A Hierarchical Approach to Landform Classification of Satellite Images Using a Fusion Strategy

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Abstract. There is increasing need for effective delineation of meaningfully different landforms due to the decreasing availability of experienced landform interpreters. Any procedure for automating the process of landform segmentation from satellite images offer the promise of improved consistency and reliality. We propose a hierarchical method for landform classification for classifying a wide variety of landforms. At stage 1 an image is classified as one of the three broad categories of terrain types in terms of its geomorphology, and these are: desertic/rann of kutch, coastal or fluvial. At stage 2, all different landforms within either desertic/rann of kutch , coastal or fluvial areas are identified using suitable processing. At the final stage, all outputs are fused together to obtain a final segmented output. The proposed technique is evaluated on large number of optical band satellite images that belong to aforementioned terrain types.

1 Introduction

Landform Classification is a problem of identifying the predefined class of landforms, given a satellite image of the area. In order to explore the navigable areas, identification of the exact landform becomes a crucial task. Due to the varying geographic nature of landforms and existence of large number of classes, landform segmentation is very much different from a conventional image segmentation problem. Geographical definitions give only a very theoretical aspect of the size, shape and several other features of the landforms. For e.g. "Barchan dunes" are caused by highly uniform environmental conditions and wind blowing only in one direction. Barchans can become aligned together along a plane perpendicular to the wind. If the line becomes somewhat straight, dune scientists refer to these forward marching ridges as "transverse dunes". For such kind of landforms shape is an important feature. However the definitions do not clarify the type of shape features to be used for processing. Another category is the coastal bar. Coastal bars have no specific color, shape or size. Formulation of these abstract geographical definitions into a single set of features and rules is

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a difficult task for the purpose of segmentation or classification. Hence a single classifier or a single set of features cannot efficiently handle various types of landforms from a satellite image, we propose a hierarchy of classifiers in a unified framework.

A few approaches have dealt with the problem of landform identification in the past. However, only a limited set of landforms were used for classification. Pennock et al. [1] has dealt with the problem by using self organizing feature map. They calculate the DEM (Digital Elevation Model) and the land cover map as features. The DEM map normally divides the area into rectangular pixels and store the elevation of each pixel. These features are then fed to the SOM for further classification. The method is used to classify the landform of Kobe city in Japan into hill, plateau, fan and reclaimed land. These classified landforms were adopted for an earthquake damage evaluation of the 1995 Hyogoken Nanbu earthquake in Kobe. Gorsevski et al. [2] proposed a method to assign digital terrain attributes into continuous classes. They used fuzzy k-means for classifying the continuous landforms. The method finds its usefulness in overcoming the problem of class overlap. The aim is to describe landslide hazard in roaded and road less areas of a forest. As the size of the data increases and when there are artifacts introduced by the derivation of landform attributes from DEM, the performance of the fuzzy k-means suffers. Burrough et al. [3] proposed a method to overcome the limitations of the above given model by using spatial sampling, statistical modeling of the derived stream topology and fuzzy k-means using the distance metric. Results are shown on images obtained from Alberta, Canada, and the French pre-Alps.

SVMs is a state-of-art pattern recognition technique whose foundations stem from statistical learning theory [4]. They have widely been used in literature for image segmentation and classification. Chen et al. [5] presented an algorithm for image segmentation using support vector machines. They used two different sets of features for image segmentation - first, the gray levels of 5x5 neighboring pixels and second, the gray level and grad orientation of 9x9 neighboring pixels. They concluded that to obtain good segmentation results feature set should be chosen appropriately, for instance they achieved superior results using second feature set. Results on these two different set of features using SVM as classifier, are shown on two images in their work. Kim et al. [6] proposed an algorithm for texture classification using multi-class SVM. The gray levels in a window of 17x17 were used as features and multi-class SVM based on one-against-others decomposition is used for classification. They have compared the results with different kernels and by varying window sizes. They concluded that polynomial kernel with degree 5 gives superior results than other kernels. Results are shown on images composed of two-five textures.

