



International Journal of Environment and Climate Change

11(2): 66-75, 2021; Article no.IJECC.66980

ISSN: 2581-8627

(Past name: British Journal of Environment & Climate Change, Past ISSN: 2231-4784)

Impact of the Spatial Resolution of Satellite's Data for Mapping Land use Land Cover in Karmala Tehsil, Solapur, India

Sanket Kolambe¹, Jeet Raj^{1*}, Krishna Lohakare², Shital Mane³ and Vikrant Nikam⁴

¹*Department of Soil Water Engineering, Indira Gandhi Krishi Vishwavidyalaya, Raipur, India.*

²*K. K. Wagh. College of Agricultural Engg, Nashik, India.*

³*Sahyadri College of Agricultural Engineering, Yeshwanthnagar, Karad, India.*

⁴*Albedo Foundation, Nashik, India.*

Authors' contributions

This work was carried out in collaboration among all authors. Authors SK, KL and SM designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors JR and VN managed the analyses of the study and also managed the literature searches. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJECC/2021/v11i230363

Editor(s):

(1) Dr. Sarfraz Hashim, Muhammad Nawaz Shareef University of Agriculture (MNSUAM), Pakistan.

Reviewers:

(1) Jean de Dieu Nambajimana, Chinese Academy of Sciences, China.

(2) Richard Mind'je, University of Chinese Academy of Sciences (UCAS), China.

(3) Vahideh Saeidi, Iran.

Complete Peer review History: <http://www.sdiarticle4.com/review-history/66980>

Received 09 February 2021

Accepted 18 April 2021

Published 24 April 2021

Original Research Article

ABSTRACT

Land use and land cover (LULC) classification mapping is important for evaluating, monitoring, protecting and planning for land resources. A key factor in extracting desired information from satellite images is choosing the right the spatial resolution. The scale of a pixel on the ground is known as spatial resolution. A pixel is the smallest 'dot' that makes up an optical satellite image which defines the level of detail as in image. In this paper estimation of the areal extent of water, built up, barren land, vegetation land and fallow land classes with its classification accuracy were reviewed particularly for January 2013 and November 2016 in Karmala tehsil of Solapur district, India. LULC is implied by different spatial resolution images of Advanced Wide Field Sensor (AWIFS), Linear Imaging Self Scanning Sensor (LISS-III), Landsat-8 Operational Land Imager

*Corresponding author: E-mail: er.jeetraj@gmail.com;

(OLI) and Sentinel-2A imageries in QGIS environment while the classification was carried out using the maximum likelihood algorithm (MLA). The classified maps obtained from AWiFS and LISS-III sensors, as well as Sentinel-2A and Landsat-8 OLI data sets, were compared separately. Spatial analysis depicts that the Kappa coefficient of Sentinel-2A, Landsat-8, LISS III and AWiFS was found 96.96%, 91.64%, 87.30% and 89.36%. Furthermore, overall accuracy of was found to be 99.07%, 94.49%, 89.84% and 94.08% respectively. The accuracy of the classified image with higher spatial resolution (Sentinal-2A) proved more informative than that of lower resolution (AWiFS) sensor. On the response, the finer spatial resolution of Sentinal-2A (10 m) delivered more precise details and enhanced LULC classification accuracy most reliably than the coarser spatial resolution of Landsat-8 (30m), LISS III (23m) and AWiFS (56m) image. A perusal of data revealed that the overall accuracy and Kappa coefficient was found proportionate to spatial resolution of satellite imageries. The higher resolution spatial data also greatly reduces the mixed-pixel problem. The study revealed that the spatial resolution plays an important role and affects classification details and accuracy of LULC level.

Keywords: Kappa; LULC; remote sensing; spatial resolution; supervised classification.

