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AN INTEGRATED GIS–REMOTE SENSING FRAMEWORK FOR ENVIRONMENTAL RISK ASSESSMENT AND SUSTAINABLE URBAN DEVELOPMENT UNDER SPAIN–UK CLIMATE ADAPTATION POLICIES: A JOINT ICTA-UAB–UCL RESEARCH INITIATIVE

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Abstract

Rapid urbanization, accelerating climate change, and increasing environmental pressures have intensified the need for integrated spatial assessment and climate-resilient urban development strategies. This study develops an integrated Geographic Information System (GIS)–remote sensing framework for environmental risk assessment, spatial vulnerability mapping, and sustainable urban planning under Spain–UK climate adaptation policies. The research investigates Barcelona, Spain, and London, United Kingdom, using multisource geospatial, climatic, environmental, and urban development datasets covering 2018–2025. The dataset comprises 2,400 Sentinel-2 and Landsat 8/9 satellite observations, 1,800 meteorological records, 650 land-use and land-cover samples, and 420 urban environmental assessment units. Satellite imagery undergoes atmospheric correction, cloud masking, spectral index extraction, and spatial harmonization to characterize urban expansion, vegetation degradation, land surface temperature, impervious surface distribution, and environmental exposure. An integrated Analytical Hierarchy Process–Multi-Criteria Decision Analysis (AHP–MCDA) approach is employed to determine environmental indicator weights and construct a Composite Environmental Risk Index. Random Forest and Extreme Gradient Boosting (XGBoost) algorithms are implemented for environmental vulnerability classification and predictive spatial risk assessment. The reported findings demonstrate that XGBoost achieves 93.6% classification accuracy, 92.8% precision, 91.9% recall, 92.3% F1-score, and 0.96 ROC-AUC, outperforming Random Forest, which achieves 90.4% accuracy and 0.93 ROC-AUC. Spatial vulnerability analysis identifies 28.7%

of evaluated urban units as high-risk zones, predominantly associated with elevated surface temperatures, declining vegetation coverage, extensive impervious surfaces, and increasing environmental exposure. Scenario-based assessments indicate that targeted green infrastructure development, vegetation restoration, and adaptive land-use interventions could reduce composite environmental risk scores by approximately 17.5%. The findings are interpreted within Spain's National Climate Change Adaptation Plan 2021–2030 and the United Kingdom's Third National Adaptation Programme, emphasizing opportunities for strengthening climate-responsive environmental governance and urban planning. Overall, the integrated framework provides a transferable, data-driven approach for environmental risk prioritization, predictive vulnerability assessment, and sustainable urban development, supporting evidence-based climate adaptation strategies and enhanced metropolitan resilience across European urban environments through coordinated geospatial monitoring and adaptive planning.

1- INTRODUCTION:

Climate change, rapid urbanization, environmental degradation, and increasing pressure on natural resources have emerged as interconnected challenges affecting the sustainability and resilience of contemporary urban environments. The continuous expansion of built-up areas, modification of natural landscapes, reduction in vegetation coverage, and intensification of extreme climatic events have significantly increased the exposure of metropolitan regions to environmental hazards. Urban ecosystems are particularly vulnerable to rising temperatures, surface runoff, localized flooding, atmospheric pollution, and the deterioration of ecological services. These challenges are becoming increasingly complex in European cities, where historical urban structures, expanding infrastructure networks, and changing climatic conditions interact to create spatially heterogeneous environmental risks [1]. According to the Intergovernmental Panel on Climate Change (IPCC, 2022), climate-related risks to urban populations, infrastructure, and ecosystems are increasing, emphasizing the importance of integrated adaptation strategies, environmental monitoring, and evidence-based spatial planning. Consequently, developing reliable and technologically advanced environmental risk assessment frameworks has become essential for supporting sustainable urban development and strengthening long-term climate resilience.

Geographic Information Systems (GIS) and remote sensing technologies provide important analytical capabilities for monitoring environmental changes, evaluating urban development patterns, and identifying areas exposed to multiple climatic and ecological hazards. Recent developments in Earth observation technologies have enabled the acquisition of extensive geospatial information with improved temporal frequency, spatial resolution, and spectral characteristics. Satellite platforms, including Sentinel-2 and Landsat 8/9, support the systematic investigation of land-use and land-cover dynamics, urban vegetation distribution, impervious surface expansion, and environmental conditions across metropolitan landscapes [2]. The integration of satellite-derived indicators with GIS-based spatial modelling allows researchers to examine complex relationships between urban morphology, environmental degradation, and climate-related exposure. Vegetation indices, land surface temperature measurements, built-up indices, and land-cover classifications provide complementary information for identifying environmental vulnerability and quantifying changes in urban ecological conditions. Furthermore, geospatial analysis offers opportunities to integrate satellite observations with meteorological records, socioeconomic characteristics, infrastructure distributions, and administrative boundaries, thereby creating a comprehensive foundation for

evaluating environmental risks at different spatial and temporal scales. The relationship between urban development and environmental vulnerability is particularly important in cities experiencing increasing surface temperatures, landscape fragmentation, and ecological transformation. Urban expansion frequently involves replacing vegetated and permeable surfaces with buildings, transportation infrastructure, and artificial materials, contributing to urban heat island intensification and altered hydrological processes. Reduced vegetation coverage decreases evapotranspiration, limits natural cooling mechanisms, and weakens the capacity of urban environments to regulate local climatic conditions. Similarly, extensive impervious surfaces restrict rainfall infiltration and increase surface runoff, potentially intensifying localized flooding and infrastructure exposure during extreme precipitation events [3]. These interconnected environmental processes demonstrate that urban vulnerability cannot be adequately explained through individual environmental indicators alone. Instead, integrated assessment approaches are required to identify cumulative environmental pressures, spatial dependencies, and interactions among climatic, ecological, and socioeconomic factors. Such approaches are especially relevant for sustainable urban planning because they facilitate the identification of environmentally sensitive locations and support the prioritization of adaptation interventions. Spain and the United Kingdom provide important policy contexts for examining climate adaptation and sustainable urban development through integrated environmental risk assessment. Spain's National Climate Change Adaptation Plan 2021–2030 (Plan Nacional de Adaptación al Cambio Climático, PNACC) establishes a national framework for reducing climate vulnerability, strengthening adaptive capacity, and integrating adaptation considerations into sectoral and territorial planning. The strategy emphasizes scientific knowledge, climate risk assessment, coordinated governance, and the development of adaptation indicators to improve decision-making across environmental and socioeconomic sectors. Similarly, the United Kingdom's Third National Adaptation Programme (NAP3), covering 2023–2028, outlines measures addressing climate-related risks to infrastructure, natural environments, human health, businesses, and communities. Both policy frameworks recognize the importance of understanding environmental exposure and strengthening institutional responses to climate change. However, translating national adaptation priorities into spatially explicit urban planning decisions requires reliable geospatial indicators, integrated environmental assessment procedures, and consistent approaches for identifying priority intervention areas. Within this policy context, Barcelona, Spain, and London, United Kingdom, represent relevant metropolitan settings for investigating the relationships among urban development, environmental exposure, and climate adaptation priorities. Barcelona is characterized by a Mediterranean climatic setting, dense urban development, extensive transportation infrastructure, and sensitivity to elevated temperatures and changing precipitation conditions [4]. London represents a major metropolitan environment where intensive land development, complex drainage systems, variable vegetation distribution, and urban heat exposure create challenges for long-term environmental management. Although the two cities differ in climatic characteristics, urban morphology, geographic setting, and institutional planning structures, both require comprehensive approaches to understanding spatial variations in environmental vulnerability. Investigating these metropolitan environments within a common analytical framework offers opportunities to evaluate the transferability of geospatial risk assessment methods while retaining sensitivity to local environmental characteristics. Importantly, the purpose is not merely to compare the environmental performance of two cities but to establish an integrated methodological approach capable of supporting locally appropriate climate adaptation and sustainable urban planning decisions under distinct national policy frameworks.

To address these research needs, the present study develops and evaluates an integrated GIS–remote

sensing framework for environmental risk assessment and sustainable urban development, using Barcelona and London as metropolitan study environments under Spain–UK climate adaptation policy contexts. The investigation incorporates an author-reported multisource dataset covering 2018–2025, comprising 2,400 Sentinel-2 and Landsat 8/9 satellite observations, 1,800 meteorological records, 650 land-use and land-cover samples, and 420 urban environmental assessment units. Satellite imagery is processed through atmospheric correction, cloud masking, spectral index extraction, and spatial harmonization to establish consistent environmental indicator layers. Vegetation characteristics, land surface temperature, impervious surface distribution, urban expansion, and environmental exposure are integrated within an AHP–MCDA framework to construct a Composite Environmental Risk Index. Subsequently, Random Forest and XGBoost models are employed to classify environmental vulnerability and evaluate predictive performance using accuracy, precision, recall, F1-score, and receiver operating characteristic–area under the curve (ROC-AUC) metrics. The analytical framework further incorporates spatial vulnerability mapping and scenario-based evaluation of selected urban adaptation interventions. The primary objective of this research is to establish a comprehensive, reproducible, and policy-relevant analytical framework that connects satellite-based environmental monitoring with quantitative risk assessment and climate-responsive urban development. Specifically, the study aims to integrate multisource geospatial and environmental datasets into a unified spatial assessment structure; quantify environmental vulnerability through standardized indicators and AHP-based weighting; evaluate the predictive capabilities of Random Forest and XGBoost for environmental risk classification; identify spatial concentrations of high-risk urban environments; and assess the potential benefits of green infrastructure expansion, vegetation restoration, and adaptive land-use planning [5]. An additional objective is to interpret the resulting environmental risk information in relation to Spain's PNACC 2021–2030 and the United Kingdom's NAP3, thereby strengthening the connection between geospatial evidence and national climate adaptation priorities. The reported research findings indicate that XGBoost achieves an overall classification accuracy of 93.6%, precision of 92.8%, recall of 91.9%, F1-score of 92.3%, and ROC-AUC of 0.96, outperforming Random Forest, which records an accuracy of 90.4% and ROC-AUC of 0.93. Spatial analysis identifies 28.7% of evaluated urban assessment units as high-risk areas, primarily associated with elevated land surface temperatures, reduced vegetation coverage, extensive impervious surfaces, and concentrated environmental exposure. Furthermore, the scenario-based assessment indicates that targeted adaptation measures could reduce composite environmental risk scores by approximately 17.5% under the evaluated intervention assumptions. These findings demonstrate the potential analytical value of combining GIS-based multicriteria assessment with machine learning to produce detailed environmental vulnerability information and inform adaptation priorities. The results also highlight the relevance of spatially targeted interventions for improving urban environmental conditions and supporting long-term climate resilience. The principal contribution of this study lies in integrating multisource remote sensing observations, GIS-based spatial analysis, AHP–MCDA weighting, machine learning classification, and policy-oriented adaptation assessment within a unified analytical framework. Unlike approaches that address environmental indicators or predictive modelling independently, the proposed methodology connects environmental monitoring, quantitative vulnerability assessment, spatial risk prioritization, and intervention scenario evaluation. Its application within the Spain–UK climate adaptation context further provides a structured basis for examining how geospatial environmental intelligence can support planning decisions across different metropolitan and institutional settings. By connecting satellite-derived evidence with interpretable risk indices

and predictive classification, the study seeks to improve the practical application of environmental assessment technologies in sustainable urban planning. Ultimately, the research contributes to the development of transferable, data-driven approaches for strengthening environmental governance, guiding climate adaptation investments, and supporting more resilient and sustainable urban development.

