Automatic Extraction of Landforms in a Complex Terrain of Western Ghats Region of India Using Earth Observation Datasets and GIS

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ABSTRACT: In this study, the SRTM digital elevation model (DEM) of 30m resolution and SENTINEL-2B satellite data (10m) were used to delineate distinct landforms in complex terrain of Pune district, Maharashtra, India using multi-resolution segmentation algorithm. The study area covered the Pune district of Western Ghats, Maharashtra, India. The SRTM DEM (30m resolution) was used to generate slope, aspect, hillshade, flow accumulation, contours, curvatures (plan, profile, total) and drainage network and Iso-cluster unsupervised classification was used for generating land use / land cover. Methods employed included of multi-resolution segmentation algorithm for generating landforms. In particular, the terrain variables employed for generating landforms in the study area are: elevation (m, above mean sea level), slope (percentage), contour (50m interval), plan curvature (m m^{-1}), profile curvature (m m^{-1}), Total curvature (m m^{-1}), hillshade, flow accumulation and drainage (200 stream cell count) and generated land use / land cover. The knowledge-based classification of the primitive objects based on their elevation and shape parameters, resulted in the extraction of the landforms. The analysis shows that alluvial plain occupies about 22.0 per cent of the TGA of the district, mostly spread in Daund, Baramati and Indapur thesils. Whereas, pediments were noticed mainly in Sirur and Purender thesils with an area of 16.4 per cent of the TGA of the district. The resulted boundaries in comparison to those by previous studies were found satisfactory. The study demonstrates that automatic extraction of landforms can be carried out using high resolution satellite data and DEM through multi-resolution segmentation algorithm.

1. INTRODUCTION

The geomorphological mapping is a central platform for recording landform data paved its role as a key organizational framework for the study of landforms, their history, materials and the processes associated with them. Landforms are regarded as “one type of geomorphological objects” that divide the surface of the Earth into fundamental spatial entities. These entities define the boundary conditions for operative processes in geomorphology, hydrology, ecology, and pedology (Evans 2012; Draguţ et al. 2012). Landform quantification and recognition gained popularity worldwide because of their vital significance in elucidating the formation mechanism and spatial heterogeneity of landform evolution (Cheng et al. 2011; Jasiewicz et al. 2013; Martins et al. 2016). Landforms are classified based on the physical characteristics such as elevation, slope, orientation, stratification, rock exposure, and soil type. There are different types of landforms such as hills, mountains, plateaus, canyons, valleys shoreline features such as bays, peninsulas, and seas, including submerged features such as mid-ocean ridges, volcanoes, and the great ocean basins. Landforms as physical constituents of landscape may be extracted from DEMs using various approaches including combination of morphometric parameters subdivided by thresholds (Dikau 1989), fuzzy logic and unsupervised classification (Adediran et al. 2004; Burrough et al. 2000; Irvin et al. 1997), supervised classification (Brown et al. 1998; Hengl and

Prima et al. 2006), probabilistic clustering algorithm (Stepinski and Vilalta 2005), automated classification using object-based image analysis (Dragut and Blaschke 2006; Yunhao et al. 2019) multivariate descriptive statistics (Dikau 1989; Evans 1972), double ternary diagram classification (Crevenna et al. 2005), discriminant analysis (Giles 1998) and neural networks (Ehsani and Quiel 2007b). The objective of this study was the use of object-oriented image analysis methods for the automatic extraction of physiographic features.

