Sensors & Transducers, Vol. 267, Issue 4, December 2024, pp. 20-33

Sensors & Transducers
Published by IFSA Publishing, S. L., 2024
http://www.sensorsportal.com

Land Use / Land Cover Change Classification and Measurement in the Middle Rio Grande Region, USA – Mexico Using Remote Sensing and Geographic Information Systems

[1,*] Omar BELHAJ, [2] Stanley MUBAKO, [1] Craig TWEEDIE, [1] Raed ALDOURI, [3] Elhadi HADIA, [1] William HARGROVE and [1] Alex MAYER

[1] University of Texas at El Paso, 500 West University Avenue, 79968, El Paso, Texas, USA
[2] California Department of Water Resources 715 P St., 6th Floor, Sacramento, CA 95814 C: 916-873-4784
Libyan Center for Sustainable Development Research, Khoms, Libya
[1] Tel.: 9152749938
E-mail: obelhaj@miners.utep.edu

Received: 10 June 2024 / Revised: 21 November 2024 / Accepted: 5 December 2024
Published: 30 December 2024

Abstract: Development and its expansion in dryland environments are experiencing climate warming and land-use/land cover change, impacting ecosystems and their sustainability and resiliency. Remote sensing (RS) and Geographic Information Systems (GIS) technologies provide opportunities to analyze land use/ landcover (LULC) change trends at local to regional scales over the past few decades. This study applied RS and GIS techniques to identify and measure land-use/ land-cover change in the Middle Rio Grande River Basin. A novel classification process is applied to assess land use and land-cover change between 1994 and 2015 in the Middle Rio Grande Region (MRGR) on the US- Mexico border, between San Antonio, New Mexico and Presidio, Texas, and Ojinaga, Chihuahua, which includes the cities of El Paso, Texas, Ciudad Juárez, Chihuahua, and Las Cruces, New Mexico. Results show that the native land cover has declined and is being replaced by urban development and agricultural expansion. Metropolitan areas across the region increased by 45 % from ~1.59 percent of the total study area in 1994 to more than 2.9 percent in 2015. The majority of expansion occurred around the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces. Other land-use changes included a decrease in agricultural land cover and a loss of wetlands, possibly as a result of a reduction in streamflow. Possible impacts of these land-use/ land-cover changes on water resources include a shortage of water allocations for agriculture and ecosystems and the transfer of some water allocations to city land developers, as Hargrove et al. [1] demonstrated. Metropolitan planners, farmers, and other stakeholders will likely find the study valuable for planning water conservation measures, preparing for future water supply and treatment infrastructure growth, and monitoring groundwater availability and quality as urban populations grow.

Keywords: Development, Sustainability, Resiliency, Infrastructure, Land use, Land cover.

1. Introduction

Land resources encounter severe challenges worldwide, especially in arid and semi-arid regions, which occupy about one-third of the global land [2, 3]. Landcover degradation, soil erosion, water depletion, and ecosystem deterioration are some land resource changes [4-13]. A range of change drivers influences land resource changes at different space and time scales, such as population growth, human activities, and climate change. These drivers put massive pressure on land resources and create uncertainty in these resources ‘availability, long-term sustainability, and resiliency [14-18].

Land use and land cover (LULC) are two terms used separately to describe the earth’s surface features and human interactions with these [19-25]. While land use states how humans have used the land, land cover indicates the biophysical characteristics of the earth’s surface [19, 21-24, 26, 27]. The LULC change is possibly the most significant challenge to land resources and sometimes the most rapid in many places [28-31]. The LULC change carried various consequences on local, regional, and global scales. Amongst the intensive consequences of the LULC change is the extinction of native species when land use is changed from a comparatively undisturbed state to more intensive uses such as farming, livestock grazing, and selective tree harvesting [28, 29, 32-35]. The LULC changes result from the interaction of a wide variety of factors like human activities, agriculture, deforestation, animal grazing, and urbanization [32, 35-40]. Also, many indirect factors, such as technological, political, economic, cultural, demographic, and social factors, cause land use/ land cover change [36, 32, 37, 41]. Extensive data on the Earth’s surface is required to monitor and analyze land use/land cover changes. Earlier, this information was created worldwide, mostly by conventional land recognition methods such as field surveys and on-site human-made observations, which required time, cost, and effort [42-44].

Modern LULC change studies typically use remotely sensed imagery, which provides excellent data sources from which information about LULC can be extracted and analyzed with various techniques and data sets [15, 30, 45-47]. Chang et al. [48] and Mubako et al. [49] demonstrated that remote sensing data and geographic information systems are valuable transboundary information sources and can be used to implement proficient cross-border studies. Remote sensing and geographic information technologies can help stakeholders map where changes occur, understand development patterns and seasonal land changes over time, and assess current activities and policies. They can also help expect and plan for future changes. Zhang et al. [9] demonstrated that medium spatial resolution imagery such as Landsat images are still the most significant data sources for urban land-cover classification, especially considering the free availability of this imagery, suitable spectral resolutions, and swath extent.

The Middle Rio Grande Region (MRGR) is a dryland ecosystem situated in the southwestern US-Mexico borderlands (50-52]. This region covers the area from southern New Mexico to far west Texas in the US and northern Chihuahua in Mexico. This region encompasses the three fast-growing cities of Las Cruces, New Mexico, El Paso, Texas, and Ciudad Juarez, Chihuahua, and is populated by more than two million people [49, 53]. The Rio Grande region faces enormous challenges with its resources, which significantly pressure these resource uses because of competition between stakeholders in areas such as agriculture, livestock raising, municipalities, industry, and wildlife [54, 49]. The Rio Grande River is the fourth largest river in North America and runs through the region from north to south. This river starts as a snow-fed stream high in the San Juan Luis Valley in southern Colorado and ends in the Gulf of Mexico. The Rio Grande River comprises the main surface water reservoirs in southern New Mexico, the Elephant Butte Reservoir and Caballo Reservoir. The Rio Grande River is one of the most significant water sources in southern New Mexico, far west Texas in the US, and northern Chihuahua in Mexico. It provides intensive agriculture practices for their irrigation needs. It also supplies the human communities and the ecosystems throughout the basin with their water needs [51, 55-58].

This MRGR contains various land use/ land cover features and practices and experiences massive changes over time due to disruptive human activities and natural conditions [57]. Urbanization is one of the region's most influential contributors to land use/ land cover change. It continues to grow, especially near the urban centers of Las Cruces, New Mexico, El Paso, Texas, and Juárez, Mexico [55]. A study conducted by Mubako et al. [49] on 4288 km^2 (1655 sq. miles) in the MRGR that included most areas of the three main cities in the region (Las Cruces, El Paso, and Ciudad Juarez) stated that the urban areas grew about 8 % in this area of interest in the 25 years 1990-2015 by taking important areas from agricultural lands and other vegetation. The agricultural lands and other vegetation areas decreased by about 11 % in this period.

The central aim of this study is to identify and measure LULC change in the MRGR. The study uses Landsat-based remote sensing and land cover classification to measure changes in the land use practices and land cover features in this region for 21 years from 1994 to 2015 (Fig. 1).

2. Data and Methodology

2.1. Study Area

This study’s selected area of interest lies along the US – Mexico border. It includes the Middle Rio Grande basin from Magdalena and San Antonio, New Mexico, in the north to the entrance of the Rio Conchos from Mexico in the south. The area of interest is located between north latitudes 34.06000000 and 29.38166667 and west longitudes 107.85694444 and 104.21555556 (Fig. 1). The total study area is ~36,988 km^2 (14281 sq. miles) and includes six water sub-basins. The study area consists of different terrain features. This region covers the area from southern New Mexico to far west Texas in the US and the northern Mexican state of Chihuahua.

The region encompasses the three fast-growing cities of Las Cruces, New Mexico; El Paso, Texas; and Ciudad Juarez, Chihuahua, with a population of more than two million [18, 49].

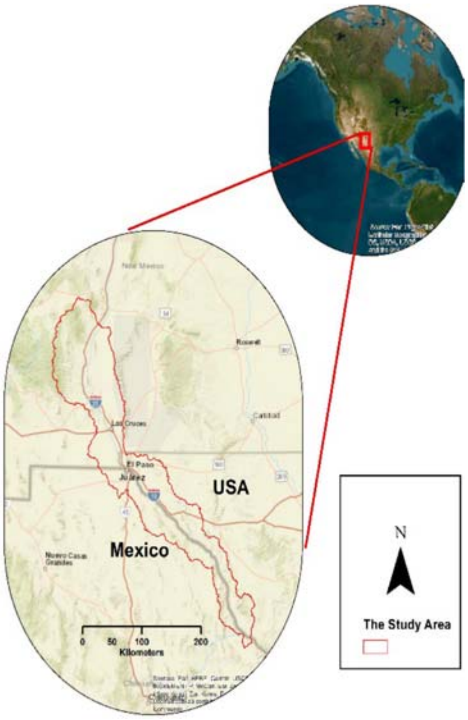

Fig. 1. The Study Area.