In the work presented in this paper, we have employed hierarchical feature-based methods using image pixel intensity and shape, for the classification of different types of landforms. The flowchart for the complete methodology is shown in Fig. 1. The hierarchical approach used in this paper has enabled us to process a large variety of landforms with varying features. The rest of the paper is

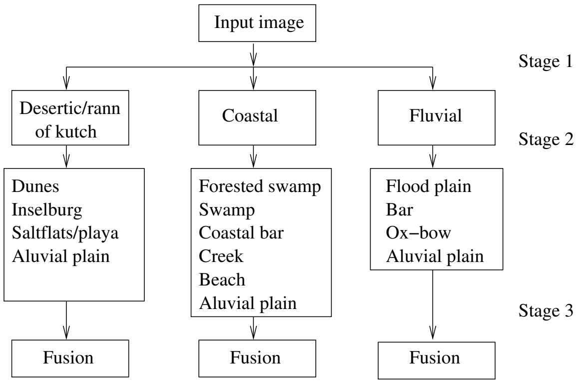


Fig. 1. Flowchart of the proposed hierarchical landform classification scheme

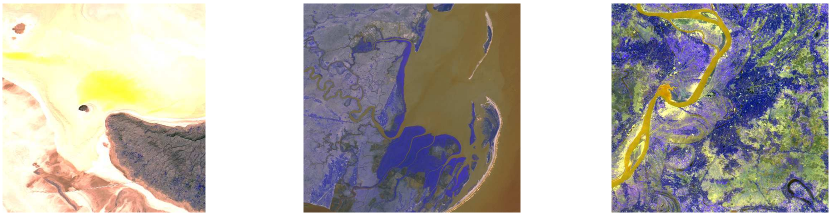
organized as follows. Section 2 gives overview of landform classification. Section 3 describes the proposed methodology. Section 4 discusses the experimental results obtained. Section 5 concludes the paper with the discussion on contribution.

2 Overview of Landform Classification

We attempt to solve the problem of landform classification from satellite images using a hierarchical method of segmentation. This is a divide-and-conquer strategy, which divides the complex problem into smaller solvable units. We have obtained training and testing samples of about 20 different landforms. The complexity lies in the fact that the rules governing a decision to obtain a landform widely varies from one to another. For example, some landform such as, dunes, inselberg, flood-plains have very distinct texture features, whereas water bodies, salt flats/playas have distinct band signatures, and others have very distinct shapes (OX-Bow, Meanders and Parabolic dunes) and sizes (swamps, plains etc.). The signatures, adjacency and association rules of these landforms are also fuzzy (uncertain), according to geo-morphologists who provide us with this ground truth.

The task is complex, as no classifier would be able to handle the wide variety of features (texture, color, size and shape), rules of association across all different landforms, and in some cases even for a particular landform. A large set of features extracted based on certain features will confuse a classifier, which will suffer from the following major disadvantages: correct and weighted combination of features, curse of dimensionality and lack of adequate training samples to capture the large variability within a class/landform.

The complete methodology for Landform classification can now be divided into three stages, which is depicted in Fig. 1. At the first stage, a SVM is used to classify an image belonging to either one of the three major terrains types found in the bed of earth (at least in India). These are Desertic/Rann of kutch



(a) (b) (c)

Fig. 2. Examples of a few set of satellite images for the three major terrains (a) Desertic terrian/Rann of kutch; (b) Coastal terrian; (c) Fluvial (river side) terrian

(we are considering rann of kutch and the desertic in a single category), Fluvial (river side) and Coastal landforms. This is a fundamental assumption in our approach and it works well for certain application, such as trafficability and disaster management for defense, GIS and resource mapping. As we are not interested in land-use patterns, urban areas are not considered. Examples of a few set of satellite images for the three major terrains are given in Fig. 2. We have assumed that coastal, fluvial and desertic are non-overlapping classes, which we typically found to be true in practical scenarios. For example, dunes can only occur in a desertic area, and coastal bars can only be found in a coastal area. Similarly, OX-BOW patterns can occur only in fluvial zones. This enables us to identify the probable set of landforms occurring in the input image, only under a particular super-group that has been determined at the first stage. Once the image is classified as desertic, fluvial or coastal, each pixel of the image is classified into the actual landforms with SVM, trained using mean of intensity features, computed as:

$$\mathbf{x}_{i,j} = \{\mu(I^r_{i,j}) \quad \mu(I^g_{i,j}) \quad \mu(I^n_{i,j})\} \tag{1}$$

where, $\mathbf{x}_{i,j}$ represents a 3D feature vector corresponding to $(i,j)^{th}$ pixel. $I^r_{i,j}$, $I^g_{i,j}$ and $I^n_{i,j}$ represent intensity values of $(i,j)^{th}$ pixel in Red, Green and NIR bands (the three spectral bands used for processing) of the input image, respectively and $\mu(h)$ represents mean of h in a 3x3 window. Other methods such as moments for shape matching [7] and pixel connectivity [8] are used to obtain other major landforms. Finally, outputs of different landforms are fused using a criteria to obtain final classification result. The complete methodology to obtain all landforms and fusion strategy employed to obtain final classification results is described in the following sections.

