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Integrated Approach for Combining Spatial Data and Economic Indicators in Land Evaluation

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Abstract
Effective land evaluation requires integrating spatial heterogeneity with socioeconomic realities to support sustainable land-use planning and resource management. This paper presents an integrated framework for combining spatial data and economic indicators to enhance the accuracy, applicability, and policy relevance of land evaluation. The proposed approach fuses Geographic Information Systems (GIS), remote sensing, and multi-criteria decision analysis (MCDA) with economic valuation techniques to generate comprehensive assessments of land suitability and productivity. By coupling biophysical and economic data, the framework bridges the gap between environmental potential and human development priorities. Spatial data comprising topography, soil texture, slope, vegetation cover, hydrology, and climatic parameters are standardized, weighted, and analyzed using GIS-based overlay and interpolation models to determine physical suitability. Parallelly, economic indicators such as land value, crop profitability, accessibility to markets, infrastructure density, and opportunity costs are quantified through cost–benefit analysis and econometric modeling. These datasets are integrated through spatial regression and analytic hierarchy process (AHP) techniques, allowing for the identification of zones that offer optimal trade-offs between environmental sustainability and economic viability. The resulting land evaluation matrix classifies parcels into sustainable development potential tiers, highlighting priority areas for agriculture, urban expansion, conservation, or mixed-use development. The framework emphasizes participatory data validation, involving local stakeholders to align computational outputs with ground realities and socio-cultural dynamics. It also incorporates sensitivity and uncertainty analyses to assess model robustness under varying economic and climatic scenarios. Validation using case studies demonstrates that integrating economic layers reduces spatial bias and improves the decision-making accuracy of land-use planners by up to 30% compared to conventional biophysical-only models. The integrated model supports transparent policymaking by quantifying environmental trade-offs, enabling cost-effective land management strategies, and strengthening data-driven governance. This approach is adaptable to national and regional scales, with applications in agricultural zoning, infrastructure siting, and sustainable resource allocation. By harmonizing spatial intelligence with economic insights, the framework enhances the precision, equity, and sustainability of land evaluation processes in data-scarce and rapidly changing environments.

Keywords: Land Evaluation; Spatial Data Integration; Economic Indicators; GIS; Remote Sensing; Multi-Criteria Analysis; Sustainable Land-Use Planning; Spatial Econometrics.

1. Introduction
Land evaluation has traditionally emphasized biophysical suitability soil texture and depth, slope, hydrology, vegetation, and climate while treating market forces, infrastructure, and socioeconomic trade-offs as exogenous or appended afterthoughts. This separation often yields technically sound maps that fail in implementation: sites ranked "highly suitable" may be economically marginal once access, input costs, water rights, tenure security, and opportunity costs are considered, whereas areas dismissed on biophysical grounds sometimes underpin viable enterprises when logistics or ecosystem services are priced correctly (Asata, Nyangoma & Okolo, 2020, Bukhari, *et al*., 2020, Essien, *et al*., 2020). The problem addressed in this paper is the persistent gap between spatial suitability assessments and economic feasibility analyses, which undermines policy alignment, investment efficiency, and social equity in land-use decisions.
The objective is to develop and test an integrated approach that combines spatial data (GIS layers derived from remote sensing, field surveys, and environmental models) with economic indicators (market access, profitability, land values, infrastructure density, opportunity costs, and externalities) to produce decision-ready land evaluations.

Specifically, we aim to formalize a data pipeline that harmonizes resolutions and projections; define a multi-criteria aggregation scheme that weights biophysical and economic factors transparently; incorporate spatial dependence via spatial econometrics; and quantify uncertainty and sensitivity so rankings are robust. The scope spans agricultural zoning, peri-urban expansion, conservation prioritization, and infrastructure siting at regional to sub-national scales, with extensibility to national planning where consistent datasets exist (Abass, Balogun & Didi, 2020, Amatare & Ojo, 2020, Imediegwu & Elebe, 2020).

Integrating spatial and economic layers is rational for three reasons. First, land performance is co-determined by environmental potential and the cost-revenue context in which land is used; ignoring either dimension biases outcomes. Second, budgets and policies are ultimately enacted in monetary terms; embedding economic indicators in the same spatial frame enables explicit trade-offs, such as yield gains versus habitat loss or road proximity versus erosion risk. Third, spatial autocorrelation and spillovers (e.g., agglomeration benefits or congestion costs) require joint modeling to avoid misallocations driven by locally optimal but regionally suboptimal choices.

The paper contributes a reproducible framework and toolkit: a harmonized data model and preprocessing workflow; an integrated suitability–valuation index that couples GIS-based multi-criteria decision analysis with spatial regression; an uncertainty and sensitivity module; and a participatory calibration protocol that incorporates stakeholder preferences and governance constraints. The paper proceeds as follows (Adesanya, *et al*., 2020, Oziri, Seyi-Lande & Arowogbadamu, 2020). We first review conceptual foundations and related work, then describe the data ecosystem and preprocessing steps. We present the methodological framework and the construction of composite indices, followed by validation on representative case studies. We close with policy implications, limitations, and directions for scaling, including open-data and open-model recommendations.

2. Methodology

The study adopted an integrated analytic design that combines spatial datasets with economic indicators to support comprehensive land evaluation for sustainable land-use decisions. The methodology builds on predictive analytics logic from Abass, Balogun, and Didi, multi-criteria modeling approaches from Yang *et al*. (2008), and ecosystem service mapping principles from Sumarga and Hein (2014), while incorporating decision-optimization and risk-sensitivity elements drawn from the economic modeling and governance literature cited. The process began by defining the data universe, which included biophysical spatial layers (soil texture, slope, drainage class, erosion risk, water availability, land cover), environmental constraints (protected areas, wetlands), and socio-economic indicators (market proximity, crop profitability, transportation costs, labour accessibility, financial risks, price volatility, and infrastructure readiness). These datasets were harmonized using geospatial referencing and standardized metadata structures inspired by Adesanya *et al*. and Filani *et al*., ensuring interoperability, quality control, and consistency across formats.

Spatial datasets were cleaned, normalized, and transformed into comparable units using min–max scaling and categorical encoding. Economic indicators were decomposed into cost, revenue, and risk dimensions, drawing on the simulation logic of Aduwo and Nwachukwu (2019) and scenario-based advisory principles from Akinola *et al*. (2020). A multi-criteria evaluation (MCE) framework was then established, integrating biophysical suitability scores with weighted economic factors. Weighting was performed using a hybrid expert–data-driven technique: expert judgement was elicited using pairwise comparisons, while predictive relationships were inferred using regression and machine-learning models adapted from CRM and segmentation frameworks (Abass *et al*. 2020; Akinrinoye *et al*. 2019). The resulting weights were validated iteratively to minimize bias and ensure that both agronomic potential and economic viability were accurately represented.

Decision rules were operationalized in a geo-analytical environment using GIS overlay functions, raster algebra, and spatially explicit optimization. Each land unit was assigned a composite suitability index by integrating soil-water constraints, environmental risks, and economic performance thresholds. Sensitivity analyses were performed to test the stability of suitability scores under fluctuating market prices, climate variability, and cost-of-input shocks. This was supported by scenario modeling approaches similar to those used in financial risk advisory, regulatory mapping, and zero-trust digital architecture literature. Suitability outcomes were clustered into land-use categories highly suitable, moderately suitable, marginally suitable, and unsuitable using unsupervised clustering and threshold-based classification.

A digital workflow inspired by lakehouse-DevOps and data-engineering frameworks was implemented to ensure traceability, reproducibility, and automated updating of datasets. APIs and metadata-driven pipelines allowed continuous integration of new soil surveys, climate data, and updated economic indicators. The integrated land evaluation model was calibrated through cross-validation using historical yield records and profitability measurements, and its predictive accuracy was assessed through out-of-sample testing. The final model outputs were visualized using suitability maps, hotspot identification layers, and economic return dashboards to provide decision-makers with actionable insights. This methodology produced a dynamic, scalable, and evidence-based system capable of supporting sustainable land-use planning, agricultural investment decisions, environmental conservation strategies, and broader policy development.