Remote sensing and Geographic Information System (GIS) tools could be helpful in getting the precise and valuable spatial information in understanding and predicting the future trends. In recent years remote sensing has achieved progress both in sensors and image analysis algorithms. At the same time, research has progressed in computer vision methods applied to remotely sensed images such as segmentation, object oriented and knowledge based methods for classification of high-resolution imagery (Schiewe J., 2002, Argialas and Harlow 1990, Kanellopoulos et al. 1997). Only very recently however, a new methodology called Object Oriented Image Analysis was introduced, integrating low-level, knowledge-free segmentation with high-level, knowledge-based fuzzy classification methods. This new methodology was made available with an object oriented environment, for the classification of satellite imagery (Benz, et al. 2004). In the past, research has been done in building knowledge bases for the interpretation of landforms and in methods for automatic landform extraction from Digital Elevation Models and satellite images (Argialas and Miliaresis 1997, Miliaresis and Argialas 2000). It is not possible to separate the mountain ranges from the basins and piedmonts by thresholds (Miliaresis and Argialas 2000). Therefore, a segmentation procedure was required to delineate the distinct landforms from a DEM using multispectral and panchromatic satellite imageries to extracts the features for understanding the land use / land cover and landforms of study area (i) to generate spatial digital database on high resolution satellite data and DEM to derive land use / land cover and various terrain parameters of the study area, and (ii) to integrate the terrain and land use parameters through multi-resolution segmentation algorithm to delineate the distinct landforms of the study area using eCongnition software.

2 STUDY AREA

Pune district is in the western part of Maharashtra and lies on the western margin of the Deccan plateau, at an altitude of 560 m (1,840 ft) above mean sea level on the eastern side (Fig. 1). It extends between 18° 31' 0.2136" N latitudes and 73° 51' 22.5180" E Longitudes and covers the geographical area of 15.642 sq.km. The study area experiences a hot semi-arid climate (BSh) bordering with tropical wet and dry (*Aw*) with average temperatures ranging between 19°C and 33°C. Due to the presence of Sahyadri ranges in its western part, the district gets an adequate supply of water through rainfall. The landscape of the district is distributed triangularly in western Maharashtra at the foothills of the Sahyadri Mountains and is divided into three parts viz. *"Ghatmatha" "Maval"* and *"Desh*". Pune district forms a part of the tropical monsoon land and therefore shows a significant seasonal variation in temperature as well as rainfall conditions. The red sandy soils have been developed in western and central part of study area and covers major part of the study area. However, the shallow black soils have developed in the eastern part of the area, whereas medium black soils have developed along the minor drainage courses in the south and south-eastern parts of the area. Major crops in the districts are Rice, Bajara, Tur, Moong, Udid, Groundnut, Soyabeen, Jawar, Wheat, Pulses, Sunflower and Sugarcane and horticulture crops like Mango, Banana, Grapes, Chiku and Pomegranate are in a large scale.

3. MATERIALS AND METHODS

3.1 Datasets used

The datasets used for the study included Sentinel-2B satellite image and Shuttle Rader Topography Mission Digital Elevation Model (SRTM DEM), were acquired form United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/). The datasets used for the study are shown in the following table 1.

Table 1 Datasets used in the Study

Datasets	**Spatial Resolution**	**source of the data**
Sentinel-2B	10 m	https://earthexplorer.usgs.gov/
SRTM DEM	30 m	https://earthexplorer.usgs.gov/

3.2 Processing of Sentinel-2B data

The Sentinel-2B satellite data (10m resolution) was acquired from the USGS for the study area. The image mosaic was generated from the data acquired. The false colour image composites were generated for the further processing. The clip function in ArcGIS 10.1 under data management tool was used for sub-setting to cover the study area. The Iso-cluster unsupervised classification algorithm was used to generate the land use/land cover map and given input as a satellite data.