2.2. Materials and Methods

The following workflow is shown in Fig. 2 reflects the remote sensing and geographic information system procedures applied in this study to perform the work and get the best results.

The processes started with downloading and preparing Landsat data. Atmospheric data correction is applied, imagery is clipped to the extent of the study area, and minimum noise fraction transforming is completed to reduce the inherent spectral dimensionality and noise within multispectral data. After data preparation processes had been accomplished, image classification was performed using several applications and tools. The classification was performed using ArcGIS 10.8.1, ArcGIS Online, ENVI 5.4, Microsoft Excel, and Google Earth Professional.

2.2.1. Landsat Data Preparation

Eight multispectral Landsat scenes cover the study area shown in Fig. 1. (Path/Row): 031/039, 031/040, 032/038, 032/039, 033/037, 033/038, 034/036, and 034/037. As shown in Fig. 1 these images were downloaded from the U.S. Geological Survey (USGS) GloVis website (http://GloVis.usgs.gov/) for 1994, 2000, 2005, 2010, and 2015. Each scene had less than 10 percent cloud cover. The scenes used for the study area were chosen from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI), as shown in Appendix (1). In fact, Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) collect data with a spatial resolution of 30 meters in the visible, near-IR, and SWIR wavelength regions [59]. The scenes were acquired between the second half of May and the first week of July, considered the "leaf-on" season in this area [18, 49, 60-62]. Substantial procedures were performed on the scenes to prepare them for classification, including mosaicking the eight scenes in one image and clipping a final image to the study area boundaries.

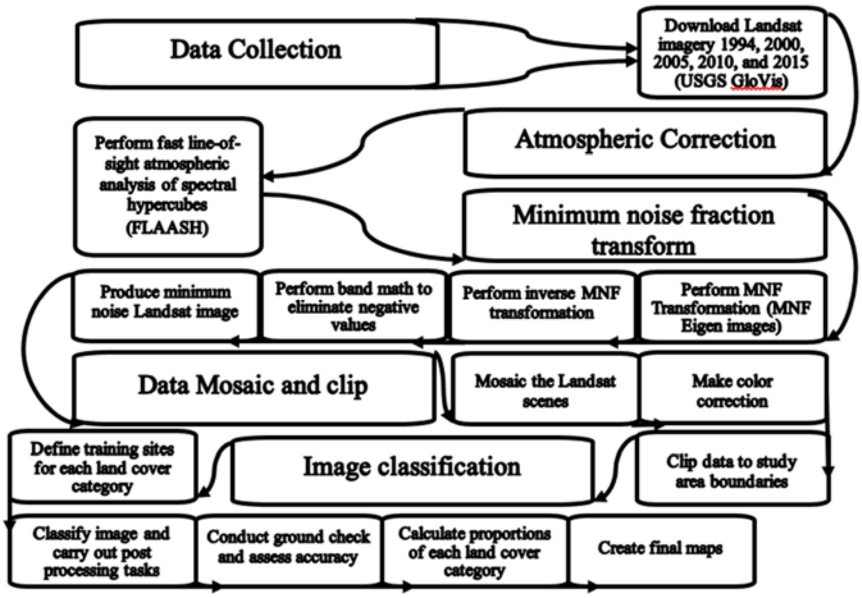

Fig. 2. The flowchart shows the RS&GIS proposed methods used in the study.

2.2.2. Atmospheric Correction

Kumar et al. [63] tested log residuals, flat field correction, IARR (Internal average relative reflectance), QUAC (Quick atmospheric correction), and FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes) atmospheric correction methods. The results showed that FLAASH is the most efficient atmospheric correction method compared to the other methods.

Chakouri et al. [64] tested two physical atmospheric corrections, FLAASH and ATCOR (Atmospheric & Topographic Correction), compared to the DOS (Dark Object Subtraction) image-based method. The researchers found that the FLAASH provided the most accurate Bottom of Atmosphere BOA reflectance estimation.

Mruthyunjaya et al. [65] applied ATCOR and FLAASH atmospheric correction modules. The FLAASH provided the most accurate Bottom of Atmosphere BOA reflectance estimation. They found that the variation in aerosol optical depth AOD using the FLAASH method did not impact the identification of bare soil pixels coverage, which corresponded to 82.4 % of the study area, while a variation in water vapor using the ATCOR method provided a variation of bare soil pixels coverage from 75.04 to 84.04 %. They recommend using the FLAASH AC method to provide BOA reflectance values from Earth Observing-1 Hyperion Hyperspectral data before soil organic carbon mapping while using the ATCOR module needs careful selection of water vapor parameter before applying the method.

Therefore, we have chosen the FLAASH method to perform the atmospheric corrections. Specific steps were implemented in the ENVI 5.4 application for the five years chosen for the study. These steps included radiometric calibration to determine reflectance at the top of the atmosphere, fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) for water vapor, and moisture correction to determine surface reflectance.

2.2.3. Minimum Noise Fraction Transform

To reduce the number of bands for processing hyperspectral remote sensing data and to improve processing efficiency, a minimum noise fraction (MNF) linear transformation process was used to transform the study area images for all analysis years [66-68]. This technique, widely applied in remote sensing, is implemented in ENVI 5.4 software [67] and reduces the inherent spectral dimensionality and noise within multispectral data. The final minimum noise fraction Landsat images were approved for classification based on both eigenvalue plots of the ground objects and visual inspection of the images.

2.2.4. Combined Classification

A newly developed object-based classification method was tested in combination with a pixel-based classification method [69, 70]. The object-based method has been shown to have greater accuracy and produce a more robust classification than the pixel-based method when using high-resolution imagery [71-76]. Object-based techniques create an image object via image segmentation and classify the images according to objects rather than pixels [77]. However, it has been shown that pixel-based land cover classification may sometimes outperform the classification accuracy results for specific land cover categories [77, 78]. Combining both methods produces optimal results [70].

The combined classification method comprises many steps that start with supervised or unsupervised classification and infiltrate the results based on the homogeneity of surface features to segment and attain the boundaries of surface features into more authentic products [75, 77] This study adopted such a generalized approach and started by implementing a supervised classification utilizing a maximum likelihood format [79-83]. Supervised classification uses the spectral information contained in individual pixels to generate land cover classes. The method requires the collection of training samples created in the study area, which are then used to derive spectral signatures of pixels in an image. It requires, therefore, prior knowledge of LULC types in the study area. Pixel signatures are generated and stored in signature files, and each pixel's digital numbers (DN) are converted to radiance values [49, 84, 85]. The interactive supervised classification module used to classify the minimum noise images is found in ArcGIS 10.8.1 software. The module was applied for the five years of analysis, 1994, 2000, 2005, 2010, and 2015, using the six broad land use categories defined in Table 1. Spectral signatures of the training samples were first analyzed using statistical methods.

According to Gao and Liu [86], a satisfactory spectral signature minimizes confusion between different land-use categories that need to be mapped. The whole region of interest was classified by assigning each image pixel to the training sample category of the match's highest probability. On average, 150 training samples were created for each land use category using the Landsat 1994_TM imagery since this was the year with the least developed land. A minimum of 500 pixels for each training sample category was used.

After producing the preliminary classified maps, field visits were made to designated features and places in the study area to find similarities and differences between the classified features on maps and their actual appearance and locations on the ground. Coordinates and information about the visited locations were collected. Other inquiry points were assigned to places familiar to our team. They were checked through high-resolution images downloaded for New Mexico and Texas states from their websites and used historical image visualization in Google Earth Professional. The chosen points were matched with the classified maps, and the misclasses were assigned to be recognized at the ultimate classification step. Reclassification procedures were processed to correct the misclassified sites depending on the object-based features of these sites shown on the high-resolution images. Therefore, final classified maps that carried more accurate results have been created. These procedures were applied to the five maps created in the study: 1994, 2000, 2005, 2010, and 2015.

Table 1. Description of Land use/ Land cover classification categories used in the study.

