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Mapping Environmental Degradation and Climate Vulnerability using GIS and Remote Sensing

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ABSTRACT

Environmental degradation and climate vulnerability pose significant threats to the stability of ecosystems, agriculture, water supply, and humans' well-being. The use of Geographic Information Systems (GIS) and remote sensing can prove beneficial in detecting spatial patterns of environmental changes, detecting signs of land degradation, and assessing regions' vulnerability to climate threats. In this study, a geospatial framework is suggested to map environmental degradation and climate vulnerability through satellite imagery analysis, vegetation indexes, land use and land cover classification, land surface temperature, precipitation, terrain properties, and socioeconomic factors. Landsat imagery, Sentinel-2 imagery, digital elevation models, and climate gridded data will be combined in GIS to assess changes in vegetation cover, urbanization, bare lands, land surface temperature, and drought. To do that, NDVI, NDBI, LST, and precipitation anomalies will be used to derive indicators of environmental degradation. Climate Vulnerability Index (CVI) will be created using weighted overlay models with environmental exposure, sensitivity, and adaptive capacity indicators. The accuracy of classification will be measured using independent reference data sets, whereas temporal variations will be evaluated via post-classification assessment. As illustrated in the figure below, a conceptual example of the application of the framework is shown by partitioning a study site into different vulnerability zones (low, medium, high, and very high), wherein 35% of the study site has been assigned to high and very high vulnerability zones. The values are purely illustrative and are not obtained from any satellite processing. This framework can contribute to environmental monitoring, climate adaptation strategy, land management, and identification of vulnerable sites.

Introduction

Environmental deterioration is another problem which has become a significant issue in relation to ecosystems, natural resources, and human development. Such phenomena as deforestation, agricultural expansion, urbanization, soil erosion, water shortage, and improper land management may change environmental processes and limit the resilience of landscapes to climate

disturbances. Additionally, climate change exacerbates all those issues through rising temperatures, changing rainfall patterns, droughts, floods, and other extreme weather events. According to the Intergovernmental Panel on Climate Change (IPCC, 2022), climate change risks can be defined as the result of interactions between climatic hazards, exposure, and vulnerability, and environmental and socioeconomic factors play a role in defining the consequences of climate change(Meyer & Turner II, 1994).

Traditional environmental monitoring depends mainly on field surveys and official statistics. Those are important sources of information; however, they may fail to reflect spatial variability in big and hard-to-reach areas. GIS and remote sensing help to overcome that problem by allowing conducting continuous monitoring of land surfaces, state of vegetation, surface temperatures, water bodies, and changes in land cover. Satellites provide us with spatially consistent information about certain territories while GIS allows using information about the environment and socioeconomics in mapping(Turner II et al., 2003).

The remote sensing variables are highly useful in detecting environmental degradation. The vegetation indices can help to show changes in the density and quality of the vegetation. The land cover classification technique can be used to detect changes among the forest, agricultural, bare, water and urbanized regions. The thermal sensing can help to detect the surface warming due to the urbanization and removal of the vegetation. The climate dataset can tell about the deficiency of precipitation and temperature anomaly, thus helping to differentiate between short-term variations and environmental changes. However, individual variables cannot help in detecting the reasons for the degradation. The interpretation of the data depends upon the climate, terrain, land use and socioeconomic conditions in the area(Lambin et al., 2001).

The climate vulnerability mapping provides the means of extending environmental monitoring to detect places where climatic risk intersects the exposed populations, sensitive ecosystems and lack of adaptive capacity. This approach was emphasized by Cutter et al. (2003). Also, Adger (2006) noted that vulnerability is created by social, institutional and environmental processes but not just the climatic exposure(Geist & Lambin, 2004)

Problem Statement

The issue of environmental degradation and climate vulnerability has been analyzed using distinct data sets, different scale levels, or varied methodologies. Studies on land cover can reveal loss of vegetation cover and growth of urban centers without assessing the level of climate vulnerability of the communities affected. On the other hand, studies on climate vulnerability can depend entirely on socioeconomic factors without considering the extent of the environmental changes captured through satellite images(Tucker, 1979).

This can limit the applicability of environmental assessment for planning purposes. A location with reduced vegetation cover can exhibit varying levels of climate vulnerability depending on such factors as its precipitation regime, soil composition, population density, availability of irrigation facilities, and economic strength. In the same way, areas with high land surface temperature may have varied levels of climate vulnerability due to differences in exposure and adaptive capacity(Pettorelli et al., 2005).

Research Objectives

1. To detect and measure multi-temporal land use change, land cover change, vegetation change, and surface temperature through satellite imagery.
2. To create a GIS-based environmental degradation index combining vegetation, land-cover, terrain, and climate.
3. To create a Climate Vulnerability Index that will combine climatic exposure, environmental sensitivity, and adaptive capacity.