3.3 Processing of SRTM DEM data

Morphometric terrain classification takes form of many different methods and is commonly used in studies that employ analyses of geomorphological ground surface mapping (Kringer, 2010). In most cases the DEM serves as source data that are used to define specific landforms or shapes in topography via parametric statistics-based raster processing (Schneider et al., 2015). These morphometric parameters (or variables) can be effectively used to indicate features with clearly distinct characteristics relative to the neighbouring terrain (Draguţ & Blaschke, 2006). Therefore, the SRTM DEM (30m resolution) data were used in this study and the data has downscaled to 10 m by neighbourhood statistic function. The slope value of this plane is calculated using the average maximum technique. The direction the plane faces is the aspect for the processing cell. The lower the slope value, the flatter the terrain; the higher the slope value, the steeper the terrain. The output slope raster can be calculated in two types of units, degrees or percent (percent rise). Flow direction determines which direction water will flow in a given cell. The flow direction is measure based on the direction of the steepest descent in each cell. In addition, the z-value difference and slope are calculated between neighbouring cells. If the Output drop raster option is chosen, an output raster is created showing a ratio of the maximum change in elevation from each cell along the direction of flow to the path length between centers of cells and is expressed in percentages.

The Flow Accumulation tool calculates accumulated flow as the accumulated weight of all cells flowing into each downslope cell in the output raster. If raster has no weight, a weight of 1 has been assigned to each cell, and the value of cells in the output raster is the number of cells that flow into each cell. Aspect defines the direction of flow. The values of each cell in the output raster indicate the compass direction that the surface faces at that location. It is measured clockwise in degrees from 0 (due north) to 360 (again due north), coming full circle. Flat areas having no downslope direction were given a value of -1. The hillshade tool obtains the hypothetical illumination of a surface by determining illumination values for each cell in a raster. It can greatly enhance the visualization of a surface for analysis or graphical display, especially when using transparency. This function uses the latitude and azimuth properties to specify the sun's position. To calculate the shade value, first the altitude and azimuth of the illumination source were needed. These values will be processed with calculations for slope and aspect to determine the final hillshade value for each cell in the output raster.