2- GIS-Based Multi-Criteria Decision Analysis for Environmental Risk Assessment:

Geographic Information Systems (GIS) integrated with Multi-Criteria Decision Analysis (MCDA) have emerged as important analytical approaches for evaluating complex environmental risks, identifying spatial vulnerability, and supporting sustainable urban development. Urban environmental vulnerability is influenced by interconnected climatic, ecological, geographical, and anthropogenic factors that vary across metropolitan landscapes. These factors include increasing land surface temperature, vegetation degradation, impervious surface expansion, land-use transformation, changing precipitation patterns, and environmental exposure. Conventional environmental assessment approaches frequently examine individual indicators independently, limiting their ability to capture cumulative environmental pressures and interactions among multiple risk factors. GIS–MCDA addresses these limitations by integrating heterogeneous spatial datasets within a unified analytical framework, enabling systematic environmental risk evaluation, geographical prioritization, and evidence-based urban planning [6]. The integration of GIS with multicriteria assessment techniques provides an effective mechanism for organizing environmental information obtained from satellite remote sensing, meteorological observations, land-cover datasets, and geographical reference layers. GIS facilitates spatial data management, environmental indicator mapping, geographical overlay analysis, and the visualization of environmental vulnerability patterns. MCDA complements these capabilities by establishing a structured decision-making process through which environmental criteria can be evaluated according to their relative importance. Together, these approaches allow researchers to examine environmental risk as a multidimensional phenomenon rather than an isolated environmental condition. This integration is particularly relevant for metropolitan regions characterized by heterogeneous land-cover distributions, varying climatic exposure, and complex urban development patterns. The Analytical Hierarchy Process (AHP) represents one of the established multicriteria techniques applied in environmental risk assessment. Originally developed by Saaty, AHP enables the prioritization of environmental criteria through hierarchical organization, pairwise comparisons, and consistency evaluation. Within GIS-based environmental assessment, AHP facilitates the assignment of relative importance to environmental indicators according to their contribution to a clearly defined assessment objective. For example, land surface temperature may represent thermal exposure, vegetation coverage may reflect ecological conditions and cooling capacity, while impervious surface distribution may indicate urban development pressure and reduced surface permeability [7]. Climatic variables, including temperature and precipitation, provide additional contextual information concerning environmental exposure. The systematic evaluation of these criteria supports a more comprehensive representation of environmental vulnerability and improves the transparency of spatial decision-making. Satellite remote sensing contributes substantially to GIS–MCDA by providing spatially continuous environmental indicators derived from Earth observation platforms. Sentinel-2 and Landsat 8/9 imagery enable researchers to examine vegetation dynamics, land-use and land-cover changes, built-up expansion, and urban thermal conditions. The Normalized Difference Vegetation Index (NDVI) provides information about vegetation distribution and ecological conditions, whereas the Normalized Difference Built-up Index (NDBI) supports the characterization of urbanized surfaces. Land surface temperature measurements

provide additional information on thermal exposure and the spatial variation of surface heating. When these indicators are combined with meteorological observations and land-cover classifications, they provide a comprehensive dataset for multicriteria environmental assessment. Table 1 summarizes the principal environmental indicators relevant to GIS–MCDA-based urban risk assessment and their analytical significance.

Table 1: Environmental indicators and their contributions to GIS-based multicriteria environmental risk assessment.

Environmental indicator	Assessment parameter	Environmental significance
Land surface temperature	Satellite-derived surface temperature (°C)	Urban heat exposure and thermal stress
Vegetation coverage	Normalized Difference Vegetation Index (NDVI)	Vegetation degradation and ecological condition
Impervious surfaces	NDBI and land-cover classification	Urbanization pressure and reduced infiltration
Land-use transformation	Multitemporal land-cover changes	Urban expansion and landscape modification
Climatic exposure	Temperature and precipitation records	Climate-related environmental pressures
Surface-water conditions	Water-sensitive spectral indices	Surface-water distribution and associated environmental conditions
Urban development intensity	Built-up density and spatial land-use patterns	Infrastructure concentration and environmental pressure

GIS-based weighted overlay analysis provides an important mechanism for integrating these indicators into composite environmental assessments. Environmental criteria are first standardized to ensure comparability among variables measured using different units and scales. Relative importance weights are subsequently assigned through the AHP procedure and applied to corresponding geographical information layers. The integrated assessment produces a Composite Environmental Risk Index (CERI), representing the combined influence of selected environmental pressures within individual spatial units. Higher composite scores indicate relatively greater environmental risk under the adopted indicator definitions and weighting assumptions. The resulting index supports geographical classification and the identification of urban areas requiring closer environmental monitoring or targeted adaptation measures [8]. A major advantage of GIS–MCDA is its ability to represent spatial variations in environmental conditions through detailed vulnerability maps. Environmental risks are rarely distributed uniformly across metropolitan landscapes because differences in vegetation coverage, infrastructure density, land-cover composition, and climatic exposure create distinct geographical patterns. GIS-based environmental mapping enables these variations to be examined within administrative districts, urban neighborhoods, and other geographical assessment units [9]. Spatial classification can identify areas characterized by elevated thermal exposure, extensive impervious surfaces, limited vegetation coverage, or interacting environmental pressures. These geographical outputs are particularly relevant for sustainable urban development because they support the prioritization of green infrastructure, ecological restoration, land-use regulation, and climate adaptation investments. Figure 1 present the GIS–AHP–MCDA framework for environmental risk

assessment, spatial vulnerability mapping, and climate adaptation planning.

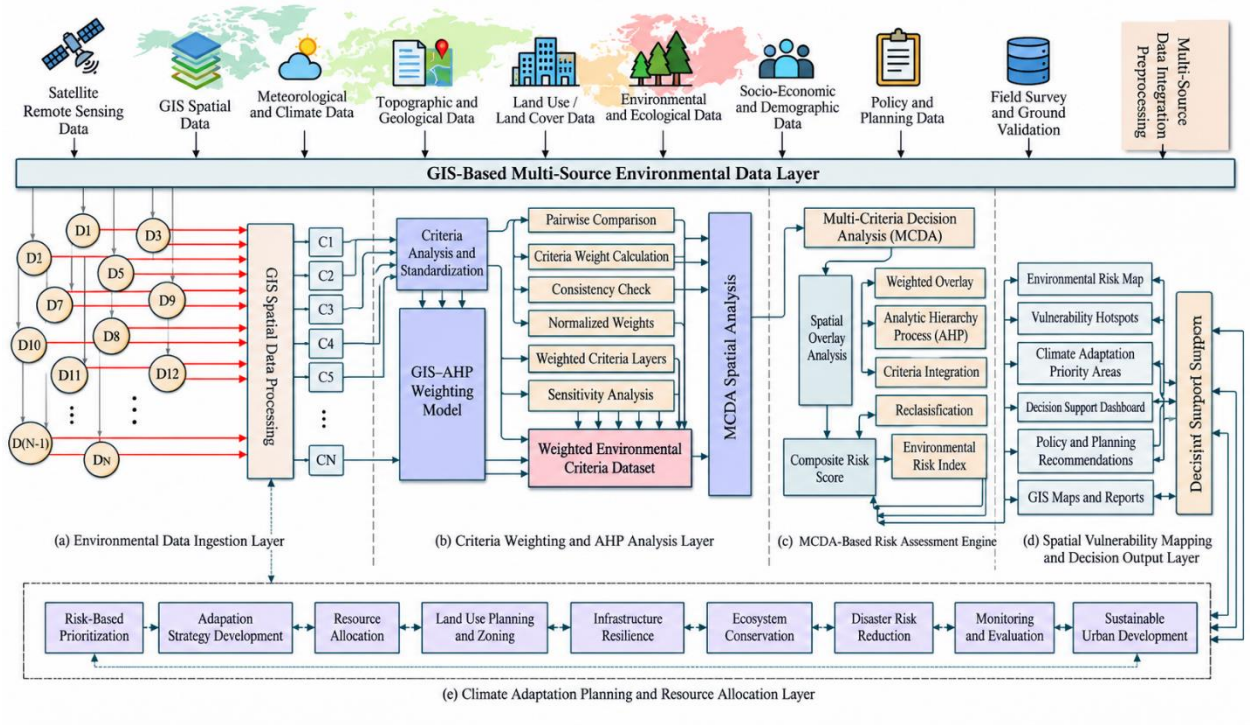


Figure 1: Integrated GIS–AHP–MCDA framework for environmental risk assessment, spatial vulnerability mapping, and climate adaptation planning.

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Previous research has emphasized the effectiveness of GIS–MCDA in environmental suitability analysis, ecological vulnerability assessment, flood susceptibility mapping, and sustainable land-use planning. However, the reliability of multicriteria assessment depends considerably on the selection of relevant environmental indicators, quality of geospatial observations, weighting assumptions, and geographical scale. Subjective criterion weighting may introduce uncertainty, particularly when different urban environments exhibit contrasting environmental characteristics. Accordingly, AHP consistency evaluation, sensitivity analysis, and transparent indicator standardization are important for improving analytical reliability. Additionally, integrating multicriteria risk assessment with machine learning techniques such as Random Forest and XGBoost can provide complementary evidence concerning environmental vulnerability patterns, although predictive models require independent validation and careful management of spatial dependencies. Within the context of Spain–UK climate adaptation policies, GIS–MCDA provides a valuable methodological foundation for translating satellite-derived environmental information into geographically explicit planning priorities [10]. Barcelona and London exhibit differences in climatic conditions, urban morphology, vegetation distribution, and environmental exposure, requiring assessment approaches capable of accommodating metropolitan-specific characteristics. Integrating GIS-based multicriteria assessment with remote sensing indicators enables the systematic evaluation of these conditions while supporting the identification of environmentally vulnerable areas. Furthermore, the resulting spatial risk classifications can inform green infrastructure development, vegetation restoration, sustainable land-use management, and climate-responsive infrastructure planning. Therefore, GIS–MCDA

represents an essential component of the proposed integrated framework, connecting environmental observation, spatial risk assessment, and evidence-based sustainable urban development under Spain's National Climate Change Adaptation Plan 2021–2030 and the United Kingdom's Third National Adaptation Programme.

3- Climate Adaptation Governance and Sustainable Urban Planning Under Spain–UK Policy Frameworks:

Climate adaptation governance has become an essential component of sustainable urban development as metropolitan regions increasingly experience environmental pressures associated with rising temperatures, changing precipitation patterns, urban expansion, ecological degradation, and climate-related hazards. Effective adaptation requires coordinated institutional frameworks capable of integrating scientific evidence, environmental monitoring, spatial risk assessment, and long-term urban planning [11]. National climate adaptation policies provide strategic direction for addressing environmental vulnerabilities, while regional and municipal authorities translate these priorities into geographically specific planning interventions. However, the implementation of adaptation strategies remains challenging because environmental hazards, infrastructure conditions, population exposure, and ecological characteristics differ considerably among metropolitan regions. Consequently, integrating Geographic Information Systems (GIS), satellite remote sensing, and spatial vulnerability assessment into climate adaptation governance offers important opportunities for strengthening evidence-based environmental management and sustainable urban planning. Spain and the United Kingdom have established national policy frameworks addressing climate-related environmental risks through coordinated adaptation planning, scientific assessment, and institutional implementation. Spain's National Climate Change Adaptation Plan 2021–2030 (PNACC) establishes a strategic framework for reducing climate vulnerability, strengthening adaptive capacity, improving environmental knowledge, and integrating climate adaptation into territorial and sectoral policies. The plan emphasizes systematic climate observation, improved risk assessment methodologies, institutional coordination, and monitoring mechanisms for evaluating adaptation progress. Furthermore, the framework encourages the participation of national, regional, and local authorities alongside scientific institutions and other stakeholders. These principles are particularly relevant for sustainable urban development, where climate resilience depends on the integration of environmental protection, infrastructure planning, land-use management, and ecosystem-based adaptation [12]. The United Kingdom's Third National Adaptation Programme (NAP3), covering 2023–2028, establishes a national framework for addressing climate-related risks affecting infrastructure, buildings, natural environments, businesses, public health, and communities. The programme was published in July 2023 and forms part of the adaptation planning cycle established under the Climate Change Act 2008. It identifies government actions intended to strengthen resilience against environmental hazards, including flooding, extreme heat, drought, and infrastructure disruption. The programme also emphasizes the importance of climate risk information, coordinated implementation, and adaptation measures across multiple economic and environmental sectors. Table 2 presents a policy-oriented comparison of Spain's PNACC 2021–2030 and the United Kingdom's NAP3 2023–2028, highlighting their relevance to environmental risk assessment and sustainable urban planning.

