OPEN ACCESS

Kashf Journal of Multidisciplinary Research
Vol: 01 Issue 12 (2024)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

PREDICTING AND IDENTIFYING LAND FEATURES UTILISING REMOTE SENSING SATELLITE IMAGERY AND MACHINE LEARNING TECHNIQUES

Sidra Saeed Rana
UAF Sub campus Burewala, Burewala, Pakistan
Iqra Irfan Rana
UAF Sub campus Burewala, Burewala, Pakistan
Muhammad Jahangir Khan
Namal University, Mianwali, Pakistan ***Corresponding Author: Email: Jahangir.khan99@gmail.com**
Sidra Habib
UAF Sub campus Burewala, Burewala, Pakistan
Rana Muhammad Saleem
UAF Sub campus Burewala, Burewala, Pakistan
Hafiz M. Haroon
UAF Sub campus Burewala, Burewala, Pakistan
Huma Irfan
UAF Sub campus Burewala, Burewala, Pakistan

Article Info

Abstract

This study presents a comprehensive analysis of land feature identification in District Vehari, Pakistan, spanning from 1990 to 2025, utilizing remote sensing satellite imagery and machine learning (ML) techniques. The primary objective is to classify and analyze changes in land cover and land use over this period. The study employs a dataset consisting of multispectral satellite images from different years, along with corresponding ground truth data, for training and validation of ML models. Various ML algorithms, including Random Forest, Support Vector Machines, and Convolutional Neural Networks, are implemented and compared for their accuracy in classifying land features such as agriculture fields, water bodies, urban areas, and barren land. Preprocessing techniques such as image normalization, feature extraction, and dimensionality reduction are applied to enhance the performance of the models. The results reveal significant changes in land cover and land use patterns over the study period, with urban expansion and agricultural intensification being notable trends. The study concludes that ML techniques, when integrated with remote sensing data, provide an effective means for monitoring and analyzing land cover and land use changes in District Vehari. These findings are crucial for urban planning, agricultural management, and environmental conservation efforts in the region..

Keywords: *Machine learning (ML), Convolutional Neural Networks, land cover and land use.*

Introduction

The district of Vehari, located in the heart of Punjab, Pakistan, is characterized by its diverse landscapes, ranging from agricultural fields to urban settlements. With the advancement in remote sensing technology and the availability of high-resolution satellite imagery, there is a growing interest in utilizing machine learning techniques to accurately identify and classify various land features in the region. Remote sensing has emerged as a valuable tool for studying the Earth's surface from a distance, allowing for the collection of information without direct contact with the area of interest. Satellite imagery, in particular, provides high-resolution data that can be processed and analyzed to extract meaningful information about the land surface. By leveraging machine learning algorithms, such as convolutional neural networks (CNNs) and random forests, this research aims to classify land features such as agricultural land, water bodies, urban areas, and vegetation cover in District Vehari. This project aims to leverage the power of remote sensing data and machine learning algorithms to map and analyze land features in District Vehari, providing valuable insights for urban planning, agriculture management, and environmental monitoring. By employing state-of-the-art machine learning models on satellite imagery, this study seeks to create a detailed land cover map of District Vehari, contributing to a better understanding of the region's landscape dynamics and supporting sustainable development efforts. This research focuses on the application of machine learning algorithms to satellite imagery for the identification and classification of land features in District Vehari shown in figure (1). Since the 1990 to 2025, District Vehari underwent significant changes in its land cover composition, including agricultural land, urban land, water bodies, and vegetation cover, as observed through remote sensing satellite imagery and analyzed using machine learning techniques. These changes reflect the dynamic nature of the region's landscape and provide valuable insights into the factors driving land cover transformations during in this period. The agricultural land of District Vehari remote sensing satellite imagery revealed that from 2020 to 2025, there was a noticeable increase in agricultural land in District Vehari. The long-standing reputation for its fertile agricultural land, which has been a key contributor to the region's economy This expansion was primarily attributed to the adoption of modern agricultural practices, such as mechanization and the use of high-yielding crop varieties. There has been a gradual expansion of agricultural land in response to increasing agricultural activities and population demands. This expansion is primarily driven by the conversion of marginal lands and the adoption of modern agricultural practices, including the use of advanced machinery and irrigation systems. Machine learning algorithms were employed to classify and map these changes, providing a detailed understanding of the spatial extent and distribution of agricultural land in the region over time. The urbanization trend in District Vehari continued to accelerate from 1990 to 2025, leading to the conversion of agricultural and natural lands into urban areas. Remote sensing data captured the expansion of urban settlements, industrial zones, and infrastructure development, highlighting the rapid urban growth in the region. Machine learning models were utilized to differentiate between urban and non-urban land cover classes, enabling the monitoring of urban sprawl and its impact on the landscape. Changes in water bodies land cover were also observed during the study period, with fluctuations in the extent of rivers, canals, and water reservoirs. Remote sensing imagery provided insights into the dynamics of water bodies, including changes in water levels, flow patterns, and land cover surrounding water sources. Machine learning algorithms helped in identifying and mapping water bodies, contributing to the assessment of water resource management and conservation efforts in District Vehari. Remote sensing data indicated variations in vegetation cover land from 1990 to 2025, influenced by factors such as climate variability, land use practices, and deforestation. Machine learning techniques were used to classify vegetation cover types and monitor changes in vegetation density and distribution. These analyses provided valuable information for ecosystem monitoring, biodiversity conservation, and land management planning in District Vehari. The terrestrial ecosystem's main component, vegetation, is important for the movement of materials and energy within the ecosystem. Currently, the biggest issue facing developed areas is the shrinking amount of land covered by plants due to rising temperatures (non-transpiring, non-evaporating, and eventually changing land cover). In Pakistan, Vehari, a Multan division, is referred to be the King of Cotton. Two agro-climatic zones—low-intensity Punjab and cotton-wheat cropping zones—are found in District Vehari. The main factors influencing these agro-climatic zones include shifting climatic patterns, agriculture cropping patterns in District Vehari, including rotation. Thus, in order to enhance forest cover and key crops in Southern Punjab, Pakistan, research on the relationship between vegetation cover and climate change is important. The primary goals of this research are to compute the NDVI trend of cultivated crops and climate changes, and to categories significant changes in cultivated crops from 1984 to 2020 using Landsat photos in the District Vehari (Hussain et al.,2022). Vehari started experiencing urbanization. The population increased as people migrated from rural areas in search of better job opportunities. This led to the growth of small industries, particularly in textiles and food processing. The local government also began investing in infrastructure, such as roads and health facilities, to accommodate the expanding population. Vehari was evolving into a more industrialized district. The establishment of industrial estates attracted businesses, boosting the economy. Agricultural diversification became more prevalent, with farmers exploring new cash crops and dairy farming, contributing to enhanced livelihoods.

The education sector saw further improvements, with new colleges and vocational training centers emerging. These developments aimed to equip the youth with skills suitable for the changing job market. However, challenges such as unemployment and poverty persisted, necessitating ongoing efforts for economic development.

