A Spatio-Temporal Assessment of Land Use Land Cover Change on Agricultural Productivity in Punjab, Pakistan

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Introduction/Importance of Study: The agricultural sector is crucial to the development of any nation, particularly where food security is a concern. In Punjab province, urban settlements are increasingly encroaching on established agricultural lands, posing a significant threat to agriculture in the region. This issue is compounded by the continuous urban expansion and encroachment on fertile lands. The primary aim of this study is to assess the impact of Land Use and Land Cover (LULC) changes on agricultural productivity in Punjab. Utilizing the Earth Engine, this research performs LULC classification and estimates wheat crop yields in the province.

Novelty Statement: This study presents an innovative application of Earth Engine analytics to monitor and analyze the effects of LULC changes on agricultural productivity in Punjab province.

Material and Method: The research employs 20 years of Land Use and Land Cover data from the MODIS dataset, accessed via Google Earth Engine (GEE). In addition, wheat crop production is estimated using the capabilities of GEE.

Result and Discussion: The findings indicate a substantial shift in land cover in Punjab, which has significantly affected wheat crop production. The study emphasizes the importance of public awareness campaigns and the adoption of advanced agricultural technologies. Continuous monitoring of LULC changes using GEE can enable timely interventions to mitigate negative impacts.

Concluding Remarks: By integrating urban growth management strategies with the preservation of agricultural lands, long-term agricultural sustainability and development can be achieved. This research highlights the urgent need for comprehensive policies and collaborative efforts to counteract the adverse effects of urban expansion on agricultural productivity.

Keywords: Land Cover change; Crop yield estimation; Earth Engine; Agricultural productivity.

Introduction:

The Land Use and Land Cover (LULC) changes over time are essential for understanding the dynamic interactions between human activities and natural environments. This is especially important in regions where agriculture is a key economic driver and vital for sustaining the population. Punjab, Pakistan's breadbasket, is an example of such a region, where agricultural productivity is closely linked to LULC patterns. Agricultural activities are crucial for meeting food requirements [1], [2]. Currently, about one billion people worldwide suffer from malnutrition and hunger due to the lack of nutritious food [3]. The issue of food security, first raised at a global level [4], can be addressed by producing sufficient food. While countries with large populations often face significant food security challenges, it is also an issue in nations with slower population growth. Additionally, food security is impacted by various factors such as climate change, urban expansion, LULC changes, and other influences [5].

This study specifically analyzes wheat crop productivity in the Punjab region, as wheat is a staple food for over half of the global population. Over time, food security has become an increasingly pressing issue in developing countries like Pakistan, where Punjab serves as the primary agricultural hub. The province plays a significant role in the national economy, with wheat and rice as two of its most important crops. Although wheat is a major commodity in Pakistan, its annual production remains low compared to countries like France and China. Punjab's rapid urbanization is expected to replace a large portion of its agricultural land with urban areas in the near future [6].

To assess LULC changes in Punjab, remote sensing and geographic information systems (GIS) are highly effective tools for analyzing shifts in land patterns [7]. This study utilized five primary LULC categories—water, cropland, barren land, vegetation, and urban land—analyzing MODIS and Landsat images collected over a 20-year period to identify LULC trends in the region [8]. Mapping wheat crops in Punjab is crucial for understanding the current and future landscape of food security, given wheat's status as a global staple. The Google Earth Engine (GEE) provides an invaluable platform for wheat cropland mapping. The workflow for this process was implemented in the GEE environment using JavaScript code, with necessary data, including reference data, uploaded to GEE assets. The classification of LULC in GEE requires preprocessed images, which were loaded into the platform. The resulting wheat maps were exported as raster files and further analyzed in ArcGIS 10.8 [9].

Training sample maps for wheat in GEE can assist future researchers by providing previous assessments of wheat crop mapping. Wheat crop data for Punjab, Pakistan, were obtained from GEE using the COPERNICUS LANDSAT SENTINEL S2 dataset, with training samples prepared in GEE. Additionally, an NDVI chart for each dataset year was created using JavaScript in GEE [10].

Objectives:

The objectives of this study are as follows:

- To assess the impact of Land Use and Land Cover (LULC) changes on agricultural productivity in Punjab province.
- To classify LULC changes and estimate wheat crop yields using satellite data.
- To analyze the relationship between LULC changes and wheat crop productivity in Punjab.

Literature Review:

Land Use and Land Cover (LULC) changes have a significant impact on the environment and food security, alongside other contributing factors. Anthropogenic activities, such as rapid population growth, increasing urbanization, and economic development, have accelerated changes in LULC [11]. Inequitable land distribution also affects food outcomes and hampers economic development. [12] noted that global food production is insufficient to meet the needs of the growing population. Continuous changes in land use can be tracked using land change models, which help predict future LULC patterns and aid policymakers in crafting effective policies [3]. Integrating these models with Geographic Information Systems (GIS) allows for the forecasting of future land use and cover in monitored areas [13]. Regularly updated land-cover maps, derived from free satellite imaging data, are essential tools for monitoring significant environmental changes.

Sustainability influences agricultural activities in various ways, with both positive and negative impacts on food security. [4] examined several factors affecting food security, concluding that creating a sustainable food system is a primary challenge of the 21st century. This requires a more cohesive policy approach than currently exists, as fragmented solutions have hindered effective policymaking. The lack of unified strategies across social, economic, and environmental sectors prevents the development of comprehensive solutions.

Urban expansion, driven by increasing populations, is becoming a significant issue for sustainability. It is a global process, predominantly influenced by human activities, and presents risks to continual progress [14]. While urban growth offers opportunities for improving energy efficiency, transportation systems, and human well-being, it also encroaches on fertile croplands surrounding cities. This reduces cropland's net primary productivity (NPP) and exacerbates food supply challenges [15]. [16] found that the rise in urban populations not only reduces cropland areas but also increases food demand, a critical issue for regions like Punjab, which is expected to continue urbanizing in the coming years.