3 Description of the Methods Used for Classification

3.1 Supergroup Classification

This is the topmost stage of the proposed hierarchical classification as shown in Fig. 1. A Support Vector Machine (SVM) based classification technique has been adopted in our design for the task of identifying an input image as belonging to one of the desertic, coastal or fluvial landform super-groups. In order to capture and exploit the variability among the different multi-spectral images belonging to each of the super-groups, histograms of all the 3 bands: Red, Green and NIR bands are used as features for classification. Thus, the SVM-classifier in our case has been trained using histograms of all the three bands of multi-spectral training samples belonging to each one of the three: Desertic, Coastal and Fluvial categories. A high degree of success has been achieved at this stage which will be discussed in Sec. 4.

3.2 Desertic/Rann of Kutch Landform Classification

The flowchart of proposed methodology for the classification of landforms in a desertic/rann of kutch area is shown in Fig. 3. It can be observed from image shown in Fig. 8 that saltflats/playas (barren areas with highly saline and alkaline soils, formed through the concentration of mineral residues in salt water) appear bright and inselberg/rocky exposure (a steep ridge or hill left when a mountain has eroded and found in an otherwise flat, typically desert plain) appear dark as compared to dunes/sandy plains (mounds of loose sand grains shaped up by the wind). We exploit this property to differentiate between these three landforms. The steps of processing used for classification are as follows:

1. A multi-class SVM (using one-against others decomposition [6]) trained using mean of pixel intensity values of all three spectral bands, is used to differentiate between dunes/sandy plains, rocky exposure and saltflats/playas.
2. The output obtained is fused using algorithm described in Sec. 3.5.

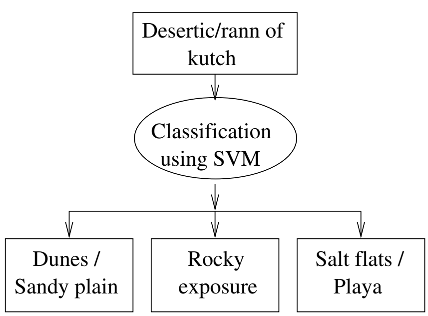


Fig. 3. Flowchart showing stages of classification of desertic landforms. Features used for SVM are mean of pixel intensity values of all three spectral bands.

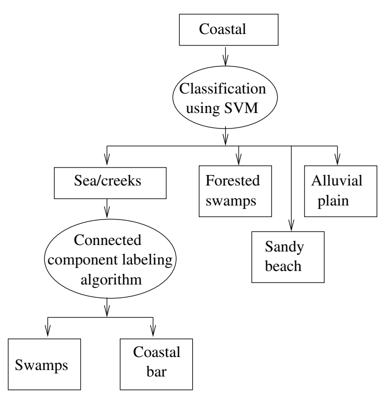


Fig. 4. Flowchart showing stages of classification of coastal landforms. Features used for SVM are mean of pixel intensity values of all three spectral bands.

3.3 Coastal Landform Classification

The flowchart of proposed methodology for the classification of landforms in a coastal area is shown in Fig. 4. It can be observed from the image shown in Fig. 9(a) that intensity-based features have a major role to play for extraction of coastal landforms. Association rules have also been employed in order to encode human-knowledge in observing certain key characteristics of coastal landforms within the system. The steps of processing for identification of landform in coastal images are as follows:

1. A multi-class SVM (using one-against others decomposition [6]) trained using mean of pixel intensity values of all three spectral bands, is used to differentiate between sea, forested swamp (a wetland containing trees), sandy beach and alluvial plain.
2. Since coastal bars are landforms that possess unique characteristic property of being enclosed by sea on all sides, a connected component [8] labeling algorithm is employed to determine all connected components surrounded by sea.
3. Similarly, swamps (a wetland that features permanent inundation of large areas of land by shallow bodies of water) are patches of land that possess high water-content and have been obtained by identifying segments classified as sea in step 1 surrounded by land.
4. The outputs obtained in steps 1,2 and 3 are fused using the algorithm described in Sec. 3.5, to obtain final classification results.

