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Landsat-8 vs. Sentinel-2: Landuse Landcover Change Analysis and Differences in Gudur Municipality

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Abstract: With the recent free availability of moderate to high spatial resolution data (10m-30m), land use analysis became more robust. The launch of Sentinel-2a by the European Space Agency, coupled with the availability of free Landsat data, availed more analysis capabilities for the science community with a wide variety of temporal, spatial, and spectral capabilities. This study compares the synergetic use of Landsat and Sentinel-2 in mapping Land Use Land cover themes in Gudur, explicitly utilizing the red edge band of Sentinel-2. A combination of both sentinel and Landsat data results in higher spatial resolution. Classification of the red edge band produces better resolution than the classification of Landsat Imagery.
Keywords: Sentinel-2, Landsat8, Landuse Land cover, Spectral Resolution, Spatial Resolution, Temporal Resolution ,LULC .

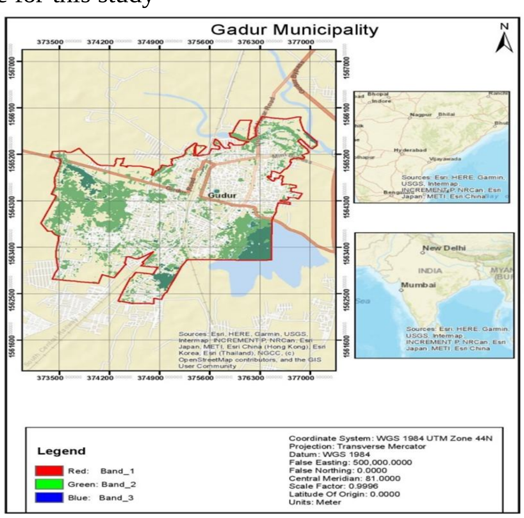
I. INTRODUCTION

Human activities are what have shaped the global LULC dynamics in the last decades of our existence. Many organizations employ the use of Land Use Land Cover for different purposes. Since the purpose and use vary, the availability of data and correct analysis of data are essential for accurate decision making. LULC maps are created from the classification of images obtained by satellites or by the use of aerial photography. Nature is dynamic, and an up to date data is required timely manner and analysis. Vegetation is a very significant part of any analysis, and good time-series information supports its accurate mapping. Besides, a mixed training data is quintessential in the provision. Besides, mixed training data facilitates the mapping of a larger are. The rapid population growth is essential in understanding the spatiotemporal pattern patterns in the global scale and the provision of climate change adaptability index. In the future, rural to urban migration is expected to be on the rise, with a total of 64% of the global population living in urban areas (UNDESA, 2018). The rural areas are characterized by low population, despite the low population in rural areas, most of the infrastructure developments are in the rural areas

II. MATERIALS AND METHODS

A. Study Site

The study was conducted in Gudur town in the state of Andhra Pradesh with a relatively high elevation ranging between 600-900m above the sea level. The study cited is an urban region with green parks at a swamp. The presence of both vegetation and urban impervious surface makes it a suitable site for this study



B. Permit

The data of the study area was accessed from the open-source USGS site, and hence there was no need to ask for permits

C. Data Acquisition and Preprocessing

The study site required six images, three from Landsat 8 OLI and the other three from the Sentinel-2A sensor. The images were downloaded from https://earthexplorer.usgs.gov/ (Accessed on 4 September 2020). In both studies, the images acquired were all radiometrically consistent. A description of the spectral band that consists of the study area is shown in the table below. Before using the images, they were atmospherically corrected.

Sentinel-2A was corrected using the sen2cor tool. Landsat 8 data is atmospherically corrected in a SNAP using the same tool. ENVI is used to correct Landsat data's atmospheric condition using the first line of sight Atmospheric Analysis of Hypercubes and the thermal atmospheric correction tool.

The algorithm minimizes atmospheric effects such as atmospheric haze and scattering, and therefore the reflectance is improved. There was no need for geometrically correcting Landsat and Sentinel images because they are provided for consumption already geometrically corrected.