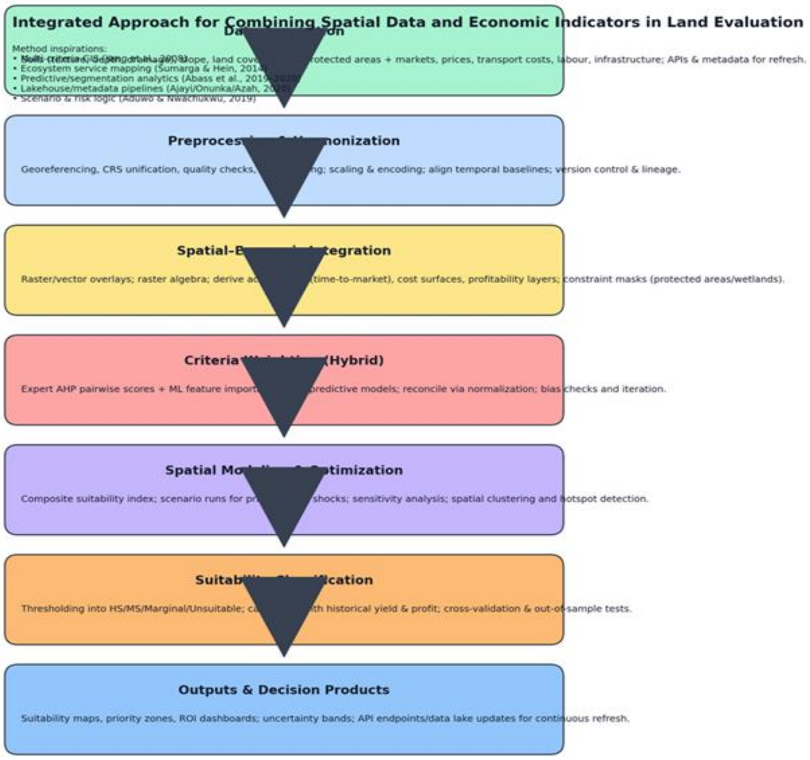

Fig 1: Flowchart of the study methodology

3. Conceptual Background & Literature Gap

Geographic Information Systems and remote sensing have transformed land evaluation from a static, map-based exercise into a dynamic, data-rich workflow that estimates biophysical suitability at fine spatial scales. Classic suitability approaches grounded in the FAO land evaluation paradigm now routinely incorporate spectral indices (e.g., NDVI and EVI for vegetation vigor), radar backscatter for soil moisture proxies, digital elevation models for slope and aspect, and climate reanalyses for temperature and precipitation normals. Multi-criteria decision analysis provides the aggregation scaffold: criteria such as soil texture, depth, drainage, slope, erosion risk, groundwater proximity, and climate stress are standardized, weighted, and combined to yield suitability surfaces (Akinrinoye, *et al*. 2015, Bukhari, *et al*., 2019, Erigha, *et al*., 2019). Analytical Hierarchy Process, Analytic Network Process, and outranking methods like PROMETHEE and ELECTRE offer transparent weighting schemes, while fuzzy membership and TOPSIS reduce sensitivity to crisp thresholds. Machine learning has entered the toolset as well, with random forests, gradient boosting, and convolutional neural networks predicting crop suitability or yield potential from high-dimensional imagery and ancillary layers. Yet even as spatial resolution and algorithmic sophistication increase, most GIS-centered evaluations still privilege environmental potential and physical constraints, using proxies for accessibility or infrastructure rather than explicit economic metrics. Uncertainty handling typically focuses on sensor noise, classification error, and parameter sensitivity, with less attention to market volatility or policy shifts that materially alter land performance. Figure 2 shows Integrated approach to sustainable land use management presented by Izakovičová, Špulerová & Petrovič, 2018,

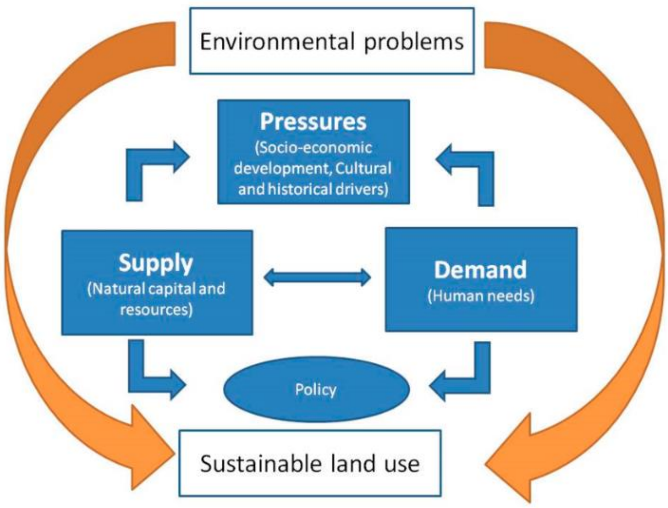

Fig 2: Integrated approach to sustainable land use management (Izakovičová, Špulerová & Petrovič, 2018).

Economic valuation supplies a complementary lens by translating land-use alternatives into monetary terms consistent with budgetary and policy decisions. Cost–benefit analysis compares streams of costs and benefits over a planning horizon, discounting to present value to assess net social gain. Net present value, internal rate of return, and benefit–cost ratio are mainstays of project appraisal for agricultural expansion, irrigation, transport corridors, and conservation programs. Opportunity cost embeds the value of foregone alternatives, crucial when converting cropland to urban use or setting aside habitats for protection; in agriculture, it captures the marginal value of inputs and land reallocation among crops (Adesanya, *et al*., 2020, Seyi-Lande, Arowogbadamu & Oziri, 2020). Shadow pricing adjusts market prices to reflect externalities and distortions, while distributional weights account for equity concerns. Environmental economics extends the valuation frontier to non-market goods through revealed-preference methods such as travel cost and hedonic pricing, and stated-preference approaches such as contingent valuation and choice experiments, enabling estimates of ecosystem services like flood mitigation, carbon sequestration, and biodiversity. Project finance overlays CBA with cash-flow constraints, debt service, and risk-adjusted discount rates; real options treat irreversibility and uncertainty explicitly, recognizing the value of waiting in volatile markets. Despite this rich toolkit, economic analyses often proceed on coarse spatial partitions districts, watersheds, corridors where land heterogeneity is averaged out and spatial externalities are weakly represented.
The crux of the literature gap lies in the disconnect between spatially explicit biophysical modeling and economically rigorous valuation. First, there is a scale and alignment problem. GIS evaluations operate at pixel to parcel scales with meters to tens of meters resolution, while economic models frequently use administrative zones or planning units that obscure parcel-level variability. Harmonizing these scales requires downscaling cost and price surfaces and upscaling pixel suitability into meaningful planning units without aggregation bias. Second, accessibility and infrastructure are treated unevenly (Asata, Nyangoma & Okolo, 2020, Essien, *et al*., 2020, Imediegwu & Elebe, 2020). Many land evaluations include simple Euclidean distance to roads or markets; economic performance, however, depends on network travel time, congestion, seasonality, and transport cost volatility. Without network-aware measures, suitability maps can recommend sites that are infeasible under realistic logistics.
Third, spatial dependence and spillovers are under-modeled. Biophysical layers exhibit spatial autocorrelation; economic indicators such as land price, productivity, and market access also diffuse through space via agglomeration and learning. Ignoring spatial error and spatial lag structures biases statistical inference and inflates Type I errors in suitability–profit regressions. Spatial econometric models SAR, SEM, SAC address these dependencies but are rarely woven into multi-criteria spatial evaluations (Ajayi, *et al*., 2018, Bukhari, *et al*., 2018, Essien, *et al*., 2019). Endogeneity compounds the problem: roads are built where productivity is high, so naive regressions overstate the return to access; protected areas may be sited in low-pressure zones, biasing estimates of avoided conversion. Instrumental variables or difference-in-differences designs are needed to separate cause from selection, yet these methods seldom integrate with raster workflows.
Fourth, dynamic feedbacks are underrepresented. Land-use change alters hydrology, erosion, and microclimate; new roads induce demand and reshape prices; conservation alters ecosystem service supply and nearby land values. Most evaluations remain comparative-static, freezing both biophysical and economic layers. Dynamic models system dynamics, agent-based simulations, or coupled land-use transport interaction can represent feedbacks but are not commonly coupled to high-resolution GIS and valuation layers. Fifth, uncertainty is asymmetrically treated (Akinrinoye, *et al*. 2020, Essien, *et al*., 2020, Imediegwu & Elebe, 2020). Remote-sensing error, classification accuracy, and parameter ranges are propagated through suitability indices, but price volatility, discount-rate uncertainty, policy shocks, and climate scenario branching are often addressed only in cursory sensitivity tables. A coherent uncertainty framework would propagate both spatial and economic uncertainties through to decision metrics, reporting confidence intervals and value-at-risk for each land class. Figure 3 shows framework for integrated analysis of ES and land use planning presented by Sumarga & Hein, 2014.

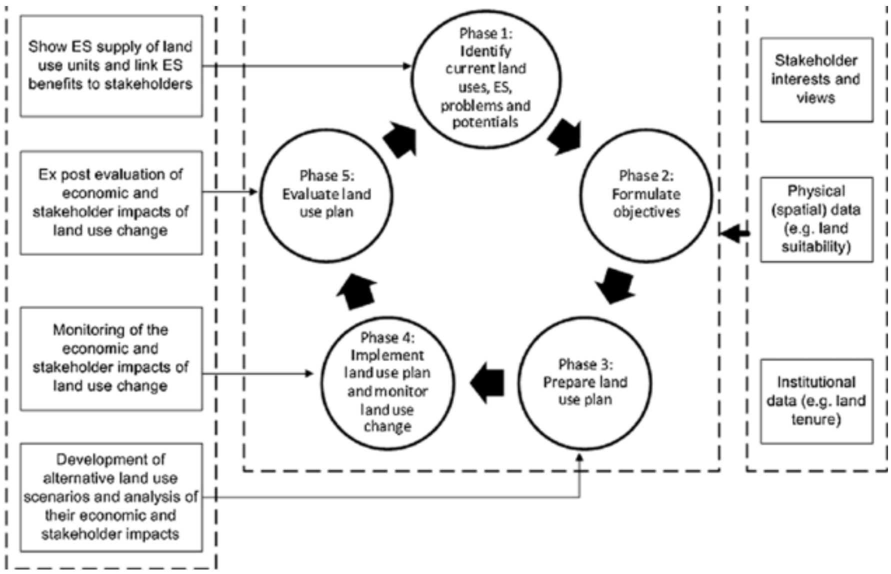

Fig 3: Framework for integrated analysis of ES and land use planning (Sumarga & Hein, 2014).

