a forest catchment in central Portugal: Using field versus remote sensing based estimates of vegetation recovery. *Land degradation & development*, 27(5), 1535-1544.
- [119]. van Til, J., Groothuis-Oudshoorn, C., Lieferink, M., Dolan, J., & Goetghebeur, M. (2014). Does technique matter; a pilot study exploring weighting techniques for a multi-criteria decision support framework. *Cost effectiveness and resource allocation*, 12(1), 22.
- [120]. Van Wee, B., & Mouter, N. (2021). Evaluating transport equity. *Advances in transport policy and planning*, 7, 103-126.
- [121]. Vecchio, G., Tiznado-Aitken, I., & Hurtubia, R. (2020). Transport and equity in Latin America: a critical review of socially oriented accessibility assessments. *Transport reviews*, 40(3), 354-381.
- [122]. Verma, P., Singh, P. K., Sinha, R. R., & Tiwari, A. K. (2020). Assessment of groundwater quality status by using water quality index (WQI) and geographic information system (GIS) approaches: a case study of the Bokaro district, India. *Applied Water Science*, 10(1), 27.
- [123]. Villacreses, G., Gaona, G., Martínez-Gómez, J., & Jijón, D. J. (2017). Wind farms suitability location using geographical information system (GIS), based on multi-criteria decision making (MCDM) methods: The case of continental Ecuador. *Renewable energy*, 109, 275-286.
- [124]. Voulvoulis, N., Arpon, K. D., & Giakoumis, T. (2017). The EU Water Framework Directive: From great expectations to problems with implementation. *Science of the Total Environment*, 575, 358-366.
- [125]. Wadoux, A. M.-C., Heuvelink, G. B., De Bruin, S., & Brus, D. J. (2021). Spatial cross-validation is not the right way to evaluate map accuracy. *Ecological Modelling*, 457, 109692.
- [126]. Wang, X., & Xie, H. (2018). A review on applications of remote sensing and geographic information systems (GIS) in water resources and flood risk management. *Water*, 10(5), 608.
- [127]. Wass, S. V., Forssman, L., & Leppänen, J. (2014). Robustness and precision: How data quality may influence key dependent variables in infant eye-tracker analyses. *Infancy*, 19(5), 427-460.
- [128]. Weigand, M., Staab, J., Wurm, M., & Taubenböck, H. (2020). Spatial and semantic effects of LUCAS samples on fully automated land use/land cover classification in high-resolution Sentinel-2 data. *International Journal of Applied Earth Observation and Geoinformation*, 88, 102065.
- [129]. Wu, H., Wang, J., Duan, H., Ouyang, L., Huang, W., & Zuo, J. (2016). An innovative approach to managing demolition waste via GIS (geographic information system): a case study in Shenzhen city, China. *Journal of Cleaner Production*, 112, 494-503.
- [130]. Wylie, B. K., Pastick, N. J., Picotte, J. J., & Deering, C. A. (2019). Geospatial data mining for digital raster mapping. *GIScience & Remote Sensing*, 56(3), 406-429.
- [131]. Yin, S., Li, J., Liang, J., Jia, K., Yang, Z., & Wang, Y. (2020). Optimization of the weighted linear combination method for agricultural land suitability evaluation considering current land use and regional differences. *Sustainability*, 12(23), 10134.
- [132]. Yu, D., Xie, P., Dong, X., Su, B., Hu, X., Wang, K., & Xu, S. (2018). The development of land use planning scenarios based on land suitability and its influences on eco-hydrological responses in the upstream of the Huaihe River basin. *Ecological Modelling*, 373, 53-67.
- [133]. Yusop, Z. B., Ahmed, K., Shirazi, S. M., & Zardari, N. H. (2015). *Weighting methods and their effects on multi-criteria decision making model outcomes in water resources management*. Springer.
- [134]. Zhang, Q., & Zhang, T. (2018). Land consolidation design based on an evaluation of ecological sensitivity. *Sustainability*, 10(10), 3736.
- [135]. Zhao, H., & Li, N. (2016). Optimal siting of charging stations for electric vehicles based on fuzzy Delphi and hybrid multi-criteria decision making approaches from an extended sustainability perspective. *Energies*, 9(4), 270.
- [136]. Zhu, J., Wright, G., Wang, J., & Wang, X. (2018). A critical review of the integration of geographic information system and building information modelling at the data level. *ISPRS International journal of geo-information*, 7(2), 66.
- [137]. Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A., & Mahecha, M. D. (2020). A typology of compound weather and climate events. *Nature reviews earth & environment*, 1(7), 333-347.
- [138]. Zwanenburg, A. (2019). Radiomics in nuclear medicine: robustness, reproducibility, standardization, and how to avoid data analysis traps and replication crisis. *European journal of nuclear medicine and molecular imaging*, 46(13), 2638-2655.