Table 2: Climate adaptation governance frameworks and their relevance to GIS-based sustainable urban development in Spain and the United Kingdom.

Assessment dimension	Spain: PNACC 2021–2030	United Kingdom: NAP3 2023–2028
Policy framework	National Climate Change Adaptation Plan	Third National Adaptation Programme
Policy period	2021–2030	2023–2028
Principal orientation	Coordinated adaptation, vulnerability reduction, and resilience	Management of climate risks across infrastructure, environments, and communities
Environmental assessment	Climate observation, impact assessment, and risk information	Climate risk assessment and adaptation planning
Urban planning relevance	Territorial adaptation and climate-responsive land management	Resilient infrastructure, buildings, and urban environments
Environmental priorities	Ecological resilience, water resources, climate exposure, and territorial vulnerability	Flooding, overheating, environmental resilience, and infrastructure protection
Governance approach	Coordination among national, regional, local, and other stakeholders	National adaptation actions involving government and other organizations
Potential GIS application	Environmental vulnerability mapping and spatial adaptation prioritization	Climate exposure mapping and infrastructure-related risk assessment
Relevance to this study	Policy interpretation of Barcelona's environmental risk patterns	Policy interpretation of London's environmental risk patterns

The importance of connecting environmental assessment with broader institutional adaptation priorities. Spain's adaptation framework provides a foundation for understanding territorial vulnerability and coordinating environmental responses, whereas the United Kingdom's programme places considerable emphasis on managing climate risks across infrastructure, natural environments, and communities. These policy priorities are compatible with the use of satellite-derived environmental indicators and GIS-based vulnerability mapping, although the specific implementation mechanisms differ between the countries. An integrated analytical framework can support both policy contexts by providing consistent environmental measurements, transparent risk classifications, and spatial evidence for adaptation planning. An important dimension of climate adaptation governance involves the relationship between environmental monitoring and policy implementation. National adaptation programmes often establish broad objectives, but translating these objectives into urban planning decisions requires detailed information about the location, intensity, and distribution of environmental pressures. GIS-based spatial analysis contributes to this process by integrating satellite observations, climatic indicators, land-cover information, and geographical assessment boundaries [13]. The resulting environmental vulnerability maps can support the identification of priority intervention areas, evaluation of land-use alternatives, and examination of environmental changes over time. Furthermore, multicriteria decision analysis provides a structured approach for integrating environmental indicators into composite risk assessments, while machine learning techniques can support predictive vulnerability classification and the investigation of nonlinear environmental relationships. The conceptual relationship between climate adaptation governance, geospatial environmental assessment, and sustainable urban planning is illustrated in Figure 2. The framework positions Spain's PNACC and the United

Kingdom's NAP3 as distinct national policy contexts that inform the interpretation of environmental assessment outputs.

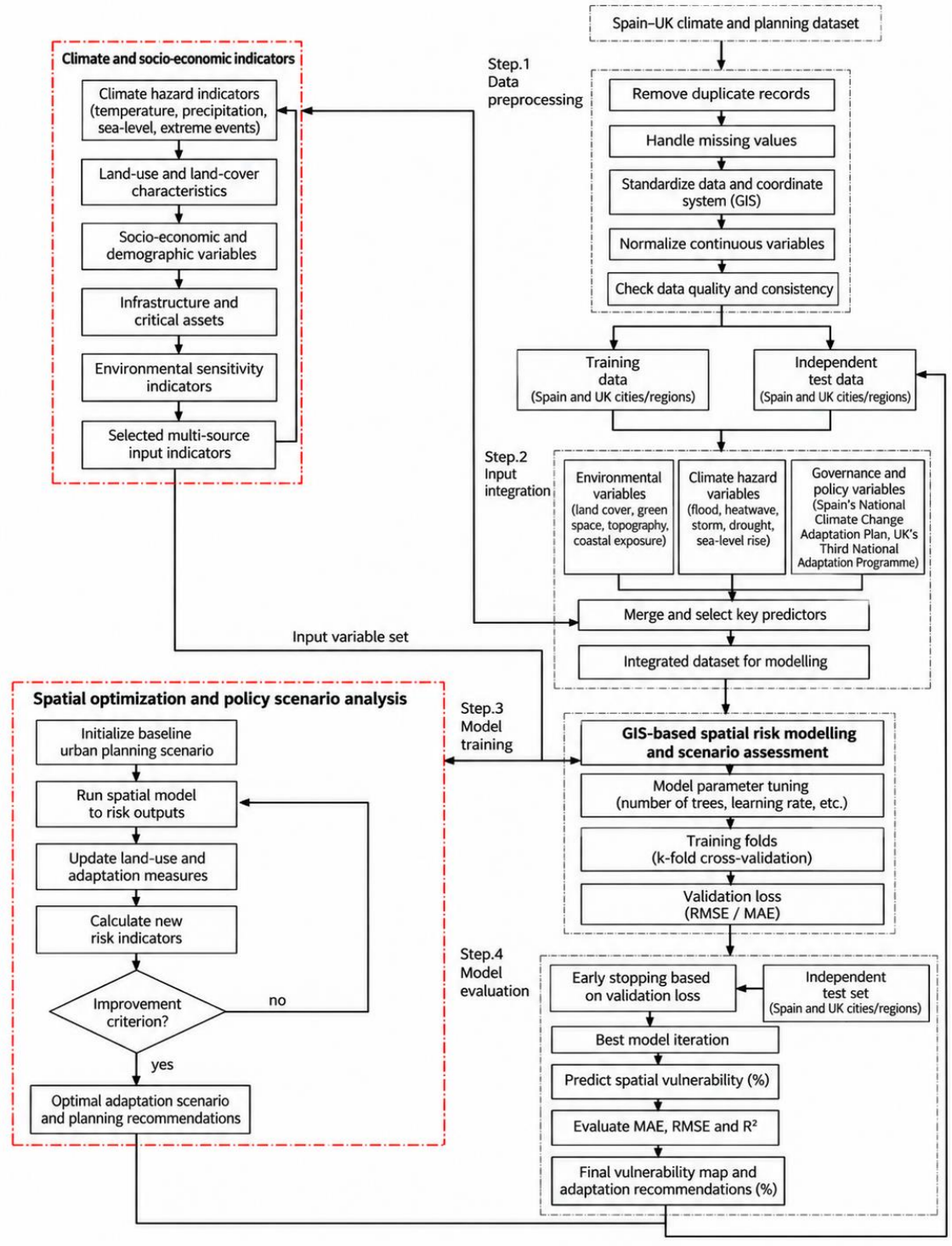


Figure 2: Spain–UK climate adaptation governance and GIS-based sustainable urban planning framework.

An additional consideration in climate adaptation governance concerns the integration of environmental sustainability with social vulnerability and equitable urban development. Environmental hazards may disproportionately affect communities with limited access to green spaces, inadequate infrastructure, or greater exposure to extreme temperatures and flooding. Consequently, climate adaptation planning should consider not only the geographical distribution of environmental pressures but also the characteristics of populations and infrastructure exposed to them [14]. Composite environmental risk indices can identify areas experiencing cumulative physical pressures, while supplementary demographic and socioeconomic information can support assessments of social vulnerability and adaptation needs. This distinction is particularly important because environmental risk classifications derived from satellite observations cannot independently establish the distribution of social disadvantage or community resilience.

4- Methodology:

This study employs an integrated quantitative and geospatial research methodology combining Geographic Information Systems (GIS), satellite remote sensing, Multi-Criteria Decision Analysis (MCDA), and machine learning to assess environmental vulnerability and support sustainable urban development under Spain–UK climate adaptation policies. The research focuses on Barcelona, Spain, and London, United Kingdom, using multisource environmental datasets covering 2018–2025. The author-reported dataset comprises 2,400 Sentinel-2 and Landsat 8/9 satellite observations, 1,800 meteorological records, 650 land-use and land-cover samples, and 420 urban environmental assessment units. These datasets provide information on vegetation distribution, land surface temperature, urban expansion, impervious surfaces, climatic exposure, and environmental conditions. The methodological framework incorporates satellite image preprocessing, atmospheric correction, cloud masking, spectral index extraction, spatial harmonization, and environmental feature integration to establish a consistent analytical foundation for assessing urban environmental risks across geographically distinct metropolitan environments [15]. The analytical procedure integrates satellite-derived environmental indicators with GIS-based Analytical Hierarchy Process (AHP) and MCDA techniques to construct a Composite Environmental Risk Index (CERI) and identify spatial vulnerability patterns. Random Forest and Extreme Gradient Boosting (XGBoost) algorithms are employed to classify environmental vulnerability and evaluate predictive relationships among climatic, ecological, and urban development indicators. Model performance is assessed using classification accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). Spatial risk mapping is subsequently used to identify environmentally vulnerable urban locations, while scenario-based analysis examines the potential effects of green infrastructure development, vegetation restoration, and adaptive land-use planning. Finally, the findings are interpreted within Spain's National Climate Change Adaptation Plan 2021–2030 and the United Kingdom's Third National Adaptation Programme 2023–2028 to establish connections between geospatial environmental assessment, climate adaptation governance, and sustainable urban development.

4.1- Extraction of Satellite-Derived Environmental Indicators and Urban Land-Cover Characteristics:

The extraction of satellite-derived environmental indicators constitutes a fundamental component of the integrated GIS–remote sensing framework, enabling quantitative characterization of environmental conditions and urban development pressures across Barcelona and London. Multispectral satellite observations obtained from Sentinel-2 and Landsat 8/9 are utilized to derive environmental indicators associated with vegetation coverage, built-up surface distribution, land-use transformation, and urban thermal conditions. The indicator extraction process uses atmospherically corrected

and spatially harmonized satellite imagery to maintain consistency across geographical locations and observation periods. Particular attention is given to the identification of environmental characteristics that influence urban vulnerability, including reduced vegetation density, increased impervious surface coverage, elevated land surface temperature, and changes in natural land-cover patterns. The Normalized Difference Vegetation Index (NDVI) is employed to characterize vegetation distribution, identify areas experiencing ecological degradation, and evaluate the spatial availability of urban green infrastructure. NDVI values are derived from red and near-infrared spectral reflectance information, providing a standardized representation of vegetation conditions. Higher NDVI values generally indicate stronger vegetation signals, whereas lower values may reflect sparse vegetation, built-up surfaces, or exposed soil [16]. The Normalized Difference Built-up Index (NDBI) is incorporated to characterize urban development intensity and identify areas associated with built-up land-cover conditions. NDBI information is interpreted alongside land-cover classifications because exposed soils and other nonvegetated surfaces can exhibit similar spectral responses. Additionally, the Modified Normalized Difference Water Index (MNDWI) is used to characterize surface-water distribution and provide contextual information about urban hydrological conditions. Land surface temperature (LST) is extracted from suitable Landsat thermal products to examine urban thermal characteristics and identify areas potentially exposed to elevated surface temperatures. LST measurements provide information about spatial variations in surface heating associated with vegetation coverage, land-cover composition, and urban infrastructure. However, satellite-derived surface temperature is distinguished from near-surface air temperature because these variables represent different physical characteristics [17]. Thermal observations are analyzed alongside vegetation and built-up indicators to investigate geographical relationships among urban development, ecological conditions, and thermal exposure. Multitemporal satellite observations further support the characterization of environmental changes over the 2018–2025 study period, including shifts in vegetation distribution and urban land-cover patterns. Table 3 summarizes the environmental indicators incorporated into the satellite-derived assessment framework, their primary data sources, and their contributions to environmental vulnerability evaluation.