Land use / Land cover	Description
Agriculture	Cultivated crops, trees, plants, and pastures
Developed Open space	Sports fields and courts, parks, picnic areas, and building yards
Developed area	Urban development constructions, buildings, concrete, and roads
Water	Open waterbodies in natural and human-made surface waterbodies
Evergreen Forest	Green trees on mountains and hills in the study area
Shrubs	Barren land, mountains, grass, and scrub/shrub features in the area

2.2.5. Finalizing Classification Mapping

Finalizing classifications of remotely sensed imagery is a balance between achieving outstanding quality classified final maps and the potential loss of essential map details through the unnecessary use of generalization tools [49, 87]. Therefore, the majority filter procedure was not applied to protect the isolated and small regions in the reclassified maps, which are real features in the study area. In addition, a boundary-cleaning filter was applied to these maps to smooth the boundaries and improve their layout. These steps were done through a series of geoprocessing tools in the Spatial Analyst Extension of ArcGIS 10.8.1.

2.2.6. Accuracy Assessment

The validity of classifications was confirmed by calculating multiple metrics indicative of the mapped accuracy of the classification. Classification accuracy was performed for individual land use categories and the total classification by creating a confusion matrix [29, 45, 49]. Six statistics were calculated: (1) overall accuracy, which represents the proportion of all correct classifications; (2) Kappa coefficient, a measure of the agreement of accuracy in classification assessment; (3) user accuracy, which calculates the probability that a classified pixel is correct on the ground; (4) producer accuracy, which is the probability that a pixel of a particular land-use type is assigned the correct land use category; (5) omission error, which represents specific categories that were omitted when they exist on the ground; and (6) commission error, which represents categories that were identified as existing on the ground when in fact they do not [45, 49].

3. Results and Discussion

3.1. Land Use / Land Cover Measurement and Change Trends

After producing the final classified maps, the areas of individual classes were calculated for the study area. This process was executed through the feature attributes related module in ArcGIS 10.8.1 for the five sample years. The final results are given in Table 2 and Fig. 3.

Table 2. Land use / land cover change 1994-2015.

Year	Land use / land cover category area (km^2)					
	Agriculture	Developed open space	Developed area	Water	Evergreen forest	Shrubs
1994	1245	29	589	241	1663	33221
2000	1190	33	768	185	1749	33063
2005	1125	36	933	122	2126	32646
2010	1111	40	1022	135	2155	32525
2015	1091	40	1078	106	1148	33825

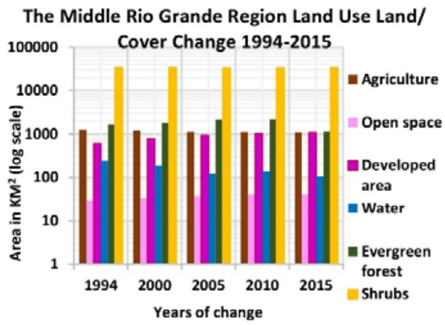

Fig. 3. The Middle Rio Grande Region LULC change 1994-2015.

The results showed many changes in the study area's land use/ land cover classes. Agriculture lands decreased from 1245 km^2 (3.37 percent) of the total study area in 1994 to 1091 km^2 (2.97 percent) in 2015. This is attributed mainly to the intensification of developing activities and the reduction of cultivation practices related to water use, and a shift from cotton and alfalfa production, with some production of chili peppers, vegetables, vineyards, and orchard crops to more profitable crops such as pecans for the analysis period [1]. The open space areas, including parks, sports fields and courses, and green areas, in cities and considered human-friendly development increased following the urban growth from 29 km^2 (0.08 percent) in 1994 to 40 km^2 (0.11 percent) in 2015. The proportion of developed areas, including urban areas and other types of construction within the study area, increased over time from 589 km^2 (1.59 percent) in 1994 to 1078 km^2 (2.94 percent) in 2015. The increase happened primarily around the central three urban cities of cities El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). However, many along the Middle Rio Grande Region scattered minor cities, towns, communities, and neighborhoods, contributing to the urban expansion through the growth of urbanization in these cities, towns, communities, and neighborhoods.

The areal extent of surface water decreased from 241 km^2 (0.65 percent) in 1994 to 122 km^2 (0.33 percent) in 2005. Surface water increased in 2010 to 135 km^2 (0.36 percent). In contrast, surface water decreased to 106 km^2 (0.29 percent) in 2015, a total decrease of the surface water area of over 56 percent for the 21 years 1994-2015. Elephant Butte and Caballo's large reservoirs comprised the majority of the surface water extent and were located in the northern part of the study area. They are also considered the primary source of surface water in the southern part of the region.

Evergreen forest cover is restricted to some marginal zones in the region and almost in the northern part of the Magdalena Mountains, San Mateo Mountains, and Black Range. The areas of evergreen forests increased from 1663 km^2 (4.5 percent) in 1994 to 2155 km^2 (5.83 percent) of the total area in 2010. However, these areas decreased to 1148 km^2 (3.1 percent) in 2015 due to fires that burned significant parts of these forests. Records indicated several fires, the largest silver fire in 2013, which burned about 138,705 acres in the Black Range, New Mexico. Also, the San Mateo Mountains fire in 2015 burned 17,843 acres [88, 89]. Shrublands covers were the most dominant land cover in the study area for each of the time periods studied. The shrublands class lost important lands in many parts across the region. The results showed that shrublands covered 33221 km^2 (89.82 percent) in 1994 and shrunk to 32525 km^2 (78.93 percent) in 2010. This component gained some areas to 33225 km^2 (90.56 percent) in 2015 due to forest fires and surface water area reduction. The changes in LULC 1994-2015 are shown in Figs. 4-8.

3.2. Results Validation

3.2.1. Accuracy Assessment

For the study area, five maps were classified for 1994, 2000, 2005, 2010, and 2015. An accuracy assessment was applied using several extension tools in ArcGIS 10.8.1 to validate the classification results, focusing on analysis years 2005, 2010, and 2015. We got their high-resolution images these three years from Texas and New Mexico. 2005, 2010, and 2015 images support in-ground checks of classification results. Also, field visits were made to New Mexico and Texas areas to support the ground check of classification results. However, Google Earth was used in the ground check in Mexico, the part that I could not check in the field because of the restrictions on border movement. The classification quality is oriented in a confusion matrix that is widely used to present accuracy assessment information in remote sensing [49, 88]. About 520 points were used for each classified map (year). A stratified random sampling method was applied for validation. The method assigned sampling points according to the proportion area of each class in the study area. An overall accuracy of 99 percent was obtained in 2005, 2010, and 2015. Subjectivity in interpreting classification results, fuzzy boundaries between land use categories, and uncertainty in the supervised classification algorithm in assigning land use categories to mixed pixels are all possible sources of intrinsic uncertainty and error that could have been propagated in this type of study. Calculating the Kappa statistics, which account for classification agreements owing to chance, is an alternative approach to measuring classification accuracy. The Kappa coefficient was 0.96 for three years, statistically supporting the classification's overall accuracy. For all land use/ land cover categories, the producer accuracy ranged from 88.2 percent to 100 percent for the three years, and user accuracy went from 90 to 100 percent. Detailed assessment results are presented in Tables 3, 4, and 5.

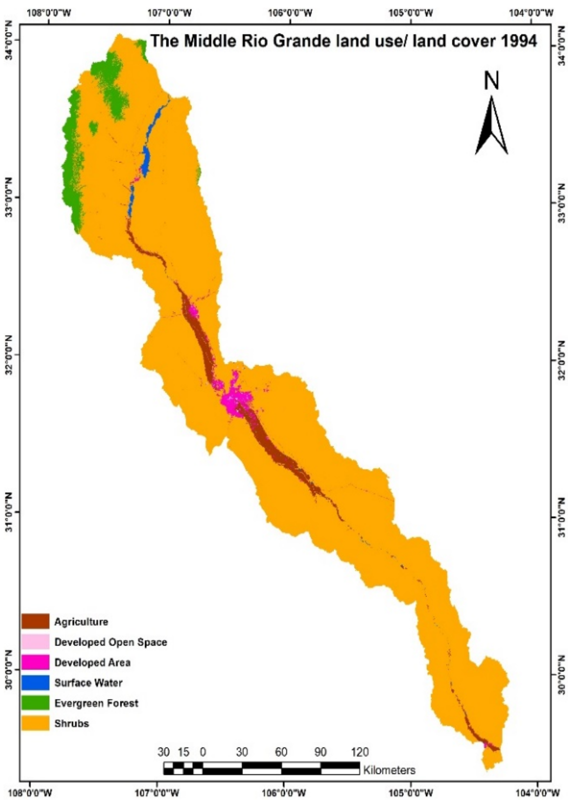

Fig. 4. The Middle Rio Grande Region LULC 1994.

