Remote Sensing Based Identification of Painted Rock Shelter Sites: Appraisal Using Advanced Wide Field Sensor, Neural Network and Field Observations

Ruman Banerjee and Prashant K. Srivastava

Abstract Recent advances in remote sensing can map the lithological and geological parameters in a synoptic way and hence opens up new dimensions in archaeological research. This work delineates accurate mappings of sandstone located and documented in the form of a suite of prehistoric rock-shelter sites in the Mirzapur district of Central India. Artificial Neural Network (ANN) and Maximum Likelihood Classification (MLC) techniques have been used to identify, classify and map the region under study using IRS-P6 Advanced Wide Field Sensor (AWiFS). Interpretation of data processing revealed that ANN performed better than MLC for mapping sandstone in and around the area of Mirzapur. A conspicuous pattern has been detected where the painted sandstone shelters followed the natural sandstone or host-rock formations revealing the painting activity. This demonstrates prehistoric social choice in terms of the production and consumption of rock art and the importance of local geology that governs this activity.

Keywords Remote sensing · GIS · Sandstone · AWiFS · ANN · MLC · Archaeological sites · Central India · Rock art

1 Introduction

Historically this region of Central India has played an important part delineating the wealth of India's cultural and natural resources (Banerjee and Srivastava 2013). Evidences of rock art and archaeology were first discovered as long as 120 years ago by the archaeologists A. C. Carlleyle and John Cockburn in the Indian sub-continent

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(Brown 1889; Cockburn 1894; Allchin and Allchin 1982). After the discovery, generations of archaeologists, anthropologists and other researchers discovered, documented various archaeological rock-shelter sites made of sandstone in this region (Tiwari 2000; Misra 2001; Pratap and Kumar 2009). Rock art research in India is shaped to its present day form through various stages. Immediately after the independence, several researchers found new sites and tried to analyse the painting in a descriptive manner without building any rigorous falsifying or confirmatory model. Next, the formative period also includes the emergence of several new painted shelters that had been properly documented, catalogued and sometimes excavated for hypothesis testing to identify the regional problem in rock-shelter archaeology. Later many researchers tried to date the paintings to assign an absolute chronology to the art of Central India with relative success. Finally, the landscape approach is incorporated by contemporary researchers to understand the locational, regional and micro-regional variations and the importance of model building in Indian rock-shelter archaeology to decode the prehistoric past through remote sensing and geographic information system applications.

The Advanced Wide Field Sensors (AWiFS) inbuilt in these satellites, map land use, land cover and vegetation. Two parallel radiometers and several channels serve as the primary equipments having brushbroom scanning technique with 740 km swath. This satellite cycles the earth within five days (Kandrika and Roy 2008; Shukla et al. 2010; Punia et al. 2011). The Cartosat data is used in this research to construct the digital elevation model of the region under purview. The elevation model accurately map the region and represent the landscape under question vividly (Yu et al. 2008; Jalan and Sokhi 2012; Lasaponara and Masini 2012). Considered together in today's world, remote sensing and geographical information system are well optimized tools to map any given features on the surface of the earth (Srivastava et al. 2012a, b). Particularly, the archaeological paradigms are directly related to the data acquisition, spatial, aspatial, temporal, visual, processual, simulation and modelling attributes of Remote Sensing and Geographical Information System (Pappu et al. 2010a, b). For the sake of brevity the entire region has been classified using two different techniques namely the Artificial Neural Network (ANN) and Maximum Likelihood Classification (MLC) (Diao et al. 2007; Gasparini et al. 2010) to evaluate their applications in prehistoric archaeology. MLC is a traditional, parametric and supervised classifier relies on the normal multivariate probability and class based representative pixilation of every image; on the contrary ANN is a non-parametric and unsupervised classifier and is supposed to generate better results than MLC (Dixon and Candade 2008; Oommen et al. 2008; Kavzoglu and Colkesen 2009).

The importance of decision making in terms of the selectivity of important materials to represent technological knowhow is well represented by Courty et al. in (2012) and this paradigm is equally relevant to understand the rock art of Central India. The sophisticated data, generated by the satellites and subsequently processed in the state of the art computer laboratory has showed high promise in the present decade in terms of vegetation and unique features mapping and monitoring (Jaiswal et al. 1999; Mukherjee 2004). Archaeological sites and survey