1. INTRODUCTION

Land Use and Land Cover (LULC) classification is one of the most used in remote sensing [1]. Land cover pertains to how forest, shrubs, wetlands, impervious surfaces, agricultural, manmade features and other forms of land and water cover the surface of the Earth [2]. LULC classification can be used for approximate estimation of production crop as well as species determination by high spatial resolution data. Moreover, the pressure on limited natural resources, which is caused by an increase in population, contributes to changes in the land surface cover [3]. The rapid transformation of land uses and also extensive deforestation, has arisen with a slew of emerging environmental issues at spatial levels with severe effects on the ecosystem. It has a direct impact on climatic conditions, habitats, and physical systems, posing a serious threat to natural resource management [4]. One of the most important aspects of a remote sensing image is the spatial resolution, the characteristic scale on the ground associated with the radiance quantification of a pixel. The scale of a pixel on the ground is known as spatial resolution. A pixel is the smallest 'dot' that makes up an optical satellite image which defines the level of detail as in image [5]. Spatial resolutions that differ inexplicably can lead to inconsistent interpretations [6]. A sensor's spectral resolution specifies the number of spectral bands in which the sensor can collect reflected radiance [7]. This paper aims at determining the spatial resolution's impact on image classification. The patterns and distributions of earth objects vary with spatial resolution. High spatial resolution images are used for accuracy assessment of LULC

classification [1]. The current study relies on data from the USGS and NOIDA NRSC, both of which are open-source platforms. The reason behind the selection of Karmala among the Solapur district is its site suitability due to all type of nature and manmade construction, bodies in it at different spatial scales. High spatial resolution data give more information about the specific region in terms as compared to low spatial resolution. The numbers of pixels are increased as resolution getting higher [1]. As well, the chances of mixing pixels of desired class in other specified class are more apparent in high-resolution images in the classification process. This study addresses the effect of different spatial resolution, pixel sizes and spectral resolution on the accuracy of land use land cover mapping of Karmala tehsil.

1.1 Study Area

Karmala is a tehsil located between 18°10'-18°50'N latitudes and 75°40'-75°75'E longitudes in Solapur district which is the southern part of Maharashtra, India. Karmala covers an area of 1609.7sq. km. As per the 2011 census, the total population of Karmala tehsil is 2,54,489 with population density of 145 persons per square kilometer.

The average rainfall of Karmala is 506mm. In the Solapur district experiences the average annual temperatures ranging from 20.3°C to 33.3°C. Mostly black soil is found abundantly in study area along with trace of red and barad soil. The crops cultivated in Karmala are Jowar, Bajra, Tur, Gram, Groundnut, and sugarcane, etc. Bhima and Sina river's flow South-East through Karmala [8].

1.2 Data Used

Present study achieved using open source satellite dataset to create the LULC map of the study area. Resourcesat-1 satellite mission of ISRO (Indian Space Research Organization) carries electrooptical cameras as its payload of LISS-3 (IRS-1C) and AWiFS (IRS-1D) along with Sentinel-2A (Earth observation mission, Copernicus programme) and Landsat-8 OLI (European Space Agency missions programme) were moderate resolution datasets was used in study.

2. METHODOLOGY

All the satellite images downloaded for Karmala tehsil which belongs to Maharashtra, India were brought under UTM projection 43N and datum WGS 84. The multispectral (MS) band from visible and NIR (near infra-red) spectrum were stacked to form geo-coded False Color Composite (FCC) images. Google Earth Images is used for image interpretation of defining different classes of LULC. QGIS v 2.18.17 and SAGA GIS v 2.3.2 software were used for image processing and analysis. The present study mostly relies on the USGS and NOIDA NRSC which is an open-source platform data. LULC

mapping classification was carried out with the help of AWiFS and LISS III for the decade 2013 and Sentinel 2A and Landsat 8 for the decade 2016 satellite images [9].

The supervised classification technique along with MLC algorithm was used for the preparation of LULC map. The training sites well known as region of interest (ROI) signature on the FCC image were generated. Then the MLC algorithm was used to classify LULC types [10]. Maximum-likelihood classifier assumes that each class in each band can be described by a normal distribution. Maximum-likelihood is a supervised classification method derived from the Bayes theorem, which states a posteriori distribution $P(i|\omega)$, i.e., the probability which is a pixel with feature vector ω belongs to class i is given by:

$$(Ci|x) = (x|Ci) * P(Ci) / P(x) \quad (1)$$

Where, $(Ci|x)$ – testing most probability; $P(x|Ci)$ – conditional probability; $P(Ci)$ - prior probability the probability that i is observed; $P(x)$ – probability of pixel for any class; Ci –that class; x – pixel [11].