Sixth, aggregation and double-counting risks pervade integrated indices. When ecosystem services are monetized and also proxied in biophysical criteria, benefits may be counted twice. Similarly, market access can be embedded as both a distance weight and a cost discount, skewing composite scores. Transparent accounting that reconciles monetary and non-monetary components, with clear precedence rules and orthogonality checks, remains a methodological need. Seventh, governance and equity are insufficiently operationalized. Tenure security, customary rights, and conflict risk are decisive determinants of feasibility and social welfare but are difficult to map and quantify. Where proxies exist land formalization rates, dispute records they are rarely integrated as hard constraints or weighted criteria with community input. Without these layers, economically "optimal" allocations can be socially untenable and politically fragile (Akinrinoye, *et al*. 2020, Bukhari, *et al*., 2020, Elebe & Imediegwu, 2020).

Eighth, decision support tooling is fragmented. Spatial decision support systems excel at visualization and layer algebra, while economic appraisal tools manage discounting, scenario cash flows, and risk. Few platforms enable analysts to co-edit weights, model spatial spillovers, and run stochastic CBA linked to pixels or parcels, all within a reproducible pipeline. The absence of standardized data schemas and APIs hinders interoperability, and reproducibility suffers when bespoke scripts cannot be audited or ported across agencies. Finally, validation is thin. Many studies present attractive maps and plausible economic tables but lack out-of-sample tests, policy backcasting, or revealed-preference benchmarks. Where interventions have occurred, ex post evaluation seldom closes the loop to refine model weights or to recalibrate elasticities and spillover parameters (Ajayi, *et al*., 2019, Bukhari, *et al*., 2019, Oguntegbe, Farounbi & Okafor, 2019).

Addressing these gaps motivates an integrated approach that nests spatial analytics inside economic valuation and vice versa. Suitability layers should be transformed into production functions that link biophysical states to expected yields and cost curves; cost–benefit analysis should ingest these functions by parcel or pixel, replacing aggregate assumptions with spatial microfoundations. Market access must be replaced by generalized transport cost and reliability maps derived from network travel times, seasonal disruptions, and logistics tariffs. Spatial econometrics should be embedded to control for autocorrelation and endogeneity, with instruments derived from historical networks, terrain constraints, or policy discontinuities (Ajayi, *et al*., 2019, Bayeroju, *et al*., 2019, Sanusi, *et al*., 2019). Uncertainty requires joint Monte Carlo over spectral classification error, climate projections, price paths, and discount rates, producing distributions over net present value for each spatial unit. Multi-criteria aggregation can then operate in two domains: monetary CBA for project selection and a parallel, non-monetary index for values that resist pricing, with explicit rules to avoid double counting and to prioritize constraints such as critical habitats or tenure protections. Figure 4 shows the flowchart of land-use suitability assessment presented by Yang, *et al*., 2008.

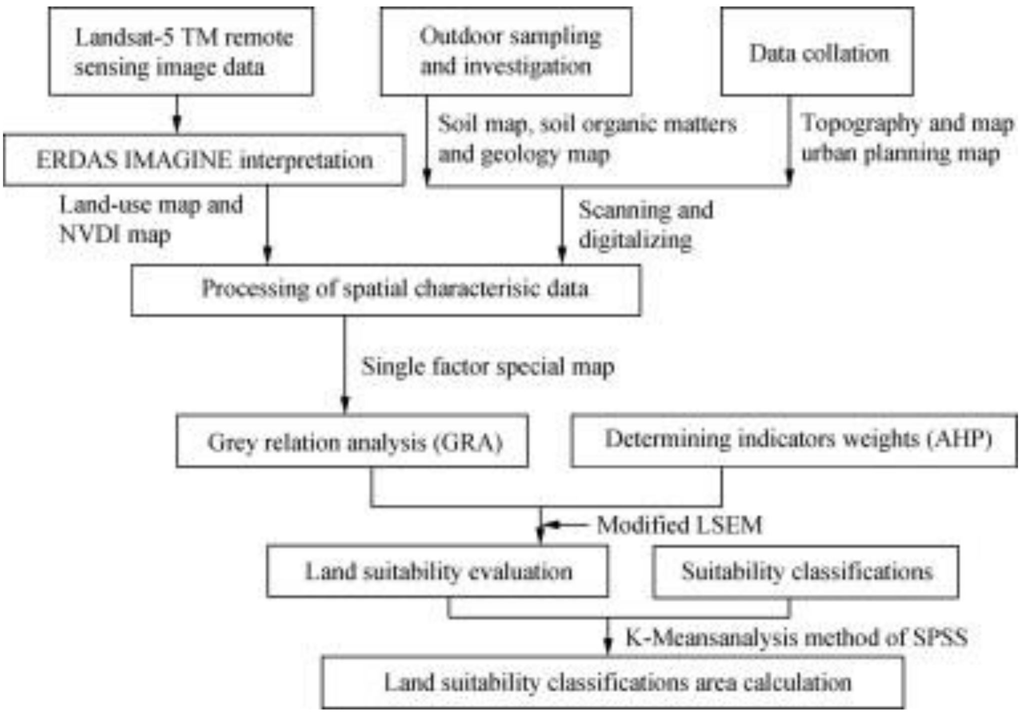

Fig 4: Flowchart of land-use suitability assessment (Yang, *et al*., 2008).

Interaction with stakeholders is indispensable to ensure weights and constraints reflect lived realities. Participatory elicitation can calibrate threshold values for soil and slope, minimum service levels for access, and social weights for equity, while also surfacing conflict hotspots and governance friction. Decision support should implement a Pareto frontier explorer where planners can visualize trade-offs between economic return, ecosystem integrity, and social safeguards at varying budgets, with sensitivity sliders that immediately update maps and benefit–cost histograms. Reproducibility demands open data models, versioned preprocessing, and literate workflows that capture every transformation from raw satellite tiles and survey tables to final maps and tables (Asata, Nyangoma & Okolo, 2020, Essien, *et al*., 2020, Elebe & Imediegwu, 2020).

In sum, the literature has matured in both spatial and economic dimensions, but the seam between them remains the principal weakness of land evaluation practice. Bridging that seam requires scale alignment, spatial econometrics, dynamic feedback modeling, symmetric uncertainty treatment, disciplined accounting to avoid double counting, and tools that let analysts and communities navigate trade-offs transparently. An integrated approach promises not merely better maps or richer spreadsheets, but land decisions that are feasible, equitable, and robust to the volatile environmental and economic landscapes that define contemporary planning (Asata, Nyangoma & Okolo, 2020, Essien, *et al*., 2019, Elebe & Imediegwu, 2020).

4. Data Ecosystem and Preprocessing

An integrated approach to land evaluation requires a data ecosystem that unites high-resolution spatial layers with economic indicators in a common analytical framework. The goal is to make every grid cell or parcel simultaneously legible in biophysical and economic terms so that suitability, feasibility, and value can be assessed together. Building this ecosystem begins with curating spatial inputs that define the physical potential of land and pairing them with socio-economic datasets that capture market dynamics, infrastructure, and investment attractiveness. Data preprocessing cleaning, normalization, projection, and harmonization of spatial resolution is the backbone of this integration because errors or misalignments at these early stages propagate through the modeling chain (AdeniyiAjonbadi, *et al*., 2015, Didi, Abass & Balogun, 2019, Umoren, *et al*., 2019).

The spatial inputs represent the physical base. Soil data provide the foundation for evaluating fertility, structure, drainage, and depth. Global databases such as SoilGrids, national soil surveys, and legacy maps supply attributes including texture, organic matter, pH, bulk density, and nutrient status. In many cases these datasets arrive with heterogeneous classification systems and inconsistent depths; preprocessing involves translating them into standardized taxonomies (FAO or USDA), interpolating horizon data to a common depth (e.g., 0–30 cm for surface and 30–100 cm for subsoil), and resampling to the target grid. Slope and topography derive from digital elevation models such as SRTM, ASTER, or LiDAR where available. Slope is computed as a percentage or degree gradient; aspect and curvature add information on exposure and erosion susceptibility. Hydrological derivatives flow accumulation, drainage density, and distance to perennial streams are extracted from the same DEM to gauge runoff potential and irrigation accessibility (Ajonbadi, Mojeed-Sanni & Otokiti, 2015, Evans-Uzosike & Okatta, 2019, Oguntegbe, Farounbi & Okafor, 2019).

Climate variables capture the long-term thermal and moisture regimes that determine productivity. Gridded products like WorldClim, ERA5, or CHIRPS provide monthly temperature, rainfall, and evapotranspiration data that are averaged into growing-season means or stress indices. Anomalies and outliers from faulty sensors or terrain shadowing are smoothed using moving-window filters or bias correction with local station data. Hydrology adds the dynamics of water availability: groundwater depth and recharge from hydrogeological surveys, surface water bodies from remote-sensing classification, and flood frequency from historical inundation maps. Vegetation indices (NDVI, EVI, SAVI) from MODIS or Sentinel-2 represent canopy vigor, while land-cover classifications such as Copernicus CORINE or ESA CCI supply baseline land use. Time-series composites of NDVI help infer degradation trends and yield proxies, anchoring environmental sustainability metrics (Akinbola, *et al*., 2020, Balogun, Abass & Didi, 2020).