D. Classification

In testing the hypothesis, the post-fire Sentinel2A image was classified by the random forest classifier (Cutler 2012) within the carpet package. The classification was performed using blue, green, red, red-edge, and the narrow infrared and the shortwave infrared spectral bands for the Sentinel 2A. For the Landsat imagery, the blue, green, and red bands and the short infrared. The water vapor panchromatic and coastal aerosols were secluded because of their irrelevance in the study of burnt area mapping. Point data obtained from the burnt area and the unburnt area were used in the training of the Random forest classification. The burnt areas were trained using the VIIR active fire data obtained from (VIIRS) downloaded from this link provided https://firms.modaps.eosdis.nasa.gov/ (accessed 24/07/2020). The data provided at a relatively low spatial resolution of 345m. The point data in the Image were converted to raster with a raster size of 375m; the output raster was https://firms.modaps.eosdis.nasa.gov/ the images are resampled to 20m and 30m to match the Sentinel and Landsat-8 imagery. The central coordinates. The unburnt regions were trained using the photo-interpreted regions from the post-fire Image. The training point for the burnt region was randomly selected.

To measure the accuracy of classification, the overall classification was measured using Cohen's Kappa and the True Skill Statistics. These measures have been applied in machine learning algorithms in measuring how machine learning is effective in discriminating different land use covers. The Kappa is calculated through bootstrapping the data at a minimum of 25 times. The TCC was calculated through the derivation from the contingency of the matrix table. The difference in the classification accuracy of the two sensors was obtained.

E. Variable Contribution

The node-impurity was measured by the Gini index is used to find the spectral band that contributes the most into the overall classification of both the Landsat and Sentinel. The applied metrics measure how significant is the variable to note homogeneity. The description of a spectral band with a high Gini index in the R environment is adopted and explained.

III. RESULTS AND ANALYSIS

A. Landsat

Landsat data, Thematic Mapper, or similar standard time-series datasets are applied for prediction, clustering, or classification purposes. Landsat data has been used for more than 18 years to analyze the bi-temporal changes in the datasets. The analysis is based on image processing where change detection for the datasets was obtained and the overall accuracy, which serves as a baseline for any image processing application which might need to perform time-series detection. This method can be further improved by using a machine learning or fuzzy logic rule engine. Still, the final evaluation will only be clear after the implementation of the suggested modifications.

While Landsat is one of the standard sets of imagery analysis in time series change detection for forest covers, another dataset, namely corona, is used by researchers to map change in forest cover in eastern U.S. and central Brazil. They have analyzed data from the mid-1960s to the 2000s for achieving the results. As per the claim, the second-order polynomial transformation on corona images resulted in good geometric accuracy as obtained by using Landsat-7 imagery. The following studies were consulted.

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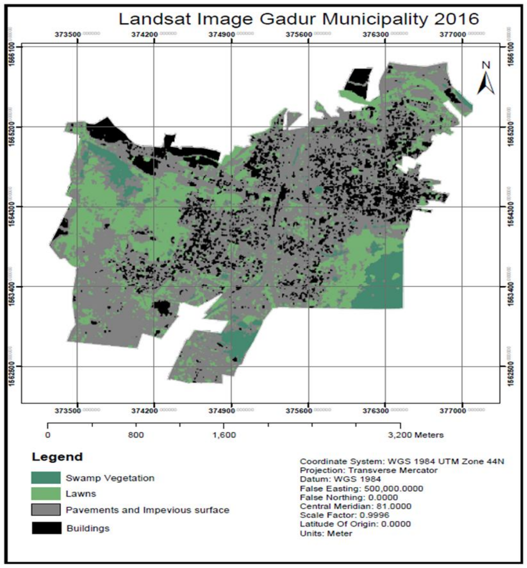
Time-series analysis of multi-resolution optical imagery for quantifying forest cover loss in Sumatra and Kalimantan, Indonesia.