Accuracy assessment was also conducted utilizing the confusion matrix tool. Which gives an

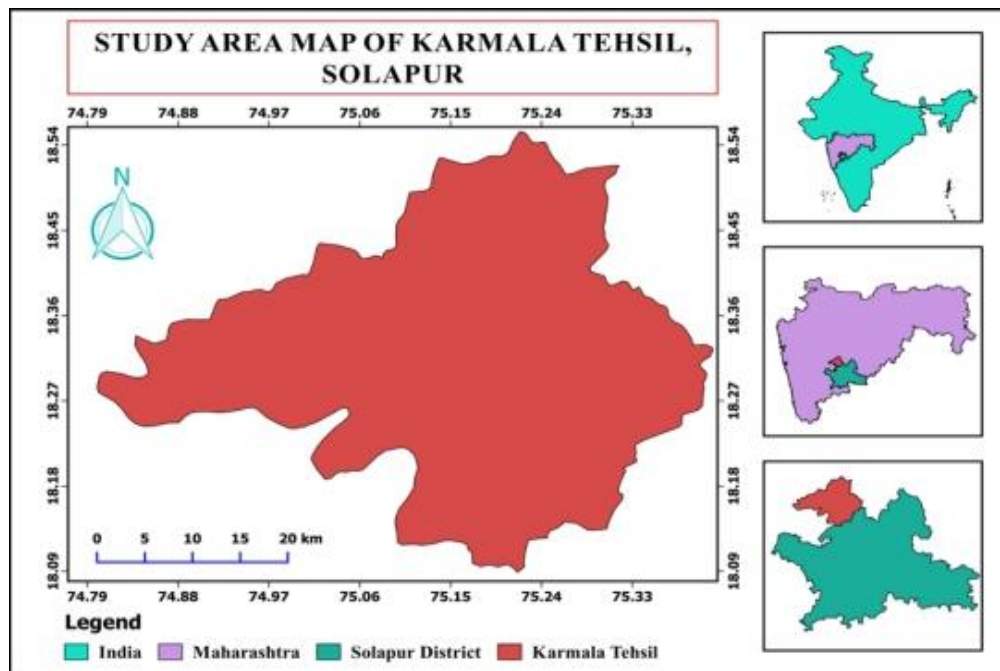


Fig. 1. Map of Study Area

Table 1. Characteristics of MS satellite data sets used in study

Sr. No.	Dataset	Resolution (m)	Date of acquisition	Swath (Km)	Revisit period	Data source
1	Sentinel-2A	10 m	16 November 2016	290	10 day	USGS Earth explorer
2	Landsat-8 OLI	30 m	29 November 2016	185	16 day	(https://earthexplorer.usgs.gov/)
3	LISS III	23.5 m	18 January 2013	140	24 day	Bhuvan (https://bhuvan-app3.nrsc.gov.in/data/download/)
4	AWiFS	56 m	13 January 2013	740	5 day	

