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Classification of Agricultural Land Use in the Chittoor Region of Andhra Pradesh

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Abstract - *Land use classification is an essential process for assessing massive transformations at various topographical and spatio-temporal dimensions. Human impacts are the source of this extensive, fast-moving, and substantial process, and in numerous instances, they also result in alterations that directly impact people. Because of the potential for wide-ranging implications for the environment, land categorization research has arisen as an important area of investigation. Currently, no research has been done to classify farmland from a non-agricultural area and its influence on the local ecological system. Thus, the current research emphasizes on the Chittoor Region in Andhra Pradesh to look at the larger-scale change in land use that has happened over the past several years. In order to analyze satellite images and examine statistical data for this research's evaluation of land use changes, we utilized ERDAS Imagine v14. With advanced Machine Learning techniques, over 94% classification accuracy is obtained. The findings of this research will be useful in the planning and execution of crucial regulatory decisions that will be made in order to preserve the agricultural land in the delta area.*

Keywords - ERDAS, Image Processing, Landsat, Machine Learning, Supervised Classification

1 Introduction

From the middle of the 1990s, there have been noticeable shifts in the proportion of irrigated land that is supplied by surface water as opposed to groundwater. The surface irrigated area decreased by around 1 lakh hectares with canal irrigation and 3 lakh hectares with tank irrigation. A decrease was also seen in the amount of land that was occupied by subsurface water sources [1]. Although there is no definitive date to show well performance and functionality, numerous investigations at the micro level have shown that an increasing number of wells are drying up and becoming inoperable. This was due to the monsoon's failure and the unsustainable expansion in groundwater extraction. Andhra Pradesh is still heavily reliant on irrigation for farming, but the state government has not increased spending on irrigation and has instead neglected the region's surface irrigation systems [2]. As a result, the number of private companies actively seeking to tap into underground water supplies has grown.

There are 10, 39,081 individuals working in agriculture in the Chittoor district, and there are 4, 40,064 agricultural holdings total. This means that there are, on average, two people living on each agricultural holding. Geographically, however, the number of working workers in each agricultural property varies very slightly, from around 2 to about 5 people.

Madanapalle has the most agricultural holdings in terms of population, with three people per agricultural holding, followed by Chittoor and Tirupati revenue divisions (2 persons per holding). The smaller number of agricultural holdings in Madanapalle division allows for larger land holdings there compared to the other two divisions in the district [3-8]. There are more farmers in the areas of Irala, Nimmanapalle, and B.Kothakota, with an average of four people per property. Most of these mandals can be found in the western part of the municipality. The larger size of holdings in this case in terms of the proportion of the population employed in agriculture is due to the relatively low density of agricultural holdings. Twenty mandals have landholdings with an average size of three individuals, or more, who work the land [10]. These mandals can be found predominantly in the south-east and north-west regions of the district. Holdings in the south and east are typically of a

moderate size because of the large number of farmers in the area.

The location of study, the Chittoor district, is well-known for agricultural operation in all cardinal directions. The district has a total of 4, 40,448 hectares of gross cropped land, according to statistics from 2009-2010. In addition to important crops including cereals, major millets, pulses, condiments, spices, sugarcane, fresh and dry fruits and vegetables, tobacco and cotton are also grown in the region, albeit on a smaller scale [11]. There are 66 revenue mandals spread among the district's three administrative revenue divisions. According to maps, more farmland can be found in the Madanapalli administrative region. In contrast, cropland is sparsest in the Tirupati administrative division. The eastern mandals of the Tirupati division, on the other hand, have a high rate of productivity and output since they are situated in places that receive a lot of rain, have rich soil, and a plentiful supply of subterranean water [12]. The western Madanapalli region, on the other hand, is in a rain-fed and frequently dry-spell-occurrence area.

The third division, Chittoor, is in the middle and receives heavy rainfall. The rugged, rocky west contrasts with the pleasant eastern plain. Madanapalli is recognised for its dry crops, Tirupati for its rice, sugarcane, groundnut, and vegetables, and Chittoor for its mango, sugarcane, vegetables, and other fruits. Peddamandyam's 21.88 percent of cropland grows food is the lowest. All three of these mandals—Tottambedu, Varadaipalem, Satyavedu, and Karvetinagaram—are in the Tirupati divisions in the eastern part of the district, where there is a greater concentration on food crops, especially cereals, millets, and vegetables, and favorable conditions like sufficient rainfall and more ground water resources. Due to its steep location and limited rainfall, Madanapalli division's Peddamandyam has a modest food crop area.

