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Climate Decision AI: Transforming Environmental Impact Assessments Through Pre-Emptive Predictive Analytics

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Abstract— Rapid infrastructure development often has unwanted climate effects, emissions, biodiversity loss, and resource consumption due to fragmented and reactive environmental impact assessments. This research introduces Climate Decision AI, a global multi-criteria decision support system that assesses climate, environment, community, and economic impact before construction using satellite imagery, climate data, socio-economic indicators, and machine learning. The system employs Digital Twins, Predictive Analytics, and XAI to ensure projects are consistent with the UN Sustainable Development Goals (SDGs) 6, 9, 11, 13, 15, and 17. For instance, it will provide global development banks and national planning authorities with a comprehensive digital transformation platform that promotes transparency in decision-making for climate action and sustainable development.

Keywords: *Environmental Impact Assessment; Decision Intelligence; Geospatial AI; Sustainable Development Goals; Predictive Analytics; Digital Twins*

1. Introduction

Infrastructure projects, such as smart cities, transport networks, mining operations, and hydroelectric dams, are expanding rapidly across the globe. However, this expansion often damages local ecosystems, economies, and public well-being because regional planning remains short-sighted. Current development decisions fail not due to a lack of environmental concern, but because planning systems depend on outdated tools.

The core issue lies in traditional Environmental Impact Assessments (EIAs), which are reactive and fragmented. Typically, evaluations take place manually after project designs are locked in. Separate teams analyze economic, social, and environmental effects using inconsistent datasets, making it difficult to predict long-term ecological risks. To solve this, Climate Decision AI offers a unified decision support platform. By running predictive analytics during the initial planning phase, the system allows project teams to evaluate environmental trade-offs before construction begins.

2. Related Work & Literature Survey

Limitations of Traditional EIA Frameworks:

Environmental Impact Assessments (EIAs) remain the primary tool for regulatory approval, but conventional workflows have clear functional drawbacks:

1. Isolated Assessments: Independent consulting teams usually evaluate different impact factors in isolation. This fragmented setup misses interconnected ecological loops, such as how localized soil loss can aggravate regional groundwater deficits and public health risks.
2. Static Data Baselines: Standard evaluations rely on historical field surveys and static baselines. As a result, they fail to model how a project site might react to severe climate shifts years into the future.
3. Delayed Timing: EIAs are usually ordered after developers finalize site selection, architectural designs, and funding. At that point, assessments rarely alter core designs and become simple regulatory formalities.
4. Subjective Scoring: Environmental rating criteria differ significantly across regions. Manual scoring leaves the process open to human error, biased weightings, and uneven regulatory enforcement.

Emergence of AI in Environmental Decision Intelligence:

Advances in Geospatial AI (GeoAI), Computer Vision, and Predictive Analytics help resolve these traditional limits. Automated machine learning and Bayesian models now reliably track forest loss, predict soil erosion, and model urban heat patterns. At the same time, spatial Digital Twins allow engineers to test physical site designs in virtual environments before breaking ground.

However, most existing environmental AI models remain narrow, single-purpose tools focused on isolated tasks like carbon accounting or satellite-based logging detection. Climate Decision AI addresses this gap by combining diverse spatial datasets into a single prediction engine, allowing teams to test alternative site layouts proactively during initial planning.

3. The methodology describes the design, data, and procedures

3.1. Data Sources

In this study, geospatial and climate data were obtained from a number of publicly available international datasets in order to assess the environmental and sustainability conditions. Sentinel-2 imagery is employed for the analysis of land cover and vegetation, allowing the identification of forests, water bodies, agricultural land and built-up areas situated around the project site. The significance of this information lies in the fact that land-cover features have a direct effect on ecological sensitivity and environmental risk assessment.

Climate observations are provided through NASA POWER while ERA5 delivers the historical climate data useful for environmental assessment over long periods of time. Thus, by integrating the climatic observation data and historical climatic records, the system manages to consider both current circumstances and environmental trends.