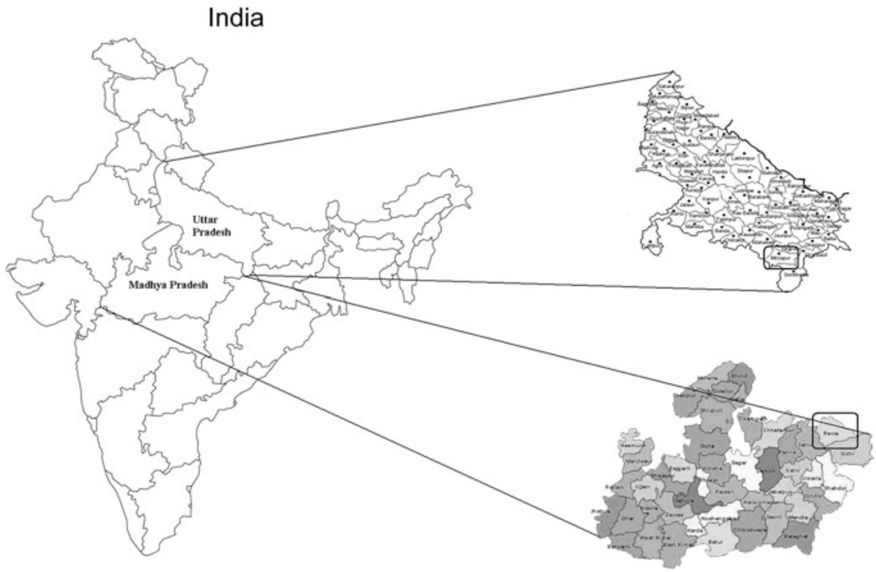


Fig. 1 Location of study area (Mirzapur and Rewa districts, India)

areas included in this research work are directly related to elevation, ranked rivulets, streams and soil types (Pappu et al. 2010a). There are very few studies reported in the Indian sub-continent, where remote sensing techniques have significantly contributed to improve field investigations, planning and management in archaeology. However, studies regarding different geographical areas are yet to be elucidated. Protection of these tangible cultural heritages now has been of utmost priority as declared by UNESCO conventions. Hence, the primary objective of this research work is; to demonstrate the results of the application of two different computational algorithms on ResourceSat-1 images to map prehistoric sandstone rock-shelters located in Mirzapur and parts of Rewa district to constrain the progressive and linear distributional trend of painted sandstone rock-shelters for predictive modelling and future archaeological surveys.

2 Material and Methodology

2.1 Study Area

Rewa (24°19′–25°12′30″ N and 81°.02′–82°.19′ E) and Mirzapur districts (23°52′ and 25°32′ N, 82°07′ and 83°33′ E), located in the state of Uttar Pradesh and Madhya Pradesh, India are well known for the archaeological and heritage value. The geographical location of the districts of Mirzapur and Rewa is shown in (Fig. 1). Both the districts are located in Central India; and specifically the study area of these two districts fall under the Vindhyan supergroup. Mirzapur district of U.P (Uttar Pradesh) shares border with the districts of Sant Ravidas Nagar and Varanasi towards the North; on the East and South-East by Chandauli and Rewa districts; on the Southern margin by Sonbhadra; and finally on the North-West by the Allahabad district of U.P. (Drake-Brockman 1911). It has an area of 4,522 km^2 and correspondingly Rewa district covers a total area of 6,240 km^2. Rewa (Luard 1907) is bounded by the districts of Mirzapur, Banda and Allahabad of Uttar Pradesh in the North and North-East; in the South by Sidhi district and it shares the boundary with Satna district in the West. Ground truth data confirms the existence of numerous new painted rock shelter sites in the region. Apart from previous studies and documentation of two hundred and fifty rock-shelters, the present research has brought to light more than forty new rock-shelters with in situ archaeological record in the region. The regions of South and South-Western Mirzapur along the North and North-Eastern parts of Rewa have been explored thoroughly, in order to document and catalogue various new archaeological sites. Sandstone outcrop is quite common in the area, although all the shelters are not painted. A propensity of painting activity is seen along the South, South-West and North, North-East boundary regions of Mirzapur and Rewa. While survey in the said part of Mirzapur has been exhaustive, only a small part of the sandstone belt of the Rewa district of M.P. (Madhya Pradesh) has been surveyed due to time, logistics, resources and other associated constraints. Field-work data and close observation of landscape modifications for three consecutive years have revealed several ground truth points in the Vindhyan sandstone belts of Mirzapur and Rewa districts. Field observation confirmed the fact that the adjoining district of Rewa, situated at the South-Western boundary of Mirzapur, also falls under the Vindhyan range and is full of archaeological sites having tremendous potential.

2.2 Satellite and GIS Datasets

This research work has been realised using multispectral data from one of the Indian satellites named as IRS-P6 (ResourceSat-1) having Advanced Wide Field Sensor (AWiFS). AWiFS has similar payload like LISS-3 and/or LISS-4 (Linear Image Self-Scanning 3 and 4). Although the spatial resolution in meter scale in ResourceSat-1 AWiFS, ResourceSat-1 LISS III and ResourceSat-1 LISS IV (Multi-spectral mode) vary from 56 (at nadir), 24 to 5.8 (at nadir) meters. The spectral bands for the said AWiFS sensors are bands 2, 3, 4 and 5. The topographic maps from the Survey of India, Kolkata; District Resource Maps (DRM) from the Geological Survey of India, Kolkata, road maps of Mirzapur and Rewa have all been utilised for this study. The GPS locations for all the shelters are implemented as ground truth data along with the digitized and geometrically corrected maps to classify the landscape of the rock art into several unique parts for supervised classification. The orthoimages gathered from satellites have been used to generate digital elevation model for the Mirzapur and Rewa districts. Ground control points,

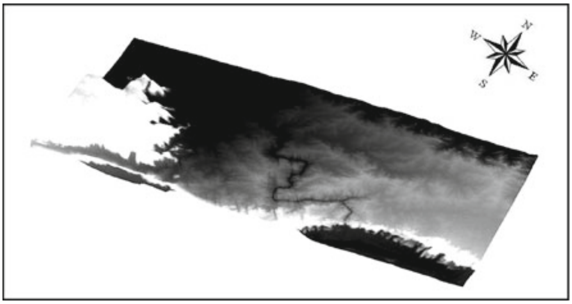


Fig. 2 Digital elevation model of the area

satellite ephemeris and radiometrically appropriated images have been included to measure the accuracy levels.