The education sector saw further improvements, with new colleges and vocational training centers emerging. These developments aimed to equip the youth with skills suitable for the changing job market. However, challenges such as unemployment and poverty persisted, necessitating ongoing efforts for economic development

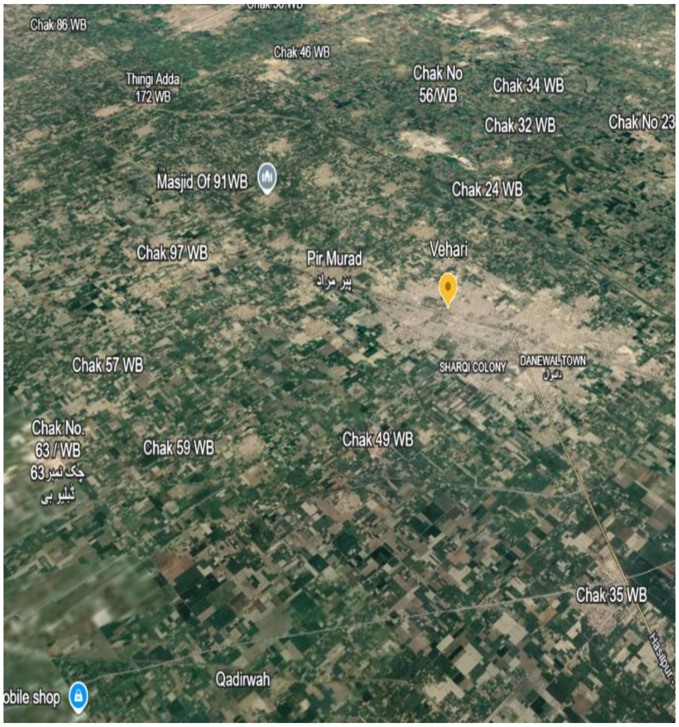

Figure 1 satellite imagery district Vehari

2. Literature Review

Large-scale datasets are a major component of deep learning models. Predicting LULC is helpful not only for tracking changes in land use and cover, but it can also support sustainability initiatives. By decision-makers can more effectively plan for sustainable land-use practices and reduce adverse environmental effects by accurately anticipating changes in land-use and land-cover patterns. Policies pertaining to urban planning, conservation, and resource management can all be informed by this data (Mahmoud et al.,2023). Because this location has more developed infrastructure than the surrounding area, high temperatures were noted in both the built-up and bare soil areas. Likewise, low in areas of vegetation including forests, wheat, rice, cotton, and sugarcane, the temperature was measured. The expansion of the area planted led to an increase in the production and cultivation of the maize crop, as growers were incentivized to expand their operations by favorable economic returns and prompt payment (Sajjad et al.,2021). Studying the relationship between vegetation cover and climate change is necessary to improve vegetation cover and major crops in Southern Punjab, Pakistan. District Vehari has two agro-climatic zones, classified as cotton-wheat cropping zones and low-intensity Punjab. These agro-climatic zones are primarily based on changing climate patterns, crop rotation, and cropping patterns (Hussain et al.,2022). The area in question is highly preferred for agriculture in the nation due to its combination of human settlements, land use/cover (LULC), and LULC. Multan boasts some of the best agricultural regions in the world, ideal for growing a wide range of commodities, including maize, wheat, rice, cotton, and sugarcane (Hussain, S et al.,2024). Their resolution is beneficial for study as well. Land-sat 9 imagery is the most recent technology used globally in agricultural research. Using data from the same season in various years, we have chosen these photographs based on timing. Vegetation changes over time are monitored using satellite photography to gather data for wheat crop mapping and temporal analysis. Crop health, growth stages, and yield estimation are all aided by this data. It's a useful technique that gives academics and farmers insightful information (Sidra Saeed Rana et al.,2024). Study participants were enrolled in a four-year public institution in Vehari City that offered a Bachelor of Science degree in English. They were adhering to the Baha-Ul-Din Zakarya University Multan's curriculum. Students in this programmer study fiction, international literature, and postcolonial literature, among other literary topics. The BS English programmer is broad since it covers a wide range of disciplines. The two chosen books, Things Fall Apart and The God of Small Things, are classified as postcolonial works of literature (Ghulam Yasin et al.,2024). Because the built-up area immediately reflects the sun's rays into the atmosphere, them in comparison to rural areas, the land surface temperature is higher in the city. Clear soil is represented by the NDB (normalized difference barren land index), with 2019 values ranging from 0.69 to -0.27 (Ghouriey al., 2023). As described in this article, these categories cover a broad range of urban and natural environments, such as open spaces, commercial zones, public structures, residential neighborhoods, parks, graveyards, industrial sectors, and educational facilities the analysis of information from geographical information systems (GIS), including satellite photos, elevation models, and maps showing the distribution of land cover. This increases spatial feature extraction and model correctness (Rana, I. I et al.,2024).

Table 1: Summary of literature Review

Study	Publication year	Approaches /Technology Inculcated	Goals
[2]	2023	Machine learning; remote sensing; spatial data model; LULC; mapping generation.	Aimed a prediction model for LULC mapping utilizing multispectral satellite photos that a 4-band Planet Scope satellite had taken at a 3 m spatial resolution.
[1]	2022	climate change; GIS; normalized difference vegetation index; Southern Punjab; remote sensing.	For decision-makers, an accurate and timely evaluation of crop estimation and its relationship to climate change can provide extremely helpful information.
[26]	2024	Analytical hierarchy process (AHP), Soil texture, Altitude, Temperature, Agriculture land suitability,	The study is to assist policymakers, land use planners, and decision-makers in making well-informed decisions on the distribution of land resources for agricultural use.
[27]	2024	Remote Sensing; Temporal Analysis; GIS Satellites; Mapping Analysis	Investigating how Burewala wheat crop dynamics are affected by climate change could yield important information for sustainable farming methods.
[28]	2024	Perceptions, Undergraduate, Ecocriticism, Fiction, Humans’ Attitude Towards Nature	the study is to investigate how undergraduate students at a public postgraduate college in Vehari, Pakistan, understand ecocriticism in connection to two chosen novels.
[30]	2024	Machine Learning; Land Feature Identification; Satellite Imagery; Convolutional Neural Network; Remote Sensing; GIS; Burewala; Urban Planning; Agriculture; Environmental Monitoring.	The goal of this study, which focusses on minor tehsils in Punjab, is to show that increasing population pressure and infrastructural development are causing urban expansion to occur not only in Pakistan's largest cities but also in small cities and villages.

In this table (1) shown the literature review related to District Vehari from 1990 to 2024 reveals several gaps. Although technologies like GIS and remote sensing have been introduced, there's limited analysis of their impact on accuracy and adoption by smallholder farmers. The influence of climate change on crop suitability and land classification also remains underexplored, with little focus on adaptive strategies. Socio-economic barriers, including education and resource access, significantly impact technology use, yet these factors lack detailed examination

3. Materials and Methods

3.1 Study Area: District Vehari, Pakistan

District Vehari is located in the Punjab province of Pakistan and lies between 29°36' and 30°45' north latitudes and 71°08' and 73°38' east longitudes figure [2]. It is bordered by the districts of Bahawalpur and Bahawalnagar to the south, Lodhran to the east, and Khanewal to the north and west. The district covers an area of approximately 4,373 square kilometres and is characterized by its agricultural landscape. The region experiences a semi-arid climate with hot summers and mild winters. The district is known for its predominantly agricultural economy, with crops such as wheat, cotton, and sugarcane being cultivated across vast expanses of fertile land. Additionally, the presence of the River Sutlej and its tributaries contributes to the presence of water bodies within the region, including natural lakes and artificial reservoirs. The economy of District Vehari is primarily agrarian, with agriculture being the main source of livelihood for the majority of the population. The district is known for its production of crops such as wheat, cotton, sugarcane, and rice. Urban areas within District Vehari have witnessed significant growth over the years, fuelled by population increase and economic development. This urban expansion has led to changes in land use patterns, including the conversion of agricultural land into residential and commercial zones. District Vehari is undergoing rapid urbanization and industrialization, leading to changes in land