Research Questions

1. How do vegetation cover, land use, built-up area, and land surface temperature change in terms of space and time through remote sensing?
2. Which environmental and climatic variables are best for detecting areas prone to degradation?
3. How is the pattern of environmental degradation linked to climate vulnerability?

Significance of the Study

The scientific significance of this study is that it integrates the use of environmental indicators derived from satellite technology into the analysis using a multidimensional vulnerability approach. The use of environmental indicators, such as vegetation index, changes in land cover, surface temperature, precipitation variation, terrain, and socio-economic factors gives a more

comprehensive evaluation compared to the use of a single environmental indicator. It will also be able to separate places undergoing environmental change from places where climatic exposure is enhanced by socio-economic constraints(Huete et al., 2002).

The practical importance is that geospatial maps can be used to determine priority places for ecosystem rehabilitation, forestation, drought mitigation, greening of cities, soil conservation, and water resource management. This can be used by government departments, environmental agencies, disaster management authorities, and development agencies.

The methodological contributions of this study include the development of a replicable spatial workflow that can be applied by using the help of software like QGIS, ArcGIS Pro, Google Earth Engine, and proper remote sensing tools. Moreover, this framework includes the clear documentation of resolution, accuracy of classification, normalization of indicators, weighting schemes, and uncertainty. This is very significant because vulnerability mapping is a decision support tool and not the measurement of an absolute level of risk(Foody, 2002).

Literature Review

Turner et al. (2003) laid out the groundwork by stressing the interactions between environmental, human, and sustainable systems in understanding land use and land cover change. They make it clear that environmental changes cannot be explained by looking at only biophysical changes. The changes in vegetation, soil, and land cover may be the consequence of agriculture, settlement, infrastructure, and institutions. This theory can explain why remote sensing observation should be linked with socioeconomic data in order to map environmental degradation and climate vulnerability.

Lambin et al. (2001) have researched the causes of land use and land cover change and have stressed the need to understand human activity and the interaction with the environment. They state that land cover change can be the result of several interacting causes rather than one cause. In similar research, Geist and Lambin (2004) have shown the combination of economic, demographic, institutional, and environmental factors related to tropical deforestation. This provides the theoretical basis to look at the relationships between vegetation change, agriculture and built-up areas, and climate stress or other forms of land use pressure.

Spectral vegetation indices were proven to be useful for vegetation monitoring based on satellite measurements by Tucker (1979). As a result, the Normalized Difference Vegetation Index became one of the most popular parameters used for assessment of vegetation greenness. The role of NDVI in ecological monitoring was described by Pettorelli et al. (2005). These authors considered NDVI usefulness for estimation of vegetation productivity and environmental variability. However, NDVI is not a measure of land degradation. Values of this parameter depend on vegetation type, season, rainfall, soil background, and atmospheric conditions. Therefore, changes in NDVI need to be interpreted taking into account land-cover classification, precipitation, and other parameters.

Huete et al. (2002) compared enhanced vegetation index (EVI) and NDVI based on MODIS observations, proving the importance of selection of correct indices depending on vegetation conditions. EVI can help overcome some disadvantages of NDVI in dense vegetation, however, both these indices do not eliminate all uncertainties connected with atmosphere, soil background, and canopies. Usage of several vegetation indicators can help in this situation, especially in case of analysis of heterogeneous landscapes (agriculture, forests, shrublands, and sparse vegetation).

According to Foody (2002), there were some developments in land-cover classification accuracy assessment at the time and the author stressed the necessity for the quantitative validation of thematic maps. In other words, a map may look spatially accurate, but have plenty of classification errors. The importance of accuracy assessment for remote-sensing classification was mentioned by Congalton (1991). Therefore, the methods of confusion matrix, overall accuracy, producer's and user's accuracy per class and adequate sampling strategies are appropriate. In addition, accuracy assessment becomes necessary when the magnitude of environmental degradation due to changes between land-cover types is estimated.

Hansen et al. (2013) mapped global forest-cover changes through Landsat observations, which showed the potential of satellite data to capture forest-cover dynamics on large-scale maps. It shows how consistent satellite data allow for assessing tree-cover changes. However, it does not necessarily mean the loss of tree cover equals deforestation or environmental degradation since the meaning of the change in question depends on land use, type of vegetation, reasons for disturbance and further restoration.

Wulder et al. (2019) have outlined a history, current state, and prospects of the Landsat program. Landsat is crucial for monitoring land-surface dynamics over time due to the availability of multi-decadal records of repeated observations from sensors that allow collecting data with spatial resolution adequate for many regional studies. Sentinel-2 imagery provides additional optical imagery with improved spatial resolution for some bands. Both Landsat and Sentinel-2 imagery may

complement each other in improving the temporal and spatial coverage of environmental monitoring; yet, different sensing properties, spatial resolution, and dates of acquisition should be taken into consideration.