[17] explored the persistent issue of food security in developing nations, where governments adopt various initiatives to address citizens' concerns. Many governments attempt to secure food availability by adjusting household income levels, but such schemes are most effective when they cover a larger supply of staple foods for poorer individuals. This underscores the importance of investing in the agricultural sector to increase food production. The existing literature on food security in developing nations reflects substantial research by policy analysts examining various options and their impacts. However, there remain several critical issues that have not yet been adequately addressed.

Food security remains a growing concern in both developed and developing nations, particularly as urban populations continue to rise, introducing new challenges such as financial and physical access to food [18]. [19] noted that, despite the fact that many nations produce enough food to meet their populations' needs, hunger persists due to unequal access. The development of biotechnology, scientific advancements, and improvements in agricultural production are essential to enhancing yields and addressing these challenges. [2] emphasized that a primary goal of food policy is to ensure easy access to food and achieve self-sufficiency in food production. The first challenge for governments is to alleviate poverty, as increasing food demand necessitates advances in technology and expanded agricultural land. To achieve food security, governments must implement changes in funding and policies that prioritize not only agriculture but also rural areas, research, technology, science, and natural resource management [20], [21]. Together, these factors can help resolve issues related to food availability and distribution within a country [3]. Therefore, any comprehensive solution must thoroughly consider the various elements of food security and address gaps in current policies and strategies.

Materials and Methods:

Study Area:

Punjab, known as the "land of five rivers" and a hub of agricultural activity, is situated between latitudes 31.17° N and 72.70° E. It is Pakistan's most populous province and the second largest in terms of land area. The Potohar Plateau lies in the northwest of Punjab, while the Indus Plain stretches to the north. The Indus Plain is divided into three regions: the Lower, Trans, and Upper Indus Plains. The Upper Indus Basin is formed by the four Derajats and Doabs, while Punjab's landscape is predominantly shaped by the alluvial plains of the Indus

River. Punjab's climate ranges from arid to semi-arid, with three main seasons: cold, hot, and rainy. The southern part of Punjab experiences more rainfall, but not enough to fully support agricultural activities. In this region, canals, wells, and rivers serve as the primary water sources for agriculture. In contrast, the northern part of Punjab is predominantly rainfed, with agriculture largely dependent on rainfall. However, crop cultivation in this region could be significantly improved through the provision of adequate irrigation water [22].

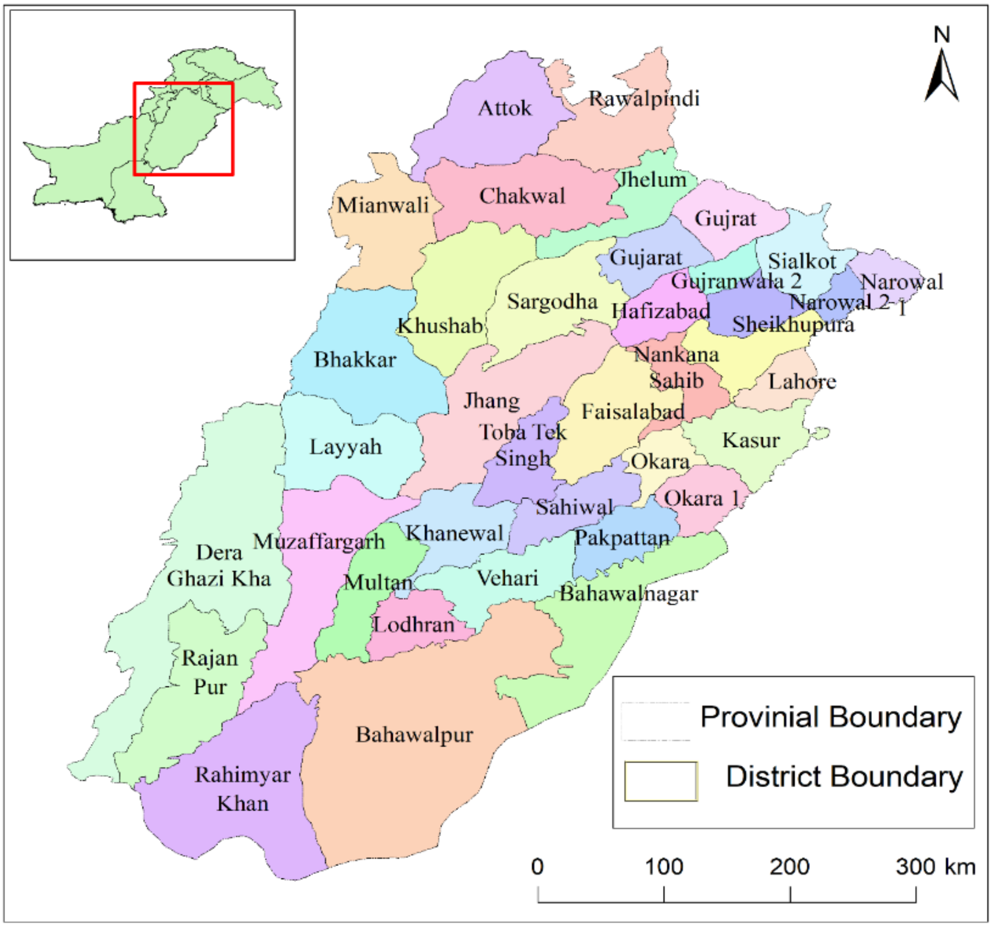

Figure 1: Showing the Punjab province as the study area.