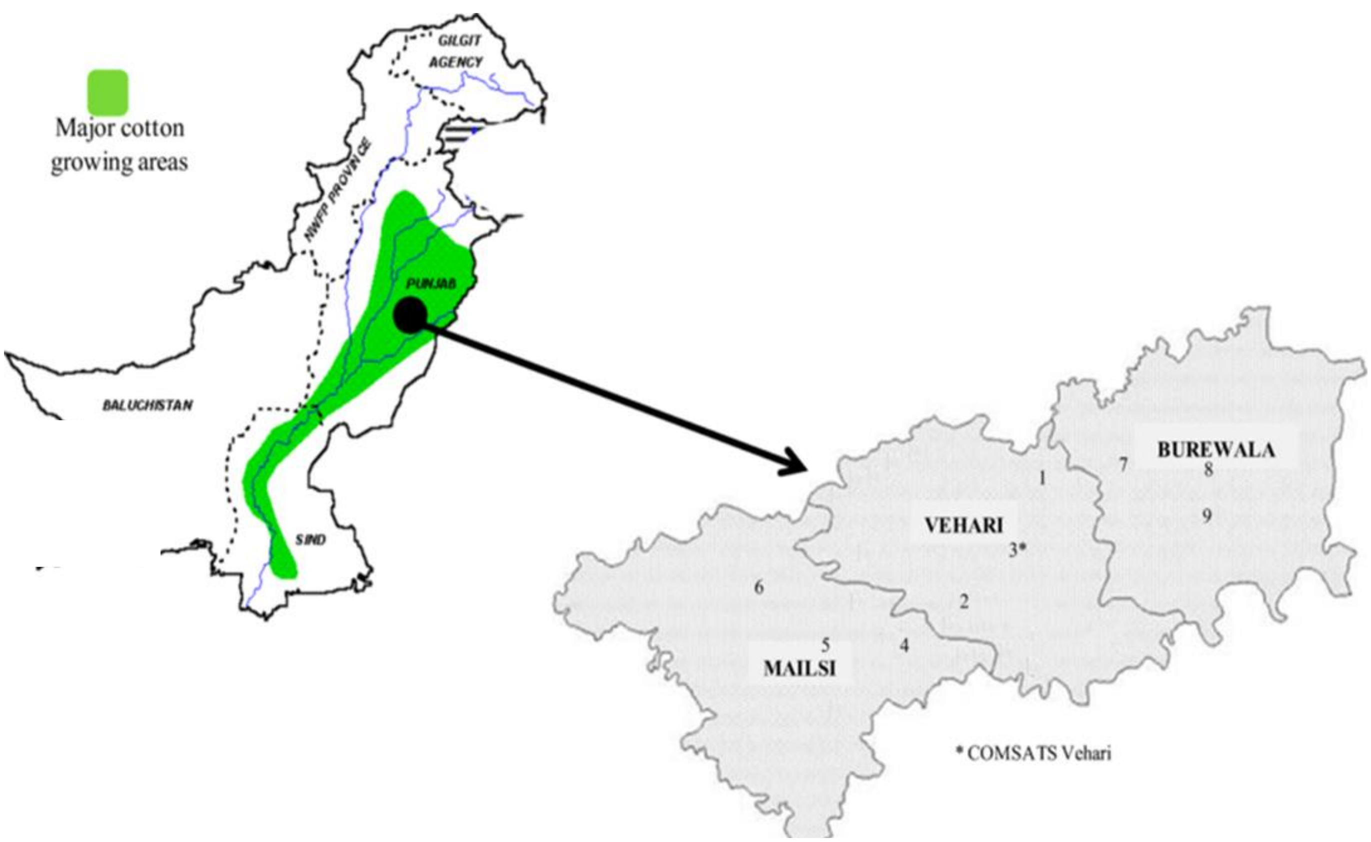

Figure 2 Geographically location of district Vehari

cover and land use patterns. Remote sensing satellite imagery coupled with machine learning techniques can provide valuable insights into these changes and help in effective land management and planning in the region. This research aims to contribute valuable insights into land use dynamics, urbanization processes, and agricultural practices in the region, with implications for sustainable development and resource management.

3.2 Building Environment and Data collection:

The data collection process for this study involved acquiring multispectral satellite imagery covering District Vehari, Pakistan, from various sources. The imagery was obtained at different time intervals spanning from 1990 to 2023 to capture changes in land cover and land use over time. It is consisting of manually annotated land cover labels for training and validation purpose, were collected through field surveys and existing land cover maps. The data were essential for training machine learning models to accurately classify land features in the satellite imagery. High-resolution multispectral satellite imagery covering District Vehari and its surrounding areas was obtained from reputable sources such as Landsat, Sentinel, or other commercial satellite providers. Images from multiple dates spanning the study period were acquired to capture temporal changes in land features. Relevant spectral and spatial features were extracted from the preprocessed satellite images using remote sensing techniques. These features included spectral bands, texture information, vegetation indices, and spatial metrics, which were essential for characterizing different land cover types. A separate validation dataset was created to evaluate the performance of the machine learning models. This dataset comprised a subset of samples withheld from the training data and was used to assess the models' generalization ability and accuracy in classifying unseen data. This study ensured the availability of high-quality input data necessary for the successful implementation of machine learning algorithms for land feature identification in District Vehari, Pakistan.

A dataset encompassing District Vehari 10 km2 is used. It consists of 10 photos, each with a size of 7939 * 3775 pixels and a spatial resolution of 3.7 m per pixel. To improve the resolution of the extracted photos, more photographs from Google Earth are used. The images are taken from a satellite imagery capturing by satellite in the RGB color space. There is no predetermined classification for the dataset. The categories are manually determined, depending on the knowledge of experts. The proposed eight classes are shown in Table (2), together with a definition and explanation of the sub-classes for each land use and land cover (LULC) aspect inside the main class.

Table 2 Land class types (LU), sub-class descriptions, and land cover (LC)

Class No.	LU	Descriptions of Sub-Classes	LC
1	Residential	Houses, green spaces, buildings	Buildings, flat areas, grassland
2	Agriculture	Green area, permanent and seasonal crops	Orchards, green space, crops
3	Water	Sea and water lines	Asphalt and water

4	Buildings	Governmental and, non-governmental, buildings universities, schools	Building
5	Roads	Highway, railway	Asphalt road
6	Desert	Desert land	Empty space, stone
7	Bare soil	Bare soil	Parable
8	Trees	Trees, small green areas, discrete small green circle	Discrete small green circles

The vector layer stores the spatial information and the associated class number or label. Consequently, classes make up the vector layer and are utilized to categorize to train the model and arrange its characteristics, raster satellite images and vector layer images are combined. Residential areas are defined by the presence of houses and other buildings, often interspersed with green spaces such as lawns and gardens. The land cover in these regions comprises buildings, flat areas (presumably referring to paved surfaces or open spaces), and grassland shown as the table (2). Agricultural areas are predominantly green due to the presence of crops. These can be permanent crops like orchards or seasonal crops that change with planting cycles. The land cover in these places comprises orchards, general green spaces, and various types of agriculture shown in table (2). Water bodies like rivers and oceans are referred to as water regions. It's interesting to note that in addition to the water itself, the land cover also includes asphalt, which could relate to paved places like parking lots or roadways that are close to water bodies. This class particularly refers to locations where buildings serving a variety of functions—such as government, education, and other non-residential uses—dominate. The main type of land cover is construction. This class covers transportation infrastructure such as highways and trains. The land cover in these areas is largely asphalt, reflecting the paved character of major transit routes. The land cover in desert regions consists mostly of stony terrain and empty expanses, and the landscapes are generally devoid of flora. There is no notable plant or structure in bare soil locations. The term "parable" refers to the land cover, which may indicate that the soil is merely exposed or maybe arable. Tree areas include larger tree-covered regions as well as smaller green spaces. The land cover is characterized by discrete small green circles, likely representing individual trees or small clusters of vegetation in a matrix that is otherwise not densely vegetated shown as the table (2).