Google Earth Engine has been introduced by Gorelick et al. (2017) as a cloud-based platform for planetary-scale environmental data analysis. This platform allows working with large satellite archives, applying consistent temporal filtering, computing various spectral indices and creating land cover products without local storage of all images. Cloud-based analysis is important for monitoring environmental degradation over large regions. Yet, cloud-based analysis does not remove the necessity of quality control, independent validation, code reproducibility, and documenting data processing steps.

Adger (2006) discussed the notion of vulnerability concerning global environmental change, arguing that vulnerability is constructed by social and institutional processes and the extent of environmental exposure. Füssel (2007) considered the conceptual basis of climate vulnerability and discussed the necessity to differentiate between exposure, sensitivity, and adaptive capacity. These conceptual approaches form the theoretical basis of the proposed Climate Vulnerability Index. If one region is exposed to high temperature or droughts, it does not necessarily mean that it faces higher vulnerability compared to another region due to differences in terms of water infrastructure, wealth, health care, and institutional factors.

Cutter et al. (2003) developed a social vulnerability index to assess the spatial variation of vulnerability among counties in the US. This paper shows how sociological factors can be integrated into a geographical evaluation of the vulnerability of regions to natural disasters. Despite the fact that social vulnerability indices should be adapted to local conditions, their conceptual value is useful for the present research because the effects of environmental degradation and climatic risks have different impact on communities depending on their resources.

According to the IPCC (2022), the climate risk is caused by interactions among the three elements: hazards, exposure, and vulnerability. In its assessment, the role of adaptation, ecosystem protection, and the reduction of exposure and sensitivity is highlighted. Based on the above statement, a spatial assessment is made possible by considering the following parameters: climatic factors (precipitation deficit and temperature extremes) and land degradation and socioeconomic factors. Furthermore, according to IPCC, the vulnerability should not be considered a static factor as the adaptation efforts, infrastructure investments, and environmental conditions can change it.

Romshoo et al. (2020) evaluated the incorporation of social, economic, and environmental parameters in the GIS-based assessment of land-degradation vulnerability in the Pir Panjal Himalaya, Kashmir. In the research, the authors showed the practical utility of incorporating environmental indicators and socioeconomic data by weighted index evaluation. Additionally, the authors provided an example of using GIS technology for identifying spatial priorities for mitigation of land degradation. The case is highly relevant to mountainous areas with diverse environment.

Dilawar et al. (2022) have designed a GIS based method for assessing drought risk in Karachi, Pakistan through hazard, exposure and vulnerability based parameters. This is useful to the current research since it shows the way in which the climate related vulnerability can be assessed using the observation and analysis of space. This includes not just the use of a single drought risk parameter.

The research in land surface temperature and land cover dynamics of Pakistan highlights the relevance of combining thermal and optical remote sensing data. Hussain et al. (2023) investigated the land use and land cover changes and their effect on land surface temperature in Southern Punjab of Pakistan. The current research finds this paper useful since it links the transformation in land cover to the thermal effects in an area which is very important from agricultural point of view. However, any changes in temperature need to be considered in light of season, weather, irrigation, soil moisture and surface conditions.

Ahmed et al. (2026) analyzed the dynamics of land-use and land-cover change as well as climate-induced environmental change in Islamabad and Rawalpindi with remote sensing methods. The results have demonstrated decreasing vegetation cover caused by urbanization and changes in land-use. This is a recent illustration of how NDVI and land-cover analyses could be useful for the environmental monitoring in the region. Nonetheless, the reliability of causal relationships is determined by the design of time series, the quality of classification and taking into account climate variability.

The issue of transparent indicators and their spatial validity is particularly emphasized in recent literature on geospatial vulnerability. In a systematic review of geospatial methods used for ecological vulnerability assessment in various environmental domains Sasi and Sawant (2026) have argued for the use of GIS-based composite index and pointed out that the comparison of different studies was necessary because of methodological differences. Differences in indicator selection, normalization and weighting, classification threshold and spatial resolution could result in the creation of vulnerability maps of the same environmental problem.

Research Methodology

For the study to be undertaken, a quantitative and geospatial methodology will be adopted. This will involve the use of satellite images, climatic data, DEM, land cover information and socio-economic parameters to analyze the environmental degradation and vulnerability to climate change. This will be done within a clearly defined study area. The study area must be clearly specified before the end of analysis process; its boundaries, coordinate system, environmental attributes and administrative divisions.

Landsat imagery will be used to analyze past land cover and vegetation data while Sentinel-2 imagery will be used to obtain high resolution optical images for more recent periods. Seasonal windows will be chosen to minimize any disparities caused by agricultural activity, seasonal rainfall and vegetation phenology. Wherever possible, multiple clear cloud scenes will be composited for seasons and years(Congalton, 1991).