The visualisation of data, data acquisition, management, exploratory spatial data analysis (ESDA), Confirmatory data analysis (CDA) and interpretation in this work have been done following two different but unique techniques to map the local rock of the area that hosts a wealth of information. The applications of Bhuvan (http://bhuvan.nrsc.gov.in) have been implemented for the Cartosat1 and ResourceSat-1 images. Bhuvan is a geoportal of Indian Space Research Organisation (ISRO), Department of Space, Government of India (http://www.isro.org/). Additionally NNRMS (National Natural Resources Management System) data (http://www.nnrms.gov.in) is included in this work to consolidate the methodological rigour. Cartosat DEM data has proved to be very valuable for this work, refining and demonstrating the digital elevation model of the area (Fig. 2) in a 3D view. The ResourceSat-1 images have been processed, reclassified and georeferenced using ground truth data; obtained in the form of GPS points. The area is first divided into different small micro-areas depending on the GPS points coming from various parts of the region. Next, the whole region is divided into five broad classes namely; forest, waterbodies, sandstone, alluvial land and cropland respectively implementing the applications of Indian Remote Sensing satellite—P6 (ResourceSat-1). Each parameter has been colour coded uniquely to represent the variations in profile and to understand the total dataset. All the rock-shelter sites have been found distributed in a cluster or dispersed fashion within the sandstone complexes of the two said districts.

2.3 Classifiers/Algorithms Implemented in this Study

2.3.1 Artificial Neural Network (ANN)

Artificial neural network is used in various disciplines that basically work through the principles of simulation. The ANN model is based on three elementary layers namely, input or encoded, cryptic and output or linear layer that might jointly assume any logical function. Every neuron signifies an encoded function in digital image processing. If one neuron is described by one image band at the input layer; therefore every neuron in the linear layer is corroborated by a representative class. This model is independent of statistical interconnectivity and does not look for a normal distribution within the data. On the contrary it is very adaptive; relying on the estimates of a series of functions derived from the data. The neural network model will become increasingly important in archaeological remote sensing applications in mapping the surface of the prehistoric sites and probable archaeological regions. In recent years it has become imperative to classify the land cover and present day land use patterns of an area of rich cultural and/or archaeological importance. The images in the artificial neural network paradigm have been classified on a pixel to pixel basis (Rumelhart 1989) that delimits the problems of pixel mixing. The ANN parameters need to be optimised for a stable result and thus require a preliminary analysis using validation data. In this paper, the ANN algorithms are optimised by the method as described in (Varshney and Arora 2004; Srivastava et al. 2012b). The number of training datasets chosen for optimisation comprises of 50 pure pixels per class. However, for accurate estimation of optimised results, another set of 30 pure pixels per class has been taken into account for the validation purposes.

The exactitude of the geo-referenced image is verified with an existing geo-referenced map of the area; in order to ascertain uniformity of the data, in terms of maps, projection information and layer stacks. The ANN classifier divided the area into five classes, namely, forest, waterbodies, alluvial land, cropland and sandstone areas. In this ANN based image the parameter, sandstone is seen distributed proportionally in the area which adheres to the field data.

The neural network classifier used was a layered feed-forward model in ENVI (Environment for Visualizing Images) version 4.8 (ITT Visual Information Solutions SA) with standard back propagation for supervised learning. This category of ANN logistic is particularly superior for supervised classification because of its facility to learn by pattern and simplify the process (Srivastava et al. 2012b). In the case of ANN, the setting of the appropriate number of hidden layers depends upon the structure of the input data. Usually, it ranges from one to three. In practice, one layer of hidden nodes is sufficient in most cases (Gao 2009), hence a hidden layer of one is used in this study. The learning algorithm uses back propagation, which is one of the most commonly used forms of neural computing in remote sensing. The ANN weights were initialized using a uniform distribution. Learning rate was set to 100 for the hidden layer and 0.01 for the output layer, while stopping criteria is fixed to 0.001. The typical logistic activation function can be expressed as Eq. 1 (Schalkoff 1997; Friedman and Kandel 1999):

$$o_j = 1/(1 + e^{-\lambda net_j}) \tag{1}$$

where, o_j is the output of external input j, λ is a gain factor. The term net_j can be computed using Eq. 2 (Schalkoff 1997):