Data concerning the forest coverage and deforestation is delivered via Global Forest Watch while human population exposure is derived based on the WorldPop population density data. The forest coverage data helps to detect environmentally sensitive areas while population density data can be used for estimating human exposure and infrastructure needs.

All this data gives a full picture of the climatic, ecological, and socio-spatial environment, and this is an essential requirement for environmental AI-based analysis and predictions.

Table 1. Geospatial and Climate Data Sources

Data Source	Purpose
Sentinel-2	Land-cover and vegetation analysis
NASA POWER	Rainfall and temperature assessment
ERA5	Historical climate analysis
Global Forest Watch	Forest-cover and deforestation monitoring
WorldPop	Population-density estimation

3.2. Feature Engineering

Following data collection, raw geospatial and environmental inputs were transformed into structured feature vectors compatible with the predictive pipeline. The primary features comprise spatial coordinates, project footprint geometry, energy generation sources, population density, local precipitation histories, and forest canopy percentages.

Because the raw input streams vary significantly in spatial resolution and format (e.g., raster grids versus vector polygons), a dedicated preprocessing step standardizes all continuous and categorical attributes into uniform continuous numerical matrices, ensuring model stability during training and inference.

3.3. Preprocessing Pipelines

Before analysis, the collected datasets were standardized so that information obtained from different sources could be compared in a consistent manner.

Raster datasets, including satellite imagery and climate grids, were clipped to the project boundary and converted to a common spatial resolution. This step ensures that spatial measurements remain comparable across all raster layers.

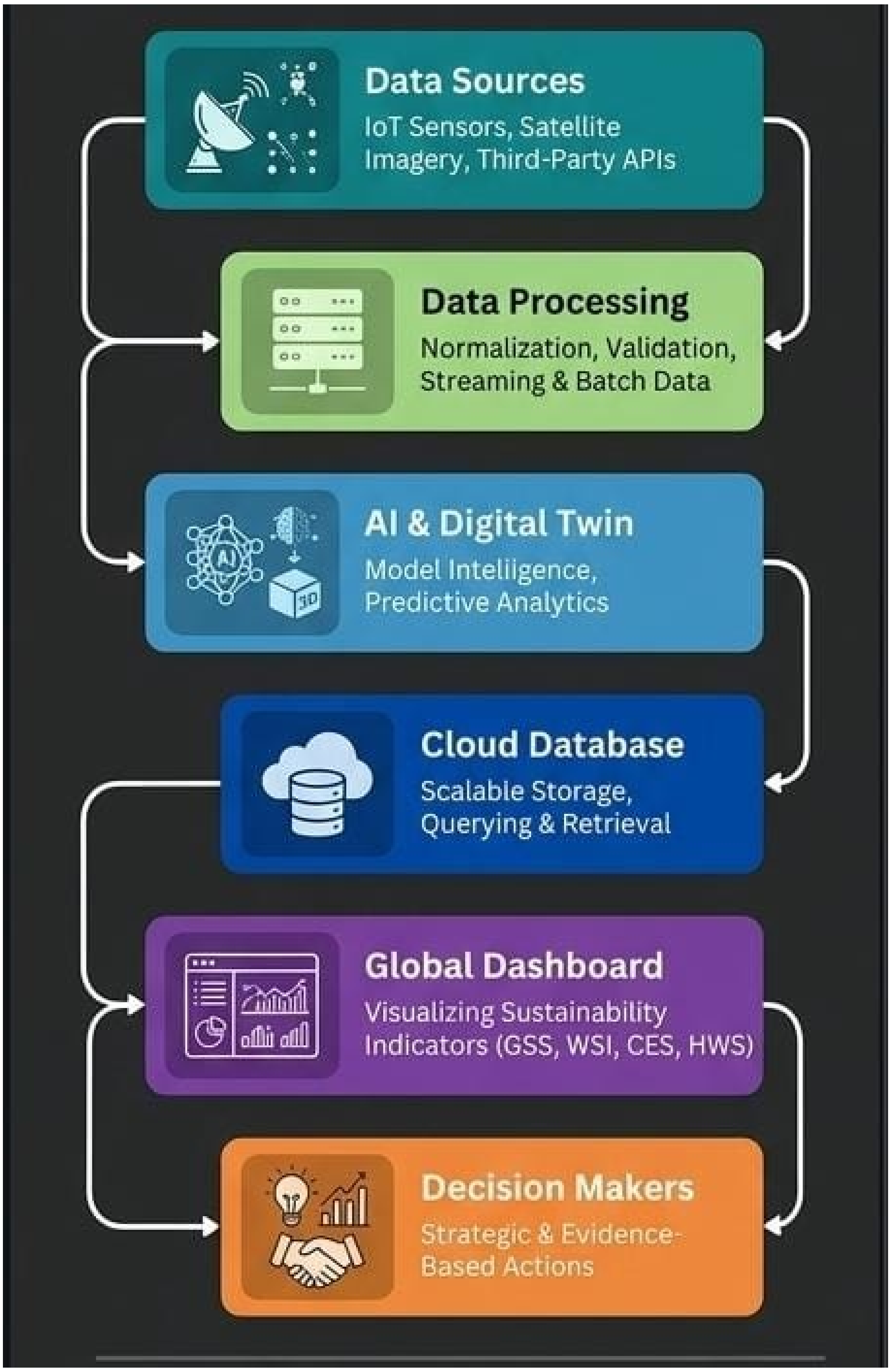
Vector datasets such as roads, rivers, and administrative boundaries were processed using spatial-intersection and distance-analysis techniques in order to derive contextual spatial relationships. These relationships help determine the proximity of the project site to environmentally sensitive or infrastructurally important features.