Data on digital elevation models will be used to generate elevation and slope. Data on precipitation and temperature will be collected from the appropriate climate grid data set or validated meteorological data. Density of population, agriculture dependence, road connectivity, irrigation facility, and access to basic amenities can be included when spatial data is available. All data sets will be standardized in terms of projection, study area, resolution, and time frame.

Table 1. Proposed datasets and analytical purposes

Dataset	Proposed source	Main analytical purpose
Historical optical imagery	Landsat archive	Long-term land-cover and vegetation change
Recent optical imagery	Sentinel-2	Detailed vegetation and land-cover mapping
Surface temperature	Landsat thermal bands or validated products	Analysis of surface heating patterns
Digital elevation model	SRTM or comparable elevation data	Slope, elevation, and terrain analysis
Precipitation	CHIRPS or validated gridded climate data	Rainfall variability and drought-related indicators
Temperature records	ERA5-Land or meteorological observations	Temperature anomalies and climatic exposure
Population data	Census or WorldPop, subject to suitability	Population exposure and sensitivity
Land-cover reference data	Field observations or independent reference imagery	Classification validation
Administrative boundaries	Official geographic datasets	Zonal statistics and reporting

The chosen time period will depend on availability of information and goals of the study. One possible design could be to contrast three representative periods like 2000, 2010, and 2025, using seasonal averages and other annual data where needed. Years suggested as analytical time points, but not as proof that the analysis has been done.

Satellite images shall be filtered out for clouds, cloud shadows, atmospheric artifacts, and poor acquisition conditions. Surface reflectance products shall be applied in the optical analysis whenever possible, whereas thermal data shall be calibrated based on the specific calibration techniques or known surface temperature product. Satellite images shall be cropped to the area of interest and sorted into similar periods by season.

Classification of land use and cover shall differentiate categories related to the current research, which may include vegetation/forest, agriculture, built-up areas, barren areas, and water bodies. Supervised classification algorithm shall be used, e.g., Random Forest since it allows modeling the nonlinear dependencies between spectral bands and indices. The training sets shall be defined using field measurements or any other reliable source of information.

The land surface temperatures will be obtained through a valid process of thermal analysis. The temperature differences will be considered during similar periods within a season to avoid any interference that weather conditions and acquisition time may cause. Precipitation anomalies will be considered relative to a certain reference period while the slope and other environmental factors will help in identifying vulnerable regions to erosion and runoff in cases that such environmental factors are pertinent(Hansen et al., 2013).

Degradation of the environment will be analyzed based on several indicators such as vegetation deterioration, changes of natural vegetation into built-up/bare land, consistent soil exposure, and climatic stress among others. Not all the low-NDVI

sites will automatically be considered as environmentally degraded since there are natural deserts and agricultural lands with naturally low vegetation indices.

Table 2. Proposed dimensions of the Climate Vulnerability Index

Dimension	Example indicators	Expected relationship with vulnerability
Climatic exposure	Temperature anomalies, rainfall deficits, drought frequency	Higher exposure generally increases vulnerability
Environmental sensitivity	Vegetation decline, erosion susceptibility, degraded land	Greater sensitivity generally increases vulnerability
Social sensitivity	Population pressure, agricultural dependence, poverty	Higher sensitivity generally increases vulnerability
Adaptive-capacity deficit	Limited water access, poor infrastructure, low service access	Larger deficits increase vulnerability

Vulnerability levels will be grouped into four groups – low, moderate, high, and very high. The thresholds for categorization will be determined using an appropriate methodology such as quantiles, natural breaks, or other thresholds based on the nature of the index. The threshold chosen will be justified in the final report together with verification of whether other thresholds alter the spatial pattern.

Evaluations of classification outcomes will be performed by means of independent reference data, which will not be used during the training stage. The confusion matrix will be constructed in order to estimate the following characteristics: overall accuracy, producers' accuracy, users' accuracy and F1-score, if necessary. It is necessary to ensure that sampling will reflect all significant types of land cover and take into consideration the problem of class imbalance.

Evaluation of the vulnerability index will be based on sensitivity analysis and its comparison with independent evidences, if possible. Possible examples of independent evidences are such regions with known drought impact, flood impact, degradation or environmental evaluation. The high value of vulnerability index should not be considered as an independent confirmation of high value of NDVI change or high surface temperature.