3.4 Fluvial Landform Classification

The flowchart of methodology followed for the classification of landforms in a fluvial area is shown in Fig. 5. An example of fluvial image is shown in Fig. 10(a) Since fluvial landforms are produced by the action of river or an active channel, a satellite image taken of a fluvial area mostly contain an active channel within it. The steps of processing for identification of landfroms in fluvial images are as follows:

1. A multi-class SVM (using one-against others decomposition) trained using mean of pixel intensity values of all three spectral bands, is used to differentiate between active channel, flood plain (the low area along a stream or river channel into which water spreads during floods) and alluvial plain.
2. Flood plains in general occur adjacent to active channel, a connected component [8] labeling algorithm is employed to confirm that all segments identified as flood plains in step 1 are connected to active channel. The segments that are not connected to active channels (river) are classified as alluvial plains.
3. A SVM trained using moment features [7] (shape) is used to distinguish oxbow (a U-shaped bend in a river or stream) and active channel among the segments which are classified as active channel in step 1.

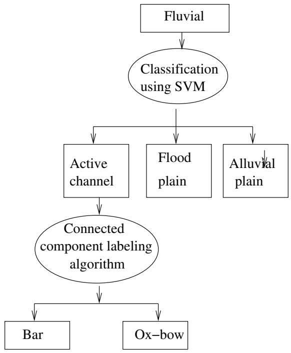


Fig. 5. Flowchart showing stages of classification of fluvial landforms. Features used for SVM are mean of pixel intensity values of all three spectral bands.

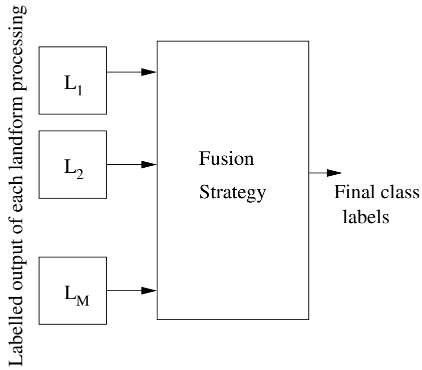


Fig. 6. Block diagram of the fusion strategy

4. Since bars are landforms that possess unique characteristic property of being enclosed by active channel on all sides, a connected component labeling algorithm is employed to determine all connected components surrounded by active channel.
5. The outputs obtained in steps 1,2,3 and 4 are fused using algorithm described in Sec. 3.5 to obtain final classification results.

3.5 Fusion

As mentioned in Sec. 2, an input image may contain multiple landforms within it. However, due to the diverse characteristics (properties) possessed by different landforms, specific processing algorithms have been designed and implemented for extraction of a few landforms. As mentioned above, all segmentation results produced from the different processing algorithms, need to be merged and combined appropriately. We need an efficient process of merging or fusing the outputs of different classifier, as a perticular pixel may be assigned to two or more number of classes by different classifiers.

The strategy adopted by the current system design, attempts to fuse segmentation results of individual landforms on the basis of their association and adjacency phenomena to occur together in nature. Using knowledge acquired from domain experts in geomorphology three adjacency Tables 1 - 3 have been built in order to encode the adjacency relationships that exist among different landforms under each super-group. Before fusing results of two different landforms under the same super-group, their corresponding entry in the adjacency table is checked. In case their association is invalid (as indicated by 'NA'), there is no chance whatsoever for the two candidate landforms to occur together and therefore cause an uncertainty. In the other case when their association is valid (as indicated by a landform index with higher precedence), the two landforms under consideration may have a pixel overlap and in such cases their fusion is

Table 1. Adjacency table for desertic/rann of kutch landforms

	Dunes (L_1)	**Rocky exposure** (L_2)	**Saltflats** (L_3)
Dunes (L_1)	-	L_2	L_3
Rocky exposure (L_2)	L_2	-	L_2
Salfflats (L_3)	L_3	L_2	-