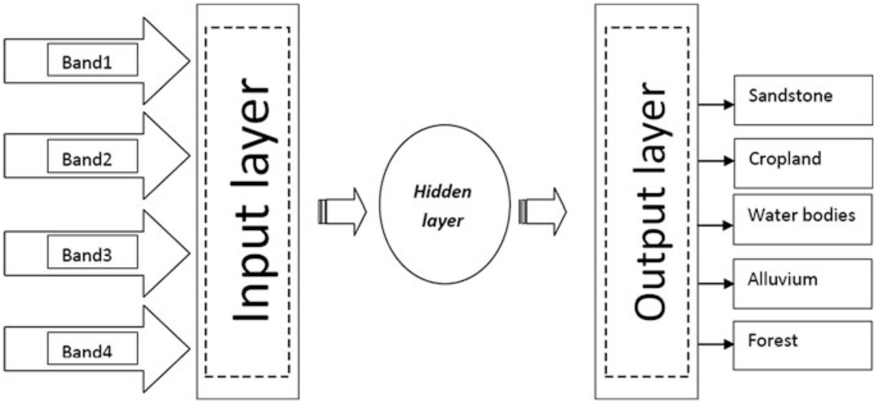


Fig. 3 Structure of artificial neural network

$$net_j = \sum\nolimits_i w_{ji} o_i \tag{2}$$

where, w_{ji} is the weight of interconnection channel to unit j from unit i and o_i is the output of external unit i. The structure of ANN is represented in (Fig. 3).

2.3.2 Maximum Likelihood Classification (MLC)

The maximum likelihood classification is a statistical technique that has varied applications in remote sensing studies. This supervised classificatory scheme for remote sensing data works through the principles of probability statistics and relies on Bayes' theorem of decision making. MLC divided the entire region under study into several specific sub classes as training zones assuming a Gaussian normality. Each unique region is modified into pixels through the computer algorithm. These pixels are then represented as uniform spectral classes; that is denoted by the mean vector and covariance matrix. The pixels belonging to every class is then calculated using probability density function. The regions are classified depending on the similarity of each pixel cells with the other related ones, which is highly probabilistic and forms a unique class. The maximum probability counts of the pixels as individual cells get the highest value in order to attain a separate entity as a class within the entire land cover (Mustapha et al. 2010). The Maximum Likelihood Classification tool is considered for image classification, as it is incorporating both the variances and covariances of the class signatures and assigning each cell to one of the classes represented in the signature file. The algorithm used by the Maximum Likelihood Classification tool is based on Bayes' theorem and the equation used in MLC classification is shown in Eq. (3) (ERDAS 1999).

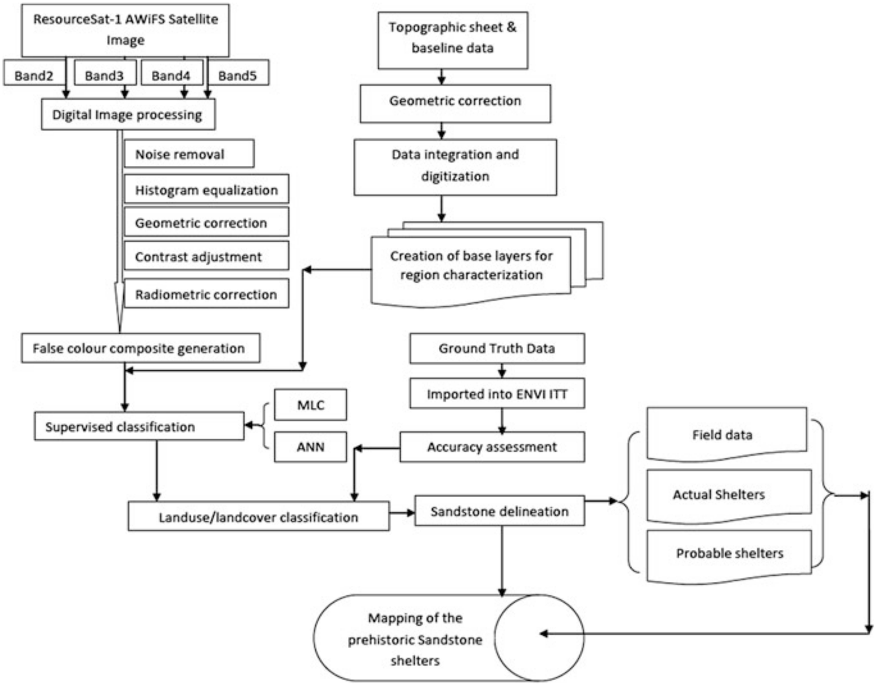


Fig. 4 Flowchart of the methodology used in the study

$$D = \ln(a_c) - [0.5\ln(|\mathrm{cov}_c|)] - [0.5(\mathbf{X} - \mathbf{M}_c)\mathrm{T}(\mathrm{cov}_c - 1)(\mathbf{X} - \mathbf{M}_c)] \qquad (3)$$

where, D is weighted distance; c is a particular class; **X** is the measurement vector of the particular pixel; $\mathbf{M}_c$ is the mean vector of the sample of class; a_c is percent probability that any particular pixel is a member of class c; (Defaults to 1.0); Cov_c is the covariance matrix of the pixels in the sample of class c; $|Cov_c|$ is determinant of Cov_c; Cov_c-1 is inverse of Cov_c; ln is natural logarithm function; T= transposition function. The MLC technique has successfully classified the documented area into forest, waterbodies, alluvial land, cropland and sandstone areas. The flowchart depicting the methodology used in this study is shown in (Fig. 4).