1) 2016 Supervised Image

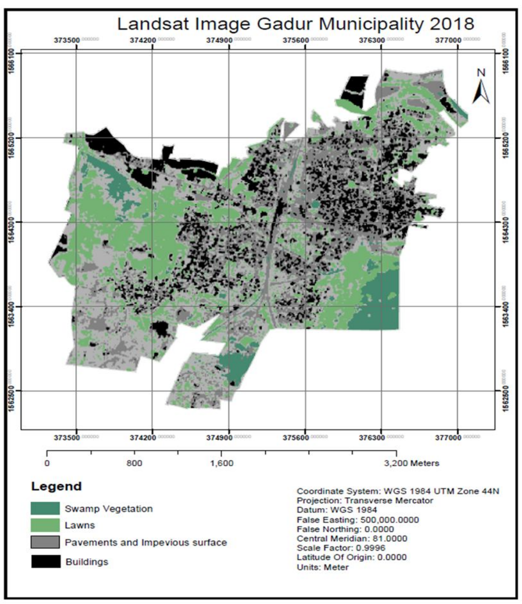


The Image was classified using the maximum likelihood algorithm, and the areas obtained as discussed below.

Zonal Area 2016

OBJECT ID	ZONE NAME	AREA	PERIMETER	THICKNESS	XCENTROID	YCENTROID	MAJORAXIS	MINORAXIS	ORIENTATION
1	Swamp Vegetation	24945745	822035	540.5754	305451.6	15320235	16156.78	4918.221	136.0812
2	Lawns	1088635	23761	195.87	279351.3	1568349	2834.182	1225.505	149.1432
3	Pavements	41173890	873592	854.567	278856.4	1567230	19318.45	6804.004	134.7658
4	Buildings	21491385	1626706	1575.95	2879573.9	1554677	52731.04	13003.9	133.9828

2) 2018 Landsat Classified Image



The classification criteria are the maximum likelihood, and the areas were computed as follows.

Zonal Areas 2018

OBJECT ID	ZONE NAME	AREA	PERIMETER	THICKNESS	XCENTROID	YCENTROID	MAJORAXIS	MINORAXIS	ORIENTATION
1	Swamp Vegetation	24945550	822138	540.5699	305531.1	1532085	16148.94	4917.118	137.0741
2	Lawns	1088640	23766	201.21	279301.2	1568379	2832.122	1223.552	152.8827
3	Pavements	41174240	873588	849.9298	278833.1	1567760	19278.04	6798.414	134.9058
4	Buildings	21491370	1626706	1550.25	287947.3	1554437	52704.88	12979.6	133.5828

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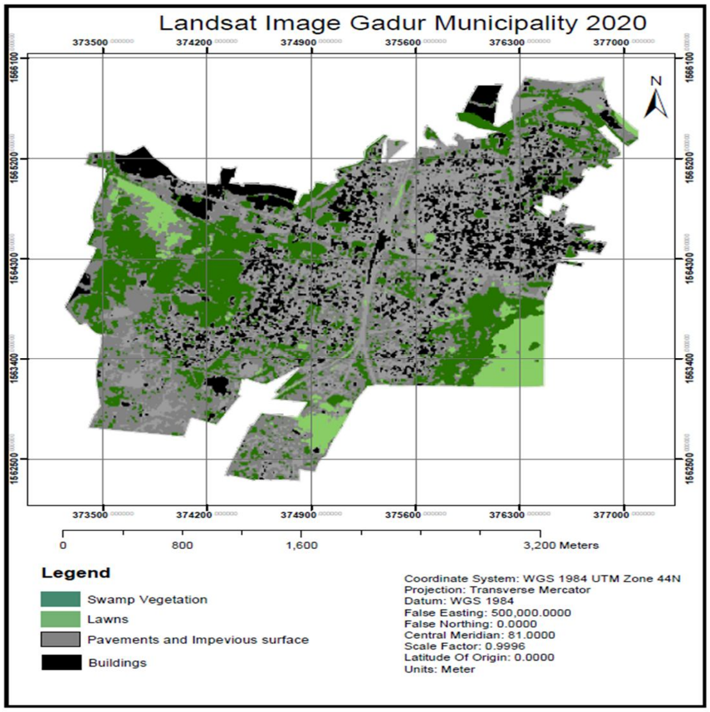
3) 2020 Landsat Classified Image



The zonal areas were obtained as follows, with an equal as presented in the figure below.