2 Agriculture land usage in Chittoor

When we talk about land, we're talking about everything above and below the surface of the earth, including the air, the soil, the geology, the hydrology, and the vegetation. Included in this is everything that has ever been or will ever be done by humans. One of the most important resources for manufacturing is land. Quantitative and qualitative factors are both studied in the process of land evaluation. It's been said that water is "the liquid gold" necessary for life on Earth. The country is vulnerable to both floods and droughts. A natural rule upon which to base a water policy is one way out of this mess. Conflicts have always arisen when states in different river basins try to divide up the river's water. Nonetheless, the water resources are distributed proportionally among the states that make up a certain river basin. The evaluation and development of water resources is the focus of numerous government agencies, academic institutions, and non-profits, including the Central Ground Water Development, Central Water and Power Commission, Indian Meteorological Department, Geological Survey of India, Exploratory Tube Well Organization, National Geophysical Research Institute, Atomic Energy Commission, State Ground Water Departments, and the Geology, Hydro-geology, Hydrology, and Geophysics departments of various universities and research institutions. Under rain fed conditions, the soil moisture is a crucial factor in determining crop growth in varying soil types and climate zones. If you want to recommend a cropping plan that works with the climate and soil in your area, you need to know exactly how much water is available on which days of the year. The way in which land in a region is used results from a complex web of environmental, economic, social, and historical influences. The concept of land use in a region is multifaceted and ever-evolving.

Today's metropolitan areas are concerned about natural and human-induced environmental changes because they degrade the environment and human health. Resource management and strategic planning require LU/LC analysis [13]. For multicomplex environmental research [3], we need modern technology like satellite remote sensing and Geographical Information Systems in addition to traditional methods like collecting and analyzing demographic data, conducting censuses, and analyzing environmental samples (GISs). These tools collect information useful for researching and tracking the state of our planet's natural resources so that we can better manage them [14].

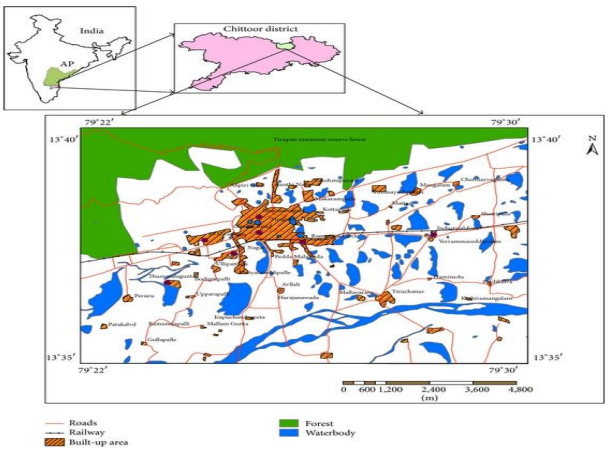

Fig. 1 Satellite image Chittoor district

In recent years, remote sensing has emerged as a powerful tool for expanding our knowledge of the global physical processes that shape our planet [15]. Using GIS in tandem with the ever-increasing amounts of geographical data accessible has become a recent trend in the interpretation of satellite data [16]. The goal of a Geographic Information System (GIS) is to facilitate development-oriented management and decision-making by collecting, storing, accessing, manipulating, analyzing, and displaying geographically referenced (spatial) information. The domains of agriculture, environmental studies, and integrated eco-environmental evaluation are only a few of the many places where remote sensing and GIS have been put to use. There have been a number of studies done on LU/LC because of the negative effects they have on the local ecosystem and vegetation [16].

Urbanization, industrialization, and population growth have all increased dramatically in the current study area during the previous few decades. This paper's primary focus is on developing methods for identifying and measuring LU/LC in a metropolitan setting.