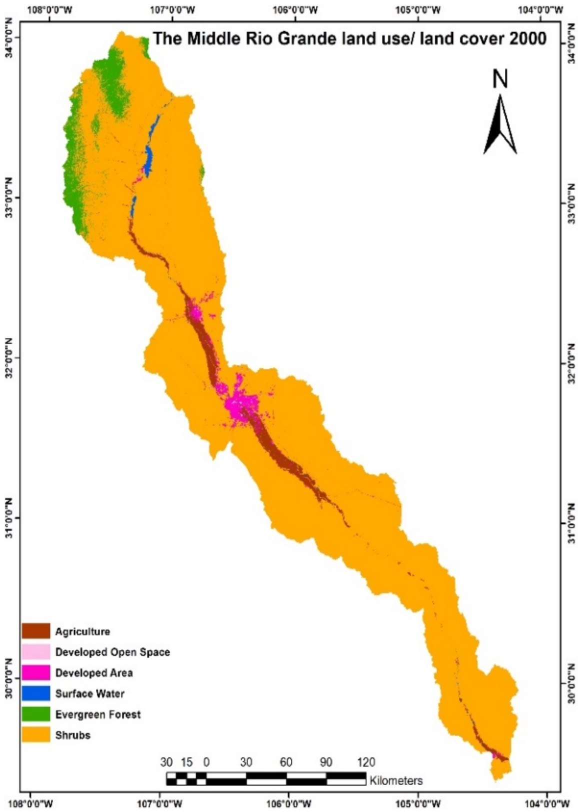

Fig. 5. The Middle Rio Grande Region LULC 2000.

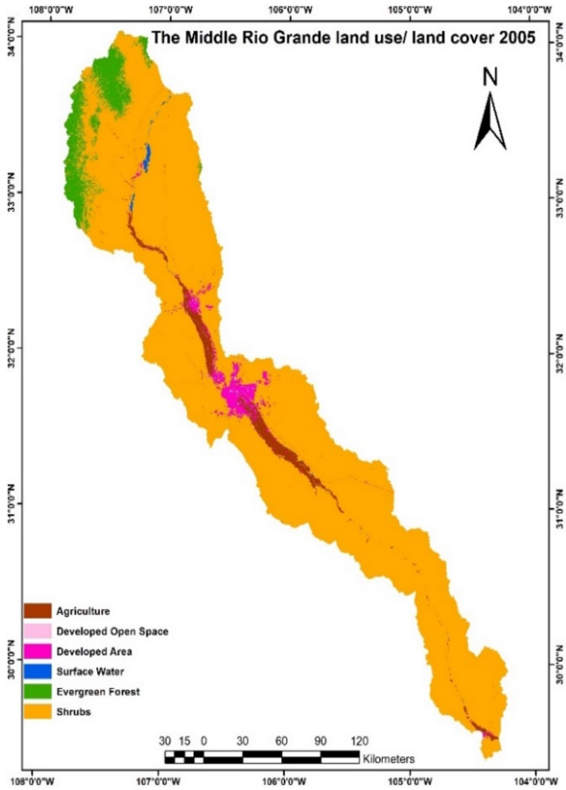

Fig. 6. The Middle Rio Grande LULC 2005.

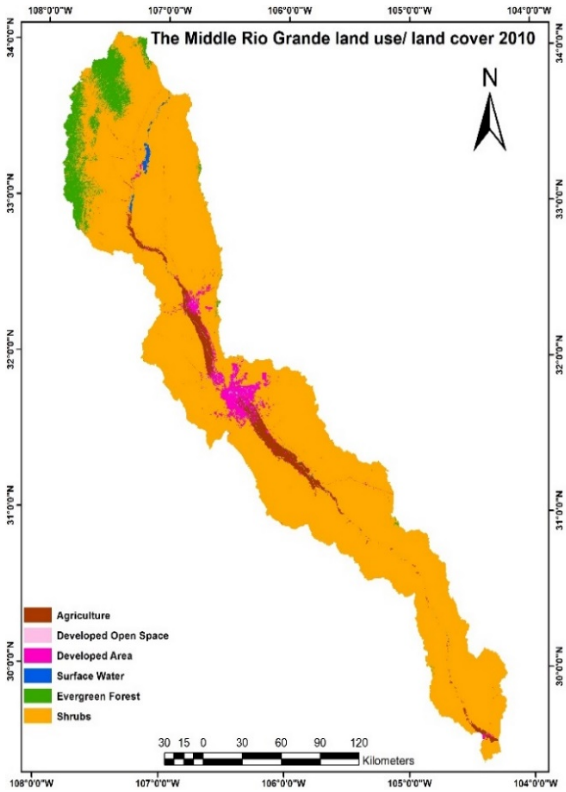

Fig. 7. The Middle Rio Grande LULC 2010.

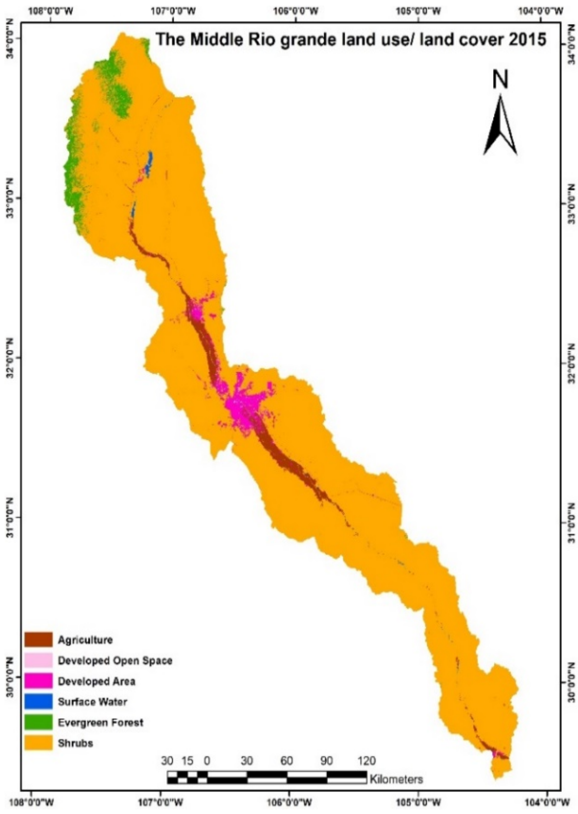

Fig. 8. The Middle Rio Grande LULC 2015.

Table 3. Confusion matrix showing classification accuracy for the 2005 map.

Classified	Ground truth								
	Agriculture	**Open space**	**Developed area**	**Water**	**Evergreen Forest**	**Shrubs**	**Total ground**	**User's accuracy %**	**The error of commission %**
Agriculture	14	0	0	0	0	1	15	93.33	6.67
Open space	0	10	0	0	0	0	10	100	0
Developed area	1	0	12	0	0	0	13	92.31	7.69
Water	0	0	0	10	0	0	10	100	0
Evergreen Forest	0	0	0	0	26	3	29	89.66	10.34
Shrubs	0	0	0	0	1	440	441	99.77	0.23
Total classified	15	10	12	10	27	444	518		
Producer accuracy %	93.33	100	100	100	96.30	99.1			
The error of omission %	6.67	0	0	0	3.70	0.90			
Overall accuracy %	98.84								
Kappa coefficient	0.96								

Table 4. Confusion matrix showing classification accuracy for the 2010 map.

Classified	Ground truth								
	Agriculture	**Open space**	**Developed area**	**Water**	**Evergreen Forest**	**Shrubs**	**Total ground**	**User's accuracy %**	**The error of commission %**
Agriculture	15	0	0	0	0	1	16	93.75	6.25
Open space	0	9	0	0	0	0	9	100	0
Developed area	0	0	14	0	0	0	14	100	0
Water	0	0	0	10	0	0	10	100	0
Evergreen Forest	0	0	0	0	29	3	32	90.625	9.375
Shrubs	0	1	0	0	0	436	437	99.77	0.23
Total classified	15	10	14	10	29	440	518		
Producer accuracy %	100	90	100	100	100	99.09			
The error of omission %	0	10	0	0	0	0.91			
Overall accuracy %	99								
Kappa coefficient	0.96								

Table 5. Confusion matrix showing classification accuracy for the 2015 map.