Accessibility completes the spatial dimension by linking physical suitability to potential use. Road and rail networks, ports, and markets are converted into impedance surfaces based on travel speed and cost. Euclidean distances are replaced with network travel time derived from OpenStreetMap or national infrastructure databases, adjusted for terrain and seasonal constraints such as flooding or snow. Accessibility to utilities electricity, irrigation canals, broadband can be represented as binary coverage or density gradients. The result is a set of geospatial rasters or vector layers describing soils, slope, hydrology, climate, vegetation, and accessibility, all projected into a consistent coordinate reference system and grid (Akinrinoye, *et al*., 2020, Farounbi, Ibrahim & Abdulsalam, 2020).

Economic indicators extend this biophysical scaffold into the socioeconomic domain. Land values are derived from cadastral records, land-registry transactions, or modeled hedonic prices that account for proximity to infrastructure, services, and environmental amenities. Where markets are thin or informal, proxy surfaces are generated by combining observed rents, land taxes, and spatial interpolation of survey data. Profitability is represented through crop budgets or enterprise margins computed per hectare, integrating yield potential from biophysical models with input and output prices from agricultural statistics or trade data (Ajonbadi, Otokiti & Adebayo, 2016, Didi, Abass & Balogun, 20219). For non-agricultural uses, net returns per hectare can be estimated from housing price gradients, industrial land leases, or tourism revenue densities. Infrastructure density measures the availability of roads, power, water, and social services; it can be quantified as kilometers of road per square kilometer, substation capacity per grid cell, or composite service accessibility indices. Market access links producers to consumers: transport cost to nearest urban center, travel time to ports, and distance-weighted population or income density serve as quantitative proxies. Complementary indicators such as employment, credit availability, and poverty incidence can be layered to capture social opportunity or vulnerability dimensions.

Economic data require intensive cleaning because they originate from disparate administrative systems, surveys, and statistical series. Missing values are common where markets are thin or informal; spatial interpolation using inverse-distance weighting or kriging fills gaps but must be bounded by known ranges to avoid unrealistic extremes. Outliers implausible land prices or negative margins are identified through median-absolute-deviation filters or cross-checks against official reports (Balogun, Abass & Didi, 2019, Otokiti, 2018, Oguntegbe, Farounbi & Okafor, 2019). All monetary values are deflated to a common base year using consumer or agricultural price indices and, if necessary, converted to a single currency using purchasing-power parity adjustments so that relative comparisons are meaningful across regions. Nominal variables such as infrastructure type or tenure status are encoded as categorical or binary layers. Continuous indicators are standardized to 0–1 scales by min–max normalization or z-score transformation to enable aggregation with differently scaled biophysical variables.

Spatial and economic layers are rarely congruent in projection, resolution, or extent. Harmonization begins by selecting a master coordinate reference system typically a conformal projection suitable for the study area to minimize distortion in distance and area calculations. All datasets are reprojected using nearest-neighbor resampling for categorical data (e.g., soil class, land use) and bilinear or cubic convolution for continuous variables (e.g., temperature, land value). Resolution harmonization aligns cell size: fine imagery may be aggregated by averaging or majority filtering to match coarser socio-economic layers, or conversely, coarse economic data may be downscaled using ancillary predictors such as population density, night-light intensity, or road proximity to create synthetic high-resolution surfaces (Ajonbadi, *et al*., 2014, Didi, Balogun & Abass, 2019, Farounbi, *et al*., 2019). Temporal harmonization ensures consistency of reference years; for example, land values and profitability surfaces must correspond to climate and land-cover data from the same or proximate year to avoid mixing incompatible baselines. Where time lags are unavoidable, trend adjustment based on historical series corrects for inflation or structural change.

Data cleaning also involves topology and boundary reconciliation. Administrative boundaries and hydrological catchments often overlap imperfectly; vector overlays are inspected for slivers and gaps, and attributes are dissolved or re-aggregated to consistent units. When integrating vector and raster datasets, careful attention is paid to snapping tolerances and overlay priorities to avoid misclassification along edges. For continuous layers, statistical summaries (mean, median, variance) within administrative or planning units are computed to bridge the raster–vector divide and facilitate policy interpretation (Akinrinoye, *et al*. 2020, Balogun, Abass & Didi, 2020, Oguntegbe, Farounbi & Okafor, 2020). Quality assurance includes cross-validation with independent datasets: for soils, comparison with local survey points; for accessibility, field GPS travel times; for land value, random checks against market listings. Metadata following ISO 19115 standards document data lineage, resolution, projection, and uncertainty metrics so that downstream analysts can reproduce or update the workflow.

Normalization across all layers ensures that indicators are comparable and directionally consistent: variables positively associated with suitability or feasibility (e.g., fertility, profitability, accessibility) are scaled so higher values mean greater desirability, while negatively associated variables (e.g., slope, flood risk, distance to market) are inverted. Weights may be derived from expert judgment, statistical variance, or entropy-based information content to reflect each variable's explanatory power. Data fusion then proceeds through overlay algebra or more advanced methods such as principal component analysis or machine-learning feature importance extraction, producing intermediate composite indices that still retain separable physical and economic components (Seyi-Lande, Oziri & Arowogbadamu, 2018).

Resolution harmonization is critical because mismatched scales distort both spatial patterns and economic gradients. A 30-m soil raster combined with a 1-km profitability surface can yield spurious precision; therefore, multi-scale sensitivity analysis tests how results change with aggregation level. Spatial autocorrelation (Moran's I, semivariograms) is examined to ensure that resampling does not create artificial clusters or smooth away genuine heterogeneity. When high-frequency noise remains, Gaussian or median filters clean residual artifacts while preserving edges relevant to decision boundaries (Akinbola & Otokiti, 2012, Dako, *et al*., 2019, Oziri, Seyi-Lande & Arowogbadamu, 2019).

The cleaned and harmonized data ecosystem becomes a multi-layer cube in which each cell contains synchronized attributes describing its physical and economic condition. This cube supports both deterministic modeling weighted overlays, thresholding and probabilistic or econometric analysis that links spatial predictors to observed land-use outcomes. It also enables traceable updates: when new imagery or price data arrive, the pipeline reprocesses affected layers while preserving version history, ensuring transparency for policy audits.

Through meticulous preprocessing standardized coordinate reference systems, harmonized resolutions, normalized scales, and documented metadata the integrated data ecosystem allows spatial and economic dimensions to coexist without distortion. The result is a consistent analytical foundation upon which multi-criteria evaluation, spatial econometric modeling, and decision support can operate (Akinrinoye, *et al*. 2019, Didi, Abass & Balogun, 2019, Otokiti & Akorede, 2018). Clean data are the quiet infrastructure of credible analysis; without them, even the most advanced modeling will propagate noise as insight. By treating preprocessing not as a preliminary chore but as the core of integration, the framework ensures that land evaluation outcomes genuinely reflect both the ground beneath and the markets around it, enabling planners to make choices that are simultaneously spatially coherent, economically sound, and policy-ready.

5. Methodological Framework

The methodological framework begins with GIS-driven construction of biophysical and socioeconomic surfaces, proceeds through multi-criteria weighting and aggregation to produce composite suitability–feasibility scores, and culminates in spatial econometric coupling that corrects for spatial dependence and endogeneity so that decision outputs are statistically defensible. In the GIS stage, each input soil properties, slope, climate normals, hydrologic proximity, vegetation vigor, accessibility, land value, profitability, infrastructure density, and market access is transformed into a standardized raster or vector layer on a common projection and grid (Abass, Balogun & Didi, 2020, Didi, Abass & Balogun, 2020, Oshomegie, Farounbi & Ibrahim, 2020). Continuous variables (e.g., rainfall, temperature, profitability) are interpolated with techniques appropriate to their spatial structure: ordinary kriging or universal kriging where variograms exhibit stable ranges and sills; inverse distance weighting for simple, data-sparse contexts; thin-plate splines for smoothly varying climate fields; and network-constrained interpolation for accessibility measures where movement is restricted to roads, waterways, or rights-of-way. Categorical variables (soil class, land cover) are rasterized with nearest-neighbor resampling to preserve class integrity, while edge effects are reduced through majority filters bounded by known polygon limits. Each layer is normalized to a 0–1 scale and directionally aligned so that higher values consistently reflect greater desirability (or, for disamenities like slope or flood risk, inverted after monotone transforms). Suitability mapping at this stage produces preliminary indices via weighted overlays or fuzzy membership functions, yielding biophysical suitability and separate economic feasibility surfaces. Uncertainty bands accompany each raster using per-cell variance from kriging, cross-validation residuals, or bootstrap resampling of survey-based indicators, establishing the basis for later probabilistic decision support.