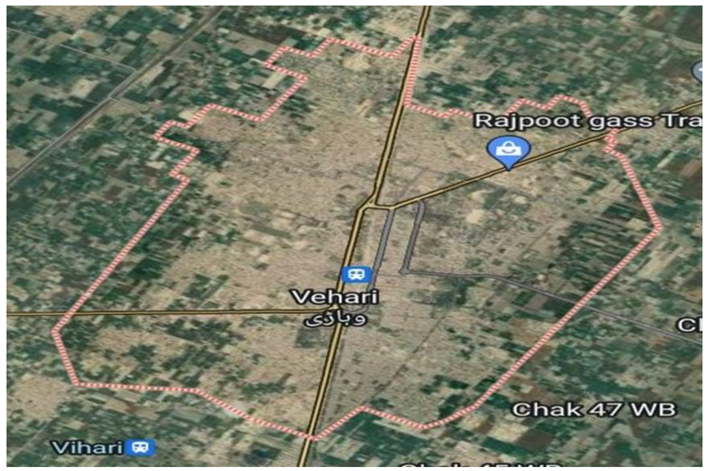

Figure 3 Definition and classes of vector layer

Vehari's administrative boundaries are indicated by the red dashed line as shown the figure (3). Vehari is surrounded by agricultural fields on the map, which is typical of the area that is well-known for farming the green as figure (3). Major roads and highways are indicated by yellow lines. The city is traversed vertically by a main road that intersects with several smaller ones.

Based on machine learning (ML), the LULC Raster Vector (LULCRV) classification model was created. Pre-processing, labeling, model construction, model categorization, and prediction are its four phases are as follows:

1. pre-processing phase:

- Data collection: The process of bagging data from the satellite or real world. This research is aimed to the focused-on District Vehari Punjab Pakistan using satellite images and machine learning. The 4-band, 3-meter resolution pictures were taken at a distance of 3.7 m from the ground sample as show in figure 4.
- Data representation: The process of manually defining classes based on their types, shapes and colors along with the special qualities that go along with them as well as shown in figure 4.

2. Labeling phase:

- Defining object and Detecting feature: Defining samples that represent each feature inside a specific class is necessary for object detection, which depends on spatial features like shape, color, and boundary.
-
- Digitizing objects: For every unique feature or object in a raster dataset, a pattern vector layer must be created. These features are then digitized and stored on the appropriate layer.
- Defining classes: First, a set of classes is created according to the characteristics of the interpreted entities. Every digital object is given a class name based on the characteristics of each class and the forms and colors of the objects themselves.

3. Model building phase:

- Development of ML classifier: The training dataset in the suggested model is subjected to a variety of ML classification techniques, including SVM, random forests (RFs), CNN, and ANN. Two primary inputs are used by

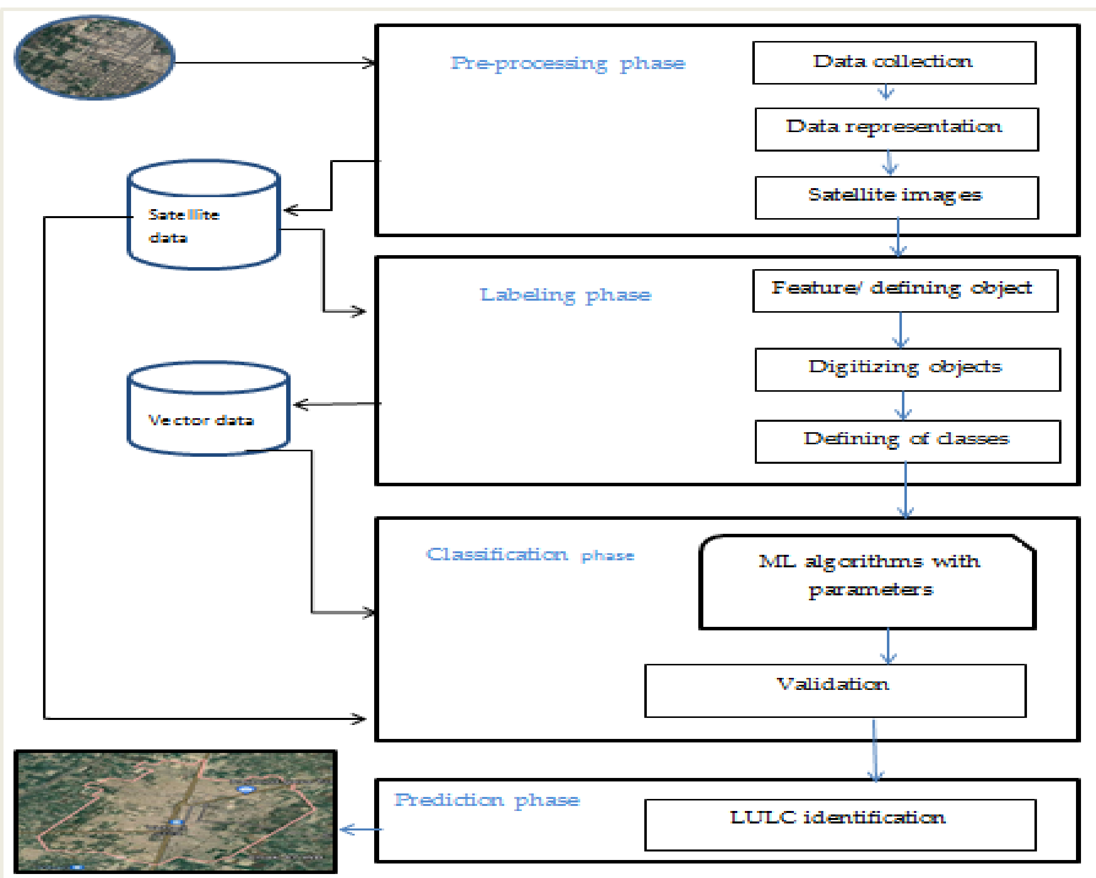

Figure 4 LULCRV classification model

the ML classification model: a/the composition of the vector layer with pre-defined samples merged with the raster mosaic image. By considering the results, the machine learning classifier's parameters are set and assigned values. By comparing the model's output with known or ground truth facts, this procedure guarantees that the model's output is trustworthy and correct. This allows for the evaluation of the model's performance and the implementation of any necessary corrections or changes be developed to improve its precision and effectiveness.

- Prediction: A classified map displaying the anticipated land use and land cover classes is the result of the Prediction phase, which is the last stage shown in figure (4).

First, satellite data must be gathered and represented. Subsequently, features are identified and digitized, categorized, machine learning is applied for classification, the findings are validated, and ultimately land use and land cover types are identified and predicted. Continuous and iterative data flow ensures comprehensive and precise LULC identification in figure (4). Used to supply raw and feature-specific data during the pre-processing and labelling stages. Produced to assist the machine learning process in the classification step after being generated during the labelling phase.