The processed spatial layers were subsequently converted into GeoJSON format to support GIS visualization and dashboard integration. In addition, climate variables were aggregated into monthly and annual statistics, enabling both long-term trend analysis and near-real-time environmental monitoring. Overall, the preprocessing stage improves data quality, reduces spatial inconsistencies, and enhances the reliability of geospatial analytics used by the AI framework.

3.4. Data Architecture and Spatial Analytics Framework

The Climate Decision AI platform processes raster and vector datasets through an end-to-end analytical pipeline:

Data Source → Data Processing → AI & Digital Twin Intelligence → Cloud Database → Global Dashboard → End Users



The workflow begins by taking the project's spatial boundary, footprint geometry, and user-defined parameters. Next, the platform gathers multi-source data—such as satellite imagery, climate records, forest density, and demographic metrics—to perform buffer analysis, layer overlays, and environmental risk mapping. Once unified, these spatial layers are formatted as GeoJSON files and processed through predictive models to derive four standardized metrics scored from 0 to 100:

3.4.1. Global Sustainability Score (GSS):

Evaluates overall ecological and socio-economic viability by balancing development benefits against localized environmental risks.

$$GSS = \frac{1}{4}((100 - WSI) + HWS + (100 - CES) + BSI)$$

The metric is calculated as an unweighted arithmetic mean of the four core dimensions. In order to ensure that higher values are more desirable, negative indicators, i.e., the Water Stress Index (WSI) and the Carbon Emission Score (CES), were reversed by subtracting them from 100.

3.4.2. Water Stress Index (WSI):

Quantifies hydrological vulnerability based on local precipitation trends and projected operational consumption.

$$WSI = \left(\frac{\text{Projected Water Demand}}{\text{Available Water Recharge}}\right) \times \left(1 + \frac{\sigma_{\text{precip}}}{\mu_{\text{precip}}}\right) \times 100$$

The primary ratio evaluates baseline operational water consumption relative to natural recharge rates. This baseline is scaled by a precipitation volatility factor σ/μ , derived from historical ERA5 climate data, to account for seasonal rainfall anomalies and drought risks.

3.4.3. Human Well-being Score (HWS):

Measures localized socio-economic benefits against population displacement and environmental health factors.

$$HWS = w_1 \cdot I_{\text{infra}} + w_2 \cdot E_{\text{access}} - w_3 \cdot P_{\text{risk}}$$

Where I(infra) denotes new infrastructure contributions, E(access) reflects clean energy accessibility, and P(risk) measures local pollution exposure. The coefficients w1, w2, w3 represent normalized weighting factors satisfying $\Sigma wi = 1$.