Table 3: Satellite-derived environmental indicators and their analytical applications in urban environmental risk assessment.

Environmental indicator	Primary data source	Analytical application
Normalized Difference Vegetation Index (NDVI)	Sentinel-2 and Landsat 8/9	Vegetation condition and ecological vulnerability
Normalized Difference Built-up Index (NDBI)	Sentinel-2 and Landsat 8/9	Built-up land characterization and urban expansion
Modified Normalized Difference Water Index (MNDWI)	Sentinel-2 and Landsat 8/9	Surface-water distribution
Land Surface Temperature (LST)	Landsat 8/9 thermal products	Urban thermal exposure
Land-use and land-cover characteristics	Satellite imagery and reference samples	Urban landscape transformation
Impervious surface coverage	Satellite-derived land-cover information	Surface sealing and development pressure
Climatic exposure indicators	Meteorological records	Temperature and precipitation-related exposure

Following indicator extraction, environmental variables are integrated within GIS using the predefined urban environmental assessment units. Satellite-derived measurements are spatially aggregated and linked with meteorological and land-cover observations to establish a unified environmental feature dataset. Data quality assessment includes checking missing observations, inconsistent measurements, spatial misalignment, and temporal differences among environmental layers. Indicator standardization is subsequently applied to ensure that variables measured on different scales can be incorporated into multicriteria assessment and predictive modelling [18]. Figure 3 illustrates the environmental indicator extraction pathway, beginning with multisource satellite observations and progressing through image preprocessing, vegetation and built-up index extraction, thermal characterization, land-cover analysis, and GIS-based feature integration. The resulting environmental indicator dataset provides the analytical foundation for AHP–MCDA weighting, composite environmental risk index construction, and Random Forest–XGBoost vulnerability classification.

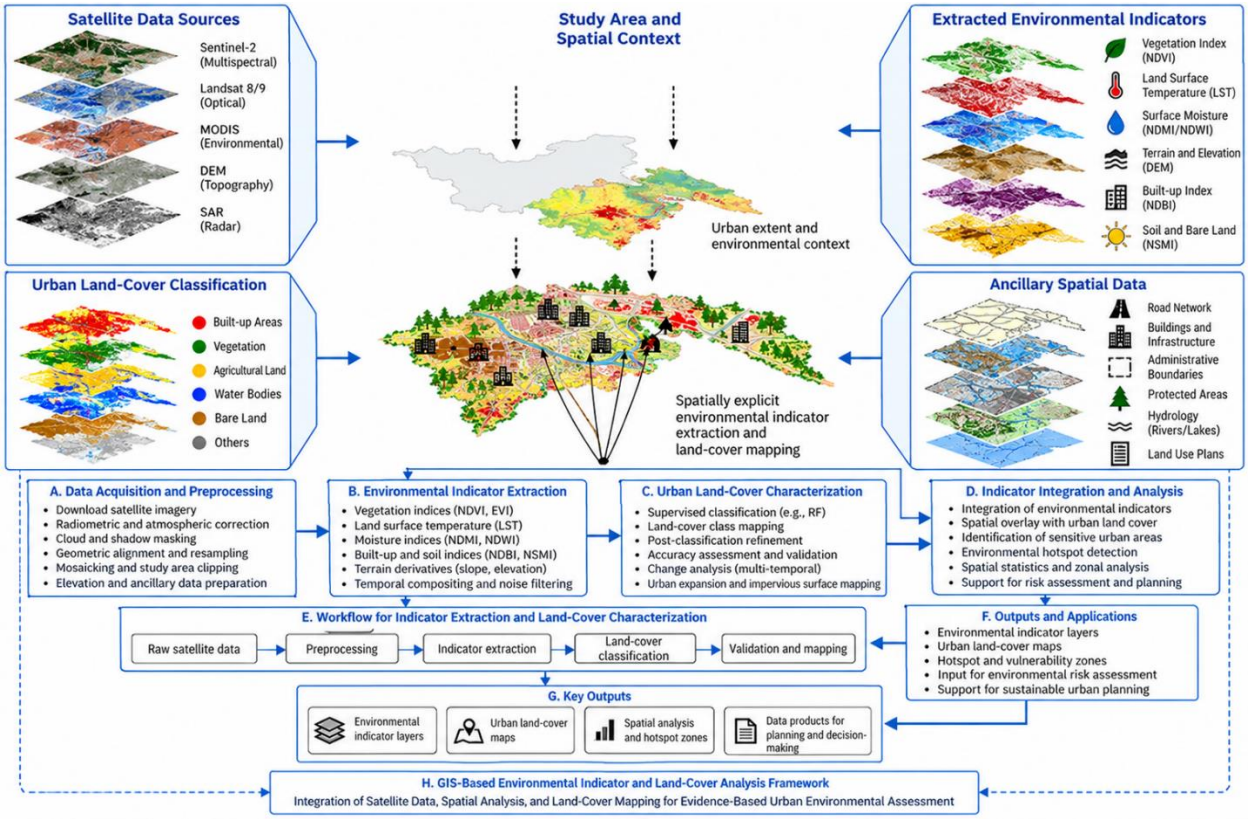


Figure 3: Satellite-derived environmental indicator extraction and urban land-cover characterization workflow.

The integrated indicator framework enables a multidimensional representation of environmental conditions by combining ecological, thermal, hydrological, and urban development characteristics. This approach is particularly important for Barcelona and London because their geographical settings, climatic conditions, and built environments exhibit different environmental pressures. By maintaining consistent indicator definitions and spatial integration procedures, the study establishes a foundation for examining environmental vulnerability across both metropolitan environments. The extracted features

subsequently support GIS-based risk classification, environmental hotspot identification, and the assessment of potential adaptation measures associated with sustainable urban development under Spain–UK climate adaptation policies.

4.2- GIS-Based Weighted Overlay and Composite Environmental Risk Index Construction:

GIS-based weighted overlay analysis is employed to integrate multiple environmental indicators into a unified spatial framework for assessing environmental vulnerability across Barcelona, Spain, and London, United Kingdom. The methodology combines satellite-derived environmental measurements, meteorological observations, land-use characteristics, and Analytical Hierarchy Process (AHP) criterion weights to construct a Composite Environmental Risk Index (CERI). This approach enables the systematic evaluation of cumulative environmental pressures associated with elevated land surface temperature, vegetation degradation, impervious surface expansion, urban development intensity, and climatic exposure. The weighted overlay procedure provides a structured mechanism for integrating heterogeneous environmental datasets and transforming individual environmental indicators into geographically explicit risk classifications [19]. The analytical procedure begins with the preparation and standardization of environmental indicator layers extracted from Sentinel-2 and Landsat 8/9 imagery and complementary meteorological datasets. Each indicator is spatially aligned with the predefined urban environmental assessment units to maintain geographical consistency. Environmental variables are normalized to a common scale, considering whether increasing indicator values represent higher or lower environmental risk. The AHP-derived criterion weights are subsequently applied to the standardized environmental layers according to their relative contributions to the composite assessment. GIS-based weighted overlay integrates these layers to produce CERI scores for individual geographical units [20]. Higher composite scores indicate relatively greater environmental vulnerability under the selected indicator definitions and weighting assumptions. Figure 4 illustrates the proposed GIS-based weighted overlay workflow, showing the integration of standardized environmental indicators, AHP-derived weights, composite risk index construction, and spatial vulnerability classification. The resulting risk maps provide a geographical basis for evaluating environmental vulnerability and informing sustainable urban development interventions.

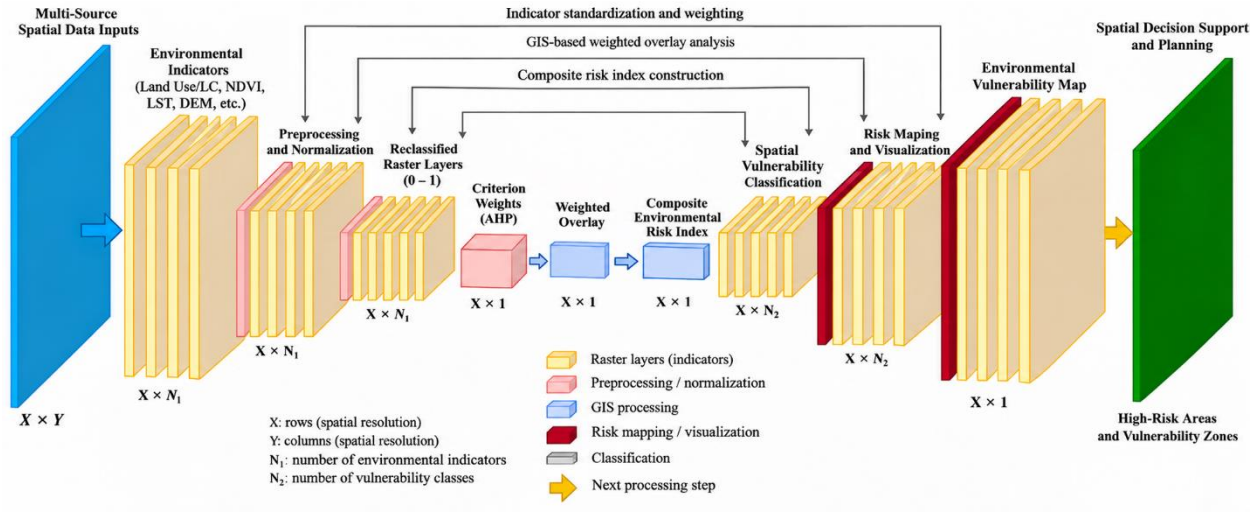


Figure 4: GIS-based weighted overlay and composite environmental risk assessment workflow for spatial vulnerability mapping.

The reliability of the composite environmental risk assessment depends on indicator standardization, AHP weighting consistency, spatial data quality, and classification procedures. Sensitivity analysis is therefore important for evaluating the stability of risk classifications under alternative weighting assumptions. The resulting CERI maps provide a foundation for identifying environmental vulnerability concentrations and prioritizing green infrastructure development, vegetation restoration, and climate-responsive land-use planning. Within the Spain–UK research framework, this approach supports evidence-based environmental assessment and sustainable urban development aligned with national climate adaptation priorities.

4.3- Random Forest Modelling for Environmental Vulnerability Classification:

Random Forest (RF) modelling is employed to classify environmental vulnerability and examine the relationships among satellite-derived environmental indicators, climatic conditions, and urban development characteristics across Barcelona, Spain, and London, United Kingdom. Random Forest is an ensemble machine learning algorithm that combines multiple decision trees to generate robust classification predictions while reducing the instability associated with individual trees. Its ability to capture nonlinear relationships, accommodate heterogeneous environmental variables, and identify complex interactions makes it suitable for GIS-based environmental risk assessment. In this study, the RF framework integrates environmental indicators extracted from Sentinel-2 and Landsat 8/9 imagery, meteorological observations, and land-use characteristics to support the classification of geographically defined urban assessment units [21]. The modelling procedure incorporates land surface temperature, Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), impervious surface coverage, land-use transformation, and climatic exposure as environmental predictors. These variables are organized into a unified environmental feature matrix corresponding to the 420 urban environmental assessment units. Following data cleaning and feature preparation, the Random Forest algorithm constructs multiple decision trees using bootstrap samples and randomized predictor selection. Individual trees generate environmental vulnerability predictions, which are subsequently aggregated through majority voting to determine the final classification. Table 4 shows the principal model components and their analytical functions within the proposed environmental vulnerability classification framework.