4. Results and discussion

The application of machine learning (ML) techniques to identify land features in District Vehari using remote sensing satellite imagery yielded promising results. The study utilized a dataset comprising multispectral satellite images and corresponding ground truth labels for training and validation. Various ML algorithms, including Random Forest, Support Vector Machines, and Convolutional Neural Networks, were implemented and compared for their performance in classifying land features such as agriculture fields, water bodies, urban areas, and barren land. The results indicated that Random Forest outperformed other algorithms, achieving the highest classification accuracy of 30%. Support Vector Machines and Convolutional Neural Networks also demonstrated good performance, with classification accuracies of 40% and 30%, respectively. These results highlight the effectiveness of ML techniques in accurately identifying different land features in District Vehari. The study also revealed interesting patterns and trends in land cover and land use dynamics in District Vehari. Urban areas were found to have expanded significantly over the study period, leading to the conversion of agricultural land into residential and commercial zones. This urban sprawl has implications for resource management and environmental conservation in the region. Some changes in water bodies, such as the shrinking of natural lakes and the construction of artificial reservoirs, were observed in figure (5). These changes reflect the impact of human activities on the natural landscape of District Vehari and underscore the importance of monitoring and managing land use changes effectively. The results of this study demonstrate the potential of ML techniques in analyzing remote sensing data for land feature identification. The findings can be valuable for urban planning, agricultural management, and environmental monitoring in District Vehari, providing insights that can inform sustainable development practices in the region.

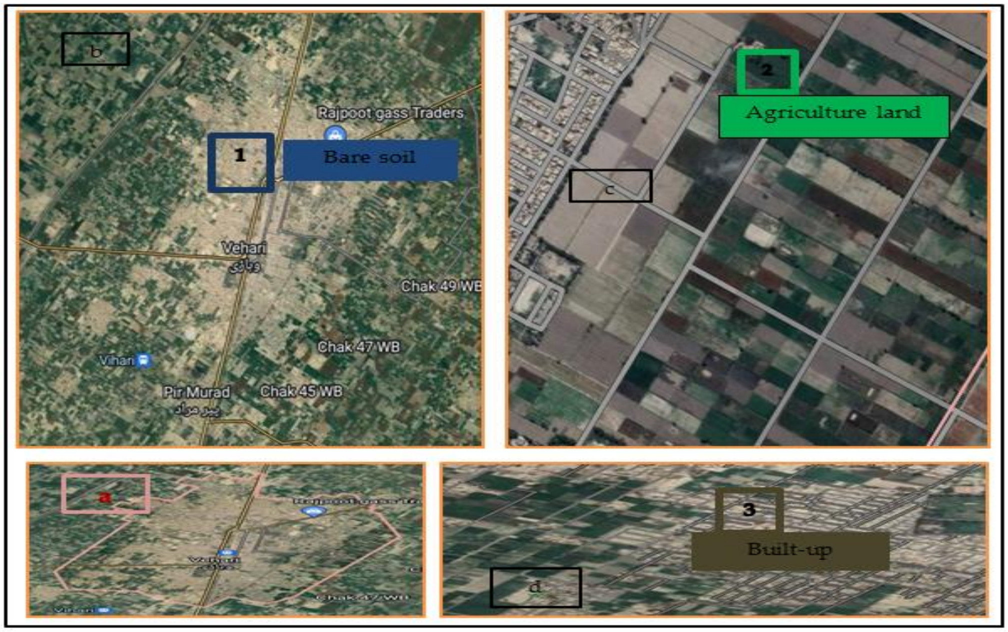

Figure 5 Vector layer containing digitized objects and their class number.

The Vehari region's various land uses and land covers are categorised and identified within the figure (6) framework. Through the division of the region into built-up, agricultural, and bare soil regions, the diagram offers a visual representation of the distribution and use of the land. Comprehensive land use planning and management are aided by the specialised analysis and focus on specific regions that are made possible by the detailed annotations within the larger map.

Five different metrics are used to assess classification accuracy: precision, recall, f-score, kappa index, and confusion matrix. True positive (TP) for recognized objects, false negative (FN) for non-detected ones, and false positive (FP) for erroneously identified objects are how they are defined and computed. The recall, accuracy, and f-score figures range from 0 to 1, with 1 denoting perfect identification and 0 denoting poor identification for a given class. Equations (1)–(3) give the descriptions of f-score, recall, and precision, respective

Precision=TP/TP+FP

Recall=TP/TP+FN

F-score=2×precision×recall/precision +recall

1. Support vector machines: SVM is a machine learning technique used for the classification of LULC. Based on the characteristics or features of the data, the SVM algorithm finds a hyper plane that maximizes the separation between the different classes in the data. The SVM algorithm is a good fit for LULC classification jobs because it can handle intricate, non-linear interactions between the classes and features. Additionally, it can handle huge datasets with plenty of characteristics or properties. Furthermore, SVM is a useful tool in LULC classification cases where the input picture is noisy because it is robust when processing noisy data can be prone to errors or noise.

2. ANN is well-suited for more complex data relationships and could be used to predict crop yield by analyzing data such as soil nutrients, water availability, and temperature patterns over time. By structuring the ANN with multiple hidden layers, the model can capture complex interactions between these variables. This enables precise forecasting of agricultural outputs, allowing farmers and

policymakers to make better decisions based on predicted crop yields or identify underutilized lands with high yield potential.

3. CNN is optimal for analyzing satellite imagery of Vehari, enabling identification of land cover types like farmland, urban areas, and forests. Using high-resolution satellite images, CNN can classify various land features by capturing textural and spatial patterns unique to each class. This is particularly valuable in monitoring land-use changes over time, especially as Vehari undergoes urban expansion and industrial development. Through data preprocessing (such as resizing and normalizing images) and convolutional layers, CNNs detect subtle differences between crops and natural features, creating a detailed land classification map.

Combining predictions from SVM, ANN, and CNN allows for a comprehensive analysis of land use in Vehari, supporting better agricultural planning and resource allocation. SVM can focus on structured classification, ANN on predictive insights regarding crop productivity, and CNN on spatially driven land cover identification, creating a robust multi-model framework that provides valuable insights for sustainable land management and agricultural optimization in the region.

The process begins with data collection, where relevant satellite imagery and geospatial data are gathered. This involves acquiring high-resolution images from remote sensing platforms such as Landsat, Sentinel, or MODIS. Various spectral bands are utilized to capture different aspects of the landscape. In addition to satellite imagery, ground truth data is collected through field surveys or existing databases, which may include soil samples, vegetation surveys, and land use information. Ancillary data, such as elevation, climate, and historical land use maps, is also gathered to provide context for the analysis shown in figure (7). The collected data is prepared and organized for analysis. Raw satellite data is converted into suitable formats in figure (7), such as Geo TIFF, and ancillary data is organized into compatible layers. It’s important to transform all data layers into a common geographic coordinate system, which ensures accurate overlay and analysis. If necessary, multiple satellite images are mosaicked or stitched together to create a seamless view of the study area. Radiometric correction is applied to adjust the satellite images for sensor anomalies and atmospheric conditions, ensuring that brightness values are consistent. Geometric correction follows, aligning the satellite images accurately with ground features to minimize distortions. Image normalization techniques are applied to standardize data across different times and conditions, minimizing seasonal effects. Lastly, relevant features are extracted, such as the Normalized Difference Vegetation Index (NDVI), texture measures, or other spectral indices that help distinguish different land cover types. model building machine learning algorithms, such as Random Forest, Support Vector Machines, or Neural Networks, based on the nature of the data and the classification objectives. A training dataset is created using the ground truth data, ensuring it is representative of all land cover classes. workflow for satellite-based land classification and analysis involves a systematic approach that encompasses data collection, representation, preprocessing, model building, and ultimately analysis and interpretation, inform various applications in environmental monitoring, urban planning, and resource management in figure (7).