3 Agriculture land usage in Chittoor

The spatial analysis of the LULC map shows that

the built-up region, as well as rivers and marsh, are more prominent and clear in the findings of SVM and random forest classifiers than those of SAM. When compared to the results of the fuzzy ARTMAP and the Mahalanobis distance classifiers, however, the output of ANN gives more weight to agricultural land and fallow land. The plant layer and sand bar are uniformly classified, according to all classifiers. Their classification performance in RF and SVM is really high (Figure 3). Overall, the SVM and fuzzy ARTMAP approaches classified the most built-up terrain, whereas the SAM and random forest methods classified the least built-up territory [17]. By contrast, the SAM classifier discovers the greatest vegetation coverage, followed by the RF and SVM classifiers, and finally the ANN classifier discovers the least vegetation coverage. All classifiers almost uniformly divide river, wetland, and sand bar coverage.

The coefficient of variation (CV) and standard deviation (SD) of the percentage of land area assigned to a single LULC class by several classifiers were calculated. The percent accuracy achieved by each classifier as measured by its Kappa coefficient (K). The RF classifier was found to be the most accurate LULC model with a value of 0.89. Very good to exceptional agreement can be shown between the categorized LULC map and the real world in the RF, ANN, and SVM models. While all of the models have value, the RF method stands out as the most promising LULC classifier [18]. The user accuracy of the RF and ANN algorithms was higher than that of the other algorithms for classifying agricultural land, river, and wetland areas (94% and 92%, respectively). Also, similar to the RF, fuzzy ARTmap, and ANN classes, most of the LULC classes were successfully classified. Area under the curve (AUC) and root mean square error (RMSE) values calculated.

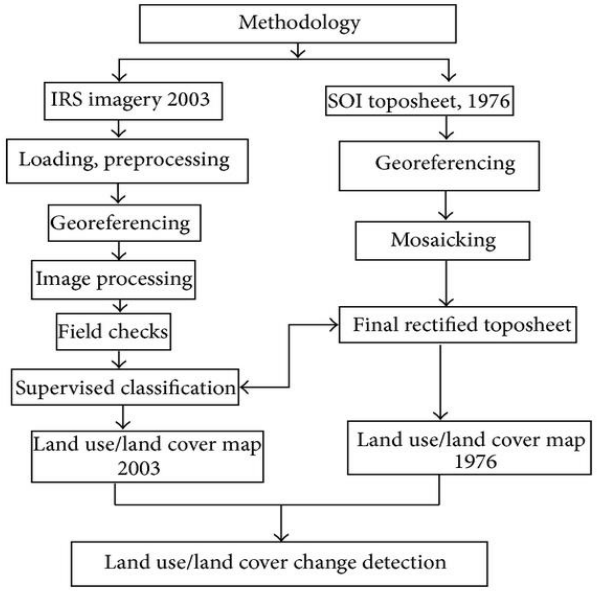

Fig. 2 Flowchart for the classification of agriculture land using machine learning

For land use/land cover mapping in 2019, a supervised signature extraction with the maximum probability technique was applied to IRS 1D georeferenced and merged LISS III and PAN digital data. A thorough field survey was performed with Global Positioning System (GPS) equipment across the whole study area prior to beginning the preprocessing and categorization of satellite photos. This study was conducted to generate training sites and signatures and to gather accurate locational point data for each land use and land cover class in the classification system.

Prior to classification, the satellite data was altered with histogram equalization in ERDAS Imagine 8.7 to boost image quality and achieve increased classification accuracy. To generate spectral fingerprints, supervised classification uses manually annotated image regions. The user is in charge of specifying the actual locations that will be used for the training. Digitally, a vector layer is usually added on top of the raster scene. Many kinds of land cover are represented by polygons in the vector layer. With the aid of the training grounds, spectral signatures for the designated regions can be developed.