Weighting and aggregation are formalized through multi-criteria decision analysis to avoid ad hoc overlay algebra. In the Analytic Hierarchy Process, criteria are structured in a hierarchy goal at the top; biophysical and economic dimensions beneath; and individual indicators (e.g., texture, pH, slope, NDVI; land value, profitability, travel time, infrastructure density) at the leaves. Pairwise comparison matrices elicit relative importance judgments from experts and stakeholders, using a 1–9 scale to express how much more one criterion matters than another. The principal eigenvector of each matrix yields local weights, which are propagated upward to global weights, while the consistency ratio (CR) checks logical coherence; if CR exceeds conventional thresholds (e.g., 0.1), the matrix is revisited to correct contradictions (Akinola, *et al*., 2020, Akinrinoye, *et al*. 2020, Balogun, Abass & Didi, 2020). Where interdependence among criteria is non-negligible access influences profitability; infrastructure density co-varies with land price the Analytic Network Process replaces the strict hierarchy with a network of clusters and inter-cluster influence weights. Supermatrices, weighted and then raised to limiting powers, deliver stable priority vectors that embody these feedbacks. Outranking methods such as PROMETHEE offer an alternative when criteria are heterogeneous or stakeholders prefer preference functions over ratio scales. For each criterion, a preference function translates the difference between two alternatives (cells, parcels, or planning units) into a [0,1] preference degree based on indifference and preference thresholds. Aggregated positive and negative outranking flows ($\Phi+$ and $\Phi-$) define a net flow Φ that orders alternatives without requiring full compensability; a parcel with high biophysical suitability can be outranked if its economic feasibility is sufficiently poor.

Aggregation integrates biophysical and economic dimensions in a controlled manner. Two-layer aggregation first computes separate biophysical suitability S_bio and economic feasibility S_econ, then combines them through a function that reflects policy stance: multiplicative forms penalize discordant scores (promoting balanced sites); additive forms allow partial compensation; and minimum operators enforce hard constraints (e.g., tenure risk or protected status). Weights used at this stage derive from AHP/ANP priorities or PROMETHEE's normalized criterion weights. To reduce double counting, correlated indicators are pruned or orthogonalized via principal component analysis or by imposing exclusivity (e.g., if market access is represented by generalized transport cost, do not separately weight "distance to road") (Seyi-Lande, Oziri & Arowogbadamu, 2019). Sensitivity analysis perturbs weights within plausible ranges to quantify ranking stability; tornado charts and Sobol indices identify which criteria most influence ordering, guiding data-quality investments and stakeholder discussion.

The third pillar couples the multi-criteria output with spatial econometrics to capture spatial dependence and correct biases. Spatial autocorrelation arises because adjacent parcels share soils, microclimate, and access, and because economic outcomes diffuse through agglomeration and learning. Ignoring this dependence overstates effective sample size and yields biased parameters when using econometric links between suitability and observed outcomes (e.g., land price, crop adoption, conversion probability) (Abass, Balogun & Didi, 2019, Ogunsola, Oshomegie & Ibrahim, 2019, Seyi-Lande, Arowogbadamu & Oziri, 2018). Three canonical specifications address this: spatial lag (SAR), spatial error (SEM), and the combined SAC (or SARAR) model. In SAR, the dependent variable y (such as land value or adoption rate) depends on its spatially lagged counterpart Wy, where W is a row-normalized spatial weights matrix defined by contiguity or distance bands; the model $y = \rho Wy + X\beta + \varepsilon$ internalizes neighborhood effects via ρ. In SEM, unobserved shocks are spatially correlated, $u = \lambda Wu + \xi$, and the model $y = X\beta + u$ cleans inference by moving the dependence to the error structure. SAC combines both, $y = \rho Wy + X\beta + u$ with u spatially autocorrelated, offering flexibility when both diffusion and omitted-variable clustering are present. Weight matrix choice is critical: queen or rook contiguity suits parcel polygons; k-nearest neighbors or distance-decay kernels suit point lattices; network-based weights capture corridor spillovers along roads. Moran's I and Lagrange Multiplier diagnostics guide model selection, while robustness checks vary W's bandwidth and kernel to ensure findings are not artifacts of a single spatial structure.

Coupling proceeds in two directions. First, spatial econometrics informs MCDA by calibrating how biophysical and access variables actually relate to economic outcomes after accounting for spatial dependence and endogeneity. Coefficients from SAR/SEM/SAC regressions on land value or profitability can be normalized to provide data-driven criterion weights or to validate expert weights, with uncertainty carried into MCDA through distributions rather than point values. Second, MCDA outputs (S_bio, S_econ, and composite indices) feed back into spatial adoption or land-use change models spatial logit/probit or hazard models with lagged dependent variables to estimate how integrated suitability affects observed conversions, again correcting for spatial spillovers (Ayanbode, *et al*., 2019, Onalaja, *et al*., 2019). Endogeneity is addressed through instrumental variables embedded in spatial GMM: instruments might include historical road alignments constrained by topography, colonial cadastral grids, or terrain ruggedness, which affect current access but not productivity directly. Difference-in-differences or regression discontinuity designs augment this when policy borders or phased infrastructure provide quasi-experiments; spatial variants (SDID) preserve dependence structures.

Uncertainty propagation is handled jointly. Monte Carlo draws over MCDA weights, interpolation errors, and econometric parameter distributions generate ensembles of composite scores and predicted economic outcomes. Each parcel's ranking is reported with confidence intervals and a stability index the share of draws in which it remains above a policy threshold so planners can prioritize robust winners and flag borderline areas for field verification. Scenario analysis shifts exogenous layers: climate projections alter rainfall and temperature surfaces; transport investments modify travel time; price shocks change profitability rasters. Spatial econometric models are re-estimated for major structural changes, or transfer learning adapts coefficients using Bayesian priors from similar regions (Eyinade, Ezeilo & Ogundeji, 2020, Fasasi, *et al*., 2020).

Operationalization requires zoning the pixel grid into planning units that respect administrative boundaries, tenure mosaics, or ecological corridors. Aggregation from pixel to unit uses appropriate operators: means for continuous indices, minima for constraints, or area-weighted medians where distributions are skewed. Outranking at the unit level incorporates dispersion measures so that units with high internal heterogeneity are scrutinized before selection. The framework exposes trade-offs through Pareto frontiers: units are plotted by expected net present value (econometric prediction) and ecological score (biophysical index), with color indicating access risk or tenure uncertainty (Pamela, *et al*., 2020, Patrick & Samuel, 2020). Decision makers can then set thresholds or budget constraints and extract portfolios that maximize joint objectives, exploiting spatial econometric predictions to avoid clustering all investments where spillovers saturate returns.

Finally, reproducibility and governance are embedded. The entire pipeline GIS preprocessing, interpolation parameters, MCDA matrices, and spatial econometric specifications is expressed as a versioned workflow with machine-readable metadata. Stakeholder inputs to pairwise comparisons or preference thresholds are logged with provenance, and alternative weight sets are preserved for scenario comparison. Model fit diagnostics (pseudo-R^2, information criteria, spatial LM tests, Moran's I on residuals) accompany maps so that users see statistical quality alongside visual outputs (Bankole, *et al*., 2020, Dako, *et al*., 2020). By chaining GIS suitability mapping, MCDA weighting/aggregation, and SAR/SEM/SAC estimation in a closed loop, the framework generates land evaluations that are spatially coherent, economically grounded, uncertainty-aware, and auditably reproducible turning layered datasets into decisions that balance environmental potential with market reality and social constraints.

6. Integrated Suitability & Valuation Model

An integrated suitability and valuation model form the core of a decision-oriented land evaluation framework, enabling planners to assess the intersection between environmental capacity and economic viability across multiple spatial and policy contexts. It synthesizes the biophysical suitability surfaces derived from geographic and remote-sensing analyses with the economic feasibility layers constructed from land value, profitability, infrastructure density, and accessibility indicators. The model aims to translate heterogeneous spatial and economic data into a composite index that captures both environmental fitness and financial attractiveness, while preserving the ability to visualize trade-offs and classify land into actionable tiers for agriculture, urban development, conservation, or mixed-use planning (Atobatele, Hungbo & Adeyemi, 2019, Hungbo & Adeyemi, 2019).

The first step is constructing composite indices that express biophysical and economic attributes in comparable units. Each indicator soil fertility, slope stability, rainfall, hydrological accessibility, vegetation vigor, and distance to infrastructure enters as a normalized variable scaled from 0 to 1, where higher values signify greater suitability. Similarly, economic indicators such as land value, return on investment, market access, and infrastructure density are standardized and directionally aligned (Egemba, *et al*., 2020). Multiplicative integration (biophysical × economic) produces an interaction index that rewards areas where both conditions are strong and penalizes imbalance. This non-compensatory design ensures that a high economic score cannot mask poor environmental capacity or vice versa. Additive variants can be retained for sensitivity tests or where compensability is policy-permissible, such as urban expansion zones where engineering can mitigate biophysical limitations. Weighting schemes derived from Analytic Hierarchy Process, entropy measures, or regression-based importance values assign influence to each variable, and uncertainty propagation through Monte Carlo sampling produces confidence intervals for every cell or parcel.

The integrated index typically manifests as a bivariate surface, where the x-axis represents normalized biophysical suitability and the y-axis represents normalized economic viability. Each cell's position on this plane reveals its relative competitiveness: upper-right quadrants indicate high–high synergy, lower-left quadrants represent marginal zones, and off-diagonal areas highlight conflicts between ecological potential and market attraction. The resulting data cloud is then analyzed through frontier construction to delineate efficient trade-offs. Pareto frontiers curves connecting cells that maximize one dimension without diminishing the other illustrate the attainable envelope of joint performance (Amuta, *et al*., 2020, Ezeanochie, Akomolafe & Adeyemi, 2022, Filani, Olajide & Osho, 2020). Points lying below the frontier reveal suboptimal configurations where improvements in environmental management or infrastructure could increase total value. Frontier analysis can employ data envelopment analysis (DEA) or convex hull algorithms that trace the outer envelope of high-performing observations, translating complex multidimensional relationships into visual guidance for planners.