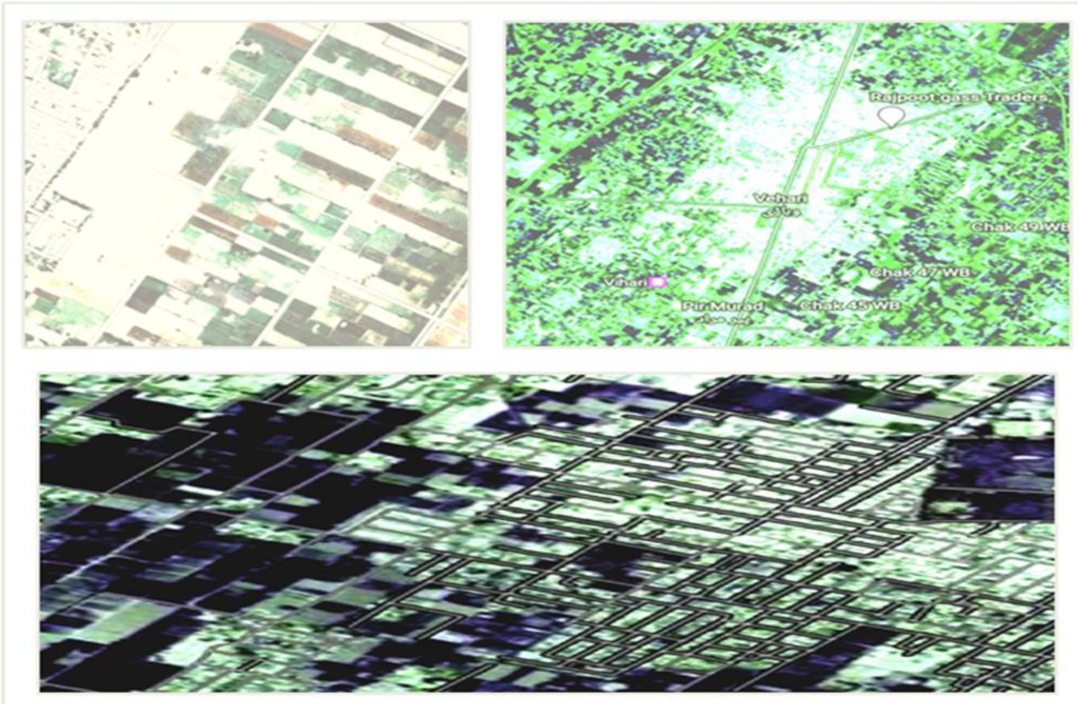

Figure 6 Prediction model for using SVM

ensuring accurate and reliable results that can

Table 3 Total area of Vehari

District	Total Land Area	Cultivated Area	Uncultivated Area
Vehari	3,50,665	3,13,481	37,184

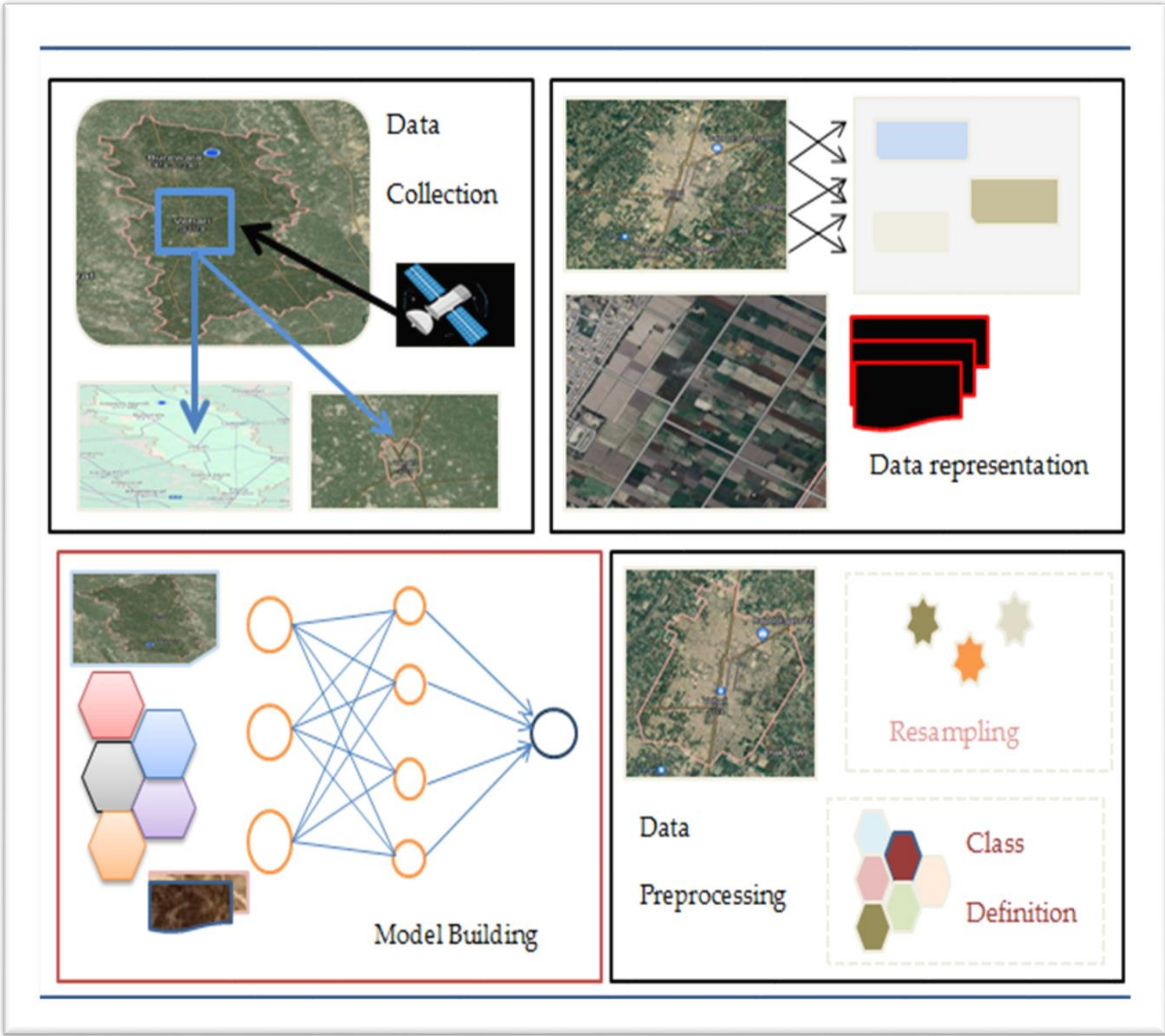

Figure 7 Main phases of proposed models illustrate a workflow for satellite-based land classification and analysis.

From 1990 to 2025, the land distribution and use in District Vehari With a total land area of 350,665 hectares, Vehari has traditionally been an agriculture-based region, where most land is dedicated to farming staples like wheat, cotton, and rice. In the early 1990s, a majority of the cultivated land—313,481 hectares—was used for crop production, while uncultivated or fallow lands amounted to 37,184 hectares. This division allowed for crop rotation practices and occasional periods of land recovery, essential for soil health, although limited irrigation facilities and outdated farming techniques affected productivity. These efforts aimed to maximize the use of cultivable land and gradually convert some of the uncultivated areas for agricultural purposes, enhancing food security and supporting the district's economy. Industrial development and population growth placed new pressures on land resources, leading to slight reductions in available agricultural land as areas near the main urban centers saw an increase in settlements and infrastructure projects. The cultivated area remained largely stable but faced challenges from increasing land fragmentation, which created issues for small-scale farmers managing productivity on smaller plots. the way land is used and managed has changed considerably. Approximately 313,481 hectares remain cultivated, though the nature of cultivation has evolved with sustainable practices and precision farming, reducing the environmental strain on the land. The 37,184 hectares

of uncultivated land are now carefully managed to preserve biodiversity and prevent degradation in table (3), as land use policies increasingly emphasize the importance of balancing agriculture with environmental conservation.