3 Accuracy Assessment of the Classified Images

In order to evaluate the performance of the algorithms, the accuracy assessment was carried out using the validation datasets collected during the field visits, assuring distribution in a sensible pattern so that a particular number of observations were assigned to each category on the classified image generated by the classifiers. The Kappa accuracy can be computed using equation (4) (Bishop et al. 1975).

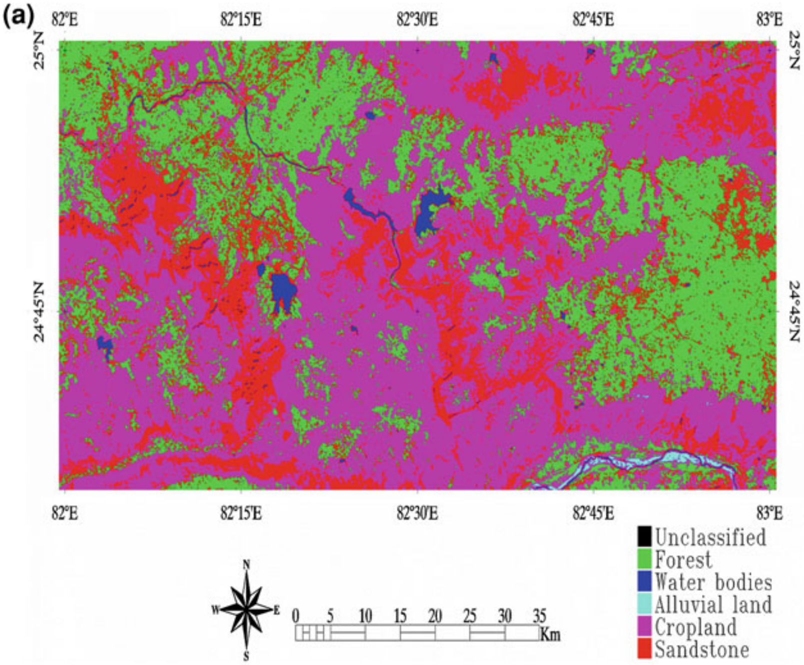
$$\kappa = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} (x_{i+})(x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+})(x_{+i})} \tag{4}$$

where, r is the number of rows in the matrix, X_{ii} is the number of observations in row i and column i (the diagonal elements), x_{+i} and x_{i+} are the marginal totals of row r and column i, respectively, and N is the number of observations. The total integrated accuracy, which has been measured according to defined proportion of the assessed area is classified correctly and can be estimated by Kappa statistics (Srivastava et al. 2012b). The user's accuracy calculated the proportion of pixels classified as belonging to a class that truly belongs to that class, while the producer's accuracy provides the proportion of pixels truly belong to a class that are classified as belonging to that class (Srivastava et al. 2010). The user's and producer's accuracies measurements are related to commission and omission errors (Congalton 1991; Mukherjee et al. 2009; Gupta and Srivastava 2010).

4 Results and Discussion

4.1 Land Covers Distribution and Accuracy Assessment

The classification maps produced from the implementation of the ANN and MLC are illustrated in (Fig. 5a, b). The highest accuracy is shown by ANN, hence only ANN classified image is taken into account for class distribution analysis. The LULC distributions and their percentage cover determined using ANN techniques is shown in (Table 1). In this study the IRS P6 ResourceSat-1 satellite images have been classified into five classes named as forest, waterbodies, sandstone, alluvial land and cropland. The classes created and the proportion of total area of the image covered by them, provide an insight to the composition of the total area (Townshend et al. 1991). On account of analysis of these classified images, it is possible to infer, to a certain extent, the changes that occurred in spatial composition of different physiographic features (Mukherjee et al. 2009). ANN classification is found to be the best by analysing the kappa statistics and accuracy. Overall ANN accuracy is 84.29 %, where ground truth data for the individual subsets vary. The IRS P6 ResourceSat-1 data is based on ANN classification, the values in terms of producer accuracies are obtained for the forest as 96.67 %, water bodies 96.3 %, alluvial land 82.35 %, cropland 91.89 % and sandstone 69.84 % respectively as separate classes, while the user accuracy obtained for the same classes in the similar order are 87.88, 92.86, 100, 61.82 and 93.62 % respectively. The kappa Coefficient for ANN classification is 0.80. On the contrary, the accuracy percent for the MLC based assessment is 81.15 %; where the Kappa Coefficient is 0.76. The percentage of the classes varies accordingly (Table 2). The producer accuracy obtained during