Data Sources:

Land Cover Data:

A Land Use and Land Cover (LULC) dataset for Punjab province was obtained from Google Earth Engine (GEE) using the MODIS dataset. LULC data for the years 2001, 2005, 2010, 2015, and 2020 were extracted from the broader country dataset. This dataset categorizes land into 17 distinct classes, with each entity assigned to a specific class. The classes used in this study include: Evergreen Needleleaf Forests, Evergreen Broadleaf Forests, Deciduous Needleleaf Forests, Deciduous Broadleaf Forests, Mixed Forests, Closed Shrublands, Open Shrublands, Woody Savannas, Savannas, Grasslands, Permanent Wetlands, Croplands, Urban and Built-up Lands, Cropland/Natural Vegetation Mosaics, Permanent Snow and Ice, Barren Lands, and Water Bodies.

Crops Production Data:

Wheat crop data for Punjab, Pakistan, was acquired from Google Earth Engine (GEE) using the Copernicus Landsat Sentinel S2 dataset. The training samples were prepared within the GEE environment, and an NDVI chart for each year's dataset was also generated using JavaScript code. However, due to limited data availability, the Copernicus Landsat Sentinel S2 dataset only provides data from 2017 onwards.

Table 1: MODIS Land Cover Classes

Name	Value	Description
Evergreen Needleleaf Forests	1	Dominated by evergreen conifer trees (canopy >2m). Tree cover >60%
Evergreen Broadleaf Forests	2	Dominated by evergreen broadleaf and palmate trees (canopy >2m). Tree cover >60%.
Deciduous Needleleaf Forests	3	Dominated by deciduous needle leaf (larch) trees (canopy >2m). Tree cover >60%.
Deciduous Broadleaf Forests	4	Dominated by deciduous broadleaf trees (canopy >2m). Tree cover >60%.
Mixed Forests	5	Dominated by neither deciduous nor evergreen (40-60% of each) tree type (canopy >2m). Tree cover >60%.
Closed Shrublands	6	Dominated by woody perennials (1-2m height) >60% cover
Open Shrublands	7	Dominated by woody perennials (1-2m height) 10-60% cover.
Woody Savannas	8	Tree cover 30-60% (canopy >2m).
Savannas	9	Tree cover 10-30% (canopy >2m).
Grasslands	10	Dominated by herbaceous annuals (<2m)
Permanent Wetland	11	Permanently inundated lands with 30-60% water cover and >10% vegetated cover.
Croplands	12	At least 60% of the area is cultivated cropland.
Urban and Built-up Lands	13	At least 30% impervious surface area including building materials, asphalt, and vehicles.
Cropland/Natural Vegetation Mosaics	14	Mosaics of small-scale cultivation 40-60% with natural tree, shrub, or herbaceous vegetation.
Permanent Snow and Ice	15	At least 60% of the area is covered by snow and ice for at least 10 months of the year.
Barren	16	At least 60% of the area is non-vegetated barren (sand, rock, soil) areas with less than 10% vegetation.
Water Bodies	17	At least 60% of the area is covered by permanent water bodies.

Source: NASA MODIS 2023

Remotely Sensed Data:

For this study, Landsat data with a 30-meter pixel resolution, freely available for public use, were utilized. All COPERNICUS/S2_SR_HARMONIZED Landsat data for the wheat crop season were obtained for the years 2019 to 2021. To map wheat-cropped areas in Punjab, Landsat imagery was used from October 2019 through May 2021. For the 2021 wheat crop mapping, imagery from the same months as the 2019 and 2020 maps was employed for consistency. This research primarily utilized Sentinel-2 multispectral satellite images (S2) as the main data source for wheat crop mapping. For the wheat cropping areas, bands B4 (Red), B8 (NIR), and B11 (SWIR) from the S2 data were used [9].

Table 2: Characteristics of Sentinel-2 data

Characteristics	Sentinel-2
Acquisition date	Oct. 2019 to May 2021
Bands	Red (B4), NIR (B8), SWIR (B12)
Wavelength range	443–2,190 nm
Spatial resolution (m)	10, 20, 60 m

Source: Sentinal-2, European Space Agency

Methodology:

Data Preparation:

In the initial step, reference data for the wheat crop in the Punjab region were prepared using the Sentinel-2 (S2) dataset. A visual interpretation of the generated data was conducted in GEE, utilizing NDVI to display reflectance values. The reference points created for each map were divided into two groups: one for validation and the other for training purposes. Of the total reference points, 70% were allocated for training, while 30% were reserved for validation [9].

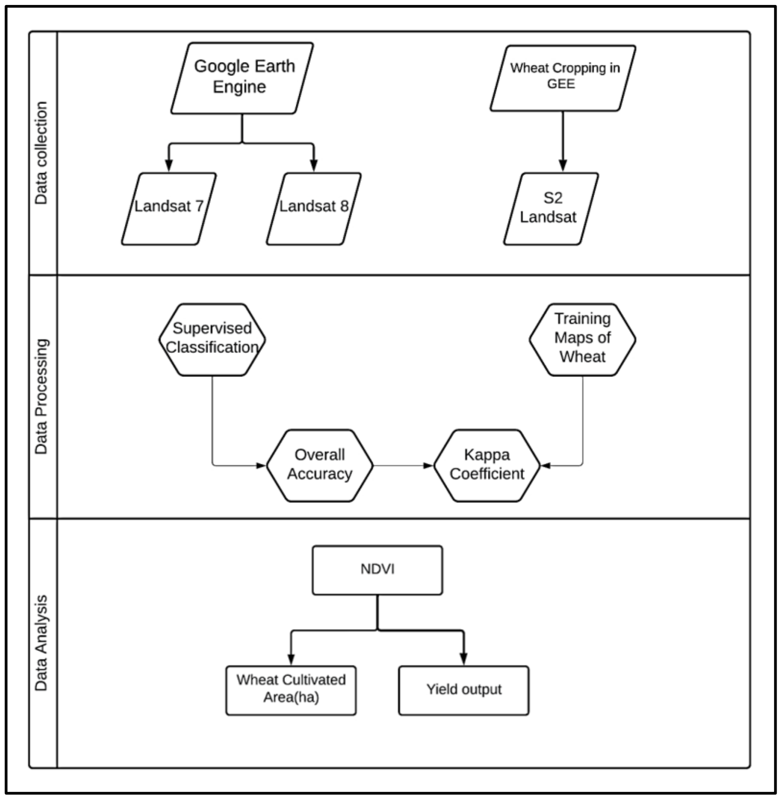

Figure 2: Methodological Framework

Random Forest (RF) Model:

The Random Forest algorithm was implemented in GEE for Land Use and Land Cover (LULC) classification and change detection. Prior to this, twenty years of historical data on land use and land cover in Punjab were analyzed to identify trends. The Random Forest algorithm improves prediction accuracy by utilizing multiple classifiers [16]. It is highly efficient, parallelizable, quick to construct, and faster to forecast, requiring no cross-validation. Unlike single classifiers, Random Forest algorithms are often more accurate and capable of handling raw data without requiring transformation or rescaling [5]. Various image classification techniques, including classification trees and their more recent versions like Random Forests (RF), have proven effective in land cover mapping [20]. Recent studies have explored machine learning techniques, such as RF, to establish robust monitoring systems using high-resolution satellite data, with RF outperforming other classifiers in terms of accuracy and resistance to noise [22].

One of the key advantages of the Random Forest algorithm is its ability to assess the relationship between input and output variables, helping to uncover the rules governing land use changes. As an ensemble classifier, Random Forest combines several decision trees to make predictions. The final forecast is based on the majority vote among the decision trees. The RF (D) model is expressed as:

$$RF(D)=h1(d1), \qquad ,hn(dn)$$

Where TN (dn) represents the nth decision tree with training dataset dn, and D represents the sample dataset. Each decision tree is generated using bootstrapped samples, a random subset of the original sample D, using the bagging technique during model training [19].

Accuracy Assessment:

Accuracy assessment is critical in remote sensing applications, especially in classification tasks. Without a rigorous evaluation, the results lack value. Accuracy is typically assessed using an error matrix, which provides insights into producer's, user's, and overall accuracy. Producer accuracy measures the omission error by calculating the proportion of a specific LULC type correctly labeled on the ground, representing the proportion of correctly identified pixels relative to the total ground truth pixels for that class [23].

Remote Sensing Tools Used:

In the GEE environment, the wheat area mapping tasks were performed using JavaScript. The necessary data, including reference datasets, were uploaded to GEE assets. Classification required the pre-processed images to be loaded, and the resulting wheat maps were exported as raster files and further processed in ArcGIS for visualization and accuracy analysis.

Results:

Land-Cover Change from 2001–2020:

Major LULC trends between 2001 and 2020 are shown in Table 3, based on MODIS data for historical land-cover change and Landsat data for predictive analysis. Significant increases were observed in cropland, natural vegetation, water bodies, and built-up areas over time. Built-up land expanded from 365,825 km² in 2001 to 380,050 km² in 2020, with the highest increase occurring in 2020. Most of this urban expansion was concentrated in northern Punjab, leading to a decrease in bare land, which shrank to 2,796,775 km² by 2020.

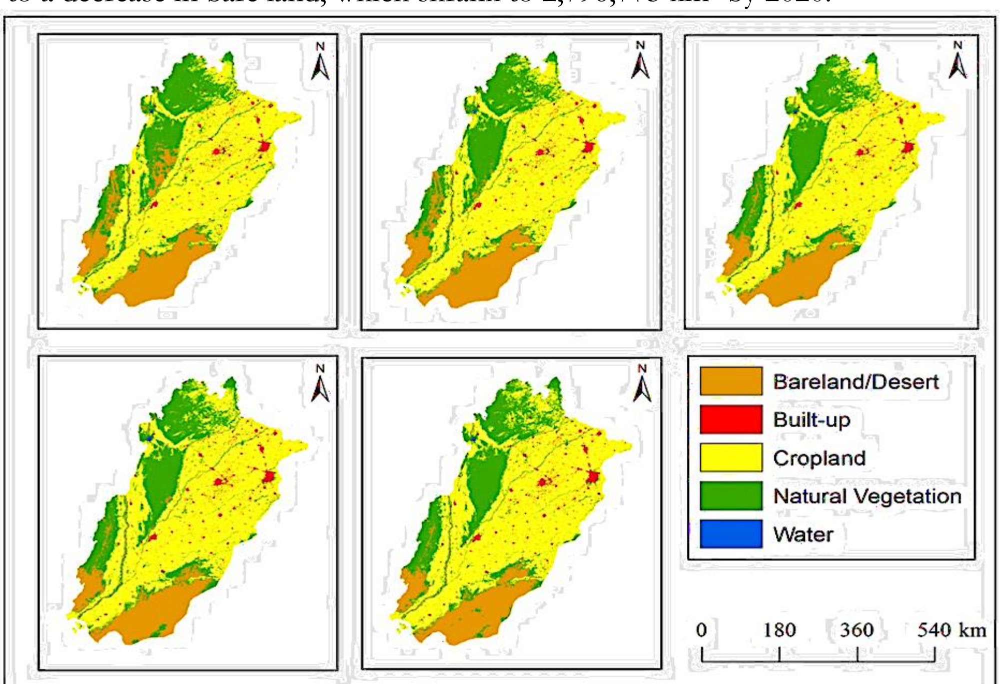

Figure 3: Dynamics of land-cover change in Punjab province from top left 2001; 2005; 2010; 2015 and 2020

Table 3 outlines these historical changes, while Figure 3 illustrates the dynamics of LULC changes in Punjab from 2001 to 2020. During this period, cropland increased to 11,635,400 km² by 2020, water bodies grew from 21,450 km² in 2001 to 32,875 km² in 2020, and bare land decreased from 3,830,350 km² in 2001 to 2,796,775 km² in 2020. These results align with previous research predicting continued urban expansion as population growth drives demand for built-up areas. Major cities like Lahore, Faisalabad, Gujranwala, and Multan experienced significant built-up growth, leading to reductions in bare land, as shown in the 20-year historical trend map.