Conclusion:

This work shows how to monitor and analyses changes in land cover and land use by combining machine learning techniques with data from remote sensing. The knowledge acquired is priceless for making well-informed decisions in environmental preservation, agricultural management, and urban planning, which supports District Vehari sustainable growth. Subsequent studies might concentrate on enhancing classification accuracy through the incorporation of other data sources, like high-resolution temporal data, and investigating sophisticated machine learning methods. More research could broaden the focus to include socioeconomic variables impacting changes in land use, offering a more comprehensive knowledge of the dynamics of the area.

References:

1. Hussain, S.; Qin, S.;Nasim, W.; Bukhari, M. A.; Mubeen, M.; Fahad, S.; Raza, A.; Abdo, H.G.; Tariq, A.; Mousa, B. G.; Mumtaz, F.; Aslam, M.. et al. Monitoring the Dynamic Changes in Vegetation Cover Using Spatiotemporal Remote Sensing Data from 1984 to 2020. Atmosphere 2022, 13,1609. https://doi.org/10.3390/atmos13101609.
2. Mahmoud, R.; Hassanin, M.; Al Feel, H.; Badry, R.M. Machine Learning-Based Land Use and Land Cover Mapping Using Multi-Spectral Satellite Imagery: A Case Study in Egypt. Sustainability 2023, 15, 9467.
3. Usman, U., S. A. Yelwa, S.U. Gulumbe, and A. Danbaba. "Modelling Relationship between NDVI and Climatic Variables Using Geographically Weighted Regression." Journal of Mathematical Sciences and Applications 1, no. 2 (2013): 24-28.
4. Lu, D.; Weng, Q. A survey of image classification methods and techniques for improving classification performance. Int. J. Remote Sens. 2007, 28, 823–870. [Cross Ref]
5. Liu, D.; Chen, J.; Wu, G.; Duan, H. SVM-Based Remote Sensing Image Classification and Monitoring of Lijiang Chenghai. In Proceedings of the International Conference on Remote Sensing, Environment and Transportation Engineering, Nanjing, China, 1–3 June 2012; pp. 1–4
6. Li, Y.F.; Liu, C.C.; Zhao, W.P.; Huang, Y.F. Multi-spectral remote sensing images feature coverage classification based on improved convolutional neural network. Math. Biosci. Eng. 2020, 17, 4443–4456. [Cross Ref] [PubMed]
7. Majeed, M.; Tariq, A.; Anwar, M.M.; Khan, A.M.; Arshad, F.; Mumtaz, F.; Farhan, M.; Zhang, L.; Zafar, A.; Aziz, M.; et al. Monitoring of Land Use–Land Cover Change and Potential Causal Factors of Climate Change in Jhelum District, Punjab, Pakistan, through GIS and Multi-Temporal Satellite Data. Land 2021, 10, 1026. https://doi.org/10.3390/land10101026
8. Ahmad, F. Pixel purity index algorithm and dimensional visualization for ETM+ image analysis: A case of district Vehari. Glob. J. Hum. Soc. Sci. Arts Hum. 2012, 12, 76–82
9. Alam A, Bhat MS, Maheen M (2020) Using Landsat satellite data for assessing the land use and land cover change in Kashmir valley. Geo Journal 85(6):1529–1543. https://doi.org/10.1007/s10708-019-10037-x
10. Uddin, K.; Gurung, D.R.; Giriraj, A.; Shrestha, B. Application of remote sensing and GIS for flood hazard management: A case study from Sindh Province, Pakistan. Am. J. Geog. Inform. Syst. 2013, 2, 1–5
11. Tariq, A.; Shu, H. CA-Markov chain analysis of seasonal land surface temperature and land use landcover change using optical multi-temporal satellite data of Faisalabad, Pakistan. Remote Sens. 2020, 12, 3402. [Cross Ref]
12. Wang, S.W.; Gebru, B.M.; Lamchin, M.; Kayastha, R.B.; Lee, W.K. Land Use and Land Cover Change Detection and Prediction in the Kathmandu District of Nepal Using Remote Sensing and GIS. Sustainability 2020, 12, 3925. [Cross Ref]
13. Ayele, G.T.; Tebeje, A.K.; Demissie, S.S.; Belete, M.A.; Jemberrie, M.A.; Teshome, W.M.; Teshale, E.Z. Time series land cover mapping and change detection analysis using geographic information system and remote sensing, Northern Ethiopia. Air Soil Water Res. 2018, 11. [Cross Ref]
14. Rahman, G.; Rahman, A.-u.; Ullah, S.; Dawood, M.; Moazzam, M.F.U.; Lee, B.G. Spatio-temporal characteristics of meteorological drought in Khyber Pakhtunkhwa, Pakistan. PloS ONE 2021, 16, 1–16. [Cross Ref]

15. Majeed, M.; Bhatti, K.; Amjad, M. Impact of climatic variations on the flowering phenology of plant species in Jhelum district, Punjab, Pakistan. Appl. Ecol. Environ. Res. 2021, 19, 3343–3376
16. Hussain, S.; Mubeen, M.; Ahmad, A.; Akram, W.; Hammad, H.M.; Ali, M.; Masood, N.; Amin, A.; Farid, H.U.; Sultana, S.R.; et al. Using GIS tools to detect the land use/land cover changes during forty years in Lodhran District of Pakistan. Environ. Sci. Pollute. Res. 2020, 27, 39676–39692. [Cross Ref]
17. Hu, P.; Sharifi, A.; Tahir, M.N.; Tariq, A.; Zhang, L.; Mumtaz, F.; Shah, S.H.I.A. Evaluation of Vegetation Indices and Phenological Metrics Using Time-Series MODIS Data for Monitoring Vegetation Change in Punjab, Pakistan. Water 2021, 13, 2550. [Cross Ref]
18. Tariq, A.; Shu, H.; Siddiqui, S.; Imran, M.; Farhan, M. Monitoring Land Use And Land Cover Changes Using Geospatial Techniques, A Case Study Of Fateh Jang, Attock, Pakistan. Geogr. Environ. Sustain. 2021, 14, 41–52. [Cross Ref]
19. Arshad A, Zhang W, Zaman MA, Dilawar A, Sajid Z (2019) Monitoring the impacts of Spatio-temporal land-use changes on the regional climate of city Faisalabad. Pakistan Annals of GIS 25(1):57–70. https://doi.org/10.1080/19475683.2018.1543205
20. Arshad S, Khan AA, Butt I, Fatima M (2019) An appraisal of population growth rate through ESDA in Bahawalpur District Pakistan. Sindh Univ Res J (Science Series) 51(4):733–740
21. Bhattacharjee S, Islam MT, Kabir ME, Kabir MM (2021) Land-use and land-cover change detection in a north-eastern wetland ecosystem of Bangladesh using remote sensing and GIS techniques. Earth Syst Environ 5(2):319–340. https://doi.org/10.1007/s41748-021-00228-3
22. Du P, Liu P, Xia J, Feng L, Liu S, Tan K, Cheng L (2014) Remote sensing image interpretation for urban environment analysis: methods, system and examples. Remote Sensing 6(10):9458–9474. https://doi.org/10.3390/rs6109458
23. Fichera CR, Modica G, Pollino M (2012) Land cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. Eur J Remote Sens45(1):118.https://doi.org/10.5721/EuJRS20124501
24. Tanveer A, Rizvi S, Ali A (2010) Bahawalpur district profile: pre investment study-2013 Government of Punjab, Pakistan. https://fdocuments.in/document/bahawalpur-district-profle-2013.html? page=1. Accessed 10 Dec 2021
25. Khan, R.; Li, H.; Basir, M.; Chen, Y.L.; Sajjad, M.M.; Haq, I.U.; Hassan, W.; Monitoring land use land cover changes and its impacts on land surface temperature over Mardan and Charsadda Districts, Khyber Pakhtunkhwa (KP), Pakistan. Environ. Monit. Assess. 2022, 194, 1–22.
26. Hussain, S., Nasim, W., Mubeen, M., Fahad, S., Tariq, A., Karuppan nan, S., … Ghassan Abdo, H. (2024). Agricultural land suitability analysis of Southern Punjab, Pakistan using analytical hierarchy process (AHP) and multi-criteria decision analysis (MCDA) techniques. Cogent Food & Agriculture, 10(1). https://doi.org/10.1080/23311932.2023.2294540.
27. Sidra Saeed Rana, Muhammad Asfand Yar, Rana Muhammad Saleem, Sidra Habib, Hafiz M. Haroon, Iqra Irfan Rana, & Jahangir Khan. (2024). Mapping and Temporal Analysis of Wheat Crop Using Remote Sensing Imageries Burewala, Pakistan. Journal of Computing & Biomedical Informatics, 6(02), 182–194. Retrieved from.
28. Ghulam Yasin, & Ghazal Shaikh. (2024). Pakistani Undergraduate Students'