Classified	Ground truth								
	Agriculture	**Open space**	**Developed area**	**Water**	**Evergreen Forest**	**Shrubs**	**Total ground**	**User's accuracy %**	**The error of commission %**
Agriculture	15	0	0	0	0	0	15	100	0
Open space	0	10	0	0	0	0	10	100	0
Developed area	0	0	14	0	0	1	15	93.33	6.67
Water	0	0	0	10	0	0	10	100	0
Evergreen Forest	0	0	0	0	15	1	16	93.75	6.25
Shrubs	0	0	1	0	2	451	454	99.34	0.66
Total classified	15	10	15	10	17	453	520		
Producer accuracy %	100	100	93.33	100	88.24	99.56			
The error of omission %	0	0	6.67	0	11.76	0.44			
Overall accuracy %	99								
Kappa coefficient	0.96								

As Mubako et al. [49] mentioned, overall classification accuracy and accuracy for all classes greater than 75-85 percent is acceptable. That accuracy assessment compromises the ideal and the affordable [18, 49]. Wickham et al. [89] recommended an acceptable overall classification accuracy between 84-85 percent for most satellite data classification studies to evaluate the National Standard Land Cover Database (NLCD) classification system. The coarse 30 m spatial resolution of the Landsat images utilized in the study also contributed to classification errors. Two or even more spectral classes were frequently recorded inside one pixel using this low-resolution data, which obviously influenced classification accuracy. Errors were experienced when performing the accuracy assessment with some pixels for some classes. Therefore, our results classification errors are partly due to impure training samples that captured mixed land use categories. Accurate reference data is essential for testing classification accuracy [90]. Therefore, accuracy errors were calculated as part of the assessment. The results showed that commissions' errors were not over 10 % for some classes, and the errors of omissions were not over 12 % for some individual classes.

3.4. Discussion

The US-Mexico border Middle Rio Grande Region is dryland covering ~36988 km^2 (14281 sq miles). We studied this region to measure land use/ land cover and find their changes for 21 years (1994-2015) by using remote sensing and geographic information systems. The study divided the period into five years: 1994, 2000, 2005, 2010, and 2015.

The results showed significant changes in land use / land cover features during the study period 1994-2015. The open space areas increased by about 27 percent. The developed area across the area of interest increased by 45 percent in 21 years between 1994-2015 by winning important extents from agricultural and shrublands, and the most growth occurred around the metropolitan areas of El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). The shrublands increased by about 1 percent. On the other hand, the agricultural land decreased by about 12 percent. Surface water decreased by more than 55 percent in this period. The evergreen forests decreased by about 30 percent.

The study results presented that the MRGR, like other drylands, faces serious challenges, such as water reduction and competitive demand growth amongst sectors such as agriculture and domestic use. Shrubs and native plants are disturbed naturally during climate change, such as temperature increases, and human activities, such as urbanization growth and construction expansion. However, there are similarities and differences in changes between the MRGR and the other drylands. The effect of the change on the area depends on the location and management of this area. A study in the Kathmandu Valley, Nepal, for the period 1989-2016 showed similarities in LULC changes with the MRGR. The results showed that urban areas expanded up to 412 % in the last three decades, and most of this expansion occurred with the conversions of 31 % of agricultural land. The majority of the urban expansion happened during 1989–2009, and it is still growing along the major roads in a concentric pattern, significantly altering the cityscape of the valley [91]. Another study in the Zayandehrood ecologic sub-basins of Central Iran Asia also showed similarities in LULC changes with the MRGR. The results revealed that from 1985 to 2016, residential areas doubled, and industrial areas increased at the expense of rangelands. The study also revealed cropland expansion at the expense of rangelands, cropland abandonment, and contraction of croplands due to residential and industrial development [92]. Also, a study focused on Palapye, a predominantly dryland agricultural region in eastern Botswana, Africa, aimed to analyze LULC change and divided the period into two intervals (1986-2000, 2000-2014). This study showed similarities in LULC changes with the MRGR. The results showed that cropland was a vibrant losing category in the first time interval, while it was a clear gaining category during the second time interval. Cropland expanded into shrublands in the southwestern part of the study area. The built-up category was active in gains during the second time interval as it targeted grasslands and shrublands [93]. On the other hand, and through good management, a study in Karoo drylands, South Africa, revealed that more than 95 % of the Karoo is comprised of land classified as Natural, which has been relatively stable since 1990. An analysis of repeat photographs shows that vegetation cover has either remained unchanged or has increased at most locations. However, the Karoo drylands appear less degraded than they were in the mid-twentieth century [94].

LULC changes in the MRGR have many implications for the region. Reducing snowpack in the headwaters of the Rio Grande River causes a growing water supply deficit and failure to sustain the competing demands of different sectors even though these demands for surface water stay the same in aggregate [1]. It increases the pressure on the reservoirs of surface water used as a water source for various uses. For example, this appears clearly in the Elephant Butte Reservoir, the primary surface water source in the MRGR. Its capacity since 2011 fluctuated between 3-25 % of the total capacity [95, 96]. Rising soil and water salinity and growing constraints on using these resources for agricultural production, drinking, and various environmental needs. Relying on the growth of groundwater to provide the necessary water supplies for various uses and the pressure and negative impacts on this limited to nonrenewable water resource also face many serious problems, such as depletion and quality deterioration [1]. The loss of grasslands, shrublands, and forests to urban development can lead to the loss of natural habitats and ecological diversity, a higher risk of flooding due to increased surface runoff in paved urban areas, and increased water pollution from point and non-point sources, such as new industries waste facilities. When considering outdoor recreation, the loss of natural landscapes may decrease tourism income associated with water-dependent natural ecosystems [49].

This change in LULC raises some critical questions that need an answer, such as what is the extent of LULC change in this region? What is the change limit for cities such as El Paso and Ciudad Juarez? How does this change affect sustainability and the region's future? Do we need to stop this change, control it, or adapt to the new situation? What are the implications of the change?

3.5. Conclusion

Remote sensing and geographic information systems technologies across boundary tools for cooperation and research were used to visualize, measure, and assess LULC change in the MRGR, a dryland environment in the USA and Mexico borderlands. This region faces significant natural consequences associated with LULC change from one type to another, especially in relation to sustainable water management.

The results from the study showed many changes in LULC. For instance, the developed area across the area of interest increased by 45 percent in 21 years between 1994-2015, and the most growth occurred around the metropolitan areas of cities El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). Surface water decreased by more than 55 percent in the period 1994-2015. The dominant shrublands in the area of interest have changed and have lost areas and parts to the urban and agriculture and gained others from forests and a reduction in surface water cover.

This study's findings stand as an excellent view for visualizing and understanding spatial and temporal environmental change in this region and helping stakeholders on different levels and responsibilities to balance development requirements and protect dynamic ecosystems.

Future research is recommended on monitoring LULC change in the region on a macro scale that can cover the cities and the local areas to understand the effect of development on natural resources such as shrublands and forests. Conservation of environmental flows by controlling human actions that disrupt the resources. This study provides a detailed assessment of the driving forces behind the trends and patterns of LULC change.

The study's results reveal the requirement to change land use policies to include guidelines and regulations that can help maintain the resources, such as restricting water consumption and changing agriculture practices towards less water use produce.

Abbreviations and Acronyms

SR: Remote Sensing;
GIS: Geographic Information Systems;
LULC: Land Use / Land Cover;
MRGR: Middle Rio Grande Region;
FLAASH: Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes;
BOA: Bottom of Atmosphere;
NLCD: National Standard Land Cover Data Base;
USGS: U.S. Geological Survey;
TM: Thematic Mapper;
OLI: Operational Land Imager;
IARR: Internal Average Relative Reflectance;
QUAC: Quick Atmospheric Correction;
ATCOR: Atmospheric and Topographic Correction;
DOS: Dark Object Subtract;
MNF: Minimum Noise Fraction;
DN: Digital Numbers.

Acknowledgments

This study was made possible through support from the National Institute of Food and Agriculture, U.S. Department of Agriculture, under award number 2015-68007-23130. The opinions in this paper are those of the authors and do not necessarily reflect the USDA's views. The authors would like to acknowledge valuable comments and inputs from various collaborators on the USDA-NIFA project.

References

[1]. W. Hargrove, J. Heyman, A comprehensive process for stakeholder identification and engagement in addressing wicked water resources problems, *Land*, Vol. 9, Issue 4, 2020, 119.