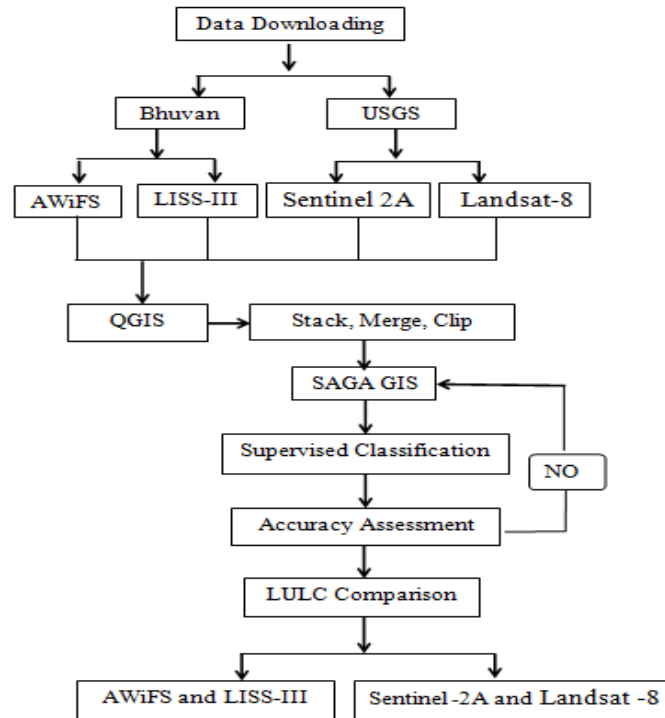


Fig. 2. Flow chart of methodology

idea about kappa coefficient, overall accuracy, user accuracy and producer accuracy [12]. Furthermore, the visual interpretation of classified maps derived from relatively coarser sensor of AWiFS and LISS-III. Similarly, interpretation of LULC maps generated from relatively higher spatial resolution sensors of Sentinel-2A and Landsat-8 OLI was performed [13].

The overall accuracy is calculated by summing the number of correctly classified values and dividing by the total number of values. The kappa coefficient measures the agreement between classification and truth values. A kappa value of 1 represents a perfect agreement, while a value of 0 represents no agreement [14]. The kappa coefficient is computed as follows:

$$K = \frac{N \sum_{i=1}^n m_{i,i} - \sum_{i=1}^n (G_i C_i)}{N^2 - \sum_{i=1}^n (G_i C_i)} \quad (2)$$

Where, i - the class number ; N - the total number of classified values compared to truth values; $m_{i,i}$ - the number of values belonging to the truth class i that have also been classified as class i (i.e., values found along the diagonal of the confusion matrix); C_i - the total number of predicted values belonging to class i ; G_i - the total number of truth values belonging to class i .

3. RESULTS AND DISCUSSION

The four different spatial scale multispectral imageries were preprocessed and supervised classification along with MLC algorithm used for LULC mapping. The error matrix results are useful for the overall classification accuracy as well as class-wise accuracy and kappa statistics. It was concluded that accuracy level of LULC map and corresponding Kappa coefficient and overall accuracy depends on spatial resolution of geospatial data. But due to some sensor problem even though at higher spatial resolution LISS III unable to give better performance when compared to Landsat 8 OLI. Fig. 3 shows the LULC maps for four imageries [15].

During visual interpretation, Sentinel-2A images give a better classification for vegetation and barren land as compared to the other three satellite imageries which is shown in Fig. 4A. In the Landsat 8 OLI image fallow land gets mixed with vegetation. As compared to Landsat- 8, LISS III gives a better classification of vegetation and fallow land. But AWiFS does not provide truthful information of vegetation and fallow land classes may be due to mixing pixels problems as

result of its coarser resolution. Furthermore, Barren land in sentinel 2A, LISS III, Landsat-8, and AWiFS gives accurate classification accordingly to their increasing resolution.

Fig. 5 gives a comparison between built-up and fallow land LULC classes where a Sentinel 2A was able to distinguish precisely minor portion of built up land while the same built-up was not classified that much precisely in sensors with coarser resolution. In Landsat-8 and LISS III built up acreage increases than actual spatial distribution of built-up land possibly because of mixing of pixels. Sentinel-2A gave an accurate classification of the fallow land while Landsat-8 gave moderate classification [16].

Table 2 shows the estimated acreage of each LULC class with different satellite imageries. For the year 2013 water bodies of 8980.51 ha and 7548.94 ha was estimated from AWiFS and LISS III imageries respectively. Sentinel 2A shows 12584.90 ha of water bodies for year 2016. The actual buildup area was accurately classified in Sentinel 2A while due to LISS III sensor's problem in our study area barren land was classified with extra acreage. Fallow land classification was somewhat similar among all imageries.

From Fig. 5, it can be revealed that the perfect classification of water bodies was given by all imageries. Although, build up area getting precised as the spatial resolution becomes finer. While built-up and vegetation classes showed no significant variation among all imageries possibly due to the mixing of pixels. The user accuracy of fallow land gets reduces with higher spatial resolution.