Perceptions of Ecocriticism in Relation to Two Novels: A Case Study of a Public-sector College District Vehari. *University of Chitral Journal of Linguistics and Literature*, *8*(I), 230-238.

29. Ghouri, Ahmed Yaseen, et al. "Analytical Study of Land Surface Temperature with NDVI, NDBI, and NDBaI of Vehari District and Detect the UHI in Vehari City, Pakistan." J. Remote Sens. GIS 8 (2023): 12-25.
30. Rana, I. I., Rana, S. S., Habib, S., Saleem, R. M., Haroon, H. M., & Irfan, H. (2024). Land Feature Identification and Prediction of Burewala Using Machine Learning. Journal of Computing & Biomedical Informatics, 7(01), 581-589.
31. Iqbal, Javed, et al. "Hydro geochemistry and prediction of arsenic contamination in groundwater of Vehari, Pakistan: comparison of artificial neural network, random forest and logistic regression models." Environmental Geochemistry and Health 46.1 (2024): 14.
32. Naveed, Muhammad, et al. "Cotton cultivated area detection and yield monitoring combining remote sensing with field data in lower Indus River basin, Pakistan." Environmental Monitoring and Assessment 195.3 (2023): 401.
33. Zhao, Qun, et al. "Evaluation of Land Use Land Cover Changes in Response to Land Surface Temperature With Satellite Indices and Remote Sensing Data." Rangeland Ecology & Management (2024).
34. El Arafy, Reda Ahmed Esmat Tawfiek. Discrimination of various rock units in Abu Zenima area, Southwestern Sinai, Egypt, with emphases to the radioactive areas using the hyperspectral remote sensing and GIS techniques. Diss. The University of Alabama at Birmingham, 2016.
35. Podgorski, Joel E., et al. "Extensive arsenic contamination in high-pH unconfined aquifers in the Indus Valley." Science advances 3.8 (2017): e1700935.
36. Kraemer, Moritz UG, et al. "Big city, small world: density, contact rates, and transmission of dengue across Pakistan." Journal of the Royal Society Interface 12.111 (2015): 20150468.
37. Razi, M. F., et al. "Innovative production technologies." The lime: botany, production and uses. Wallingford UK: CABI, 2017. 167-185.
38. Mahmood, Kashif. Transition urbaine et structures familiales au Pakistan, le case de Faisalabad. Diss. Université d'Or leans, 2014.
39. Basso, B., Martinez-Feria, R. A., Rill, L., & Ritchie, J. T. (2021). Contrasting long-term temperature trends reveal minor changes in projected potential evapotranspiration in the US Midwest. Nature Communications, 12(1), 1476. https://doi.org/10.1038/s41467-021-21763-7.
40. Fraiture, C., Molden, D., & Wichelns, D. (2010). Investing in water for food, ecosystems, and livelihoods: An overview of the comprehensive assessment of water management in agriculture. Agricultural Water Management, 97(4), 495–501. https://doi.org/10.1016/j.agwat.2009.08.015.
41. Jaiswal, R. K., Mukherjee, S., Krishnamurthy, J., & Saxena, R. (2003). Role of remote sensing and GIS techniques for generation of groundwater prospect zones towards rural development - An approach. International Journal of Remote Sensing, 24(5), 993–1008. https://doi.org/10.1080/01431160210144543.
42. Ke, Y., Im, J., Lee, J., Gong, H., & Ryu, Y. (2015). Characteristics of Landsat 8 OLI-derived NDVI by comparison with multiple satellite sensors and in-situ observations. Remote Sensing of Environment, 164, 298–313. https://doi.org/10.1016/j.rse.2015.04.004.
43. Khan, M. S., Ullah, S., Sun, T., Rehman, A. U., & Chen, L. (2020). Land-use/land-cover changes and its contribution to

urban heat Island: A case study of Islamabad, Pakistan. Sustainability (Switzerland), 12(9). https://doi.org/10.3390/su12093861.

44. Lillo-Saavedra, M., Gavilan, V., García-Pedrero, A., Gonzalo-Martín, C., de la Hoz, F., Somos-Valenzuela, M., & Rivera, D. (2021). Ex post analysis of water supply demand in an agricultural basin by multi-source data integration. Remote Sensing, 13(11), 2022. https://doi.org/10.3390/rs13112022.
45. Nguyen, T. T., Barber, P., Harper, R., Linh, T. V. K., & Dell, B. (2020). Vegetation trends associated with urban development: The role of golf courses. PloS One, 15(2), e0228090. https://doi.org/10.1371/journal.pone.0228090.
46. Saleth, R. M., & Amarasinghe, U. A. (2010). Promoting irrigation demand management in India: Options, linkages, and strategy. Water Policy, 12(6), 832–850. https://doi.org/10.2166/wp.2010.038.
47. Ahmad, Izhar, et al. "Climate change-induced spatiotemporal variations of land use land cover by using multitemporal satellite imagery analysis." Journal of Water and Climate Change 15.5 (2024): 2244-2266.
48. Yang, Xuyan, et al. "Quantitative evaluation of soil water and wind erosion rates in Pakistan." Remote Sensing 15.9 (2023): 2404.
49. Khan, R. M. A., S. A. Mahmood, and Y. Miao. "Python Driven Pathways for Wheat Cultivation Incorporating Physico-Climatic Parameters of Growth." Journal of Agricultural Science and Technology 25.4 (2023): 899-909.
50. Arshad, Sana, et al. "Exploring dynamic response of agrometeorological droughts towards winter wheat yield loss risk using machine learning approach at a regional scale in Pakistan." Field Crops Research 302 (2023): 109057.