Zonal Areas 2020

OBJECT ID	ZONE NAME	AREA	PERIMETER	THICKNESS	XCENTROID	YCENTROID	MAJORAXIS	MINORAXIS	ORIENTATION
1	Swamp Vegetation	249460500	8220350	540.5754	305451.6	15320235	16156.78	4918.221	136.0812
2	Lawns	10886350	237610	195.87	279351.3	1568349	2834.182	1225.505	149.1432
3	Pavements	411738900	8735920	854.567	278856.4	1567230	19318.45	6804.004	134.7658
4	Buildings	214912800	16267060	1575.95	2879573.9	1554677	52731.04	13003.9	133.9828

B. Sentinel 2A

Sentinel land use/land cover database obtained from satellite imagery also has additional information Lands change analysis ' spatial structure. Serpil studied the role of vegetation in mitigating the Urban Heat Island phenomena use for

To analyze the impact of human infrastructure on biodiversity and UHI mitigation, current information about the quantities, qualities, and configuration of UGS is needed. The most recent data on land cover, including change detection, are available from Sentinel-2A (S2A), a high-resolution optical Earth observation mission developed within the Copernicus program (previously called GMES). The program is a joint initiative of the European Commission and European Space Agency to establish a European capacity for the provisioning and use of information for environmental monitoring and security applications. Fletcher (2012) provides an overview of this mission, including the technical concept, image quality, and operational applications. S2A multispectral imager is covering 13 spectral bands with a swath width of 290km and spatial resolutions of 10 m (three visible and a near-infrared band), 20 m (6 red-edge/shortwave infrared bands), and 60 m (3 atmospheric correction bands). The mission is intended to monitor variability in land surface conditions, and its full swath width and high revisit time (10 days with one satellite and five days with two satellites after Sentinel-2B is launched in 2016) will support the monitoring of changes to vegetation within the growing season. It also provides data and applications for operational land monitoring, emergency response, and security services. The coverage limits are between latitudes 56° south and 84° north. According to Drush et al. (2012), the mission the objective is to provide systematic multispectral imaging for land cover, land use, and land-use change detection maps of biogeophysical variables such as leaf chlorophyll content, leaf water content, leaf area index (LAI) risk mapping acquisition and rapid delivery of images to support disaster relief efforts.

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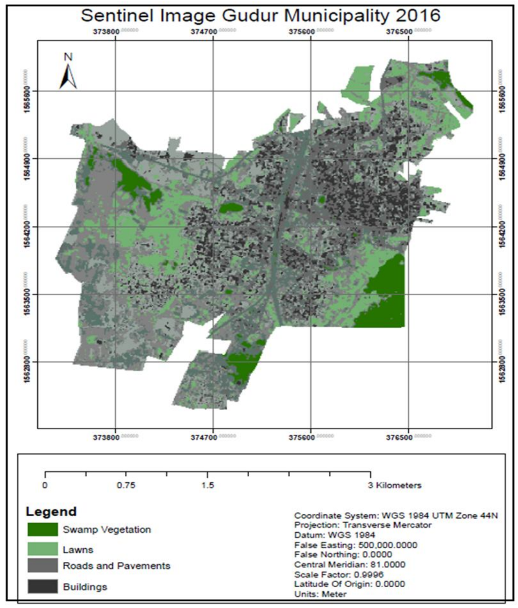
1) 2016 Sentinel-2A classified Image

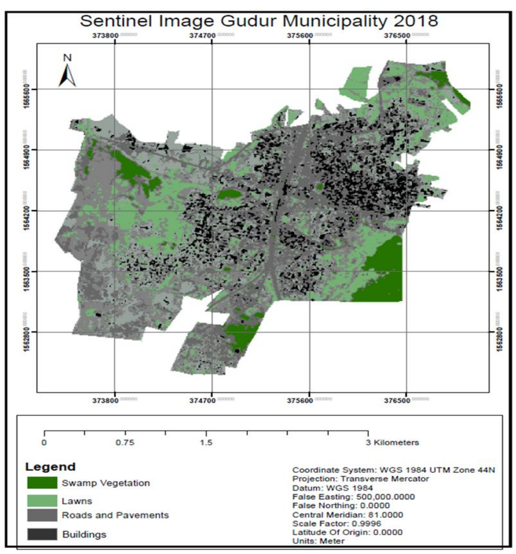


The areas of the respective themes were extracted and exported as an excel file. Sentinel Image differs from Landsat image, as evident from the areas extracted.