Regularly updated land-cover maps using free satellite imagery are essential tools for tracking major environmental changes. Assessing the spatial and temporal trends of LULC changes offers critical insights into the drivers behind these shifts, such as population growth, industrialization, agricultural practices, and infrastructure development. LULC change assessments in Punjab help understand the evolving landscape, guiding policies for resource management, biodiversity conservation, disaster preparedness, and sustainable development. They are vital for balancing economic growth with environmental protection in this dynamic region.

Table 3: Land cover trend

LULC Classes	2001	2005	2010	2015	2020
Cropland	52.13	54.01	55.42	56.04	56.58
Natural Vegetation	22.59	22.48	23.39	23.58	23.05
Water	0.10	0.11	0.11	0.16	0.15
Built up	1.77	1.78	1.79	.81	1.84
Bare land/Desert	18.62	16.84	14.50	13.63	13.60

Wheat Mapping:

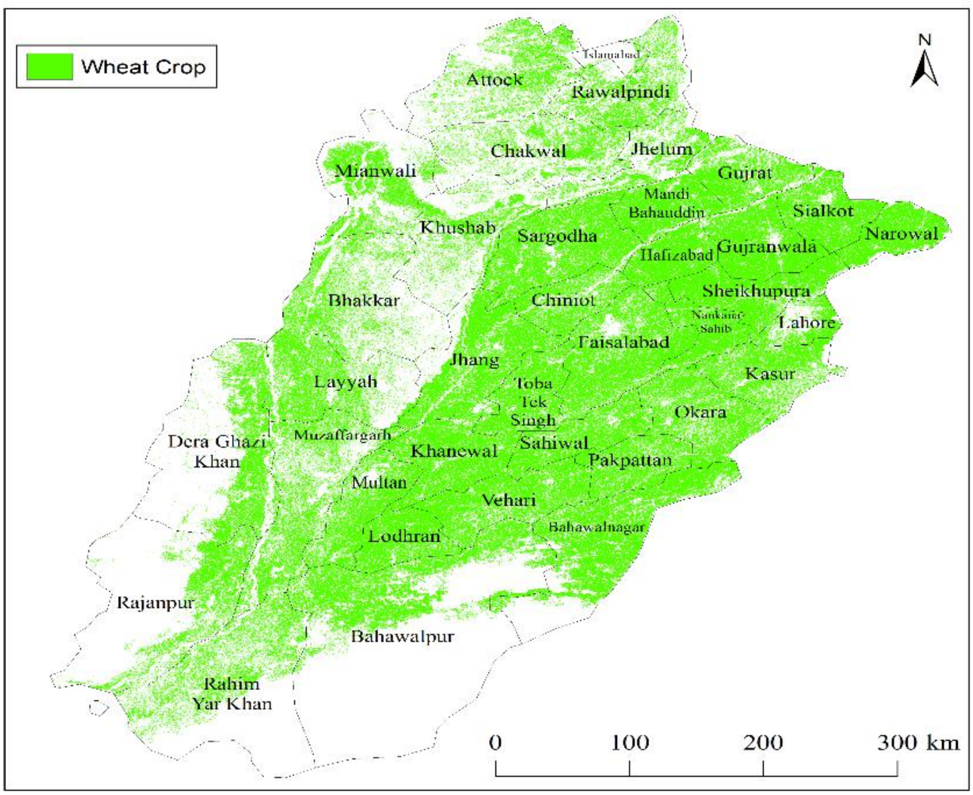

Figure 4: Map of wheat cultivation in Punjab for year 2019-2020

The wheat maps used as the training dataset for this research were meticulously prepared using GEE, leveraging Sentinel-2 (S2) and Landsat satellite data, specifically targeting the Punjab region. These maps cover two distinct growing seasons: 2019–2020 and 2020–2021. The integration of multi-temporal satellite data allowed for the creation of highly detailed and accurate wheat maps, providing a robust foundation for the analysis. Figure 4 illustrates the extent of wheat cultivation in Punjab during the 2019–2020 season, while Figure 5 shows wheat cultivation for the 2020–2021 season. This comprehensive dataset enabled an in-depth examination of wheat crop patterns, growth stages, and spatial distribution across the Punjab region, thereby improving the reliability and precision of the research outcomes. The maps are displayed as follows:

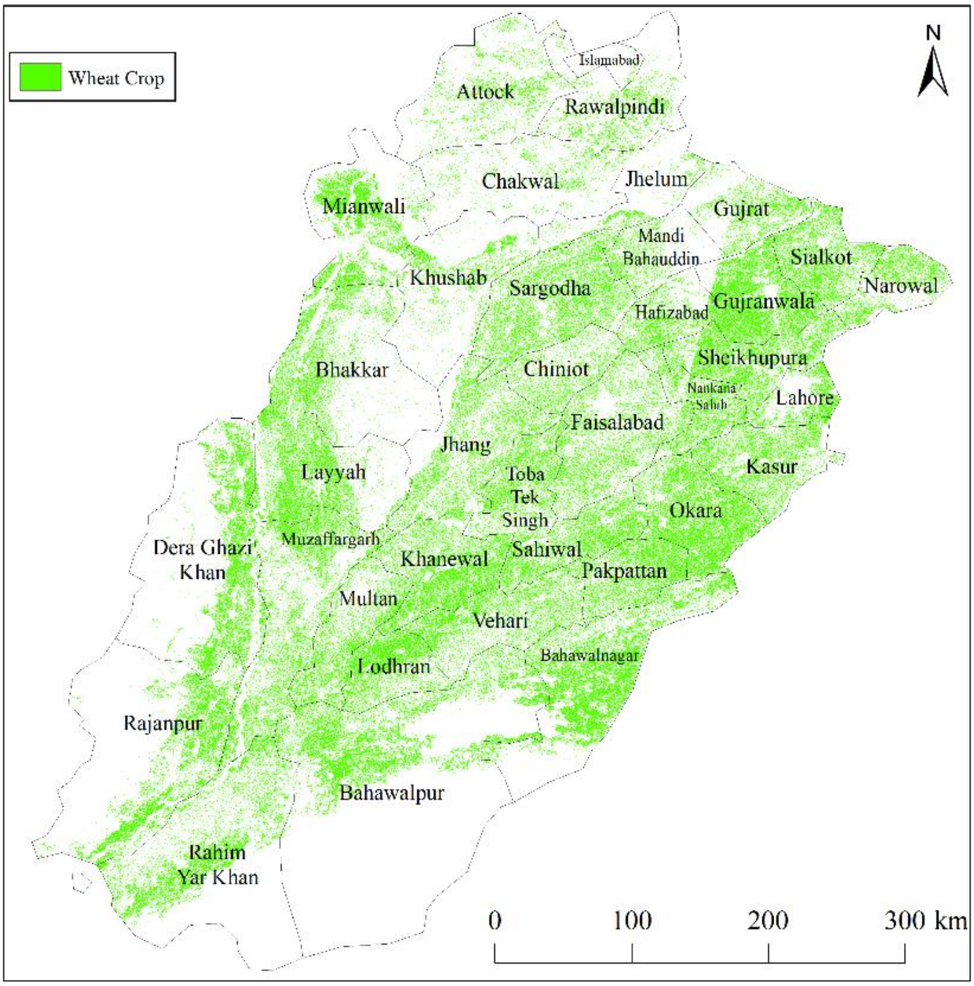

Figure 5: Map of wheat cultivation in Punjab for year 2020-2021

NDVI Index:

The NDVI index was utilized to display the reflectance of wheat maps in this research. NDVI charts for both the 2019–2020 and 2020–2021 wheat maps were generated in GEE using JavaScript. These charts provide insights into the vegetation health and growth patterns of wheat. The NDVI charts are displayed below:

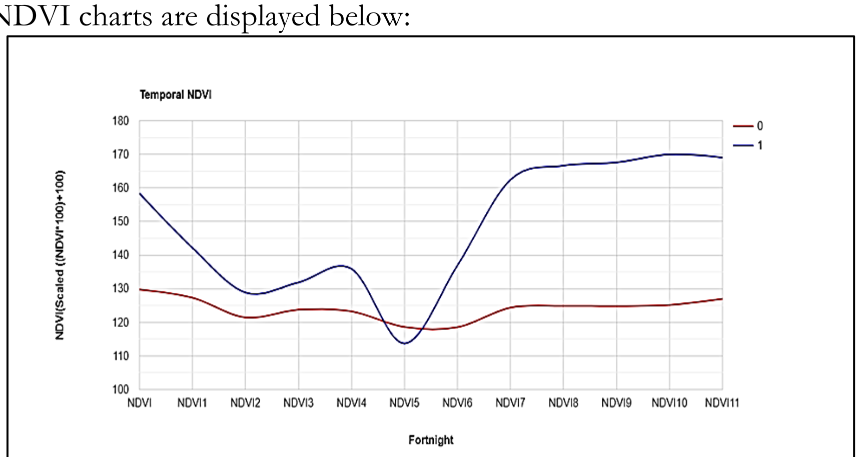

Figure 6: NDVI Chart for wheat map 2019-2020

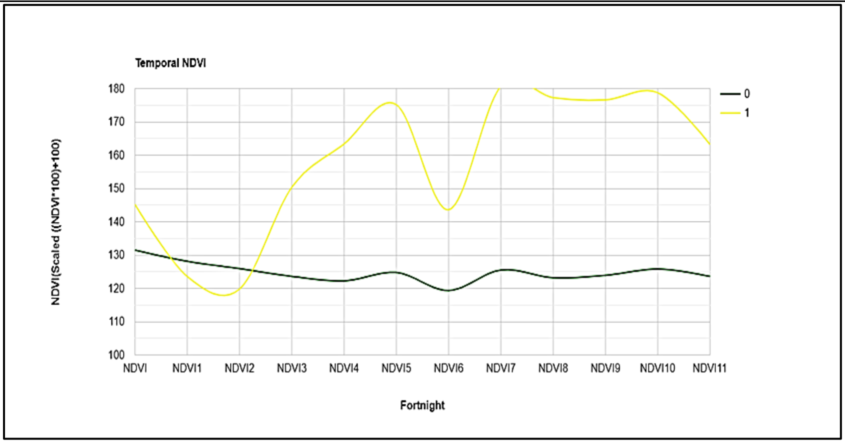

Figure 7: NDVI Chart for wheat map 2020-2021

In the above-mentioned Figure 6 and Figure 7, the NDVI charts for the wheat maps of 2019–2020 and 2020–2021 are displayed separately. The charts include two classes: '0' and '1.' Class '0' represents non-wheat crops, encompassing all Kharif crops, water bodies, built-up areas, natural vegetation, and deserts. Class '1' represents wheat crops. High NDVI values indicate dense green vegetation, while low NDVI values suggest moisture-stressed vegetation.

Yield Output:

The yield output results for each map are shown in separate tables, detailing the per-hectare production of wheat. According to the Pakistan Bureau of Statistics, the wheat yield per hectare for the 2019–2020 season was 19,401.86 metric tons, whereas our calculations indicated 18,373.93 metric tons. For the 2020–2021 season, the Bureau reported a yield of 20,901 metric tons, while our results showed 17,365.53 metric tons. Notably, the highest yield reported by the Bureau was for 2020–2021, while our calculations indicated higher yield in 2019–2020. The total area under wheat cultivation for the 2019–2020 season was 6,515.32 hectares (Bureau data) and 8,711.83 hectares (our calculations), whereas for 2020–2021, the area was 6,745.99 hectares (Bureau data) and 5,226.02 hectares (our calculations), as illustrated in the figures below.