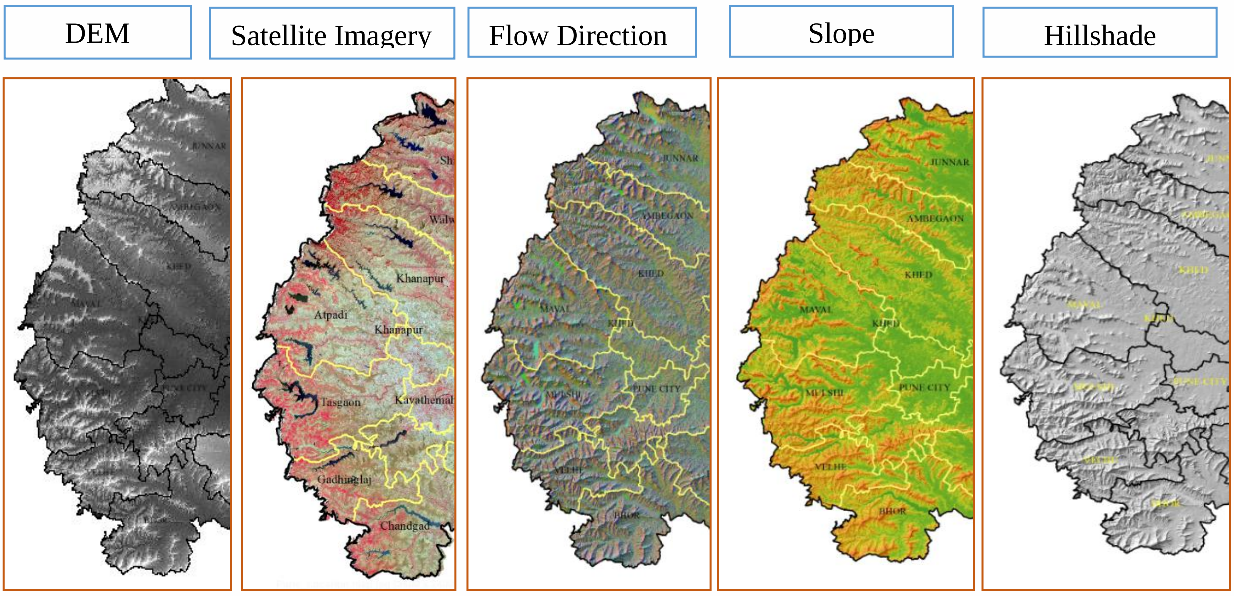

Figure 1 The processing of DEM data

3.4 Multi-resolution segmentation algorithm

Multi-resolution segmentation is a bottom-up multi-scale segmentation algorithm and is one of the most widely used and successful algorithms. The algorithm requires image band weights, scale parameter, shape, and compactness values to be specified prior to segmentation. The persistent challenge was how to identify these values, which were often determined by trial and error experimentation. A Multiresolution Segmentation (MRS) algorithm is frequently used in geomorphological studies; it minimizes the average intra-unit heterogeneity whereas maximizes the inter-unit heterogeneity of image objects by applying a mutual best-fitting approach. MRS is a bottom-up region-merging technique that merges the most similar adjacent regions as long as the internal heterogeneity of the resulting object does not exceed the user-defined threshold of the scale factor as well as both compactness and shape (Blaschke T., 2013). However, due to size variations of the target landforms, one cannot expect their accurate delineation as single objects at only one segmentation scale. Therefore, multiple segmentation levels were generated for a specific scene with the estimation-of-scale-parameter (ESP) tool (Dragut et al. 2010). The resulting local variance graphs indicated the statistically significant scales for MRS by showing the scale parameter at which local variance and rate of change is minimum. Once segmentation was optimized, knowledge-based rules were employed to classify the resulting segments into targeted landforms. The classification results were quantitatively compared with independent reference data.

4. RESULTS AND DISCUSSION

4.1 Analysis of parameters derived from digital elevation model

Slope analysis is an important parameter in geomorphic studies. The Slope has major implication for land use. The speed and extent of runoff depend on slope of the land. The degree of the slope sets limits on land use for annual crops, plantation and even on land reclamation depending on soil depth, stoniness, etc. Therefore, the degree and length of slope were important aspect in the study. The slope map was calculated into 8 classes for the study area. One of the keys to deriving hydrologic characteristics of a surface is the ability to determine the direction of flow from every cell in