Fig. 6 shows that producer accuracy is similar for vegetation class and decreases for barren land. Accuracy was found least in water pixels of water bodies, built up area and fallow land for the LISS III imagery. We randomly overlaid our ground truth measurements on the land cover classification map and made validation for Landsat 8 OLI and AWiFS imagery. In the confusion matrix table, we show the matrix evaluation for the validation. In the Table 3 water, built up, vegetation, fallow land was selected as ground truth classes.

From Table 4 it can be seen that sentinel 2A has greatest overall accuracy and Kappa coefficient, while AWiFS and LISS III (sensor problem) shows lower overall accuracy and Kappa coefficient.

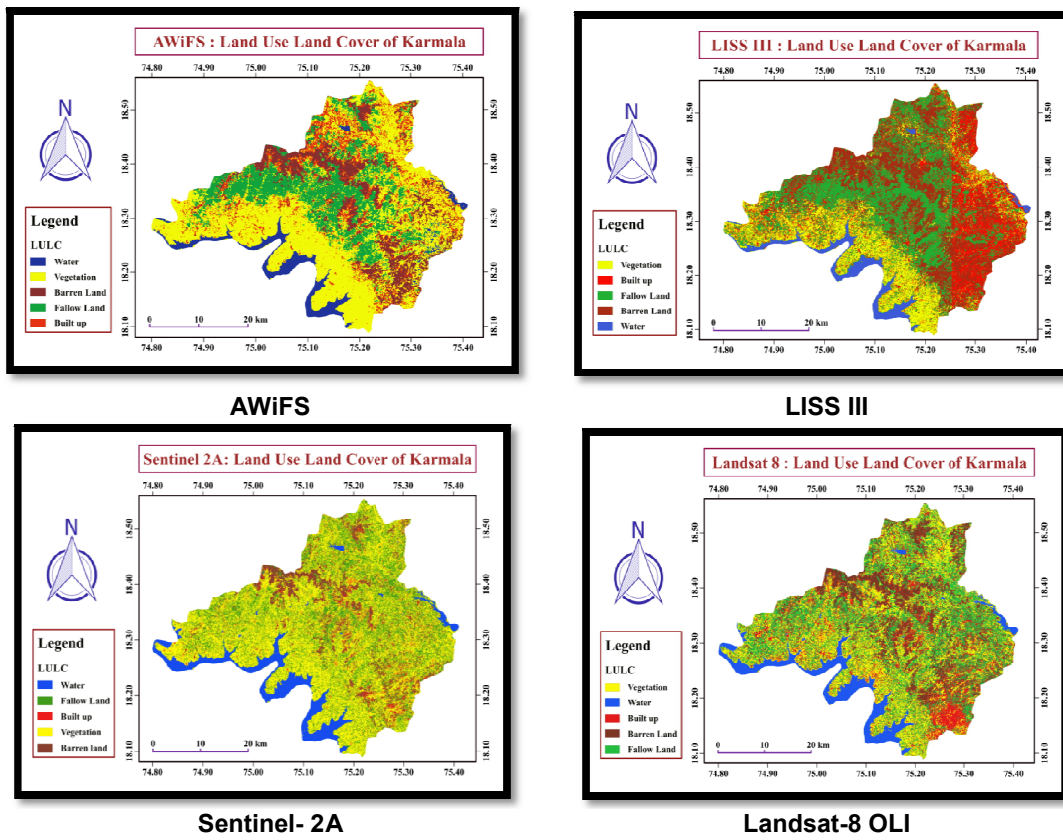


Fig. 3. LULC maps per satellite imagery

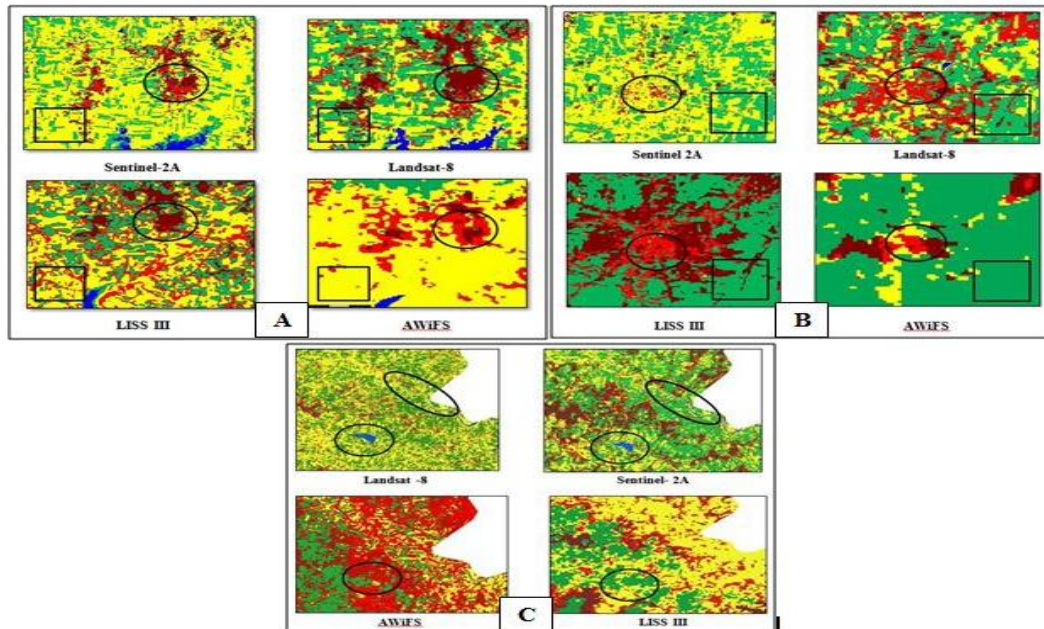


Fig. 4. Shows the comparisons between vegetation, barren and built-up, fallow land and water bodies respectively