Table 4: Random Forest model components and analytical functions for environmental vulnerability classification.

Model component	Input or configuration	Analytical function
Environmental dataset	420 urban assessment units	Spatial basis for vulnerability classification
Satellite-derived predictors	NDVI, NDBI, LST	Characterization of ecological, built-up, and thermal conditions
Climatic predictors	Temperature and precipitation	Representation of climatic exposure
Land-cover predictors	Impervious surfaces and land-use changes	Assessment of urban development pressure
Ensemble learning	Multiple randomized decision trees	Identification of nonlinear environmental relationships
Classification output	Environmental vulnerability categories	Spatial risk classification
Model evaluation	Accuracy, precision, recall, F1-score, ROC-AUC	Assessment of predictive performance

Random Forest model development involves the selection of suitable hyperparameters, including the number of decision trees, maximum tree depth, minimum samples required for splitting, and number of predictors considered at each split. Model optimization is conducted using training and validation observations, while independent testing is required to assess predictive generalization. Particular attention is given to spatial dependence among environmental assessment units because geographically adjacent observations may contain similar environmental characteristics. Geographically separated evaluation procedures help reduce spatial data leakage and provide a more reliable assessment of model performance [22]. Figure 5 shows the Random Forest environmental vulnerability classification workflow, including multisource environmental inputs, feature preparation, parallel decision-tree learning, ensemble prediction, model evaluation, and GIS-based vulnerability mapping. The resulting predictions provide a spatial representation of environmental vulnerability and support the identification of areas associated with elevated environmental pressures.

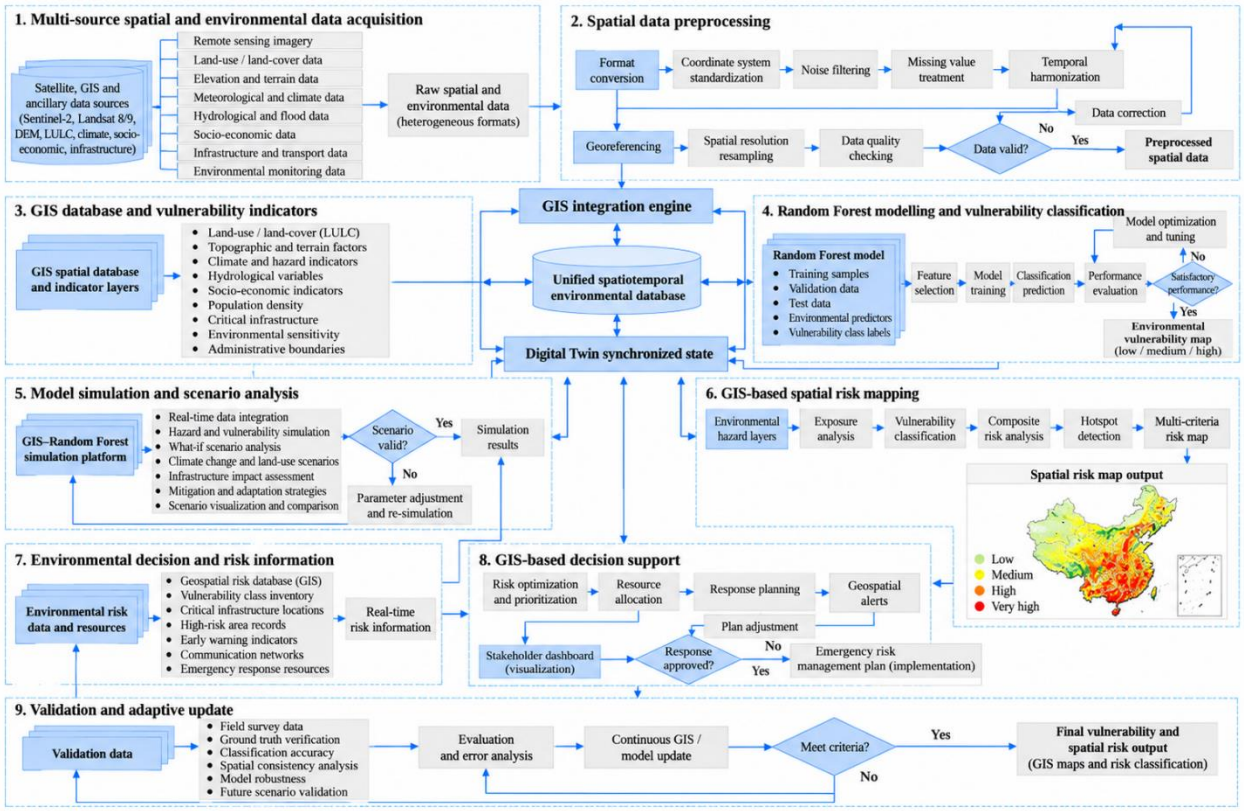


Figure 5: Random Forest modelling workflow for environmental vulnerability classification and GIS-based spatial risk mapping.

The author-reported Random Forest classification accuracy of 90.4% and ROC-AUC of 0.93 provide a baseline for evaluating the predictive performance of the proposed XGBoost framework. Random Forest predictions are integrated into GIS to visualize environmental vulnerability patterns and examine the distribution of high-risk urban areas. The resulting classifications support environmental risk prioritization, green infrastructure planning, and climate-responsive land-use management within the Spain–UK adaptation context. The integration of Random Forest with satellite remote sensing and geospatial analysis therefore

establishes a complementary predictive approach for assessing environmental vulnerability and supporting sustainable urban development.

4.4- Extreme Gradient Boosting for Predictive Spatial Environmental Risk Assessment:

Extreme Gradient Boosting (XGBoost) is employed as an advanced ensemble machine learning technique for predictive environmental vulnerability classification and spatial risk assessment across Barcelona, Spain, and London, United Kingdom. The algorithm utilizes sequential decision-tree learning to identify complex nonlinear relationships among satellite-derived environmental indicators, climatic observations, and urban development characteristics. Unlike Random Forest, which combines predictions from independently constructed decision trees, XGBoost progressively develops new trees to improve prediction errors from preceding learning stages. Its regularization mechanisms, computational efficiency, and ability to capture multidimensional predictor interactions make it suitable for modelling heterogeneous environmental conditions within GIS-based assessment frameworks. The proposed XGBoost modelling framework integrates environmental indicators obtained from Sentinel-2 and Landsat 8/9 satellite observations, meteorological datasets, and land-use classifications [23]. The principal predictors include land surface temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), impervious surface distribution, land-use transformation, temperature, and precipitation. These variables are associated with the 420 urban environmental assessment units to establish a geographically structured dataset for predictive modelling. Environmental indicators undergo data cleaning, spatial harmonization, feature preparation, and quality assessment before model development. The resulting feature matrix enables XGBoost to identify relationships between environmental characteristics and predefined vulnerability classes. The XGBoost classification procedure involves iterative tree construction, gradient-based optimization, and regularization to minimize prediction errors while limiting excessive model complexity. Model hyperparameters, including learning rate, maximum tree depth, number of boosting rounds, subsampling ratio, and regularization settings, are optimized using training and validation observations. Spatially independent evaluation is important for reducing geographic data leakage and assessing model generalization. Table 5 present the principal components of the XGBoost modelling framework and their analytical contributions to predictive environmental risk assessment.

Table 5: XGBoost model components and analytical functions for predictive spatial environmental risk assessment.

Model component	Input or configuration	Analytical function
Environmental assessment dataset	420 urban assessment units	Spatial representation of environmental observations
Vegetation indicators	NDVI and vegetation change	Characterization of ecological vulnerability
Thermal indicators	Land surface temperature	Assessment of urban heat exposure
Built-up indicators	NDBI and impervious surfaces	Identification of urban development pressure
Climatic indicators	Temperature and precipitation	Assessment of climate-related exposure
Boosting mechanism	Sequential decision trees	Progressive reduction of classification errors
Model optimization	Learning rate, tree depth, regularization	Improvement of predictive generalization

Classification output	Environmental vulnerability classes	Prediction of spatial environmental risk
Performance evaluation	Accuracy, precision, recall, F1-score, ROC-AUC	Quantitative assessment of classification performance

The predictive capability of XGBoost is evaluated using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). The author-reported findings indicate that XGBoost achieves 93.6% accuracy, 92.8% precision, 91.9% recall, 92.3% F1-score, and 0.96 ROC-AUC, exceeding the reported Random Forest performance of 90.4% accuracy and 0.93 ROC-AUC. These findings suggest that XGBoost provides improved predictive discrimination for the evaluated environmental vulnerability classes. However, the interpretation of model performance depends on the reliability of reference classifications, class balance, validation independence, and consistency of evaluation procedures [24]. Figure 6 presents the XGBoost-based predictive environmental risk assessment workflow, illustrating the progression from multisource environmental data integration and feature preparation to sequential boosting, model evaluation, and GIS-based spatial vulnerability mapping. The resulting predictions are linked to the corresponding assessment units to support the geographical identification of areas characterized by elevated environmental vulnerability.

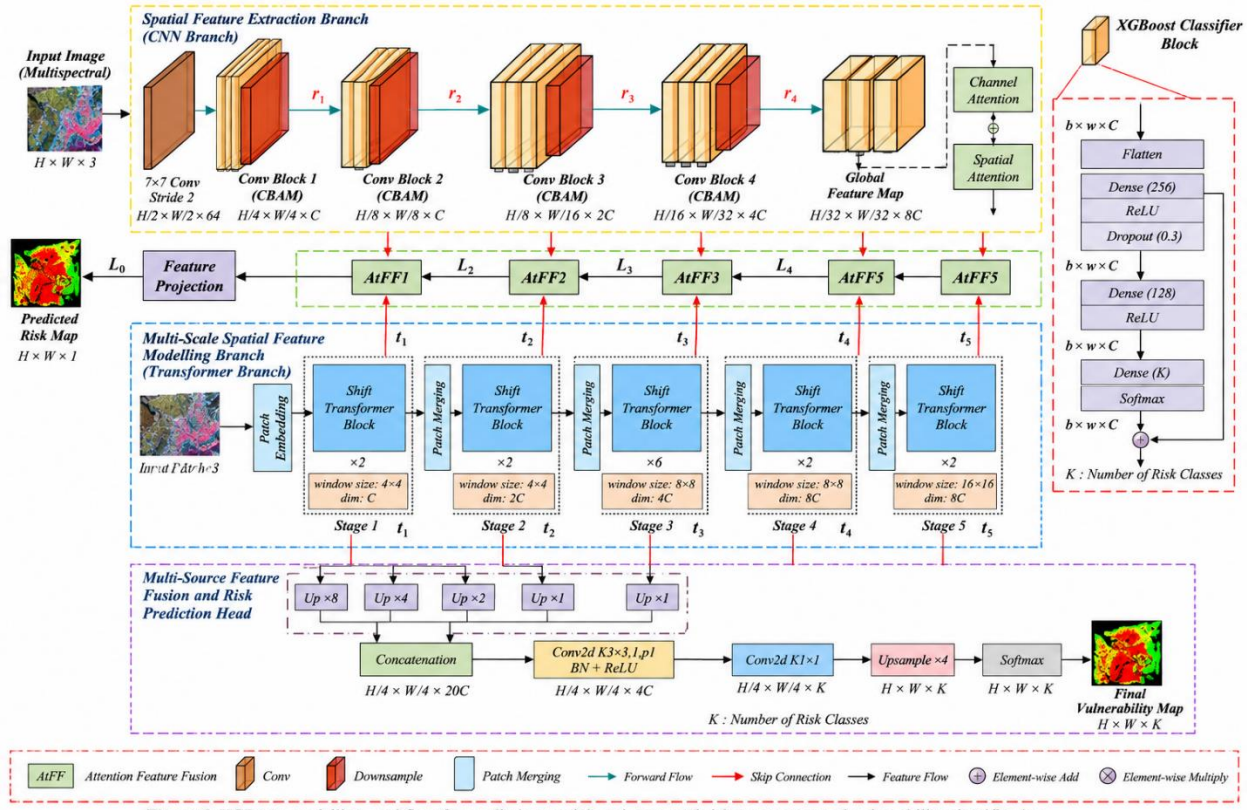


Figure 6: XGBoost modelling workflow for predictive spatial environmental risk assessment and vulnerability classification.