the raster. This was done with the flow direction tool. The tool takes a surface as input and outputs a raster showing the direction of flow out of each cell. The above figure (1) shows the flow direction map calculated in eight classes. The Aspect identifies the downslope direction of the maximum rate of change in value from each cell to its neighbours. Based on Aspect result, we can easily identify directions of the slope and what are the possible ways to water can flow. Contours were high in the western region of study area covers the high elevation of 1479 above the mean sea level. Contours were found less in the middle region and eastern region of study area covers the low elevation of 105 above the mean sea level. Displaying contours over a raster may help with understanding and interpreting the data resulting from the execution of the Curvature tool. The western region the talukas Purandhar, Velhe, Khed, Junner, Ambegaon, Maval, Mulshil, Bhor etc. were found in the high hilly areas.

The flow accumulation can be used to create a stream network by applying a threshold value to select cells with a high accumulated flow. The result of flow accumulation was a raster of accumulated flow to each cell, as determined by accumulating the weight for all cells that flow into each downslope cell. Output cells with a high flow accumulation were areas of concentrated flow and can be used to identify stream channels. Output cells with a flow accumulation of zero were local topographic highs and can be used to identify ridges. Using plan curvature and profile curvature equations the values for plan and profile curvature were calculated for all DEM cells except along the border of the DEM. Border cells values would have been calculated on the bases of non-existing cell values outside the raster, which cannot be estimated with sufficient accuracy. For the classification of landforms both curvatures values were encoded according to the most common signing convention with negative values for concave areas and positive values for convex areas. Drainage network of the study area was classified into 5 stream orders. As per law of stream number, the number of streams decreases as the stream order increases. The streams have been formed in dendritic drainage pattern. The calculation number of streams in number of orders retrieved that number of stream segments were decreases as the stream order increases.