Table 2. Spatial distribution of each class for four satellites (in ha)

Data product	Water bodies	Built Up	Barren land	Vegetation	Fallow land
AWiFS	8980.51	18994.11	21457.32	77864.40	32368.60
LISS III	7548.94	34550.95	35084.39	27944.70	54494.41
Sentinel 2A	12584.90	8522.13	11704.75	80417.31	46396.86
Landsat 8	13112.19	30312.99	18212.90	44209.35	53779.80

Table 3. Confusion matrix table for Landsat 8 OLI and AWiFS imagery

CLASS	Water		Built up		Barren land		Vegetation land		fallow land		
	Satellites	Landsat 8	AWiFS	Landsat 8	AWiFS	Landsat 8	AWiFS	Landsat 8	AWiFS	Landsat 8	AWiFS
Water		338	300	0	0	0	0	0	0	0	0
Built up		0	12	80	22	5	0	0	0	3	0
Barren land		0	0	3	1	57	43	0	0	1	0
Vegetation		5	16	0	0	0	0	67	52	0	0
Fallow land		0	0	0	0	9	0	9	0	59	44

Table 4. Accuracy and kappa coefficients for the images per spatial resolution

Satellite data	AWiFS	LISS III	Sentinel 2A	Landsat 8
Spatial resolution (m)	56	23.5	10	30
Overall accuracy (%)	94.08	89.84	99.07	94.49
Kappa Coefficient (%)	89.36	87.30	96.96	91.64