Additionally, the total wheat production per hectare in the nine divisions of Punjab for the 2019–2020 season, based on our calculations, was as follows: Bahawalpur Division – 44.53 metric tons, D.G. Khan Division – 43.46 metric tons, Faisalabad Division – 44.53 metric tons, Gujranwala Division – 47.94 metric tons, Lahore Division – 29.52 metric tons, Multan Division – 40.76 metric tons, Rawalpindi Division – 27.31 metric tons, Sahiwal Division – 27.34 metric tons, and Sargodha Division – 39.53 metric tons. For the 2020–2021 season, our calculations indicated: Bahawalpur Division – 27.16 metric tons, D.G. Khan Division – 28.60 metric tons, Faisalabad Division – 17.55 metric tons, Gujranwala Division – 19.65 metric tons, Lahore Division – 15.22 metric tons, Multan Division – 20.17 metric tons, Rawalpindi Division – 16.07 metric tons, Sahiwal Division – 17.63 metric tons, and Sargodha Division – 20.09 metric tons. The highest wheat yield was recorded in Gujranwala Division for the 2019–2020 season, while Rawalpindi Division had the lowest. In the 2020–2021 season, overall yields were lower compared to the previous year.

Table 4: Accuracy of Wheat estimation

Map Product	**Accuracy (%)**	**User Accuracy (%)**		**Producer Accuracy (%)**	
		Wheat	**Non-Wheat**	**Wheat**	**Non-Wheat**
Map 1 (19-20)	83	80	75	75	80
Map 2 (20-21)	80	75	85	85	75

Accuracy of Wheat Mapping:

ArcGIS software was used to evaluate the accuracy of the non-wheat and wheat crop classifications for each year. Ground truth points were randomly collected from various locations, and the accuracy of the maps was assessed using an area-based methodology with Google Earth Pro software. Maps with accuracy rates exceeding 85% are generally considered acceptable. Overall, the wheat maps demonstrated accuracy rates of over 80%.

Discussion:

The analysis of land-cover change in Punjab from 2001 to 2020 reveals substantial urban expansion, particularly in the northern regions, which has encroached upon bare land and other natural land covers. This rapid transformation in land use and land cover (LULC) has led to a significant reduction in bare land, affecting agricultural areas and potentially influencing crop yields. While both cropland and built-up areas increased during this period, the overall reduction in bare land highlights the pressure on agricultural land due to expanding urban areas. The wheat mapping data for the 2019–2020 and 2020–2021 growing seasons, derived from Sentinel-2 and Landsat satellite data in Google Earth Engine, showed a decline in wheat yield per hectare. This decrease is attributed to factors such as urban expansion, climatic variations, and changes in agricultural practices. [7] similarly documented the adverse effects of urban sprawl on agricultural land in rapidly urbanizing regions.

The NDVI analysis corroborated these findings, indicating better crop health and productivity in the 2019–2020 season compared to 2020–2021. The accuracy assessment of the wheat mapping demonstrated reliability, with mapping accuracy exceeding acceptable thresholds for both years. These findings highlight the critical need for integrated land management strategies to balance urban growth with agricultural productivity. This is in line with the work of [8], who emphasized the utility of NDVI in assessing vegetation health and predicting crop yields under varying environmental conditions. Public awareness campaigns, advanced agricultural technologies, and continuous monitoring of LULC changes using tools like Google Earth Engine are essential for timely interventions. Comprehensive policies and collaborative efforts are needed to promote sustainable development, ensure food security, and maintain agricultural productivity amidst rapid urbanization.

Finally, this research provides valuable insights into the dynamics of land-cover change and its impact on wheat crop production in Punjab. The study offers a robust framework for understanding and managing the interactions between urbanization and agricultural land use, serving as a crucial resource for policymakers and stakeholders in devising sustainable development strategies.

Conclusion:

This study utilized pixel-based classification algorithms and assessed their precision using Google Earth Engine (GEE) for computations and analysis. It proposes a conceptual shift towards creating agricultural maps using multi-date remote sensing techniques [24]. The study employed GEE for LULC change detection, analyzing twenty years of historical land-use and land-cover data for Punjab to identify transition trends. MODIS data were used to show historical land-cover changes, while Landsat data facilitated prediction analysis. Historical trends indicated significant increases in cropland, natural vegetation, water, and built-up areas. The built-up area expanded from 365,825 km² in 2001 to 380,050 km² in 2020, with the most significant increase occurring in 2020. Urban expansion primarily affected the northern part of Punjab, leading to a decrease in bare land, which contributed to rapid built-up expansion over previously bare areas. The most considerable decrease in bare land occurred in 2020, measuring 2,796,775 km². Cropland mapping, particularly for staple foods, provides a clear picture of production levels, allowing authorities to address food demands and production.

The results revealed that wheat production was highest in 2019–2020, at 19,401.86 metric tons according to the Pakistan Bureau of Statistics, and lowest in 2020–2021, at 20,901 metric tons. Our results showed a wheat yield per hectare of 17,365.53 metric tons for 2020–2021, compared to 20,901 metric tons according to the Bureau. In contrast, our calculated yield for 2019–2020 was 18,373.93 metric tons, higher than the 17,365.53 metric tons reported for 2020–2021. These results closely align with field validation data and official statistics.

References:

[1] P. Schleifer and Y. Sun, "Reviewing the impact of sustainability certification on food security in developing countries," Glob. Food Sec., vol. 24, Mar. 2020, doi: 10.1016/J.GFS.2019.100337.

[2] W. Yu, C. Elleby, and H. Zobbe, "Food security policies in India and China: implications for national and global food security," Food Secur., vol. 7, no. 2, pp. 405–414, 2015, doi: 10.1007/s12571-015-0432-2.

[3] K. Havas and M. Salman, "Food security: its components and challenges," Int. J. Food Safety, Nutr. Public Heal., vol. 4, no. 1, p. 4, 2011, doi: 10.1504/ijfsnph.2011.042571.