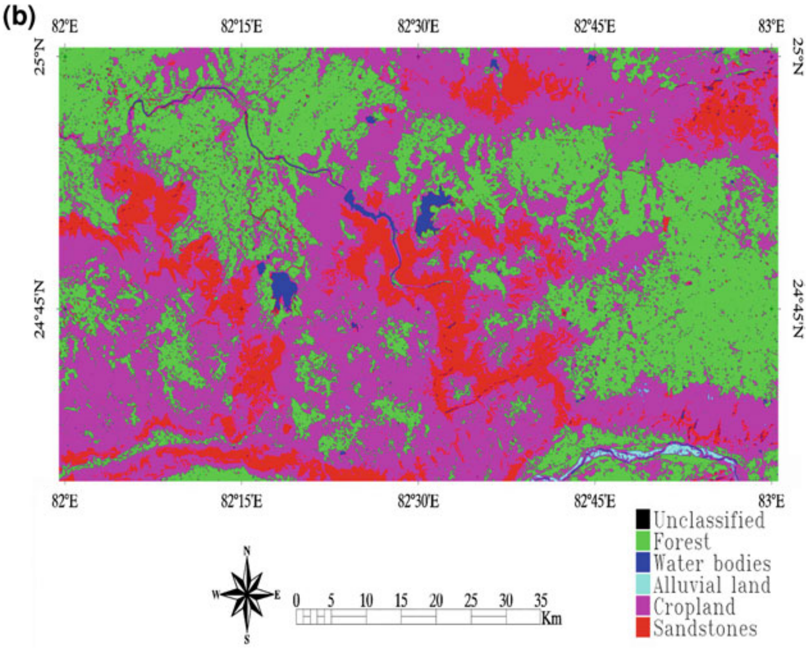


Fig. 5 Classified image of IRS P6 (ResourceSat-1) using ANN (**a**) and MLC (**b**)

Table 1 Land use/land cover distribution of the study area

Class name	Land cover (%)
Forest	29.58
Waterbodies	1.06
Alluvial land	0.27
Cropland	48.54
Sandstone	20.55
Total	100.00

Table 2 Brief results of the overall classification accuracies procured by applying the ANN and MLC methods on the IRS P6 ResourceSat-1 data

LULC	ANN		MLC	
	Producer accuracy (%)	User accuracy (%)	Producer accuracy (%)	User accuracy (%)
Forest	96.67	87.88	96.67	82.86
Waterbodies	96.30	92.86	85.19	92.00
Alluvial land	82.35	100.00	82.35	100.00
Cropland	91.89	61.82	89.19	57.89
Sandstone	69.84	93.62	66.67	91.30
Overall accuracy (%)	84.29		81.15	
Kappa coefficient	0.80		0.76	

MLC classification are Forest (96.67 %), waterbodies (85.19 %), alluvial land (82.35 %), cropland (89.19 %) and sandstone (66.67 %), while the user accuracy obtained for the similar class order are 82.8, 92.0, 100, 57.89 and 91.3 % respectively. This demonstrates the quality and strength of two different techniques where they are able to map the same landscape cover allotting different values and percentages to discrete elements. The overall area distribution based on ANN method assigns 20.55 % to sandstone, 48.54 % to cropland, 0.27 % to alluvial land, 1.06 % to waterbodies and finally 29.58 % to the forest cover. The classification of the archaeological landscape helps to characterize the parameters directly associated with the site formation processes (Binford 1981; Mol and Viles 2010; Grab et al. 2011). In this work, delineation of sandstone has got ultimate importance to map the rock-shelters in the surveyed and unexplored parts of the Mirzapur and Rewa districts.

4.2 Interpretation of the Results and Archaeological Relevance

The applications of two techniques in this study have been successfully able to map the distribution of sandstone in the field area and beyond it. Invariably one method produces relatively better results than the other one with a certain degree