Table 2. Adjacency table for coastal landforms

	Swamp (L_1)	**Forested swamp** (L_2)	**Coastal bar** (L_3)	**Beach** (L_4)	**Creek/ sea**(L_5)	**Alluvial plain** (L_6)
Swamp (L_1)	-	NA	L_3	L_4	NA	L_1
Forested swamp (L_2)	NA	-	Both	L_4	NA	L_2
Coastal bar (L_3)	L_3	Both	-	L_4	L_3	L_3
Beach (L_4)	L_4	L_4	L_4	-	L_4	L_4
Creek/Sea (L_5)	NA	NA	L_3	L_4	-	L_5
Alluvial plain (L_6)	L_1	L_2	L_3	L_4	L_5	-

Table 3. Adjacency table for fluvial landforms

	Ox-bow (L_1)	**Active channel** (L_2)	**Bar** (L_3)	**Flood plain** (L_4)	**Alluvial plain** (L_5)
Ox-bow (L_1)	-	NA	NA	L_1	L_1
Active channel (L_2)	NA	-	L_3	L_2	L_2
Bar (L_3)	NA	L_3	-	L_3	L_3
Flood plain (L_4)	L_1	L_2	L_3	-	L_4
Alluvial plain (L_5)	L_1	L_2	L_3	L_4	-

done by assigning the area of overlap to the landform with higher precedence. The block diagram of the fusion stage has been shown in Fig. 6.

The fusion strategy adopted for combination of labeled outputs of each landform processing is given below. For combination of two labeled outputs $L_k(X, Y)$ and $L_j(X, Y)$ to form the combined output $O(X, Y)$, (where k and j are the highest labels in precedence among all the class labels assigned before fusion, $1 \leq k, j \leq M$). M being the number of possible landform classes with in that super-class (desertic, fluvial or coastal).

Algorithm for Fusion

1. If landforms k and j do not occur together then output $O(X, Y)$ is given as:

$$O(X, Y) = \underset{1 \leq j \leq M}{\operatorname{argmax}} \, c_j(X, Y) \tag{2}$$

   where, c_j is the number of times label j appears in the neighborhood of point (X, Y).

2. If landforms k and j may occur together then output $O(X,Y)$ is given as:

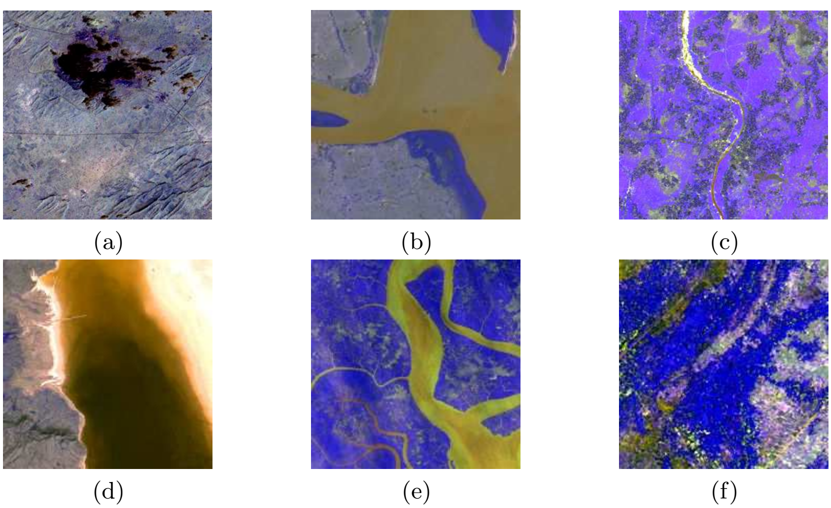
$$O(X,Y) = \begin{Bmatrix} L_k(X,Y) & if & prec(k) > prec(j) \\ L_j(X,Y) & if & prec(j) > prec(k) \\ \Psi(X,Y) & if & prec(j) = prec(k) \end{Bmatrix} \tag{3}$$

where, the function $prec()$ is encoded in the adjacency table and $\Psi(X,Y)$ is the new label assigned to the pixel (X,Y).