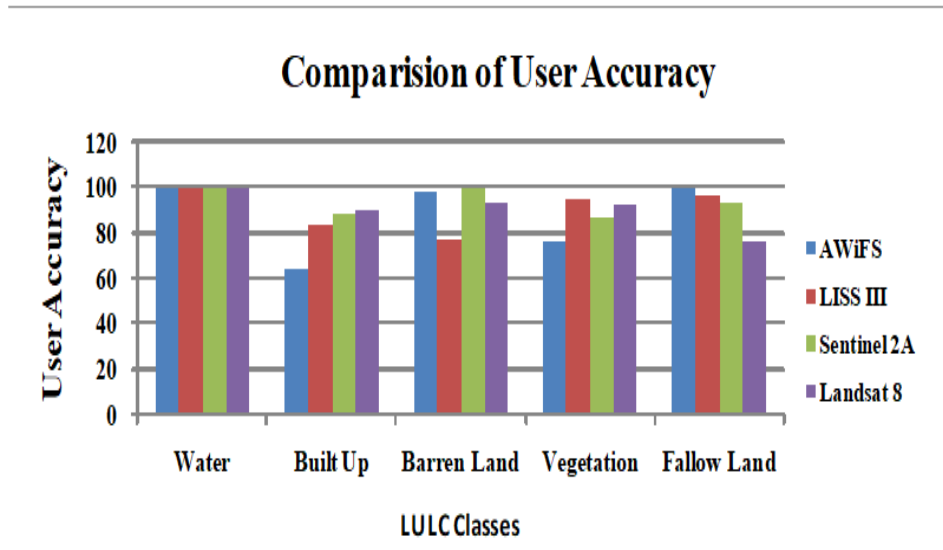


Fig. 5. Comparison of user accuracy for four satellites

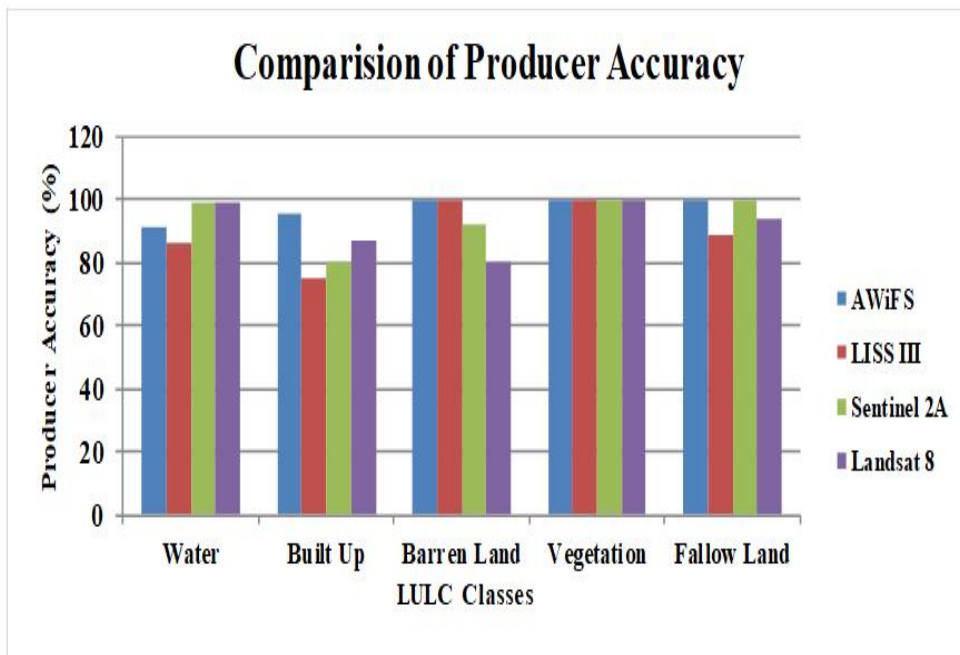


Fig. 6. Comparison of producer accuracy for four satellites

Moreover, because of coarser resolution AWiFS could be merges both agricultural and fallow land leading to give false estimates than actual acreage. In Landsat imagery fallow land gets increase while vegetation cover reduces may be due to mixed pixel, since pixel size of Landsat 8 image may be smaller as compared to agricultural fields.

4. CONCLUSIONS

The spatial resolution effects and classification accuracy were carried out using multispectral imageries of Sentinel-2A, Landsat-8, LISS III and AWiFS. The overall accuracy and Kappa values obtained at different spatial resolutions were also presented. Spatial analysis depicts that the