4.2 Analysis of Land Use/Land Cover (LU/LC)

The land use/land cover (LU/LC) map was prepared based on visual analysis of current season images of SENTINEL-2B data so as to get the reliable land. The Land Use / Land Cover was classified in 12 classes including crop lands, crop plantation, terrace cultivation, fallow lands, forest, moderate forest, rivers, scrub lands, settlements, waste land and waterbody covers the total area of 1564329.2 hectors. Among the land use / land cover, the crop land covers the maximum area of 675771.8 ha. Crop plantation covers the area of 16948.0 ha. Terrace cultivation covers the area of 13116.4 ha, Fallow land covers the area of 210570.8ha., Forest covers the area of 347343.5, Moderate Forest covers the area of 41447.9 ha, River covers the area of 24722.2 ha, Scrub land covers the area of 109588.4 ha., Settlement covers the area of 80398.9 ha, Waste land covers the minimum area of 2288.4 ha and Waterbody covers the area of 39206.1 ha in Figure 2.

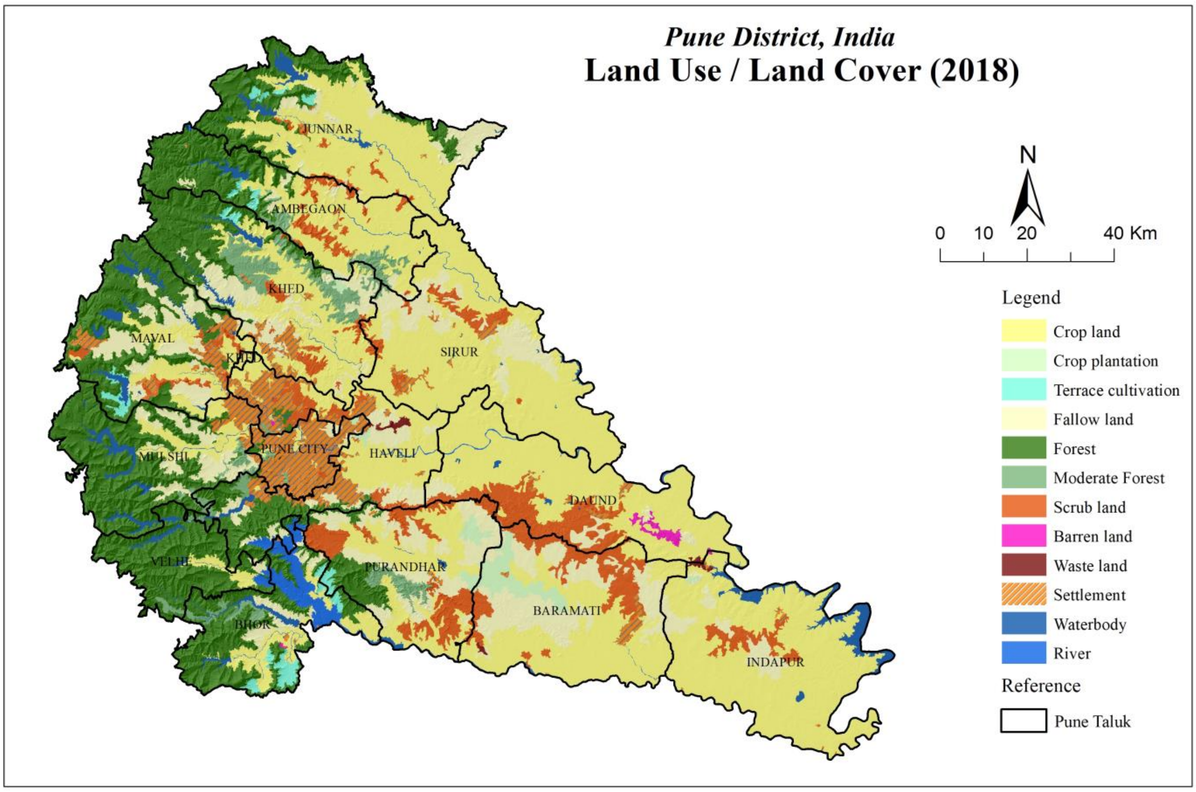

Figure 2 Land Use / Land Cover map of study area

4.3 Modelling of multi-resolution segmentation algorithm

The generated land use / land cover map from satellite imageries and Slope, plan curvature, profile curvature, total curvature, hill shade, flow accumulation, satellite image, Contours were generated from SRTM DEM (30m) were used as input layers for performing segmentation to extract landforms. After adding all the layers, a multi resolution segmentation algorithm was applied for extracting image primitives. Visual check using each of the three significant scale parameters in some of the window areas over the DEM scene helped in finalizing the optimum scale parameter as 150 and shape as well as compactness as 0.5 and 0.3, respectively. Once segmentation was optimized, knowledge-based rules were employed to classify the resulting segments into targeted landforms.

4.4 Analysis of landforms for Pune district

The landforms derived using multi-resolution segmentation algorithm modelling was presented Figure 3. The Overall spatial distribution of landforms in the study area has been modelled. The previous knowledge about the study area reveals the existence of major landforms as Hills and Ridges, Escarpment, Isolated Hillocks, Pediment, Alluvial Plains, High hills, Pedi plain, Valleys, Undulating Uplands and hill side slope, Settlements, River, and Water body. Henceforth, the landforms were modelled accordingly and further subdivided by the elevation factor wherever applicable. Among the landforms, Pediments cover maximum area of 255,954.3 ha followed by Pedi plain (220,834.2ha). The alluvial plains occupying maximum double cropped area was having 344,442.4 ha of coverage. Presence of considerable extent of escarpment (47,936.6 ha) along with the pediments signify the existence of eroded landscape to a greater extend. The dissected nature of landscape has been captured well through the channel landform identification using the stream ordering based growing region algorithm. The analysis shows that alluvial plain occupies about 22.0 per cent of the TGA of the district, mostly found in Daund, Baramati and Indapur thesils. Whereas, pediments were noticed mainly in Sirur and Purender thesils with an area of 16.4 per cent of the TGA of the district.