Results and Analysis

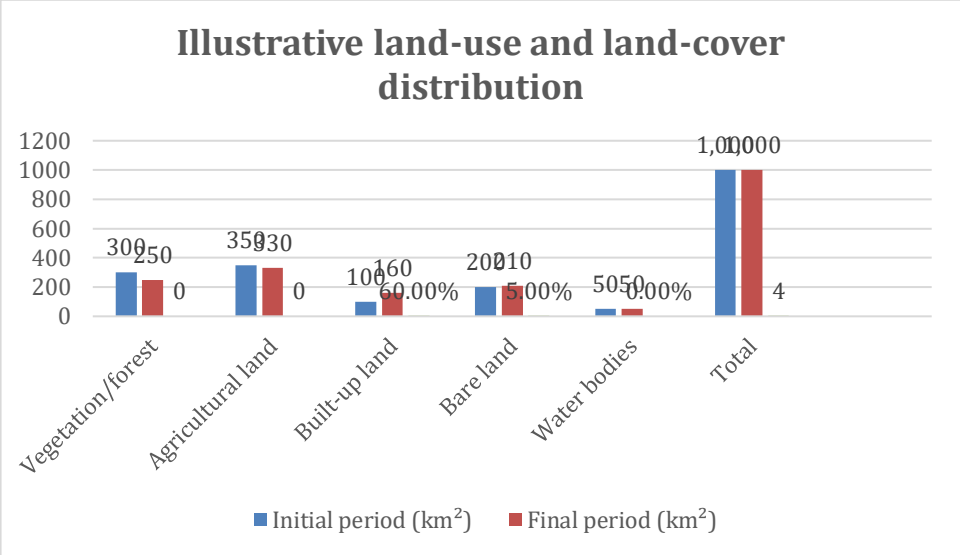
Land-Use and Land-Cover Change

The first analytical stage will quantify changes in vegetation, agricultural land, built-up surfaces, bare land, and water bodies. The following hypothetical example assumes a study area of 1,000 km^2 and illustrates how the land-cover results could be presented.

Table 3. Illustrative land-use and land-cover distribution

Land-cover category	Initial period (km^2)	Final period (km^2)	Percentage change
Vegetation/forest	300	250	−16.7%
Agricultural land	350	330	−5.7%
Built-up land	100	160	+60.0%
Bare land	200	210	+5.0%
Water bodies	50	50	0.0%
Total	**1,000**	**1,000**	4

Given this theoretical situation, there will be a change in vegetation coverage from 300 km^2 to 250 km^2, which means that there is a loss of 50 km^2 or 16.7%. Built-up area increases from 100 km^2 to 160 km^2, resulting in a 60% increase compared to its original size. This kind of change may imply significant changes in land cover if proven by proper classification and change analysis.



Nevertheless, changes in the sizes of categories only do not prove that there is causality between urbanization and reduction in vegetation. It will take a transition matrix to identify how many hectares of vegetation were changed into built-up areas, agriculture, and bare areas. Accuracy of classification must also be independently assessed to determine if changes made exceed the uncertainty of classification.

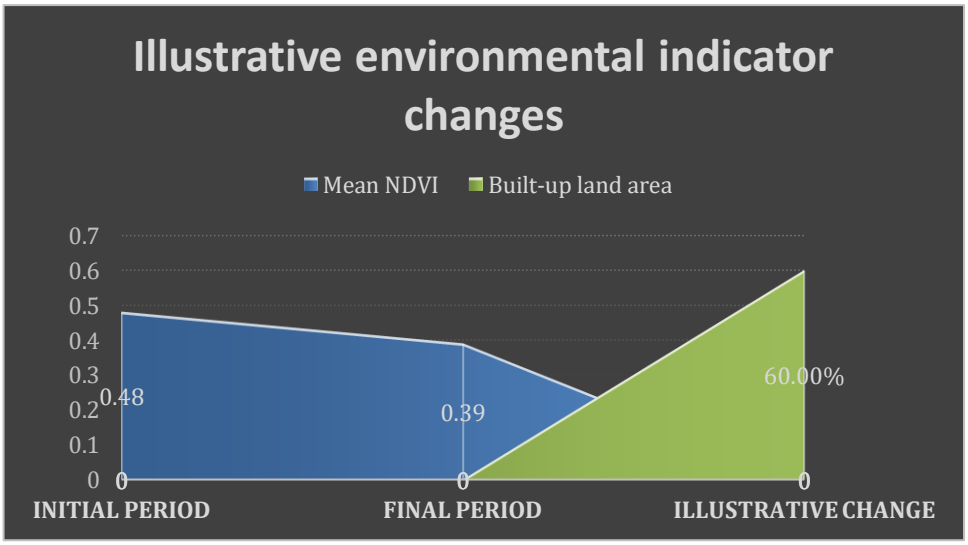
Vegetation Condition and Surface Temperature

NDVI and land surface temperature are going to be analyzed concurrently to determine whether the sites with lower vegetation greenness have high surface temperature. This association can be important in relation to urban sprawl, loss of vegetation, drought stress, and surface moisture change.