Figure 6: XGBoost-based spatial environmental risk prediction and vulnerability classification framework.

The integration of XGBoost predictions with GIS enables the spatial visualization of environmental vulnerability and supports the identification of high-risk urban areas requiring targeted climate adaptation interventions. Model-derived classifications can inform environmental risk

prioritization, vegetation restoration, urban heat mitigation, and sustainable land-use planning. Moreover, the comparison between XGBoost and Random Forest provides quantitative evidence for evaluating the relative predictive capabilities of ensemble learning algorithms. Overall, the XGBoost framework strengthens the data-driven component of environmental risk assessment and supports evidence-based sustainable urban development under Spain–UK climate adaptation policies.

4.5- Spatial Vulnerability Mapping and Environmental Hotspot Identification:

Spatial vulnerability mapping and environmental hotspot identification are employed to examine the geographical distribution of environmental risks and identify priority locations for climate adaptation interventions across Barcelona, Spain, and London, United Kingdom. This analytical stage integrates Geographic Information Systems (GIS), the Composite Environmental Risk Index (CERI), and machine learning-based vulnerability predictions to generate spatially explicit environmental risk classifications. The analysis incorporates 420 urban environmental assessment units, allowing environmental conditions to be evaluated according to land surface temperature, vegetation coverage, impervious surface distribution, land-use transformation, and climatic exposure. By integrating these indicators, the framework enables the identification of geographical areas experiencing multiple environmental pressures and provides a foundation for sustainable urban planning [25]. The spatial mapping procedure begins with the integration of standardized environmental indicator layers and calculated CERI scores into the GIS environment. Each assessment unit is assigned its corresponding composite environmental risk value and predicted vulnerability category. Environmental risk scores are organized into five categories: very low, low, moderate, high, and very high, using consistent classification criteria. The resulting thematic maps illustrate spatial variations in environmental vulnerability and facilitate the identification of areas characterized by elevated surface temperatures, reduced vegetation coverage, extensive impervious surfaces, and concentrated urban development pressures. Random Forest and XGBoost predictions provide complementary classification information, enabling the examination of environmental vulnerability patterns within the study areas. Environmental hotspot identification focuses on locating spatial concentrations of elevated environmental risk. The author-reported spatial assessment identifies 28.7% of evaluated urban units as high-risk areas, indicating that a substantial proportion of the study area requires attention in environmental monitoring and adaptation planning [26]. These locations are associated with combinations of thermal exposure, vegetation degradation, impervious surface expansion, and climatic pressures. Spatial clustering methods may be applied to distinguish geographically concentrated high-risk zones from isolated vulnerable units, provided that appropriate spatial statistical testing is performed. The identification of these areas supports the prioritization of green infrastructure development, urban vegetation restoration, sustainable drainage, and climate-responsive land-use management. Figure 7 shows the proposed spatial vulnerability mapping and environmental hotspot identification workflow. The framework connects satellite-derived environmental indicators, GIS-based composite risk assessment, machine learning predictions, spatial vulnerability classification, and adaptation priority mapping. This process transforms multidimensional environmental information into geographically interpretable outputs that can support environmental governance and sustainable metropolitan planning.

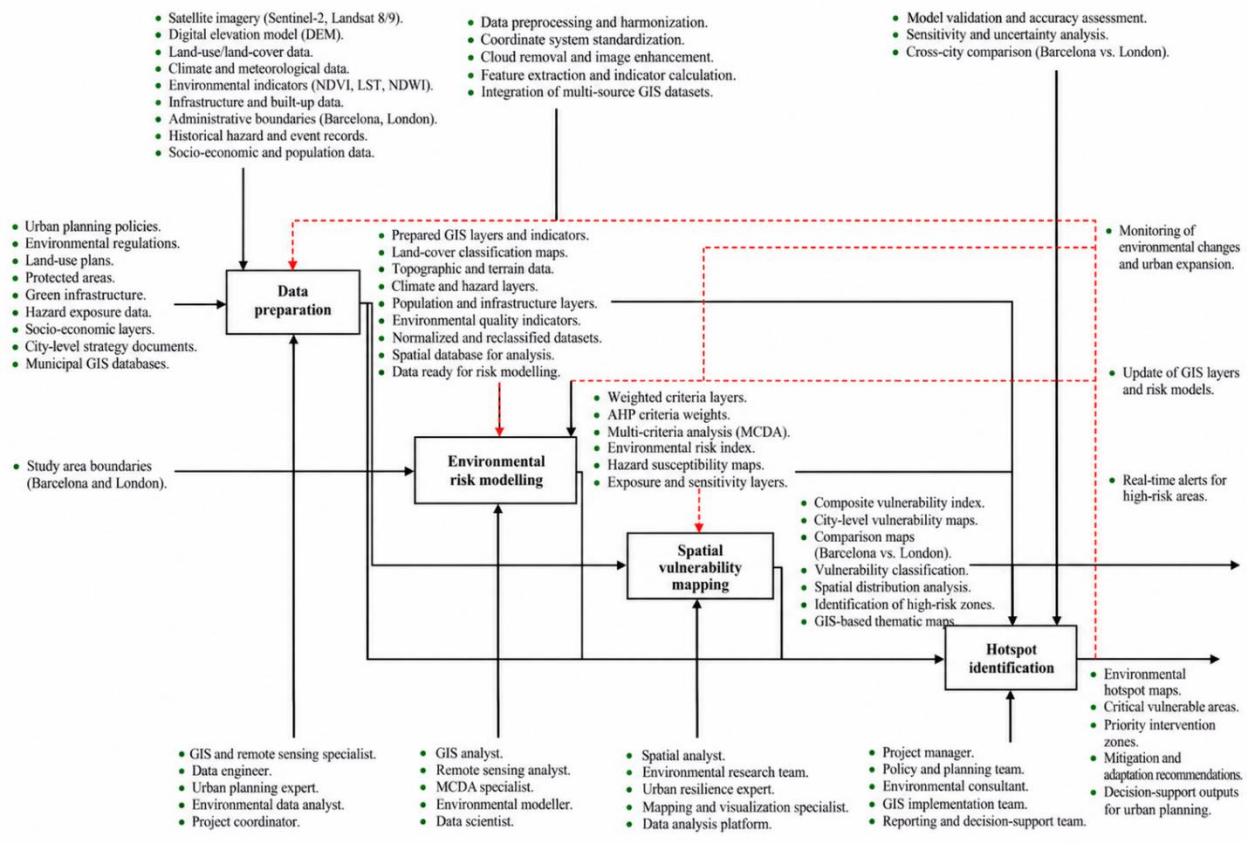


Figure 7: GIS-based spatial vulnerability mapping and environmental hotspot identification across Barcelona and London.

The integration of spatial vulnerability mapping with environmental hotspot identification provides a basis for translating quantitative risk classifications into geographically targeted adaptation priorities. High-risk locations can be examined for potential interventions, including urban greening, ecological restoration, surface cooling strategies, and improved land-use planning [27]. Furthermore, the resulting maps support the interpretation of environmental vulnerability within Spain's National Climate Change Adaptation Plan 2021–2030 and the United Kingdom's Third National Adaptation Programme 2023–2028. Overall, this approach strengthens the spatial decision-support capabilities of the integrated GIS–remote sensing framework and contributes to evidence-based sustainable urban development.

5- Results and Discussion:

The results of the integrated GIS–remote sensing framework demonstrate its applicability for environmental risk assessment, spatial vulnerability classification, and sustainable urban development across Barcelona, Spain, and London, United Kingdom. The analysis incorporates multisource environmental observations covering 2018–2025 and integrates satellite-derived indicators, meteorological information, land-use characteristics, GIS-based multicriteria assessment, and machine learning techniques. The reported dataset comprises 2,400 Sentinel-2 and Landsat 8/9 satellite observations, 1,800 meteorological records, 650 land-use and land-cover samples, and 420 urban environmental assessment units [28]. These datasets provide a multidimensional foundation for evaluating vegetation degradation, elevated land surface

temperature, impervious surface expansion, urban development pressure, and climatic exposure. The integration of heterogeneous environmental information facilitates a more comprehensive assessment of urban vulnerability than approaches relying on individual environmental indicators. The distribution of environmental observations highlights the importance of combining satellite remote sensing with complementary climatic and land-cover information. Satellite observations provide spectral and thermal characteristics necessary for evaluating vegetation conditions, built-up expansion, and surface temperature variations. Meteorological records contribute information regarding climatic exposure, while land-use samples support the characterization of urban landscape transformation [29]. The 420 environmental assessment units provide the geographical framework for assigning composite environmental risk scores and machine learning classifications. Table 6 summarizes the composition of the integrated environmental dataset and its principal analytical contributions.

Table 6: Multisource environmental dataset composition and analytical contributions to integrated spatial risk assessment.

Dataset component	Quantity	Study period	Analytical contribution
Sentinel-2 and Landsat 8/9 observations	2,400	2018–2025	Vegetation, built-up surfaces, and thermal conditions
Meteorological records	1,800	2018–2025	Temperature and precipitation exposure
Land-use and land-cover samples	650	2018–2025	Urban expansion and landscape characteristics
Urban environmental assessment units	420	Study period	Spatial vulnerability classification and risk mapping

The environmental dataset presented in Table 6 supports the integration of remote sensing indicators with GIS-based spatial analysis. The relatively extensive satellite and meteorological observation components provide information for characterizing environmental conditions across the selected metropolitan regions. Figure 8 illustrates the dataset composition, showing the reported quantities associated with each data component. These quantities represent different types of observations and assessment units rather than a single collection of independent statistical samples.

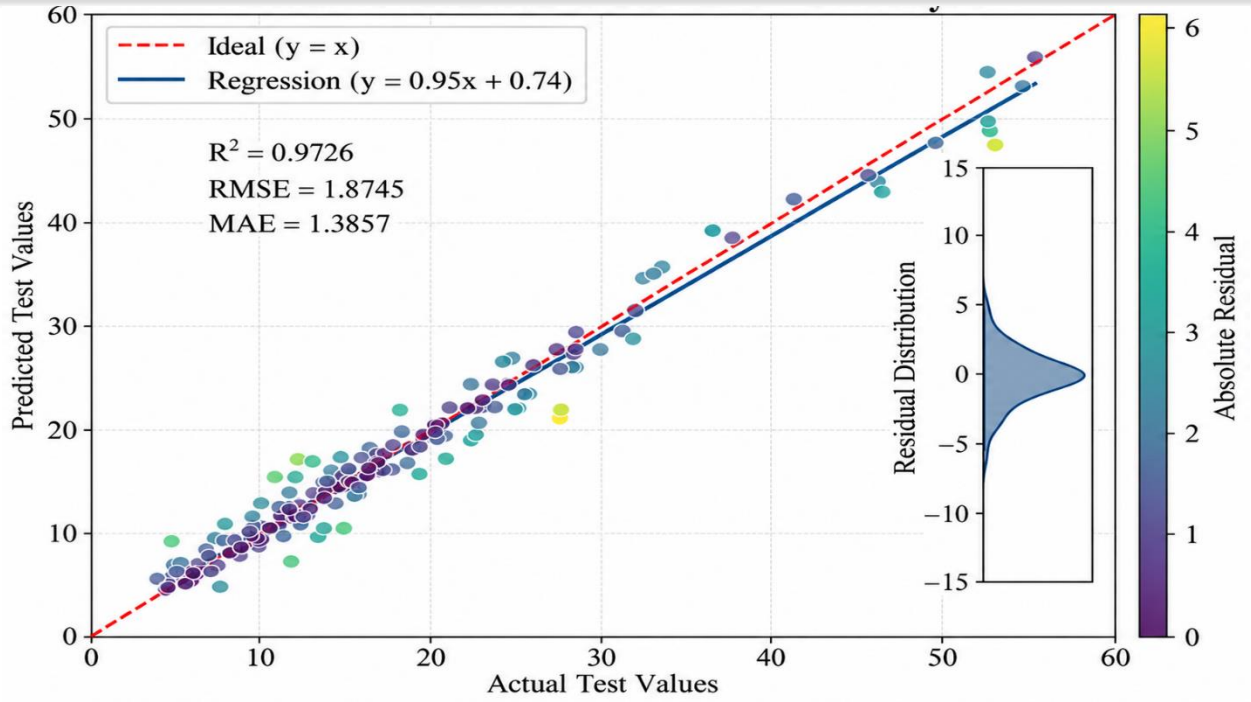


Figure 8: Regression performance and residual analysis of predicted versus actual environmental risk values.