[2]. K. Liu, X. Li, S. Wang, G. Zhou, Past and the future adverse response of terrestrial water storages to increased vegetation growth in drylands, *npj Climate and Atmospheric Science*, Vol. 6, Issue 1, 2023, 113.

[3]. A. M. El Kenawy, Hydroclimatic extremes in arid and semi-arid regions: status, challenges, and future outlook, in Hydroclimatic Extremes in the Middle East and North Africa, *Elsevier*, 2024, pp. 1-22.

[4]. P. H. Verburg, K. Neumann, L. Nol, Challenges in using land use and land cover data for global change studies, *Global Change Biology*, Vol. 17, Issue 2, 2011, pp. 974-989.

[5]. K. Biro, B. Pradhan, M. Buchroithner, F. Makeschin, Land use/land cover change analysis and its impact on soil properties in the northern part of Gadarif region, Sudan, *Land Degradation & Development*, Vol. 24, Issue 1, 2013, pp. 90-102.

[6]. N. N. Omoyo, J. Wakhungu, S. Oteng'i, Effects of climate variability on maize yield in the arid and semi-arid lands of lower eastern Kenya, *Agriculture & Food Security*, Vol. 4, Issue 1, 2015, 8.

[7]. J. Heo, J. Yu, J. R. Giardino, H. Cho, Water resources response to climate and land-cover changes in a semi-arid watershed, New Mexico, USA, TAO:

Terrestrial, *Atmospheric and Oceanic Sciences*, Vol. 26, Issue 4, 2015, 463.

[8]. L. Zhu, H. Gong, Z. Dai, T. Xu, X. Su, An integrated assessment of the impact of precipitation and groundwater on vegetation growth in arid and semiarid areas, *Environmental Earth Sciences*, Vol. 74, Issue 6, 2015, pp. 5009-5021.

[9]. C. Zhang, Y. Chen, D. Lu, detecting fractional land-cover change in arid and semiarid urban landscapes with multitemporal Landsat Thematic mapper imagery, *GIScience & Remote Sensing*, Vol. 52, Issue 6, 2015, pp. 700-722.

[10]. J. Yin, F. He, Y. J. Xiong, G. Y. Qiu, Effects of land use/land cover and climate changes on surface runoff in a semi-humid and semi-arid transition zone in Northwest China, *Hydrology and Earth System Sciences*, Vol. 21, Issue 1, 2017, pp. 183-196.

[11]. C. R. Randklev, T. Miller, M. Hart, J. Morton, N. A. Johnson, K. Skow, C. Robertson, A semi-arid river in distress: Contributing factors and recovery solutions for three imperiled freshwater mussels (Family Unionidae) endemic to the Rio Grande basin in North America, *Science of the Total Environment*, Vol. 631, 2018, pp. 733-744.

[12]. M. A. Abdel Rahman, An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications, *Rendiconti Lincei, Scienze Fisiche e Naturali,* Vol. 34, Issue 3, 2023, pp. 767-808.

[13]. N. Liliwirianis, N. N. M. Isa, M. N. Suratman, Land resources and its degradation in Asia: its control and management, in Land and Environmental Management through Forestry, *Wiley*, 2023, pp. 23-45.

[14]. A. O. Arowolo, A. K. Bhowmik, W. Qi, X. Deng, Comparison of spatial interpolation techniques to generate high□resolution climate surfaces for Nigeria, *International Journal of Climatology*, Vol. 37, 2017, pp. 179-192.

[15]. A. Halefom, A. Teshome, E. Sisay, I. Ahmad, Dynamics of land use and land cover change using remote sensing and GIS: a case study of Debre Tabor Town, South Gondar, Ethiopia, *Journal of Geographic Information System*, Vol. 10, Issue 02, 2018, 165.

[16]. M. A. Boggie, D. P. Collins, J. P. Donnelly, S. A. Carleton, Land use, anthropogenic disturbance, and riverine features drive patterns of habitat selection by a wintering waterbird in a semi-arid environment, *PloS One*, Vol. 13, Issue 11, 2018.

[17]. Q. Shen, Y. Ma, Did water diversion projects lead to sustainable ecological restoration in arid endorheic basins? lessons from long-term changes of multiple ecosystem indicators in the Lower Heihe River Basin, *Science of The Total Environment*, Vol. 701, 2020, 134785.

[18]. O. S. Belhaj, Land use/land cover change patterns and trends in two dryland regions, PhD Thesis, *The University of Texas at El Paso*, 2022.

[19]. C. Liping, S. Yujun, S. Saeed, Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques – A case study of a hilly area, Jiangle, China, *PloS One*, Vol. 13, Issue 7, 2018.

[20]. O. Stromann, A. Nascetti, O. Yousif, Y. Ban, Dimensionality reduction and feature selection for object-based land cover classification based on Sentinel-1 and Sentinel-2 time series using Google Earth Engine, *Remote Sensing*, Vol. 12, Issue 1, 2020, 76.

[21]. S. Merdas, N. Boulghobra, T. Mostephaoui, M. Belhamra, H. Fadlaoui, Assessing land use change and moving sand transport in the Western Hodna Basin (central Algerian steppe ecosystems), *Forestist*, Vol. 69, Issue 2, 2019, pp. 87-96.

[22]. V. R. Rajeswari, S. N. Reddy, Change detection analysis using landsat multi-temporal imagery and GIS techniques: a case study for Tirupati, South India, *Journal on Image Processing*, Vol. 6, Issue 2, 2019, 34.

[23]. J. Sun, S. Ongsomwang, Multitemporal land use and land cover classification from time-series landsat datasets using harmonic analysis with a minimum spectral distance algorithm, *ISPRS International Journal of Geo-Information*, Vol. 9, Issue 2, 2020, 67.

[24]. M. Dagnachew, A. Kebede, A. Moges, A. Abebe, Land use land cover changes and its drivers in Gojeb river catchment, Omo Gibe Basin, Ethiopia, *Journal of Agriculture and Environment for International Development (JAEID)*, Vol. 114, Issue 1, 2020, pp. 33-56.

[25]. R. Pacheco Quevedo, A. Velastegui-Montoya, N. Montalván-Burbano, F Morante-Carballo, O. Korup, C. Daleles Rennó, Land use and land cover as a conditioning factor in landslide susceptibility: a literature review, *Landslides*, Vol. 20, Issue 5, 2023, pp. 967-982.

[26]. P. H. Verburg, K. Neumann, L. Nol, Challenges in using land use and land cover data for global change studies, *Global Change Biology*, Vol. 17, Issue 2, 2011, pp. 974-989.

[27]. W. Tesfaye, E. Elias, B. Warkineh, M. Tekalign, G. Abebe, Modeling of land use and land cover changes using Google Earth engine and machine learning approach: implications for landscape management, *Environmental Systems Research*, Vol. 13, Issue 1, 2024, 31.

[28]. A. C. Guzha, M. C. Rufino, S. Okoth, S. Jacobs, R. L. B. Nóbrega, Impacts of land use and land cover change on surface runoff, discharge, and low flows: Evidence from East Africa, *Journal of Hydrology: Regional Studies*, Vol. 15, 2018, pp. 49-67.

[29]. K. Islam, M. Jashimuddin, B. Nath, T. K. Nath, Land use classification and change detection by using multi-temporal remotely sensed imagery: The case of Chunati wildlife sanctuary, Bangladesh, *The Egyptian Journal of Remote Sensing and Space Science*, Vol. 21, Issue 1, 2018, pp. 37-47.

[30]. O. S. Belhaj, S. T. Mubako, Land use land cover change and urban growth in Khoms District, Libya, 1976-2015, *International Journal of Applied Geospatial Research (IJAGR)*, Vol. 11, Issue 2, 2020, pp. 42-58.

[31]. S. Li, Y. Cao, J. Liu, S. Wang, Simulating land use change for sustainable land management in China's coal resource-based cities under different scenarios, *Science of The Total Environment*, Vol. 916, 2024, 170126.

[32]. A. O. Arowolo, A. K. Bhowmik, W. Qi, X. Deng, Comparison of spatial interpolation techniques to generate high-resolution climate surfaces for Nigeria, International Journal of Climatology, Vol. 37, 2017, pp. 179-192.

[33]. P. K. Langat, L. Kumar, R. Koech, M. K. Ghosh, Monitoring of land use/land-cover dynamics using remote sensing: a case of Tana River Basin, Kenya, *Geocarto International*, Vol. 36, Issue 13, 2019, pp. 1470-1488.