The adjacency table for all super-group classes (types of terrains) are shown in Tables 1 - 3. Each adjacency table is a symmetric matrix of size $N * N$, where N is the total number of landforms within that super-group. The entries in any adjacency matrix are:
L_i - Landform number with higher precedence among the two adjacent landforms.
N/A - Invalid (not possible).
Both - If both landform occur with equal precedence.
Knowledge of geoscientists is encoded in the table. Experts opinion is conseiderd to form the adjacency matrix.

4 Experimental Results

To verify the effectiveness of the proposed method, experiments were performed on several test images of size 300x300. The SVM used for super group classification was trained using 180 training samples (60 for each class) and tested



(a) (b) (c) (d) (e) (f)

Fig. 7. Examples of classified ((a)-(c)) and missclassified ((d)-(f)) images at stage 1 (supergroup classification): (a) Desertic Image; (b) Coastal Image; (c) Fluvial Image; (d) Rann of kutch image misclassified as coastal; (e) Coastal image misclassified as fluvial; (f) Fluvial image misclassified as coastal

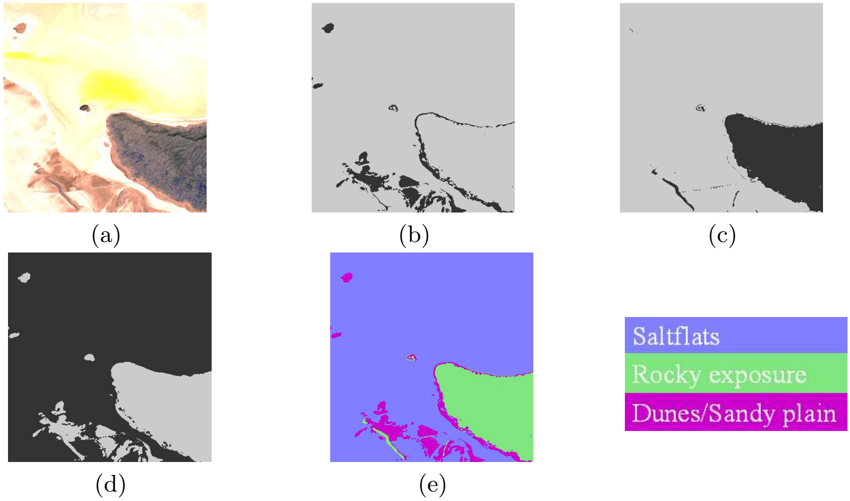


Fig. 8. (a) Input image consists of desertic landforms (b) Dunes/Sandy plains; (c) Inselburg/rocky exposure; (d) Saltflats/playa; (e) Fused Result

using 600 samples (200 each class). We obtained 99.2% of classfication accuracy, with a SVM using polynomial kernel of degree 2. Figs. 7(a)-(c) show examples of correctly classified images of desertic, coastal and fluvial terrians, respectively at stage 1 (supergroup classification). Figs. 7(d)-(f) show examples of a rann of kutch, coastal, fluvial terrians misclassfied as coastal, fluvial, coastal terrians, respectively at stage 1 (supergroup classification).

Results obtained at stages 2 and 3 using our proposed methodology are shown in Figs. 8 - 10. Fig. 8(a) shows input image of a desertic/rann of kutch area. The corresponding landfroms obtained after classification are shown in: (b) dunes/sandy plains; (c) rocky exposure; and (d) saltflats/playas. Result obtained after fusing the individual outputs is shown in Fig. 8(e). Fig. 9(a) shows input image of a coastal area. The corresponding landforms obtained after classification are shown in: (b) coastal bar; (c) forested swamp; (d) swamp; (e) beach; (f) sea/creek and (g) alluvial plain. Result obtained after fusing the individual outputs is shown in Fig. 9(h). Fig. 10(a) shows input image of a fluvial area. The corresponding landforms obtained after classification are shown in: (b) active channel; (c) flood plain; (d) bar; (e) ox-bow; and (f) alluvial plain Result obtained after fusing the individual outputs is shown in Fig. 10(g). Although active channel is not a landform but it is shown because other landforms are associated with the active channel. It can be observed from Figs.8-10, that each landform has been identified correctly in the final output.