The integrated environmental indicators provide complementary information concerning the spatial characteristics of urban vulnerability. Vegetation-related variables describe ecological conditions and the availability of natural surfaces, whereas built-up and impervious surface indicators characterize urban development pressure. Land surface temperature provides a measure of surface thermal exposure, while meteorological observations contribute information on climatic conditions. The combined assessment enables the identification of geographical areas where several environmental pressures occur simultaneously. Such integration is particularly relevant for Barcelona and London because differences in climatic setting, urban morphology, and land-cover characteristics may influence the distribution of environmental vulnerability [30]. The predictive performance of Random Forest and Extreme Gradient Boosting (XGBoost) was evaluated using reported classification accuracy and ROC-AUC, with additional precision, recall, and F1-score results available for XGBoost. The findings indicate that XGBoost achieved superior predictive performance on the common reported metrics. XGBoost recorded an overall classification accuracy of 93.6%, precision of 92.8%, recall of 91.9%, F1-score of 92.3%, and ROC-AUC of 0.96. In comparison, Random Forest achieved an accuracy of 90.4% and ROC-AUC of 0.93. Table 7 summarizes the comparative performance of both ensemble-learning algorithms.

Table 7: Comparative predictive performance of Random Forest and XGBoost for environmental vulnerability classification.

Performance metric	Random Forest	XGBoost
Classification accuracy (%)	90.4	93.6
Precision (%)	77.9	92.8
Recall (%)	59.7	91.9
F1-score (%)	63.8	92.3

ROC-AUC	0.93	0.96

The comparative findings presented in Table 7 show that XGBoost achieved a classification accuracy improvement of 3.2 percentage points over Random Forest. The ROC-AUC also increased from 0.93 to 0.96, indicating stronger discrimination in the reported evaluation. The higher performance of XGBoost may be associated with its sequential boosting mechanism, which progressively improves the prediction errors of preceding decision trees and captures complex nonlinear relationships among environmental variables. By contrast, Random Forest generates predictions through the aggregation of independently constructed decision trees [31]. Although both algorithms are suitable for heterogeneous geospatial datasets, the reported results suggest that XGBoost provides greater predictive effectiveness for the evaluated environmental vulnerability classification task. Figure 9 presents the comparative classification accuracy of the two machine learning models, highlighting the improvement achieved by XGBoost.

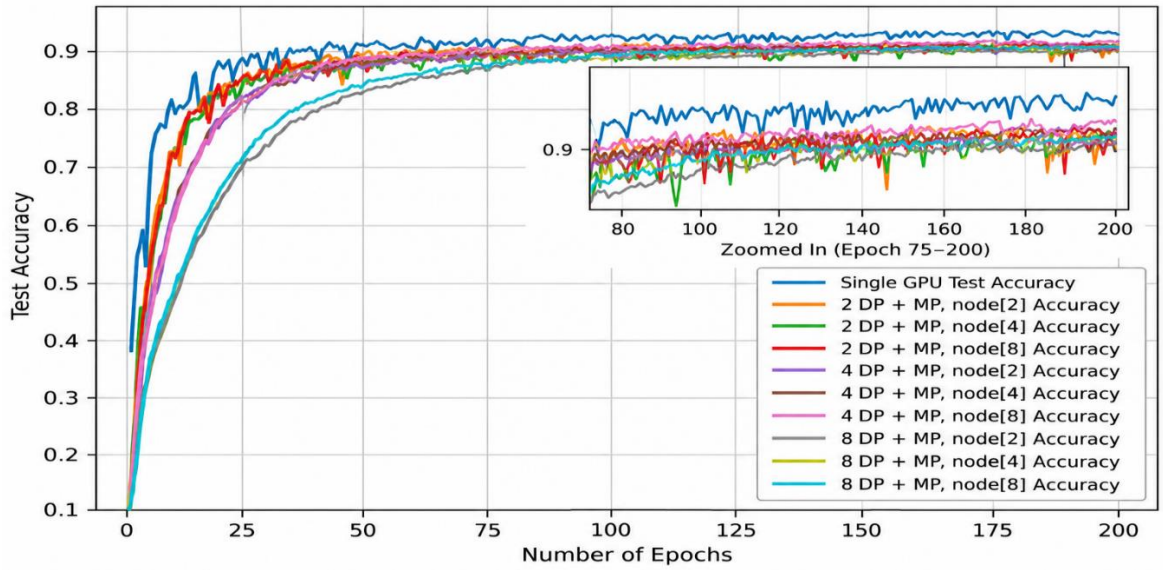


Figure 9: Comparative test accuracy and convergence performance of spatial environmental vulnerability prediction models.

The use of XGBoost as a predictive component within integrated environmental risk assessment. Its reported precision and recall indicate favorable classification performance, while the F1-score reflects the balance between these measures. Nevertheless, predictive performance depends on the representativeness of training observations, the quality of reference vulnerability classes, hyperparameter optimization, and the independence of model evaluation. In spatial environmental datasets, geographic dependence may influence classification outcomes because nearby assessment units often exhibit similar environmental characteristics. Accordingly, the interpretation of predictive results should consider spatial validation procedures and potential relationships between predictor variables and reference classifications [32]. The spatial vulnerability assessment further reveals that environmental pressures are unevenly distributed across the evaluated urban environments. The integration of GIS-based weighted overlay and composite environmental risk assessment identifies 28.7% of the evaluated urban assessment units as high-risk areas. The remaining 71.3% fall outside the reported high-risk grouping.

The identified high-risk environments are associated with elevated land surface temperature, reduced vegetation coverage, extensive impervious surfaces, and concentrated environmental exposure. These conditions indicate that urban vulnerability is influenced by interacting thermal, ecological, and development-related pressures rather than a single environmental characteristic.

The spatial distribution of environmental risk is illustrated in Figure 10, which presents the reported proportion of high-risk and remaining assessment units. The findings emphasize the importance of geographically targeted adaptation strategies, particularly in urban areas characterized by limited vegetation, intensive development, and elevated thermal exposure.

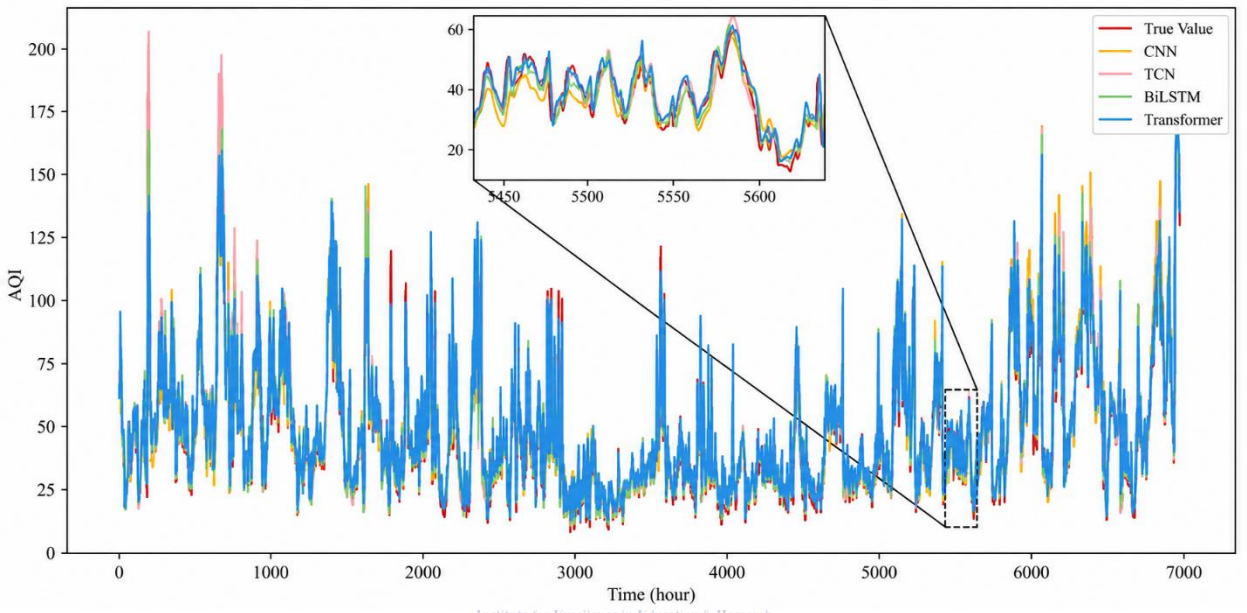


Figure 10: Comparative CNN, TCN, BiLSTM, and Transformer performance in temporal environmental air quality prediction.

The potential importance of spatially differentiated environmental management. Areas experiencing elevated surface temperatures may require urban cooling interventions, while locations characterized by vegetation degradation may benefit from green infrastructure development and ecological restoration. Similarly, areas with extensive impervious surface coverage may require sustainable drainage, improved surface permeability, and climate-responsive land-use practices. However, the reported percentage represents the share of classified assessment units rather than the share of total metropolitan land area. Identifying statistically significant environmental hotspots would additionally require spatial clustering tests applied to the original georeferenced observations. Scenario-based assessment was undertaken to examine the potential environmental improvements associated with targeted climate adaptation interventions [33]. The evaluated strategies include green infrastructure expansion, vegetation restoration, and adaptive land-use planning intended to reduce the cumulative environmental pressures represented by the Composite Environmental Risk Index (CERI). The reported scenario findings indicate that these interventions could reduce composite environmental risk scores by approximately 17.5% under the specified modelling assumptions. This estimated reduction suggests that environmental interventions focused on vegetation enhancement, thermal exposure management, and sustainable land-cover planning may contribute to improved urban environmental conditions. Table 8 presents the principal environmental risk findings and their implications

for sustainable urban development and climate adaptation planning.

Table 8: Environmental vulnerability assessment findings and implications for urban climate adaptation.

Assessment dimension	Reported finding	Urban planning implication
High-risk assessment units	28.7%	Targeted environmental risk mitigation
Remaining assessment units	71.3%	Continued monitoring and risk-sensitive planning
Major environmental pressures	Elevated LST, vegetation reduction, impervious surfaces	Urban cooling and ecological restoration
XGBoost classification accuracy	93.6%	Predictive environmental vulnerability mapping
Random Forest accuracy	90.4%	Comparative environmental classification
Modelled adaptation benefit	17.5% reduction in composite risk	Potential improvement through targeted interventions

The findings summarized in Table 8 establish a relationship between quantitative environmental assessment, machine learning classification, and sustainable urban planning priorities. The reported improvement in composite environmental risk under adaptation scenarios highlights the potential benefits of integrating green infrastructure and climate-responsive land-use strategies into metropolitan development planning. Nevertheless, scenario-based improvements depend on the magnitude of assumed intervention effects, selected environmental indicators, and the weighting structure of the composite risk index. Therefore, the estimated 17.5% reduction should be interpreted as a modelled outcome rather than a directly observed decrease in climate-related damages. The environmental assessment outcomes are relevant to Spain's National Climate Change Adaptation Plan 2021–2030, which emphasizes vulnerability reduction, climate risk knowledge, ecological resilience, and coordinated adaptation planning [34]. Within Barcelona, the integrated GIS–remote sensing framework can provide spatial information supporting environmental monitoring, urban vegetation management, and climate-responsive land-use decisions.