[4] T. Lang and D. Barling, "Food security and food sustainability: Reformulating the debate," Geogr. J., vol. 178, no. 4, pp. 313–326, 2012, doi: 10.1111/j.1475-4959.2012.00480.x.

[5] A. Molotoks, P. Smith, and T. P. Dawson, "Impacts of land use, population, and climate change on global food security," Food Energy Secur., vol. 10, no. 1, pp. 1–20, 2021, doi: 10.1002/fes3.261.

[6] B. Rimal, L. Zhang, H. Keshtkar, N. Wang, and Y. Lin, "Monitoring and modeling of spatiotemporal urban expansion and land-use/land-cover change using integrated Markov chain cellular automata model," ISPRS Int. J. Geo-Information, vol. 6, no. 9, 2017, doi: 10.3390/ijgi6090288.

[7] T. M. Radwan, G. A. Blackburn, J. D. Whyatt, and P. M. Atkinson, "Dramatic loss of agricultural land due to urban expansion threatens food security in the Nile Delta, Egypt," Remote Sens., vol. 11, no. 3, pp. 1–20, 2019, doi: 10.3390/rs11030332.

[8] S. Hussain et al., "Using GIS tools to detect the land use/land cover changes during forty years in Lodhran District of Pakistan," Environ. Sci. Pollut. Res. Int., vol. 27, no. 32, pp. 39676–39692, Nov. 2020, doi: 10.1007/S11356-019-06072-3.

[9] V. Tiwari et al., "Wheat Area Mapping in Afghanistan Based on Optical and SAR Time-

Series Images in Google Earth Engine Cloud Environment," Front. Environ. Sci., vol. 8, Jun. 2020, doi: 10.3389/fenvs.2020.00077.

[10] A. Khan et al., "Evaluating Landsat and RapidEye data for winter wheat mapping and area estimation in Punjab, Pakistan," Remote Sens., vol. 10, no. 4, 2018, doi: 10.3390/rs10040489.

[11] M. H. Bazai, * Contact, Z. Khan, P. Z. Khan, and A. Saeed, "Land use/land cover change detection and prediction using the CA-Markov model: A case study of Quetta city, Pakistan Land use/land cover change detection and prediction using the CA-Markov model: A case study of Quetta city," J. Geogr. Soc. Sci., vol. 2020, no. 2, pp. 164–182, 2021.

[12] Y. Liu and Y. Zhou, "Reflections on China's food security and land use policy under rapid urbanization," Land use policy, vol. 109, no. August, p. 105699, 2021, doi: 10.1016/j.landusepol.2021.105699.

[13] P. Ghosh et al., "Application of Cellular automata and Markov-chain model in geospatial environmental modeling- A review," Remote Sens. Appl. Soc. Environ., vol. 5, pp. 64–77, 2017, doi: 10.1016/j.rsase.2017.01.005.

[14] B. Rimal, L. Zhang, H. Keshtkar, B. N. Haack, S. Rijal, and P. Zhang, "Land Use/Land Cover Dynamics and Modeling of Urban Land Expansion by the Integration of Cellular Automata and Markov Chain," ISPRS Int. J. Geo-Information 2018, Vol. 7, Page 154, vol. 7, no. 4, p. 154, Apr. 2018, doi: 10.3390/IJGI7040154.

[15] Q. Huang et al., "The occupation of cropland by global urban expansion from 1992 to 2016 and its implications," Environ. Res. Lett., vol. 15, no. 8, 2020, doi: 10.1088/1748-9326/ab858c.

[16] L. Liu, X. Xu, and X. Chen, "Assessing the impact of urban expansion on potential crop yield in China during 1990–2010," Food Secur., vol. 7, no. 1, pp. 33–43, 2015, doi: 10.1007/s12571-014-0411-z.

[17] K. Boratyńska and R. T. Huseynov, "An innovative approach to food security policy in developing countries," J. Innov. Knowl., vol. 2, no. 1, pp. 39–44, 2017, doi: 10.1016/j.jik.2016.01.007.

[18] R. Sonnino, "The new geography of food security: Exploring the potential of urban food strategies," Geogr. J., vol. 182, no. 2, pp. 190–200, 2016, doi: 10.1111/geoj.12129.

[19] A. Y. Prosekov and S. A. Ivanova, "Food security: The challenge of the present," Geoforum, vol. 91, no. August 2017, pp. 73–77, 2018, doi: 10.1016/j.geoforum.2018.02.030.

[20] M. W. Rosegrant and S. A. Cline, "Global Food Security: Challenges and Policies," Science (80-.)., vol. 302, no. 5652, pp. 1917–1919, 2003, doi: 10.1126/science.1092958.

[21] S. K. Wegren, F. Nilssen, and C. Elvestad, "The impact of Russian food security policy on the performance of the food system," Eurasian Geogr. Econ., vol. 57, no. 6, pp. 671–699, 2016, doi: 10.1080/15387216.2016.1222299.

[22] S. Abbas, S. Kousar, and M. S. Khan, "The role of climate change in food security; empirical evidence over Punjab regions, Pakistan," Environ. Sci. Pollut. Res., vol. 29, no. 35, pp. 53718–53736, 2022, doi: 10.1007/s11356-022-19315-7.

[23] A. Samie, X. Deng, S. Jia, and D. Chen, "Scenario-based simulation on dynamics of land-

use-land-cover change in Punjab province, Pakistan," Sustain., vol. 9, no. 8, 2017, doi: 10.3390/su9081285.
[24] R. M. A. Latif, J. He, and M. Umer, "Mapping Cropland Extent in Pakistan Using Machine Learning Algorithms on Google Earth Engine Cloud Computing Framework," ISPRS Int. J. Geo-Information, vol. 12, no. 2, 2023, doi: 10.3390/ijgi12020081.