Table 4. Illustrative environmental indicator changes

Indicator	Initial period	Final period	Illustrative change
Mean NDVI	0.48	0.39	−18.8%
Mean land surface temperature	29.0°C	31.5°C	+2.5°C
Built-up land area	100 km²	160 km²	+60.0%
Vegetation area	300 km²	250 km²	−16.7%

In this case, the decrease in the mean NDVI value is observed concurrently with an increase in the mean land surface temperature. Such behavior can be explained by decreased vegetation coverage or surface moisture content, but it is not enough to prove causality between the vegetation decrease and increase in temperature. Different seasonal patterns, meteorological conditions, irrigation, soil moisture, and instrumental effects should be accounted for before the interpretation.



In this case, it is necessary to compare measurements in similar seasons, analyze the spatial pattern of the changes, and check whether the same trend is observed for several years in a row. The negative correlation between NDVI and land surface temperature is interesting, but the strength of the correlation needs to be assessed based on observations.

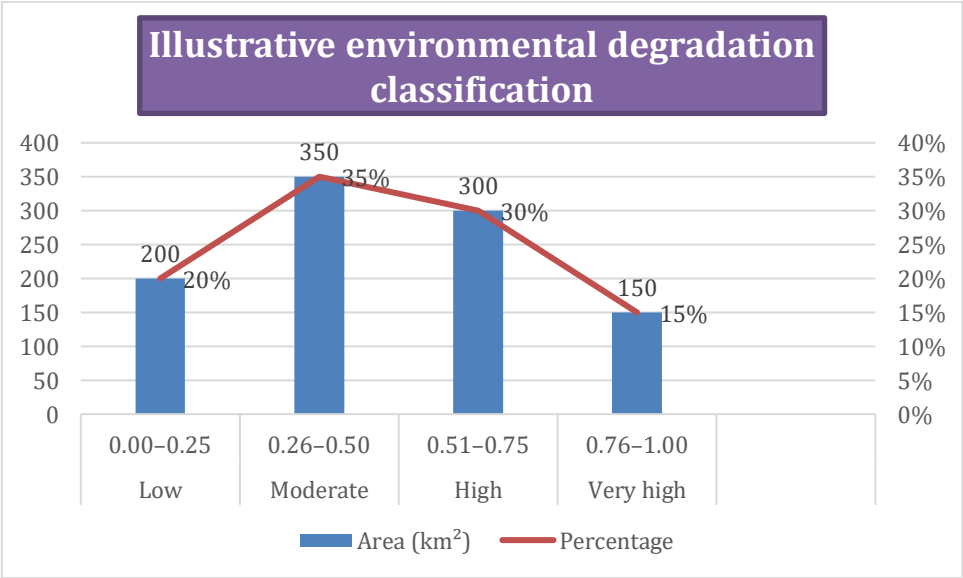
Environmental Degradation Index

The EDI will comprise normalized indicators measuring degradation due to reduction in vegetation, conversion of land cover, erosion susceptibility, and climatic stress. All of these indicators will be normalized for consistent direction such that higher numbers indicate more degradation pressure.

Table 5. Illustrative environmental degradation classification

Degradation category	Index range (illustrative)	Area (km^2)	Percentage
Low	0.00–0.25	200	20%
Moderate	0.26–0.50	350	35%
High	0.51–0.75	300	30%
Very high	0.76–1.00	150	15%

According to the classification proposed, 45% of the study area would be considered highly or very highly degraded. Given such results in practice, a further examination of the spatial distribution of these classes would be conducted to pinpoint areas that need to undergo field inspection or restoration.



It is important to emphasize that the index cannot be considered as a precise measure of the percent of land that is irrevocably degraded. It is a combined indicator, whose significance is determined by the choice of variables, normalization, weighting, and classification thresholds. The final step would be to assess how stable the spatial pattern will be under alternative weights and classifications.