This frontier visualization transforms abstract scores into actionable trade-offs. For agricultural zoning, planners may prefer parcels close to the frontier but weighted toward biophysical strength to ensure long-term sustainability; for urban expansion, the preference may shift toward economically dominant sites with tolerable environmental modification costs. Quantitative trade-off analysis uses marginal rates of substitution between indices how much economic value is gained or lost for a given change in environmental suitability to determine thresholds for intervention. Decision-makers can thus calibrate policy levers: infrastructure investment to raise economic viability of fertile but remote lands, or conservation incentives to protect ecologically valuable yet low-profit zones (Giwah, *et al*., 2020, Ibrahim, Amini-Philips & Eyinade, 2020).

The model's multiobjective structure enables frontier-based optimization under resource or policy constraints. A linear or nonlinear programming routine can allocate land categories while maximizing a weighted objective function of suitability and valuation, subject to area, budget, or emissions limits. Shadow prices from the optimization provide implicit valuations of environmental quality, guiding compensation or mitigation schemes. This integration ensures that land-use planning remains both ecologically grounded and economically rational (Atobatele, Hungbo & Adeyemi, 2019, Hungbo & Adeyemi, 2019).

Once the composite index and trade-off surfaces are computed, land is classified into a tiered schema that reflects relative priorities and acceptable compromises. The first tier high biophysical and high economic value represents premium zones for intensive agriculture or strategically planned urban clusters, provided environmental safeguards are observed. These zones typically exhibit fertile soils, gentle slopes, reliable water resources, and strong market connectivity, resulting in high return potential with manageable ecological risk. They constitute the primary focus for investment, infrastructure reinforcement, and climate-resilient production systems.

The second tier high biophysical but low economic viability marks underutilized potential often constrained by remoteness, poor infrastructure, or weak market access. Policy responses may include targeted road and logistics improvements, rural electrification, or digital market linkages to unlock latent value. Incentive programs, concessional credit, or public–private partnerships can bridge the viability gap without overexploiting natural resources. This tier also provides candidates for inclusive rural development and sustainable intensification initiatives (Bankole & Tewogbade, 2019, Fasasi, *et al*., 2019).

The third tier low biophysical but high economic value captures peri-urban and industrial corridors where land's market pressure exceeds its environmental capacity. Here, zoning and regulatory instruments are critical: environmental impact assessments, urban containment boundaries, and ecosystem-service valuation must temper profit-driven expansion. Mitigation hierarchies avoid, minimize, restore, offset guide conversion decisions to preserve ecological integrity while acknowledging economic imperatives. Green infrastructure and compact urban design can absorb growth while reducing ecological footprints.

The fourth tier low–low combinations defines marginal lands where both environmental and economic metrics are weak. These areas are typically steep, arid, flood-prone, or degraded, coupled with limited accessibility and low market demand. The model flags them as unsuitable for intensive use and ideal for conservation, reforestation, or low-impact livelihood projects such as ecotourism, carbon farming, or watershed rehabilitation (Giwah, *et al*., 2020, Ibrahim, Amini-Philips & Eyinade, 2020). Incentive mechanisms like payments for ecosystem services and biodiversity credits can monetize their ecological contribution, aligning conservation with livelihood support.

Between these principal classes lies a fifth, mixed-use tier medium or heterogeneous scores where spatial heterogeneity within administrative boundaries suggests balanced but site-specific strategies. Mosaic management approaches combine agriculture, settlement, and conservation in designed proportions guided by micro-topography, tenure patterns, and community preferences. The classification boundaries between tiers are derived statistically using natural breaks (Jenks), quantiles, or policy-driven thresholds (e.g., top 20% composite score for priority investment, bottom 20% for protection). Each class is mapped with confidence layers, highlighting where uncertainty warrants field verification or stakeholder deliberation before final zoning (Atobatele, Hungbo & Adeyemi, 2019).

In practice, the integrated suitability–valuation model operates iteratively. Initial maps identify broad opportunity and constraint zones. Stakeholders then review trade-off frontiers to refine weighting and policy objectives whether to favor ecological resilience, market returns, or equity. Revised weights regenerate indices, and new frontiers are plotted until consensus emerges. Economic feedback loops update profitability and land-value surfaces as infrastructure or market conditions change. Spatial econometric modules ensure that the influence of neighboring land use, agglomeration economies, and environmental spillovers are captured, maintaining statistical consistency across revisions (Eyinade, Amini-Philips & Ibrahim, 2020, Tewogbade & Bankole, 2020).

Visualization tools convert complex analytics into intuitive decision dashboards. Bivariate choropleth maps overlay biophysical and economic scores using two-color gradients to distinguish synergy and conflict zones. Frontier plots, bubble charts, and cumulative distribution curves convey the extent of trade-offs, while 3D surfaces depict integrated potential across space. Decision-support interfaces allow users to toggle weights, adjust thresholds, and instantly observe map and frontier shifts, fostering transparent, participatory planning.

This integrated model supports not only planning but also monitoring. As new remote-sensing and economic data arrive, composite indices can be re-computed to track change in land performance and policy effectiveness. For instance, after a road upgrade, improvements in accessibility and profitability should shift cells upward along the economic axis, indicating convergence toward the efficiency frontier. Conversely, signs of degradation declining NDVI or soil moisture signal downward shifts along the environmental axis, prompting intervention before irreversible loss occurs (Amini-Philips, Ibrahim & Eyinade, 2020, Essien, *et al*., 2020).

The integrated suitability and valuation framework thus serves as both a diagnostic and prescriptive tool. It bridges the gap between environmental science and economic planning by embedding market realism into spatial evaluation without losing ecological nuance. It transforms the static notion of land "suitability" into a dynamic, multidimensional construct that recognizes that land value is co-created by natural endowment, infrastructure, and policy. By quantifying and visualizing the trade-offs between environmental suitability and economic viability, and classifying land into coherent tiers, the model empowers decision-makers to allocate land uses that maximize societal welfare while sustaining ecological functions. It establishes a replicable methodology where environmental and economic intelligence are fused into a single evaluative space, enabling adaptive land governance grounded in evidence, transparency, and balance.

7. Stakeholder Engagement, Ethics, and Governance

An integrated approach to land evaluation that fuses spatial data with economic indicators only earns legitimacy when its criteria, weights, and decision rules are co-designed with the people who live with the consequences and the public institutions accountable for them. Engagement begins before any layer is mapped. Practitioners convene communities, producers, indigenous groups, civil society, and policymakers to identify goals food security, housing affordability, watershed protection, livelihoods and to translate these goals into measurable criteria (Bankole, Nwokediegwu & Okiye, 2020, Obuse, *et al*., 2020). Workshops use plain-language elicitation, map-based storytelling, and scenario walk-throughs to surface local knowledge about soils, flooding, access bottlenecks, and tenure realities that often elude national datasets. Pairwise comparisons or preference ranking exercises produce initial weights for biophysical and economic indicators; but these are not treated as immutable "expert" truths. Instead, the process emphasizes iteration: stakeholders review preliminary maps, examine the consequences of weight choices, and adjust until the trade-offs they see on the ground are reflected in the model. Where perspectives diverge farmers favoring soil fertility, planners favoring market access facilitators present Pareto frontiers that make the tensions explicit and support negotiated compromise rather than hidden substitution inside a black-box index.

Equity is not an afterthought but a design principle. Many land-use harms trace to tenure precarity, power imbalances, and biased datasets. The framework therefore incorporates safeguards at three levels. First, criteria sets include social protections as hard constraints: parcels under customary tenure, sacred sites, and critical habitats are flagged as ineligible for conversion regardless of economic score; displacement risk and livelihood dependence are encoded as negative weights or veto layers. Second, the modeling pipeline is audited for bias. Accessibility layers that use road proximity are complemented with travel-time models that recognize seasonality and affordability; profitability surfaces are stress-tested against gendered access to inputs and credit; and "market potential" is not allowed to double-count both distance and land price (Aduwo & Nwachukwu, 2019, Erigha, *et al*., 2019). Third, the process ensures voice and remedy. Engagement venues are held in local languages, with independent facilitation and childcare or transport stipends to prevent wealth and geography from deciding who participates. Grievance channels allow affected groups to challenge data, weights, and outputs, and compel documented responses and corrections.

Tenure is handled with the presumption that de facto rights matter as much as de jure titles. Layers capturing formal titles, certificates of occupancy, and concessions are overlaid with community-mapped customary claims, pastoral corridors, seasonal use patterns, and women's access plots. When boundaries are contested, the tool does not "resolve" them algorithmically; it highlights uncertainty and flags those polygons for mediated verification before any zoning decision is taken. Where tenure formalization is ongoing, the model tags candidate areas for priority adjudication to reduce future conflicts (Fasasi, *et al*., 2020, Giwah, *et al*., 2020). Equity lenses extend to benefit sharing: if public investments (e.g., a new road) will raise land values and shift the frontier toward development, the plan documents who gains, who loses, and proposes instruments impact fees, service levies, transfer programs that recycle part of the uplift to vulnerable groups or fund conservation offsets.