Kappa coefficient of Sentinel-2A, Landsat-8, LISS III and AWiFS was found 96.96%, 91.64%, 87.30% and 89.36%. Furthermore, overall accuracy of was found to be 99.07%, 94.49%, 89.84% and 94.08% respectively. A perusal of data revealed that as spatial resolution increases, the overall accuracy; and Kappa coefficient also gets improved. On the response, the finer spatial resolution of Sentinel-2A (10 m) delivered more precise details and enhanced LULC classification accuracy most reliably than the coarser spatial resolution of Landsat-8 (30m), LISS III (23m) and AWiFS (56m) image. However, the kappa coefficient in LISS III is less than Landsat-8 and AWiFS owing to the sensors unselective image capture errors. Furthermore, the finer spatial resolution image Sentinel 2A eliminates mixed pixel problems in classification by eliminating the effect of boundary pixels. As a result, Sentinel 2A offered more precise view and better LULC classification more reliably than the coarser spatial resolution image. Therefore, spatial resolution plays an important key role and affects classification details and accuracy. The supervised classification along with maximum likelihood classification algorithm was used to successfully classify the LULC map. Such information is critical for making faithful planning decisions, as it provides the potential information needed to track development and enhance environmental sustainability.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Sharma J, Prasad R, Mishra VN, Yadav VP, Bala R. Land use and land cover classification of multispectral Landsat- 8 satellite imagery using discrete wavelet transform. ISPRS-International Archive of the Photogrammetry, XLII. 2018;5:703-706.
2. Prakasam, Chakkra. Land use and land cover change detection through remote sensing approach: A case study of Kodaikanal taluk, Tamilnadu International Journal of Geomatics and Geosciences. 2010;1.
3. Islam K, Jashimuddin M, Nath B, Nath TK. 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. 2018;21(1):37-47
4. Koko AF, Yue W, Abubakar GA, Hamed R, Alabsi AAN. Monitoring and predicting spatio-temporal land use/land cover changes in Zaria city, Nigeria, through an integrated cellular automata and Markov chain model (CA-Markov). Sustainability. 2020;12:10452.
5. Landviewer. What is spatial resolution of satellite imagery data? 2019. Available:<https://eos.com/blog/satellite-data-what-spatial-resolution-is-enough-for-you/#:~:text=Spatial%20resolution%20refers%20to%20the,30m%20area%20on%20the%20ground.>
6. Suwanprasit C, Srichai N, Impacts of spatial resolution on land cover classification. Proceedings of the Asia-Pacific Advanced Network. 2012;33(39)
7. Geoimage Pty Ltd. SWIR Resolution+ Unlocks Potential. 2018. <https://www.geoimage.com.au/SWIR%20Series/resolution.>
8. Nileshwari Yeole, Suyog P. Urade. Study on high-resolution satellite data for mapping in Karamala Taluka. International Journal of Science and Research (IJSR). 2015;8(6).
9. Chavare SG. application of remote sensing and gis in land use and land cover mapping of sub-watershed of Wardha river basin Subhash G. Chavare; 2015.
10. Ondieki CM, Murimi S. Applications of geographic information systems. Inyang H. I. Daniels J. (Eds.), Environmental Monitoring. 2009;2:314-340.
11. Norovsuren B, Tseveen B, Batomunkuev V, Renchin T, Natsagdorj E, Yangiv A, Mart Z. Land cover classification using maximum likelihood method (2000 and 2019) at Khandgait valley in Mongolia. IOP Conf. Ser.: Earth Environ. Sci. 2019;381-012054.
12. Sharma NK, Lamay JB, Kullu NJ, Singh RK, Jeyaseelan AT. Land Use and Land Cover Analysis of Jharkhand Using Satellite Remote Sensing. J Space Sci & Tech. 2012;1:1-10.
13. Topaloglu RH, Sertel E, MUSAOĞLU N. Assessment of classification accuracies of sentinel-2 and landsat-8 data for land cover/use mapping. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences. 2016;41.
14. Kaul HA, Sopan I. Land use land cover classification and change detection using

- high-resolution temporal satellite data. Journal of Environment. 2012;1 (04):146-152.
15. Chen D, Stow DA, Gong P. Examining the effect of spatial resolution and texture window size on classification accuracy: an urban environment case. International Journal of Remote Sensing. 2004; 25(11):2177-2192.
16. Deeksha Mishra, Singh BN. Classification and assessment of land use land cover in Bara tehsil of Allahabad district Sentinel-2 satellite imagery; 2017.

© 2021 Kolambe et al.; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:
The peer review history for this paper can be accessed here:
<http://www.sdiarticle4.com/review-history/66980>