[34]. M. Fushimi, G. N. de Lima, V. Capoane, Changes in land use and cover and their environmental impacts in the Cerrado of Mato Grosso Do Sul, Brazil, *Sustainability*, Vol. 16, Issue 10, 2024, 4266.

[35]. B. T. Edosa, M. D. Nagasa, Spatiotemporal assessment of land use land cover change, driving forces, and consequences using geospatial techniques: The case of Naqamte city and hinterland, Western Ethiopia, *Environmental Challenges*, Vol. 14, 2024, 100830.

[36]. B. A. Miheretu, A. A. Yimer, Land use/land cover changes and their environmental implications in the Gelana sub-watershed of Northern Highlands of Ethiopia, *Environmental Systems Research*, Vol. 6, Issue 1, 2018, 7.

[37]. A. T. Testfaw, A. Pfaff, R. E. G. Kroner, S. Qin, R. Medeiros, M. B. Mascia, Land-use and land-cover change shape the sustainability and impacts of protected areas, *Proceedings of the National Academy of Sciences*, Vol. 115, Issue 9, 2018, pp. 2084-2089.

[38]. M. S. Khan, S. Ullah, T. Sun, A. U. Rehman, L. Chen, Land-use/land-cover changes and its contribution to urban heat island: a case study of Islamabad, Pakistan, *Sustainability*, Vol. 12, Issue 9, 2020, 3861.

[39]. Y. A. Bununu, A. Bello, A. Ahmed, Land cover, land use, climate change and food security, *Sustainable Earth Reviews*, Vol. 6, Issue 1, 2023, 16.

[40]. K. Ashwini, B. S. Sil, A. A. Kafy, H. A. Altuwaijri, H. Nath, Z. A. Rahaman, Harnessing machine learning algorithms to model the association between land use/land cover change and heatwave dynamics for enhanced environmental management, *Land*, Vol. 13, Issue 8, 2024, 1273.

[41]. B. Abbasnezhad, J. B. Abrams, S. J. Wenger, The Impact of Projected Land Use Changes on the availability of ecosystem services in the Upper Flint River Watershed, USA, *Land*, Vol. 13, Issue 6, 2024, 893.

[42]. P. C. Pandey, N. Koutsias, G. P. Petropoulos, P. K. Srivastava, E. Ben Dor, Land use/land cover in view of earth observation: data sources, input dimensions, and classifiers – a review of the state of the art, *Geocarto International*, Vol. 36, Issue 9, 2019, pp. 957-988.

[43]. O. Belhaj, S. Mubako, R. Aldouri, C. Tweedie, W. Hargeove, A. Mayer, E. Hadia, measuring land use/land cover change in the Middle Rio Grande Region, USA-Mexico using remote sensing and geographic information systems, *Sensors and Electronic Instrumentation Advances*, Vol. 162, 2024.

[44]. N. Abid, M. Eman, G. Kovács, F. Shafait, M. Liwicki, Multi-UCL: multi-class unsupervised curriculum learning for image scene classification case study: earth observation, *TechRxiv*, September 06, 2024.

[45]. A. Butt, R. Shabbir, S. S. Ahmad, N. Aziz, Land use change mapping and analysis using remote sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan, *The Egyptian Journal of Remote Sensing and Space Science*, Vol. 18, Issue 2, 2015, pp. 251-259.

[46]. N. A. Kadhim, A. K. Hussein, A. S. Jaber, A. A. Abojassim, Land use and land cover change detection using satellite images for the Kufa District, Najaf, Iraq, *Journal of XI an University of Architecture & Technology*, Vol. 12, Issue 3, 2020, 3632.

[47]. G. A. Afuye, L. Nduku, A. M. Kalumba, C. A. G. Santos, I. R. Orimoloye, V. N. Ojeh, P. Sibandze, Global trend assessment of land use and land cover changes: A systematic approach to future research development and planning, *Journal of King Saud University-Science*, Vol. 36, Issue 7, 2024, 103262.

[48]. Y. Chang, K. Hou, X. Li, Y. Zhang, P. Chen, Review of land use and land cover change research progress, *IOP Conference Series: Earth and Environmental Science*, Vol. 113, Issue 1, 2018, 012087.

[49]. S. Mubako, O. Belhaj, J. Heyman, W. Hargrove, C. Reyes, Monitoring of land use/land-cover changes in the arid transboundary Middle Rio Grande Basin using remote sensing, *Remote Sensing*, Vol. 10, Issue 12, 2018, 2005.

[50]. F. A. Ward, J. F. Booker, A. M. Michelsen, Integrated economic, hydrologic, and institutional analysis of policy responses to mitigate drought impacts in Rio Grande Basin, *Journal of Water Resources Planning and Management*, Vol. 132, Issue 6, 2006, pp. 488-502.

[51]. Z. Sheng, Impacts of groundwater pumping and climate variability on groundwater availability in the Rio Grande Basin, *Ecosphere*, Vol. 4, Issue 1, 2013, 5.

[52]. O. Olofinsao, J. Wang, R. P. Berrens, Reuse of treated municipal wastewater in drylands: multi-sector optimization analysis for Middle Rio Grande case study, https://papers.ssrn.com/sol3/Delivery.cfm/4932099.pdf?abstractid=4932099&mirid=1

[53]. W. L. Hargrove, J. M. Heyman, A. Mayer, A. Mirchi, A. Granados-Olivas, G. Ganjegunte, D. Gutzler, The future of water in a desert river basin facing climate change and competing demands: A holistic approach to water sustainability in arid and semi-arid regions, *Journal of Hydrology: Regional Studies*, Vol. 46, 2023, 101336.

[54]. L. F. Nava, C. Brown, K. Demeter, F. Lasserre, M. Milanés-Murcia, S. Mumme, S. Sandoval-Solis, Existing opportunities to adapt the Rio Grande/Bravo Basin water resources allocation framework, *Water*, Vol. 8, Issue 7, 2016, 291.

[55]. A. Szynkiewicz, D. M. Borrok, G. K. Ganjegunte, G. Skrzypek, L. Ma, M. S. Rearick, G. B. Perkins, Isotopic studies of the Upper and Middle Rio Grande, Part 2 – Salt loads and human impacts in South New Mexico and West Texas, *Chemical Geology*, Vol. 411, 2015, pp. 336-350.

[56]. H. D. A. Sanchez, Determining sources of nitrate in the semi-arid Rio Grande using nitrogen and oxygen isotopes, MD Thesis, *University of Tennessee*, 2017.

[57]. C. R. Randklev, T. Miller, M. Hart, J. Morton, N. A. Johnson, K. Skow, C. Robertson, A semi-arid river in distress: Contributing factors and recovery solutions for three imperiled freshwater mussels (Family Unionidae) endemic to the Rio Grande basin in North America, *Science of the Total Environment*, Vol. 631, 2018, pp. 733-744.

[58]. C. Cox, L. Jin, G. Ganjegunte, D. Borrok, V. Lougheed, L. Ma, Soil quality changes due to flood irrigation in agricultural fields along the Rio Grande in western Texas, Applied Geochemistry, Vol. 90, 2018, pp. 87-100.

[59]. Landsat – Earth Observation Satellites, Ver. 1.2, April 2020, Fact Sheet, *U.S. Geological Survey*, 2016.

[60]. O. S. Belhaj, S. T. Mubako, R. E. Aldouri, C. E. Tweedie, W. L. Hargrove, E. A. Hadia, Determination of change in surface waterbodies in the middle Rio Grande basin by modified normalized difference water index (MNDWI) 1994-2020, *Journal of Eco. & Enviro. Sci. and Tech.*, Vol. 4, Issue 2, 2022, pp. 67-80.

[61]. D. G. Dye, B. R. Middleton, J. M. Vogel, Z. Wu, M. Velasco, Exploiting differential vegetation

Phenology for satellite-based mapping of semiarid grass vegetation in the Southwestern United States and Northern Mexico, *Remote Sensing*, Vol. 8, Issue 11, 2016, 889.

[62]. N. Aboagye, Twenty-five years (1995-2020) of land cover changes in the Northern Rio Grande Corridor, New Mexico, MD Thesis, *New Mexico State University*, 2024.

[63]. M. V. Kumar, K. Yarrakula, Comparison of efficient techniques of hyper-spectral image preprocessing for mineralogy and vegetation studies, *Indian Journal of Geo-Marine Sciences*, Vol. 46, 2017, May 2017, pp. 1008-1021.