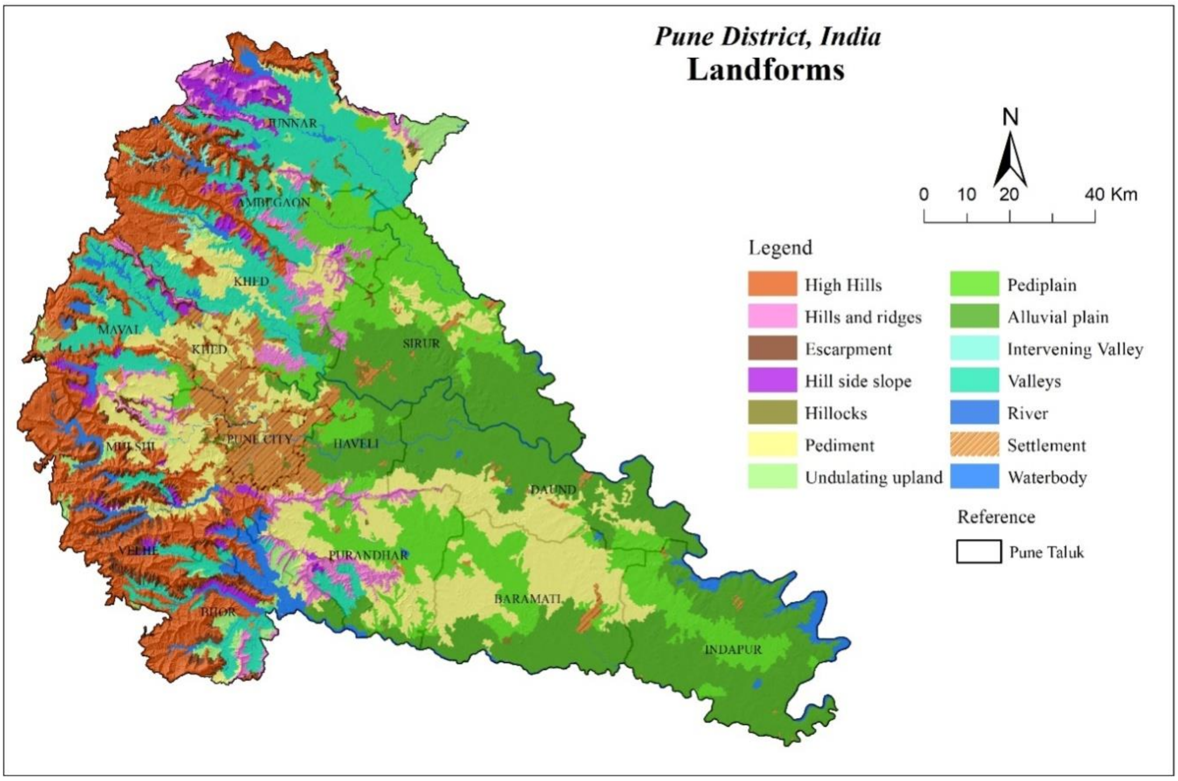

Figure 3 Landforms of Pune District

Table 2 Landforms of Pune district

Sr. No.	Landforms	Area (ha)	%
1	High hills	214174.2	13.7
2	Hills and ridges	68042.6	4.3
3	Escarpment	47936.6	3.1
4	Hill side slope	33467.5	2.1
5	Hillocks	10103.5	0.6
6	Pediment	255954.3	16.4
7	Undulating upland	29462.5	1.9
8	Pediplain	220834.2	14.1
9	Alluvial plain	344442.4	22.0
10	Intervening valley	4192.4	0.3
11	Valley	189879.7	12.1
12	River	861.5	0.1
13	Settlement	81267.9	5.2
14	Waterbody	63710.1	4.1
	Total	**1564329.3**	**100**

5. CONCLUSIONS

Landforms are the building blocks of landscapes, so measuring the morphometric properties of landforms can help evaluate how and why the physical attributes of landscapes vary over time and space and landform morphometry, based on geomorphological mapping, can therefore help distinguish between landscapes of different regions and their relative values. In this study an effort was made to extract landforms using multi-resolution segmentation algorithm from the SRTM DEM (30m) and SENTINEL-2B satellite data. The eastern part of the study area has very low elevation in the range of 95-577m above MSL and very high elevation in the range of 918-1,460m above MSL was found in the western part of the study area. A detailed understanding of slope distribution as the map helps in planning for various aspects like, settlement, agriculture, planning of engineering structure, etc. Slope was calculated as level in the range of <1 about area of 736,039 ha and very steep slope covers the area of about 4983 ha in the range of >60. Contours were high in the western region of study area covers the high elevation of 1,479 above the mean sea level and less in the medium region of study area covers the low elevation of 105 above the mean sea level. Contours are also a useful surface representation, because they allow you to simultaneously visualize flat and steep areas and ridges and valleys. From an applied viewpoint, the output of the curvature tool can be used to describe the physical characteristics of a drainage basin in an effort to understand erosion and runoff processes. The drainage network follows the dendritic drainage pattern in the western region to parallel in eastern region of the study area. Hills and Ridges, Escarpment, Isolated Hillocks, Pediment, Alluvial Plains, High hills, Pedi plain, Valleys, Undulating Uplands and hill side slope, Settlements, River, and Water body were the major landforms found in the study area. The analysis shows that alluvial plain occupies about 22.0 per cent of the TGA of the district, mostly spread in Daund, Baramati and Indapur thesils. Whereas, pediments were noticed mainly in Sirur and Purender thesils with an area of 16.4 per cent of the TGA of the district.

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