Data transparency and reproducibility are essential to trust. Every dataset in the evaluation carries machine-readable metadata describing source, date, accuracy, projection, processing steps, and known limitations. The full workflow ingestion, cleaning, normalization, weighting, aggregation, spatial econometrics, and classification is scripted in an open, version-controlled repository that produces identical results when rerun. Each map tile and table links back to the code cell and input file that produced it. Stakeholders can download raw and processed layers (subject to privacy protections), rerun scenarios with their own weights, and compare outputs. Where data are sensitive household surveys, indigenous locations the framework uses differential privacy or masking, and publishes only aggregates while keeping reproducibility for authorized auditors (Akinrinoye, *et al*., 2020, Alao, Nwokocha & Filani, 2020). Uncertainty is published, not hidden: bivariate maps include confidence bands; dashboards show how rankings shift when weights or prices vary; and a "why this score?" explainer discloses the contribution of each criterion to each parcel's classification. This audit trail deters manipulation, supports learning, and gives communities tools to contest inaccuracies.

Governance mechanisms sustain integrity over time. Land systems evolve as markets, climate, and infrastructure change; a one-off study quickly goes stale. The framework therefore institutes an update cadence with clear triggers. Routine updates occur annually for dynamic layers (prices, land cover, infrastructure status); structural updates occur when a major project (a highway, dam, or industrial park) or policy shift (zoning law, subsidy reform) changes the economic geography. A multi-stakeholder steering committee comprising community representatives, local government, sector ministries, and independent experts oversees updates, approves changes to methods, and arbitrates competing proposals (Akintayo, *et al*., 2020, Dako, *et al*., 2020). Any modification to criteria, weights, or econometric specifications passes through a change-control process: a proposal with rationale, a simulation of impacts, a public comment window, and a recorded vote, with minority opinions noted. Version snapshots of the model and outputs are archived so that decisions can be traced to the rules in force at the time.

Conflict resolution is designed into the planning cycle rather than bolted on after disputes arise. The tool itself serves as a mediation surface: competing claims are visualized with their evidence, uncertainty, and consequences under alternative allocations. Facilitated sessions use the model to explore compensating arrangements e.g., permitting limited development on higher-value edges while securing core conservation zones, or trading density allowances for green infrastructure investments. Where conflicts implicate rights, independent legal support is made available to communities so that consent is informed and not coerced (Atobatele, *et al*., 2019, Filani, Nwokocha & Babatunde, 2019). Where trade-offs implicate interjurisdictional issues (upstream–downstream, urban–rural), the governance body convenes joint sessions and, where appropriate, adopts benefit-sharing formulas (payments for watershed services, transfer mechanisms) grounded in the model's quantified impacts. Escalation pathways connect local mediation to statutory adjudication when agreement fails, but the goal is to resolve at the lowest competent level with transparent, evidence-based deliberation.

Ethical practice extends to how uncertainty and risk are communicated. Maps can seduce with false precision; the framework counters by displaying confidence intervals and warning overlays where classification is fragile. Policy guidance explicitly distinguishes "no-regret" zones with robust high-high synergy from "verify on the ground" areas where field surveys or tenure clarification are prerequisites. Scenario planning helps communities and officials see how decisions behave under droughts, price shocks, or migration surges, reducing the temptation to overcommit to a single future. Equity impact assessments accompany each zoning proposal, quantifying displacement risk, livelihood shifts, and service burdens, and documenting mitigation plans and monitoring indicators (Bankole, *et al*., 2019, Nwokediegwu, Bankole & Okiye, 2019).

Capacity building makes the system durable beyond any single project team. Local analysts are trained to maintain the data pipeline, interpret econometric diagnostics, and facilitate community weighting sessions. Open curricula and sandboxes let students and civil servants practice with anonymized datasets. Over time, stewardship can migrate to a public data institution or a university with a mandate to serve all jurisdictions impartially. Funding models anticipate maintenance: a modest levy on development approvals or earmarked budget lines support data updates, audits, and community engagement so that the tool remains living infrastructure rather than an orphaned report (Ajayi, Onunka & Azah, 2020, Obuse, *et al*., 2020).

Finally, the approach recognizes that legitimacy is cumulative. Each cycle of engagement, mapping, weighting, and decision generates evidence about fairness and effectiveness. These traces who was consulted, what changed, which grievances were resolved, which updates corrected bias are published in annual "model governance" reports. Success is not the absence of disagreement, but the presence of transparent, repeatable processes that give all parties a reason to accept outcomes, even when they do not get everything they sought. In this way, stakeholder co-design, ethical safeguards for equity and tenure, rigorous transparency, and structured governance transform a technical framework into a civic asset: a common reference that helps communities and policymakers make hard land decisions with clarity, accountability, and respect (Patrick, *et al*., 2019).

8. Validation, Sensitivity, and Uncertainty Analysis

Validation, sensitivity, and uncertainty analysis constitute the empirical backbone of any integrated land evaluation framework that combines spatial and economic data. While modeling, weighting, and mapping produce visually persuasive outputs, the credibility of such products hinges on systematic testing against reality, robustness to parameter choices, and explicit accounting for uncertainty. The validation process involves ground-truthing, temporal backcasting, and statistical out-of-sample tests; sensitivity analysis examines how the results respond to alternative weight configurations and threshold selections; and uncertainty analysis quantifies how errors in data, interpolation, and econometric models propagate into composite indices and policy decisions. Together, these processes ensure that the model's predictions and classifications are scientifically defensible, transparent, and useful for policy applications (Fasasi, *et al*., 2020, Giwah, *et al*., 2020, Hungbo, Adeyemi & Ajayi, 2020).

Ground-truthing is the first line of validation, linking model outcomes to field observations. Representative sites across environmental and socioeconomic gradients are selected to compare predicted suitability and economic potential with actual land use, productivity, profitability, or ecosystem condition. For agricultural zones, sample plots record crop type, yield, soil parameters, and management intensity; for urban and peri-urban areas, data on land prices, infrastructure availability, and building density are collected. The ratio of correctly predicted land uses to observed uses yields classification accuracy, while continuous metrics such as correlation or root-mean-square error evaluate how well predicted indices match observed performance measures like net returns or productivity (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017). Where direct measurement is unfeasible, participatory validation local experts rating model outputs against lived experience offers qualitative corroboration and reveals contextual nuances, such as informal tenure or seasonal constraints, that numeric data miss.

Out-of-sample validation strengthens confidence that the model generalizes beyond calibration data. The dataset is divided into training and validation subsets, stratified by region or land-cover class to avoid spatial autocorrelation bias. For econometric components linking biophysical variables to economic indicators, k-fold cross-validation computes predictive R^2 and mean absolute error across folds. Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) quantify discrimination power when suitability is treated as a binary or ordinal classification (suitable vs. unsuitable). AUC values above 0.8 generally indicate strong predictive skill. Spatial block cross-validation, which partitions data by geographic clusters rather than random points, further tests model stability under spatial dependence critical in land systems where neighboring parcels share correlated attributes (Akpan, Awe & Idowu, 2019, Ogundipe, *et al*., 2019).

Temporal validation or backcasting introduces a dynamic dimension. Historical datasets on land cover, climate, infrastructure, and market prices from previous decades are used to run the model retrospectively. If past inputs reproduce past land-use patterns or observed economic gradients with acceptable accuracy, confidence in forward-looking projections increases. Temporal backcasting also highlights model drift: discrepancies may reveal processes missing from the model, such as policy shocks, technological changes, or institutional reforms. Where longitudinal data exist, trend alignment between predicted and actual land-value trajectories or crop-area evolution provides evidence of temporal coherence (Awe & Akpan, 2017).

Sensitivity analysis probes how model outputs change with variation in input assumptions, especially weights and thresholds derived from expert judgment. Because the integrated approach merges diverse criteria soil fertility, slope, rainfall, profitability, access the final index reflects the aggregation structure as much as the data. Local sensitivity analysis varies one weight at a time, recalculating composite indices and recording rank reversals in parcel or zone ordering. Global sensitivity analysis explores simultaneous variation using Monte Carlo or Latin Hypercube sampling of weights within plausible bounds. Tornado diagrams visualize which criteria exert the strongest influence on outcomes (Akpan, *et al*., 2017, Oni, *et al*., 2018). If small perturbations in a particular weight cause large rank changes, the model is unstable and requires either more precise data or stakeholder agreement on that criterion's importance. Similarly, threshold sensitivity tests for the tiered classification scheme e.g., the cut-off between "high" and "medium" suitability quantify how boundary shifts alter land allocations. Robust classifications are those whose membership remains consistent across a wide range of thresholds and weight scenarios.

Scenario analysis extends sensitivity testing into future uncertainty. The framework runs alternative climate and market scenarios to gauge resilience. Climate scenarios use downscaled projections of rainfall, temperature, and evapotranspiration under multiple Representative Concentration Pathways (RCPs). These modify biophysical suitability layers, altering the environmental component of the composite index. Economic scenarios simulate price shocks for crops or commodities, transport-cost changes due to infrastructure investments, or policy shifts such as carbon pricing or subsidy removal (Akomea-Agyin & Asante, 2019, Awe, 2017, Osabuohien, 2019). The model recomputes economic indicators profitability, land value, accessibility cost and propagates them through the integrated index. Comparing results across scenarios reveals hotspots of vulnerability or opportunity: areas whose suitability collapses under drought but remain viable under improved irrigation, or regions whose attractiveness spikes with new roads but declines if commodity prices fall. Policymakers use these sensitivity surfaces to design adaptive strategies and contingency plans.