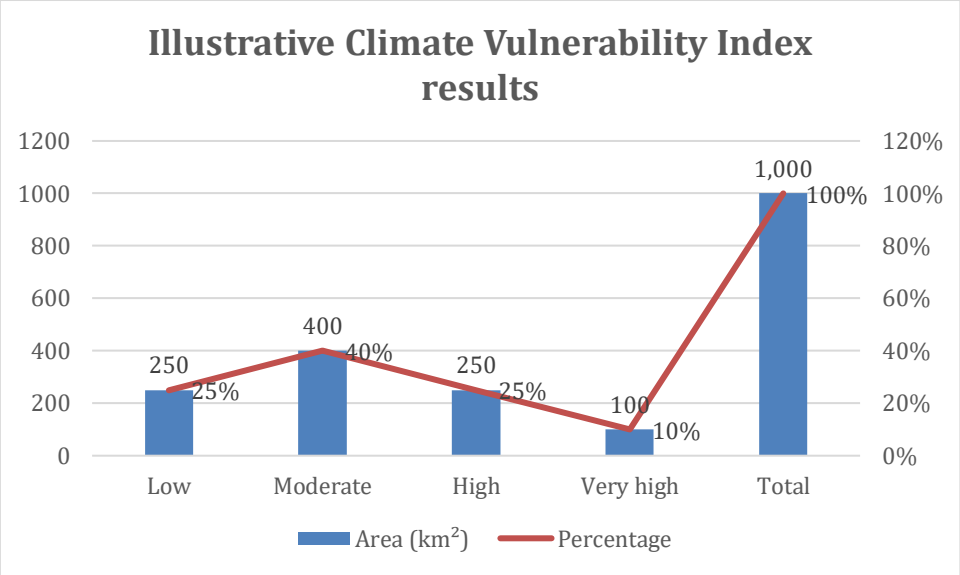
Climate Vulnerability Mapping

The Climate Vulnerability Index will take into account the climate exposure, environmental and social sensitivity, and lack of adaptive capabilities. The ultimate map will differentiate areas where high climatic exposure coexists with the environmental degradation and lack of response capabilities.

Table 6. Illustrative Climate Vulnerability Index results

Vulnerability category	Area (km^2)	Percentage
Low	250	25%
Moderate	400	40%
High	250	25%
Very high	100	10%
Total	**1,000**	**100%**

Here, 35% of the area studied is considered to have high and very high vulnerability, which amounts to 350 km^2. This is an illustration of how one can obtain the area of each class once the composite index is developed. It is never to be presented as the percentage area of a real region until the GIS-based study has been carried out.



The high-vulnerability class will be further examined for its association with climatic exposure, environmental sensitivity, lack of access to water, high population pressure, or combinations of these factors. This will assist in knowing whether the areas need different adaptive measures.

Relationship Between Environmental Degradation and Climate Vulnerability

The connection between Environmental Degradation Index and Climate Vulnerability Index will be analyzed through spatial overlays, correlation analyses, and in appropriate cases, spatial regression. At this stage, regions with higher levels of environmental degradation with relatively low levels of social vulnerability will be differentiated from those where environmental stress coexists with lack of adaptation.

Table 7. Illustrative spatial overlap between degradation and vulnerability

Environmental degradation category	Low/moderate vulnerability	High/very high vulnerability	Total
Low/moderate degradation	500 km^2	100 km^2	600 km^2
High/very high degradation	150 km^2	250 km^2	400 km^2
Total	**650 km^2**	**350 km^2**	**1,000 km^2**

In the above illustration, 250 km^2 is both highly degraded and highly vulnerable to climate change, covering 25% of the study area. This overlapping area would make an important area for consideration because it combines high environmental pressure and high climate vulnerability.

However, the existence of overlap in the map does not in itself show a causal connection between the two variables. A more comprehensive examination should examine the degree of the overlap relative to what could be expected from other maps and explore the underlying causes behind the phenomenon.

Accuracy Assessment and Model Reliability

Remote-sensing classification accuracy will be assessed independently from the vulnerability index. The following table demonstrates the type of reporting required after classification validation.

Table 8. Illustrative accuracy-assessment results

Accuracy indicator	Illustrative value
Overall land-cover classification accuracy	88%
Producer's accuracy for vegetation	90%
User's accuracy for vegetation	87%
Producer's accuracy for built-up land	89%
User's accuracy for built-up land	91%
Number of independent reference samples	500

However, if actual validation showed identical figures, it would mean that the classification gave a 88% total accuracy, but there was variation in class-wise accuracy. The confusion matrix would have to be looked into to know which classes were mostly confused with each other, mainly bare land and built-up surfaces or agricultural land and natural vegetation.

Sensitivity analysis for the vulnerability model must also be part of the final assessment. For instance, the research could compare equal weighting of the factors with weighting done through expert elicitation or a proven multicriteria decision approach. Those areas which show high vulnerability in all cases would offer better options for intervention compared to those areas which show changes in classification with slight alterations in the model.

Discussion

The proposed approach shows how GIS and remote sensing can be combined in studying the issue of environmental degradation and climate vulnerability by using a number of indicators including land cover, vegetation, thermal, climate, and socio-economic indicators. The main benefit is the possibility to detect spatial patterns which remain unseen when studying environmental change based on statistical data from official sources or on individual field measurements. This approach aligns with existing literature focused on the relationship between environmental and social systems in assessing land-use change and vulnerability (Turner et al., 2003; Adger, 2006).

Land-use and land-cover change can be a good starting point since it refers to transformations of vegetation, agricultural lands, water bodies, and man-made landscapes. In order to assess multi-decadal changes, Landsat archive is suitable; Sentinel-2 data can help to enhance spatial resolution of recent optical images (Wulder et al., 2019). However, classification techniques should be chosen properly since the quality of change detection analysis is determined by the accuracy of maps being used (Congalton, 1991; Foody, 2002).