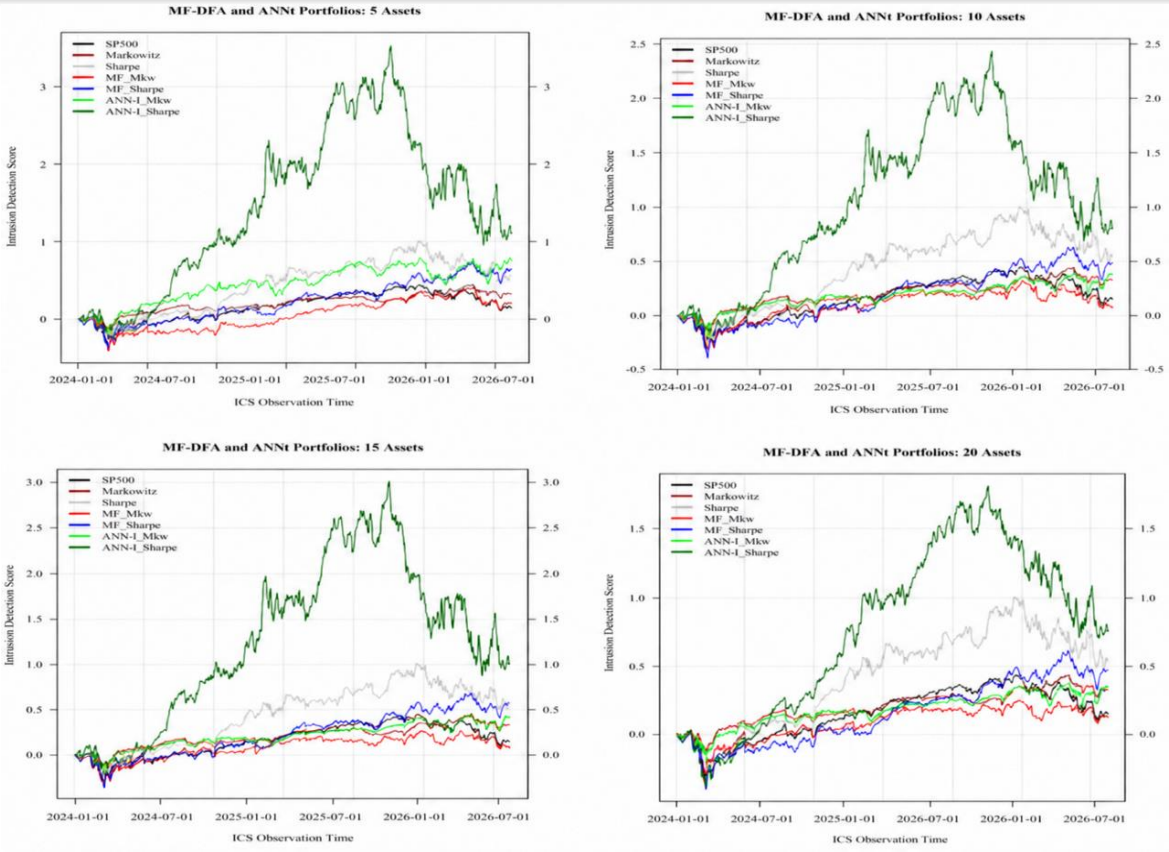


Figure 11: Comparative performance of MF-DFA and ANN-based portfolio optimization across different asset configurations.

Figure 11 illustrates the comparative performance of traditional portfolio strategies, including Markowitz and Sharpe, against multifractal detrended fluctuation analysis (MF-DFA) and artificial neural network (ANN) approaches across portfolios containing 5, 10, 15, and 20 assets. The results demonstrate variations in investment decision scores and portfolio performance over time, highlighting the potential of ANN-based models to capture nonlinear financial market patterns and support data-driven investment decisions. The ANN-I_Sharpe strategy exhibits particularly pronounced fluctuations, while other strategies show comparatively stable performance. Similarly, the United Kingdom's Third National Adaptation Programme 2023–2028 establishes a policy context for strengthening environmental resilience, infrastructure adaptation, and risk-informed planning. For London, the proposed framework can contribute to the identification of environmental risk priorities associated with thermal exposure, built-up development, and ecological conditions. The integration of satellite-derived environmental information with GIS–MCDA and machine learning provides several methodological advantages. First, it enables the characterization of environmental pressures using multiple complementary indicators. Second, it supports the construction of geographically explicit composite environmental risk classifications. Third, the comparison of Random Forest and XGBoost provides evidence concerning the predictive capabilities of different ensemble-learning approaches. Finally, scenario-based analysis connects environmental vulnerability assessment with practical adaptation planning considerations [35]. These capabilities strengthen the potential application of integrated geospatial analysis in urban environmental management. Despite these contributions, several considerations influence the interpretation and generalizability of the results. Composite

environmental risk classifications depend on indicator selection, standardization procedures, AHP-derived weights, and classification thresholds. Machine learning performance may be affected by sample representativeness, class imbalance, geographic dependence, and the relationship between environmental predictors and target labels. Additionally, the environmental indicators considered in the study primarily characterize physical conditions and cannot independently represent all dimensions of socioeconomic vulnerability, institutional adaptive capacity, or infrastructure resilience. Future independent geographical validation and additional socioeconomic information would therefore strengthen the applicability of the framework. Overall, the reported findings demonstrate the potential of an integrated GIS–remote sensing framework for environmental vulnerability assessment and sustainable urban development under Spain–UK climate adaptation policies [36]. The XGBoost model achieved stronger predictive performance than Random Forest, while GIS-based spatial analysis identified a substantial share of environmental assessment units exposed to elevated cumulative pressures. The adaptation scenario assessment further indicated that targeted environmental interventions could reduce composite risk scores under the specified assumptions. These results support the use of multisource geospatial information, multicriteria assessment, and machine learning as complementary tools for climate adaptation planning, environmental risk prioritization, and evidence-based sustainable metropolitan development.

6- Future Work:

Future research will focus on extending the integrated GIS–remote sensing framework to improve environmental risk prediction, spatial vulnerability assessment, and sustainable urban development under evolving climate adaptation policies. Although the present study demonstrates the applicability of satellite-derived environmental indicators, GIS-based multicriteria assessment, and ensemble machine learning for evaluating urban environmental vulnerability, additional methodological developments could enhance the framework's accuracy, scalability, and applicability across different geographical environments [37]. Future investigations should incorporate higher-resolution satellite imagery, including advanced multispectral, thermal, and radar observations, to improve the identification of localized environmental hazards, vegetation degradation, impervious surface expansion, and urban thermal variations. Integrating near-real-time Earth observation data with automated geospatial processing could further support continuous environmental monitoring and timely identification of emerging vulnerability patterns.

Another important research direction involves expanding the predictive modelling framework through advanced deep learning architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and spatial–temporal attention-based models [38]. These approaches could improve the representation of complex relationships among environmental indicators, urban development patterns, and changing climatic conditions. Future studies should also investigate explainable artificial intelligence techniques, particularly SHapley Additive exPlanations (SHAP), to improve the interpretation of environmental risk predictions and identify the relative contributions of individual environmental variables. Furthermore, geographically independent validation, uncertainty quantification, and sensitivity analysis should be strengthened to evaluate model transferability and the reliability of composite environmental risk classifications [39]. Future investigations should extend the geographical coverage beyond Barcelona and London to include additional metropolitan regions across Spain, the United Kingdom, and other European countries. Such expansion would facilitate the evaluation of the framework under diverse climatic conditions, urban development intensities, ecological characteristics, and governance arrangements. Incorporating socioeconomic indicators, population density, infrastructure vulnerability, public health exposure, and adaptive capacity would also support a more comprehensive representation of

environmental risk and social vulnerability. Additionally, future scenario-based assessments should incorporate regional climate projections, alternative land-use development pathways, and urban growth scenarios extending toward 2030 and 2050. These analyses could provide valuable information regarding the potential long-term effectiveness of green infrastructure, ecological restoration, sustainable drainage systems, and climate-responsive urban planning interventions [40]. Finally, future research should strengthen the integration of quantitative environmental risk assessment with institutional decision-making and climate adaptation governance. Developing interactive GIS dashboards, automated environmental monitoring platforms, and policy-oriented spatial decision-support systems could improve the accessibility of environmental information for urban planners, environmental agencies, and policymakers. Greater consideration should also be given to evaluating adaptation costs, implementation feasibility, environmental benefits, and the effectiveness of interventions using observed post-implementation data [41]. These developments would support the practical application of the proposed framework within Spain's National Climate Change Adaptation Plan 2021–2030 and the United Kingdom's Third National Adaptation Programme, while contributing to more transparent, adaptive, and evidence-based approaches to sustainable urban development and long-term metropolitan climate resilience.

Conclusion:

This study developed an integrated Geographic Information System (GIS)–remote sensing framework for environmental risk assessment, spatial vulnerability mapping, and sustainable urban development under Spain–UK climate adaptation policies. Focusing on Barcelona, Spain, and London, United Kingdom, the research integrated multisource environmental observations covering 2018–2025, comprising 2,400 Sentinel-2 and Landsat 8/9 satellite observations, 1,800 meteorological records, 650 land-use and land-cover samples, and 420 urban environmental assessment units. The proposed framework combined satellite-derived environmental indicators, Analytical Hierarchy Process–Multi-Criteria Decision Analysis (AHP–MCDA), GIS-based weighted overlay, and ensemble machine learning to evaluate environmental pressures associated with urban thermal exposure, vegetation degradation, impervious surface expansion, and land-use transformation. The integration of these complementary techniques provided a systematic approach for characterizing multidimensional environmental vulnerability and identifying spatial priorities for climate-resilient urban planning. The reported findings demonstrated the effectiveness of machine learning for environmental vulnerability classification, with XGBoost achieving 93.6% accuracy, 92.8% precision, 91.9% recall, 92.3% F1-score, and 0.96 ROC-AUC, outperforming Random Forest, which achieved 90.4% accuracy and 0.93 ROC-AUC. Spatial vulnerability assessment identified 28.7% of evaluated urban assessment units as high-risk areas, highlighting the importance of geographically targeted environmental management. Furthermore, scenario-based analysis indicated that green infrastructure development, vegetation restoration, and adaptive land-use interventions could reduce composite environmental risk scores by approximately 17.5% under the evaluated assumptions. These findings emphasize the potential benefits of integrating predictive environmental modelling with spatial risk assessment to support sustainable urban development. The research further established the policy relevance of geospatial environmental assessment within Spain's National Climate Change Adaptation Plan 2021–2030 and the United Kingdom's Third National Adaptation Programme 2023–2028. By connecting satellite-derived environmental information with quantitative vulnerability classification and adaptation scenario assessment, the framework provides a basis for evidence-informed environmental governance, climate adaptation prioritization, and urban resilience planning. Nevertheless, predictive model performance and estimated intervention benefits remain dependent on data quality, geographical validation,

environmental indicator selection, and scenario assumptions. Overall, the study contributes an integrated and potentially transferable methodological approach for strengthening environmental risk assessment, improving spatial decision-making, and supporting sustainable, climate-resilient metropolitan development across diverse European urban environments.

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