[64]. M. Chakouri, R. Lhissou, A. El Harti, S. Maimouni, Z. Adiri, Assessment of the image-based atmospheric correction of multispectral satellite images for geological mapping in arid and semi-arid regions, *Remote Sensing Applications: Society and Environment*, Vol. 20, 2020, 100420.

[65]. P. Mruthyunjaya, A. Shetty, P. Umesh, C. Gomez, Impact of atmospheric correction methods parametrization on soil organic carbon estimation based on Hyperion hyperspectral data, *Remote Sensing*, Vol. 14, Issue 20, 2022, 5117.

[66]. L. K. Sharma, R. K. Verma, AVIRIS-NG hyperspectral data analysis for pre-and post-MNF transformation using per-pixel classification algorithms, *Geocarto International*, Vol. 37, Issue 7, 2022, pp. 2083-2094.

[67]. B. Liu, Y. Li, P. Chen, X. Zhu, Extraction of oil spill information using decision tree based minimum noise fraction transform, *Journal of the Indian Society of Remote Sensing*, Vol. 44, Issue 3, 2016, pp. 421-426.

[68]. H. Wang, G. Yu, J. Cheng, Z. Zhang, X. Wang, Y. Xu, Fast hyperspectral image classification with strong noise robustness based on minimum noise fraction, *Remote Sensing*, Vol. 16, Issue 20, 2024, 3782.

[69]. J. Aguirre-Gutiérrez, A. C. Seijmonsbergen, J. F. Duivenvoorden, optimizing land cover classification accuracy for change detection, a combined pixel-based and object-based approach in a mountainous area in Mexico, *Applied Geography*, Vol. 34, 2012, pp. 29-37.

[70]. Y. Chen, Y. N. Zhou, Y. Ge, R. An, Y. Chen, Enhancing land cover mapping through integration of pixel-based and object-based classifications from remotely sensed imagery, *Remote Sensing*, Vol. 10, Issue 1, 2018, 77.

[71]. C. Cleve, M. Kelly, F. R. Kearns, M. Moritz, Classification of the wildland-urban interface: A comparison of pixel-and object-based classifications using high-resolution aerial photography, *Computers, Environment and Urban Systems*, Vol. 32, Issue 4, 2008, pp. 317-326.

[72]. P. Corcoran, A. Winstanley, Using texture to tackle the scale problem in land-cover classification, in Object-Based Image Analysis, *Springer*, Berlin, Heidelberg, 2008, pp. 113-132.

[73]. F. Hájek, Process-based approach to automated classification of forest structures using medium format digital aerial photos and ancillary GIS information, *European Journal of Forest Research*, Vol. 127, Issue 2, 2008, pp. 115-124.

[74]. H. Costa, G. M. Foody, D. S. Boyd, Supervised methods of image segmentation accuracy assessment in land cover mapping, *Remote Sensing of Environment*, Vol. 205, 2018, pp. 338-351.

[75]. H. Lu, L. Ma, X. Fu, C. Liu, Z. Wang, M. Tang, N. Li, Landslides information extraction using object-oriented image analysis paradigm based on deep learning and transfer learning, *Remote Sensing*, Vol. 12, Issue 5, 2020, 752.

[76]. D. K. Behera, G. S. Pujar, R. Kumar, S. K. Singh, A comprehensive approach towards enhancing land use land cover classification through machine learning and object-based image analysis, *Journal of the Indian Society of Remote Sensing*, 2024.

[77]. G. Shivakanth, P. S. Tanwar, Review on conventional and advanced classification approaches in remote sensing image processing, *Int. J. Comput. Sci. Eng.*, Vol. 6, 2018, pp. 871-879.

[78]. D. Flanders, M. Hall-Beyer, J. Pereverzoff, Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Canadian Journal of Remote Sensing*, Vol. 29, Issue 4, 2003, pp. 441-452.

[79]. M. Gutierrez, E. Johnson, Temporal variations of natural soil salinity in an arid environment using satellite images, *Journal of South American Earth Sciences*, Vol. 30, Issue 1, 2010, pp. 46-57.

[80]. J. S. Rawat, V. Biswas, M. Kumar, Changes in land use/cover using geospatial techniques: A case study of Ramnagar town area, district Nainital, Uttarakhand, India, *The Egyptian Journal of Remote Sensing and Space Science*, Vol. 16, Issue 1, 2013, pp. 111-117.

[81]. C. E. Churches, P. J. Wampler, W. Sun, A. J. Smith, Evaluation of forest cover estimates for Haiti using supervised classification of Landsat data, *International Journal of Applied Earth Observation and Geoinformation*, Vol. 30, 2014, pp. 203-216.

[82]. M. S. Boori, V. Voženílek, K. Choudhary, Land use/cover disturbance due to tourism in Jeseníky Mountain, Czech Republic: A remote sensing and GIS-based approach, *The Egyptian Journal of Remote Sensing and Space Science*, Vol. 18, Issue 1, 2015, pp. 17-26.

[83]. J. S. Rawat, M. Kumar, Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, District Almora, Uttarakhand, India, *The Egyptian Journal of Remote Sensing and Space Science*, Vol. 18, Issue 1, 2015, pp. 77-84.

[84]. J. R. Jensen, Introductory Digital Image Processing: A Remote Sensing Perspective, 2005, *Prentice-Hall Inc*., 2005.

[85]. J. B. Campbell, R. H. Wynne, Introduction to Remote Sensing, *Guilford Press*, 2011.

[86]. J. Gao, Y. Liu, Determination of land degradation causes in Tongyu County, Northeast China via land cover change detection, *International Journal of Applied Earth Observation and Geoinformation*, Vol. 12, Issue 1, 2010, pp. 9-16.

[87]. K. Keranen, R. Kolvoord, Making Spatial Decisions Using GIS and Remote Sensing: A Workbook, *Esri Press*, 2014.

[88]. US Forest Service, Red Canyon Fire, The Magdalena Ranger District, https://www.fs.usda.gov/publications?forestgrassland=10230&publication_topic=All&topic=All&year=all

[89]. New Mexico Fire Information, The Magdalena Ganger District Fires. Silver Fire, San Mateo Mountains. https://nmfireinfo.com/

[90]. A. Tilahun, B. Teferie, Accuracy assessment of land use land cover classification using Google Earth, *American Journal of Environmental Protection*, Vol. 4, Issue 4, 2015, pp. 193-198.

[91]. J. D. Wickham, S. V. Stehman, L. Gass, J. Dewitz, J. A. Fry, T. G. Wade, Accuracy assessment of NLCD

2006 land cover and impervious surface, *Remote Sensing of Environment*, Vol. 130, 2013, pp. 294-304.
[92]. R. Martin, L. Brabyn, C. Beard, Effects of class granularity and cofactors on the performance of unsupervised classification of wetlands using multi-spectral aerial photography, *Journal of Spatial Science*, Vol. 59, Issue 2, 2014, pp. 269-282.
[93]. A. Ishtiaque, M. Shrestha, N. Chhetri, Rapid urban growth in the Kathmandu Valley, Nepal: Monitoring land use land cover dynamics of a Himalayan city with landsat imageries, *Environments*, Vol. 4, Issue 4, 2017, 72.
[94]. B. Mazloum, S. Pourmanafi, A. Soffianian, A. Salmanmahiny, A. V. Prishchepov, The fate of rangelands: Revealing past and predicting future land-cover transitions from 1985 to 2036 in the drylands of Central Iran, *Land Degradation & Development*, Vol. 32, Issue 14, 2021, pp. 4004-4017.
[95]. F. O. Akinyemi, G. Mashame, Analysis of land change in the dryland agricultural landscapes of eastern Botswana, *Land Use Policy*, Vol. 76, 2018, pp. 798-811.
[96]. M. Timm Hoffman, A. Skowno, W. Bell, S. Mashele, Long-term changes in land use, land cover and vegetation in the Karoo drylands of South Africa: implications for degradation monitoring, *African Journal of Range & Forage Science*, Vol. 35, Issues 3-4, 2018, pp. 209-221.
[97]. A. V. Vaisvil, Natal source and the influence of environmental stressors on the timing and persistence of largemouth bass reproduction in Elephant Butte Reservoir, PhD Thesis, *New Mexico State University*, 2019.
[98]. N. T. Townsend, Evaluating Future Reservoir Storage in the Rio Grande Using Normalized Climate Projections and A Water Balance Model, University of New Mexico UNM Digital Repository, Earth and Planetary Sciences ETDs, https://digitalrepository.unm.edu/eps_etds/259

___