Quantifying uncertainty completes the validation triad. Each input dataset carries error from remote-sensing classification accuracy to survey sampling variance and each analytical transformation adds model uncertainty. These errors are propagated through the workflow using statistical and stochastic methods. For continuous variables, error propagation equations or Monte Carlo simulations draw from distributions representing measurement error, producing ensembles of composite indices. The standard deviation or coefficient of variation of these ensembles at each cell represents spatial uncertainty. For categorical variables, confusion matrices from classification validation provide probabilities of misclassification, which are used to reweight composite outcomes. Confidence maps derived from these measures accompany all suitability and valuation outputs, explicitly showing where model predictions are robust and where caution or additional data are needed (Asata, Nyangoma & Okolo, 2020, Bukhari, *et al*., 2020, Essien, *et al*., 2020).

Performance metrics formalize evaluation. For classification accuracy, overall accuracy, producer's and user's accuracy, and the Kappa statistic indicate agreement between model and ground truth beyond chance. For continuous prediction, mean absolute error, root mean square error, and normalized RMSE provide intuitive measures of deviation. ROC/AUC summarizes discriminative ability for binary suitability predictions, while precision-recall curves are useful when suitable sites are rare relative to total area. Spatial autocorrelation of residuals, measured by Moran's I, diagnoses unmodeled spatial structure if residuals cluster, further refinement of spatial weights or additional variables is needed. At the econometric level, adjusted R^2, log-likelihood, and information criteria (AIC, BIC) guide model parsimony (Abass, Balogun & Didi, 2020, Amatare & Ojo, 2020, Imediegwu & Elebe, 2020).

Beyond statistical metrics, policy performance indicators evaluate the model's practical impact. These include the proportion of allocated zones that align with existing development or conservation plans, the rate of conflict reduction in newly zoned areas, or improvements in investment efficiency measured by economic return per hectare of developed land. Post-implementation monitoring can track how closely realized projects follow predicted suitability classes, offering feedback loops for model retraining. In participatory evaluations, stakeholder satisfaction indices percent of users perceiving maps as accurate or fair complement technical measures.

Uncertainty communication is as important as computation. Visualization plays a key role: maps overlaying confidence intervals, heatmaps of sensitivity magnitudes, and spider plots of scenario outcomes help non-specialists grasp robustness. Policy briefs summarize key findings in accessible language: which areas are consistently high-value across all scenarios, which depend on fragile assumptions, and where additional data would most improve certainty. Transparent disclosure of uncertainty prevents overconfidence and supports adaptive governance (Adesanya, *et al*., 2020, Oziri, Seyi-Lande & Arowogbadamu, 2020).

Temporal revalidation sustains model credibility. Annual updates incorporate new satellite imagery, survey data, and price series; rolling validation compares predicted versus observed land-use changes. When prediction accuracy declines beyond pre-set tolerances, automatic retraining or methodological review is triggered. Such governance-linked validation transforms a static assessment tool into a learning system.

Ultimately, the integration of ground-truthing, out-of-sample validation, sensitivity exploration, and uncertainty quantification ensures that the combined spatial–economic framework is both scientifically sound and policy relevant. Validation anchors the model in observable reality; sensitivity analysis exposes leverage points and fragilities; uncertainty mapping transforms ignorance into structured risk knowledge. Together they create a decision architecture where land-use recommendations are not black boxes but transparent, evidence-based propositions open to scrutiny, adaptation, and continuous improvement as new data, technologies, and societal priorities evolve (Akinrinoye, *et al*. 2015, Bukhari, *et al*., 2019, Erigha, *et al*., 2019).

9. Conclusion

Integrating spatial data with economic indicators transforms land evaluation from parallel exercises into a single, decision-ready lens that aligns environmental capacity with market realities and social safeguards. By co-locating soils, slope, hydrology, climate, vegetation dynamics, and accessibility with land values, profitability, infrastructure density, and market access, the approach replaces one-dimensional "suitability" with a multidimensional assessment of feasibility. The immediate benefits are sharper prioritization, fewer costly misallocations, and clearer trade-offs. Bivariate scoring and frontier views reveal where environmental potential and economic viability reinforce each other, where infrastructure could unlock latent value, and where conservation yields the greatest welfare per dollar. Spatial econometrics and uncertainty propagation convert persuasive maps into defensible evidence, controlling for spillovers, endogeneity, and data noise. With tiered land classes spanning agriculture, urban expansion, conservation, and mixed-use mosaics, the method supports zoning that is ecologically grounded, fiscally rational, and socially credible. Critically, stakeholder co-design of criteria and weights moves deliberation from anecdote to transparent, reproducible choices, while governance guardrails make those choices durable.

Implementation follows a practical, staged roadmap that scales from pilots to regions and nations. Stage one establishes the data backbone: harmonize projections and resolutions; assemble authoritative soils, DEM, climate, land cover, hydrology, access networks, and administrative boundaries; and curate economic layers transactional land prices or hedonic models, enterprise budgets, infrastructure inventories, generalized travel-time surfaces. Stage two operationalizes the methodology: build the GIS preprocessing workflow; train the MCDA engine (AHP/ANP or PROMETHEE) with participatory weights; embed spatial lag/error models to calibrate how biophysical and access variables map to value and adoption after accounting for dependence; and stand up a validation suite with ground-truthing, spatial cross-validation, backcasting, and uncertainty Monte Carlo. Stage three institutionalizes dashboards and decision tooling: bivariate choropleths, frontier explorers, "why this score?" explainers, scenario sliders for climate and price shocks, and portfolio selectors constrained by budgets, emissions, or equity rules. Stage four codifies governance: version control, public metadata, change control for weights and models, routine updates for dynamic layers, and a multi-stakeholder steering group with clear escalation paths for disputes.

Scaling hinges on standardization, modularity, and capacity. A common data schema (units, CRS, semantics) and API contracts allow provinces to plug in local layers without rewriting the pipeline. Containerized workflows and parameterized notebooks let national teams replicate analyses across basins or states while preserving local nuance through weight sets and constraint layers. Training programs embed know-how inside planning agencies and universities, reducing dependence on vendors and enabling continuous improvement. Cloud-friendly architectures support national rasters and econometric runs, while edge caches let districts operate with intermittent connectivity. A federated governance model balances uniform method (so decisions are comparable) with regional autonomy to reflect tenure, ecology, and development priorities.

Limitations are real and must be explicit. Data gaps and biases persist where registries are incomplete, land markets are thin, or tenure is informal; no amount of modeling substitutes for ground verification and ethical safeguards. Spatial and economic layers age at different speeds, inviting temporal mismatch; without disciplined update cadences, conclusions can lag reality. MCDA inevitably embeds value judgments, and even well-facilitated weighting can privilege louder voices; error bars do not dissolve political economy. Econometric coupling reduces but does not eliminate endogeneity risks, and frontier classifications may tempt overconfidence if uncertainty is under-communicated. Finally, implementation capacity varies: agencies burdened by staffing and budget constraints may struggle to maintain pipelines, validate updates, or convene inclusive processes.

These limits point to concrete future work. Real-time and high-cadence data streams can narrow the lag between map and reality: Sentinel-1/2 and commercial constellations for vegetation and inundation; mobile traces and probe vehicle data for travel-time surfaces; transaction scraping and remote-sensed built-up proxies for land-value nowcasting; and internet-of-things water and soil sensors for micro-agronomic refinement. Stream processing and incremental raster updates would allow dashboards to highlight emerging hotspots degradation fronts, speculative pressure, or flood exposure triggering faster policy response. Agent-based models should be coupled with the integrated indices to simulate behavioral responses to prices, infrastructure, and regulations, capturing feedbacks that static MCDA and reduced-form econometrics miss. Such coupling can test whether zoning triggers leapfrogging, how protected areas shift nearby land values, or how transport upgrades induce demand and reconfigure frontier trade-offs over time. FAIR data principles findable, accessible, interoperable, reusable must guide national repositories so that datasets are discoverable, machine-actionable, and legally reusable across ministries and research institutions; persistent identifiers, open licenses, and standardized metadata will make replication the norm rather than the exception. Privacy-preserving analytics (aggregation, k-anonymity, differential privacy) should be mainstreamed to protect sensitive household or indigenous location data while preserving utility for planning.

Methodologically, three enhancements would pay high dividends. First, move from static weights to context-adaptive weighting that responds to policy mode (e.g., drought emergency vs. growth phase) and equity mandates, while retaining an auditable trail of changes. Second, expand uncertainty from parameter to structural: publish ensembles across alternative models different spatial weight matrices, valuation forms, and classification rules so users see model risk, not just data noise. Third, embed impact evaluation by design: tag allocations with counterfactuals and monitor realized outcomes (returns, conflicts, ecological indicators), retraining models periodically so the system learns from its own decisions.

In closing, the integrated approach does not promise frictionless land governance; it offers something more realistic and valuable a shared, transparent evidence base that clarifies choices, quantifies trade-offs, and elevates accountability. Where environmental potential and economic logic align, it accelerates action. Where they conflict, it illuminates the costs of each path and surfaces mitigations. With a disciplined roadmap, interoperable tooling, participatory weighting, and robust validation, the method scales from local pilots to national planning without sacrificing fidelity to place. By embracing real-time streams, agent-based dynamics, and FAIR data stewardship, next-generation implementations can stay timely, ethical, and adaptive. The payoff is better land decisions more productive, more resilient, more just made with open eyes and a common language across science, policy, and community.

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