3.4.4. Carbon Emission Score (CES):

Calculates embodied baseline emissions alongside long-term operational carbon footprint against regional offsets.

$$CES = \min\left(100, \left(\frac{C_{\text{embodied}} + \sum C_{\text{operational}}}{C_{\text{threshold}}}\right) \times 100\right)$$

Embodied carbon C(embodied) encompasses all emissions from materials manufacturing, transport, and on-site construction, while ΣC(operational) aggregates emissions from all operational stages throughout the asset's life cycle. The resulting value was normalized by the corresponding regional emission threshold C(threshold) and capped at 100 to account for extreme values.

3.5. Recommendation Engine

If a proposed layout triggers environmental risk threshold warnings, our recommendation engine proposes practical engineering adjustments to lower the impact without canceling the project. The engine matches site data against sustainable construction standards to generate targeted interventions.

For example, when predicted carbon outputs exceed safety targets, the system suggests local solar microgrids or direct air capture units. If water stress models show high risk, it generates designs for rainwater capture networks; if construction breaks up local ecosystems, it adds structural wildlife corridors. The model ranks these choices by cost-effectiveness and practical feasibility, giving planning boards actionable options for immediate design revisions.

Table 2: Recommendation Engine

Feature	Description
Purpose	Suggests eco-friendly alternatives
Input	Environmental and project data
Examples	Carbon capture, renewable energy, rainwater harvesting

3.6. Digital Twin & Simulation

The platform integrates real-time remote sensing feeds with localized IoT telemetry to construct a dynamic spatial Digital Twin. This virtual environment allows planners to evaluate proposed development impacts under climate projections extended through 2050. Key operational applications of the simulation framework include:

- Micro-climate Modeling: Evaluates hyper-local temperature fluctuations and precipitation shifts to safeguard ecosystem stability.
- Urban Infrastructure Tracking: Monitors resource allocation and energy demands across high-density urban zones.
- Disaster Risk Reduction: Simulates extreme weather events to detect structural vulnerabilities and generate dynamic emergency evacuation routes.
- Environmental Compliance Tracking: Continuously measures canopy cover changes, surface water depletion, and ambient emission levels against regulatory standards

3.7. Explainable AI (XAI)

To keep policy decisions transparent, Climate Decision AI integrates Explainable AI (XAI) into its prediction workflow. The platform provides detailed decision logs for every risk score and design recommendation, helping domain experts trace the specific factors behind each result.

Using SHAP (SHapley Additive Explanations), the platform calculates global feature weightings to show how variables like initial forest cover or seasonal rainfall influence final risk scores. Alongside SHAP, LIME (Local Interpretable Model-Agnostic Explanations) breaks down specific individual predictions through local linear approximations. This dual setup keeps automated recommendations transparent and ensures human planners maintain final oversight.

4. Policy Impact, SDG Alignment, Stakeholder Framework and Case Study Comparisons

The Climate Decision AI platform maps directly to key United Nations Sustainable Development Goals (SDGs):

Target SDG:

● **SDG 6: Clean Water & Sanitation:** By applying algorithms that calculate water stress indices, the software allows to predict water basin pollution and depletion rates before the start of construction.

● **SDG 9: Industry, Innovation & Infrastructure:** The impact of the construction based on carbon-emission related indicators is embedded in the early design stages to minimize the long-term cost and inefficiency of infrastructure.

● **SDG 11: Sustainable Cities & Communities:** Using Digital Twin technology and Geographic Information Systems (GIS), the impact assessment considers the air quality, heat distribution, and access to transportation infrastructure.

● **SDG 13: Climate Action:** The projection of climate-related hazards such as flooding, wildfires, and extreme weather patterns is integrated into the financial models of infrastructure projects.