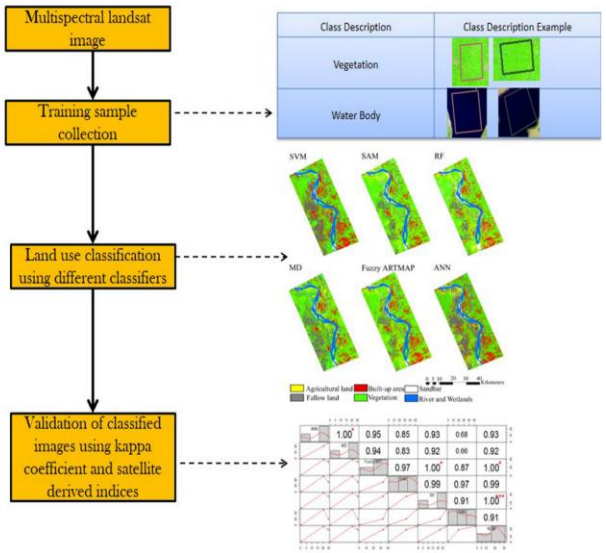

Fig. 3 Classification of agricultural land

Post-classification analysis based on a comparison of land use maps from two time periods allowed for a more accurate estimation of the magnitude and rate of change within each land use category. The most popular quantitative approach to change detection [15-17] with decent results is post classification comparison. The process of comparing two groups of classifications after the fact is sometimes called "delta classification" [18]. Pixel-by-pixel or segment-by-segment comparisons are made between two or more datasets to identify shifts in class membership. Figure 2 provides an in-depth explanation of the methods used.

Accuracy evaluation takes numerous forms, measuring things like mean accuracy, overall accuracy, errors included, and errors excluded. Accuracy is determined by applying decision tree categorization to the GIS data [19]. Based on the AR 3D data model, the satellite data is processed and trained.

4 Case study and discussion

From a high of 68.23 km2 in 1976, the area utilized for growing paddy and other food and vegetable crops, as well as mixed types like mango, coconuts, and other homestead trees, has steadily declined to a low of 21.45 km2 in 2003, a net loss of 46.78 km2. Most farmland in the area under consideration has been repurposed for residential and commercial use. There was a net loss of 2.18 square kilometers of water spread area between 1976 and 2003, from 12.09 square kilometers to 9.91 square kilometers due to the decline of both natural and artificial water features such rivers, streams, tanks, and reservoirs. Reduced water spread area is the result of decades of population growth, during which time much of the once-abundant land was developed into housing and other human uses. The total area of dense forest, defined as any area with a tree cover of 70% canopy density or above, has decreased dramatically, from 22.35 km2 in 1976 to 4.25 km2 in 2003, a net loss of 18.10 km2. Reasons for this include the elimination of forested regions in favour of urbanization and other forms of urbanization.

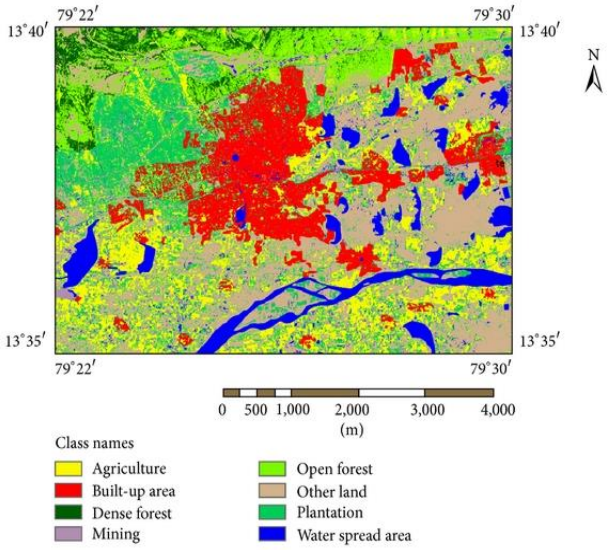

Fig. 4 Land use or land cover satellite image

The decline of biogeochemical cycles, the disappearance of once-thriving ecosystems, the decimation of once-vibrant biodiversity, the deterioration of environmental quality, the disappearance of once-productive agricultural lands, the destruction of once-thriving wetland ecosystems, and the loss of habitat for fish and wildlife all highlight the importance of understanding land use and land cover. Causes of LU/LC shifts include rapid population growth, rural-to-urban migration, reclassifying rural areas as urban areas, failing to place a value on ecological services, poverty, lack of knowledge about biophysical limitations, and the adoption of technologies that are not compatible with the environment.

What we call "land" is actually what makes up the planet's surface. There are two primary methods for acquiring information about land cover—field survey and analysis of remotely sensed imagery—and each category of land cover—grass, asphalt, trees, barren ground, water, etc.—is represented in the data. This type of information is useful for building land change models, which may be used to predict future land cover. In different parts of the world, people make vastly different kinds of use of the land. "Land use covers the products and benefits received from the usage of the land, as well as the land management actions carried out by humans to produce those products and benefits," said the Water Development Division of the United Nations Food and Agricultural Organization. Around 13% of the planet was used for agriculture in the early 1990s, compared to 26% for grazing, 32% for forests and woodland, and 1.5% for urban areas. Future changes in land use can be predicted and evaluated with the use of land change models (Figure 6).