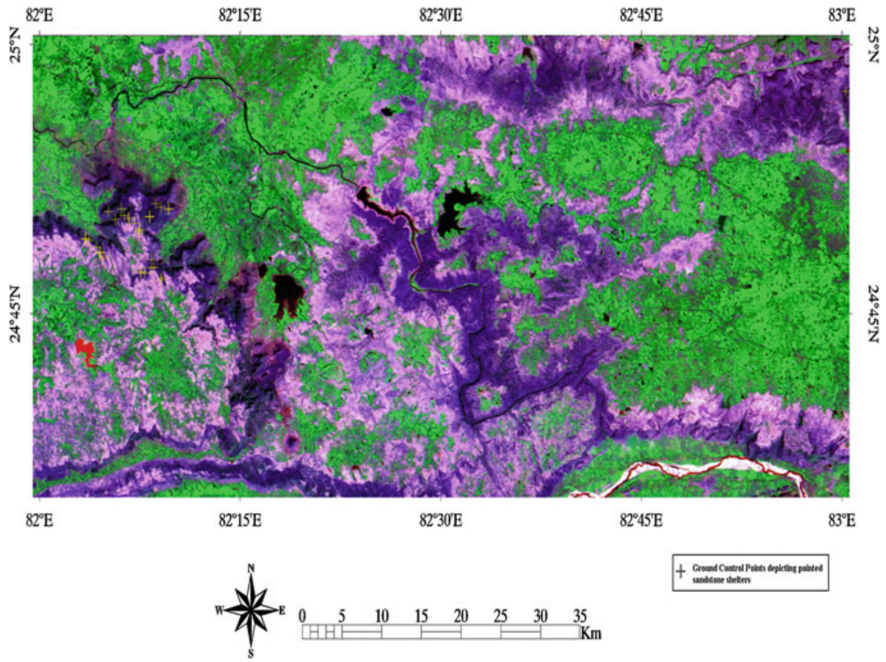


Fig. 6 Ground truth points collected during field survey

of accuracy. In this research particularly the investigation and mapping of sandstone within the landscape has been of primary importance, since all the documented painted rock-shelters are made of sandstone. Most importantly constructing the archaeological predictive map for sandstone as a locational tool for finding out new and potential painted shelters in central Indian context would open up new research paradigms. The number of sites and their preservation, conservation is directly related to the nature and patterning of sandstone. The South-Western part of Mirzapur has been exhaustively surveyed and more than forty new sites have been discovered. The region towards the North and South of Mirzapur district, where it shares border with Rewa also has very many painted rock-shelters, whereas a paltry of them could be catalogued in the field recently. The ANN and MLC both detected a linear trend of rock-shelters distributed across the landscape of Rewa. The present field-work data comes from the mid ridge of the elongated sandstone belt consisting of South-Western Mirzapur and parts of Rewa. The land cover in the later resembles the landscape of Mirzapur, revealing cropland, forest areas, waterbodies, alluvial land and finally sandstone. The accurate mapping of sandstone made it possible to pinpoint the sites within the proper context of the art, since GPS locations for all of the sites have been included in the data analyses (Fig. 6). The patterning of the sites show a tendency of propagation, where the sites are following the natural formation of sandstone in both directions, southwards and northwards from the borders of Mirzapur towards and across the Rewa district of Madhya Pradesh.

The practical and logical parameters set by the local microclimate at Mirzapur, occasionally represent environmentally and climatologically disturbed landscape. The distribution of painted sandstone shelters is indicative of the function of elevation and terrain morphology. Ground survey suggested that topography could be an important parameter which can affect the rock art of an area. In ancient times also, the area with very low slope and nearer to river might have had a greater chance of flood risk than higher one, which is here assumed that this might affect the hunter gatherers also in the past. So, it is presumed that the chances of getting rock art are more towards higher slope than lower ones. Hence, the DEM of the area has been utilized to delineate and understand the possible terrain features. It has been found that the frequency of the sites decreases gradually with a lower slope. The comparison with GPS points reveal that almost all the sites are situated in higher slope areas along the South-Western parts of the Mirzapur and adjoining Rewa district and thus supported the hypothesis outlined in the study. Characterising the present sites in terms of DEM and the classification results there is possibility of finding other new sites in the higher slope areas of the Mirzapur and the Rewa district. The models generated in this study along with the supposedly theoretical premises also support this observation. Enhanced density of rock-shelters are located at the higher elevations suggesting sacred or ritual sites hidden within the thickly vegetated forest cover and the presence of fewer sites at the lower elevations along the small rivulets suggesting camp sites where the prehistoric hunter-gatherers might have preferred to carry out their utilitarian activities.

A clear trend has been observed from the ground truth data and field-work that the rock-shelter sites are following the extension of the sandstone formation. The sandstone shelters documented at the South-Western part of the Mirzapur district have shown a gradual progression in two directions towards the adjoining Rewa district. Field data suggests that geologically Rewa district belongs to the Mesoproterozoic to late Neoproterozoic Vindhyan Supergroup revealing Rewa sandstone, shale, Kaimur and Bhander group of rocks (Tiwari 2011) and is bordered by the Mirzapur district of U.P. in the Northwest, North and Northeast. Field-data and/or ground truth data suggest that the total number of painted sites gradually increases towards the Rewa district following the distribution of the host-rock, which is sandstone. The paintings here ranged from the hunting gathering stage, depicting different types of animals (Fig. 7a) to the historic phase, where battle scenes predominate (Fig. 7b). The models generated in this work, by means of different techniques and satellite imageries therefore suggest, that further field-work along the sandstone formations might assist to detect numerous new painted shelters and other Mesolithic to late upper Palaeolithic, and ultimately sites of historic age consisting of archaeological artefacts (Fig. 7c). The sandstone in and around the areas of Mirzapur today is a subject of large scale quarrying. The recent knowledge on the relationship of sandstone and painted rock-shelters authenticated the beginning of a new research paradigm in Central Indian rock art and