Zonal Area 2016

OBJECT ID	ZONE NAME	AREA	PERIMETER	THICKNESS	XCENTROID	YCENTROID	MAJORAXIS	MINORAXIS	ORIENTATION
1	Swamp Vegetation	24945734	822034	540.5754	305451.6	15320235	16156.78	4918.221	136.0812
2	Lawns	1088640	237613	195.87	279351.3	1568349	2834.182	1225.505	149.1432
3	Pavements	41173893	16267020	854.567	278856.4	1567230	19318.45	6804.004	134.7658
4	Buildings	21491389	1626704	1575.95	2879573.9	1554677	52731.04	13003.9	133.9828

2) 2018 Sentinel-2A Classified Image



The area extracted was presented as follows in the following spreadsheet below.

Zonal Areas 2018

OBJECT ID	ZONE NAME	AREA	PERIMETER	THICKNESS	XCENTROID	YCENTROID	MAJORAXIS	MINORAXIS	ORIENTATION
1	Swamp Vegetation	24945557	822138	540.5699	305531.1	1532085	16148.94	4917.118	137.0741
2	Lawns	1088649	237614	201.21	279301.2	1568379	2832.122	1223.552	152.8827
3	Pavements	41173839	873588	849.9298	278833.1	1567760	19278.04	6798.414	134.9058
4	Buildings	21491372	1626723	1550.25	287947.3	1554437	52704.88	12979.6	133.5828

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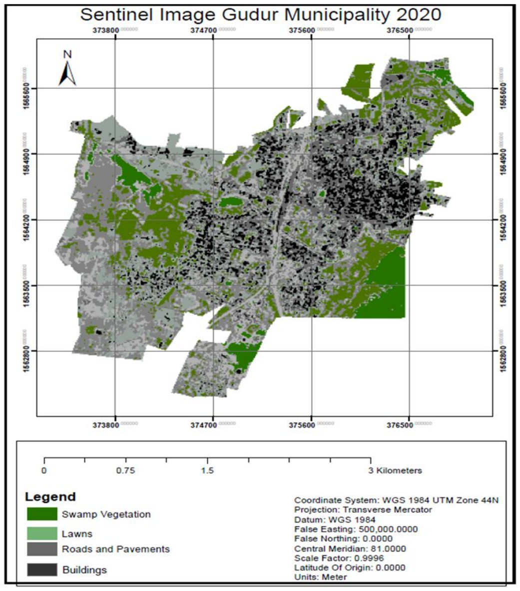
3) 2020 Sentinel-2A Classified Image



The areas are represented as follows.

Zonal Areas 2020

OBJECT ID	ZONE NAME	AREA	PERIMETER	THICKNESS	XCENTROID	YCENTROID	MAJORAXIS	MINORAXIS	ORIENTATION
1	Swamp Vegetation	24945850	822138	540.5699	305531.1	1532085	16148.94	4917.118	130.0781
2	Lawns	1088640	23766	201.21	279301.2	1568379	2832.122	1223.552	152.8827
3	Pavements	41173940	873588	849.9298	278833.1	1567760	19278.04	6798.414	135.3958
4	Buildings	21491370	1626702	1550.25	287947.3	1554437	52704.88	12979.6	133.5828

IV. CONCLUSION

In this study, we compared the performance of the Sentinel-2 MSI and Landsat 8 OLI sensors for detecting Urban Area growth and Urban Green Spaces in Gudur. The area-adjusted overall accuracy for both sensors was similar, with a slightly higher accuracy recorded for Sentinel-2. No large differences in terms of accuracy were found by adding three unlogged areas to the original seven study sites. We expected to find more substantial differences between the maps derived from Landsat 8 versus Sentinel-2 data, given the nature of the forest disturbances investigated. However, our results show similarities between the two sensors, both in terms of accuracy and urban infrastructure detectability using field data. This provides evidence of the potential for the interoperability of the two sensors' data in the context of forest canopy cover change. Moreover, it was shown that Landsat 8 maps larger areas containing forest disturbances, compared to Sentinel-2, both in the pixel-based and grid-based approaches, due to the lower spatial resolution. However, the two approaches deliver very different figures of Landsat overestimation, with the grid-based overestimation being much smaller than the pixel-based approach. The higher spatial resolution of Sentinel-2 leads to a more precise pixel-based mapping of urban themes, making it possible to map accurately.

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