Vegetation indexes like NDVI have the ability to detect the change in vegetation greenness which is helpful when it comes to studying ecological conditions and drought stress. But a fall in NDVI values could either be due to vegetation seasonality, harvesting, drought, changes in land management practices or land cover change. Therefore, an effective assessment of degradation will include both the NDVI value as well as land cover change, precipitation data and field verification wherever possible. The inclusion of other vegetation indices like EVI can provide better interpretation for those locations where NDVI might be influenced by dense canopy and background conditions (Huete et al., 2002; Pettorelli et al., 2005).

Surface temperature provides a further dimension by detecting the thermal signatures in relation to the surface type. Built-up areas, bare land and areas with low vegetation cover will have different thermal properties compared to irrigated agricultural lands and vegetation cover. But this is not true always as surface temperature is influenced by the time of acquisition, atmosphere, soil moisture, surface material properties and local climate.

Vulnerability to climate involves a more comprehensive definition than just the environmental impact. One area can be exposed to high climatic events but have good adaptive capacity due to adequate infrastructure, water supply and institutions. On the other hand, one area with low climatic exposure may be highly vulnerable due to poverty, dependence on climate sensitive

livelihoods or lack of access to basic amenities. Thus, differentiation between exposure, sensitivity and adaptive capacity is crucial for intervention addressing environmental and socioeconomic factors (Füssel, 2007; IPCC, 2022).

Combining environmental and socioeconomic indicators also poses methodological challenges. Composite indexes reduce complex data to a single map but are subject to choice of indicators, normalization, weights and classification criteria. Equal weights provide clarity but do not capture relative importance of each indicator in a particular area. Weights assigned by experts can better capture local context but introduce subjective bias. As such, the final project must explain the reasons behind each weight and analyze how different weighting schemes would affect identification of high vulnerability areas.

This research framework would be applicable to Pakistan due to the interaction between climatic threats and urbanization, lack of water resources, agriculture-based economy, and different environmental conditions in various regions. Some studies conducted in Kashmir and Karachi provide evidence of using geographical information systems to analyze such factors as environmental and socioeconomic aspects in order to assess land degradation and drought risks (Romshoo et al., 2020; Dilawar et al., 2022). Studies in Southern Punjab also prove the importance of land cover changes and land surface temperature analysis (Hussain et al., 2023). These studies provide the possibility of the implementation of the proposed framework, but a new study will have to choose its geographic area and process the necessary datasets on its own.

As one can see in Section 4, some hypothetical results show that the use of numerical analysis makes it possible to identify those regions which have high degradation, vulnerability, and overlap of environmental and social factors. However, these values cannot provide enough evidence to say that a certain area faces certain levels of degradation or vulnerability.

Conclusion

In this research, an approach to using GIS and remote sensing technology in mapping environmental degradation and climate vulnerability is proposed based on a combination of the use of satellite imagery, vegetation indices, land use and land cover changes, land surface temperature, rainfall variation, terrain conditions, and socio-economic factors. The framework differentiates the process of assessing environmental degradation from climate vulnerability and then analyzes the relationship between the two processes in space using GIS overlays and statistics.

The proposed approach will involve the use of Landsat and Sentinel-2 satellite imagery to analyze land cover and vegetation changes, use of climate data to analyze climatic exposure and socioeconomic factors to analyze sensitivity and adaptive capacity deficits.

The example tables illustrate the way that changes in vegetated areas, built-up areas, surface temperature, and vulnerability categories could be measured and reported. Nevertheless, these numbers are purely hypothetical and should not be treated as empirical results. Conclusions concerning the magnitude of environmental destruction, the proportion of vulnerable areas, or the association between environmental change and climate vulnerability have to be drawn based on an analysis of a definite research area with valid data.

In general, GIS and remote sensing present a useful approach to spatial environmental assessment and adaptation to climate change. Its true potential is revealed when satellite measurements are complemented by reliable climatic data, socio-economic information, independent verification, and local environmental expertise. The above-discussed conceptual framework may be used to make informed decisions related to land management, ecological restoration, drought prevention, urbanization, and climate adaptation.

Recommendations

1. Determine its geographical boundaries, environmental parameters, administrative boundaries, and the period of time before analyzing satellite images.
2. Make use of satellite images of various dates. Pick similar seasonal images and several observation years to differentiate between long-term environmental changes and short-term variability.
3. Use a combination of NDVI, land cover transitions, land surface temperatures, precipitation anomalies, and topography rather than using a single environmental indicator.
4. Independent verification of the land cover classification. Calculate the overall accuracy, producer's accuracy, user's accuracy, and class-specific errors using reference samples.
5. Differentiate between degradation and vulnerability to climate changes. Create indices for both environmental degradation and climate vulnerability before researching their correlation.

6. Choose relevant indicators for population exposure, livelihood dependence, water availability, infrastructure, and adaptation capacities.

7. Describe the choice, normalization, and weighting of indicators and check if alternative weights will affect vulnerability mapping.

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