● **SDG 15: Life on Land:** The analysis of satellite images enables the detection of disrupted habitats and estimation of forested areas' loss for the assessment of ecological damage.

● **SDG 17: Partnerships for the Goals:** The software provides international organizations with standardized sustainability performance data to ensure the efficient use of global financial markets.

Case Study Comparison:

To ensure the framework's applicability across different geographical and economic contexts, three development projects were assessed:

1. Lithium Mining in Chile: Despite the economic benefits that the region would experience from the operation, the analysis revealed that local water sources would be significantly impacted by the endeavor. The recommendation function suggested the implementation of a water recycling system that would minimize aquifer usage.
2. Solar Power Production in Kenya: The project was found to have a high score on most of the criteria used, as the production process emits low levels of greenhouse gases. The optimization process suggested the minimization of land use to reduce the disruption of local livestock routes.
3. Hydroelectric Power Station in Brazil: The assessment indicated that the proposed solution would entail substantial benefits for the region while posing a significant risk to the local ecosystem. The recommendation function suggested designing the project around the creation of wildlife corridors that would facilitate biodiversity.

5. Conclusion

Validation through representative case studies shows that Climate Decision AI effectively compares projects, predicts long-term impacts, and recommends sustainable improvements before construction begins. The framework improves planning quality, reduces environmental risks, increases transparency, and supports smarter policy decisions. Future enhancements include blockchain security, advanced AI models, live satellite integration, and smart-city deployment.

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Data Availability Statement

The geospatial, satellite, and socio-economic datasets analyzed during this study are publicly available through Sentinel-2 (ESA Copernicus Hub), NASA POWER, ERA5 (ECMWF), Global Forest Watch, and WorldPop repositories. Processed feature layers and code repositories supporting the findings of this paper are accessible from the authors upon reasonable request.

AI Usage Disclosure

Generative AI tools were utilized solely for grammar refining, structural formatting, and sentence clarity enhancement during drafting. All conceptual frameworks, feature definitions, methodological structures, and analytical conclusions were verified and finalized by the authors.

Author Contributions

[1]Gopika K M :

- CRediT Roles: Methodology, Formal Analysis, Writing—Original Draft (Sections: Introduction, Related Work/Literature Survey, Policy Impact & SDG Alignment)
- Contributions: Researched EIA framework limitations, mapped SDG alignments (SDGs 6, 9, 11, 13, 15, 17), and integrated global stakeholder policy frameworks (UN, World Bank, ADB).

[2]Archana K A:

- CRediT Roles: Data Curation, Resources, Writing—Original Draft (Section: Data Architecture & Spatial Analytics Framework)
- Contributions: Mapped global data pipelines (Sentinel, NASA POWER, ERA5, Global Forest Watch), defined feature engineering parameters, and structured preprocessing pipelines for spatial data formats (Rasters, Vectors, GeoJSON).

[3]Rodha K A:

- CRediT Roles: Software, Investigation, Writing—Original Draft (Section: Predictive Methodology & AI Architecture)
- Contributions: Developed predictive AI model architecture, computer vision algorithms for remote sensing (CNNs, Vision Transformers), tabular/time-series predictive models (XGBoost, LSTMs), and socio-economic impact modeling frameworks.

[4]Jyothika K S:

- CRediT Roles: Validation, Conceptualization, Writing—Original Draft (Sections: Recommendation Engine, Digital Twin Simulation, Explainable AI)
- Contributions: Designed counterfactual recommendation engine optimization logic, developed Digital Twin simulation models forecasting through 2050, and integrated Explainable AI (SHAP/LIME) transparency frameworks.

[5]Ayisha Nazwa:

- CRediT Roles: Visualization, Software, Writing—Original Draft (Sections: System Architecture, Scoring Formulas, Case Study Results, Conclusion)
- Contributions: Formulated composite scoring algorithms (GSS, WSI, HWS), designed global system/dashboard architecture, modeled real-world validation case studies (Lithium Mining in Chile, Solar Farm in Kenya, Hydroelectric Dam in Brazil), and authored final paper synthesis.

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