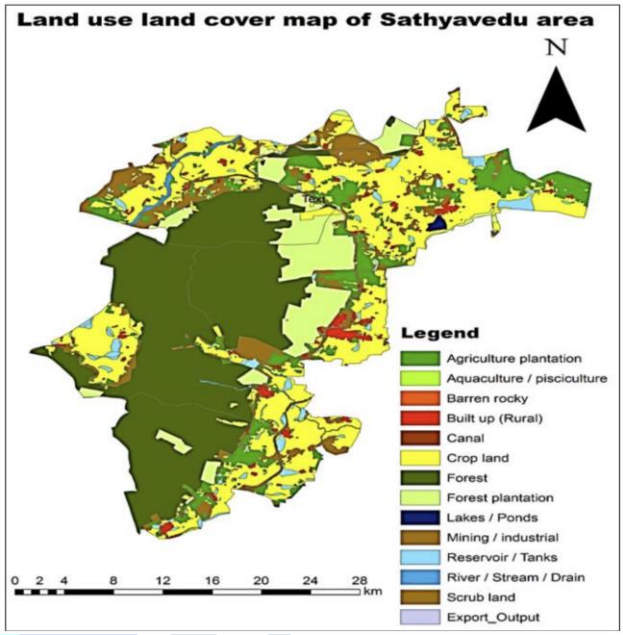

Fig. 5 Land use and land cover map

Land that is farmed and utilized to grow food, fibre, and other commercial and horticultural crops is called "agricultural land." Agricultural plantations, fisheries, and croplands are all part of this category. Cropland refers to arable land where crops can be grown. It accounts for roughly 28.9785% of the total area, or about 72.0078 km2. The majority of the world's arable land is devoted to crop production, including food, fibre, and industrial and ornamental plants. Included in this category are the various crops harvested during the Kharif and Rabi Zayd seasons. Pisciculture refers to the practice of artificially propagating fish populations by breeding, rearing, and transfer. Area under pisciculture is 0.03556 km2, or 0.14% of the total land area. Plantation refers to the land where trees are grown using specific agricultural management practices. The research region is primarily covered by plantations of mango and eucalyptus trees. In percentage terms, the agricultural plantation occupies 9.4036% of the overall land area, or 23.1099 km2.

5 Conclusion

Land resources, water balance elements, water availability days and calendar, soil moisture characteristics, land use and irrigation, cropping pattern, agriculture productivity, and agricultural development, as well as the relationship between water balance elements and cropped area and crop yield, were studied in the Chittoor district, which has an area of about, 15,152 sq. km.

This article uses GIS and remote sensing to examine LU/LC

shifts in the city of Tirupati, India. The results we present here demonstrate unequivocally the importance of LU/LC shifts between 1976 and 2003. Human settlements have grown noticeably in recent years. Conversely, the amount of land used for farming, water distribution, and forest cover has shrunk. This research unequivocally demonstrates the enormous effect that population and its development activities have on LU/LC shifts. This research shows that combining GIS with remote sensing technology makes for a powerful instrument in the service of urban planning and management. Environmental management organizations, policymakers, and the general public can all benefit from a more precise understanding of the LU/LC shifts in the Tirupati area. According to the land use/land cover analysis conducted, Altogether, forest covers 90.034 (36.3135) km2 of the area, with arable land covering only 72 km2. In this paper, we will discuss the land usage and irrigation practices of the Chittoor area. Net sown area made up 32.9% of the total land area in 1997–98, followed by forest area at 30%, barren land at 11.1%, land used for purposes other than agriculture at 9.3%, other fallows at 6.6%, culturable wastelands at 3.1%, permanent pastures at 2.7%, current fallows at 2.5 %, and miscellaneous trees and groves at 1.7%. For 1987–1988, the district as a whole had 24 mandals with inefficient land use of 40% or less. There are roughly 28 mandals that fall between 40% and 50%, and another 14 that are 50% or more. In 1997–98, it was estimated that 18 mandals had a land use efficiency of less than 40%, 32 mandals had a land use efficiency of 40% to 50%, and 16 mandals had a land use efficiency of 50% or more. Six mandals saw a drop in land use efficiency from 1987–1988 to 1997–1998; four mandals saw a rise, from 40% to 50%; and two mandals saw an increase from 50% and above.

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