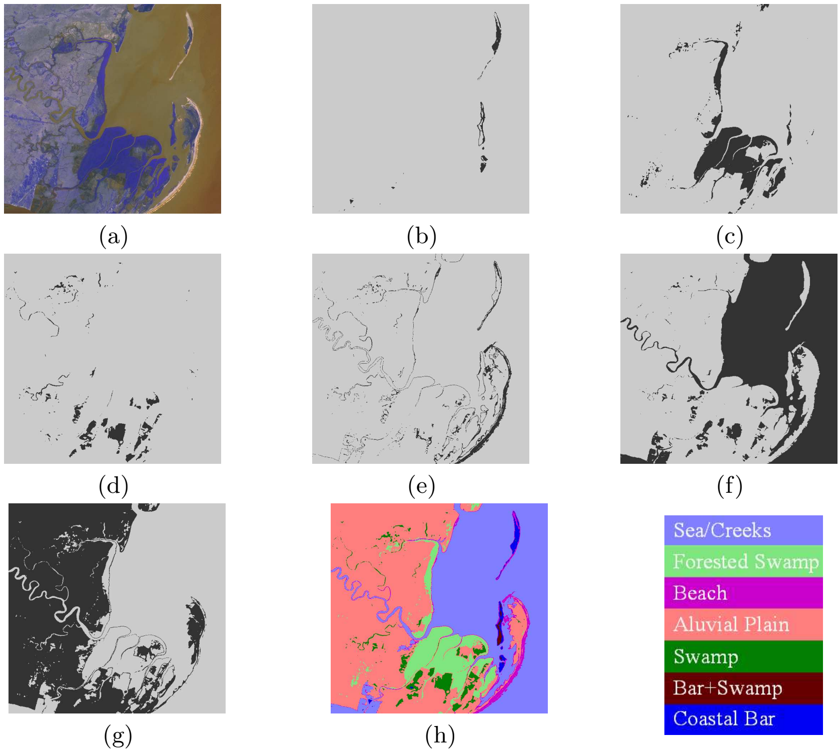


Fig. 9. (a) Input image consists of coastal landforms; (b) Coastal bar; (c) Forested swamp; (d) Swamp; (e) Beach; (f) Creeks/sea; (g) Alluvial plain; (h) Fused result

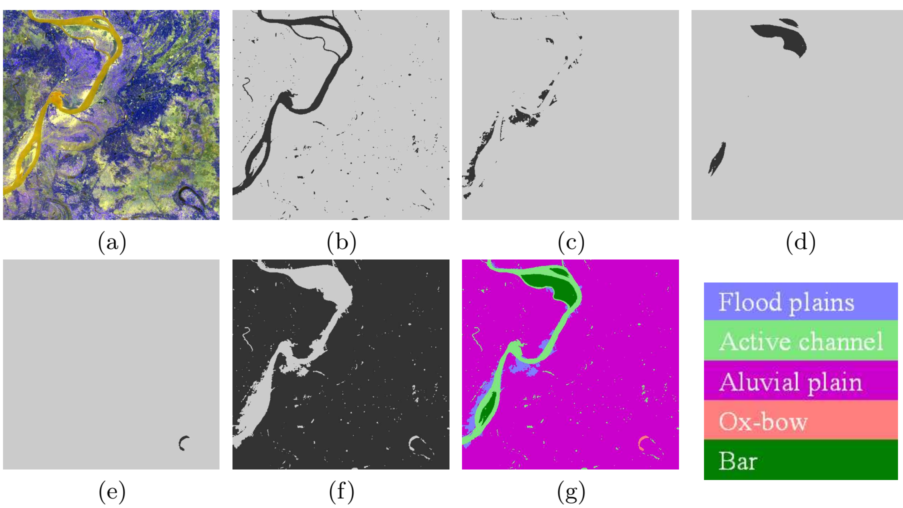


Fig. 10. (a) Input image consists of fluvial landforms; (b) Active channel; (c) Flood plain; (d) Bar; (e) Ox-bow; (f) Alluvial plain; (g) Fused Result

5 Conclusion

A hierarchical approach for landform classification has been proposed in the paper. The proposed hierarchical framework enables us to consider large number of landform classes for segmentation of satellite images. The proposed methodology has been tested on a large number of images. Results show that all major landforms have been identified correctly. With the increase in the number of landforms the complexity of the adjacency table will also increase, as well as the super-classes in Fig. 1. However the performance of the system has yet to be analysed for such situations. Future work includes expanding the system to handle more set of landforms, for instance, a method to discriminate among different dunes.

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