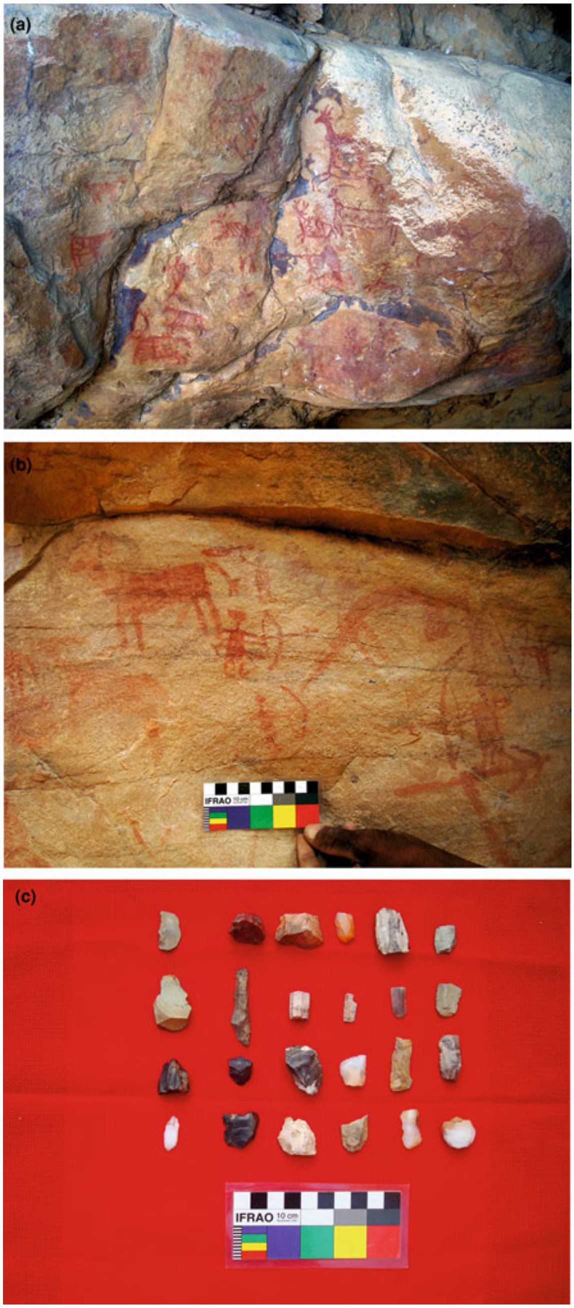


Fig. 7 **a**–**c** Rock shelter and Painted sites located on the landscape discovered during field survey (**a** Animals depicted in the rock art; **b** battle scene in the rock art; **c** Stone tools or archaeological artefacts found from the rock-shelters)

archaeology. Therefore, it is not widely known yet. The lack of specialist knowledge and neglect from the local population is leading to the destruction of several painted sites of intense heritage value in Mirzapur. This predictive model would help to determine new regions for pilot surveys to discover new sites. Apart from this, the models for locational and landscape archaeology would be beneficial to come up with the contingency plans to rescue and protect the sites, that are under the constant threat of destruction. Most of the times, painted shelters have been detected along with large amount of archaeological materials, present on the surface of the sites. The quarrying of sandstone, sometimes panels with prehistoric paintings of invaluable tangible heritage value in this region is gradually obliterating all the traces of prehistoric cultural heritage from the area. Therefore, accurate mapping of sandstone, along with the land cover and present day land use pattern in this region play an important role not only to locate new sites, but also to protect the global cultural heritage and local natural resources.

5 Conclusion

The accurate mapping of sandstone that hosts prehistoric art has been able to reveal a few important parameters in terms of the understanding of local geology, used and exploited by the prehistoric hunter-gatherers and technicalities involved in the process and methodologies of RS and GIS. The ground truthing and survey work together identified the distribution and patterning of rock-shelter sites in the Mirzapur and Rewa districts. Preliminary survey and cataloguing of the art in the region showed basic inter-site clustering and rudimentary patterns. The innumerable number of sites located in this region demonstrates the importance of rock in rock art and archaeology and that rock in itself is very important just as rock art. The movement of rock art, in terms of shelters scattered across the landscape of the art is defined and constructed by sandstone. The prehistoric hunter-gatherers understood the value of sandstone, not only to create art for communicative purposes but also to demarcate the landscape. The host-rock, which is sandstone, both represents prehistoric lifeways through long painting activities and local geology that remained partly unaltered in the region. The applications of ANN and MLC for the dataset on rock art suggests a higher accuracy level for the ANN subset and hence the classifiers. With a differential degree of accuracy, both ANN and MLC have been able to map the natural sandstone outcrop and the location of painted rock-shelters within the landscape characterising all other features; which indicates the viability for these techniques in landscape archaeology and archaeological locational modelling. This study has detected a clear combination of the co-existence of geological formation of sandstone and archaeological sites in the form of painted rock-shelters in the districts of Mirzapur and Rewa. The sandstone shelters followed a linear trend criss-crossing the South-Western border of the Mirzapur district and Eastern part of the Rewa district establishing the importance of local geology in archaeological site formations and the mobility of rock art in the region exposing the elements of hunter-gatherer ways of life. Finally, the present results on sandstone mapping suggest that future studies could be focussed on the adjoining and extended sandstone belts of the Mirzapur and Rewa districts in order to find several new archaeological sites with prehistoric and/or historic paintings and stone tools.

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